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Thiago Ângelo Gelaim

Situation Awareness and Practical Reasoning in Dynamic Environments

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Orientador: Prof. Ricardo A. Silveira, Dr.
Coorientador: Prof. Bruno M. Fazenda, Dr.

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O presente trabalho em nível de doutorado foi avaliado e aprovado por banca examinadora composta pelos seguintes membros:

Profa. Anarosa Alves Franco Brandão, Dra.
Universidade de São Paulo

Profa. Graçaliz Pereira Dimuro, Dra.
Universidade Federal do Rio Grande

Prof. Elder Rizzon Santos, Dr.
Universidade Federal de Santa Catarina

Profa. Silvia Modesto Nassar, Dra.
Universidade Federal de Santa Catarina

Certificamos que esta é a **versão original e final** do trabalho de conclusão que foi julgado adequado para obtenção do título de doutor em Ciência da Computação.

Documento assinado digitalmente
Vania Bogorny
Data: 18/01/2021 08:50:57-0300
CPF: 684.586.570-15

Profa. Vania Bogorny, Dra.
Coordenadora do Programa

Documento assinado digitalmente
Ricardo Azambuja Silveira
Data: 17/01/2021 12:11:51-0300
CPF: 231.225.790-49

Prof. Ricardo A. Silveira, Dr.
Orientador

Florianópolis, 2021.

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RESUMO

A criação, a proliferação e o consumo de informações são constantemente observados na sociedade. Um agente situado em um ambiente dinâmico está suscetível a perceber grande quantidade de informações, sendo que muitas delas são irrelevantes para os seus objetivos atuais. Além disso, dado o estado do ambiente, uma situação pode ser modelada utilizando diferentes representações de conhecimento, como por exemplo, ontologias para modelar situações com semântica bem definida, e redes Bayesianas para situações de incerteza. Dessa forma, o agente deve ser capaz tanto de perceber de acordo com seus objetivos, quanto integrar essas percepções conforme a representação da situação utilizada. A literatura descreve agentes BDI como adequados para atuar em ambientes dinâmicos, porém considera a percepção do ambiente como dependente da implementação e independente do raciocínio do agente e a flexibilização do raciocínio para representar situações é limitada. Com base nisto, esta pesquisa investiga a utilização de mecanismos de percepção e de representação de situações no raciocínio do agente de modo a aprimorar sua tomada de decisão. O agente é modelado com a perspectiva de sistemas multicontexto, permitindo a decomposição modular de seus componentes. Essa abordagem possibilita a adição de situações representadas em diferentes formalismos e seus relacionamentos com os demais componentes do agente. Um componente pode ser representado por um ou mais contextos do sistema multicontexto, e a troca de informações entre contextos é feita por meio de regras de ponte. Uma regra de ponte é formada por uma cabeça, o contexto que adicionará uma nova informação, e um corpo, o conhecimento que precisa ser satisfeito em um ou mais contextos para que a informação seja adicionada na cabeça. Para avaliar a operacionalização é desenvolvido o framework Sigon, a primeira implementação para o desenvolvimento de agentes situados em ambientes dinâmicos como sistemas multicontexto. São apresentadas implementações realizadas no framework adicionando contextos para representar situações com ontologias e redes Bayesianas, e estratégias para estender a arquitetura do agente por meio de regras de ponte. A parte experimental da pesquisa é desenvolvida no contexto da computação urbana. Inicialmente são realizados três experimentos utilizando realidade virtual para encontrar novos entendimentos do impacto de distrações em smartphones na consciência situacional de pedestres. Testes estatísticos foram realizados nos conjuntos de dados criados, e associações foram encontradas mostrando que eventos inseguros e tempo de resposta aumentam com distrações no smartphone. Por fim, é simulado um ambiente urbano para avaliar o processo perceptivo e a utilização no apoio a tomada de decisão de um agente implementado em Sigon. A análise destes experimentos seguiu a abordagem *Factorial Designs* para avaliar a influência dos fatores de percepção ativa e passiva, recebimento contínuo de dados, ontologias e redes Bayesianas no tempo de tomada de decisão. A percepção de informações irrelevantes para os objetivos atuais aumentam o tempo para a tomada de decisão em ambientes dinâmicos, mas percepção ativa e políticas de percepções são estratégias para reduzir esse problema. Os resultados fomentam o desenvolvimento de agentes como sistemas multi-contexto para a computação urbana.

Palavras-chave: Agente. Consciência Situacional. Sistemas Multicontexto. Computação Urbana. Ontologia. Rede Bayesiana.

RESUMO ESTENDIDO

Introdução

A criação, a proliferação e o consumo de informações são observados em nossa sociedade (GANDOMI; HAIDER, 2015; HILLS, 2019). Por exemplo, em ambientes dinâmicos, a todo instante estão sendo criadas novas informações e um agente situado no ambiente precisa considerar essas informações em sua tomada de decisão. Dispositivos computacionais nestas circunstâncias apresentam restrições de tempo, espaço e comunicação para processar todos os dados disponíveis. De forma similar, um humano operando em um ambiente complexo e dinâmico pode *'ser severamente desafiado a organizar todas as informações disponíveis de uma forma que seja gerenciável para tomar decisões precisas'* (ENDSLEY, 2016, pag. 3). Em um ambiente urbano é possível observar tanto a limitação de dispositivos computacionais quanto a de seres humanos. Um smartphone apresenta capacidade de detecção física, cognitiva, emocional e social, porém, a sua capacidade para armazenar e processar essas informações é limitada (KONSOLAKIS et al., 2018). Um pedestre ou motorista utilizando smartphone enquanto anda ou dirige apresenta redução no processo de tomada de decisão (JIANG et al., 2018; OVIEDO-TRESPALACIOS et al., 2018). Nestas situações, um agente inteligente pode atuar como uma interface entre o ambiente complexo e dinâmico e a consciência situacional limitada do usuário (FERNANDEZ-ROJAS et al., 2019). O paradigma de agentes em ambientes dinâmicos permite a criação de agentes para o gerenciamento distribuído e descentralizado de informações (JULIAN; BOTTI, 2019; RAKIB; UDDIN, 2019). Isso permite que o agente escolha uma ação adequada para a região, contexto, em que ele está situado. Para um objetivo atual, ele deve decidir quais partes do ambiente são relevantes e construir um modelo do estado futuro (DAHNL; GRASS; FUCHS, 2018; GEHRKE, 2009). Um agente precisa combinar informações representadas em diferentes formalismos para melhorar as decisões tomadas. Existem várias formas de combinar conhecimento contextual, por exemplo, filtros de Kalman, *co-training*, *ensemble learning*, e sistemas multicontexto (GJORESKI, 2015; GIUNCHIGLIA; SERAFINI, 1994). Um sistema multicontexto permite representar um agente como um conjunto de contextos, onde um contexto é definido usando o formalismo que melhor descreve uma característica do ambiente, situação ou capacidade do agente (GIUNCHIGLIA; SERAFINI, 1994). As regras de ponte descrevem como serão realizadas as trocas de informações entre os contextos (BREWKA; EITER, 2007; BREWKA et al., 2018). De acordo com a perspectiva de representação de conhecimento, essa decomposição modular permite o desenvolvimento de agentes utilizando múltiplas representações, em que cada contexto representa um componente do agente, aumentando a sua representatividade e simplificando-o conceitualmente (SABATER et al., 2002; DYOUB; COSTANTINI; GASPERIS, 2018). O uso de sistemas multicontexto é proeminente em ambientes dinâmicos, porém seu uso prático ainda é abstrato (BREWKA et al., 2018; CABALAR et al., 2019). O modelo de agentes BDI é adequado para ambientes complexos e dinâmicos com recursos limitados (RAO, 1995; CHONG; TAN; NG, 2007; ALECHINA et al., 2011). Normalmente, o processamento e controle de percepções no modelo BDI é independente do agente, e isso é uma limitação para ambientes em que os dados são heterogêneos e dinâmicos (OIJEN; DIGNUM, 2011; JR; PANTOJA; SICHMAN, 2018; DENNIS et al., 2016; DÖTTERL et al., 2019). Um fator agravante ocorre quando os dados dos sensores chegam em maior frequência do que a capacidade do agente de processá-las (DENNIS et al., 2016). As percepções podem ser vistas como parte do processo de entender a situação do ambiente para realizar os objetivos do agente (SO; SONENBERG, 2009). Filtros e políticas de percepções podem ser utilizadas para reduzir o número de dados percebidos (CRANEFIELD; RANATHUNGA, 2015; JR; PANTOJA; SICHMAN, 2018). Portanto, esta tese investiga o problema de integração de dados heterogêneos no processo de tomada de decisão de agentes em ambientes dinâmicos. Quatro fatores relevantes são: (i) dados heterogêneos são aqueles que podem ser percebidos por diferentes sensores, com taxas de atualização variadas e semântica própria na representação interna do agente; (ii) em adição a estar situado em um ambiente dinâmico, é analisado o conhecimento da situação para tomada de decisão; (iii) um agente é construído como uma abstração de sistemas multicontexto para atuar em ambientes dinâmicos; e (iv) computação urbana é a área de estudo. Este trabalho investiga as seguintes perguntas de pesquisa: **P1** - Como modelar e implementar agentes inteligentes para combinar conhecimento com múltiplas representações utilizando a abordagem de sistemas multicontexto? **P2** - Como restringir o processo perceptivo com base no estado interno de um agente BDI? **P3** - Qual é a influência de smartphones na consciência situacional de pedestres em ambientes urbanos?

Objetivos

O **objetivo geral** deste trabalho é desenvolver um modelo de raciocínio prático para agentes inteligentes situados em ambientes dinâmicos, seguindo a abordagem de sistemas multicontexto, para suportar o raciocínio contínuo de dados heterogêneos situacionais. Os **objetivos específicos** são: definir um *framework* para implementar agentes, dando flexibilidade para raciocinar em fontes heterogêneas de conhecimento; medir o impacto do uso de smartphones na consciência situacional de pedestres; identificar estratégias de priorização de percepções de acordo com o estado interno do agente; analisar o uso de raciocínio prático com recursos limitados e representações heterogêneas de situações em ambientes dinâmicos.

Metodologia

O delineamento deste trabalho é dado pela abordagem de *design science research*. Esse método de pesquisa pode ser considerado como um paradigma de resolução de problemas, onde as duas principais atividades são construir e avaliar. A primeira envolve criar um artefato com um propósito específico e a segunda determina o desempenho deste artefato (MARCH; SMITH, 1995; HEVNER et al., 2004). Com base no *design science research*, quatro iterações foram realizadas para essa pesquisa. A primeira iteração foi constituída dos seguintes passos: estudo sobre a área de sistemas multicontexto, a sua aplicabilidade no desenvolvimento de agentes, e a implementação do framework Sigon para o desenvolvimento de agentes como sistemas multicontexto. O código do Sigon está disponível para a comunidade e é utilizado por pesquisas derivadas desta tese. Na segunda iteração foram realizados três experimentos utilizando realidade virtual para analisar o impacto de diferentes níveis de distração em smartphones na consciência situacional de pedestres em ambientes urbanos. O desenvolvimento dos experimentos considerou os elementos de percepção, compreensão e projeção de acordo com o modelo de consciência situacional proposto por Endsley (1988). A terceira iteração apresentou o estudo de modelos de percepção que podem ser aplicados em agentes e sua adequação em um agente BDI-*like* implementado em Sigon. Os experimentos desta iteração seguem a abordagem 2^k *factorial design*. A quarta iteração foi construída considerando os produtos das três iterações anteriores. Variações de agentes implementados em Sigon são utilizados em um ambiente urbano para analisar a tomada de decisão utilizando representações heterogêneas de situações e com diferentes formas de percepção.

Resultados e Discussão

O Sigon é o primeiro *framework* para desenvolvimento e implementação de agentes baseados em sistemas multicontexto encontrado na literatura para atuar em ambientes dinâmicos. Um agente Sigon é uma definição abstrata, permitindo alta customização. No contexto desta pes-

quisa, foi utilizado o modelo BDI como base. O Sigon foi testado utilizando integração de conhecimento representado em ontologias e redes Bayesianas, e algoritmos de percepção passiva e ativa. Além disso, em trabalhos derivados, o Sigon foi utilizado para estudo de agentes negociadores e integração com redes neurais *multilayer perceptron*. Os experimentos com realidade virtual forneceram um novo entendimento do uso de smartphones por pedestres em vias urbanas. Como resultados, foram encontradas associações mostrando que eventos inseguros e tempo de resposta aumentam com o nível de distração do smartphone. O cenário urbano criado para analisar o nível de consciência situacional de pedestres serviu como base para um conjunto de experimentos utilizando implementações de agentes Sigon com representações heterogêneas de situações e com estratégias diferentes de percepções. Diferentes formalismos podem ser aplicados para representar situações e modelar a tomada de decisão. Ontologias são aplicadas para modelar situações e permitir que o agente raciocine utilizando semântica bem definida e detalhada. Uma rede Bayesiana é aplicada para modelar a consciência situacional do pedestre e permitir o raciocínio em condição de incerteza. A percepção de informações irrelevantes para os objetivos atuais aumentam o tempo para a tomada de decisão em ambientes dinâmicos, mas percepção ativa e políticas de percepções são estratégias para reduzir esse problema. Os resultados mostram a capacidade de flexibilização do raciocínio em ambientes dinâmicos utilizando sistemas multicontexto.

Considerações Finais

Esta tese investigou mecanismos para permitir a representação e o raciocínio em fontes heterogêneas de conhecimento de agentes com recursos limitados. O ponto principal para isso foi a criação do framework Sigon seguindo a abordagem de Sistemas Multicontexto para representação de conhecimento. Cada contexto representa um componente do agente e regras de ponte fornecem a troca de informação entre os contextos. No Sigon, a ordem de execução das regras de ponte definem a arquitetura do agente. Os resultados alcançados mostram a capacidade de flexibilização do raciocínio em ambientes dinâmicos, permitindo representar situações em diferentes formalismos. Na perspectiva da computação urbana, novos entendimentos do uso de dispositivos móveis em ambientes urbanos por pedestres foram encontrados, tais como fatores que implicam na redução de consciência situacional durante interação com um smartphone. Simulações mostraram que o paradigma de agentes pode ser utilizado como interface entre o ambiente urbano e o pedestre e também apoiar à tomada de decisão. Contudo, é interessante a realização de novos experimentos em realidade virtual considerando os resultados desta tese.

Palavras-chave: Agente. Consciência Situacional. Sistemas Multicontexto. Computação Urbana. Ontologia. Rede Bayesiana.

ABSTRACT

The creation, proliferation and consumption of information are frequently observed in our society. An agent situated in a dynamic environment is susceptible to perceiving a large amount of information, several of which are irrelevant to its current goals. Also, given the state of the environment, a situation can be modelled using different representations of knowledge, such as ontologies to model situations with well-defined semantics, and Bayesian networks for situations of uncertainty. The agent must be able to perceive according to its goals and to integrate these perceptions conforming to the situation's representation. The literature describes BDI agents as suitable to act in dynamic environments. However, it examines the perception of the environment as being dependent on the implementation and independent of the agent's reasoning, and the flexibility in representing situations is limited. This research investigates the use of perception mechanisms and representation of situations in the agent's reasoning to improve its decision making. The agent is modelled with the multi-context systems approach, allowing the modular decomposition of the agent's components. This approach enables to represent situations in different formalisms and their relationships with other agent's components. A component can be represented by one or more contexts of the multi-context system, and bridge rules exchange the information between contexts. A bridge rule has a head, the context that will add new information, and a body, the knowledge that has to be satisfied in one or more contexts to add the information in the head. The Sigon framework is developed to evaluate the application of multi-context systems in the agent paradigm. Sigon is the first implementation for the development of agents situated in dynamic environments using multi-context systems. We created contexts to represent situations with ontologies and Bayesian networks, and strategies for extending the agent's architecture through bridge rules. We conducted three experiments using virtual reality to find new understandings of pedestrian behaviour when interacting with smartphones. We applied statistical tests in the created data sets, finding associations showing that unsafe events and reaction time increase with smartphone distraction. Finally, an urban environment is simulated to evaluate the perceptual process in a Sigon agent, and a decision support agent for pedestrians. The experimental analysis followed the Factorial Designs approach to evaluate the impact of active and passive perception, continuous data gathering, ontologies and Bayesian networks in the decision-making time. The perception of irrelevant information to current goals increases the time for decision making in dynamic environments. However, active perception and perception policies are strategies to reduce this problem. The results instigate the development of agent as multi-context systems for urban computing.

Keywords: Agent. Situational Awareness. Multi-context Systems. Urban computing. Ontology. Bayesian Network.

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LIST OF SYMBOLS

C_i	Context i
L_i	Logical language i
Ax_i	Knowledge base (set of axioms) i
δ_i	Inference rules i
Δ_{br}	Bridge rules
br_i	Bridge rule i
ψ, φ, θ	Well-formed formulae
μ_i	Mean of response variable i
α	Significance
χ^2	Pearson's χ^2 of Independence
S_i	Sensor i
ω	Sensor identifier
ξ	Function mapping an observation to a perception
A_i	Actuator i
ρ	Actuator identifier
λ	Action to be performed
γ	Preconditions of an action or plan
ζ	Postconditions of an action or plan
c_a	Cost to execute an action or plan
β	Action or set of actions
Ac_i	An agent's action i
P_i	An agent's plan i
P	All agent's plans
r	Belief's probability

CONTENTS

1 INTRODUCTION

The creation, proliferation, and consumption of information is a phenomenon present in our society (GANDOMI; HAIDER, 2015; HILLS, 2019). This is a typical characteristic of dynamic environments, in which the environment changes while a decision-maker is combining information to choose the next action. Computational devices in these circumstances have time, space, and communication restrictions in processing the amount of available data. Similarly, a human operator in a complex and large-scale environment *'can be severely challenged in rapidly bringing all of the available information together in a form that is manageable for making accurate decisions in a timely manner'* (ENDSLEY, 2016, pag. 3).

In an urban environment, it is possible to observe both device and human limitation: on the one hand, smartphones have possibilities of physical, cognitive, emotional, and social sensing, but at the same time, they have limited battery and processing power to evaluate all those sensing modalities (KONSOLAKIS et al., 2018); on the other hand, drivers and pedestrians consuming smartphone data have a reduction in the decision-making process (JIANG et al., 2018; OVIEDO-TRESPALACIOS et al., 2018). In such a situation, an intelligent agent can act as an interface between the complex and dynamic environment and the limited human situation awareness (FERNANDEZ-ROJAS et al., 2019).

Agent paradigm in dynamic environments allows the creation of agents for the distributed and decentralised management of information (JULIAN; BOTTI, 2019; RAKIB; UDDIN, 2019). This enables an agent to choose the appropriate action for the neighbourhood in which it is situated. For a given goal, the agent should know which parts of the environment are relevant and build a model of how it may evolve (DAHNL; GRASS; FUCHS, 2018; GEHRKE, 2009). Keeping attention on the relevant aspects of the situation is an approach to reduce the data amount processed.

Intelligent systems have to fuse and integrate localised contexts from different sensors to improve mission success or act as decision support to human beings, and context-awareness is an approach for this (KIM; YOON, 2018; FERNANDEZ-ROJAS et al., 2019). In this direction, agent-oriented is an emerging programming paradigm for context-aware systems (ALEGRE; AUGUSTO; CLARK, 2016). For example, in mobile computing, there are three broad fields for context awareness: localisation, tracking user movement and sensing the surrounding environment (CAPURSO et al., 2018). An agent in a mobile device may need to perceive and process the available data in all sensors to be aware and decide which action to take.

There are many ways to combine multiple contextual knowledge, for example, Kalman filters, ensemble learning, and Multi-Context Systems (GJORESKI, 2015; GIUNCHIGLIA; SERAFINI, 1994). A Multi-Context System (MCS) allows representing an agent as a set of contexts, in which a context is defined using the formalism that best describes a characteristic of the environment, situation or an agent's capability (GIUNCHIGLIA; SERAFINI, 1994). Bridge rules describe the information exchange between contexts (BREWKA; EITER, 2007; BREWKA et al., 2018). From a knowledge representation point of view, this modular decomposition allows the agent's development through multiple representations, and each one represents a component or a part of it. This decomposition increases the representativeness and conceptually simplifies agents (SABATER et al., 2002; DYOUB; COSTANTINI; GASPERIS, 2018). The use of MCS in agents allows the development of context-aware agents using contextual information from heterogeneous knowledge sources (UDDIN et al., 2018). MCS is also prominent in dynamic environments with continuous online reasoning. However, its practical use is still too abstract (BREWKA et al., 2018; CABALAR et al., 2019).

The BDI (Beliefs-Desires-Intentions) agent model is suitable for complex, dynamic environments with limited resources (RAO, 1995; CHONG; TAN; NG, 2007; ALECHINA et al., 2011).

This model is based on Bratman's (BRATMAN, 1987) theory of practical reasoning, in which reasoning is directed towards actions, with two main processes: deliberation and means-end reasoning. The first deciding which goals to achieve and the latter deciding how to do it (WOOLDRIDGE, 2000).

The perception processing and control in the BDI model is usually an independent component of the agent, and this is a limiting factor in environmental sensors, such as the mobile device one, in which data is low-level and dynamic (OIJEN; DIGNUM, 2011; JR; PANTOJA; SICHMAN, 2018; DENNIS et al., 2016; DÖTTERL et al., 2019). An aggravating factor occurs when the sensor's data arrives faster than the agent's ability to process it (DENNIS et al., 2016). Perceptions can be seen as part of the process involving understanding the environment's situation to achieve an agent's goals (SO; SONENBERG, 2009). Perception policies and filters can be applied to reduce the number of data perceived (CRANEFIELD; RANATHUNGA, 2015; JR; PANTOJA; SICHMAN, 2018). The analysis of the factors that influence performance in many models, such as BDI agents is still limited (JR; PANTOJA; SICHMAN, 2018). The representation of BDI agents as MCS started with Parsons, Sierra & Jennings (1998) work, and there are a variety of works adding capabilities such as reasoning under uncertainty, trust, reputation, norms, emotions, preferences and negotiation (PINYOL; SABATER-MIR, 2009; PINYOL et al., 2010; CASALI; GODO; SIERRA, 2011; CRIADO et al., 2014; KOSTER; SCHORLEMMER; SABATER-MIR, 2013; GELAIM; SILVEIRA; MARCHI, 2015; MELLO; GELAIM; SILVEIRA, 2018). However, none of them describing the perception process.

1.1 PROBLEM

This thesis investigates the problem of integrating heterogeneous data streaming in intelligent agents decision making with limited resources situated in dynamic environments. The problem description contemplates: (i) heterogeneous data streams refer to data that can be perceived by different sensors, with varying update rates and own semantics in the agent's internal state; (ii) in addition to being situated in a dynamic environment, the agent, a BDI-like, demands a more comprehensive understanding of the situations to act appropriately; (iii) this work creates an abstraction in MCS to act in dynamic environments; (iv) urban computing is the field in which this problem is evaluated.

As such, this work intends to answer the following research questions:

- **RQ1**: How to model and develop intelligent agents to combine knowledge with multiple representations following the Multi-Context Systems approach?
- **RQ2**: How to restrict the perceptual process based on a BDI agent's internal representations of situations?
- **RQ3**: What has been the influence of smartphone in pedestrian's situational awareness on the vicinity of urban traffic?

1.2 OBJECTIVES

This section presents the objectives of the thesis.

1.2.1 General Objective

To develop a practical reasoning model for intelligent agents situated in a dynamic environment, following the multi-context systems approach, to handle heterogeneous overwhelming situational data.

1.2.2 Specific Objectives

- To define a framework for developing agents, giving flexibility to the reasoning in heterogeneous sources of knowledge;
- To measure the impact of smartphones in a pedestrian's situational awareness;
- To identify perception prioritisation strategies according to the agent's internal state;
- To analyse practical reasoning for heterogeneous representations of situations in dynamic environments with limited resources.

1.3 RESEARCH METHOD

The Design Science Research gives the outline of this thesis. Design science can be considered as a problem-solving paradigm. It consists of two main activities: build and evaluate. The first one involves creating an artefact with a specific purpose, and the second one determines the performance of this artefact (MARCH; SMITH, 1995; HEVNER et al., 2004).

Peffers et al. (2007), presents a design science research methodology, including six activities:

1. **Problem identification and motivation.** The problem formalisation is useful to develop an artefact to create a solution. The motivation helps to understand the reasoning associated with the problem of integrating heterogeneous data streaming in intelligent agents decision making with limited resources situated in dynamic environments.

2. **Definition of the objectives for a solution.** Infer the objectives of a solution from the problem specification rationally. Resources required for inferring objectives include knowledge of the state of problems and current solutions.

3. **Design and development.** Create a design research artefact. It can be 'any designed object in which a research contribution is embedded in the design'. Resources required for this include knowledge of theory to develop a solution.

4. **Demonstration.** Demonstrate the use of the design research artefact to solve one or more instances of the problem. Resources required for this include adequate knowledge of how to use the artefact.

5. **Evaluation.** Compare the objectives of a solution to actual observed results from use of the artefact in the demonstration. This evaluation could include appropriate empirical evidence or logical proof.

6. **Communication.** Communicate the problem, the artefact, its utility, its design, and its effectiveness.

This research follows this methodology to investigate the problem presented. Iterations are performed on activities 2 to 6, aiming to obtain solutions incrementally.

1. Iteration 1

    - Objective: to define a framework for developing agents, giving flexibility to the reasoning in heterogeneous sources of knowledge; A resource to achieve this objective are related works presented in section 3.1;
    - Design and development: the creation of the Sigon framework;
    - Demonstration: Section 4.4 presents a set of examples adding custom contexts to show flexibility and heterogeneity in Sigon agents;
    - Evaluation: Chapter 6 compares the results of the examples;
    - Communication: Chapter 4 and paper (GELAIM et al., 2019b).

2. Iteration 2

    - Objective: to measure the impact of smartphones in a pedestrian's situational awareness. Resources required for it is presented in Section 5.1;

- Design and development: development of three experiments with human beings interacting with smartphones in virtual reality urban environment;
- Demonstration: statistical analysis of the experiments are presented in Chapter 5;
- Evaluation and Communication: Chapter 5 and paper (GELAIM et al., 2019a).

3. Iteration 3

   - Objective: to identify perception prioritisation strategies according to the agent's internal state; Section 3.2 analyses the literature of perception in BDI-like agents;
   - Design and development: development of a perception model in an MCS-based agent;
   - Demonstration: application of the model in a Sigon agent. This is presented in subsection 4.4.3;
   - Evaluation and Communication: Chapter 6 and paper (FREITAS et al., 2020).

4. Iteration 4

   - Objective: to analyse practical reasoning for heterogeneous representations of situations in dynamic environments with limited resources;
   - Design and development: specification of an urban environment to evaluate the integration of the artefacts presented in iterations 1, 2 and 3;
   - Demonstration: application of the model with Bayesian and Ontological representations in Sigon agents. This is presented in Chapter 6;
   - Evaluation and Communication: Chapter 6.

1.4 ASSUMPTIONS, LIMITATIONS, AND SCOPE

This thesis focuses on the single-agent concept within the integration of heterogeneous knowledge sources. In this sense, it is possible to draw a parallel between the model developed in this thesis, Sigon, with programming languages and development platforms of BDI agents, such as AgentSpeak and Jason (RAO, 1996; BORDINI; HüBNER; WOOLDRIDGE, 2007). Sigon adds an abstraction according to the agent paradigm in an MCS, where the BDI model is the basis for the agent's abstract layer created for this thesis experiments.

This research is limited to the use of Sigon to combine situation knowledge in the decision-making process, in which the BDI theory is simplified. Sigon's implementation is still a prototype, with a primary focus on how different knowledge representations affect the agent's reasoning. Therefore, it is assumed that comparing performance with other frameworks or other BDI-like implementations is not adequate. As it is a prototype, the agent's performance can be improved.

1.5 CONTRIBUTIONS

The work presented in this thesis constitutes a contribution to the following areas:

- **The Sigon framework for modelling intelligent agents within heterogeneous knowledge sources based on the MCS approach**: Sigon is a framework for developing intelligent agents following **RQ1** to combine heterogeneous knowledge sources. The BDI agent model is the basis for the majority of experiments produced so far in Sigon. BDI is suitable for resource-bounded reasoning (BRATMAN; ISRAEL; POLLACK, 1988) and there are applications in several areas: healthcare (CROATTI et al., 2019), distributed data mining (LIMÓN et al., 2019) and social simulations (ADAM; GAUDOU, 2016). MCS is the ground of the Sigon framework; it is part of the Computational Logic, and it allows reasoning under different formalisms. In this work, we focus on ontological and Bayesian reasoning, but other approaches are possible. For example, Mello (2016) implements a negotiation logic in Sigon Framework; in a seminal work, Eichstaedt et al. (2019) investigates the use of sensors with neural networks to integrate with symbolic reasoning in a Sigon agent.

- **A situation awareness decision-making agent for urban environments**: A situation can be modelled under several representations, implying distinct forms of reasoning, such as a Bayesian network (for reasoning about partial beliefs in the presence of uncertainty) or an ontology (shared and detailed description of the domain). The agent can build models for the situations relevant to its current intention. Once a situation is modelled and associated with the agent's intention, it is up to the agent's perception mechanism to prioritise or filter perceptions. Following **RQ2**, this thesis presents mechanisms and experiments for reasoning under heterogeneous representations in an MCS agent. More precisely, it shows how a resource-bounded device can handle an overwhelming perception in an urban environment.

- **New understanding of pedestrians' behaviour in urban environments when using smartphones**: The motivational application of this thesis is the use of a mobile device by pedestrians in urban environments. It is an example of a resource-bounded computational device acting in a dynamic environment. It had support from Royal Society International Exchange Award Nr. IE150542 and is the motivation for **RQ3**. We developed three experiments to analyse pedestrian situational awareness interacting with mobile devices. They are presented in Chapter 5. Also, these studies corroborated in the development of experiments for agents in dynamic environments with heterogeneous data.

1.6 THESIS ORGANISATION

This thesis is organised as follows: Chapter 2 presents the main concepts related to the research topic. Chapter 3 presents the related work in: (i) the use of MCS and agents; and (ii) perception in BDI agents. Chapter 4 describes the model developed in this research to combine heterogeneous knowledge sources and examples of the agent's implementation. Chapter 5 presents an experimental analysis of the use of mobile devices by pedestrians in urban environments. In Chapter 6, experiments in the field of urban computing are presented, including the knowledge of Chapters 4 and 5. Finally, Chapter 7 presents conclusions and future works.

2 BACKGROUND

This Chapter aims is to give the reader an understanding of the context surrounding the work described within this thesis. Section 2.1 provides an overview of the terms context, situation, and awareness. Section 2.2 gives a formal definition of MCS. Section 2.3 presents the main properties of agents and environments. Section 2.4 defines urban computing.

2.1 CONTEXT, SITUATION, AND AWARENESS

The Oxford Dictionary defines context as '*the circumstances that form the setting for an event, statement, or idea, and in terms of which it can be fully understood*' [1]. This is a broad definition. Dey (2001, pag. 5) defines context according to the computer science perspective as

> any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves.

This characterisation is widely accepted. However, some variations are found in the literature based on the application domain (SCHILIT; ADAMS; WANT, 1994; BROWN; BOVEY; CHEN, 1997; BENERECETTI; BOUQUET; BONIFACIO, 2001; LI et al., 2015). Giunchiglia (1993) defines the term context in an agent perspective as a partial and approximate theory. It is a partial theory because the agent's complete knowledge of the environment is the result of all contexts, and is an approximate theory because the world is not fully described. We use Giunchiglia (1993)'s definition in Chapter 4 to integrate heterogeneous knowledge sources using the Sigon framework, and Dey (2001) definition in Chapter 6 for testing agents in dynamic environments.

The word *situation* is defined as '*a set of circumstances in which one finds oneself; a state of affairs*'[2]. It is closely related to the term context. Mccarthy & Hayes (1969, pag. 18) describe the word situation as '*the complete state of the universe at an instant of time*'. Based on this definition, computer modelling of a situation is not feasible. In many cases, the goal is to evaluate an individual's situation with some environmental constraints. Artificial Intelligence looks for ways to model situations based on different theories, mainly intending to develop abstract contexts for reasoning about situations, such as Bayesian networks and ontologies.

The term *Context-aware* was presented in the early 90s by Schilit, Adams & Want (1994, pag. 1) as a software that '*adapts according to its location of use, the collection of nearby people and objects, as well as changes to those objects over time*'. Dey (2001, pag. 5) describes a system as context-aware *if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task.* They are applied in different

[1] https://www.lexico.com/en/definition/context
[2] https://www.lexico.com/en/definition/situation

domains, such as in recommender systems (VILLEGAS et al., 2018) and mobile applications (CAPURSO et al., 2018).

Situation awareness (SA) is a term used to describe one's attention to a certain situation. It is a state of knowledge (ENDSLEY, 1995). In this thesis, the experiments conducted are based on Endsley's definition of situation awareness (ENDSLEY, 1988, pag. 792). '*Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*'.

This definition has three phases. The first level of SA is the *perception* of the situational elements and their current states. A situational element can be an object, such as a white car in the road's left side at a certain speed, a person standing on the sidewalk, or a traffic light. The second level is comprehension, it is the fusion of the main pieces of perceived situational elements. For example, the pedestrian is standing on the sidewalk because the traffic light is green, and there is a car approaching. The third level is the projection of the future actions of the elements in the environment. The car will follow the road, the traffic light will become red, and the pedestrian will cross the street. A poor SA can result in an accident.

Several factors can cause limited situational awareness, such as data overload, unintegrated data, automation, excess attention demands (ENDSLEY, 2016, pag. 58). The process to achieve/aquire/maitain situation awareness is called Situation Assessment (ENDSLEY, 1995). An appropriate SA is critical for various domains, such as air traffic control, education, and driving (ENDSLEY, 2016, pag. 13).

Kokar, Matheus & Baclawski (2009) divide situation awareness for humans and for computers. Endsley, Garland et al. (2000)'s model is usually referenced in both domains, but with different views: '*Human situation awareness process needs to be measured and possibly supported*', '*computer processes need to be defined and implemented*' (KOKAR; MATHEUS; BACLAWSKI, 2009, pag. 83). Feng, Teng & Tan (2009, pag. 455) distinguish between situation awareness and context awareness. The first is about helping the user to be "aware of his current situation" and the latter focuses on dynamically changing the system's behaviour to help the user to have a more effective interaction.

In this thesis, it is investigated the level of situational awareness of pedestrians in urban environments. A pedestrian situation awareness is modelled using Bayesian networks and evaluated in section 6.2. Situations are computationally modelled in an agent using an ontology according to the description of Kokar, Matheus & Baclawski (2009) about computational situation awareness. It is presented in Section 4.4.1 and evaluated in an urban environment in Section 6.3.

2.2 MULTI-CONTEXT SYSTEMS

Intuitively, a multi-context system allows representing knowledge in multiple contexts, where a context C_i is constituted of a logical language L_i, a knowledge base (set of axioms) Ax_i

and inference rules δ_i. Bridge rules, Δ_{br}, are the mechanism to exchange information between contexts. A bridge rule has two components: head and body. The head represents a context and some fact to be added in it; the body represents the knowledge that needs to be held in a set of contexts to add knowledge in the head context. For example,

$$\frac{C_1 : \psi,\ C_2 : \varphi}{C_3 : \theta} \tag{2.1}$$

means that when ψ is deduced in context C_1 and φ is deduced in context C_2 (the body), θ is added to context C_3 (head) (CASALI; GODO; SIERRA, 2005). This gives the ability of a context to "learn" through the inter-context exchange (CABALAR et al., 2019).

A multi-context system is formally defined as:

Definition 2.1 (Multi-Context System (GIUNCHIGLIA; SERAFINI, 1994))**.** Let I be a set of finite indexes, $\{L_i\}_{i \in I}$ a set of languages, $\{Ax_i\}_{i \in I}$ a set of axioms, $\{\delta_i\}_{i \in I}$ a set of inference rules, and $\{C_i = \langle L_i, Ax_i, \delta_i \rangle\}_{i \in I}$ a set of contexts.
A *Multi-Context System M* is a pair $\langle \{C_i\}_{i \in I}, \Delta_{br} \rangle$, where $\{C_i\}_{i \in I}$ is the set of contexts and Δ_{br} is the set of bridge rules over M.

Managed MCSs (mMCSs)(BREWKA et al., 2011) is a generalisation allowing arbitrary (e.g. deletion, revision) operations on context knowledge bases. It addresses the problem of integration of different knowledge representation formalisms, it is a reactive device and not able to incorporate new data items, i.e., not suitable in dynamic environments. Related work presented in Chapter 3 presents current approaches to overcome this issue.

2.3 AGENT

The definition of agent converges to be a particular software component, situated in an environment and with the autonomy to accomplish its project goals (BELLIFEMINE; CAIRE; GREENWOOD, 2007; WOOLDRIDGE, 2002, pag. 3). It is rational when it chooses to perform actions following its interests, i.e. maximising its performance criteria, considering the beliefs it has about the world (WOOLDRIDGE, 2000). For example, if the agent is an autonomous vehicle and its goal is to reach its destination safely, it is rational that it respects traffic rules on the way.

The properties available in rational agents are: being situated in an environment, autonomous, proactive, reactive and possessing social ability (WOOLDRIDGE; JENNINGS, 1995). Autonomy is related to the agent's ability to perceive and act in the environment, over time, according to its schedule and in order to affect what its will notice in the future (FRANKLIN; GRAESSER, 1997). Proactivity is the ability to display behaviour directed at achieving its goals. A reactive agent is capable of responding to changes in the environment. Social ability is the ability to communicate at a level of knowledge, i.e. communicating beliefs, goals, and plans (BORDINI; HüBNER; WOOLDRIDGE, 2007).

The BDI is one of the main agents' models found in the literature and is suitable for this research. The decision-making process in a BDI agent is defined under the deliberation and the means-end reasoning (WOOLDRIDGE, 2002). There are several architectures to describe the working process in such an agent. One of the main architectures is the *Procedural Reasoning System* (PRS), that is the basis for the language AgentSpeak(L) (INGRAND; GEORGEFF; RAO, 1992; RAO, 1996). The semantics of AgentSpeak(L) is developed in the Jason interpreter (BORDINI; HüBNER; WOOLDRIDGE, 2007), a framework for the development of agent and multi-agent systems.

2.3.1 Agent's Perception

The information about the current state of the environment is required for agent's decision-making. Perception of environmental situations allows the realisation or abandonment of one's goals. It transforms raw inputs into data according to the agent's internal representation to execute cognitive tasks (KOTSERUBA; TSOTSOS, 2018).

Perception usually can be active or passive. Active perception attempts to define processes for data acquisition intelligently, and the agent plays the role of leading their perceptions to the most relevant aspects of the environment; In passive perception, the agent does not deliberate on what to perceive (SO; SONENBERG, 2009; WEYNS; STEEGMANS; HOLVOET, 2004).

Active perception allows an agent to decide which environmental information is relevant to his current goal or goals. This ability is essential for agents situated in dynamic environments, including a large amount of information, several representations and inaccurate data (SO; SONENBERG, 2009). Agent's internal state defining which environmental data will be perceived can decrease its reactivity since it requires reasoning about what is relevant. Thus, this reasoning is applied to situations where the cost to it is smaller than adding all perceptions in the agent's beliefs (JR; PANTOJA; SICHMAN, 2018).

Bajcsy, Aloimonos & Tsotsos (2018) describe a complete framework to implement active perception in agents, using a tuple: why, what, when, where and how to perceive. The *why* component is the capacity of the agent to decide, based on the expectations that current state generates, what its next actions might be. *What* is the process of choosing a subset of the environment to sense. *When* describes when the perception is valid, and how long it should be. In a broad sense, *how* to perceive is the set of actions that precede the observation itself. The *where* to perceive component describes the needed position of the agent and its sensors.

2.3.2 BDI Agent as MCS

The development of BDI agents as MCS started with Parsons, Sierra & Jennings (1998) work. The authors' model has four contexts, one for each component of beliefs, desires, intentions, and communication with the environment. These contexts can define three BDI architectures through bridge rules: (i) strong realism, a cautious agent, '*if an agent does not believe something, it will neither desire nor intend it*'; (ii) realism, an enthusiastic agent, '*if an agent believes something, it both desires and intends it*' ; and (iii) weak realism, an agent between strong and realism, it will not desire something if its negation is believed, will not intend something if its negation is desired, and will not intend something if the negation is believed (PARSONS; SIERRA; JENNINGS, 1998). In addition to these rules that describe the architecture, the authors pointed that the agent may have specific rules according to application needs (PARSONS; SIERRA; JENNINGS, 1998; PARSONS et al., 2002).

The graded BDI model as MCS (CASALI; GODO; SIERRA, 2005) enables beliefs, desires, and intentions to be graded so that the agent can reason about uncertainty Graded beliefs represent the credibility of the agent's beliefs about the world. Graded desires, can be positive or negative, where positive means what the agent wants and negative what it rejects or not wants that became true. Graded intentions have the cost and benefices of an intention becoming true. The model also briefly presents two functional contexts, planner, and communication. The planner is responsible for building plans, and the communication is the agent's communication with the environment (CASALI; GODO; SIERRA, 2008; CASALI; GODO; SIERRA, 2011; CASALI; GODO; SIERRA, 2009).

2.3.3 Environment

The environment in which the agent is situated is categorised as (RUSSELL; NORVIG, 2016): *Fully observable* if agent's sensors are able to receive the complete environmental state at any time, otherwise it is *partially observable*. *Deterministic* if the current state of the environment and the agent's action determine the next environment state, else it is *stochastic*. In an *episodic* environment, the agent performs one action, and the next episode does not depend on actions in previous episodes, on the other hand, a *sequential* environment, the current actions can affect the future one. The distinction between a *discrete* and *continuous* is defined by how time is handled, and the agent's percepts and actions.

If the environment is *dynamic*, it can change while the agent is deliberating. On the other hand, in a *static* environment, the agent does not have to pay attention to the environment while deciding the next action. This feature of static environments simplifies the agent's deliberation process, once there is no chance of a new state of the environment invalidating the current reasoning. In a dynamic environment, the agent has to keep looking to perform a valid action, and at the same time, it has to execute an action as soon as possible.

2.4 URBAN COMPUTING

Urban areas have an increasing potential in the use of devices to assess the situation of the environment. At the environmental level, it is possible to evaluate congestion, air quality, and fuel consumption (ZHENG et al., 2014). At the entity (agent) level, smartphones can play a relevant role in decision making for pedestrians or drivers, and the autonomous vehicles can decide the next actions to be taken based on their sensors and information from nearby systems (KUUTTI et al., 2018).

Urban computing is an interdisciplinary field that seeks to solve urban issues. It is "*a process of acquisition, integration, and analysis of big and heterogeneous data generated by diverse sources in urban spaces, such as sensors, devices, vehicles, buildings, and humans, to tackle the major issues that cities face*" (ZHENG et al., 2014). The smartphone is one of the technologies used in urban computing (SALIM; HAQUE, 2015) and is suitable for this thesis case study. This thesis adopts a computational and psychological perspective of urban computing. In the computational perspective, we use agents and MCS to study it, and in the psychological, we apply the Endsley model to evaluate pedestrian's situation awareness. Others perspectives of urban computing, such as civil engineering and economics, are not evaluated.

2.5 STATISTICAL METHODS

Analyses described in Chapter 5 make use of analysis of variance (ANOVA) for hypothesis testing. A hypothesis is a conjecture about the problem (MONTGOMERY, 2017, pag.34). For each situation, we can have one, two or three independent variables, we specify a null hypothesis ($H_0 : \mu_1 = \mu_2$), an alternative hypothesis ($H_1 : \mu_1 \neq \mu_2$) and a significance level (p-value). There are three primary assumptions in ANOVA: (i) independence of observations; (ii) normality of experimental errors; (iii) equal variances between treatments (QUEEN; QUINN; KEOUGH, 2002, pag. 191). The first assumption is considered at the design stage, the second was evaluated using the Shapiro-Wilks test for normality, and to verify the third assumption we applied the Bartlett test for homogeneity of variances.

The Kruskal-Wallis is a non-parametric rank-based test. It is an alternative to the one-way ANOVA. The test statistic H, representing the variance of the ranks among groups, is evaluated by:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{2.2}$$

where N is the total number of observations in all k groups, n_i is the number of observations contained in the i^{th} group, and R_i is the sum of ranks in the i^{th} group. Under the null hypothesis, H's value follows an χ^2 distribution with degrees of freedom of $k-1$ and significance α (KRUSKAL; WALLIS, 1952).

The Pearson's χ^2 of Independence is a method for testing the significance of associations between two qualitative variables expressed in a contingency table, and to compare two or more samples when the results of the dependent variable are in categories (BARBETTA, 2011). The statistical test χ^2 is measured from its expected frequency (E)

$$E = \frac{(row\ total) \times (column\ total)}{(Grand\ total)} \tag{2.3}$$

as

$$\chi^2 = \sum \frac{(O-E)^2}{E} \tag{2.4}$$

where O is the number of observations in the cell, and E is the expected frequency in the cell. Fisher's exact test is an alternative to the χ^2 test in analysing contingency tables when the sample sizes are small (MCCRUM-GARDNER, 2008). The Cramer's Phi coefficient is a measure of association between categorical variables in a contingency table (SHESKIN, 1996, pag. 678). The odds ratio is a measure of association representing the odds of an outcome given an exposure (SZUMILAS, 2010).

3 RELATED WORK

Intelligent agents situated in dynamic environments are likely to receive large volumes of data and in different representations. Two essential abilities for the agent are (i) reasoning in different formalisms and, (ii) if it is a system with limited resources, perceive the situation related to its current goals. Section 3.1 presents a systematic literature review (SLR) for the first premise under the Multi-Context System view. An SLR is ‘ *a means of identifying, evaluating and interpreting all available research relevant to a particular research question* (KEELE et al., 2007). Section 3.2 shows the main works on the topic of the second premise for BDI-like agents.

3.1 MULTI-CONTEXT SYSTEMS AND AGENTS

Following the thesis objectives and the research question: “***RQ1****: How to model and develop intelligent agents to combine knowledge with multiple representations following the MCS approach?*”, this section reports an SLR aiming to identify studies about the development of agents and multi-context systems in dynamic environments. The SLR process presented in this section is an adaptation of the guidelines proposed by Keele et al. (2007). Adaptations are in the number of researchers reviewing papers (one), in the secondary study (not reported) and the PICOC (Population, Intervention, Comparison, Outcome, Context) criteria (examining Population and Intervention).

The search query is:

((“BDI” OR “beliefs-desires-intentions” OR “agent”) AND (“Multi-context”))

The search in all document was initially executed on July/2017 and the last update on the May/2020. Initial searches are undertaken using the following digital libraries: *Scopus*, *ACM Digital Library*, *IEEE Xplore* and *SpringerLink*. The next step had as inclusion criteria: Last 10 years and in Computer Science.

Table 1 – Systematic Literature Review: Works from search and first selection stages.

Data Source	**Search Results**	**2011 - 2020 /CS**
Scopus	407	191
ACM Digital Library	506	277
IEEE Xplore	117	75
SpringerLink	296	99

Source: The author.

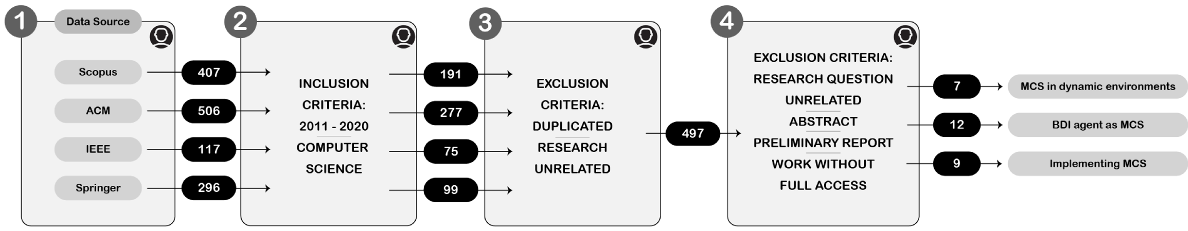
642 works remain after the first exclusion criteria. Table 1 shows the result of these stages. In the subsequent step, duplicates and the “ Table of contents ” were removed, resulting in 497 documents. In the next stage, all abstracts and all relevant works were evaluated. In this round, the exclusion criteria are:

- not related to multi-context systems based on computational logic;
- poster abstract;
- preliminary report;
- publication without full access.

Figure 1 shows the steps in data selection and extraction. Possible bias and validity problems:

- one researcher performed the review;
- researcher's subjective analysis of works quality.

Figure 1 – Systematic Literature Review: Data selection and extraction processes.



Source: The author.

The related work is organised into three groups aiming to answer the research question **RQ1**: MCS in dynamic environments (7 papers), BDI agent as an MCS (12), and implementing MCS (9). The next subsection presents these works.

3.1.1 MCS in Dynamic Environments

Reactive MCS (rMCS) (BREWKA; ELLMAUTHALER; PüHRER, 2014) is an mMCS with a set of sensors and bridge rules to incorporate the information of multiple external streams of data. rMCS have a bridge rule with the operator *next* in the head. These rules are used to specify how the configuration of knowledge bases evolves. Bridge rules define which information a context should obtain based on the results of all the contexts asynchronously.

Ellmauthaler & Pührer (2014) present asynchronous multi-context systems (aMCSs), allowing online reasoning in dynamic environments. Communication between contexts is through streams of data. A data is asynchronously communicated to a context on its input stream.

Evolving MCS (GONÇALVES; KNORR; LEITE, 2014) is a framework to integrate heterogeneous knowledge representation formalisms, and can reason in dynamic observations, and evolve by incorporating new knowledge (GONÇALVES; KNORR; LEITE, 2015). There are special *observation contexts* reserved for dynamic incoming data, where the observations made over time may change a state according to what is perceived.

Dao-Tran & Eiter (2017) introduce Streaming MCS (sMCS) a proposal to add time in mMCS to handle dynamic data. The main idea is to keep continuously receiving input from other contexts, compute, and then send output to other contexts. This approach extends bridge rules with window atoms for snapshots of input streams at contexts.

Cabalar et al. (2019) present timed MCS (tmMCS) a formal extension of MCS for practical use in dynamic environments (CABALAR; COSTANTINI; FORMISANO, 2017). The main feature is the notion of *action* as operations that can be performed to update a context. The base application is a smart Cyber-Physical Systems for the e-Health field. In such a setting, there are a set of computational entities, knowledge bases, and sensors, all immersed in the IoT. In the e-Health application, an agent is in charge of each patient, and it interacts with other computational entities, with the patient, and with the environment. Ontologies are mechanisms allowing more flexible knowledge exchange.

In this thesis, the MCS is the basis of a single-agent model. The agent is developed as an abstraction layer in an MCS, being this the main difference from these related works. In a distributed MCS and multi-agent, it is essential to know which context can query which one, in a single agent, this role is defined by the agent's model. In this work, controlling information exchange with the heterogeneous and dynamic environment is a task achieved by a communication context. There are specific bridge rules to connect received information from the communication context to the context that should get this data.

3.1.2 BDI Agents as MCS

Parsons, Sierra & Jennings (1998), Parsons et al. (2002)'s and Casali, Godo & Sierra (2005)'s research represent the foundation for the main works of BDI agents as MCS. Section 2.3.2 presents a discussion of them. Despite the last graded BDI agent as MCS presented by Casali, Godo & Sierra (2011) be from 2011, it is also shown in the background Chapter.

Zhang et al. (2012) present a formal graded BDI agent model based on MCS to explicitly represent the uncertainty of beliefs, desires and intentions. Pinyol et al. (2012) take as the starter MCS BDI agent, the Casali, Godo & Sierra (2005)'s approach for integrating a reputation context in BDI agents. The agent can employ probabilistic reasoning in beliefs context. Koster, Schorlemmer & Sabater-Mir (2013) propose a method for integrating trust models (an algorithm to calculate a trust evaluation) into an MCS BDI agent. Criado et al. (2014) define an MCS normative BDI agent (n-BDI) based on Casali, Godo & Sierra (2005) approach allowing agents to reason about norms under uncertainty in dynamic environments (CRIADO; ARGENTE; BOTTI, 2011). An n-BDI agent has two normative contexts: one for all norms which are valid at a given moment, and one for relevant norms at a specific moment. To reason about norms and its probabilities, bridge rules are proposed in the perception and deliberation phases. Othmane et al. (2016), Othmane et al. (2017) propose a BDI agent as MCS being motivated in Parsons, Sierra & Jennings (1998) and Casali, Godo & Sierra (2005) work to act as a recommender system. Plans and intentions are described using ontologies, and there are specific contexts to the agent's goals and social capabilities. Fuzzy sets are defined for representing and reasoning about spatial-temporal knowledge in recommendations (OTHMANE et al., 2018).

IATE's research group of the Federal University of Santa Catarina presents two main works about agents as MCS. Gelaim, Silveira & Marchi (2015) add contexts for emotions and trust in a multi-context BDI agent following Casali, Godo & Sierra (2005) approach. Mello, Gelaim & Silveira (2019) create a negotiation context in an MCS-based BDI agent following Gelaim, Silveira & Marchi (2015) work.

Works in BDI agents as MCS show the potential for flexibility in the agent's reasoning. It shows the capability to add different theories, such as trust, reputation, norms, emotions and negotiation in reasoning through bridge rules (PINYOL et al., 2012; CRIADO et al., 2014; KOSTER; SCHORLEMMER; SABATER-MIR, 2013; GELAIM; SILVEIRA; MARCHI, 2015; MELLO; GELAIM; SILVEIRA, 2019). To explore this potential in the creation of different components, the model developed in this thesis allows the combination of various capabilities in a single agent.

Although various works attempt to illustrate how to develop such models, the literature's solution is somewhat limited to a descriptive set of examples or simulations in the NetLogo environment (OTHMANE et al., 2018). Casali, Godo & Sierra (2013) described a language for the execution of graded BDI agents under uncertainty and dynamic environments. Their work proposed a multi-context calculus (MCC), based on ambient calculus (CARDELLI; GORDON, 1998) to describe the language. In Sigon language, we enable the developer to create other agents than only graded BDI ones and others agent architectures as well. It is, therefore, more flexible. Also, we present a framework for the implementation of agents.

It is important to note that none of the BDI agents as MCS evaluates how to perceive heterogeneous data in a dynamic environment. Perceptions is part of the process that involves understanding the situation in order to act appropriately. Also, there is more than one way to represent a situation, for example, using ontologies or Bayesian networks.

3.1.3 Implementing/Practical MCS Agents

Bikakis, Antoniou & Hasapis (2011) propose a distributed approach for reasoning in Ambient Intelligence environments based on MCS. The authors apply preferences to express the confidence that an agent (a context in the MCS) has in the knowledge imported by other agents. Le, Son & Pontelli (2018) have a similar approach modelling each agent as a context to express its preferences in an MCS. The work presents a *ranked logic* for representing and reasoning about multi-agents preferences.

Agent Computational Environment (ACE) is a software engineering approach for designing modular intelligent logical agents (COSTANTINI, 2015) using MCS. An agent in the ACE framework is composed by (i) the 'main' agent program; (ii) Event-Action modules; (iii) external contexts in order to gather information. The main agent program is independent of the Agent-Oriented Programming (AOP) language. The aim to integrate MCS and AOP. In this sense, bridge rules are a device for interaction and knowledge integration among an agent and modules (contexts) that are components able to perform a task or respond to queries (COSTANTINI; GASPERIS, 2016). Costantini & Formisano (2018) enable ACEs to choose the modules to use dynamically. The authors also create a new generalisation called K-ACE (COSTANTINI; PITONI, 2019) to gather and organise agents, components and sub-systems.

Haque & Khan (2018) develop a context-aware reasoning framework, following MCS approach which extracts the set of rules derived from heterogeneous knowledge sources, to model and verify interesting properties of a multi-agent system (HAQUE; RAKIB; UDDIN, 2017). The work incorporates mapping rules using the notion of contextual defeasible reasoning.

Uddin et al. (2018) present a conceptual framework and multi-agent model based on MCS for context-aware decision support in dynamic environments. According to the authors, each context-aware agent is a context with a set of bridge rules in the MCS. The work also incorporates users' preferences and provides personalised services. A context is defined in two levels: (i) to model heterogeneous systems, and (ii) as a *subject, predicate and object* triple.

Bögl et al. (2010) present a multi-context plugin for semantic evaluation and inconsistency explanation in *DLVHEX* systems (a logic-programming reasoner, which is an extension of answer set programming with external atoms and higher-order features, where heterogeneous knowledge bases are linked via nonmonotonic rules (REDL, 2016)). In their work, there is no description of the development of agent architectures such as the BDI. It is work before 2011, but applicable in recent works (REDL, 2016).

In this thesis, the main aim is to evaluate a single agent's perspective as MCS and not as a multi-agent system. Several contexts, or modules, can be defined to express agents capabilities, such as beliefs, desires, and intentions or agent's knowledge representation for situations such as ontologies and Bayesian networks. Bridge rules have the role of defining the agent's behaviour. This distinction in the role of MCS in the dynamic environment gives more autonomy and context-awareness for agents, but at the same time may increase the time to act.

Table 2 presents the comparison of related works considering MCS in dynamic environments, BDI agents as MCS and Implementing and practical MCS. The related works are organised according to the following numbering: 1. (BREWKA; ELLMAUTHALER; PüHRER, 2014), 2. (ELLMAUTHALER; PüHRER, 2014), 3. (GONÇALVES; KNORR; LEITE, 2014; GONÇALVES; KNORR; LEITE, 2015), 4. (DAO-TRAN; EITER, 2017), 5. (CABALAR et al., 2019; CABALAR; COSTANTINI; FORMISANO, 2017), 6. (PARSONS; SIERRA; JENNINGS, 1998; PARSONS et al., 2002) 7. (CASALI; GODO; SIERRA, 2011), 8. (ZHANG et al., 2012), 9. (PINYOL et al., 2012), 10. (KOSTER; SCHORLEMMER; SABATER-MIR, 2013) 11. (CRIADO et al., 2014; CRIADO; ARGENTE; BOTTI, 2011), 12. (OTHMANE et al., 2016; OTHMANE et al., 2017; OTHMANE et al., 2018) 13. (GELAIM; SILVEIRA; MARCHI, 2015), 14. (MELLO; GELAIM; SILVEIRA, 2019) 15. (BIKAKIS; ANTONIOU; HASAPIS, 2011), 16. (LE; SON; PONTELLI, 2018) 17. (COSTANTINI, 2015; COSTANTINI; GASPERIS, 2016; COSTANTINI; FORMISANO, 2018; COSTANTINI; PITONI, 2019),

18. (HAQUE; KHAN, 2018; HAQUE; RAKIB; UDDIN, 2017) 19. (UDDIN et al., 2018).

Table 2 – Comparison of the state of the art.

	Work	**Approach**	**Purpose**	**Perception**
MCS in dynamic environments	1	rMCS	heterogeneous reasoning	bridge rules
	2	aMCS	heterogeneous reasoning	computation controller
	3	Evolving MCS	heterogeneous reasoning	observation contexts
	4	sMCS	heterogeneous reasoning	window atoms
	5	tmMCS	heterogeneous reasoning	observation contexts
BDI agents as MCS	6	Single agent as MCS	negotiation, realisms	passive
	7	Single agent as MCS	graded BDI	passive
	8	Single agent as MCS	graded BDI	passive
	9	Single agent as MCS	reputation and norms	passive
	10	Single agent as MCS	trust models	passive
	11	Single agent as MCS	norms, uncertainty	passive
	12	Single agent as MCS	recommender system	passive
	13	Single agent as MCS	emotions and trust	passive
	14	Single agent as MCS	negotiation	passive
Implementing/ practical MCS	15	multi-agent as MCS	preferences	*
	16	multi-agent as MCS	preferences	*
	17	agent and MCS	heterogeneous reasoning	*
	18	multi-agent as MCS	context-aware reasoning	*
	19	multi-agent as MCS	context-aware reasoning	*
	This work	Single agent as MCS	heterogeneous reasoning, single-agent development	active

Source: The author. (* Application or bridge rules.)

3.2 PERCEPTION AND BDI AGENTS

The systematic literature review presented in section 3.1 indicates that there are MCS for continuous online reasoning in dynamic environments (BREWKA et al., 2018). However, there is no work doing this for MCS BDI agent restricting the perception process. This is a relevant feature to handle heterogeneous data in agents and related to the second research question. The RQ2 is " *how to restrict the perceptual process based on a BDI agent's internal representations of situations?*"

Relevant researches of perceptions in BDI agents are selected to formulate a perception model in a BDI agent as MCS. The first step in the selection process was to find works related to RQ2. The second step was to read the papers citing the selected papers. The last step was to read the works in the citation list of related papers of previous steps. The source to perform the search was Google Scholar.

Rodriguez & Favela (2008) describe an agent middleware for ubiquitous computing in healthcare with heterogeneous data sources. The main goal is to facilitate the development of autonomous agents in such a situation. The agent's life cycle reasoning is described based on perceiving, reasoning and acting. The perception component has the premises of passive and active perception. The passive perception is based on the Observer design pattern (GAMMA et al., 1995, pag. 326). Data sent from a device, agent or user is observed from the perception component, and action is taken according to the information received. Active perception implements the Adapter design pattern (GAMMA et al., 1995, pag. 157). An agent decides when to perceive using actions to get information from a sensor or device. The component reasoning has an abstract method *think()* that should be implemented by the developer. The component of action also has abstract methods to implement agents' actions.

In the work of van Oijen and Dignum (OIJEN; DIGNUM, 2011) it is presented a framework to perceptual attention for BDI agents. Ontologies are used to model the information coming from the environment to semantic sensory information. With that, the perceptions can be filtered accordingly to the agent's objectives. Besides, it can dynamically change the filter according to the current objectives.

Cranefield & Ranathunga (2015) propose a design for an agent percept buffer to simplify the perceived information from external systems, especially those producing high-frequency streams. The agent's percept buffer has the assignment of receiving perceptions from the environment and delivering them to a 'configurable percept management policies'. Three application-independent policies are presented: Keep the latest percept, keep the latest with history and keep most significant.

In Dötterl et al. (2018) approach, the perceptual process is driven by the agent's expectations — agent's subjective attitude towards percepts, and interpretations — detect higher-level knowledge in low-level percept streams. The agent behaviour has two main components: (i) a percept pattern using the SQL-inspired SELECT-FROM-WHERE structure; (ii) specification of the action to be executed when a pattern match occurs. The goal is enabling mobile agents to perceive higher-level knowledge in low-level streaming data.

Jr, Pantoja & Sichman (2018) describe a perception mechanism removing percepts that the agent is not interested in based on filters. When the agent's intentions change, an agent's internal action has the role of changing the perception filter. A filter is defined in an XML file and the Jason interpreter (BORDINI; HüBNER; WOOLDRIDGE, 2007).

In a broad sense, we find in literature two classes of related work: models of perception for Intelligent Agents, and filtering perception in BDI agents (SO; SONENBERG, 2009; WEYNS; STEEGMANS; HOLVOET, 2004; BAJCSY; ALOIMONOS; TSOTSOS, 2018; OIJEN; DIGNUM, 2011; CRANEFIELD; RANATHUNGA, 2015; DÖTTERL et al., 2018; JR; PANTOJA; SICHMAN, 2018). In this thesis, we enable active perception in the MCS agent architecture. Rodriguez & Favela (2008) have a conceptual view similar to this work but without a formal representation in heterogenous knowledge sources and an explicit relationship between active perception and current intention. Oijen & Dignum (2011) use an interface between the agent reasoning and the perception, while in this work, this is integrated with the agent's reasoning. Also, the use of ontologies has different purposes, van Oijen and Dignum use it to filter perception, and we use first to create situations and then filtering data. Cranefield & Ranathunga (2015) have a focus on perception policies (bottom-up), and this thesis has a focus on the agent's goals (top-down). However, we also use perception policies once they are complementary. Dötterl et al. (2018) have an expectations/interpretations approach of perception and reasoning, and in this thesis, we have an active perception and heterogeneous representation of situation approach. Jr, Pantoja & Sichman (2018) have a Jason agent approach with internal action and filtering and we use Sigon (and MCS) with agent's internal representation of situations and agent's plans.

3.3 SUMMARY

This thesis work fuses the theories in the fields of MCS and intelligent agents. One of the main characteristics of MCS is the ability to connect heterogeneous knowledge sources. The RSL shows recent efforts to adapt MCS in dynamic environments where it is crucial to adapt contexts according to heterogeneous data streaming, confirming this thesis study's relevance. Chapter 4 shows a framework for the development of intelligent agents as MCS.

The literature of agents based on BDI theory presents recent work for the processing of perceptions. These efforts are still limited when talking about large volumes and heterogeneous data. Also, there no approach to evaluate the perception processing of agents modelled as MCS. In section 4.4.3, we present a multi-context active perceiver agent, and in Chapter 6, we evaluate this agent.

4 SIGON: A MULTI-CONTEXT SYSTEM FRAMEWORK FOR INTELLIGENT AGENTS

Sigon [1] is a framework aiming at the development of agents based on MCS. The main focus is on BDI-like agents, but Sigon enables the development of other deductive-based agent architectures. The key factor in developing different models is the correct definition of bridge rules, which describe the relationship between contexts, thus defining the agents' components (GELAIM et al., 2019b).

This Chapter aims to describe the Sigon framework. The language specification is based on multi-context systems and on BDI multi-context agent models found in the literature, as presented in section 3.1. Section 4.1 presents the definition of agents as MCS. In Section 4.2, we define the grammar rules for representing the Sigon language. Section 4.3 describes the main elements of the framework that implements Sigon language. In Section 4.4, we present four examples of reasoning flexibility in Sigon agents.

4.1 SIGON AGENT MODEL

One of the main objectives in creating Sigon is to facilitate the development of MCS-based agents, in which the developer can add components and describe the relationship between them. This flexibility is relevant in two main aspects: describing situations in different representations and extending the agent's architecture. A Sigon agent is defined as:

Definition 4.1 (Sigon Agent)**.** Let AG be an agent. AG is defined as:

$$AG = \langle CC \cup \bigcup_{i=1}^{n} C_i, \Delta_{br} \rangle \tag{4.1}$$

where CC is the Communication Context. C_i with $0 \leq i \leq n$ are the n contexts representing agent's capabilities/knowledge sources. A bridge rule $br_j \in \Delta_{br}$ is a rule exchanging knowledge between contexts.

The communication context (CC) is the interface between the agent's internal state and the environment. In its most basic form, a Sigon agent is reactive, mapping perceptions to actions using only CC. In this sense, any other agent's capability is optional and defined according to domain demands.

CC is composed of a set with sensors and actuators. A sensor S_i is an ordered pair

$$S_i = (\omega, \xi), \tag{4.2}$$

where ω is the sensor identifier, and ξ is a function mapping an observation to a perception. The function's behaviour is domain-dependent, allowing both the creation of symbolic sensors,

[1] The ability to choose what sign (*Sig*) will be put into operation (*on*).

e.g. a query in an ontology, and non-symbolic sensors, such as a neural network for mapping image objects to tokens (FREITAS et al., 2020; EICHSTAEDT et al., 2019).

An actuator A_j is formalised as an ordered pair

$$A_j = (\rho, \lambda), \tag{4.3}$$

where ρ is the actuator identifier, and λ is the action to be performed. For a reactive agent, it is necessary to map perceptions to actions:

$$\frac{CC:\ sense(\varphi)}{CC: action(\rho)} \tag{4.4}$$

where $sense(\varphi)$ is the resulting perception from a sensor S_i, and $action(\rho)$ is the action to be executed when φ is perceived. CC is defined as:

Definition 4.2 (Communication Context)**.** Let CC be the Communication Context:

$$CC = \langle \bigcup_{i=1}^{n} S_i \cup \bigcup_{j=1}^{m} A_j \rangle, \tag{4.5}$$

where S_i with $1 \leq i \leq n$ are the agent's sensors, and A_j with $1 \leq j \leq m$ are its actuators.

The Planner Context is the other specific context in Sigon. It has the task of creating and controlling plans execution. In the literature, the Planner Context consists of two main components: actions and plans. In Sigon, we define these elements as presented by Casali, Godo & Sierra (2005). An action is defined as

$$action(\lambda,\ \gamma,\ \zeta, c_a) \tag{4.6}$$

where λ is the name of the action. γ are preconditions of the action, i.e., things that must be true before the action execution. ζ are the postconditions, that is, what the agent will believe to be true after the action execution of λ. c_a is the cost to execute this action. A plan is defined as

$$plan(\psi, \beta,\ \gamma,\ \zeta, c_a) \tag{4.7}$$

where ψ is a postcondition representing what the agent beliefs to be true after the plan execution. β is the action or the set of actions the agent must execute to achieve the plan. γ is a set of preconditions of the plan. ζ is a set of postconditions. c_a is the cost of the plan execution. This plan construction is a variation on the work of Casali, Godo & Sierra (2005), since there is not a certain degree of plan achievement. We denote the set of all defined plans by P.

Definition 4.3 (Planner Context)**.** Let PC be the Planner Context. PC is defined as:

$$PC = \langle \bigcup_{i=1}^{n} Ac_i \cup \bigcup_{j=1}^{m} P_j \rangle, \tag{4.8}$$

where Ac_i with $1 \leq i \leq n$ are the set of agent's actions, and P_j, with $1 \leq j \leq m$ the set of plans.

According to this thesis scope, the planner context is a predefined collection of plans specified by the developer. This approach is common in many implemented practical reasoning agents (WOOLDRIDGE, 2009, pag. 75). However, planning algorithms can use actions pre/-postconditions to create a plan able to achieve an agent desire/intention. In this sense, LaValle (2006) present a wide variety of planning algorithms.

The other agent's contexts are defined as:

Definition 4.4 (Context)**.** Let C be a context. C is defined as:

$$C = \langle L, Ax, \delta \rangle, \tag{4.9}$$

where L is the context's language, Ax is the set of axioms, and δ are the inference rules. A context can be built based on propositional, first-order, dynamic, and probabilistic logic.

The knowledge exchange between contexts is done declaratively through bridge rules. The model does not impose any rules, allowing the developer to specify the contexts and relate them according to application requirements. The structure of bridge rules follows the literature, with a context to add a belief (head) based on knowledge from other contexts (body). For example:

$$\frac{C_1 : \psi,\ C_2 : \varphi}{C_3 : \theta} \tag{4.10}$$

describes the addition of θ in C_3 (head), when ψ and φ are deduced respectively in C_1 and C_2 (body).

The complexity of a Sigon agent depends on its contexts. If all contexts complexity are in P, the consistency checking is NP. Eiter et al. (2014) presents the complexity of consistency checking of standard knowledge-representation formalisms in MCS.

4.1.1 A BDI Agent in Sigon

As presented in Chapter 1, BDI agents are the base model to analyse the use of heterogeneous data streaming in this thesis. Therefore Sigon has a predefined BDI agent:

$$AG_{BDI} = \langle \{CC, BC, DC, IC, PC\}, \Delta_{br} \rangle \tag{4.11}$$

where CC is the Communication Context as presented in definition 4.2, PC is the Planner Context following definition 4.3, and BC, DC, IC are Logic Contexts for beliefs, desires, and intentions according to definition 4.4 and Δ_{br} are the bridge rules presented in 4.12.

$$
\Delta_{br} = \{
\quad \frac{CC:\ sense(\varphi)}{BC:\ \varphi}
\quad \frac{DC:\ \varphi\ and\ BC:\ not\ \varphi\ and\ IC:\ not\ \varphi\ \ and\ PC:\ plan(\varphi,\beta,\gamma,\zeta,c_a)}{IC:\ \varphi}
\quad \frac{PC:\ plan(\varphi,\beta,\gamma,\zeta,c_a)\ \ and\ IC:\ \varphi\ and\ BC:\ \gamma}{CC:\ \beta}
\quad \} \tag{4.12}
$$

The reasoning of this agent follows the approach defined by RAO (1995). First, the agent perceives the environment and update its beliefs (BC). Then the agent decides which intention (IC) it may achieve based on what it beliefs (BC), in its desires (DC) and the plans (PC) it has to fulfil the desires. The last step of the reasoning cycle is to choose one action to be executed (CC) based on agents' intentions, plans and beliefs. The agent can execute a plan if all the preconditions are deduced in its beliefs. This BDI-based reasoning is a simple example, in which the agent does not have many abilities, such as create new desires. Each context has its machinery for reasoning, and the bridge rules have the role of integrating the knowledge and controlling the reasoning steps. Also, the agent may have other bridge rules, adding other knowledge representation or capabilities. Subsections 4.4.1, 4.4.2, 4.4.3, and 4.4.4 present more complex examples.

4.2 SIGON LANGUAGE

In this section, the key elements of the Sigon language are described. The goal is to create an abstraction in MCS according to AOP. An agent is built mandatory from the Communication context, and it can have other contexts and bridge rules. The grammar rule in equation 4.13 describes this specification.

$$
agent : communicationContext\ (context \mid bridgeRule)^{*}; \tag{4.13}
$$

Sigon has two groups of contexts: functional and logical. Functional contexts have specific roles for an agent, they are the Communication — an interface with the environment; and the Planner — a set of plans and actions. A logical context may represent a mental state, such as beliefs, desires, and intentions, or represent a situation with specific semantics.

Studies in this thesis are based on BDI agents. In this sense, Sigon has a structure to develop this agent model. All other contexts or agents' capabilities that are not Belief, Desire, Intention, Communication, and Planner, are defined in the agent's grammar as *custom contexts*. In equation 4.14 it is presented the structure of contexts according to Sigon language. It is important to note that the grammar enables a context to be called many times in different agent's code points. For example, the developer can call the Intention context and add some intentions, call the Planner context to add plans related to these intentions, and then call the Intention context and repeat the strategy. The main idea is to abstract MCS and developing thinking in the agent's capabilities.

$$\begin{aligned}
\mathit{context} &: \mathit{logicalContext} \mid \mathit{functionalContext};\\
\mathit{logicalContext} &: \mathit{logicalContextName}\ \text{‘:’}\ \mathit{formulas};\\
\mathit{functionalContext} &: \mathit{communicationContext} \mid \mathit{plannerContext};\\
\mathit{communicationContext} &: \mathit{COMMUNICATION}\ \text{‘:’}\ \mathit{sensor}+\ \mathit{actuator}+;\\
\mathit{plannerContext} &: \mathit{PLANNER}\ \text{‘:’}\ \mathit{plansFormulas};\\
\mathit{logicalContextName} &: \mathit{primitiveContextName} \mid \mathit{customContextName};\\
\mathit{primitiveContextName} &: \mathit{BELIEFS} \mid \mathit{DESIRES} \mid \mathit{INTENTIONS};\\
\mathit{customContextName} &: \text{‘_’}\ (\mathit{LCLETTER} \mid \mathit{UCLETTER}) + \mathit{character}*;
\end{aligned} \tag{4.14}$$

The structure to represent a knowledge fact in a logical context is a formula, which is a propositional or first-order clause or a logical expression. In all cases, there is the possibility to add the classical negation and the negation as failure. Sigon grammar permits graded values and appending an action to a clause, and this representation is used in the graded BDI of Casali, Godo & Sierra (2005). But, a Sigon agent may have graded values in other contexts, such as a Bayesian context to represent a situation. Rules presented in 4.15 show these components of the grammar.

$$\begin{aligned}
\mathit{formulas} &: (\mathit{term}\ \text{‘.’})*;\\
\mathit{term} &: \mathit{negation}?\ \mathit{constant}\ (\mathit{annotation} \mid (\text{‘(’}\mathit{atom}(\text{‘,’}\ \mathit{atom}) * \text{‘)’})\mathit{annotation}?)?\\
&\quad \mid \mathit{term}(\mathit{AND} \mid \mathit{OR})\ \mathit{term}\\
&\quad \mid \text{‘[’}\mathit{term}\ (\text{‘,’}\ \mathit{term}) *\ \text{‘]’})\\
&\quad \mid \mathit{term}\ \text{‘:-’}\ \mathit{term};\\
\mathit{annotation} &: (\mathit{preAction}\ \mathit{gradedValue}?) \mid \mathit{gradedValue};\\
\mathit{gradedValue} &: \text{‘->’}\ (\mathit{ZERO.NUMERAL} \mid \mathit{ONE});
\end{aligned} \tag{4.15}$$

Agent's sensors and actuators are represented in the Communication context according to equation 4.16. Each sensor/actuator has an identifier, which can be called by bridge rules by other contexts, and a path to its implementation.

$$\begin{aligned}
\mathit{sensor} &: \mathit{SENSOR}\ \text{‘(’}\mathit{sensorIdentifier}\text{‘,’}\ \mathit{sensorImplementation}\text{‘)’‘.’};\\
\mathit{actuator} &: \mathit{ACTUATOR}\ \text{‘(’}\mathit{actuatorIdentifier}\text{‘,’}\ \mathit{actuatorImplementation}\text{‘)’‘.’};
\end{aligned} \tag{4.16}$$

In the Planner context, the agent has a set of plans and actions. For a plan or an action to be executed, preconditions must be satisfied. A Sigon agent may have an empty precondition if the environment's condition is irrelevant to its execution. Plans and action have the option to add a cost to its execution. This is similar to Casali, Godo & Sierra (2005) work, in which the degree of beliefs are factors in achieving a plan. A Sigon agent has the rule '*operator*' to describe the possibilities of adding and removing clauses for postconditions. Another important aspect of a plan is its invocation. The goal of a plan execution is to get *something to be true*. In a BDI perspective, this is represented by intentions. The structure of Planner context is presented in equation 4.17.

$$\begin{aligned}
\mathit{plansFormulas} &: ((\mathit{plan} \mid \mathit{action})\ \text{`.'})*; \\
\mathit{plan} &: \mathit{PLAN}\ \text{`('}\mathit{somethingToBeTrue}\text{`,'}\ \mathit{compoundAction} \\
&\quad (\text{`,'}\ \mathit{planPreconditions}\text{`,'}\ \mathit{operator}?\ \mathit{planPostconditions})? \\
&\quad (\text{`,'}\ \mathit{cost})?\text{`)'}; \\
\mathit{action} &: \mathit{ACTION}\ \text{`('}\mathit{functionInvocation}\text{`,'} \\
&\quad (\mathit{actionPreconditions}\text{`,'}\ \mathit{operator}?\ \mathit{actionPostconditions})? \\
&\quad (\text{`,'}\ \mathit{cost})?\text{`)'};
\end{aligned} \tag{4.17}$$

The last main component of Sigon language, as in MCS, are the bridge rules. In an agent, a bridge rule starts with the symbol *'!'* and the head and body are separated by the symbol *':-'*. The head context will add a knowledge fact if all the conditions in the body are satisfied. The key elements of the grammar for bridge rules are presented in 4.18. The complete grammar is presented in Appendix A.

$$\begin{aligned}
\mathit{bridgeRule} &: \mathit{head}\ \text{`:-'}\ \mathit{body}\text{`.'}; \\
\mathit{head} &: \text{`!'}\ \mathit{negation}?\ \mathit{contextName}\ (\mathit{clause} \mid \mathit{negation}?\ \mathit{variable}); \\
\mathit{body} &: \mathit{negation}?\ \mathit{contextName}\ ((\mathit{clause} \mid \mathit{negation}?\ \mathit{variable}) \mid \mathit{plan}) \\
&\quad ((\mathit{AND} \mid \mathit{OR})\ \mathit{negation}?\ \mathit{contextName}\ (\\
&\quad (\mathit{clause} \mid \mathit{negation}?\ \mathit{variable}) \mid \mathit{plan}))*;
\end{aligned} \tag{4.18}$$

4.2.1 An Urban Agent in Sigon

To exemplify the Sigon syntax, consider the following example: an agent in the smartphone of a pedestrian situated in an urban environment. The main goal of this agent is to keep the user safe. To achieve it, the agent keeps observing the traffic flow and smartphone usage through five sensors: three to get information from smartphone device (screen, headphone, and GPS), one to communicate with vehicles (vehicle), and one to do a query in an ontology base (query). It is important to note that all sensor have their own update rates and all information perceived may be added to the agent's beliefs.

In the Belief context, the agent has the current status of the screen, microphone, headphone, GPS, a safe distance from cars (*safe(radius, 10)*), and information about cars based on this distance. This agent has 2 desires (*safe(user), aware(user)*), two intentions (*safe(user), do(something)*), and 4 plans (3 to achieve *safe(user)*, and one to achieve *do(something)*). This agent has a specific bridge rule to add a belief about a car based on the distance between the car and the smartphone. Listing 4.1 presents the code for this agent.

Listing 4.1 – The main status of an agent in an urban environment

```
communication:
    sensor("screen", "perceptionExperiment.SmartphoneSensor").
    sensor("headphone", "perceptionExperiment.SmartphoneSensor").
    sensor("gps", "perceptionExperiment.SmartphoneSensor").
    sensor(" vehicle ", "perceptionExperiment.MessageSensor").
    sensor("query", "perceptionExperiment.OntologySensor").

    actuator("blockHeadphone", "perceptionExperiment.BlockActuator").
    actuator("blockScreen", "perceptionExperiment.BlockActuator").
    actuator(" notifyDriver ", "perceptionExperiment.NotifyActuator").
    actuator(" textNotification ", "perceptionExperiment.NotifyActuator").
    actuator(" audioNotification ", "perceptionExperiment.NotifyActuator").
    actuator("do", "perceptionExperiment.Something").

//This bridge rule add in beliefs a car W if it is in the notification region T.
! beliefs car(W, T) :- beliefs smartphone(gps, X, Y, Z) &&
                           beliefs safe(radius, S) &&
                          communication car(W, X1, Y1, Z1) &&
                          communication distance(T, S, X, Y,Z, X1, Y1, Z1).
beliefs :
    smartphone(screen, off).
    smartphone(gps, 0, 0, 0). // Simplification coordinate x, y and z.
    smartphone(microphone, off).
    smartphone(headphone, off).
    safe(user).
    car(myCar, far).
    //minimum distance between the agent and other entity
    safe(radius, 10).

desires :
    safe(user).
    aware(user).
```

```
intentions :
    safe ( user ) .
    do(something) .

planner :

    plan(do(something) ,
        [ action ( do(something)) ],
        [ do(something) ],
        _) .

    plan( safe ( user ) ,
        [ action ( audioNotification ( user , audio)) , action (blockHeadphone(true)) ],
        [ car (_, close ) , smartphone(headphone, on) , smartphone(screen , off ) ],
        [ smartphone(headphone, off ) ]) .

    plan( safe ( user ) ,
        [ action ( textNotification ( user , text )) , action (blockScreen( true )) ],
        [ car (_, close ) , smartphone(screen , on) , smartphone(headphone, off ) ],
        [ smartphone(screen , off ) ]) .

    plan( safe ( user ) ,
        [ action ( notifyDriver (X, yes)) ],
        [ car (X, close ) , smartphone(screen , on) , smartphone(headphone, on) ],
        _) .
```

4.3 SIGON FRAMEWORK

This section presents the key features developed in the current version of Sigon[2]. The structure is divided into two main modules: (i) the parser module — the transformation of agents' source code into an executable object; and (ii) the agent module built of contexts and bridge rules. Each bridge rule can add, remove or update knowledge in only one context at a time. Also, the order in which bridge rules are presented describes the agents' reasoning cycle. ANTLR (ANother Tool for Language Recognition) (PARR, 2013) is the parser generator used to implement the language. It generates recursive-descent parsers from Sigon grammar rules.

The agent source code is defined in text files with the extension *'.on'*. The parser module performs lexical and syntactical analysis in the source code. The result of this process creates the agent as an object and it is executed by the agent module (GELAIM et al., 2019b).

[2] https://github.com/sigon-lang/sigon-lang

4.3.1 The Agent Module

An agent's context has a unique name, a theory, methods for checking, updating, removing its theory, and a set of internal inference rules. This makes possible to create contexts with specific characteristics. A bridge rule consists of a data structure that contains a head proposition or its negation, and a body. The head has a term or variable and a context reference; the body is recursively composed of contexts with clauses and the connectors *and* and *or*. Each context is established on inner rules of inference, that is, on its own theory. Furthermore, each bridge rule performs reasoning in a larger scope of theories between different contexts (GELAIM et al., 2019b).

The sequence of bridge rules defines the agent's reasoning. This implies in preferences on queries/updates/addition in contexts. It is also important to note that at a specific reasoning cycle, a bridge rule is able to update several knowledge facts in a context, but only one action in the environment is taken. Another relevant feature is concerning the sequential execution of bridge rules, enabling algorithms' creation to define the agent's architecture.

Sensors and actuators are developed in the communication context and provide an interface for integration with the environment. They are low coupling structure with the environment. This enables the agent to create sensors and actuators to integrate with different knowledge representations. However, the result of a sensor perception must be a literal according to agents' contexts. An actuator is an abstract object able to handle the result of a reasoning cycle.

The agent's semantics in the urban environment presented in subsection 4.2.1 is: The agent is always executing and choosing the action based on the current environment state. The agent's reasoning is described according to the bridge rules presented in 4.12. The desire *aware(user)* will not be added to intentions once the agent does not have a plan for it. If the agent's belief context has a belief about a car close (*car(carName,close)*), and there are distractions in the smartphone (*smartphone(headphone, on), smartphone(screen, on)*), the agent will have the intention to keep the user safe. The plan the agent will execute depends on its beliefs. For example, if it believes in a car approaching, and it senses, the headphones on, and the screen off, it will execute the actions of blocking the headphone, and send an audio notification.

4.4 EXTENDING A BDI-LIKE AGENT IN SIGON

Taking as starter point the BDI agent presented in subsection 4.2.1, this section presents four examples giving flexibility in a Sigon agent: the first shows how to integrate an ontologic knowledge based on Description Logic; the second one is an example of reasoning under uncertainty; the third describes the agent as an active perceiver; the last one extends the agent architecture with a computational model of emotions.

4.4.1 Case 1 - Adding Ontologies

This example adds an ontological context for reasoning about situations in the agent presented in subsection 4.2.1. A well-known and well-accepted definition of ontology in computer science is "*a formal, explicit specification of a shared conceptualisation*" (GRUBER, 1993; STUDER; BENJAMINS; FENSEL, 1998). The use of ontologies for knowledge representation in a heterogeneous environment permits a shared and detailed description of the domain. Thus, the agent can use shared knowledge for its decision-making process. For example, the agent situated in the urban environment can verify in a shared urban ontology that a particular driver is speedy, and act differently than for a rational driver.

The logical representation of ontologies in this context is based on Description Logics (DL). DL are a family of formalisms to knowledge representation and reasoning (BAADER et al., 2003, pag. 47). Sigon language does not have a specific way for representing and reasoning with description logic knowledge, but a context can access an OWL DL ontology[3] engine. For simplification purposes, the result of ontology reasoning is represented in Horn clauses. Many ontologies used in practice are formed mostly of Horn axioms (GLIMM et al., 2014).

This context's core is the Situation Theory Ontology (STO) (KOKAR; MATHEUS; BACLAWSKI, 2009). It is an ontology based on the situation theory of Barwise (PERRY; BARWISE, 1983), in which a situation is a limited part of the world, "*a part of reality that can be comprehended as a whole in its own right — one that interacts with other things.*" (BARWISE, 1989). The key classes of STO ontology for this experiment are: `Situation`: its instances are specific situations; `Individual`: represent the class of individuals; `Relation`: captures the *n*-ary relations; `Rule`: is used for inferring whether a specific relation holds in a situation; `Attribute`: locations and time instants of individuals and situations.

The key properties are:

- `relevantIndividual`: individual of a situation. The domain is `Situation` and range is `Individual` and its inverse is `inSituation`;

- `relevantRelation`: relation relevant to a given situation. The domain is `Situation` and the range is `Relation`;

The class `Situation` has three subclasses: `UtteranceSituation` — queries from a formal situation awareness system, probably referring to another situation; `ResourceSituation` —- used as 'background for reasoning with the current situation'; `FocalSituation` — the relevant part of the world to a given utterance. Based on these concepts, the following situations were built based on the STO:

- `PedestrianInteractingWithSmartphone`: a pedestrian (subject) interacts with a smartphone (object) in the relevant relation `interacts`. Smartphone attributes are distraction

3 https://www.w3.org/TR/owl2-syntax/

type and location. The interaction with the smartphone may reduce pedestrian's situation awareness.

- `CarLifeThreatenPedestrian`: in this situation, a specific car may collide with the pedestrian in the relevant relation *lifeThreaten*. Attributes of this situation are vehicles in the region and pedestrian's distractions. Vehicle attributes are the location, speed, type of driver (speedy, nervous, rational). Situation `PedestrianInteractingWithSmartphone` plays the role of resource situation.

Although there are other objects in the environment, for simplification purposes, only those mentioned are part of the ontological component. Reiterating that each agent's component is a context, with a mechanism for reasoning, and bridge rules exchange information between contexts.

The code presented in Listing 4.2 is added on the agent allowing the representation of ontological situations and influencing the agent's reasoning. There is a new plan in the planner context, and it only can be executed when the ontological context deduces that there is a car threatening the pedestrian. This plan also needs the belief context to deduce that the car is close. The ontological context (*_ontologic*) presents the predicate of the situation (*carLifeThreatenPedestrian(X, user)*). The bridge rule decides the action *Y* to be performed based on the reasoning the contexts of intentions, planner, beliefs and ontological. The OWL API[4] is the engine for manipulating the ontology.

Listing 4.2 – The aditional code for ontologic reasoning

```
planner:
    plan(safe(user),
    [action(notify(driver))],
    car(X, close), smartphone(screen, on), smartphone(headphone, on),
        carLifeThreatenPedestrian (X,user),
[notify(driver)]).

_ontologic:
    carLifeThreatenPedestrian (X, user).

!communication Y :- planner plan(safe(user),Z,W,_)
    & planner member(Y,Z)
    & intentions safe(user)
    & planner member(carLifeThreatenPedestrian(X, T),W)
    & beliefs car(X, close)
    & _ontologic carLifeThreatenPedestrian (X, T).
```

4 https://github.com/owlcs/releases

The situation `CarLifeThreatenPedestrian` has the following semantics: the car X is life threatening the pedestrian '*user*'. To know the X' value, the ontology uses the attributes about the pedestrian and the vehicles to infer if there is really a car harming the pedestrian. Figure 2 presents in orange the main class addition in STO ontology enabling these inferences.

Figure 2 – Main classes created in STO ontology for pedestrian safety agent.

Source: Adapted from (KOKAR; MATHEUS; BACLAWSKI, 2009).

This example adds to the agent a mechanism for representing and reasoning about situations using ontologies. It formalises a situation and how to use it in the decision-making process according to DL axioms. A problem with this approach emerges when the agent has access to the position of all vehicles that may constitute the situation, and does not have a mechanism to optimise it. In fact, the data collection problem can be formulated as a scheduling optimisation problem and it is NP-complete (HE; ZHANG, 2017).

4.4.2 Case 2 - Adding Bayesian Networks

This example adds a Bayesian context for reasoning about situations in the agent presented in subsection 4.2.1. Bayesian methods are applied to reason about partial beliefs in the presence of uncertainty (PEARL, 1988, pag. 29). Bayesian networks have advantages in simplifying conditionals, planning decisions under uncertainty, and explaining the outcome of stochastic processes (ZELTERMAN, 2005). For example, it is possible to create a Bayesian network to check the probability that a pedestrian using a smartphone is aware of the situation (GELAIM et al., 2019a).

In this example, the Bayesian network (BN) is constructed based on the knowledge obtained from the experiments on pedestrian situation awareness presented in Chapter 5. The main reasons for using BN for situational awareness are: it combines graph theory and Bayesian inference — directed arcs can propagate new information, experts can specify relevant information, the knowledge can be updated, it presents a temporal continuity for SA (NADERPOUR, 2015; SU et al., 2011). On the other hand, BN is domain-dependent, and when adding one to an agent, it will probably be about a specific domain or situation.

The developed BN is added in the agent's reasoning according to the MCS approach. An agent's sensor captures the evidence from the environment and then adds the information in Bayesian Network Context (BNC). A perception and evidence φ, obtained by CC, is added in the BNC through the bridge rule 4.19.

$$\frac{CC : \varphi \,\wedge\, BNC : (\varphi)}{BNC : (\mathtt{update}(\varphi)))} \tag{4.19}$$

BNC influence the decision-making process through plans. Let φ be a variable (belief) from a BN with probability r, ψ an intention having a plan with precondition φ, and s is the minimum probability of φ enabling the plan's execution for intention ψ. The bridge rule 4.20 allows the agent to try to achieve intentions considering the uncertainty of the situation. It is important to note that the ontologic context has focused on describing the situation, and the Bayesian in the uncertainty situation.

$$\frac{BNC : (\varphi,\, r) \,\wedge\, IC : \psi \,\wedge\, PC : plan(\psi, \beta, \varphi, \zeta, s) \,\wedge\, r \,>\, s}{CC : (\mathtt{do}(\beta)))} \tag{4.20}$$

The code presented in Listing 4.3 is added on the agent code allowing the representation and reasoning of bayesian situations. The Bayesian network, and therefore the Bayesian context, of this agent, has four nodes (*userAware, carNearby, soundDistraction, screenDistraction*). The *carNearby, soundDistraction, screenDistraction* nodes present conditional probability to the *userAware* node. For example, if a car is nearby, there is a 20% chance of the user being aware and an 80% chance of not being at any specific time.

The bridge rules presented in lines 13 and 15 perform the addition of information about the smartphone and cars in BNC. In the planner context, there is a plan which has as a precondition an inference from the *userAware* node. Its value is obtained through line 23 of the agent's code and according to the bridge rule 4.20. The predicate *userAware(T, X)* has the role of checking the probability of user awareness at a specific moment. For example, if the Belief context has the belief *userAware(no, 40)* (the threshold), and the result in the Bayesian context the value of the *userAware* node is higher than 40, the plan will be executed. The substitution of the threshold value impacts the plan execution. A lower value in the *userAware* belief implies in the agent performing more actions to ensure the pedestrian's safety. Higher value implies that the plan only will be executed when the level of awareness is small.

Listing 4.3 – The aditional code for bayesian reasoning

```
_bayesian:
    userAware(50,50).
    carNearby(userAware).
    soundDistraction (userAware).
    screenDistraction (userAware).
    carNearby(yes, 20, 80).
    carNearby(no, 95, 5).
    soundDistraction (yes, 80, 20).
    soundDistraction (no, 95, 05).
    screenDistraction (yes, 20, 80).
    screenDistraction (no, 95, 05).

!_bayesian addEvidence(X,Y) :- beliefs smartphone(X,Y) && _bayesian
    isVariable (X).

!_bayesian addEvidence(car,yes) :- beliefs car(_,close).

planner:
    plan(safe(user),
        [action(notify(driver))],
        [car(_, close), smartphone(screen, on), smartphone(headphone, on),
            userAware(false)] ,
        [notify(driver)]).

!communication Y :- planner plan(safe(user),Z,W,_)
   & planner member(Y,Z)
    & intentions safe(user)
    & planner member(userAware(false),W)
    & beliefs car(_, close)
    & _bayesian userAwareT(T, X)
    & beliefs userAware(T, X).
```

Adding a context of Bayesian networks does not guarantee consistency with the other components of the agent. In this way, it may have conflicting beliefs in different contexts. For example, in the ontological context, the agent can infer user awareness by evaluating declarative information, without uncertainty, and the Bayesian network context can provide this information with a degree of certainty. The use of Bayesian networks, in this case, allows choosing the action to be performed based on a situation of uncertainty. In this sense, it is even possible to combine unambiguous contexts knowledge, with Bayesian reasoning, making the agent's decision-making more flexible.

4.4.3 Case 3 - A Multi-Context Active Perceiver Agent

Actively perceiving is a relevant skill for agents situated in dynamic environments, enabling the agent to decide which environmental aspects are relevant to its current goals and having situational awareness. This section describes a BDI-like agent as an active perceiver following the generic framework presented by Bajcsy, Aloimonos & Tsotsos (2018) and introduced in section 2.3.1.

The first element of active perception of Bajcsy, Aloimonos & Tsotsos (2018)'s framework is *why* to perceive. A BDI agent must perceive certain aspects of the environment because it has an intention that expects the situation's knowledge. For example, the intention to have the user safe depends on the knowledge of the user's interaction with the smartphone and the traffic flow.

The second element is *what* to perceive of Bajcsy, Aloimonos & Tsotsos (2018)'s model. A BDI agent's intention comprises one or more plans to achieve it. Plans can be in a library of precompiled plans, each one of these includes a set of preconditions in which it is applied. Thus, what to perceive is defined by plans preconditions. That is, monitoring the aspects of the environment that can drive the agent to maintain/achieve the desired situation.

A perception φ obtained in the communication context will only be added to the Belief context if the agent has an intention ψ where φ is part of the preconditions γ of at least one of its plans, or if φ represents the fulfilment of the intention γ. Bridge rules 4.21 and 4.22 show these formalisations, and Listing 4.4 presents its mapping to Sigon. For example, considering `user(safe)` from Listing 4.1, the plan presented on line 45, the agent needs to know that: (i) there is a car nearby, (ii) the user is listening in the headphone, and (iii) the smartphone screen is off.

$$\frac{CC : \varphi \wedge PC : plan(\psi,\ \beta,\ \gamma,\ \zeta, c) \wedge (\varphi \in \gamma) \wedge IC : \psi}{BC : \varphi} \tag{4.21}$$

$$\frac{CC : \varphi \wedge IC : \varphi}{BC : \varphi} \tag{4.22}$$

Listing 4.4 – Adding active perception in the urban agent

```
! beliefs  X :− communication sense(X) and planner  plan(Y,_,Z,_)
```

```
      and planner member(X, Z) and intentions Y.

! beliefs X :− communication sense(X) and intentions X.
```

The third component is *when* to perceive. This aspect is temporal, corresponding to the update rate of objects perceived. For example, the update of knowing that a driver is speedy has minor importance than the update rate of an oncoming car position. And also, an oncoming car should have a higher priority in the perception process than a leaving one. A problem in this temporal aspect occurs when perceptions arrive faster than the agent's capability of processing it. In this case, perceptions policies are useful to define when to perceive. Freitas et al. (2020) present two policies for the sensors' prioritisation in Sigon agents: progressive and sudden. The first increases/decreases sensors' priority based on the number of new information; The last strategy focus on the amount of unforeseen perception detected in a specific moment.

The fourth element of active perception from Bajcsy, Aloimonos & Tsotsos (2018) generic model is *how* to perceive. This is an abstract element in a Sigon agent. It is limited to enabling/disabling a perception function and combining sensors' data to create a percept. For example, if the agent enables the smartphone's camera and the microphone, it can obtain a car position and know that it has a combustion engine. The last element is *where*. It gets information from the smartphone sensors related to current intention. For example, the intention `user(safe)` requires attention to the traffic flow.

Active perception improves the effectiveness of beliefs revision. The association is straightforward: fewer beliefs in the knowledge bases mean lower costs for searching and updating beliefs. On the other hand, adding a mechanism to choose which aspects of the environment to examine can imply in increasing the time for decision making, since it requires comparing what is perceived with the agent's goals (JR; PANTOJA; SICHMAN, 2018). In this way, active perception is beneficial in situations where the cost to apply it is less than the cost to add all perceptions in the agent's beliefs.

4.4.4 Case 4 - Creating An E-BDI Agent

The intent of examples presented in subsections 4.4.1 and 4.4.2 is to show how to represent knowledge of the situation with different approaches: uncertainty and description logic. Subsection 4.4.3 shows how a Sigon agent can perceive in dynamic environments. In this subsection, we create an example to show the flexibility in an agent's architecture implemented in Sigon, in which the new component may cause a different action.

In its core, this research uses BDI-like architecture to test practical reasoning in decision making. To demonstrate an example of integration, this subsection describes how to add a computational model of emotions in BDI agents. However, the purpose of this example is not to present a discussion of how emotions can impact in decision making, neither to argue about its benefits. It is only to show how to extend an architecture of agent with new capabilities.

The literature of computational models of emotion presents applications in areas such as improving human-machine interaction and optimising decision-making reasoning (MARSELLA; GRATCH; PETTA, 2010). Taking as a starting point the BDI agent in an urban environment presented in section 4.2.1, to add a new context representing emotions, the first step is to create a new custom context to it. This context will have the logic to reason about agents' emotions.

The logic of emotions follows the Ortony Clore and Collins (OCC) model, which focuses on the cognitive structure of emotions (ORTONY; CLORE; COLLINS, 1990) and its integration in the agent reasoning described by Silveira et al. (2016). For this example, the agent has only three emotions: *hope, fear*, and *joy*. Also, in this context, the agent is able to evaluate events as: *pleased*(X) if it is positive about an event X; and *displeased*(X) if it is negative about X.

Bridge rules are defined to update the agent's emotional state (emotional context). The bridge rule in Sigon code presented in Listing 4.5 adds the emotion of *hope* for the event X in the agent emotional context, if it has an intention Y and a plan to achieve Y in which the event X is a postcondition. If the agent finds a plan to achieve the event X and is pleased about it, it will have *hope* on this.

Listing 4.5 – Adding the emotion *hope* in emotional context

```
!_emotional hope(X) :- intentions Y
  & planner plan(Y, _, _, Z)
  & member(X, Z)
  & _emotional pleased(X).
```

The bridge rule described in Listing 4.6 adds the emotion of fear in the emotional context when the agent has an intention Y, and some plan that will bring X in its postcondition. In this sense, the agent may avoid such a plan and try to choose one without X because it is displeased about X.

Listing 4.6 – Adding the emotion *fear* in emotional context

```
!_emotional fear(X) :- intentions Y
  & planner plan(Y, _, _, Z)
  & member(X, Z)
  & _emotional displeased(X).
```

The joy of emotion is added in the emotional context when the agent is pleased with an event X, and in its beliefs, it has X or when it senses it. It is presented in Listing 4.7.

Listing 4.7 – Adding the emotion *joy* in emotional context

```
!_emotional joy(X) :- _emotional pleased(X)
  & ( beliefs X | communication sense(X)).
```

This abstraction can change agent decision-making, and it is common in Emotional-

BDI agents. For example, according to Listing 4.8, the agent will try to execute an action T in which a belief X will bring joy.

Listing 4.8 – Using *joy* to influence BDI reasoning

```
!communication T :- _emotional joy(X)
  & planner plan(Y, W, _, Z)
  & planner member(T, W)
  & planner member (X, Z).
```

4.5 SUMMARY

This Chapter applied MCS theory to build the Sigon framework for agent development. This approach is based on MCS's ability to combine heterogeneous knowledge sources and in the literature of BDI agents as MCS. From a theoretical point of view, this approach allows the selection of the formalism that best describes the desired functionality. In a practical perspective, this provides more flexible reasoning for the agent. To the developer, a context is a component, a module of the agent. Furthermore, a bridge rule is a path to connect components.

The flexibility of reasoning allows agent modelling in different ways. This Chapter presented paths for representing the situation with different formalisms (ontology and Bayesian networks), adding mechanisms for perceiving the environment and adding another mental state, emotions, in the decision-making. Consequently, the agent's reasoning cycle is defined by the combination of contexts and the sequence in which bridge rules are executed.

The Sigon framework was designed during the thesis for studies in situation awareness, perception and decision-making. The experiments in the thesis are limited to these domains. However, Sigon has already proved interesting for applications considering negotiation in BDI agents (MELLO; GELAIM; SILVEIRA, 2019).

5 PEDESTRIANS SITUATION AWARENESS

Pedestrians are a fragile class of vulnerable road users in urban environments. To guarantee pedestrian's safety it is essential to respect the rules, such as walking in a crosswalk or be aware of the surroundings. Improving their safety in these environments can be analysed from at least two perspectives: (i) vehicles, by adding pedestrian behaviour recognition algorithms (KOOIJ et al., 2019; SOTO et al., 2019; NEOGI et al., 2017; PHAN et al., 2014; PHAN et al., 2015; VASISHTA; VAUFREYDAZ; SPALANZANI, 2017); (ii) pedestrians, by improving their situational awareness, usually achieved by changes of behaviour, re-education policies, or by improving the environment's infrastructure (ASADI-SHEKARI; MOEINADDINI; SHAH, 2015; NESOFF et al., 2019). In this Chapter, we investigate how to measure pedestrian situation awareness based on their smartphone usage, and in Chapter 6, we evaluate how an agent with heterogeneous data can improve pedestrian decision making in an urban environment.

There are several activities for pedestrians that may limit their situational awareness, such as talking on a mobile phone or with other pedestrians, eating or, using headphones (BUNGUM; DAY; HENRY, 2005; THOMPSON et al., 2013). This work analyses the situation awareness related to the use of mobile devices. Mobile device usage is growing. In Brazil, the number of smartphone users increased from 14% in 2012 to 67% in 2017, tablet expansion is from 1% to 15% (BAROMETER, 2017a). In the UK, in the same period, the growth is from 51% to 77% for smartphones and from 11% to 53% for tablets (BAROMETER, 2017b). Besides, there is a growth in the number of tasks that can be performed on mobile devices, attracting more attention to devices than to the environment.

This Chapter presents a comprehensive study on aspects affecting situational awareness of smartphone users in the vicinity of urban traffic. Virtual environments are used to simulate the immersion in the urban environment, free of the inherent dangers of testing in real scenarios. In all experiments reported, we are interested in the impact caused by distractions from using a smartphone on safe behaviours around moving traffic.

The remainder of this Chapter is structured as follows. Section 5.1 presents similar works found in the literature. Sections 5.2 and 5.3 present experiments performed on the Octave multimodal system[1], and section 5.4 presents the experiment using the HTC VIVE virtual reality glasses. Endsley's situation awareness model is the base of all experiments (ENDSLEY, 1988).

5.1 RELATED WORK

This section presents previous research on pedestrians' situation awareness using smartphones. There are three main groups of environments: (i) real environment — urban or laboratory (PLUMMER et al., 2015; HAGA et al., 2015; LICENCE et al., 2015; PIZZAMIGLIO

[1] An octagonal virtual reality environment in which the user is immersed with the ability to interact using devices and his own body. Source: http://www.salford.ac.uk/octave/home

et al., 2017; JIANG et al., 2018; YEN; ZHENG, 2018; CHEN; PAI, 2018; FELD; PLUMMER, 2019); (ii) semi-virtual environment — use of single or multiple video screens without necessarily forming a Computer Automated Virtual Environment (CAVE) (SCHWEBEL et al., 2012; BYINGTON; SCHWEBEL, 2013; LIN; HUANG, 2017) or use of sound reproduction without a visual counterpart (DAVIS; BARTON, 2017); or (iii) a fully immersive multimodal virtual environment (NEIDER et al., 2010; BANDUCCI et al., 2016; RAHIMIAN et al., 2016; RAHIMIAN et al., 2018). The three experiments in this Chapter were run in fully immersive, multimodal virtual environments. The first and second are run in a CAVE environment — Octave, whilst the third one is run in a head-mounted display (HMD) — HTC VIVE.

The use of a virtual environment allows full control and capture of environmental and participant variables, whilst avoiding the inherent risks of running situational awareness experiments in real urban environments with real threats. On the other hand, the environment's ecological validity may be limited — the difference can influence participants' behaviour in their perception between the real and virtual world. For example, Rahimian et al. (2016) argue that pedestrians may assume risks that would not take in real environments. Thus, it is critical to balance between the real environment and the conditions tested in the virtual environment.

The test conditions in related works usually involve typing, talking, walking and listening to music. Few studies analyse the impact of games (HAGA et al., 2015; LICENCE et al., 2015; LIN; HUANG, 2017; CHEN; PAI, 2018; HAGA et al., 2015; LICENCE et al., 2015; LIN; HUANG, 2017; CHEN; PAI, 2018). The three experiments conducted in this work use games and music on the smartphone to analyse the level of situational awareness. In the second and third experiments, it is added a walking variable.

Two studies in the literature showed samples greater than 100 participants. The largest sample has 2556 in a real environment without strict control over the environment variables (CHEN; PAI, 2018). 2215 participants had some distraction, of which 834 were playing. This value corroborates with the premise of this research in using games to analyse pedestrians' situational awareness. In this thesis, twenty participants took the first two experiments and twenty-nine the third. Like many works of literature, the participants belong to the academic community (NEIDER et al., 2010; SCHWEBEL et al., 2012; PLUMMER et al., 2015; HAGA et al., 2015; RAHIMIAN et al., 2016; JIANG et al., 2018; RAHIMIAN et al., 2018).

Related work shows that there are impacts on mobile devices' usage, such as the reduced perception of the environment, movement and decision making. Also, the type of distraction is related to the level of impact of using mobile devices. Typing has the most significant adverse impacts, being part of the study in 15 of the 16 studies. The impact of playing is the least explored. Thus, the chosen distraction. It is important to collect data from these factors for developing a support agent.

5.2 EXPERIMENT 1: PEDESTRIAN CONTROLLING A TRAFFIC LIGHT

In this experiment we test whether a distraction on the smartphone screen is likely to lead to unsafe behaviour by pedestrians. The experimental setting requires the participant to make a decision on whether a kitten can safely cross a road on a pedestrian crossing whilst under different levels of engagement with the smartphone and under different visual and auditory occlusion conditions. Two dependent variables are investigated: (i)*The number of times a kitten is likely to be run over due to unsafe behaviour by the participant*; (ii) *the time taken to detect and signal the presence of a car in the environment.* The scenarios and the smartphone applications were developed in the Unity engine (Unity Technologies, 2019). A set of scripts were written in C# and Python to configure and collect data.

5.2.1 Experimental Design

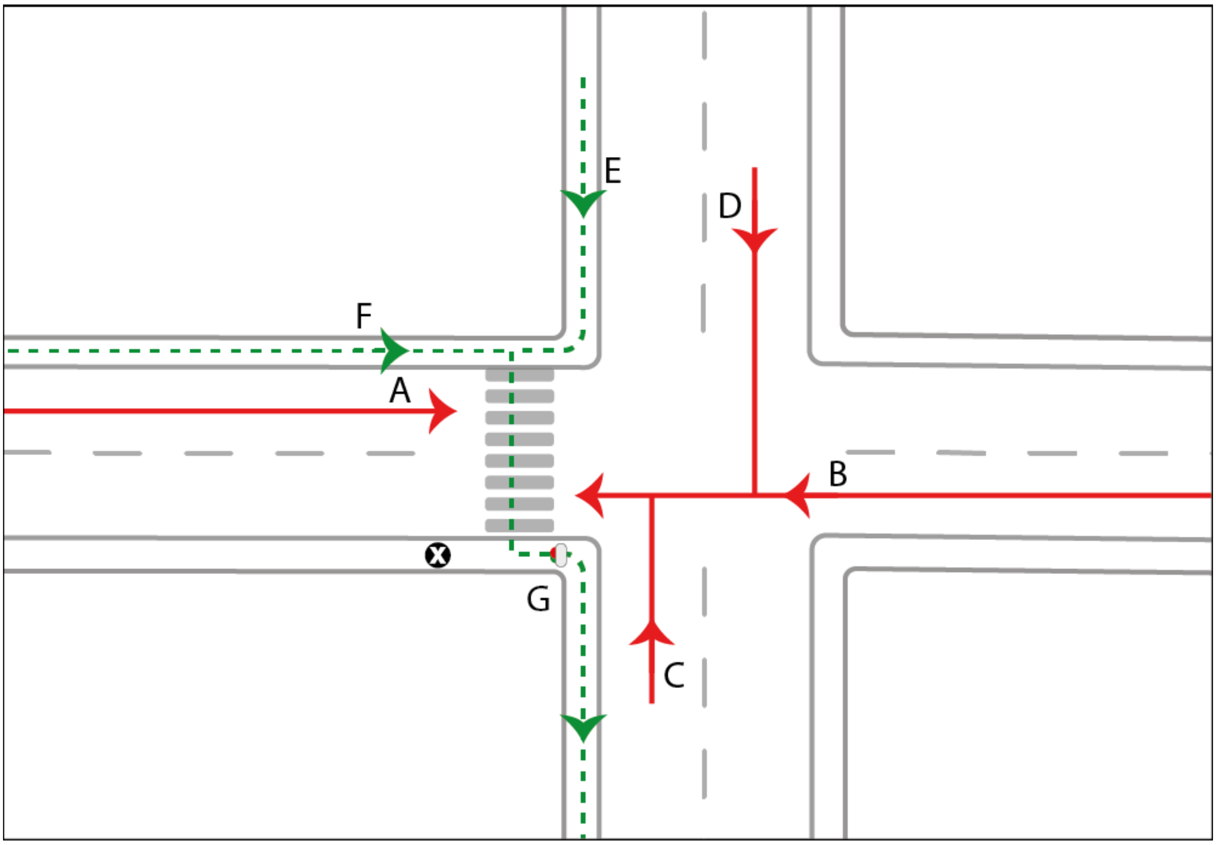
The virtual environment consists of an urban intersection in a residential area, in which the participant is situated and interacting with the mobile device while observing the moving traffic. In the environment, three types of simulated entities form the basis of the situation: a pedestrian crossing and corresponding traffic light, controlled via the smartphone; cars, travelling in four possible directions - front, back, left and right; and kittens, spawned on the sidewalk across the street intending to cross it but respecting the signalling on the traffic light. Figure 3 presents the top view of the environment with the possible car and kitten paths, as well as a space marked with an ‘X’ representing the participant’s location.

An experimental trial run consists of 16 travelling cars. Only one car is allowed in the environment at any one time, randomly approaching from one of four possible directions, two of which are partially occluded as the car travels behind buildings - paths C and D in Figure 3 - to allow the measurement of effects of visual occlusion on awareness. The number of cars is balanced for all directions with a total of four vehicles per direction. Of these, two cars will emit sound — a combination of combustion engine noise and tyre noise — whilst the other two are silent, allowing measurement of car noise’s affordance on awareness. There are always two kittens present in the environment following paths E and F. The only acoustic signal present in the environment is that generated by the cars with sound.

A participant signals detection of a car by pressing a button on the mobile device screen which brings a ‘do not cross’ icon on the pedestrian traffic light and programmatically prevents kittens from crossing the street and being run over. Once the car travels over the pedestrian crossing, the traffic light turns green, allowing kittens to cross the street once again. Figure 4 presents a participant in the Octave environment with all these elements: a car that has travelled over the crossing, a kitten crossing and the traffic light showing green.

Participant distraction conditions have been set as follows: (i) ‘No distraction’ simply presents the button for signalling detection of a car. This button is present in all conditions; (ii) ‘Game only’ presents a multiple-choice game where the participant is asked to solve simple

Figure 3 – Experiment 1: Top view of the scenario. Car routes are in red (A, B, C, D) and kitten routes in green (E, F). The place with an 'X' is the participant position near the crosswalk and the traffic light (G).



Source: The author.

mathematical problems of addition and subtraction. In this condition, the participant is not wearing a headset; (iii) 'Game and music' has participants playing the game in (ii) whilst also listening to music in a headset (set at a comfortable listening level).

Figure 5 presents a version of the app with the game and the car notification button. A Samsung Galaxy S7 Edge 5.5" was used for the experiment. Data on the traffic light control and participant's performance during the game was sent via Bluetooth to a control computer.

Twenty participants took part in the test. Most participants were students or staff at The University of Salford in 2016. Each participant performed three trial runs, one for each distraction condition listed above. Before starting the test, participants trained running a test with five cars under condition (iii) and were given the option to repeat the training, but no one requested this. Distraction conditions were presented in random order between participants, defined by randomising conditions (i), (ii) or (iii) in a list of 20 entries prior to the tests. The variables of car direction and sound were randomised at runtime. As such, we assume test conditions to be independent.

In summary, for this experiment: Dependent Variables: Failing to safely signalling the presence of a car leading to kitten and car in the crossing at the same time - 'Unsafe Event'; Time

Figure 4 – Experiment 1: The participant situated in the simulated urban environment while interacting with the smartphone.

Source: The author.

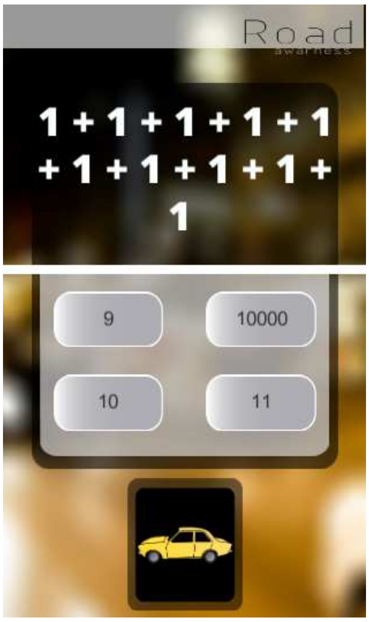
taken to signalling the presence of a car - ‘Reaction Time’. Independent Variables: Car Sound (Silent/With Sound); Visual Occlusion (Occluded/Unoccluded); distraction (None, Game and Game And Music).

5.2.2 ‘Unsafe’ Events

The data set consists of 960 records, disregarding the training data. After removing 9 records of missing data and 39 outliers in the response time (under $Q1 - 1.5 \times IQR$ and above of $Q3 + 1.5 \times IQR$) for car perception, the data set resulted in 912 records, split by condition as (i) 282, (ii) 325 and (iii) 305. Of these events, 458 cars had sound and 454 emitted no sound, 458 were visually unoccluded (directions A and B), and 454 were occluded (directions C and D). On 838 occasions, the participant signalled the car’s presence, and the kittens crossed the street safely. Table 3 lists unsafe events for analysis. Most unsafe events were due to the car having no sound (55), and/or because it was approaching from an occluded region (51), as expected. The number of unsafe events grows with distraction condition and is also higher for cars without sound or those appearing from an occluded direction.

A number of significant associations are presented between each distraction level and car sound, tested with a Pearson χ^2 test of association (A Fisher’s exact test was used for the *No Distraction* condition due to the small number of unsafe events). Cramer’s Phi effect sizes and

Figure 5 – Experiment 1: App developed to distract participant with the game and the car notification button.



Source: The author.

Table 3 – Experiment 1: Number of unsafe events where participant *failed* to signal the presence of a car for each of the distraction conditions and grouped by independent variable level: car sound (silent and with sound) and visual occlusion (occluded and Unoccluded).

Condition	**Silent**	**With Sound**	**Occluded**	**Unoccluded**
No Distraction	9	1	8	2
Game Only	21	7	18	10
Game and Music	25	11	25	11
Total	55	19	51	23

Source: The author.

odds-ratios are also presented. Table 4 shows a significant association between unsafe events and car sound even when the subject is under *no distraction* from the smartphone (Fisher's exact = 0.0193, Odds Ratio = 9.5454). Under our experimental conditions, a pedestrian is almost 10 times more likely to report the presence of a car in time if the car has sound. This falls to 3.3 times if the subject is distracted by the smartphone but can still hear their surrounding environment (Table 5; p = 0.0048, Cramer's Phi = 0.156, Odds Ratio = 3.3642), and to 2.5 times if the subject is, in addition, listening to music (Table 6; p = 0.0122, Cramer's Phi=0.1435, Odds Ratio = 2.5412). As expected, the degree of distraction appears to affect the number of unsafe events significantly. The sound of a car seems to be important as an early warning of its presence. However, this diminishes rapidly if the subject is distracted regardless of whether the auditory system becomes occluded or not.

The cars' visual occlusion is only significant in the case where full distraction by both the game and the music are present (Table 7; p = 0.0138, Cramer's Phi = 0.141, Odds Ratio =

2.5036). In this case, subjects are 2.5 times more likely to report the car's presence on time if it is travelling via an unoccluded direction.

Table 4 – Experiment 1: Safe and Unsafe events per car sound under No distraction condition (Fisher's exact = 0.0193, Odds Ratio = 9.5454).

No Distraction		
	Silent	With sound
Safe	132	140
Unsafe	9	1

Source: The author.

Table 5 – Experiment 1: Safe and Unsafe events per car sound under Game distraction condition (p = 0.0048, Cramer's Phi = 0.156, Odds Ratio = 3.3642).

Game Distraction		
	Silent	With sound
Safe	140	157
Unsafe	21	7

Source: The author.

Table 6 – Experiment 1: Safe and Unsafe events per car sound under Game and Music distraction condition (p = 0.0122, Cramer's Phi=0.1435, Odds Ratio = 2.5412).

Game and Music Distraction		
	Silent	With sound
Safe	127	142
Unsafe	25	11

Source: The author.

Table 7 – Experiment 1: Safe and Unsafe events per occlusion type under Game and Music distraction condition (p = 0.0138, Cramer's Phi = 0.141, Odds Ratio = 2.5036).

Game and Music Distraction		
	Occluded	Unoccluded
Safe	128	141
Unsafe	25	11

Source: The author.

5.2.3 Reaction Time

It is hypothesised that, when distracted, participants will take longer to detect the presence of a car in the environment, potentially leading to near misses or fatalities on the pedestrian crossing under their control. This thus defines *reaction time* as the time taken by the participant in signalling the presence of a car in the environment. This was coded as the time between the spawn of a new car in the environment and the participant pressing the smartphone screen's traffic light button.

A Shapiro-Wilk test (Shapiro-W: stats = 0.98, p-value = 5.53e-11) and a Bartlett's test (stats = 2.15, p = 0.90) were used to check assumptions for the application of an ANOVA. Although the assumption that the residuals are normally distributed is violated, it is known that, for large sample sizes such as this one, a small deviation will not affect the results of a parametric test (ÖZTUNA; ELHAN; TÜCCAR, 2006). A three-way ANOVA has been calculated and is shown in Table 8. There are no significant interaction effects, and the effects on car sound and direction are significant. A non-parametric Kruskal-Wallis test applied independently for each variable (distraction: Stats=9.770, p=0.008; car sound: stats=24.876, $p < 0.001$; occlusion stats=94.777, $p < 0.001$) confirms the main effects without assumptions required for the parametric ANOVA. The eta squared values in Table 8 show that the effect sizes for main effects are in the range small to medium. Figure 6 presents the box plot of reaction time, distraction

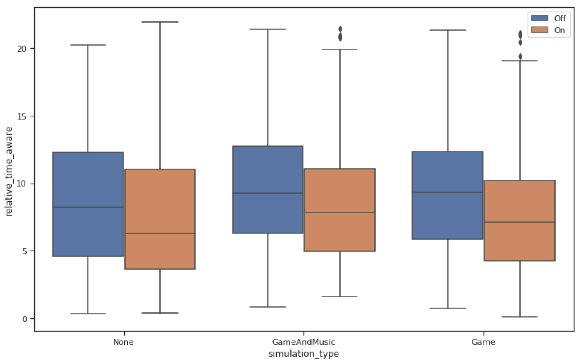
Table 8 – Experiment 1: ANOVA reaction time per simulation type.

	df	sum sq	mean sq	F	PR(>F)	eta sq	omega sq
Intercept	8954.6236	8954.6236	1.0	458.1348	1.75e-82	0.3311	0.3302
distraction	4.1058	2.0529	2.0	0.1050	9.00e-01	0.0001	-0.0012
car_sound	147.1847	147.1847	1.0	7.5302	6.18e-03	0.0054	0.0047
direction	222.4457	222.4457	1.0	11.3807	7.73e-04	0.0082	0.0074
distraction: car_sound	34.9485	17.4742	2.0	0.8940	4.09e-01	0.0012	-0.0001
distraction: direction	56.3941	28.1970	2.0	1.4426	2.36e-01	0.0020	0.0006
car_sound: direction	0.0271	0.0271	1.0	0.0013	9.70e-01	0.0000	-0.0007
distraction: car_sound: direction	28.5877	14.2938	2.0	0.7312	4.81e-01	0.0010	-0.0003
Residual	17591.243	19.5458	900.0				

Source: The author.

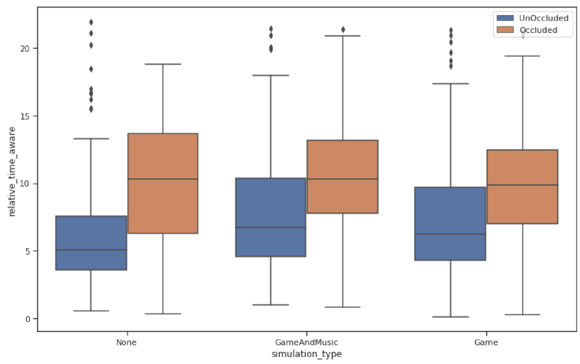
level and car sound. It shows that in the three conditions, the reaction time is higher with silent cars. Figure 7 shows the box plot in the occlusion perspective of reaction time, showing that the reaction time increases when the car is occluded.

Figure 6 – Experiment 1: Box plot of reaction time, distraction level and car sound.



Source: The author.

Figure 7 – Experiment 1: Box plot of reaction time, distraction level and occlusion.



Source: The author.

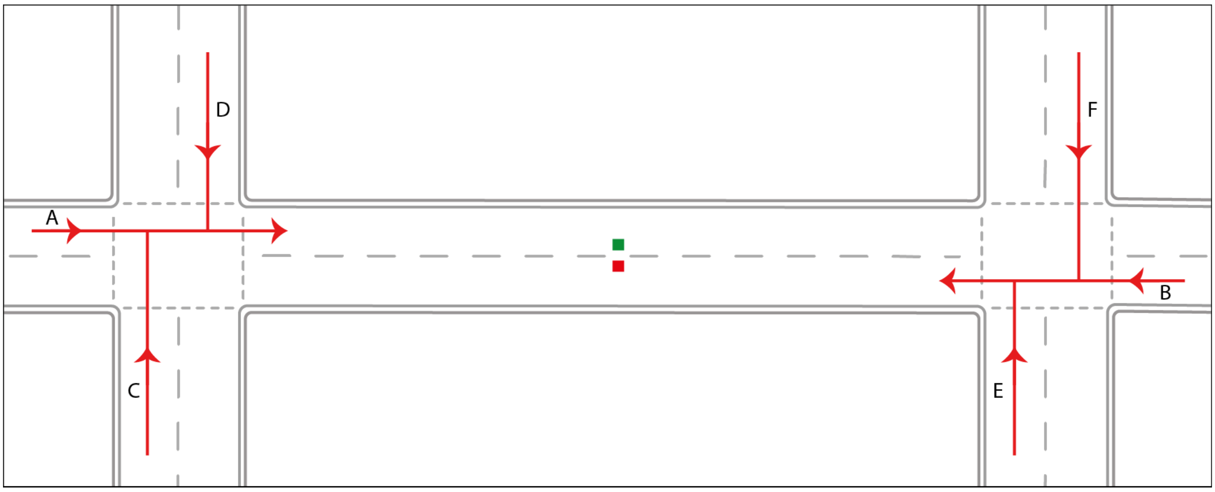
5.3 EXPERIMENT 2: PEDESTRIAN AVOIDING BEING RUN OVER

This experiment focuses on (i) evaluating pedestrian's reaction time to detect the presence of a car in the environment; and (ii) evaluating pedestrian's ability to make a decision to move to the safe side of the street. This allows the assessment of the three levels of situational awareness (perception, comprehension, projection) (ENDSLEY, 2016). The chosen environment is a street in an urban residential area, similar to experiment 1. In this case, the participant is positioned in the middle of the road, in front of oncoming cars. As in experiment 1, the scenario and the smartphone applications were developed in the Unity engine.

5.3.1 Experimental Design

An experimental trial run consists of a total of 12 cars each randomly chosen to travel through the six directions shown in Figure 8. At any one time during the experiment, only one car is present in the environment so we can test the pedestrian's awareness of that one car. Two car sound conditions are simulated for each of the possible directions, one with combustion sound, and one silent. The pedestrian is placed on one of two squares marked on the floor, one green (representing the current participant side), and one red (on the opposite side).

Figure 8 – Experiment 2: In red, the six possible paths for cars (A, B, C, D, E and F). The green and red squares represent, respectively, the side that the participant considers safe and dangerous, changing according to the participant's movement.



Source: The author.

The participant is asked to move to the safe side of the road and avoid being run over immediately after signalling a car's detection by using the smartphone. This is done under different distraction levels as in experiment 1. Figure 9 shows a participant in the test environment.

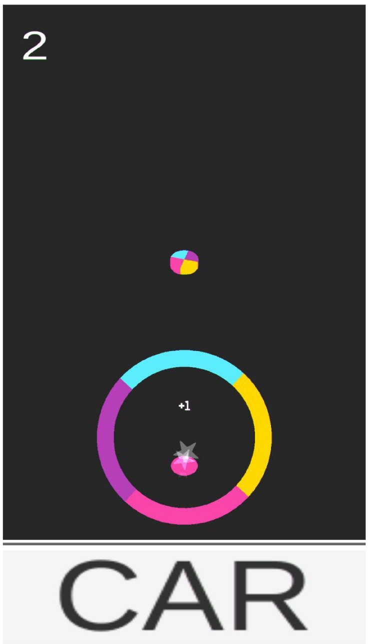
This experiment has three levels of distraction: (i) no distraction, just the car detect button; (ii) add game distraction to the previous condition; (iii) add music distraction to the previous condition (playing on headphones). The game consists of tapping the screen to maintain a virtual ball bouncing between moving objects. This requires a very high level of attention and has been designed such that the operator cannot look away from the screen for too long without loosing and the game restarts. The idea was to attempt to simulate the same engagement level required when users use text messaging apps or read content on the smartphone screen. As in experiment 1, the application contains a 'CAR' button used to signal the detection of car in the

Figure 9 – Experiment 2: A participant in the environment. On the left side, before the approach of a car. On the right side, the result of the participant's movement after perceiving the car.

Source: (GELAIM et al., 2019a)

environment. Figure 10 shows the game screen. The smartphone used was a Samsung Galaxy S7 Edge 5.5".

Figure 10 – Experiment 2: Application with the game *Colour Switch* and the button for cars' detection notification.



Source: The author.

Twenty participants took part in this experiment. Each of the three levels of distraction consists of 12 travelling cars. The order in which the distractions were presented varied uniformly among the participants. At the beginning of the tests, the participants went through a training session where they could learn how to play the game and interact with the experimental procedure. This training consisted of playing the game whilst 5 cars, one at a time, were driving through the road.

5.3.2 'Unsafe' Events

The data set consists of 732 records, disregarding the data of adaptation to the environment, on the cars' perception of the 20 participants. After removing missing data and speed outliers, the resulting set contains 654 records. The speeds that were not in the interquartile range of the original data were considered outliers. From these records, 223 are of car perception without distraction, 215 of game distraction, and 216 of game and music distraction. 328 records are of cars with combustion engine noise and friction with the ground, and 326 silent cars. The directions A, B, C, E, F of Figure 8 had 122 cars, and the direction D had 44.

The average speed is $30,5411$ mph, with a standard deviation of $5,1997$. This high standard deviation is due to the complexity of the system. Nevertheless, when comparing the three simulations, it is possible to observe homoscedasticity in the speed variances. In the Bartlett test, $p = 0.4540$, i.e., the populations have the same variance. Thus, the ANOVA was performed, obtaining $F = 0.1409$ and $p = 0.8685$.

On 102 occasions, the participants did not report the perception of the car. Of these, 80 times the participant's position was the same as in the previous car, i.e., he did not change sides. In half of these, he was virtually run-over. In 22 situations the participant changed side, probably perceiving the car, but without notifying.

There were 58 situations with the participant being 'run over'. In most circumstances, the car had no sound (55). The pedestrian was run over in 22 situations without any distraction, with game distraction in 17 cases, and with game and music, there were 19 occurrences. For each distraction level, we had only 1 run over of a combustion engine car.

The instruction given to all participants was '*press the car's perception button as soon as you perceive it*'. This notification was taken for 552 of the 654 cars, with 522 being done before the car reached the participant's position. The assumption of first deciding to be saved, i.e., crossing the street, to later notifying the car perception, presented 311 situations in which the participant changed his side of the street, being hit in one of them. In just 11 of these situations, he moved before pressing the car's perception button.

The level of cars' occlusion does not demonstrate to impair the participants' perception in this experiment. Of the 102 occurrences of non-notification of cars, 62 were from direction 'A' and 9 from 'B' as presented in Figure 8. 39 situations of a pedestrian being 'run over' were from the region 'A'. These regions are considered non-occluded in the experiment. A probable justification for these numbers is how participants position themselves in the environment, observing the region 'B' more and leaving the region 'A' occluded.

We apply the Pearson χ^2 for each distraction level comparing pedestrian's safety with occlusion or car sound. A pedestrian is safe if he notifies the car's perception before the intersection, and he is not run over. Outcomes of analysing pedestrian's safety and occlusion are: Game distraction — Pearson χ^2 p-value = 0.0398, Cramer's Phi = 0.1402 and Odds Ratio = 1.9259 (Table 9). Game and Music distraction — Pearson χ^2 p-value = 0.0158, Cramer's Phi = 0.1642 and Odds Ratio = 2.1552 (Table 10). No distraction — Pearson χ^2 p-value = 0.0004, Cramer's Phi = 0.2367 and Odds Ratio = 3.7553 (Table 11). Under occlusion condition, a pedestrian is 3.75 times more likely to report the presence of a car if he is not distracted and the car is not occluded. This falls to 2.15 if he has game and music distraction and 1.92 if he has only the game distraction.

Table 9 – Experiment 2: Safe and Unsafe events per occlusion type under Game distraction (p = 0.0398, Cramer's Phi = 0.1402, Odds Ratio = 1.9259).

Game Distraction		
	Occluded	Unoccluded
Safe	108	54
Unsafe	27	26

Source: The author.

Table 10 – Experiment 2: Safe and Unsafe events per occlusion type under Game and Music distraction (p = 0.0158, Cramer's Phi = 0.1642, Odds Ratio = 2.1552).

Game and Music Distraction		
	Occluded	Unoccluded
Safe	110	53
Unsafe	26	27

Source: The author.

Table 11 – Experiment 2: Safe and Unsafe events per occlusion type under No distraction (p = 0.0004, Cramer's Phi = 0.2367, Odds Ratio = 3.7553).

No Distraction		
	Occluded	Unoccluded
Safe	127	63
Unsafe	12	22

Source: The author.

Table 12 – Experiment 2: Safe and Unsafe events per car sound under Game distraction (p = 1.7436e-10, Cramer's Phi = 0.4236, Odds Ratio = 10.8805).

Game Distraction		
	withSound	Silent
Safe	101	61
Unsafe	7	46

Source: The author.

Table 13 – Experiment 2: Safe and Unsafe events per car sound under Game and Music distraction (p = 0.0001, Cramer's Phi = 0.2690, Odds Ratio = 3.7950).

Game and Music Distraction		
	withSound	Silent
Safe	94	69
Unsafe	14	39

Source: The author.

Table 14 – Experiment 2: Safe and Unsafe events per car sound under No distraction (p = 0.0000, Cramer's Phi = 0.3761, Odds Ratio = 22.2784).

No Distraction		
	withSound	Silent
Safe	110	79
Unsafe	2	32

Source: The author.

Outcomes of analysing pedestrian's safety and car sound are: (i) Game distraction — Pearson χ^2 p-value = 1.7436e-10, Cramer's Phi = 0.4236 and Odds Ratio = 10.8805 (Table 12). That is, 10.88 times more likely to perceive a car with sound. Game and Music distraction

Table 15 – Experiment 2: ANOVA reaction time per simulation type.

	df	sum sq	mean sq	F	PR(>F)	eta sq	omega sq
Intercept	5162.6382	5162.6382	1.0	157.2970	1.98e-32	0.1759	0.1745
distraction	463.5591	231.7795	2.0	7.0619	9.25e-04	0.0157	0.0135
car_sound	982.7233	982.7233	1.0	29.9419	6.38e-08	0.0334	0.0323
direction	300.1412	300.1412	1.0	9.1448	2.59e-03	0.0102	0.0090
distraction: car_sound	545.5684	272.7842	2.0	8.3112	2.73e-04	0.0185	0.0163
distraction: direction	236.3296	118.1648	2.0	3.6002	2.78e-02	0.0080	0.0058
car_sound: direction	390.7452	390.7452	1.0	11.9053	5.96e-04	0.0133	0.0121
distraction: car_sound: direction	196.5518	98.2759	2.0	2.9943	5.07e-02	0.0066	0.0044
Residual	21071.0490	32.8209	642.0				

Source: The author.

— Pearson χ^2 p-value = 0.0001, Cramer's Phi = 0.2690 and Odds Ratio = 3.7950 (Table 13). This conditions reduced participants perception of oncoming cars to 3.79. No distraction — Pearson χ^2 p-value = 0.0000, Cramer's Phi = 0.3761 and Odds Ratio = 22.2784 (Table 14), i.e. a pedestrian is 22.27 times more likely to report the presence of a vehicle with sound.

5.3.3 Reaction Time

The evaluated hypothesis is: *The time to perceive a car is longer when the participant is playing games with or without listening to music.* A three-way ANOVA was computed, as shown in Table 15. All the main effects for distraction, car sound and direction are significant. There is evidence for significant interaction effects between distraction and car sound, distraction and direction, car sound and direction. The eta squared values show that the effect sizes are in the range small to medium. The normality assumption is violated ($p < 0.001$), but is assumed that the deviation will not affect the results. Figure 11 presents the box plot of reaction time, distraction level and car sound. There is a high variation in the reaction time in cars without sound. Figure 12 shows the box plot of reaction time, distraction level and occlusion.

The second analysis considers only safe perceptions: perceptions that occur before the intersection between car and participant. It has a total of 522 occurrences. Bartlett's test for the reaction time obtained $p = 0.7052$, thus verifying homoscedasticity of variance. In the oneway ANOVA between the level of distraction and the reaction time, the value obtained was $p = 0.0015$. Table 16 shows a significant difference in the reaction time between playing and listening to music and not being distracted.

There is no significant difference between the time to change the side of the street for

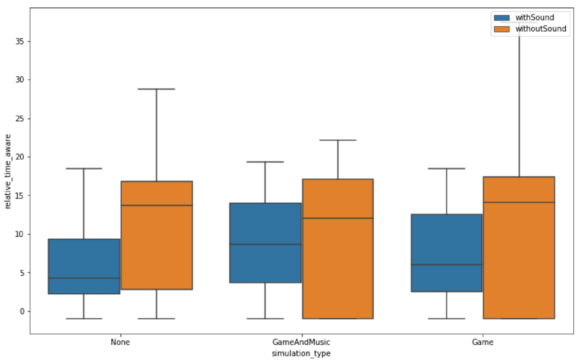
Table 16 – Experiment 2: Multiple Comparison of Means.

Group 1	Group 2	Mean difference	Lower	Upper	Reject
Game	Game and Music	1.0511	-0.4965	2.5987	False
Game	No distraction	-1.2312	-2.7258	0.2634	False
Game and Music	No distraction	-2.2823	-3.772	-0.7926	True

Source: The author.

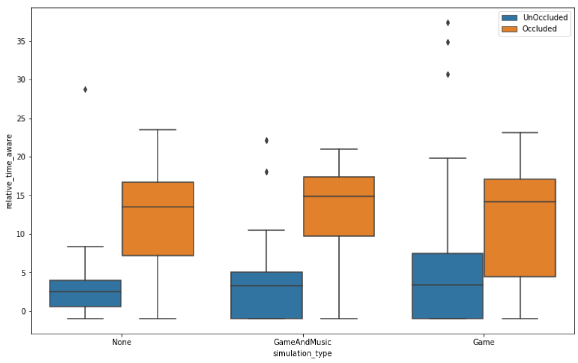
the different levels of distraction. This result is inconsistent from those found in the literature. A probable cause is a significant difference in the time to change sides in occluded cars with combustion engine sound. In this sense, the absence of sound probably had a more significant impact on decision making than a distraction on the smartphone. Based on these results, experiment 3 compares perception regarding cars emitting combustion and only friction of the wheel with the ground sounds without occlusion.

Figure 11 – Experiment 2: Box plot of reaction time, distraction level and car sound.



Source: The author.

Figure 12 – Experiment 2: Box plot of reaction time, distraction level and occlusion.



Source: The author.

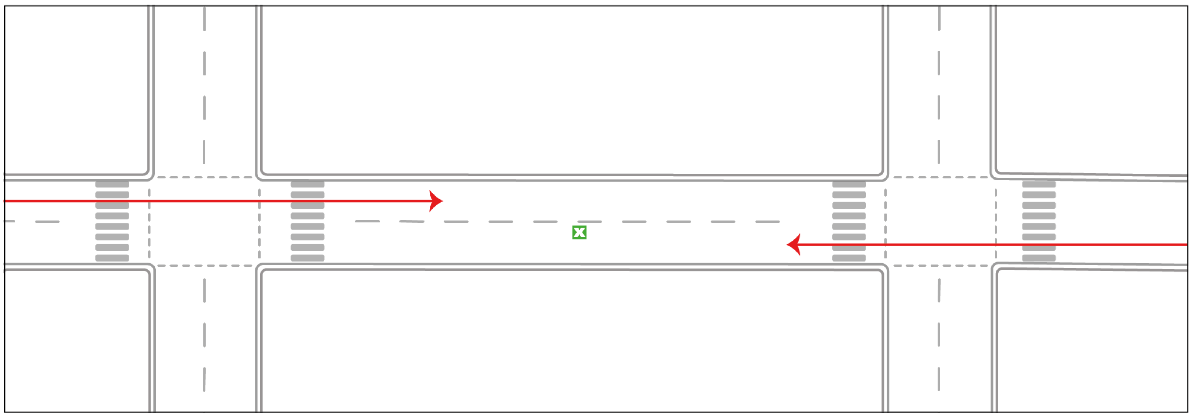
5.4 EXPERIMENT 3: PEDESTRIAN AVOIDING BEING RUN OVER IN A HEAD MOUNTED VIRTUAL REALITY DISPLAY

This experiment had significant technological changes from the previous ones. The first change is the replacement of the Octave environment by the virtual reality headset HTC VIVE. While looking up at the Octave, the participant observes the laboratory ceiling, with the headset, the participant observes the virtual environment. Another important factor in switching to VIVE is to have better control of the average speed of cars. In the VIVE, only one application is managed; on Octave, it is necessary to synchronise the same application in different clusters. On the other hand, the field of view of the HTC VIVE is approximately 110 degrees (DEMPSEY, 2016), this value is less than that of humans, which is 180 degrees horizontally and 150 vertically (MAZURYK; GERVAUTZ, 1996). Another limitation that can occur on the VIVE is delay and latency, that can cause instability in the update and perception of the environment (MESTRE, 2017). The experiment dependent variables are: (i) '*the time taken to detect and signal the presence of a car*'; (ii) '*the ability to make a decision to move to he safe side of the street*'.

5.4.1 Experimental Design

The urban environment is similar to experiment 2, with a simulated smartphone in one of the HTC-VIVE controllers. Based on the results of previous experiments, in this version, all driving cars are unoccluded. Only two directions are possible, as shown in Figure 13. Unlike experiments 1 and 2, there may be 1, 2 or 3 cars in the environment at any given time. Another difference is the substitution of cars without sound by cars with a sound of friction of the wheel with the ground to represent electric-like cars. The goal is to analyse the difference in the perception of electric and combustion cars. Davis & Barton (2017) indicates this direction conduction analysis for the acoustic perception of cars.

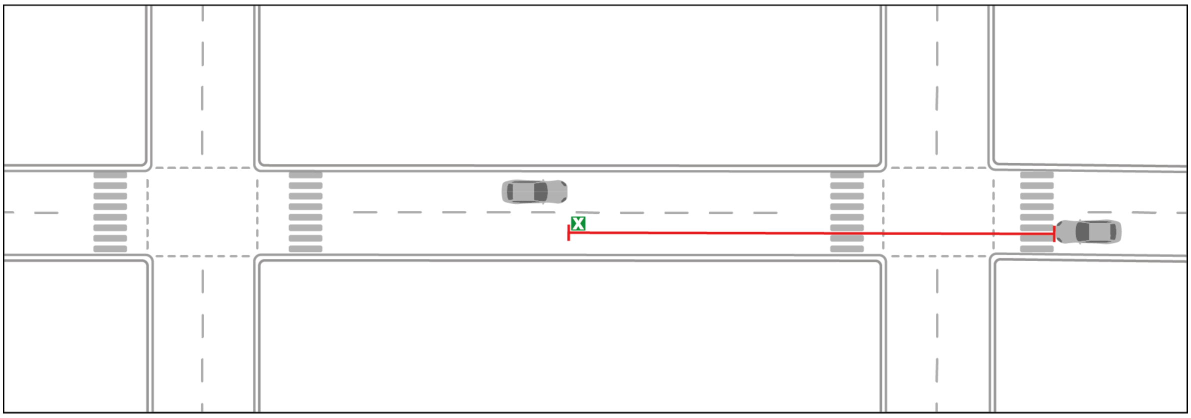
Figure 13 – Experiment 3: In red, the two possible paths for the cars. The green square with an 'X' is a guide for the participant to know which side of the street he is on.



Source: The author.

The experiment consists of an initial training period with game and music distractions and two situations with 1, 2 or 3 cars at a time on the street, i.e., 12 cars in training. After the initial training period, there are 4 classes of tests: *no distraction*, *game*, *music* and *game and music*. Each of these tests consists of 24 cars, half with electric sound emission and a half with combustion sound emission. In situations with 2 or 3 cars, the second or third car always moves in the opposite direction from the previous one and combustion and electric cars are not at the same time in the street. A new car is only added to the environment after at least 4 seconds after the previous one's spawn. Considering the average speed of 27.1mph (i.e., 43,6132km/h), this represents the minimum distance of 48,45 meters. Figure 14 presents the minimum distance between two cars when one of them is in the participant's position.

Figure 14 – Experiment 3: In red, the minimum distance between 2 opposite cars in the environment.



Source: The author.

The experiment game is 'Colour Switch', the same one used in experiment 2 and is presented on one of the controllers on HTC-VIVE. Both controllers have a trigger to notify the perception of cars. The participant needs to be *looking* at the car to be able to notify the awareness of it. A perceived car has its colour changed from white to green so that the participant can confirm the awareness. We applied the strategies of experiments 1 and 2 to guarantee the independence of the tests in this experiment.

Resources used in the ecological validity of this experiment are improved from those used in Octave. The sound calibration is performed using the artificial ear B&K Artificial Ear Type 4153. It has an 'acoustic impedance similar to that of humans'[2]. The source of the sound used for the calibration of the artificial ear is the B&K *Acoustical Calibrator Type 4231*, with the measuring amplifier B&K *Measuring Amplifier Type 2610*. The headset sound calibration considering a combustion engine sound[3]. Cars sound behaviour is described with the Unity's logarithmic roll-off with ending in the sound at a distance of 260m. In this way, the car's highest volume is noticeable when it is in the participant's position and increases or decreases logarithmically and under the influence of the Doppler effect. The volume perceived in the headset is defined according to the operating system's volume level, using the combustion car engine at 30 mph is normalised to 3dB.

The sound of the cars at a distance of 1 meter from the participants is 70 dB (A). This value is close to the ISO 362 limit of 74 dB (A) (SANDBERG; GOUBERT; MIODUSZEWSKI, 2010; GARAY-VEGA et al., 2010; PAPAIOANNOU; ELLIOTT; CHEER, 2018). Also, in 2020 the limit may be reduced to 70 dB(A) and 68 dB(A) by 2024 (CAPRIOLI, 2018). In tests where it is simulated to be listening to music on headphones, car noise is reduced by 18 dB (A) to simulate noise isolation from the headset used, DT 770 PRO. Furthermore, in simulations

[2] Artificial Ears — Types 4152 and 4153: https://www.bksv.com/-/media/literature/Product-Data/bp0265.ashx
[3] "Car Engine, Exterior, B.wav" by InspectorJ: https://freesound.org/people/InspectorJ/sounds/345557/

with distraction by music, the music volume is 78.6 dB (A). This value is based on a study of the level of music from iPods in the London subways (DANCE; WASH, 2008). The recommended maximum is 85 dB (A) (ORGANIZATION et al., 2015; BERGLUND; LINDVALL; SCHWELA, 1999).

The experiments were taken in the *Listening Room* at the Acoustic Research Centre at the University of Salford, United Kingdom. This space is a ‘room within a room’ in order to prevent noise from entering. It follows the ITU-R BS 1116-1 standards, BS 6840-13 and IEC 268-13 (FAZENDA et al., 2012; BECH; ZACHAROV, 2006). The room’s size is 6.6m x 5.8m x 2.8m and the background noise is 5.7 dB(A) (University of Salford, 2019). Figure 15 presents a participant in the Listening Room with the HTC-VIVE Headset.

Figure 15 – Experiment 3: On the left side, the participant’s view of the environment. The green cars represent that the participant has already noticed them. On the right side, the participant located in the Listening Room.

Source: The author.

5.4.2 ‘Unsafe’ Events

The dataset consists of 2784 records on the reaction time of 29 participants in the four conditions (*no distraction*, *game*, *music* and *game and music*). Speeds outside the interquartile range of original data are outliers. The dataset after outliers removal has 2285 data points. The average speed of cars is 27.0467 mph (i.e. 43,52 km/h) and the standard deviation of 0.0215 with the variance of 0.0004. There was no significant difference between the speeds.

The participant was virtually run over in 30 of the 2285 situations. This value corresponds to approximately 1.31% of the cars. The experiment was designed to analyse perception in a low-traffic road, and many pedestrians run over could be considered unrealistic. The hypothesis that cars with a combustion sound cause more pedestrians to be run over has not been confirmed. Cars with a combustion noise caused 17 run overs against 13 in electric cars. Playing with or without music corresponded to 13 pedestrian accidents with combustion cars and 12 electric cars. Due to the reduced number of unsafe events, we did not find significance in the Pearson χ^2 test in the car sound study.

Table 17 summarises the relationship between (i) perceiving the car in time according to the level of distraction and (ii) the number of people being hit by cars for each situation. A participant is *Aware* when he presses the car perception button before the car is 1 meter from a collision. *Late Aware* occurs when the participant perceives the car after 1 meter distance. A *Critical* is when the participant does not press the car perception button. *Run Over* represents the participant being virtually run over.

Table 17 – Experiment 3: Number of awareness and run over.

	Aware	**Late Aware**	**Critical**	**Run Over**
No distraction	578	0	0	3
Music	568	0	0	2
Game	582	5	2	11
Game and Music	538	5	7	14
Run Over	26	2	2	30

Source: The author.

Participants were instructed to report cars perception as soon as possible. In 560 situations, the participant notified the car's perception and did not change his side of the street before the intersection with the car. Of these, in 32 situations, the pedestrian changed the side before notifying the car's perception. With no distraction, or listening to music, the safe crossing occurred in 3 situations each. Playing games and listening to music had 11 occurrences. A pedestrian changed his side in 15 situations while only playing games. Of these 26 occurrences with games (with or without music), 14 were from 3 participants. That is, in most cases, 1725, the participant chose to notify first and then change the side of the street, if necessary.

5.4.2.1 Questionnaires

All participants took three questionnaires: Five-Factor Model (FFM) of personality (MCCRAE; JOHN, 1992); Empathy Quotient and Systemizing Quotient (EQ/SQ) (WAKABAYASHI et al., 2006); and Immersive Tendencies Questionnaire (ITQ) (WITMER; SINGER, 1998). The goal is to examine the profile of the participants.

Five-Factor Model (FFM) of personality (MCCRAE; JOHN, 1992) has five basic dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience. It is a high hierarchical model. The profile is constructed considering the participants' responses to 44 questions with 5 possible answers (strongly disagree, disagree a little, neither agree or disagree, agree a little and strongly agree) (MCCRAE; JOHN, 1992). Table 18 presents the descriptive statistics.

Extraversion describes how active, assertive, energetic, enthusiastic, outgoing and talkative the person is. A high score on Agreeableness suggests a person more appreciative, forgiving, generous, kind, sympathetic, trusting. A highly conscientious person is efficient, organised, planful, reliable, responsible, thorough. The neuroticism trait measure how anxious, self-pitying, tense, touchy, unstable, worrying a person is. Openness is about how open or closed the person thinking is, an open person appreciates arts, is curious, imaginative, insightful, original and with broad interests.

Table 18 – Experiment 3: Descriptive statistics for BIG FIVE responses.

	Min	**1st Q**	**Median**	**Mean**	**Std**	**3rd Q**	**Max**
Extraversion	1	2.5	3.0	2.879	0.787	3.375	4.500
Neuroticism	1.625	2.875	3.375	3.375	0.871	4.125	5.00
Conscientiousness	1.0	2.556	3.0	3.050	0.791	3.667	4.667
Openness	1.8	3.5	3.7	3.652	0.618	4.1	4.6
Agreeableness	2.111	3.778	4.0	3.835	0.623	4.222	4.889

Source: The author.

The empathising - systemising theory is based on folk psychology and consists of two dimensions: empathising and systemising (BARON-COHEN, 2002). The first is an intentional agency, it allows to predict and care about others feelings, and the last is causal, it involves predicting the behaviour of non-agentive events or objects (WAKABAYASHI et al., 2006). The Empathy Quotient and Systemising Quotient are instruments to evaluate the empathising — systemising theory. In this work, we used the short version of these instruments, as they are highly correlated with the full scale versions (WAKABAYASHI et al., 2006). It has 22 items of the EQ (EQ-Short) and 25 items of the SQ (SQ-Short). Table 19 presents the descriptive statistics.

The results of Shapiro-Wilks tests for normality shows that EQ does not conform to a normal distribution (with $\alpha = 0.05$, $p \cong 0.023$). The validation report of the EQ-short and SQ-short ($N = 1761$) presents a mean EQ of 23.8 and the standard deviation of 8.75. In this sense, the non-normality may be related to the sample size ($N = 29$) of this study. On the other hand, SQ found to be normal ($p \cong 0.479$), but with significant differences from the validation report (mean = 19.0 and std = 10.05).

Immersive Tendencies Questionnaire (ITQ) measures individuals' propensity for the experience of *presence* (WITMER; SINGER, 1998). Witmer & Singer (1998) defines presence as 'the subjective experience of being in one place or environment, even when one is physically situated in another.'. The answers to the questions are on a scale of 1 to 7. There are three sub-scales: involvement — propensity to be passively involved in activities such as watching, reading books; focus — mental alertness, ability to concentrate on enjoyable activities; and

Table 19 – Experiment 3: Descriptive statistics for EQ-SQ responses.

	Min	**1st Q**	**Median**	**Mean**	**Std**	**3rd Q**	**Max**
EQ	6	24	34	30.483	9.451	38	42
SQ	8	24	34	31.31	10.971	38	50

Source: The author.

game — how often they play and whether they feel they are in the game. Table 20 presents the descriptive statistics. Shapiro-Wilks test for normality shows a normal distribution ($p = 0.850$) in total ITQ scores. Figure 16 presents the correlation matrix for personality factors (FFM, EQ/SQ and ITQ).

Table 20 – Experiment 3: Descriptive statistics for ITQ responses.

	Min	**1st Q**	**Median**	**Mean**	**Std**	**3rd Q**	**Max**
Focus	23	31	33	33.379	4.663	37	43
Involvement	19	27	32	32.172	6.228	36	45
Games	2	4	7	6.655	3.265	9	13
Total	52	73	83	81.241	12.412	90	104

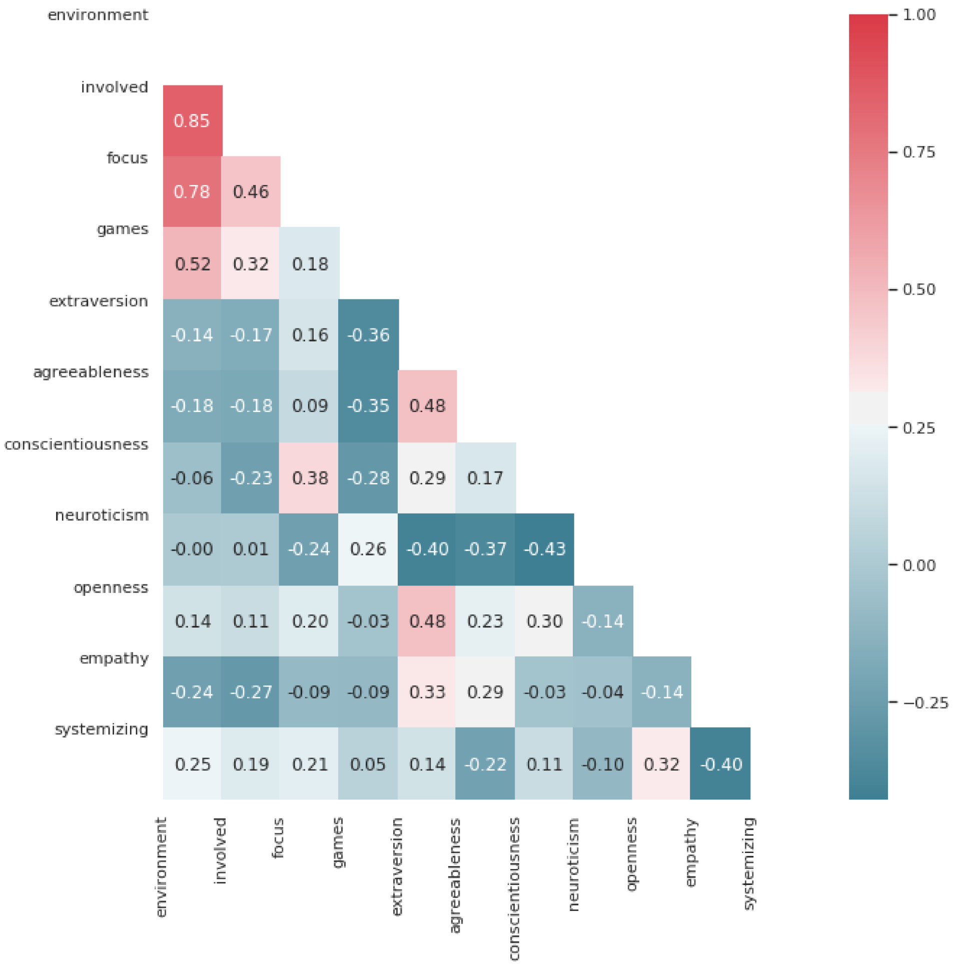
Source: The author.

5.4.3 Reaction Time

The experiment allows 1, 2 or 3 cars at a time in the environment. Thus, the first hypothesis tested is: *'the time to perceive a car may be conditioned by the perception of another perceived car and smartphone distraction '*. We had to perform a new outlier removal considering the reaction time for each car spawned order once the reaction time for each car order is different. In the first car, we reduced from 1387 to 1326 records, for the second car, the number of records decreased from 902 to 859, and the third car from 438 to 434. Figure 17 shows a point plot representing the central tendency for the reaction time variable for the first, second and third spawned vehicle in all distraction conditions. It is possible to observe the influence of playing games in the reaction time.

This hypothesis has two independent categorical variables: distraction and car spawned order; and one dependent variable: reaction time. Again, probably due to the size of the data set, the Shapiro-Wilk test failed to prove the normality (stats = 0.9576, p-value = $3.9077e-24$). Bartlett test was applied to show the homogeneity of variances (stats = 19.0894, p-value = 0.05950). In this hypothesis, we found significance in distraction ($p = 2.6350e-37$), in spawned order ($8.5905e-04$) and the interaction between them ($5.9176e-03$). The results presented a small effect size (eta _sq $\leq$ 0.080), as shown in Table 21. The car sound as an independent variable does not have significance for this hypothesis.

Figure 16 – Experiment 3: Correlation matrix for personality factors.



Source: The author.

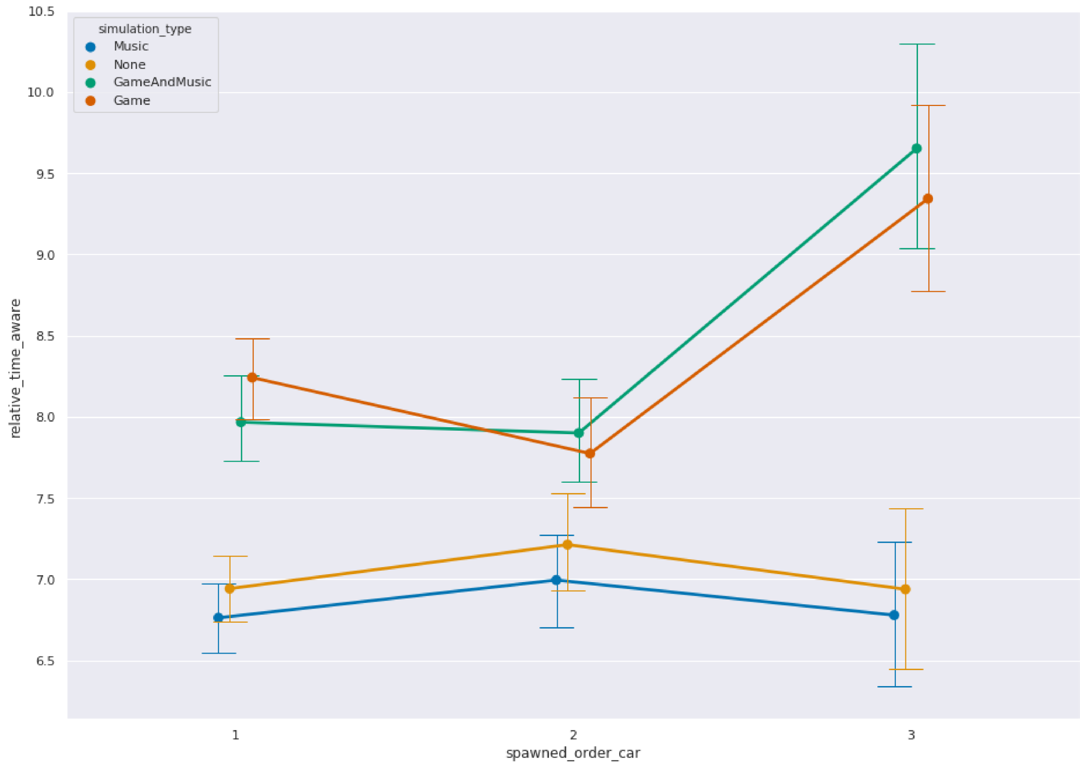
Table 21 – Experiment 3: ANOVA reaction time per Car Spawn Order and test condition (distraction).

	sum sq	df	mean sq	F	PR(>F)	eta sq	omega sq
distraction	18.3847	3.0	6.1282	60.1894	2.63e-37	0.0793	0.0780
spawned order	1.1343	1.0	1.1343	11.1416	8.59e-04	0.0048	0.0044
distraction: spawned order	1.2738	3.0	0.4246	4.1703	5.9176e-03	0.0054	0.0041
Residual	210.8609	2071.0	0.1018				

Given that the distraction condition and the spawned order influence the reaction time, we will present analyses for each of these situations individually. Figure 18 presents the box plot of the log reaction time for the first car regarding the distraction and car's sound engine. The Bartlett test shows that the data is homogeneous (p-value = 0.5111). The ANOVA shows significance in the distraction level (P = $8.7079e-25$, eta _sq = 0.0832).

The analysis of second car had similar results. Figure 19 presents the box plot of log reaction according to car sound and distraction level. The Bartlett test shows the data is

Figure 17 – Experiment 3: Point plot of reaction time per Car Spawned Order and hue being the test condition.



Source: The author.

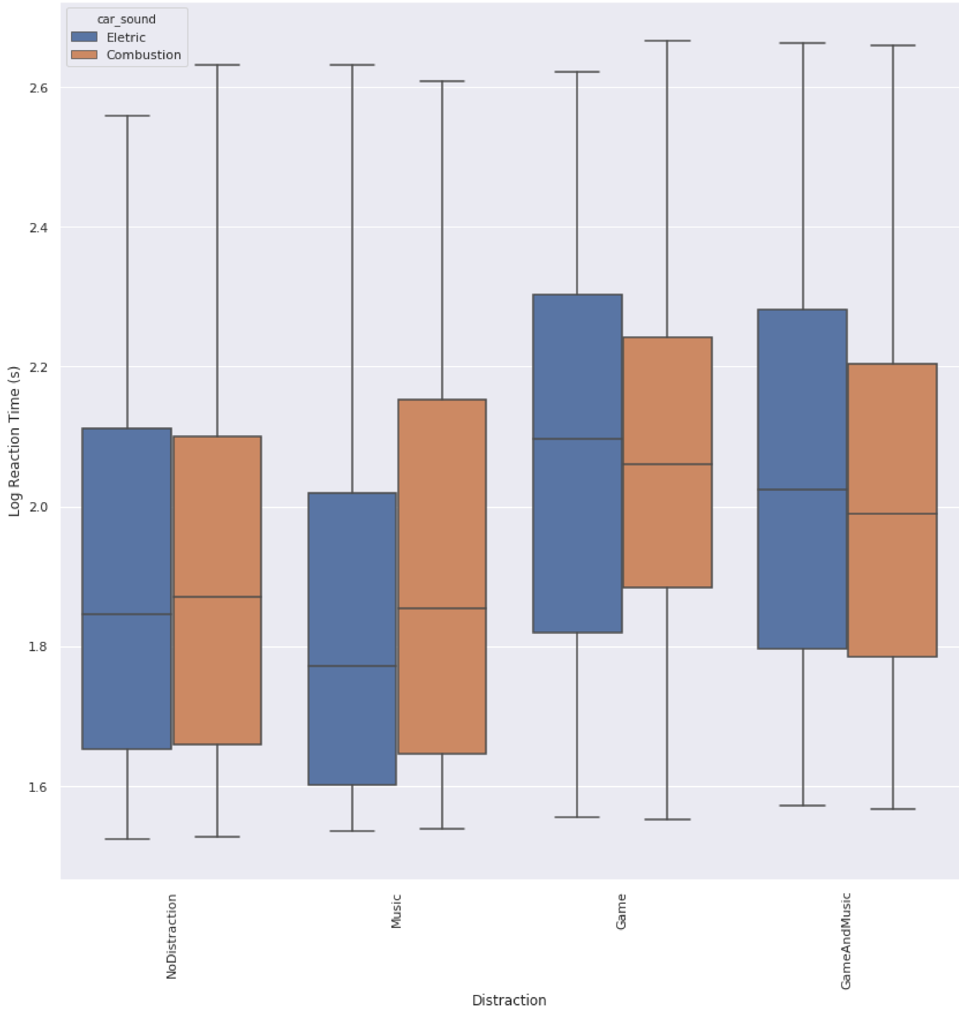
homogeneous (p-value = 0.5975). The ANOVA shows significance in the distraction condition (p = 0.00001, eta _sq = 0.0295) and car engine (p = 0.0178, eta _sq = 0.0063).

The box plot of the third car is presented in Figure 20. Results of this analysis are: Bartlett test shows homogeneity of variances (p-value = 0.8139). The ANOVA shows significance in the distraction condition (p = $2.2230e-20$, eta _sq = 0.1989). It is important to note that the Shapiro-Wilk test failed to prove the normality test in all these analyses.

The next evaluated hypothesis is: *'the time to move to the safe lane may be conditioned by the perception of another perceived car and distraction level'*. In 2103 (first 774, second 895, third 434) situations the user changed his position. IQR removal reduced this number to 2079 (first 762, second 888, third 429) records. Figure 21 shows a point plot representing the central tendency for the *moved to the safe lane* variable for the first, second and third spawned vehicle in all distraction conditions. For the first vehicle, the pedestrian can change the lane's side as soon as he perceives it and for the second and third cars, the pedestrian must wait to avoid being hit by the previous one. It is also possible to observe the influence of playing games in the time moved to the safe lane.

This hypothesis has one independent categorical variable: distraction; and one dependent variable: log time moved to the current lane. It is not possible to compare the three cars at the same time. For the first car we have: Bartlett test shows the data is homogeneous (p-value = 0.4217); ANOVA presents significance in the distraction (p = $1.5376e-07$, eta _sq

Figure 18 – Experiment 3: Box plot of log reaction time from the first car.



Source: The author.

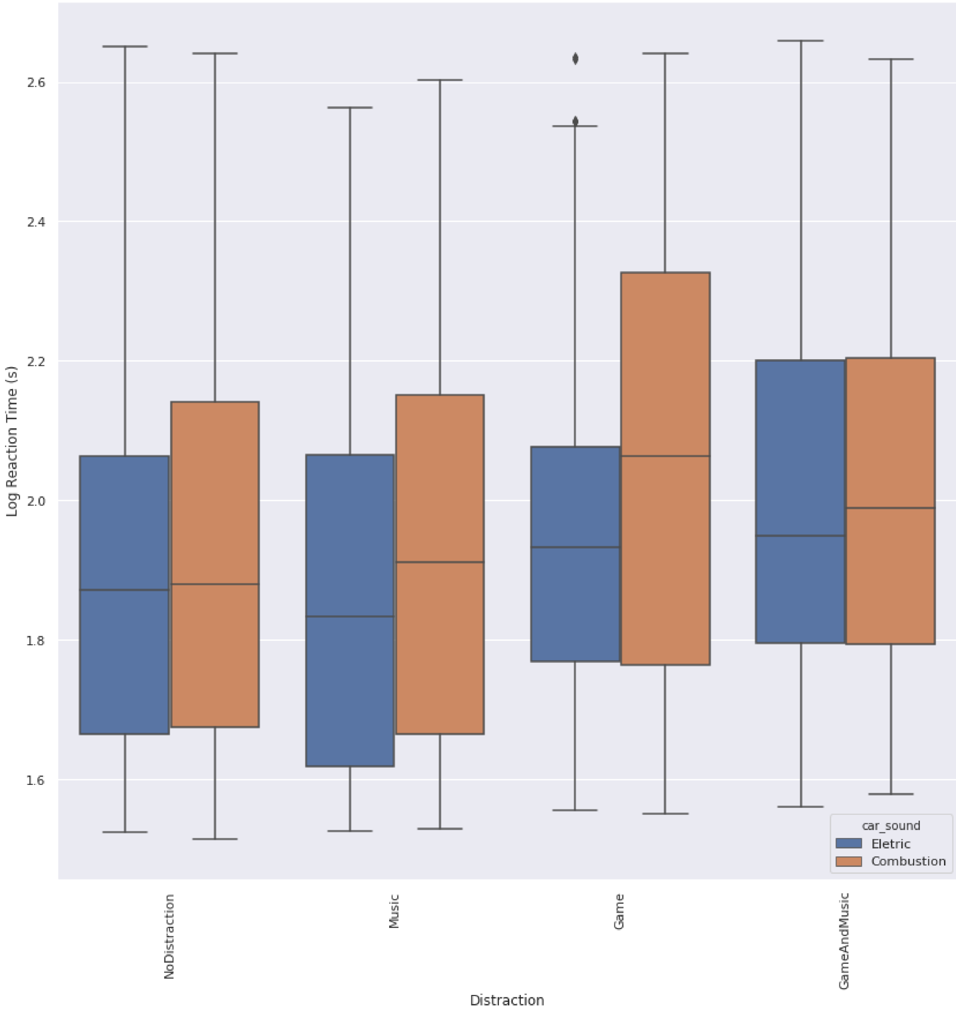
= 0.0440) and the interaction between distraction and car engine (p = $1.0491e-02$, eta _sq = 0.0141). For the second and third car we have: Bartlett test presents the data is homogeneous (p-value = 0.5940); ANOVA presents significance in the distraction (p = 0.000022, eta _sq = 0.0181) and the interaction between distraction and car engine (p = 0.0312, eta _sq = 0.0066).

5.5 SUMMARY

This Chapter presented a new understanding on the behaviour of pedestrians in urban environments when using smartphones. The first experiment was conducted in the Octave environment to analyse the unsafe behaviour by pedestrians. We found a significant number of associations between unsafe events and car sound. Also, the smartphone's distraction level appears to have a significant effect on unsafe events. Car sound and direction are significant in the reaction time three-way ANOVA.

Experiment 2 was also conducted in the Octave to analyse the difference in perception

Figure 19 – Experiment 3: Box plot of log reaction time from the second car.

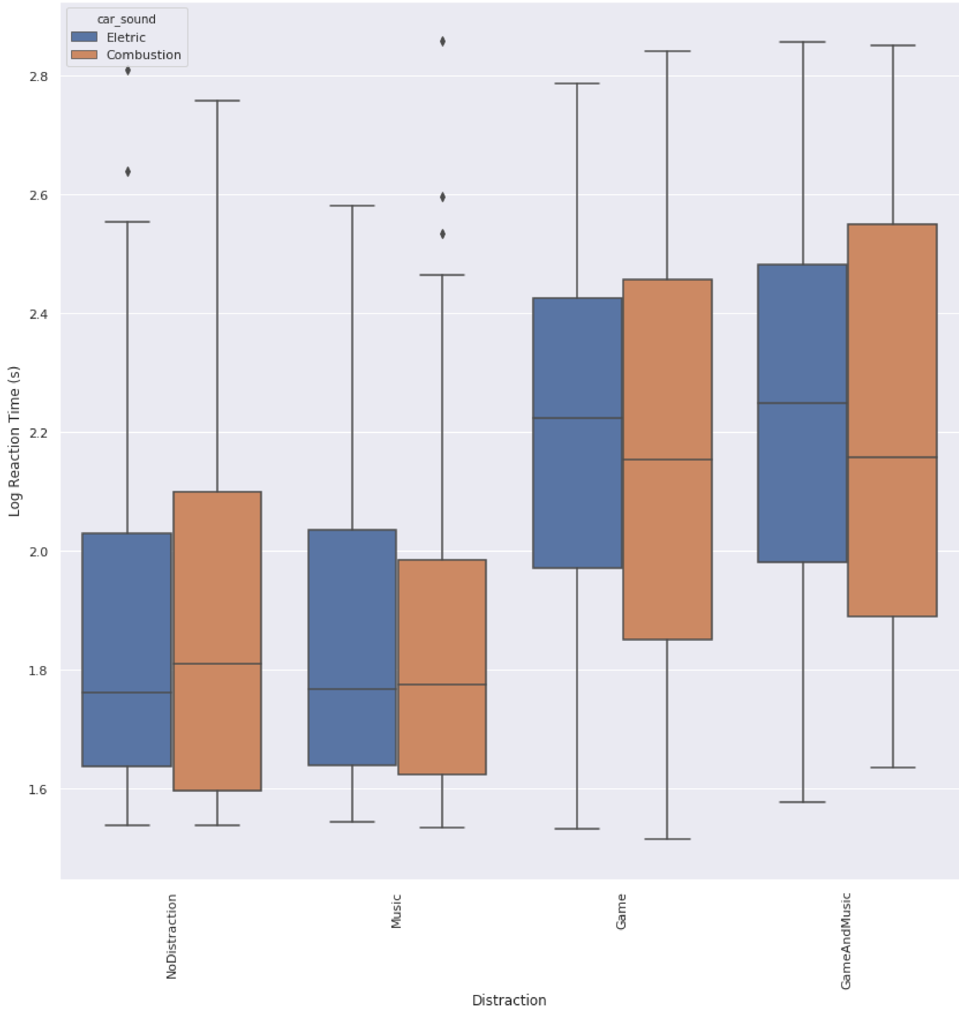


Source: The author.

and decision making with three levels of distraction on the smartphone. The level of stress and involvement of the participants in this experiment is higher than experiment 1. The game demanded more attention to the smartphone, and at the same time, the environment required the participant attention to avoid being run over. The results show a difference between not being distracted and being distracted by games and music. All the main effects for distraction, car sound and direction are significant in the three-way ANOVA. There are significant interaction effects between main effects. The second objective of this experiment was to evaluate the decision to cross the street. The results did not show significant values. This result does not match the recent literature results (JIANG et al., 2018; PLUMMER et al., 2015). A probable cause for this is the difference between the sounds emitted by cars in our experiment. Another relevant result is the higher number of pedestrians being run over in non-occluded regions.

The third experiment was in a similar environment from experiment 2, but conducted in the HTC VIVE. There is a replacement of silent cars by cars with a sound of friction of wheels with the ground, and a new test condition — only music distraction. We found significance in

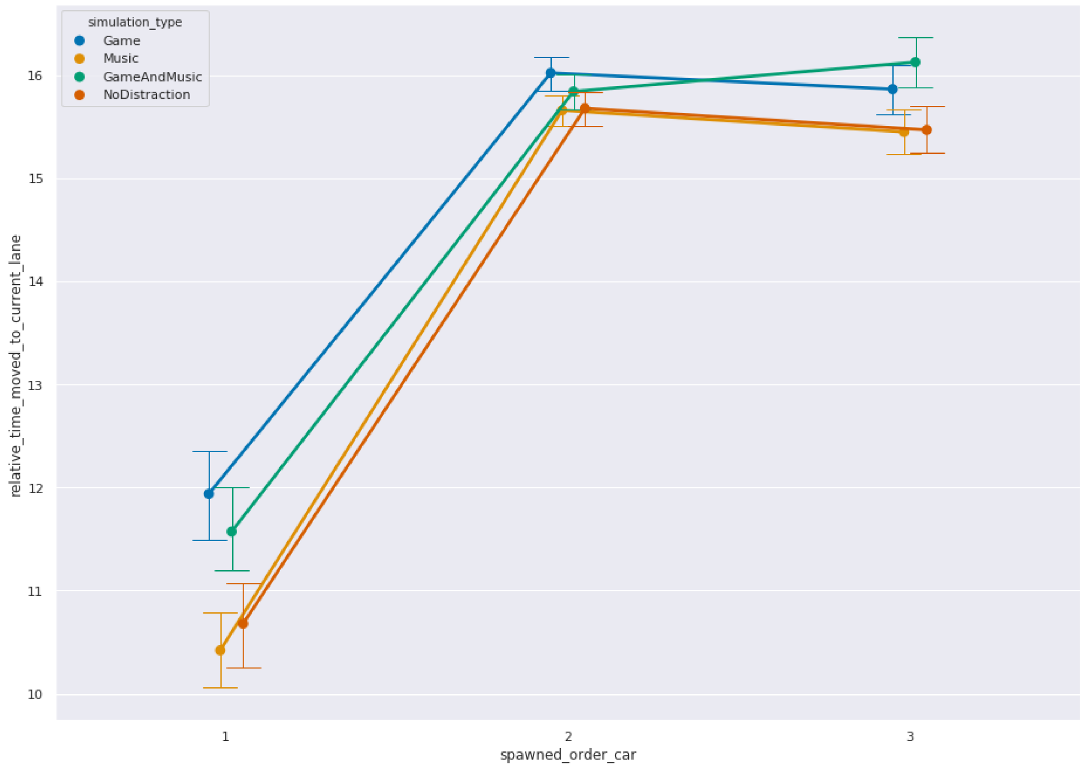
Figure 20 – Experiment 3: Box plot of log reaction time from the third car.



Source: The author.

the reaction time (perceive the car) and the movement to the safe lane, mainly when playing games, but with a small effect size (eta_sq ≤ 0.08). The only case with a large effect size (eta_sq $= 0.1989$) is in the third car's reaction time.

Figure 21 – Experiment 3: Point plot of Moved to Current Lane per Car Spawn Order and hue being the test condition.



Source: The author.

6 SITUATION AWARENESS IN DYNAMIC ENVIRONMENTS

A dynamic environment evolves during the agent's reasoning cycle. Moreover, an agent may not have all current environmental data. To be aware of a situation, an agent, in the broad definition of the term, first, have to perceive according to the relevant situation. Then he uses the obtained data to comprehend and project the future state of the perceived data in the decision-making process (ENDSLEY, 1988).

The BDI agent model is suitable for dynamic environments and is based on a practical reasoning theory. The main BDI concepts' are implemented in Sigon framework and constitute the basis for this Chapter's evaluation. We developed an agent to perceive the environment using active and passive perception as described in Section 4.4.3, and uses the ontological context, presented in Section 4.4.1, or Bayesian context, presented in Section 4.4.2, for representing situations.

Active perception enables perceiving the situation related to current goals, from an ontological or Bayesian representation. The ontological knowledge enables the agent to reason about individuals belonging to a specific situation, in well-defined and detailed semantics. Bayesian knowledge uses an environmental situation to attach probabilities to events. From the agent's practical reasoning, ontological and Bayesian reasoning enables different plans execution to the same situation. The first one chooses from the situation description and the last one the situation uncertainty.

Following the thesis problem of integrating heterogeneous data in the decision making with limited resources, the contributions of this Chapter are: (i) Sigon: (a) analysing the agent's practical reasoning time when acting in a dynamic environment; (b) the ability to develop a flexible reasoning mechanism, which uses different perceptions process, varying update rate, and uses different types of knowledge representation; (ii) urban and mobile computing: (a) a framework to analyse pedestrian warning safety systems from a Vulnerable Road User (VRU) perspective using the agent paradigm.

This Chapter is organised as follows: Section 6.1 presents the environment created for experiments. Subsection 6.1.1 presents the factorial design approach for experimental design. In section 6.2 we evaluate a Bayesian agent's reasoning cycle. Section 6.3 evaluates the use of ontology for representing situations.

6.1 EXPERIMENTAL DESIGN: A SIGON AGENT IN AN URBAN ENVIRONMENT

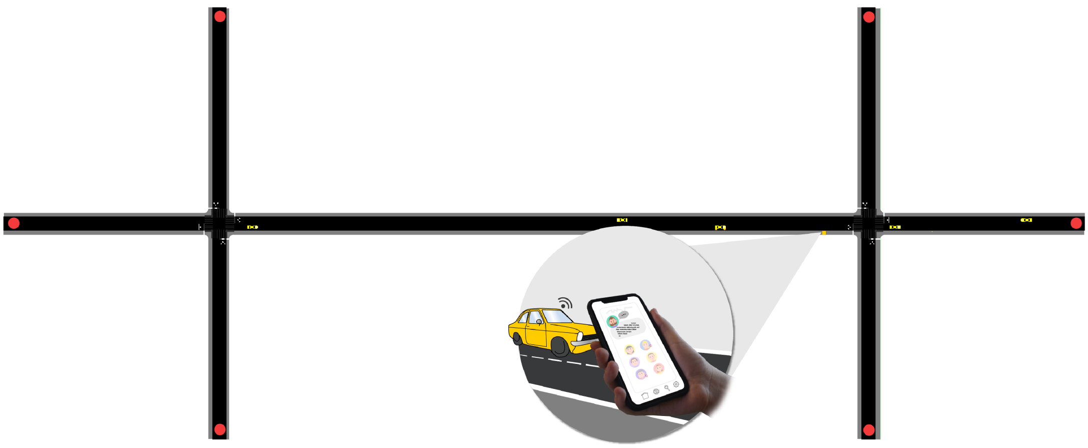
Experiments in this Chapter are built over the urban computing perspective. The urban environment is similar to those from experiments presented in Sections 5.3 and 5.4. Vehicles travel at 40 km/h and one pedestrian (the subject of analysis) walking at 5 km/h. The pedestrian's smartphone interacts with all the nearby vehicles. A Sigon agent is simulated in the smartphone, acting as decision support to the pedestrian. The pedestrian interacts with the smartphone and is notified when the agent perceives a hazardous situation.

In the urban computing perspective, the concept of vehicle-to-everything (V2X) includes vehicle-to-pedestrian (V2P), vehicle-to-infrastructure (V2I), and vehicle-to-vehicle (V2V) communication (SEWALKAR; SEITZ, 2019). The data collection problem in a V2X is a scheduling optimisation problem (NP-complete) (HE; ZHANG, 2017). These experiments evaluate the V2X in a pedestrian agent perspective (P) of data collection involving V2V and V2P communication. The network simulated enables the communication between all vehicles in the region and the evaluated pedestrian.

On the pedestrian's smartphone, it is simulated the following sensing data: (i) web data; (ii) vehicle's communication; and (iii) smartphone data sensors. Web data are the information presented in an ontology about traffic, in which the agent can retrieve contextual information about a specific driver.

The communication with vehicles gets information about noise emission (electric or combustion) and vehicle position. The communication between all vehicles and pedestrian's smartphone follows an IEEE 802.11 network, operating in 5.9 GHz frequency, 10 MHz bandwidth, and transmission power of 20mW. Data from smartphone sensors are GPS (we assume the pedestrian's exact position), data about the screen, microphone, and headphones. All of these data are available to the agent at any given time, enabling him to obtain a detailed description of the situation and deciding the best action that should be taken. In a particular reasoning cycle, the agent receives *n* data from *m* sensors, evaluate the current situation and acts once. Figure 22 presents a superior view of the environment.

Figure 22 – Pedestrian Safety: Circles in red represent the six places where cars are spawned. The pedestrian only walks in crosswalks and sidewalks.



Source: The author.

The development of a computational representation of this experiment enables more accurate control over the variables. We can specify the number of spawned cars and pedestrians, its routes, current position, speed, and the duration of each simulation. On the other hand, we have certain restrictions. For instance, in a real environment, the position defined by the GPS may not be accurate and may be conditioned by environmental factors or employed technology

(MERRY; BETTINGER, 2019; SZOT et al., 2019). Experiments are built based on the literature and tools of urban computing (SEWALKAR; SEITZ, 2019), using the following tools:

- SUMO (Simulation of Urban MObility): is a road traffic simulator (BEHRISCH et al., 2011). It simulates vehicles and the pedestrian routes during a certain period;
- Veins (Vehicles in Network Simulation): is an open-source vehicular network simulation framework (802.11p-based V2P network) (SOMMER; GERMAN; DRESSLER, 2010). Every SUMO vehicle and pedestrian is represented by a network object, where each object can exchange messages with other objects;
- OMNeT++: is an event-based network simulator (VARGA; HORNIG, 2008). Every interaction between vehicles and pedestrian's smartphone is controlled by this tool;
- Sigon: is a framework for developing agents based on multi-context systems introduced in Chapter 4.

The infrastructure to create simulations in SUMO, Veins, and OMNET++ is available by Veins developers[1]. The more significant additions developed in this thesis are in simulating a pedestrian smartphone and allowing a Sigon agent perceiving environmental data and event manipulation. We developed methods to simulate a smartphone sensing screen, microphone, camera and web data. It is important to note that each sensor has an update rate and different processing capabilities. The smartphone can also send warning messages to objects in the environments, blocking sound and screen. The agent can control smartphone sensing and acting functions.

6.1.1 2^k Factorial Design

The experimental design and analysis follow the guideline presented in Jain (1990). It is applied in similar literature works from both vehicular ad-hoc networks (FOGUE et al., 2011) and perception filters in agent systems (JR; PANTOJA; SICHMAN, 2018).

The key terms of factorial design for the context of this research are: (i) *response variable* — the outcome of the experiment; (ii) *factor* — a variable that affects the response variable; (iii) *level* — a value that a factor can assume; (iv) *replication* – repetition of all or some experiment; (v) *design* — specification of the number of experiments, factors and replications.

A full factorial design is a type of experimental design in which every possible combination of levels and factors are examined. A fractional factorial design is commonly used when it is impracticable to apply a full factorial design — too many factors or levels. The 2^k factorial design is a type of factorial design, in which all k factors have two levels. Replications of all conditions are used to estimate experimental errors. In a 2^k factorial design with r replications, we have $2^k r$ observations.

[1] https://veins.car2x.org/

Table 22 – 2^k Factorial Design: Analysis of a 2^2 design.

Experiment	A	B	AB	y
1	-1	-1	1	20
2	1	-1	-1	65
3	-1	1	-1	40
4	1	1	1	95

Source: adapted from (JAIN, 1990).

The following scenario explains this approach's basis: an agent can perceive the environment every 10ms or 100ms, and each time it perceives the environment, it receives 5 or 15 percepts. This is a 2^2 experimental design with 2 factors (perception time and the number of perceptions) and 2 levels each factor (10ms - 100ms and 5 or 15 perceptions). Let

$$x_A = \begin{cases} -1 & \text{if 10 ms} \\ 1 & \text{if 100 ms} \end{cases} \tag{6.1}$$

and

$$x_B = \begin{cases} -1 & \text{if 5 perceptions} \\ 1 & \text{if 15 perceptions} \end{cases} \tag{6.2}$$

The response variable (reasoning time in ms) can be described on x_A and x_B as

$$y = q_0 + q_A x_A + q_B x_B + q_{AB} x_A x_B \tag{6.3}$$

Testing each condition of the model produces four responses (y_i). Using the results from Table 22, we have the following equations

$$\begin{aligned} 20 &= q_0 - q_A - q_B + q_{AB} \\ 65 &= q_0 + q_A - q_B - q_{AB} \\ 40 &= q_0 - q_A + q_B - q_{AB} \\ 95 &= q_0 + q_A + q_B + q_{AB} \end{aligned} \tag{6.4}$$

where q_A, q_B and q_{AB} are linear combinations of the responses. This regression can be solved as

$$y = 47.5 + 15x_A + 7.5x_B + 5x_{AB} \tag{6.5}$$

and be interpreted as the mean reasoning cycle is 47.5 ms; the effect of perception time is 15 ms; the effect of the number of perception is 7.5 ms; and the interaction between perception time and the number of perception is 5 ms.

The next step is to measure the total variation of the Sum of Squares Total (SST) of responses values y

$$\text{Total variation of } y = \text{SST} = \sum_{i,j}^{2^2} (y_i - \bar{y})^2 \tag{6.6}$$

The variation of each factor can be described as

$$SSA = 2^2 q_A^2 \tag{6.7}$$

$$SSB = 2^2 q_B^2 \tag{6.8}$$

$$SSAB = 2^2 q_{AB}^2 \tag{6.9}$$

and the sum of these variation is equals to SST. Thus, it is possible to measure each component's proportion as a fraction: SSA/SST explains factor A; SSB/SST explains factor B; and $SSAB/SST$ explains the interaction between factors A and B.

In the study presented in this section, the total variation is 1225, of which 73.469% can be attributed to factor A (perception time), and 18.367% to factor B (number of perceptions), and 8.163% to the interaction factors A and B. As a consequence, to increase agent performance, the perception time factor should be improved.

6.2 BAYESIAN AGENT

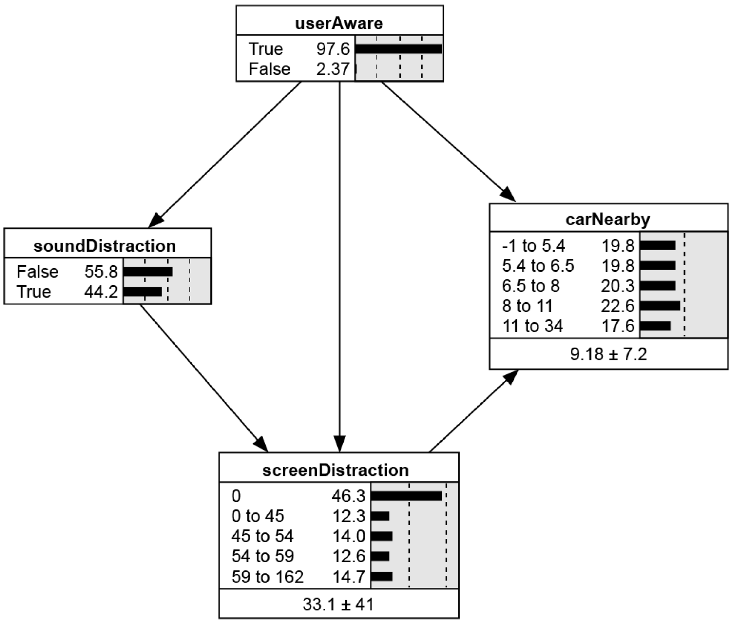
The experiment objective is to *evaluate the agent's reasoning cycle time in an urban environment under a set of constraints* using the Bayesian agent presented in Section 4.4.2. In the Bayesian context, the agent has a network with 4 nodes: userAware, soundDistraction (listening to music), screenDistraction (number of times the screen is tapped for an oncoming car) and carNearby (time to collision). The agent's goal is to keep the user safe. Data collected from experiments presented in Section 5.4 are applied to construct the network structure and cases. There is a threshold for safety in the node "userAware". If there is a probability $>= 0.15$ in the user not being aware, the agent must act. Figure 23 shows the network included in the Bayesian Context.

Factors (independent variables) are: density of vehicles, periodicity of messages, perception type (active or passive), and relevant information. The response variable (dependent variable) is the agent's needed time to act in the environment. Each simulation lasts for 360 seconds. The experimental factors determination follows 2^k factorial analysis.

The density of vehicles and roadmap (road topology) are factors pointed out by Fogue et al. (2011) to take into account in Vehicular ad hoc networks (VANETs) simulations. In their work, the periodicity of messages had little impact in a warning message delivery process. However, in this experiment, the periodicity of messages may increase the agent's reasoning time. The periodicity message levels are 1 packet/s (level -1) and 10 packets/s (level 1). The levels for vehicle spawning (density of vehicles) are 10s (-1) and 20s (1). There is only the roadmap presented in Figure 22. It is similar from the studies presented in Chapter 5.

The perception factor follows the model presented in section 4.4.3. In active perception (-1), only perceptions related to current goals are added to the agent's knowledge. On the other

Figure 23 – Bayesian reasoning: Bayesian network in the Bayesian Context.



Source: The author.

hand, in passive perception (1), the agent's knowledge receives all information about the near environment. The Relevant information is the amount of useful information received from the agent's sensors (33,3% or 100%). These factors' levels are the extremes values in this thesis perspective. Table 23 summarises the experimental factors.

Table 23 – Bayesian reasoning: Factors and their values.

Factor	Level -1	Level 1
Density of Vehicles	10s	20s
Message Periodicity	1 packet/s	10 packets/s
Perception	Active	Passive
Relevant information	33,3%	100%

Source: The author.

The experimental setting introduced in section 6.1 is applied to run 2^4 experiments 3 times (3 replications). That is, there are 48 simulations and 149712 records of agent's reasoning cycle. The number of reasoning cycles for perception and relevant information factors was equally distributed (74856 each). The agent had more reasoning cycles when the simulation had more vehicles (97056 cycles/10s spawning vehicles and 52656 / 20s). The growth of message periodicity is linear in the agent's reasoning cycle (10 times more message implies 10 times more reasoning cycle). Table 24 summarises this description.

Results of the 2^k factorial analysis show that the factors of irrelevant data (74,149%), perception type (12,4959%) and its intersection (12,6411%) have all influence in the agent's reasoning cycle practically. This result shows that if the sensors receive a significant quantity of irrelevant data (i.e., not related with current goals), the perception algorithm has limited

Table 24 – Bayesian reasoning: Number of reasoning cycles by factor.

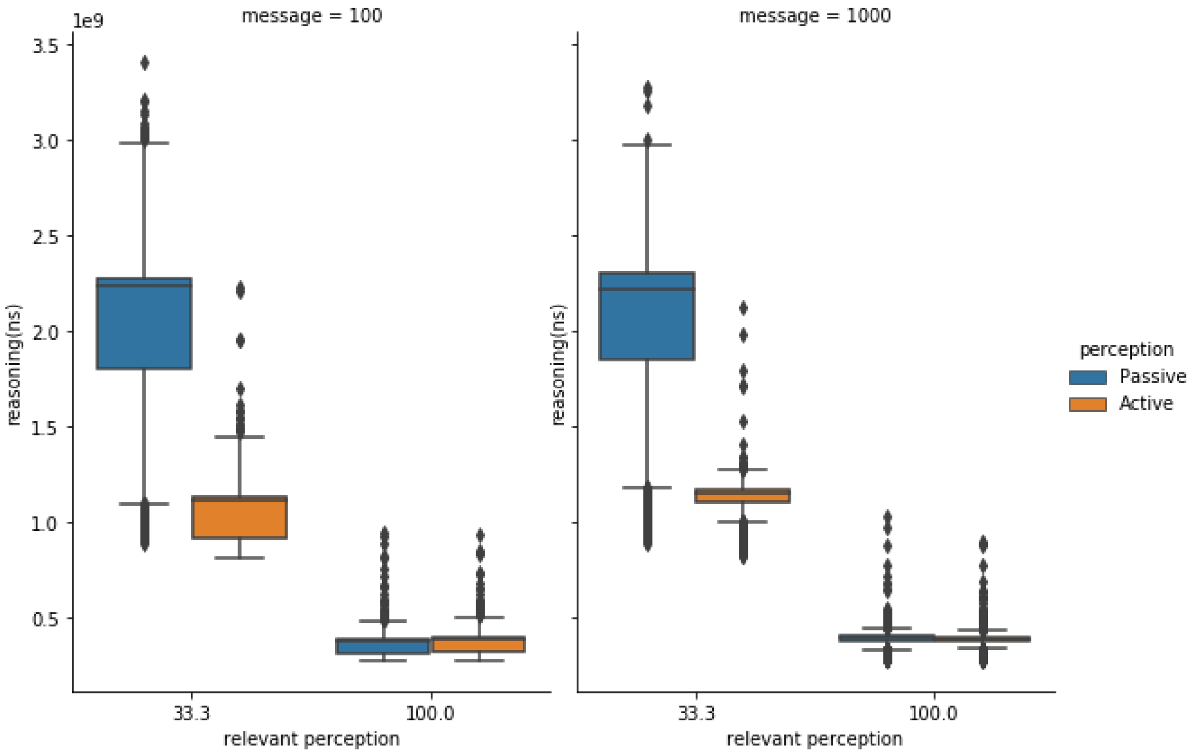
Factor	**Level -1**	**Level 1**
Density of vehicles	97056	52656
Message Periodicity	13692	136020
Perception	74856	74856
Relevant information	74856	74856

Source: The author.

relevance, which requires a specific mechanism for each agent's sensor. Figure 24 presents the box plot of reasoning time for active and passive perception.

To solve the problem of irrelevant data in the agent's reasoning, Freitas et al. (2020) developed two perceptions policies allowing processing less perception data: progressive — add a new perception if it is different information, and sudden — give more priority for a given sensor. These policies are a filter in the agent's sensors avoiding agent's deliberation about all perceptions.

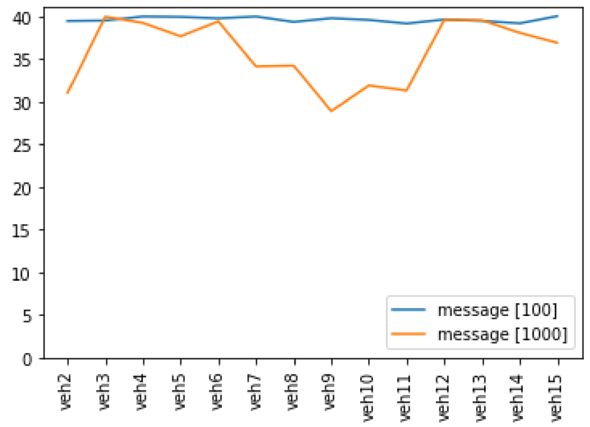
Figure 24 – Bayesian reasoning: Reasoning time in active and passive perception with irrelevant data and message periodicity.



Source: The author.

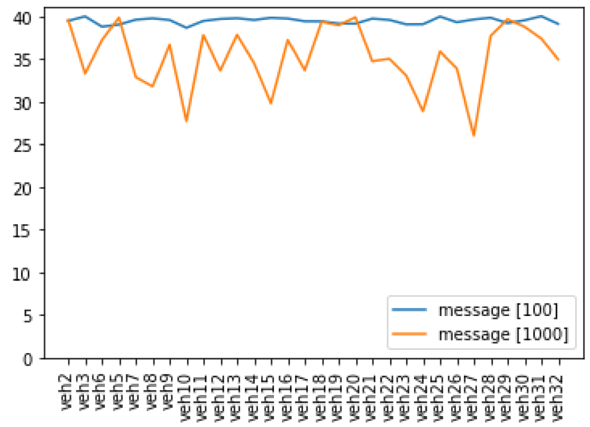
The agent interrupts the pedestrian's interaction with the smartphone in situations where the pedestrian is distracted, and the distance to a vehicle is less than 40 meters. During the experiments with vehicle density of 20s, in 14 of 18 possible situations, the pedestrian and the vehicle were less than 40 meters apart. The message periodicity ended up influencing the distance the vehicle was perceived, with higher oscillation in the level of 1000ms. Figure 25 shows the distance between the vehicle and the pedestrian at the time the agent intervened. In simulations with a density of a car spawning at every 10 seconds, 30 of 36 cars crossed a warning region, but only 26 represented a real hazard. The variation of the distance intervention is also observed at message periodicity of 1000ms. Figure 26 shows the distance between the vehicle and the pedestrian at intervention action.

Figure 25 – Bayesian reasoning: Distance (0 - 40) between the vehicle (veh_i) and the pedestrian at the time of the agent's intervention (density 20s).



Source: The author.

Figure 26 – Bayesian reasoning: Distance (0 - 40) between the vehicle (veh_i) and the pedestrian at the time of the agent's intervention (density 10s).



Source: The author.

6.3 ONTOLOGICAL AGENT

This experiment applies the agent using the STO ontology presented in section 4.4.1 to describe the situations in which there is a car life-threatening the pedestrian. While to model a situation in Bayesian networks it is essential to have an understanding of the probabilities associated, in the ontology, the situation is described based on the environment description.

This experiment's premises are: agent's sensors have perception policies reducing the amount of irrelevant data sent to the agent, and active perception reduces what is added in the agent's deliberative component.

The motivation for creating this experiment is from the work of Soto et al. (2019). The authors addressed the problem of generating too many warnings in the drivers perspective of a pedestrian protection system, where there is a trade-off between capturing all the situations and generating alerts. The experiment presented in this section analyses the problem from the pedestrian's perspective. Each simulation lasts for 360 seconds.

The dependent variables are:

- Reasoning time;

- The number of actions to protect the user.

The independent variables are:

- The distance between car and pedestrian is below a threshold (rational driver: 40m, speedy driver: 60m);
- Ontology Situation *CarLifeThreatenPedestrian*: below the threshold (Algorithm 1) vs below the threshold and be decreasing (Algorithm 2);
- Message periodicity: thresholds are 100ms or 500ms;
- Relevant information: assuming the use of perception policies, the new levels of relevant information are 100% or 75%.

This experiment's variables are different from the previous one, once the agent has some performance improvements and has a new dependent variable. Table 25 presents the factors of this experiment.

Table 25 – Ontological reasoning: Number of reasoning cycles by factor.

Factor	**Level -1**	**Level 1**
Algorithm	v1	v2
Message periodicity	100	500
distance threshold	40	60
Relevant information	100	75

Source: The author.

Algorithms 1 and 2 are two possible ways to develop a pedestrian notification system. These algorithms have limitations regarding the information's representation received as input, the veracity of the data received, and have no degree of autonomy. The use of the agent paradigm to execute this kind of algorithm (as agent's plans) adds an abstraction layer capable of improving decision-making. In addition to giving autonomy to actions, context representation of situations and active perception are approaches to improving the number and quality of the information received.

The execution of the 16 simulations produced 71708 records of agent's reasoning cycle. The agent had more reasoning cycles when the simulation had more interaction with vehicles (60012 when message periodicity is 100 ms and 11692 when it is 550 ms). The result displayed several outliers even after interquartile range removal as can be seen in Figure 27.

Results of the 2^k factorial analysis under reasoning cycle assumption determine that the factors of the algorithm (83,159%), and the intersection between message periodicity and relevant information (10.05%) have more influence in agent's reasoning cycle. The interaction between message periodicity and relevant information had only 2.65% of the influence, and

Algorithm 1: Naive pedestrian notification algorithm.

Input: Pedestrian p, vehicle v
Output: Notify pedestrian
if !*p.distracted()* **then**
    return *false*
distance := *p.position()* − *v.position()*
if *distance* < *v.getDriversThreshold*() **then**
    return *true*
return *false*

Algorithm 2: An improved pedestrian notification algorithm.

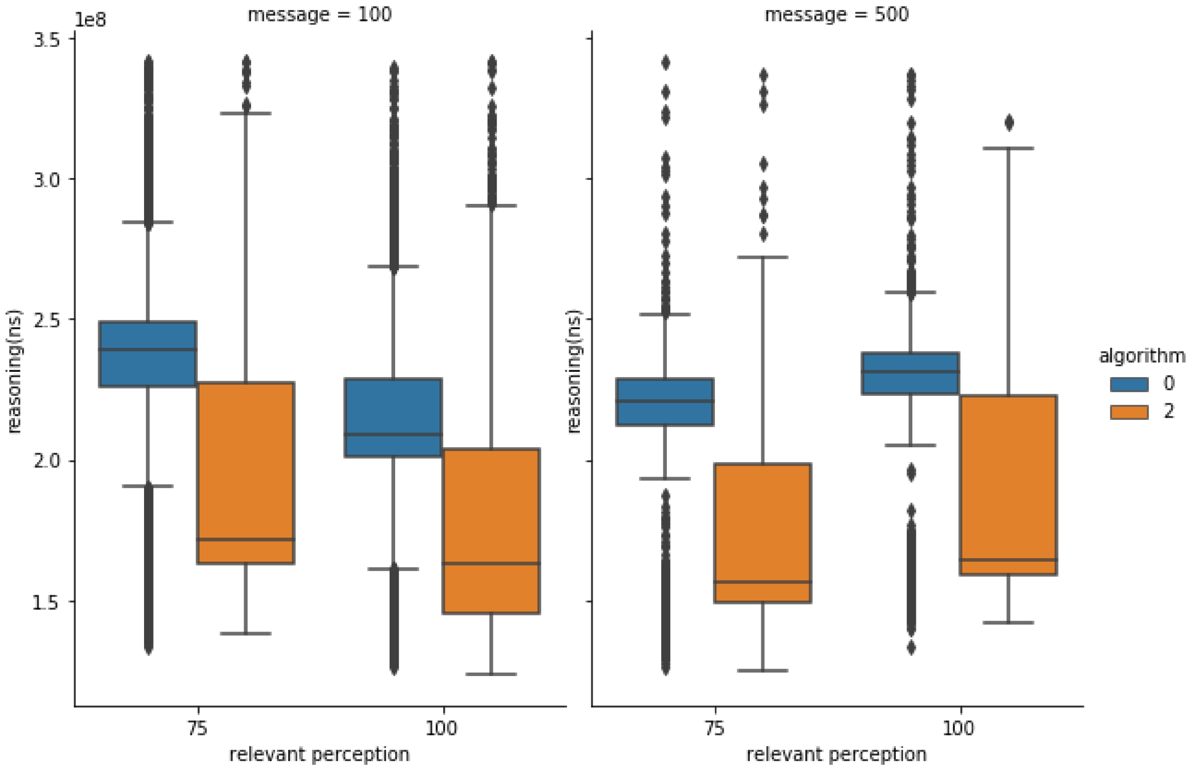
Input: Pedestrian p, vehicle v
Output: Notify pedestrian
if !*p.distracted()* **then**
    return *false*
lastDistance := *p.lastPosition()* − *v.lastPosition()*
distance := *p.position()* − *v.position()*
if *distance* > *lastDistance* **then**
    return *false*
if *distance* < *v.getDriversThreshold*() **then**
    return *true*
return *false*

other factors have $< 1\%$ of influence. The number of warnings sent shows this influence: using algorithm 1, there are 12426 warnings, and using algorithm 2, the total is 1722.

Algorithm 1 sends more warning messages, yet the variation in the distance for notification is smaller than using algorithm 2 (std = 2.4362 and mean = 37.2044 in algorithm 1 and std = 12.6955 and mean = 22.1131 in algorithm 2). It is impossible to apply ANOVA since the assumption of independence between samples ends up being violated (the agent will perceive the nearest car first). Figures 28 and 29 show the time to perceive each car considering the two algorithms and the message periodicity. Vehicle 17 and vehicle 18 were in the opposite direction and joined the warning zone with a difference of 1 perceived message, resulting in more time for the agent deciding the action for the vehicle 18 (the pedestrian was already aware of the situation).

An experimental trial run consists of a total of 36 vehicles. The algorithm 2 notified 23 vehicles of the 26 that crossed its path, taking longer to recognise the possibility for collision. Algorithm 1 notified 30 vehicles. In this manner, for environments where there is a risk to human safety, a more conservative view tends to be more appropriate. However, this thesis does not define which approach is better. It only presents possible approaches to the problem.

Figure 27 – Ontological reasoning: Reasoning time in active and passive perception with irrelevant data.



Source: The author.

6.4 SUMMARY

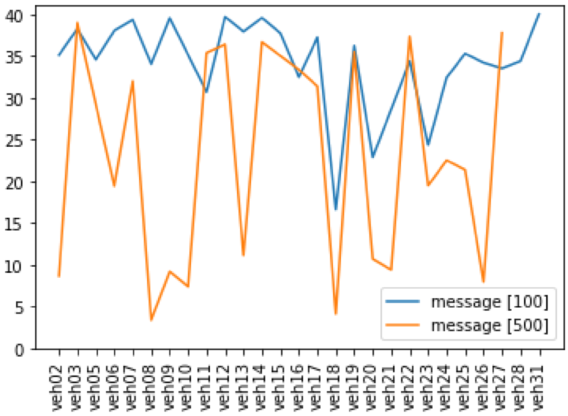
This Chapter investigated the use of BDI-like agents implemented in Sigon, considering the representations of situations through a Bayesian network and an ontology, and comparing active and passive perception. The experiments were built based on the computational model presented in Chapter 4, and with the data and knowledge obtained in experiments of mobile device users presented in Chapter 5.

Given a problem that can be solved computationally, different strategies can be applied. First-order languages, ontologies and Bayesian networks are approaches of reasoning in an environment under different conditions. A multi-context system is a way to combine these approaches. With the Sigon framework, we presented how an agent can use a deductive system to act in a dynamic environment.

The experimental analysis follows the guidelines presented by Jain (1990). Bayesian experiments show the impact of receiving irrelevant data for decision-making, and how active perception can reduce it. Experiments with an ontology of situation awareness show how to use contextual data in a decision support agent.

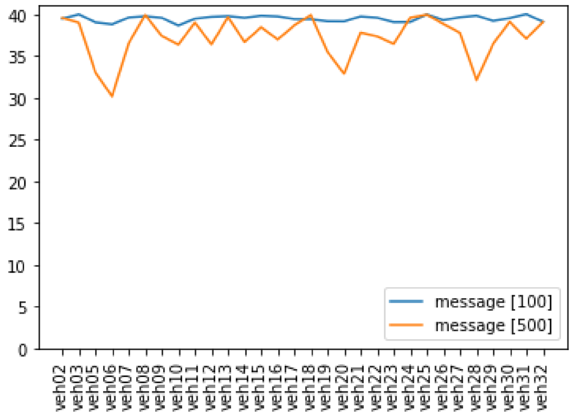
The agent using ontology started from the STO ontology, and the agent using Bayesian networks is domain-dependent. Thus, whenever a Bayesian network is applied to model a

Figure 28 – Ontological reasoning: Distance between the vehicle (veh_i) and the pedestrian at the time of the agent's intervention (algorithm 1).



Source: The author.

Figure 29 – Ontological reasoning: Distance between the vehicle (veh_i) and the pedestrian at the time of the agent's intervention (algorithm 2).



Source: The author.

situation, it is necessary to analyse relevant data. On the other hand, using the STO ontology, it is enough to describe the situation based on the concepts defined in the ontology itself. However, the ontology does not have mechanisms to handle uncertainty.

The simulations performed were built using the Sigon framework and the urban computing tools SUMO, Veins and OMNeT++. The findings of this Chapter are related to previous studies in which the processing of overwhelming perceptions reduce the time to act in a dynamic environment. Perception policies and active perception are possibilities to reduce the amount of data processed in the agent's decision making.

The comparison between these solutions' performance was out of the scope of this thesis and is still an open research topic. Comparing the performance of agents developed with other frameworks, such as Jason, is also not part of the scope. There are different ways to implement agents to act in dynamic scenarios and different frameworks. The analysis presented was restricted to the ability of reasoning in different knowledge representations and active perception using the Sigon framework.

7 CONCLUSION

This thesis investigated mechanisms allowing agents with limited resources to represent and reason about heterogeneous knowledge sources in dynamic environments. The Multi-Context System approach enables applying different formalisms to define the agent's knowledge and capabilities. The systematic literature review presented in section 3.1 demonstrates that gaps in knowledge remain in agents as MCS, mainly in the development of single agents in dynamic environments.

To address these gaps in knowledge Chapter 4 presented Sigon, the first framework allowing agents to be modelled and developed according to the MCS approach. To create it, it was analysed the main components of theoretical agents as MCS. First, it was described formally how a Sigon agent is defined. A Sigon agent is an abstract definition, leading to high customisation that can be a problem if it is unknown the agent's architecture. In this sense, Sigon has a BDI architecture in its framework, to facilitate the addition of behaviours and knowledge sources. The framework has the structure for representing the agent, its contexts, bridge rules, sensors, and actuators.

In this thesis context, Sigon is evaluated on practical reasoning using BDI-like agents. However, the key factor in developing different agent's behaviours in the Sigon framework is the correct definition of bridge rules. The sequential execution of bridge rules enables the creation of algorithms to define the agent's architecture. The Sigon framework achieves the thesis' specific objective '*to define a framework for developing agents, giving flexibility to the reasoning in heterogeneous sources of knowledge*'.

Situations are modelled with ontology and Bayesian networks to demonstrate the agent's ability to represent and reason in heterogeneous knowledge sources. The ontological knowledge enables the agent to reason about individuals belonging to a specific situation, in well-defined and detailed semantics. We use the Situation Theory Ontology (STO) (KOKAR; MATHEUS; BACLAWSKI, 2009) for modelling pedestrian situations. Bayesian knowledge uses an environmental situation to attach probabilities to events. We create a Bayesian network to describe pedestrian awareness. These studies with ontology and Bayesian network answer the RQ1 (*How to model and develop intelligent agents to combine knowledge with multiple representations following the MCS approach?*).

The addition of an active perception model to restrict the agent's perceptual process allows the agent's internal state to guide the decision of relevant environmental aspects for the current intention. An agent's intention may have several plans, and each plan can have a different set of preconditions. A precondition may be represented in a specific formalism, thus reiterating the importance of different knowledge representations in the agent's decision making. Section 4.4.3 presents a multi-context active perceiver agent. It achieves the specific objective *'to identify perception prioritisation strategies according to the agent's internal state'*, and answer to RQ2 (*How to restrict the perceptual process based on a BDI agent's internal representations of situations?*).

Agent's definition and the representation of situations allows the analysis of its performance in dynamic environments. Therefore, this thesis's experimental Chapters are contextualised in urban environments, in the usage of smartphones by pedestrians. The two main points concerning this subject are: (i) to identify factors that decrease situational awareness of pedestrians, and (ii) how to model agents to act as a decision-supporting system in these situations.

Chapter 5 argued the first point, showing a comprehensive study on pedestrian situational awareness when using smartphones and providing a new understanding of their behaviour. We conducted three experiments in virtual environments, two in the Octave, and one using the HTC VIVE virtual reality glasses. In these experiments, we found a significant number of associations between unsafe events, reaction time, and factors of distraction level and car sound. The Chapter's study achieves the specific objective '*to measure the impact of smartphones in a pedestrian's situational awareness*' and answers the RQ3 (*What has been the influence of smartphone in pedestrian's situational awareness on the vicinity of urban traffic?*). This analysis also allowed the development of models of situations that can be analysed individually, for example, as a Bayesian network, or as a component of the agent's decision process.

The second point of the experimental Chapters regards the agent paradigm in the urban computing context. It creates an abstraction layer in the interaction between entities in the environment. Vehicles, pedestrians, and infrastructure elements can use the autonomy, proactiveness, reactivity, and social ability to interact with their peers acting correctly in the environment. Section 4.4 presented some approaches for modelling agents to act in such situations using an ontology, a Bayesian network and active perception. These examples were applied in Chapter 6, to evaluate the impact of receiving irrelevant data for decision-making, and how active perception can reduce it. Chapter 6 also presented a method to apply contextual data in a decision support agent. The studies presented in sections 6.2 and 6.3 achieve the specific objective '*to analyse practical reasoning for heterogeneous representations of situations in dynamic environments with limited resources*'.

The outcome of specifics objectives produces a practical reasoning model, based on BDI and implemented in the Sigon framework. It achieves the general objective of this thesis '*To develop a practical reasoning model for intelligent agents situated in a dynamic environment, following the multi-context systems approach, to handle heterogeneous overwhelming situational data*'. The model developed in Sigon enables the use of different representation for modelling situations of the dynamic environment, and perception policies and active perception are mechanisms to improve overwhelming situation data.

The Sigon framework is a prototype, and several optimisations are still needed. Consequently, the comparison with Agent Programming Languages can be tricky. This characteristics also impact the experiments performed in Chapter 6. Although the infrastructure has been developed for simulation in urban environments, the analysis ended up being limited to ontology and Bayesian network. Some optimisations are characterised as future work and are described below.

7.1 FUTURE WORKS

The main future works are organised into two perspectives: Sigon development and urban computing.

7.1.1 Sigon Development

Several properties of the MCS theory can be added to Sigon. For example, preferences, inconsistency analysis and answer set programming (BREWKA; EITER; TRUSZCZYŃSKI, 2011; EITER et al., 2014; MU; WANG; WEN, 2016). These theories can be used in the development of both a single agent and a multi-agent system.

The addition of answer set programming ability in the Sigon framework is useful for BDI agents, in which it is possible to verify all the applicable intentions at a given moment. To do such analysis is necessary to evaluate all bridge rules applicable at a given time. However, the agent having to evaluate it at every reasoning cycle can be a costly task. Thus, a preference mechanism may also be useful for searching applicable bridge rules examining only a subset of intentions.

The concept of preferences is also applied to other contexts. For example, if the Bayesian context states that the pedestrian will be run over, and the ontological states the opposite, the agent needs a mechanism to choose one. Other operators can be added to Sigon, both at the bridge rules level — adding bridge rule uncertainty; and at the context level — generation of new beliefs through the function execution.

Costantini & Pitoni (2019) presented K-ACE, a more general approach for agent development than the one presented in this thesis, using bridge rules and any other communication device. However, the authors suggest the use of Sigon to implement it. Future research is creating a mechanism to enable the development of a K-ACE agent in the Sigon framework.

Multi-Entity Bayesian Networks (MEBN) (LASKEY, 2008) is a related approach integrating First-order Language (FOL) with probabilistic knowledge. It is modular — the probability distributions are local, over a small group of hypothesis; and it is compositional — the global probability is consistent over sets of hypotheses. There are applications of MEBN with probabilistic ontologies (COSTA; LASKEY; CHANG, 2009) and Predictive Situation Awareness (PARK; LASKEY, 2018). Future research is to integrate a MEBN in an MCS and in the Sigon.

All the studies developed in this thesis examine a single agent situated in a dynamic environment perspective and with the requirement to use heterogeneous knowledge sources. The information contained therein can be extended to analyse collective behaviour. It is a process that involves social interactions and can imply in capabilities as negotiation and trust. A gap in the context-awareness systems literature is at '*how it can trust its own understanding of its context*' (FERNANDEZ-ROJAS et al., 2019). The agent literature presents trust models that can be studied and adapted to this problem.

7.1.2 Urban Computing

This research presented several facets of mobile devices in urban environments: tasks that can reduce pedestrian situational awareness; V2X simulation with agents; development of models to improve safety. The following work is to perform tests similar from those presented in Chapter 5 using the agent developed and tested in Chapter 6 as context-aware decision support.

The urban experiments reflected the thesis goals, but the integration of Sigon with these tools allows for further analysis. For example, other environmental factors are available, such as speed variations, interaction with other pedestrians and infrastructure. For example, an application study is representing the pedestrian and/or drivers as Sigon agents and thus simulating the user's behaviour. Additionally, our experiments examined the interaction between vehicles and pedestrians, and this interaction may involve criteria such as the truthfulness of previous information. Thus, the use of security devices is motivated, such as a trust model for interacting or negotiating with other devices/agents. In this sense, a current challenge for agent societies in urban environments is negotiating resources and services (BAARSLAG et al., 2017).

Dynamic Bayesian networks is a Bayesian network allowing to model situations by including temporal dependencies of dynamic behaviours of situation variables. A pedestrian situation awareness model in a Dynamic Bayesian networks perspective can be developed using the dataset created in this thesis.

We plan to develop a model to improve situation awareness of people with lower attention, blind or elderly in urban environments. To achieve it, we are investigating how to get the surrounding environment sound to measure the distance between blind people and close objects.

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APPENDIX A – SIGON GRAMMAR

```

grammar Agent;

agent
 :
 communicationContext (context | bridgeRule)*
 EOF
 ;

context
 :
 logicalContext | functionalContext
 ;

bridgeRule
 :
 head ':-' body '.'
 ;

logicalContext
 :
 logicalContextName ':' formulas
 ;

functionalContext
 :
 communicationContext |
 plannerContext
 ;

communicationContext:
 'communication' ':' (sensor | actuator)+
 ;

plannerContext
 :
 'planner' ':' plansFormulas
 ;


```

```
logicalContextName
 : primitiveContextName
 | customContextName
 ;

primitiveContextName
 : 'beliefs' | 'desires' | 'intentions'
 ;

customContextName
 :
 CUSTOMNAME
 ;

CUSTOMNAME :
 '_'  ALPHA CHARACTER*
;
plan
 : 'plan' LeftParen somethingToBeTrue ',' compoundAction (','
   planPreconditions ',' internalOperator? planPostconditions)? (','
   cost)? RightParen '.'
 ;



somethingToBeTrue
 : term
 ;

planPreconditions
 : conditions
 ;

planPostconditions
 : conditions
 ;

conditions
 : ('_' | term)
 ;

action
```

```
 : 'action' LeftParen functionInvocation (',' actionPreconditions ','
     internalOperator? actionPostconditions)? (',' cost)? RightParen
 ;

actionPreconditions
 : conditions
 ;

actionPostconditions
 : conditions
 ;

functionInvocation
 : functionName LeftParen argumentList? RightParen
 ;

functionName
 : CONSTANT
 ;

sensor
    : 'sensor' LeftParen sensorIdentifier ',' sensorImplementation
        RightParen '.'
    ;

sensorIdentifier
    : STRING
    ;

sensorImplementation
    : STRING
    ;

actuator
    : 'actuator' LeftParen actuatorIdentifier ',' actuatorImplementation
        RightParen '.'
    ;

actuatorIdentifier
    : STRING
    ;

```

```
actuatorImplementation
    : STRING
    ;

internalOperator
 : beliefAdition | beliefRemotion | desireAdition | desireAdition
 ;

beliefAdition
 : '+'
 ;
beliefRemotion
 : '-'
 ;

desireAdition
 : '+!'
 ;
desireRemotion
 : '-!'
 ;
argumentList
 : expression (',' expression)*
;

expression
 : CONSTANT | VARIABLE
 ;

compoundAction
 : ('[' action (',' action)* ']') |'_'
 ;

plansFormulas
 : ((plan | action )) *
 ;

contextName:
 logicalContextName | 'planner' | 'communication'
 ;

head
```

```
:
'!' negation? contextName (term | negation? VARIABLE)
;

body
: negation? contextName ((term | negation? VARIABLE) | plan)
((AND | OR) negation? contextName ((term | negation? VARIABLE) | plan))*
;

term
:  negation? CONSTANT ( annotation | (LeftParen atom (',' atom )*
   RightParen) annotation?)?
| term (AND | OR) term
| ('[' term (',' term)* ']')
| term ':-' term
;

formulas
: (term '.' )*
;

atom
    : (NUMERAL | CONSTANT | VARIABLE | '_') (operator (NUMERAL |
       CONSTANT | VARIABLE | '_') )?
    ;

operator
    : '<' | '=<' | '>' | '>=' | '-' | '+'
    ;

negation
: 'not ' | '~';

annotation
     : (preAction gradedValue ? ) | gradedValue
     ;

preAction
    : '['CONSTANT']'
    ;

gradedValue
```

```
    : '->0.' NUMERAL
    ;
cost
    : '0.' NUMERAL
    ;
NUMERAL
 : DIGIT+
 ;

CONSTANT
 : LCLETTER CHARACTER*
 ;

VARIABLE
 : UCLETTER CHARACTER*
 ;

AND
   : '&'
   ;

OR
   : '|'
   ;

LeftParen : '(';
RightParen : ')';

STRING
 :
    '"' (~["\\\r\n])* '"';
fragment ALPHA:
 LCLETTER | UCLETTER
 ;
fragment CHARACTER
    : LCLETTER | UCLETTER | DIGIT
    ;
fragment LCLETTER
    : [a-z_];
fragment UCLETTER
    : [A-Z];
fragment DIGIT
```

```
    : [0-9];
WS
   : [ \t\r\n] -> skip
;
BlockComment
    : '/*' .*? '*/' -> skip
    ;
LineComment
    :   '//' ~[\r\n]*
        -> skip
;
```