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Context Classification for Service Robots

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«Com organização e tempo, acha-se o segredo de fazer tudo e bem feito»

Pitágoras

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Resumo

Esta dissertação apresenta uma solução para que um AGV consiga percepcionar o ambiente em que se insere, usando para isso técnicas de fusão sensorial e classificação, com o objectivo final de que o robô consiga alterar e adaptar os seus comportamentos conforme os diferentes resultados obtidos pelo sistema de inferência para os diferentes contextos/ambientes.

A título de exemplo, se o robô reconhecer que está num campo ao ar livre, tem em conta que pode haver solos com areia, em que terá de circular mais lentamente. Contrariamente, em ambientes interiores é pouco provável que haja solos com areia num escritório. Esta pequena hipótese denota a importância de um sistema ciente do seu contexto para AGVs (Automated Guided Vehicles).

Palavras-chave: Context-aware, fiabilidade, classificação de ambientes, inteligência artificial, aprendizagem máquina.

Abstract

This dissertation presents a solution for environment sensing using sensor fusion techniques and a context/environment classification of the surroundings in a service robot, so it could change his behavior according to the different reasoning outputs.

As an example, if a robot knows he is outdoors, in a field environment, there can be a sandy ground, in which it should slow down. Contrariwise in indoor environments, that situation is statistically unlikely to happen (sandy ground). This simple assumption denotes the importance of context-aware in automated guided vehicles.

Keywords: Context-aware, reliability, environment classification, artificial intelligence, machine learning.

Contents

Acronyms List

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
API	-	Application Programming Interface
ARFF	-	Attribute-Relation File Format
BPA	-	Basic Probability Assignment
CAIROW	-	Context-aware Assisted Interactive Robotic Walker
CAMUS	-	Context aware middleware for URC systems
CASS	-	Context-Awareness Sub-Structure
CLI	-	Command Line Interface
CML	-	Context Model Language
CoBrA	-	Context Broker Architecture
COMANTO	-	Context Management Ontology
CV	-	Cross Validation
DB	-	Database
dB SPL	-	Decibel Sound Pressure Level
DL	-	Description Logics
DT	-	Decision Trees

FCL	-	Fuzzy Control Language
FLC	-	Fuzzy Logic Controllers
FN	-	False Negatives
FP	-	False Positives
FPR	-	False Positives Rate
FRBs	-	Fuzzy Rule Based Systems
GPS	-	Global Positioning System
GUI	-	Graphical User Interface
HMM	-	Hidden Markov Model
I²C	-	Inter-Integrated Circuit
IDE	-	Integrated Development Environment
IMU	-	Inertial Measurement Unit
LADAR	-	Laser Detection and Ranging
LPG	-	Liquefied Petrolium Gas
ML	-	Machine Learning
MRF	-	Markov Random Field
NN	-	Nearest Neighbor
ORM	-	Object-role Modeling
OS	-	Operating system
OWL	-	Web Ontology Language
PID	-	Proportional-Integral-Derivative
PWM	-	Pulse Width Modulation
PWS	-	Personal Weather Station
QREN	-	Strategic Reference National Framework
RH	-	Relative Humidity
ROC	-	Receiver Operating Characteristic

ROS	-	Robot Operating System
SI I & DT	-	System of Incentives for Research and Technological Development
SOCAM	-	Service-oriented Context-Aware Middleware
SVM	-	Support Vector Machines
TN	-	Total Negatives
TNR	-	True Negative Rate
TP	-	True Positives
TPR	-	True Positives Rate
UART	-	Universal Asynchronous Receiver/Transmitter
UDM	-	Universal Data Model
UML	-	Unified Modeling Language
URC	-	Ubiquous Robotic Companion
URL	-	Uniform Resource Locator
USB	-	Universal Serial Bus
WEKA	-	Waikato Environment for Knowledge Analysis
XML	-	eXtensible Markup Language

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1. Introduction

Aside from our language and the common understanding of the world and its operation, what contributes to a much more efficient exchange of knowledge between human beings, is the notion of context [1]. Humans are able to add and take into account situational information (context) in a conversation to better understand the subject, retain more information in a more efficient way and to respond appropriately to it, in other words, to increase conversational bandwidth as said in [1]. When humans interact with machines or machines interact with each other, that awareness can be lost and so can the information richness [2].

1.1 Definition of context

Generally speaking and according to [1]:

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

We can also refer to context as a user's emotional state, focus of attention, objects, people around the user's environment and also location, orientation, date and time [3].

Context can be low-level (like time and location, tightly coupled with direct data from the context source) or high level (in a more abstract level but still using low-level data provided by the source). This context source is related to any device that can provide context information, typically smartphones, sensors, computers, etc. [4].

1.2 What is context-awareness?

The term 'Context-aware' was first introduced by Schilit and Theimer [5] and they proposed "context" as 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". Context-aware applications need to sense and interpret the environment around, in order to be adaptive, reactive, responsive, situated, context-sensitive and environment-directed. The main questions that context-aware applications must take into account are: who, where, when and what the user is doing, to understand and classify his situation [1]. There are applications that just inform an entity about its context and others that dynamically change and adapt their behavior according to its environment. They are both considered to be context-aware.

In general, context-aware applications monitor a variety of environment input sources and reason what is the entity situation, based on previous rules and guidelines that the developer has established. This can be done using several different methods, according to what's best suited. The major existing inference methods will later be presented and compared.

Adding context access to machines (computers, robots, etc.) can produce a more interesting and efficient way to exchange information [2], to build smarter environments, also to adapt and tailor the relevant data for each situation. Without knowing its context, applications are "blind" and require more attention. An old phone can be an example of a "blind" application because it can ring at any moment without sensing the environment (if it's appropriate or not). One way to solve this can be by sensing where the user is (if it's driving, etc.) or what is the average noise level in the room to change its volume accordingly.

Concepts like context and context-aware are connected with pervasive computing (also called *ubiquitous computing)* techniques. According to [6], a pervasive computing environment, is one full of computing and communication capabilities, but so gracefully integrated with humans, in a way that we don't even perceive it [7], so in [6] they said "the most profound technology is the one that disappears". Pervasive computing is seen as an evolution of distributed systems together with mobile computing, providing, among other features, a more dynamic, adaptive and effective use of smart spaces (environment sensing and reaction).

1.3 Environment Definition

According to the Oxford dictionary [8], environment consists essentially in the surroundings or conditions in which an entity operates (here it's assumed that this entity isn't necessarily a living being). It can also refer to the set of conditions that a particular activity is carried on. In computing, it can refer to the structure where a program operates (like a "development environment").

It sums up to anything that is external to an entity. Regarding this document, referring to environment stands for the external environment conditions and surroundings of the robot that affect and influence its operation.

1.4 Dissertation Structure

This dissertation is divided into four chapters.

Chapter 1, introduction, explains the main concepts and definitions related with the main subject of this dissertation, enlightening the reader.

Chapter 2, state-of-the-art, reviews the tools and existing background work in order to make this dissertation possible, enumerating and describing the different methods that are relevant.

Chapter 3, implementation, relates to the explanation about the architecture of this work, regarding its execution.

Finally, on chapter 4, regards conclusions and future research to be done on this subject.

2. State-of-the-art Analysis

In this chapter it will be described how the data is acquired from the context-sources, what are the main techniques used in the context classification system, what are the main existing frameworks and architectures for building context applications, how to deal with uncertainty when reasoning higher level information and finally an overview on how these techniques and concepts are used in robotic systems.

2.1. Context data acquisition methods

There are different architecture approaches to acquire context information according to [4,9,10]. The chosen method depends on the required application and it's relevant for the design of the whole system's architecture. Sentient objects (defined below) and centralized or distributed middleware were added on this dissertation to better classify the different models (described in the next chapter) regarding data acquisition, although the authors in [4] presented a good data acquisition tabulation, it seems to be lacking some focus. Thus the following enumeration tries to bridge that gap, inserting sentient objects and subtypes of middleware:

- **Direct sensor access** – drivers from the sensor feed data directly into the application. It doesn't have processing capability or support for multiple concurrent sensing.
- **Sentient objects** - may be smart sensors with actuators, which interact with the environment and can interact with each other. They can make use of a simple rule engine and perform simple actions like, for example: a light sensor that is connected to a headlight and turns on the headlight when it's dark [11].
- **Middleware infrastructure** – implemented with a layered architecture that hides low level data and allows separation between several structure interfaces. Middleware infrastructures can be distributed or centralized:
    - Distributed middleware – Inference results can be shared in a distributed system for various applications.
    - Centralized middleware – Where context sources, inference system and applications are running only locally and in the same system.

2.2. Context Models

There are several approaches to develop the rules which will compose the context classification system. These rules/deductions/methods establish the relations between the sensed data and the overall context situation.

Some early approaches refer key-value and markup models for context applications. Key-value models use simple key-value pairs and define a list of attributes and their values [12], for example a "color" can be a key and "red" a value. Markup models use markup languages like XML, tagging data in a hierarchical way. There are some hybrid models than can be both markup and key-value since they can store key-value pairs under appropriate tags [12]. These models have known limitations about reasoning support, timelines and more complex relations and dependencies [13].

There are also graphical models that use visual implementation such as UML (Unified Modeling Language) like in [14]. In extension of graphical mod-

els there is object-based modeling (like Object-Role Modeling, ORM) techniques that supports better processing and reasoning to satisfy the more demanding requirements; CML (Context Model Language) is an example. CML and ORM emerged from conceptual modeling databases [12]. In [12] it's stated that CML adds some features in ORM like obtaining information from the different context sources and classes (static, sensed, derived, etc.) and distinguish its different backgrounds, also capturing history of its fact types, constraints and relations/dependencies.

There are logic-based models in which context is defined based on a set of rules, facts and statements. Logic defines the conditions needed to reach a fact or expression derived from the facts and rules [15].

Finally there are the ontology-based models. Context involves knowledge and between knowledge representation languages, DL (description logic) has emerged with a good tradeoff between expressiveness and complexity [12]. They give us a description about the world in terms of concepts (classes), roles (relationships and properties) and individuals (instances) [16].

In [15] the authors claim that ontology based models are the more expressive and fulfill most of their requirements. Since ontologies consist in descriptions of concepts and their relationships, they are a powerful instrument for modeling contextual information [4]. A formalism called OWL-DL (web ontology language) is frequently used to represent context information distinguished by categories of objects and objects interrelation [17].

In [18] the authors present some of the guideline requirements for ontology models: the relations must be simple (simplicity) to ease the debug process, they should support adding new relations and elements (flexibility and extensibility), they should not be focused on only one type of context but to support several (generality) and finally they should be expressive and meaningful in describing the context details.

Ontologies have a key role and are widely used in many applications nowadays, such as databases, semantic-web, etc.

There are also hybrid models that combine different formalisms and techniques. In [12] the authors believe this is a promising direction since different

models and reasoning tools need to be integrated with each other towards a better tradeoff between expressiveness, complexity and support for uncertainty. In that same article, authors also present two existing hybrid approaches. One that combines a fact-based approach with ontological models [19] and other that combines markup-model with ontological model [20].

2.3. Context Frameworks

When choosing the design of a context model it should be analyzed what features are best suited to the required application, regarding the architecture, inference system and how the data is processed and sensed. Similarly in [4] the authors evaluate and classify some existing context frameworks and architectures according to their main features and aspects.

According to [4] the most common architectures use layers (similarly to Figure 2.1), are hierarchical and have one or many centralized components. There are advantages and disadvantages in using centralized components. One advantage is that it lightens processor and memory usage which is crucial in mobile devices. The obvious disadvantage is that it generates one single point of failure (reduce reliability). Bellow there's a typical context-aware application's layered framework, presented in [4].

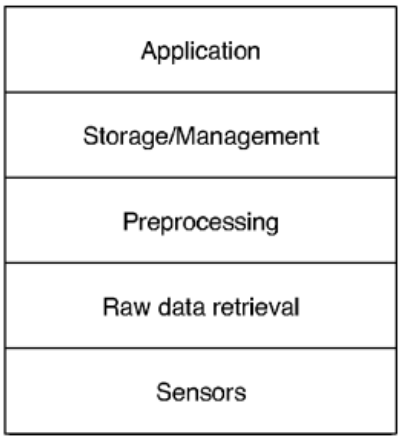


Figure 2.1 - Layered Architecture

The bottom layer "Sensors" refers to every data source that can provide information useful to context classification. They can be physical (hardware sensors that capture physical data), logical (combine information from physical and virtual sensors) or virtual (information from software applications or ser-

vices). The next layer is "Raw data retrieval" which consists in the drivers and simple functions to facilitate the access to the low-level data from the sources. Next there is a "Preprocessing" layer which processes the raw data from the previous layers, making information more abstract and useful to the application goals. It's where the reasoning and inference methods are implemented. Therefore, in this layer, the information provided from the various sources is combined to find a more accurate classification, because, most of the times, one sensor value is not enough to reach a conclusion about the entity situation. The fourth layer "Storage/Management" is where the data is gathered and organized to be accessed by the application layer (the clients). This access from the clients can be made by an asynchronous or synchronous method (publish-subscribe and client-server respectively)[4]. Finally, the "Application" layer is where the client lies. It's also in this layer that a possible reaction to the context is implemented. It can also exist some minor logic and reasoning required for the application specifications.

The most relevant examples of context frameworks are presented in the next section of this dissertation.

2.3.1 CASS

In the Context-Awareness Sub-Structure (CASS) architecture, the middleware contains an interpreter, a context retriever, a rule engine and a sensor listener. The sensor listener senses for data updates from sensor nodes and stores that information in the database. The context retriever retrieves the stored data from the database. That data passes through a rule engine, where it verifies some required conditions and can also use the interpreter to consider what context type is checked. Out of the middleware there is a client with communication capabilities to access its data. It can be seen in the scheme below, at the left side. The client has a change listener where he listens for changes in context events. Note that the sensor node can also have communication capabilities as it can also be a mobile device that senses the environment.

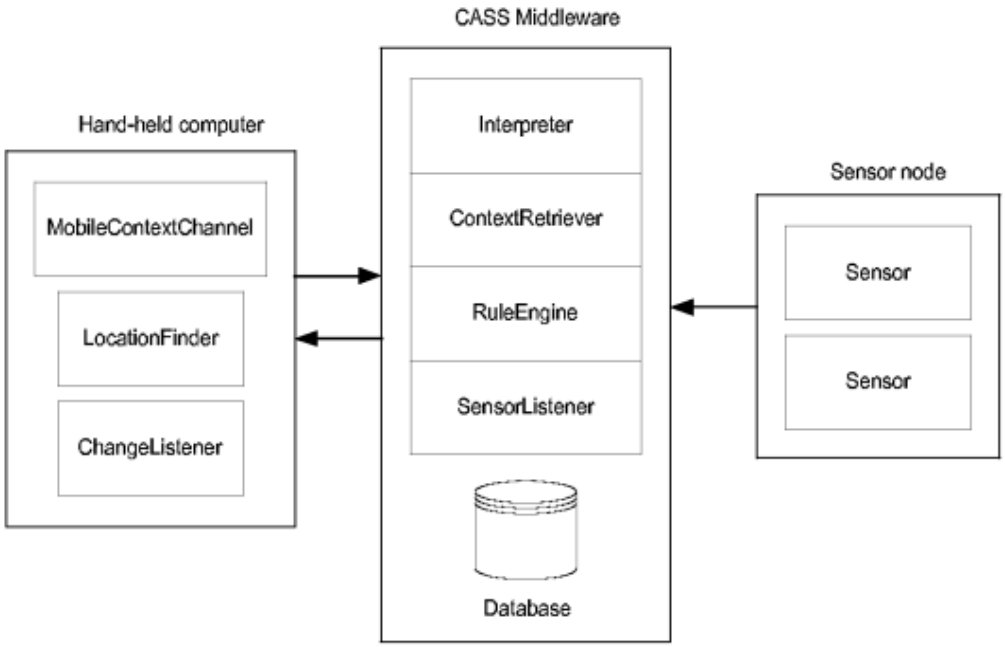


Figure 2.2 - Scheme of the CASS architecture [9]

The rule engine is the central part of the design diagram.[15]

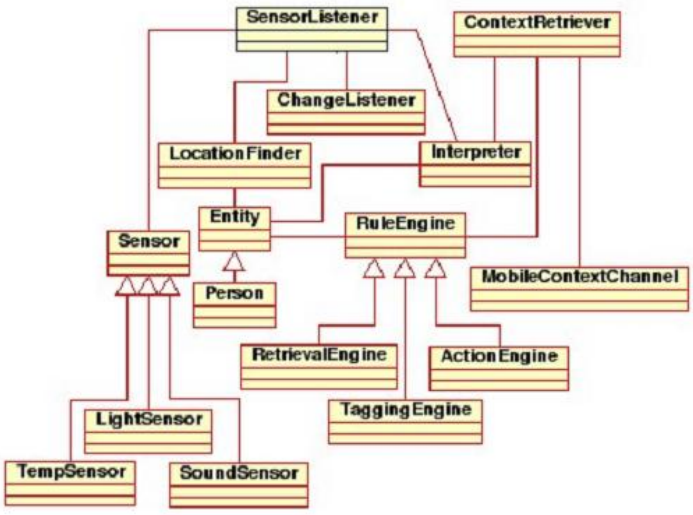


Figure 2.3 - CASS Context Architecture in a UML class diagram[15]

2.3.2 Hydrogen

The Hydrogen project consists in another layered architecture focused on mobile devices. In this system instead of a centralized component, they have a

distributed system. Hydrogen is capable of exchanging and sharing context information with a remote client [4]. As it can be seen from Figure 2.4 there are three layers: Application, Management and Adaptor layer. The adaptor layer is directly connected to the sensors, obtaining raw data by querying them. The management layer is where the context-server is located, which stores the data from the sensors and provide contexts to the application layer. At last, the application layer is where the actions will be implemented according to context changes [4]. There is a context-client in application layer that does the communication with the context-server, it can query a context, open ports and subscribe to receive updates for a specific context [21].

It is important to note that all communication between layers is based on the XML protocol, which makes it more multi-platform [4], in the sense that other platforms can be used, as long as they supply XML-formatted messages according to the specifications.

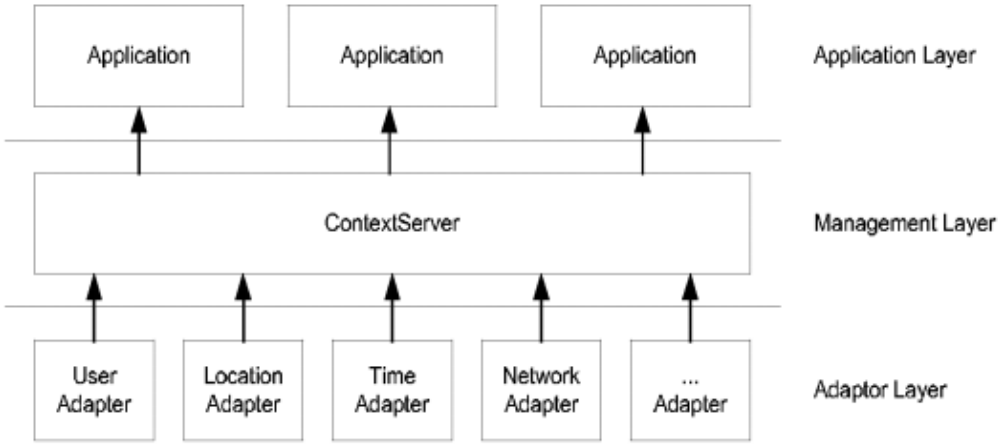


Figure 2.4 - Hydrogen Architecture [9]

Hydrogen uses Object-oriented data structures, below, some of the different classes used to classify context types, are presented

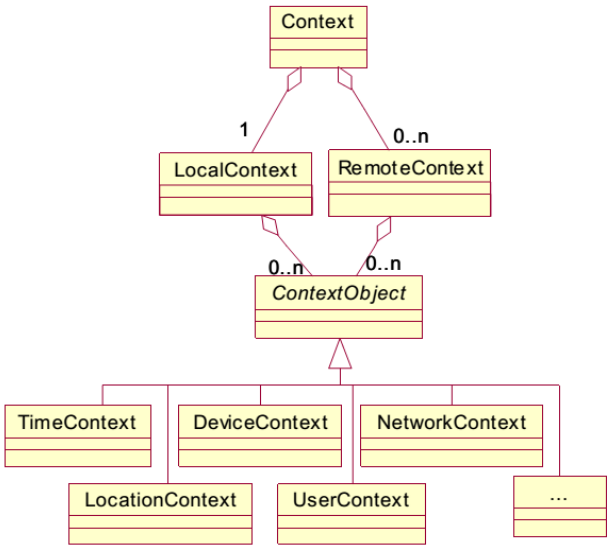


Figure 2.5 - Hydrogen Context Architecture in a UML class diagram [16]

In the Hydrogen system, applications can also be able to consider the context of remote devices that are communicating with them. This explains why there is a "LocalContext" and a "RemoteContext" in Figure 2.5.

The "LocalContext" contains several "ContextObjects", which own information provided by attached sensors. In the standard version of the framework it has information about time, location, device (identifier and device type), user and network but new specialized context objects can be added, creating more context types [21].

2.3.3 CORTEX

The CORTEX project is more oriented to research, cooperation and interaction between sentient objects and its environment[11,22] and is still in an early stage of development.

2.3.4 CoBrA

CoBrA systems were designed to support context-aware applications in intelligent spaces (rooms with intelligent systems)[4]. CoBrA has a centralized context broker that manages and shares information between agents in a particular environment. In large smart spaces multiple brokers can be grouped and exchange knowledge, this is the reason why, in Table 2.1, it was classified as a distributed middleware [10].

2.3.5 Gaia

The Gaia project consists in a layered architecture with operating system concepts. Gaia systems are more focused on the interaction between users and smart/intelligent spaces like homes, rooms, etc. For the Gaia systems, each space is self-contained, although interaction may occur between spaces [23,24].

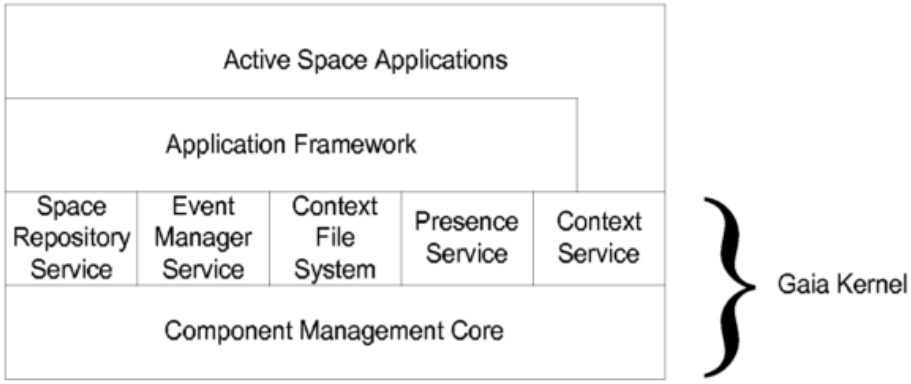


Figure 2.6 – Gaia architecture

The Gaia kernel consists in a component management core (which manipulates all components and applications) and a set of services [24]. Regarding the Gaia services, they are space repository, event manager, context file system, presence and context, all presented in Figure 2.6. The event manager is responsible for letting applications learn about system changes, the context service provides information about context to the applications so that they can adapt to their environment, the context file system stores files with context information, in a hierarchical way, the presence service deals with aspects of the active space resources like presence of an entity (whether physical or digital), finally the space repository stores information about all hardware and software in the active space and its properties [24]. On the top layers there are the application framework and active space applications. The application framework main objective is to provide the tools to build or adapt active space applications and these active space applications that interact to the users using multiple inputs, outputs and processing devices[24]. The Gaia system implements ontologies to describe context predicates [23,25].

2.3.6 SOCAM

SOCAM is a service oriented context aware middleware architecture for mobile services [26]. In the SOCAM architecture, although it is a general ontol-

ogy-based model, it is difficult to relate data with different granularity and constrain important data to specific contexts[27].

2.3.7 COMANTO

COMANTO (COntext MAnagement oNTOlogy) is more of a semantic vocabulary based on ontologies that can describe generic context types[28]. According to [27] COMANTO lacks the possibility to discard useless contexts, although it is a very expressive formal model.

2.3.8 Summary of the Discussed Approaches

Table 2.1- Overview of the features of the existing context frameworks, adapted from [4,27]**.**

System	Context Model	Context History	Data Acquisition Methods	Learning ability
CASS [29]	Logic + KNW	Yes	Centralized middleware	No
CoBrA	Ont. (OWL)	No	Distributed Middleware	No
SOCAM[26]	Ont.(OWL)	No	Distributed Middleware	No
GAIA	Ont. (DAML+OIL)[23][25]	Yes	Distributed Middleware	Yes [30][23][12]
Hydrogen[21]	Obj.	No	Distributed Middleware	No
CORTEX	Logic	Yes	Sentient Object	Yes[11]
COMANTO	Ont.	No	-	-

In Table 2.1 there is a summarization about various context modeling systems and its capabilities. Note that "Ont" refers to ontology-based formalism, "Obj" refers to object-based formalism, "logic" to a logic based model formalism and "KNW" to a knowledge-based approach.

As can be seen from Table 2.1, ontology-based context models combined with distributed middleware acquisition methods are the most widely used.

2.4 Reasoning on uncertain environments

As the matter of environment regards the physical world, there is also uncertainty associated with the environment sensing. That uncertainty can be caused, for example, by inaccuracy or incompleteness of sensed information

[31]. There is a need for models that manage and take into account that uncertainty [12].

Fuzzy logic is used to set transitions of an element between membership and non-membership in a certain group and involves ambiguity [32]. This transition can be gradual and its boundaries are vague and must be established. They can be used to describe subjective contexts and perform a multi-sensor fusion between those contexts. They generally reflect the impression of human reasoning [33]. As an example: when the temperature is considered to be "cold", "hot" or "pleasant" instead of being represented by a numeric value. In [31] the authors present a Fuzzy Situation Inference technique to deal with uncertain situations.

Dempster-Shafer theory combines evidences from different sources and reach a certain level of belief. It's suitable to deal with evidence combination and data fusion [34]. To assign a belief to a hypothesis given the evidences (attributes like symptoms of a disease), Dempster-Shafer theory gives that belief a number in the interval [0, 1] and the importance of each evidence is represented by the function of basic probability assignment (bpa). In [35] the authors make use of the Dempster-Shafer technique as key contribution to fusion data from multiple sensors with weight attributions.

Knowledge-based learning is a technique that takes into account prior knowledge of the world, in most cases represented as general first-order logical statements [36]. They make use of the full power of logical inference, regarding previous hypothesis and logical statements to construct new ones. According to [36], knowledge-based learning is suitable for a hierarchical representation of states.

Hidden Markov Model is used to model situations where the signal source is unknown (where the states are not observed, but associated with observable evidences [12]). This model can be used to know about the source nature and/or to make future assumptions regarding the sequence of observations [37]. According to [36] this technique is more suitable to use with an atomic representation of states, in which each state is indivisible and has no internal structure (simple A to B relation).

Since it is dealt with automated reasoning (a sub-field of Artificial intelligence) and uncertainty, at this step, a bridge will be made to a less semantic/deductive/logic and more numerical/probabilistic concept called machine learning.

2.4.1 Machine Learning

Below is given a brief overview over some major concepts and a description on the most significant machine learning techniques. Note that topics like artificial intelligence, machine learning, data mining and statistics are often conflated and overlapped concepts. Below, a brief clarification of those terms is presented.

Artificial intelligence can be seen as "the science and engineering of making intelligent machines"[38], said Dr. John McCarthy, one of its founders. To make these machines doesn't always have to involve learning or induction. So it can be said that machine learning is a large field within artificial intelligence and implies algorithms that extract information automatically from data, building knowledge (most of them using the support of statistics and probabilistic models).

The area of data mining takes inspiration partly from machine learning (and therefore, statistics) but for the purpose of pattern recognition in, quite often, large datasets. So it is an interdisciplinary field that involves and intercepts machine leaning, statistics and artificial intelligence methods. Data mining is often named of unsupervised machine learning or clustering, this will be stated further on.

Finally, statistics can be seen as an "old discipline" based on classical mathematical models (for instance, Bayesian probability).

Machine learning algorithms are used in a wide variety of fields (finances, computer science, biology, etc.). They use computational methods to learn information from datasets (most commonly spreadsheets or database tables), those datasets serve as examples to learn from and give to the algorithm the ability to generalize and perform future tasks.

In the last decade machine learning has been a strongly addressed subject and its use has been growing in many fields [39], particularly in the computer

science. This phenomenon can be explained by the increase volume of data available everyday on the web and many other sources and powerful computers, able to process vast amounts of information. This generates another problem since only a small amount of data features are crucial for classification and it is difficult to distinguish the other irrelevant information, compromising the systems performance [40]. It's shown below the growth in popularity of some well-known supervised machine learning methods (although it is in biomedical literature, other fields follow this growth tendency, particularly computer science).

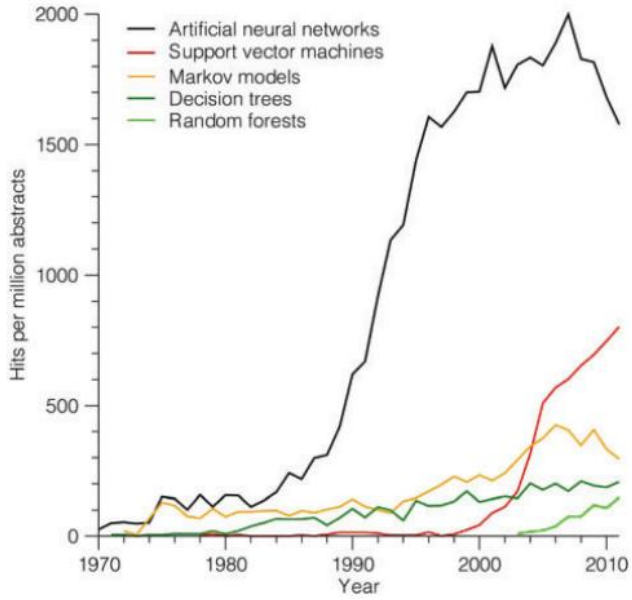
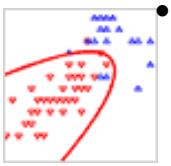
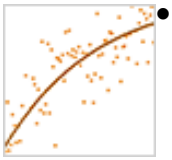


Figure 2.7 - The growth of supervised machine learning methods in PubMed (biomedical literature)[41]

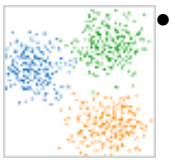
A separation in three main categories can be made regarding the application purpose of machine learning techniques: Classification, Regression and Clustering [42].



- **Classification**: uses algorithms like Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbor, Naïve Bayes, Bayes Network and Neural Network to assign a class to instances of data described by a set of attributes [43].



- **Regression**: uses algorithms like Linear/Non-Linear Model, Stepwise Regression and also Decision Trees and Neural Networks to predict continuous data.



- **Clustering**: uses algorithms like K-Means, Hierarchical Clustering and Hidden Markov Models to find patterns and group the data regarding its patterns.

Machine learning algorithms can also be sub-classified in **supervised** learning and **unsupervised** learning (there are other taxonomies, but those two are essential).

- In **supervised learning** the rules/steps for the classification are generated automatically from a sample set of examples (training dataset) that already has the correct class assigned to each data point [43,44] (pre-classified). The model must generate decent results in presence of new data. The user must have pre-classified datasets, so classification and regression fields are included in supervised learning.

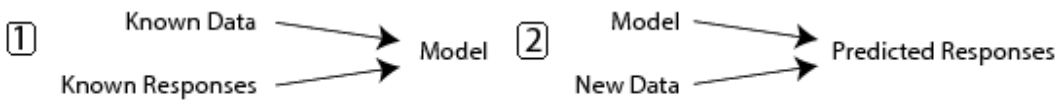


Figure 2.8 - Steps in Supervised Learning [45].

- In **unsupervised learning** the algorithm must detect patterns in data and group/cluster the data according to its content. There is no need to input pre-classified data, so clustering field is included in unsupervised learning.

Note that the same algorithm can be applied in more than one category of application, due to its flexibility.

Machine Learning Techniques

As the purpose of this dissertation relies of classification, only classification algorithms will be described.

Nearest neighbor (NN) is the simplest data association technique and is a well-known clustering algorithm that selects and groups the most similar values.

How close the one measurement is to another depends on the employed distance metric and typically depends on the threshold that is established by the designer (k-nearest neighbor). The value of "k" specifies how many nearest neighbors are to be considered when defining the class of an instance. In general, the employed criteria could be based on an absolute distance, the Euclidean distance, or a statistical function of the distance.

Although this is a very simple technique (its main advantage), it is more oriented to pattern recognition (clustering), which often requires huge datasets. Its main disadvantages are the memory limitation, the slow running speed and the fact that it is easily fooled by irrelevant attributes [46]. Many different techniques have been developed to minimize these disadvantages and are stated by the authors of [46].

Bayesian networks consist in nodes (variables representing events) and arcs (representing relationships – conditional dependencies) forming a tree. Nodes that are not connected represent variables that are conditionally independent. Bayesian networks are widely used to process data sets and to deduce high level information [12], assigning the most likely class to a given observation, described by a set of attributes [43]. As an example they could relate symptoms with diseases and give the most probable disease given the symptoms. Bayesian networks can be considered a mechanism for automatically applying Bayes rule complex decisions, that rule is mathematically stated above, which gives the relationship between the probabilities of A ($P(A)$) and B ($P(B)$) and conditional probabilities of A given B ($P(A|B)$) and A given B ($P(B|A)$).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$ [47]

According to [36] this technique e best suitable for a factored state representation in which a state consists of a vector of attributes.

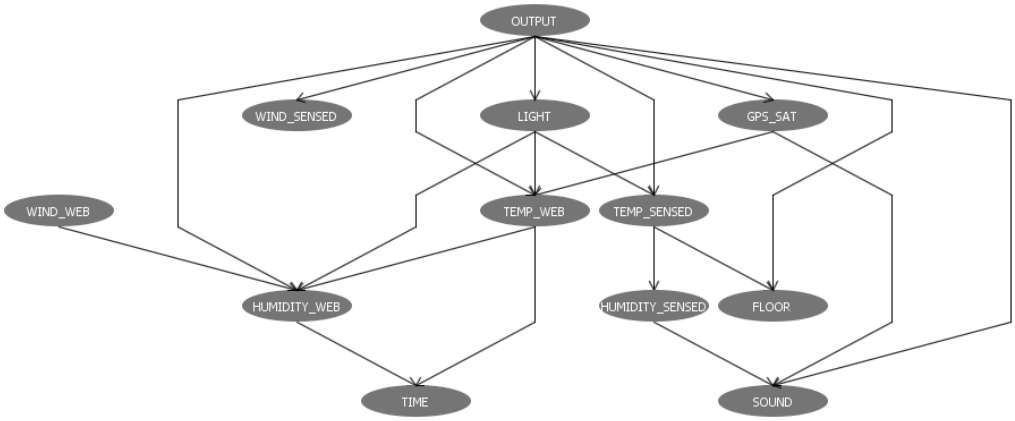


Figure 2.9 - Bayesian Network graph using weka

Naïve Bayes are one of the most widely used graphical models. They can be seen as simple Bayesian networks that are represented with only one root/parent node (unobserved data or class label) and the several children nodes (observed data or attributes). The fact that it is "Naïve" is because it assumes that all attributes are statistically independent from each other. This assumption is called class conditional independence. Only the conditional probabilities are computed. Considering C as parent node and A as an evidence of children nodes (attributes), we can represent pieces of evidence as a_1, a_2,…a_n respectively related to the attribute A_1, A_2,...A_n and c_i as a possible class value and its combined probability can obtained as:

$$P(c_i|A) = \frac{P(a_1|c_i)\cdot P(a_2|c_i)\cdot \ldots \cdot P(a_n|c_i)\cdot P(c_i)}{P(A)}[48]$$

Naïve Bayes have the issue (not always a disadvantage) of losing the ability to exploit the interactions between features but this isn't a problem in most classification tasks.

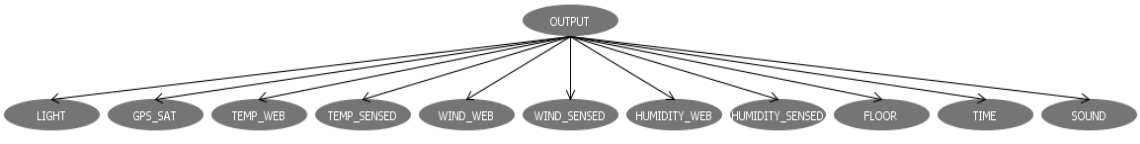


Figure 2.10 - Naive Bayes graph using weka

In the Figure 2.10 an example of a Naïve Bayes graph is shown, being "OUTPUT" the class label (parent node) and the corresponding child nodes (attributes) note that the different attributes take their value independently.

SVM (Support Vector Machines) is a relatively recent (1992) ML technique and popular because of its success with handwritten digit recognition. It maximizes a large decision boundary (as far away from the data of both classes as possible). In the Figure 2.11 it's possible to see the margin separating the two hyperplanes (classes). The circled points lying under the hyperplanes are called the support vectors (whose removal would change the solution found). The main disadvantages of SVM are the high algorithmic complexity, memory requirements and the choice of the kernel function parameters [49]. Although they generally have a high generalization ability [50].

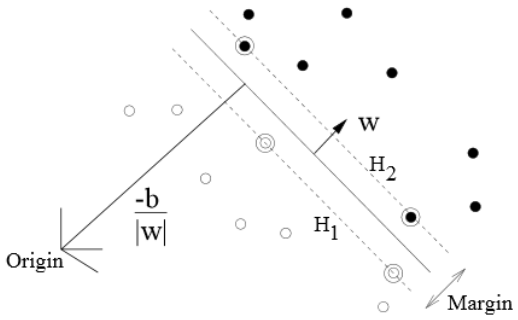


Figure 2.11 - Linear separating hyperplanes [49]

Decision Trees can be defined as a "classification procedure that recursively partitions a dataset into smaller subdivisions on the basis of a set of tests defined at each branch (or node) in the tree" [51]. The tree is composed by a root node (that contains all data), splits (test nodes) and leafs (terminal nodes that represent a class label). As main advantages, they can handle numeric and categorical inputs, nonlinear relations between features and are easily interpretable (because it can be represented in a tree, showing its classification structure). However, from computation point of view, the construction of a naïve Bayes classifier is much faster than decision trees. Besides, naïve Bayes is more efficient in learning and in the classification task (7 times faster than decision trees), as said in [48].

Artificial Neural networks are computational models inspired by a biological brain (interconnected neurons). They have the ability to model complex nonlinear relations between variables but they are slow to train every time that there is another class to assign and usually require large training sets in order to have sufficient understanding of its underlying structure. They have "black

box" nature, with only inputs and outputs (the internal working is unknown) [52] and are typically easy to implement.

Below, in Figure 2.12 there is a basic example of a feedforward neural network, with M input units and N output units. Each input unit is connected to each of the output units and each connection has a (adaptive) weight associated [53].

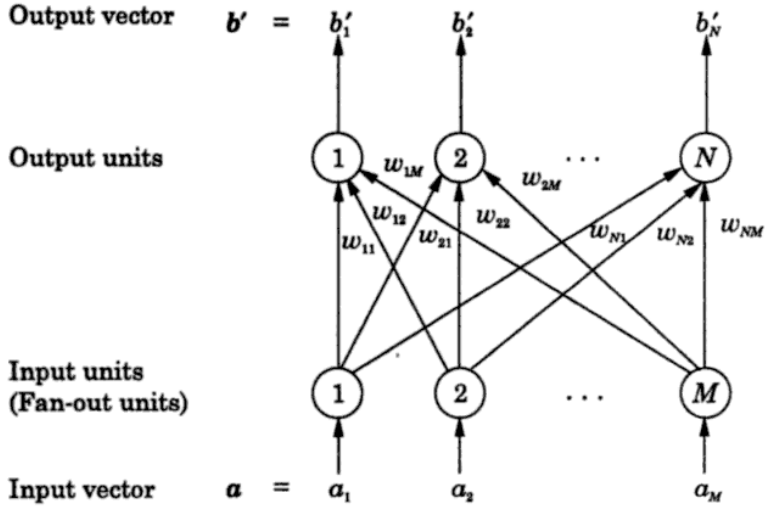


Figure 2.12 - Basic feedforward neural network[53]

2.5 Context in robotics

Systems like social, cooperative or service robots have to perceive and interpret its surroundings and take into account many variables to make correct decisions. In [54], the authors made a survey on social interactive robots and state that they must be able to distinguish other social agents and other objects in the environment. Most importantly, in order to communicate with humans, robots must perceive the same things that humans find to be relevant and interact with the environment similarly to living beings [55].

In social interactive robots, perceiving human's feedback actions and behaviors is also a context concern (by the robot), in order to communicate properly. Emotions however are also often tightly coupled to social context (from humans) [54].

Still in social interactive robots and facial expressions, the authors in [56] reinforce the importance of context-awareness in the field of humanoid robotics, particularly the generation of robots facial expressions, selecting appropriate combination of facial cues depending on inner feelings, generated by polynomial classifiers.

In [57] the authors introduce CAMUS (Context Middleware for URC Systems) which is a framework to support context-aware services for network-based robots. This article is inserted in a relatively new concept named URC (Ubiquitous Robotic Companion) which are ubiquitous service robots that provide services to users, anytime and anywhere in ubiquitous computing environments[58].

Returning to [57], this system uses UDM (Universal Data Model) to represent context information (relations between nodes) and their reasoning system is based on JENA which is a framework for java that support the use of OWL (Web Ontology Language). The rule engine is based also on a java environment called JESS. This robot could provide multiple services like entertainment, home guard, home monitoring and information.

In [59], the authors use context-awareness to improve vehicle-to-vehicle applications in terms of its driving safety and efficiency. The techniques used on this approach, for modeling context and situations, are Context Spaces (a context-aware architectural framework [60]) combined with the Dempster-Shafer rule of combination, for situation reasoning.

In [61] the authors presented a machine-understandable representation of objects (their shapes, functions and usages). They analyzed certain combinations or sets of objects and its features in order to perform context/scene understanding and to deduce corresponding possible activities in those scenes. Both reasoning about object and scene recognition use an ontological representation (OWL) and relational databases.

Still in object recognition, in [62] the authors present an indoor furniture and room recognition combined with online sources so that robots can be able to fluidly collaborate with humans. For solving that, the authors developed a 3D object classifier and use an online database (Wordnet [63]). It is also used a Markov Random Field (MRF) as a final probabilistic classifier to model object-

object and object-scene context. Another work on object recognition to model context is presented in [64], in which the authors use ontologies to identify objects in changing and unpredictable environments.

In [65] a context aware fusion is made to overcome the possible failures that speed limit information systems, like digital maps, can have. So they fused digital maps speed information with sign recognition system. A Dempster-Shafer technique is used to implement such system. The conclusion of this work is that this kind of fusion is able to recognize speed limits when sensors fail and reduces conflicts between sources of information.

There is also an application of context in robots localization/navigation. For example, in [66] the authors use a semantic representation and a Bayesian model for robot localization, measuring the distance relations between known objects in the environment. The authors named it a topological-semantic distance map. The data in the methods are represented by means of ontology and asserted with ontology inference. Sensor reading errors are filtered with the use of rules and relationships of logical reasoning.

In [67] the authors made a survey emphasizing the need for creating a standard ontology language for robotic systems and in [68] the authors present their current results on that same task. There is also a review of some robotic ontology projects and applications on both references.

The authors in [69] describe the development of an ontology for robots in the field of urban search and rescue, based on OWL.

There is also an attempt to use ontologies for autonomous vehicle navigation planning in [70] in order to increase performance of route planning and improve capabilities of autonomous vehicles.

Context-aware systems are also useful in smart environments. The authors in [71] presented an ontology-based approach to implement context-awareness in a smart environment like ambient assist living. The authors also present positive experiment results in an assist living facility (smart home) and with a mobile robot in an automated building. The main objective is to have reliable information about what is happening in a smart home, based on its datasets.

Similarly, in [72] the authors propose an architecture for context-aware applications and ubiquitous robotics, where robots navigate in smart environments. The proposed architecture integrates ontologies with logic approach. It is also presented some experimental results of a service robots team performing missions in a hospital environment (transporting biological waste between floors and patrolling).

The authors in [73] develop *CAIROW* (Context-aware Assisted Interactive RObotic Walker) for Parkinson disease patients. They use a Hidden Markov Model (HMM) to analyze the gait of the patient. Both patient and road conditions contexts are considered. The robot should adjust their speed or direction according to user gait and road conditions.

A different approach is made by the authors of [74]. This paper presents collaboration techniques between multiple robots welcoming and guiding visitors through a building. The guiding topics are selected by the robots according to the participant's interests, resulting in personalized tours. It is used an ontological approach to develop this system.

Table 2.2 - Overview of context models in robotic systems their application purpose

Application Purpose	**Context Model/Reasoning Technique**
Object Recognition	Markov Random Field (probabilistic classifier)[62], Ontologies[61], [64]
Safety	Dempster-Shafer[59], [65], Ontologies[69]
Human-machine interface	Polynomial classifiers[56], Hidden Markov Model[73]
Localization	Ontologies + Bayesian model[66]
Navigation	Ontologies[70]
Smart Environments	Ontologies + Logic[71][72], Ontologies[74][57]

As it can be understood from Table 2.2, many times ontologies are used to support machine learning techniques in the robotics field.

3. Implementation

3.1 Problem's Approach

As it was stated before there are several applications for context in the robotics field but context can also be integrated in other applications. The reliability field hasn't explored context in complete way. Context can and should be integrated in the reliability field allowing reliability calculation optimization.

Regarding this dissertation, it is proposed a classification hierarchy, displayed in the Figure 3.1, in which it is first classified the context as indoor environment or outdoor environment and then there will be another computational model created to sub-classify in more detail the type of environment present.

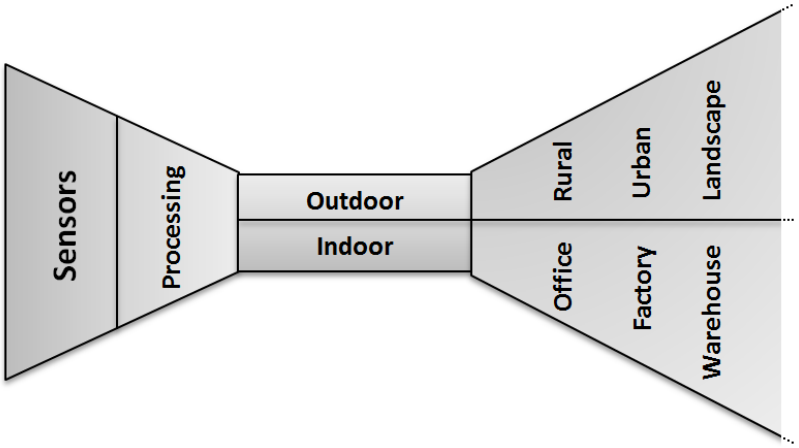


Figure 3.1 - Context classification hierarchy

The sensor processing module's (present in Figure 3.1) main objective is to remove the noise, outlier values and to abstract the measured data to a high-

er level information (for instance to give a "hot" temperature result instead of 33ºC) from the "Sensors" layer.

3.2 Tools and Platforms

In this section it will be presented and described some practical tools (either in terms of hardware or software) substantial to this work.

3.2.1 Hardware

ServRobot

ServRobot is an all-terrain service robot created for remote surveillance and monitoring. It is a project developed by Holos, co-financed by QREN (Strategic Reference National Framework) and inserted into the System of Incentives for Research and Technological Development (SI I & DT). The ServRobot should adapt to different types of usage and environmental conditions and already has several features: following people, following lines, autonomous navigation, teleoperation, defining paths and cargo transportation [75].

The purpose of this dissertation, inserted on this project, is to add the capability to detect and classify the environmental context of the robot, when moving in the several conditions of operation. This will add an important value when collecting and interpreting sensory information, and then to act autonomously over that information.

Also, the result information of the present dissertation would be integrated in the development of a new reliability and prognostic technique, in order to improve the robot's maintenance, forecasting potential fault zones.

The ServRobot already has included several sensing devices, among them, there is an xsens MTI IMU (Inertial Measurement Unit) which measures velocity, orientation and gravitational forces using gyroscopes, accelerometers and magnetometer. There is also a kinect device for video recording and movement detection, a Sick 111 LADAR (LAser Detection And Ranging) for obstacle avoidance and mapping and ultrasonic range finder to support obstacle detection. There is also an USB camera with infrared lighting used in the line follow feature. All this sensory devices are connected to an ITX motherboard which contains an Ubuntu OS (Operating System) and ROS (Robot Operating System).

The motors are controlled with a Roboteq ax3500 motor controller together with a PID (Proportional-Integral-Derivative) controller and connected to a Diamond Systems Hercules II, which is a data acquisition board to gather information about the sensors mentioned before as well as encoders, electrical currents and voltages.

ServRobot is also capable of retrieving the type of the soil that is under him (concrete, roadway or pavement), using the IMU, frequency spectrums (Fourier) and a Neural Network.

Figure 3.2 - ServRobot

Added Input Sources (sensors)

In order to sense the environment, several sensors were added to the ServRobot.

Arduino Platform

For the acquisition board it was chosen the Arduino Mega 2560 R3, which is a microcontroller board with a ATmega2560, it has 54 digital input/output pins, 15 PWM outputs, 16 analog inputs, 4 UARTs, 16MHz of clock speed and 256KB of flash memory, which is more than sufficient for our purpose. The main reason for this selection was that this is an open-source electronics platform, it's easy to use for prototyping, it has support for many sensors and the author was acquainted to this device use, which facilitates the deployment time [76].

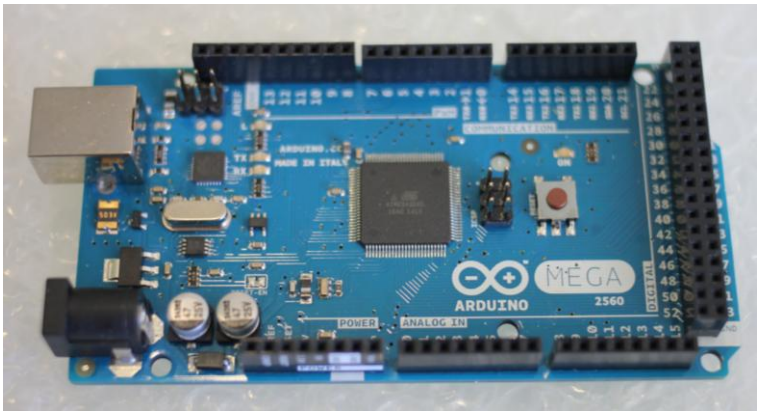


Figure 3.3 - Arduino Mega 2560

Weather Shield

At this stage, a weather shield was added to the Arduino, which already contains several useful sensors, like barometric pressure, relative humidity, luminosity, and temperature. There are also the possibility to connect wind speed/direction, rain gauge and GPS for location and accurate timing. Unfortunately the wind and rain sensors had inappropriate dimensions to include on the robot, but the GPS was included. Finally, the weather shield can operate from 3.3V up to 16V and has built in voltage regulators [77].

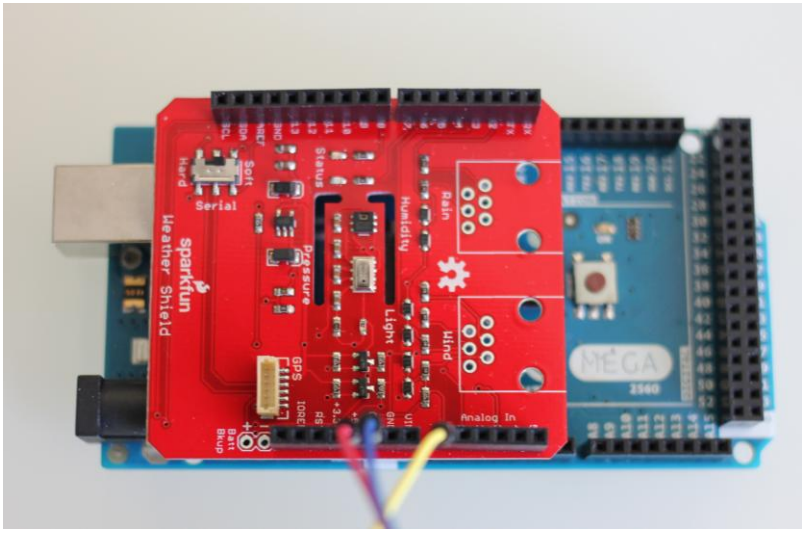


Figure 3.4 - Arduino + Weather Shield

Luminosity

The weather shield's luminosity sensor consists in a ALS-PT19 that can perceive light from a wavelength from 390nm to 700nm, which is what the human eye can perceive (visible spectrum). It also has an operating temperature range from -40ºC to +85ºC [78].

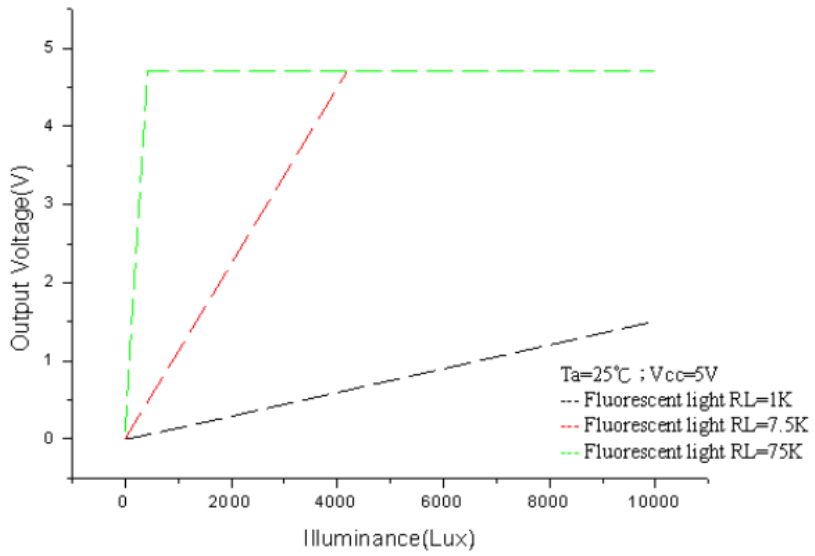


Figure 3.5 - Output Voltage Vs Iluminance [78]

Temperature and Humidity

In order to sense temperature and humidity, the weather shield has a HTU21D which is a new, reliable, accurate and low power consumption sensor.

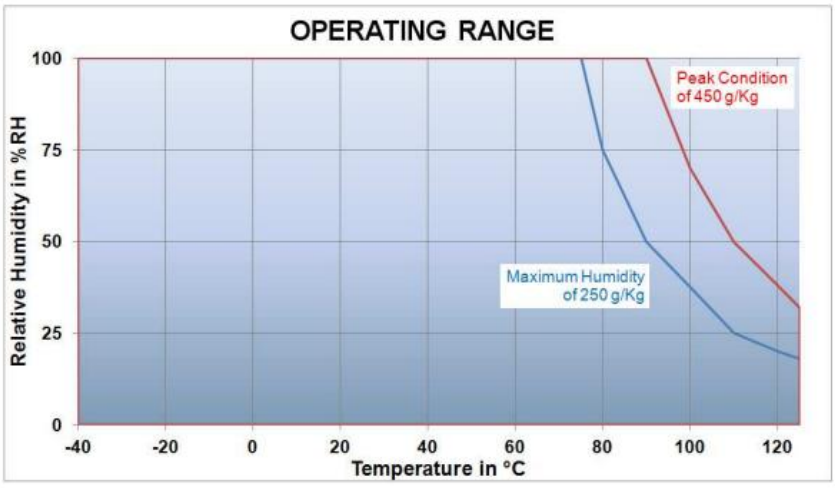


Figure 3.6 - Operating range of the HTU21D [79]

For the temperature it has a typical accuracy of ±0.3ºC (@25ºC) and for the humidity is has a typical accuracy of ±2%RH (@25ºC and from 20%RH to 80%RH) [79].

Barometric Pressure

For measure the barometric pressure, the weather shield has a MPL311A2 pressure sensor. This sensor provides accurate pressure, altitude and also temperature data. This sensor can operate from -40ºC up to 85ºC. Its pressure absolute accuracy is ±0.4kPa with a measurement range of 50kPa to 110kPa. The altimeter resolution is down to 30cm and the temperature measurement range is from -40ºC to +85ºC with an accuracy of ±1ºC (@25ºC). This temperature sensor is used for internal pressure compensation purposes [80]. The HTU21D value will be used for temperature, since it has superior accuracy.

GPS

For the GPS receiver it is used a GP-635T which is a slim module with -161dBm tracking sensitivity and only 27 second cold start time. It is based on uBlox 6 chipset, has 50 channels, an antenna and from 1Hz to 5Hz of update rate. It has low power consumption (50mA) and similar to the other sensors, it has an operating range from -40ºC up to +85ºC.

In terms of accuracy, it has horizontal position accuracy of <2.5m, a velocity accuracy of <0.1m/s (speed), <0.5º (heading) and can perceive altitude until 50000m and a max velocity of 1852 Km/h [81].

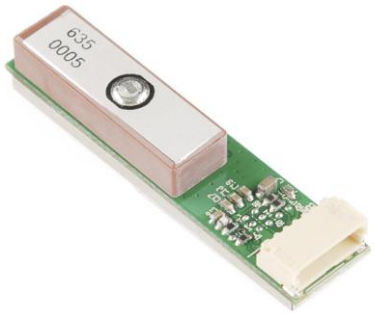


Figure 3.7 - GP-635T

Gas Sensor

In order to sense dangerous gases it is used an MQ-2 sensor. This sensor is useful for detect gas leakage and can sense LPG (Liquefied Petroleum Gas), propane, i-butane, methane, alcohol, hydrogen and smoke, so it has a wide detecting scope. This sensor has a fast response and high sensitivity (adjustable by the load resistor). It has an operating range from -20ºC to 50ºC and his detection concentration scope is: 200ppm-5000ppm for LPG and propane, 300ppm-5000ppm for butane and hydrogen, 5000ppm-20000ppm for methane, 100ppm-2000ppm for alcohol. The manufacturer recommends calibrating the sensitivity to 1000ppm LPG, so it was used a resistance of 20KΩ (from 5KΩ to 47KΩ) [82].

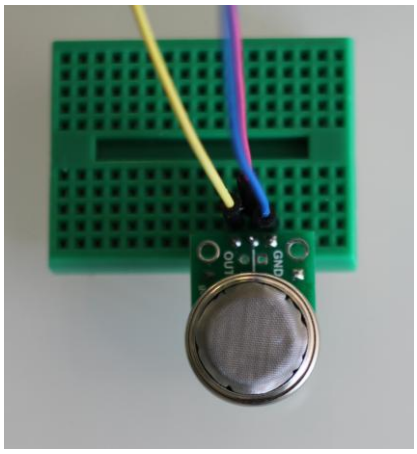


Figure 3.8 - MQ-2 Gas Sensor

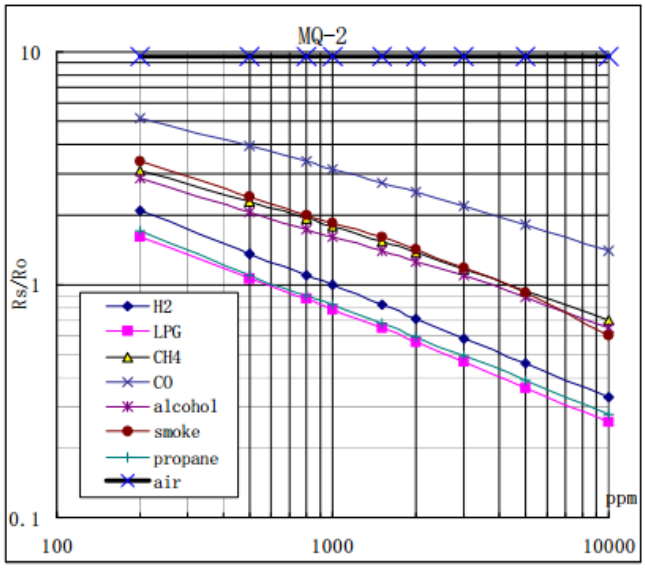


Figure 3.9 - Sensitivity characteristics of the MQ-2 [82]

All sensors from weather shield use I²C protocol, which is a computer bus invented by Phillips used for attaching peripherals (e.g. sensors) to computer motherboards and embedded systems. The gas sensor use a simple analogic output.

3.2.2 Software

ROS

The Robot Operating System (ROS) is a flexible, distributed, modular and powerful framework for developing robot software. It contains a collection of tools, libraries and conventions that aim to simplify the task of creating complex and robust robot behavior between many different robotic platforms. The main motivation for its creation was the need for a general purpose robot software that deals with a wide variety of environments that need to be managed when developing these systems. To simplify this task, ROS was built based on collaborative robotics software development. In this sense, for instance, a group that is expert in mapping can provide tools for the community to work with their system and improve its performance and/or add it more features, in a collaborative way. Everything is open source and offers support from low level tasks (like sensor access) to high level tasks (like autonomous navigation). There is still a recent and rapidly growing community inside ROS. At the time of writing, the ROS wiki had more than 22,000 wiki pages and more than 30 wiki page edits per day [83].

JFuzzyLogic

jFuzzyLogic is an open source fuzzy logic library aimed to simplify the development of fuzzy logic systems. It implements a FCL (Fuzzy logic Control Language) specification and includes the feature of easily plotting the membership functions of the fuzzified variables. It also has a decent support and documentation to ease its use. This library imports an FCL file with all input and output variables and linguistic terms configured, then checks the rule block (how input variables affect output variables). It also provides a parameter op-

timization framework, allowing it to learn or refine fuzzy parameters using machine learning algorithms.

WEKA

WEKA (Waikato Environment for Knowledge Analysis) is a software "workbench" that incorporates several standard machine learning techniques. This software has a GUI interface as well as a CLI, both very useful for rapid prototyping. With WEKA it's possible to input a dataset from a data file (arff recommended), from an URL or even connect directly to a DB. It also has a wide variety of classifiers to choose from. To choose the more appropriate classifier there is the possibility to perform several tests on the collected dataset to see which one gives more accurate results. There are four test options (to validate the model) [84]:

- The first is to **use a training set** to build the classifier based on its training instances and to use it again in testing purposes. This usually provides overoptimistic results.
- The second consists in **supplying a new dataset** for testing purposes (after the model/classifier was made out of the initial training set). This option gives more accurate results if the data is available.
- The third option performs an n-fold **cross-validation**. This is a well-known strategy for model selection and evaluation. In this option, the dataset is split n times (most commonly 5-10 folds) part of the data (the training sample) is used for training purposes and the remaining data (validation sample) is used for validation purposes[85]. After that, a cross validation is made with the various data splits. This technique is useful when the amount of data is somehow limited.
- Finally the fourth option consists in **percentage split**, in which the user chooses what percentage of the data will be for training, and the remainder will be for testing.

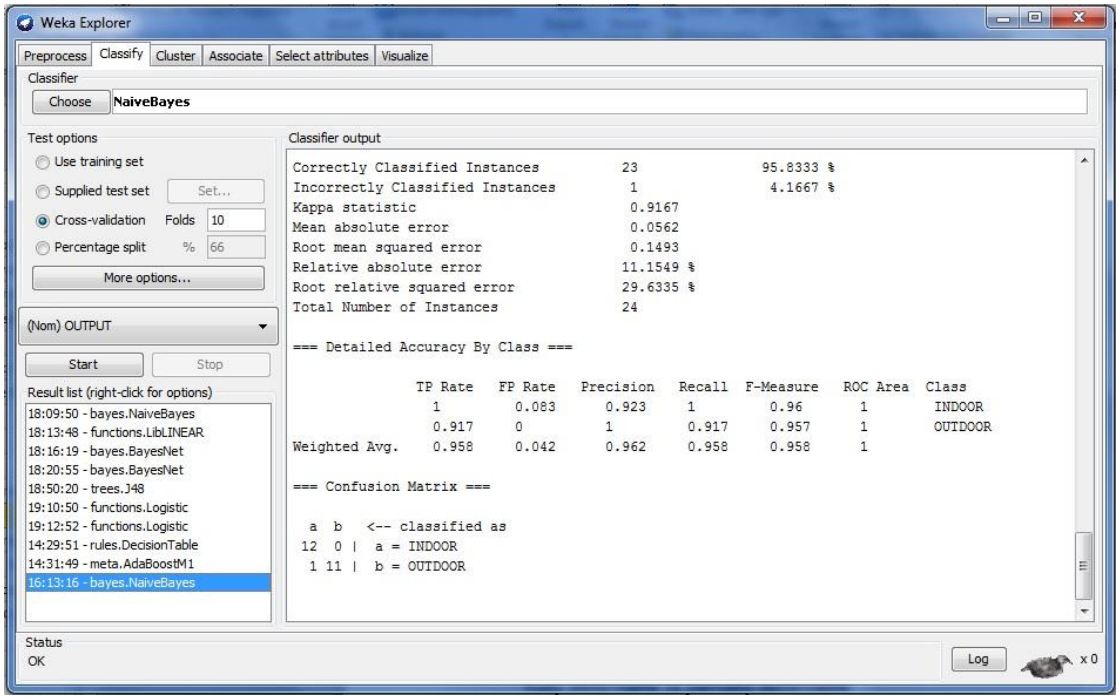


Figure 3.10 - WEKA GUI - classifiers, test options and outputs

There is also a useful filter called attribute evaluator to select the most pertinent attributes in the dataset considering its consistency and predicting capabilities.

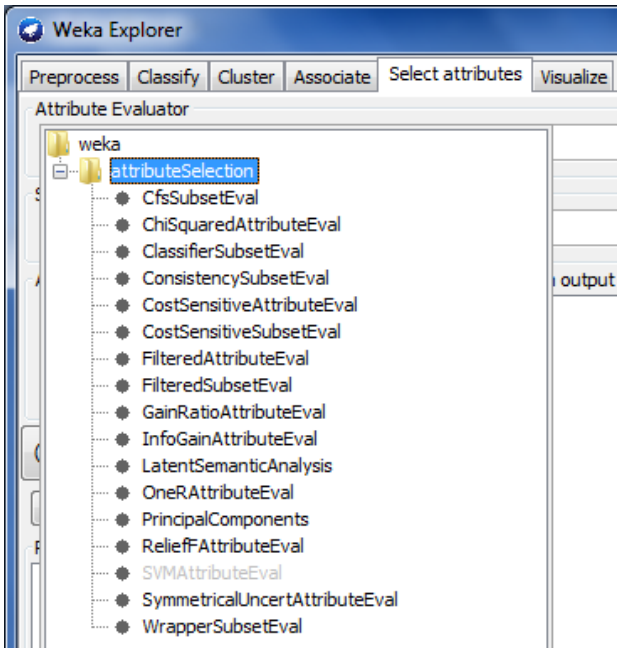


Figure 3.11 - WEKA attribute evaluator

As can be seen, there are a lot of different algorithms to perform attribute evaluations.

There is also a wide variety of visualization capabilities, from the dataset analysis to the obtained graphical model (to plot decision trees, Bayesian networks, etc.).

In the latest developer version of WEKA software (3.7.11), it has a package manager to install external packages from the different categories (visualization, classification, clustering, attribute selection, etc.).

Qt Creator

Qt creator is a cross-platform IDE, focused on the development of Qt applications (GUI designs, etc.) providing features that increase productivity and help the new users to Qt applications. Qt creator also provides a code editor, a visual debugger and a GUI designer and uses mainly C++ programming language [86].

3.3 Architecture Overview

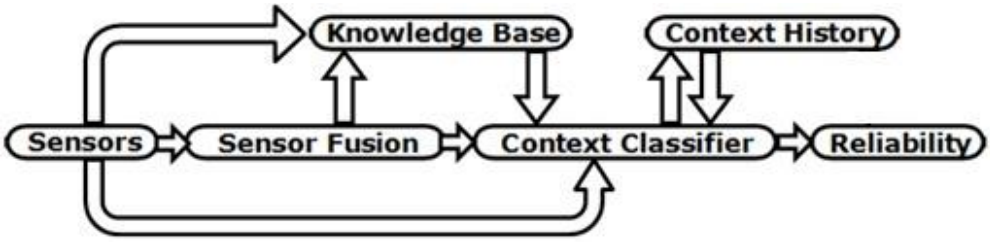


Figure 3.12 - Reliability context integration architecture

In Figure 3.12 the reliability context architecture is presented. It will first receive the sensor inputs and process its signals in order to reduce any noise and outlier values as well as necessary sensor fusion. In the knowledge base, the raw information from sensors and sensor fusion is stored. It will be created a context classifier that will provide contextual information to the reliability calculation. Those classifications will be also stored in a context history module. This history can be re-fed to the classification module to improve performance. From that history it will be included the last state attribute to the current classification.

It is believed that the environmental conditions will influence a great deal the reliability calculation and estimation. The key elements present in the surroundings may be crucial for optimizing reliability assessment, for example if a mobile robot is working under a very dusty environment it may be more prone to have mechanical failures thus reducing its reliability.

The soil conditions, atmosphere and the environment of the robot will be considered. The main objective is to build an accurate tool to classify the robots context regarding the type of environment, without heavy and energy drain algorithms like image processing. In some projects only GPS satellites signal is used to infer outdoor/indoor environment, at first glance it seems obvious but this approach lacks accuracy and takes too much time.

In [87] the authors propose an approach for indoor/outdoor detection in mobile devices using light sensor, cellular module and magnetism sensor. Since many robotic systems also use cellular modules to communicate, it's a valid option to consider monitor its signal strength for possible drops that can indicate a presence of an indoor environment. This drop is due to building walls that stand in the line of sight between the cellular module and the cell tower. The same authors claim that the light signal exhibit different patterns depending on the source (natural or artificial light) and that the magnetic field varies significantly between indoor environments but stays less fluctuated between outdoor environments (this is due to metal surfaces, electronic appliances, etc. present in a typical indoor environment).

3.4 Architecture Implementation

3.4.1 Managing Input Sources

Since this project similarly consists in environment classification, although in different scenarios and for different purposes, some studies and experiments will be taken into account made by the authors of [87], particularly the variation of light intensity between indoor and outdoor environments. According to their study, the light intensity inside buildings it's much lower than in outdoor envi-

ronments, even in cloudy or rainy days. They observed an interesting phenomenon: even if the light sensor is pointing to the ground the previous statement remains true. This happens because different light sources have different spectrums, although sometimes they both look with the same brightness, the sunlight spectrum has more intensity in visible light than the lighting lamps.

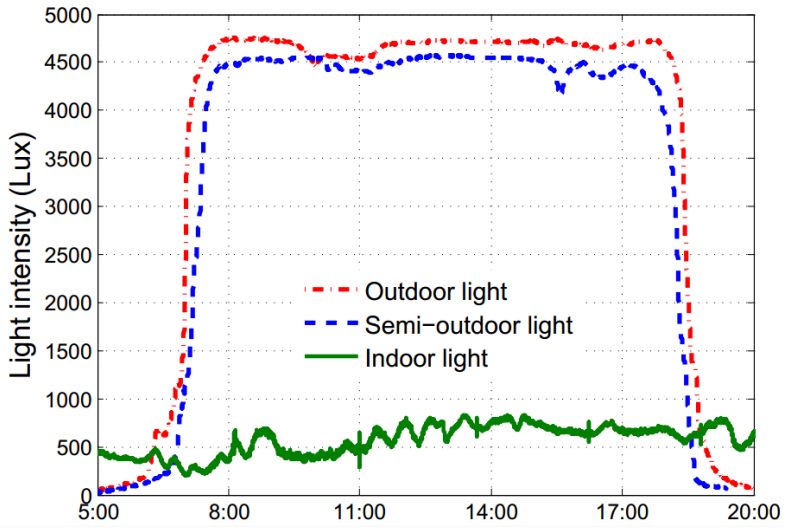


Figure 3.13 - Light variation in outdoor and indoor environments in one day [87].

In the scope of this dissertation, it will also be taken into account the soil conditions (smooth, concrete, pavement, etc.) and weather conditions.

The main physical sensors taken into account for the first approach architecture are shown below, in Table 3.1, as well as their sensed information and type of formalism.

Before modeling the data and managing all the environment information, it has to be gathered using a flexible and multiplatform tool to ensure support and compatibility between the different platforms (operating systems, programing languages, etc.). So, in order to integrate the Arduino (and all these input sources) seamlessly with the ServRobot, ROS – Robot Operating System is used.

Table 3.1 - Formalism outputs from the multiple physical sensors

Physical Sensor	Sensed Information	Type of formalism
Camera/Kinect:	Color histogram Object identification and classification	Predominant color Presence of objects
Gyro /Accelerometer/Inertial	Unevenness Shake/trepidation	Even/uneven floor Bumpy soil
Anemometer	Wind Speed/direction	Low/Moderate/Strong
Thermometer	Temperature	Hot/Comfortable/Cold
Hygrometer	Humidity	Humid/Comfortable/Dry
Rain Drops Detector	Rain	Rainy/Dry
LADAR	Edge direction	Regular/irregular lines
Photosensor	Light	High/Medium/Low
Clock	Daytime	Day/Night
Microphone	Audio	Loud/Comfortable/Quiet
Gas Detector	Gas	Dangerous /Non
Wheel Speed	Velocity	Fast/Moderate/Slow
GPS	Position	Number of Satellites detected
CellTower	Signal Power	Weak/Medium/Strong
Wireless APs	Signal Power	Weak/Medium/Strong

For acquiring the various sensor values, a publish/subscribe method over ROS is used, firstly by publishing the data in C++ topics and then using ROSJAVA (which is the first pure Java implementation of ROS) to make it concordant with the Fuzzy logic library.

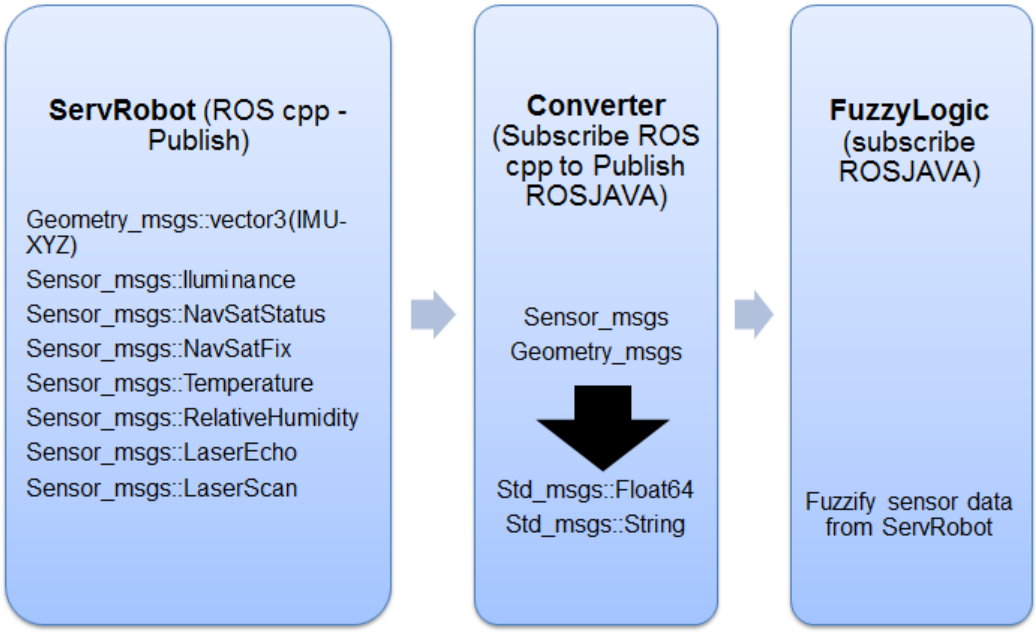


Figure 3.14 - Main steps in acquiring sensor data from the AGV - ServRobot

This "Converter" had to be implemented because ROSJAVA, at the time of implementation, does not have all the "Sensor_msgs" types, so the "Sensor_msgs" topics had to be converted to "Std_msgs" (which stands for standard messages), so they can be fully integrated with the fuzzy logic library and, further, with the classifier.

3.4.2 Fuzzy Logic Membership Functions

A very brief definition of fuzzy logic theory was previously made in the section 2.4, here the focus is on describing its use in this dissertation.

Based on fuzzy logic theory, there are Fuzzy Logic Controllers (FLC) that are FRBSs (Fuzzy Rule Based Systems) with a knowledge base, a fuzzification module, an inference system and defuzzification module. The knowledge base relates to the information about the world in the form of control rules, the fuzzification module transforms the crisp values of the inputs into fuzzy sets, the inference system intersects the fuzzy sets and the knowledge base performs the reasoning process and the defuzzification module takes away the results from

the inference system and turns them into crisp values for the control purposes [88].

For the purpose of this dissertation, fuzzy logic was implemented to transform sensed numeric values into linguistic terms (a qualitative semantic), therefore, fuzzification was used to aggregate the sensor inputs (sensor fusion). This will increase the flexibility and modularity of the overall algorithm over the slight changes in the sensor values (also decreasing its complexity and load).

In order to implement this technique in the project, a very useful java library, called jFuzzyLogic was used.

Below, some of the membership functions used to fuzzify the attributes and their linguistic terms are shown.

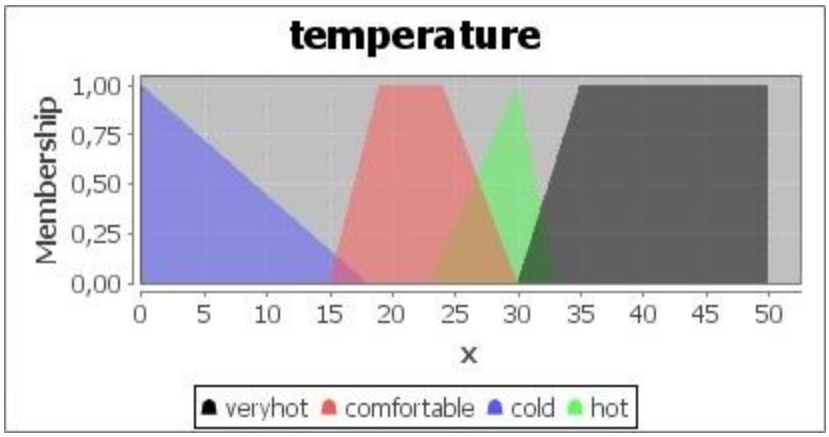


Figure 3.15 - Fuzzified temperature function

In the temperature function, it's observed a membership of 1 for the "cold" temperature around 0ºC, a membership of 1 for the "comfortable" temperature from around 19ºC to 24ºC, a membership of 1 in temperatures considered "hot", around 30ºC and a membership of 1 for "very hot" temperature from 35ºC to 50ºC. The chosen sets were studied after a research for comfortable temperatures (although the comfort level varies with humidity) and the reason why "very hot" temperatures reach 50ºC is that, since this classifier is to be deployed in a service robot, he can move around fires, oil pipelines and other hostile environments. A temperature higher than 50ºC can compromise some components of the ServRobot.

In a similar way, below are the membership functions for the humidity, sound, light and time variables.

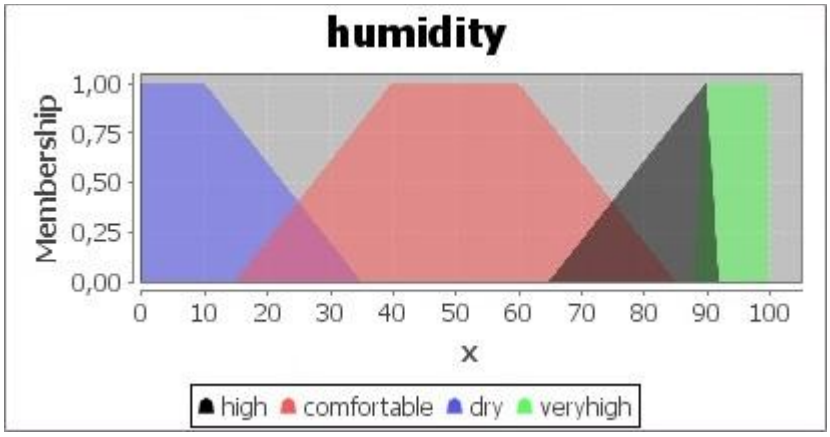


Figure 3.16 - Fuzzified humidity function

The "very high" humidity from 90%RH to 100%RH was added since it is common that humidity at night ascend to "high" (at least with the mediterranean climate) and the "very high" category may be useful to improve the classification accuracy in some specific environments.

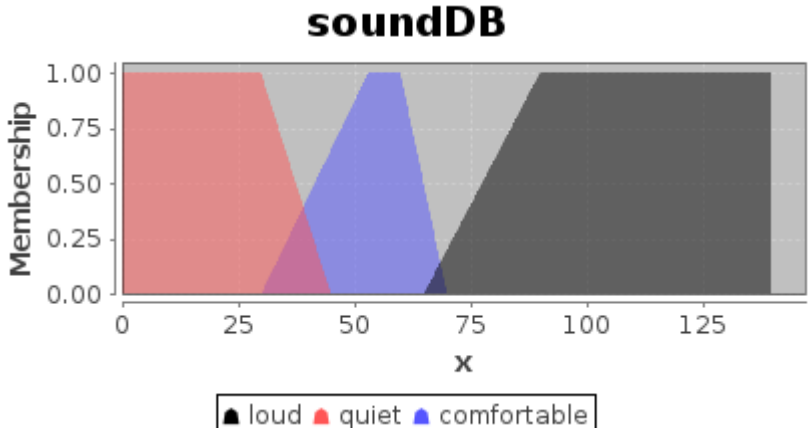


Figure 3.17 - Fuzzified sound function

As for the sound, to achieve this function a research was made in sound levels and their corresponding sources. As can be ascertained from the references [89] and [90], an average car stereo at maximum volume cast about 100dB. The comfort zone it is assigned at around 50dB (average home, conversational speech and quiet library) and the quiet level is below 26dB (quiet bedroom at night).

Table 3.2 - Sound sources and their corresponding levels[90]

Sound sources (noise) Examples with distance	Sound pressure Level L_p dB SPL
Jet aircraft, 50 m away	140
Threshold of pain	130
Threshold of discomfort	120
Chainsaw, 1 m distance	110
Disco, 1 m from speaker	100
Diesel truck, 10 m away	90
Kerbside of busy road, 5 m	80
Vacuum cleaner, distance 1 m	70
Conversational speech, 1 m	60
Average home	50
Quiet library	40
Quiet bedroom at night	30
Background in TV studio	20
Rustling leaves in the distance	10
Hearing threshold	0

Concerning light, another research was made around the lux level of each source and environment. Unfortunately the available light sensor complicates its conversion to lux units (the SI unit of illuminance). To measure light level it was used a simple analog read from 0 to 676. This range is due to the reference voltage being automatically regulated to 3.3V (1024 for 5V, so $\frac{3.3\,V}{5\,V} \times 1024 = 675.84$). In order to achieve these fuzzy sets for light function, several tests were made in indoor and outdoor environments, at different time and weather conditions. So, roughly, from 400 to 600 it is asserted as "very high" light intensity (outdoor sunny day), from 200 to 430 as "high" light intensity (outdoor shadow or late afternoon), from 80 to 220 as "medium" (typical office light), from 50 to 110 as "low" and from 0 to 60 as "very low" (indoor low bedroom light at night)

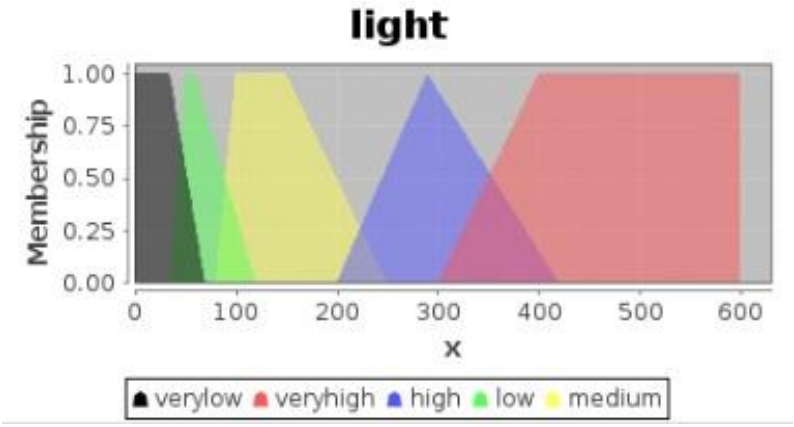


Figure 3.18 - Fuzzified light function

An example of the used code from the .FCL file can be seen below, in Figure 3.19

```
FUZZIFY temperature_sensed
    TERM cold := (0, 1) (18, 0);
    TERM comfortable := (15, 0) (19,1) (24,1) (30,0);
    TERM hot := (23, 0) (30, 1) (33,0);
    TERM veryhot := (30,0) (35, 1) (50, 1);
END_FUZZIFY

FUZZIFY humidity
    TERM dry := (0, 1)(10, 1) (35, 0);
    TERM comfortable := (15, 0) (40,1)(60,1) (85,0);
    TERM high := (65, 0) (90, 1) (92,0);
    TERM veryhigh := (88,0) (90, 1)(100, 1);
END_FUZZIFY
```

Figure 3.19 - Example of the FUZZIFY functions in FCL files

To fuzzify attributes in jFuzzyLogic is as easy as to specify the name of the variable, “temperature_sensed” and “humidity” in the example, then assigning the linguistic terms of each variable (“cold”, “comfortable”, “hot”, “veryhot”, “dry”, etc.) and lastly assign the membership functions of each linguistic term. For example, the term “veryhigh” for the variable humidity is set to a membership of “0” at 88%RH but from 90%RH to 100%RH is set to a membership of 1 (maximum). In this case the functions were chosen with no specific form, but there are many forms that can be assigned (triangular, trapezoidal, Gaussian, Bell, sigmoidal, singleton and piece-wise).

3.4.3 Choosing the Classification Model

At first glance, it was thought that ontologies could provide the semantic hierarchy to describe sensors and observations but, at this point, regarding the multiple physical sensors and its outputs, a change of course was made. Since ontologies are often specialized to some domain-specific applications (although they are used for many different purposes), it was preferred not to model the world around the robot "statically "describing its relations "manually "in the beginning. Instead, the main interest is in one technique that could learn and that can adapt to new situations.

A semantic reasoner or rule engine to infer logical consequences from a set of asserted facts is more difficult to train and adapt to new classification labels or input sources, as well as to maintain and debug. Since in this project the main focus is to, initially, classify two classes, it did not justify the use of such conceptualization, because there is only a few concepts regarded. Perhaps, in the second step of sub-classification, ontologies will be a much valuable resource. At this stage, it was considered using a probabilistic machine learning technique, that supports supervised learning and that can be updatable.

The environment is partially observable because the robots sensors cannot give access to all the complete state of the environment at each point in time. Since its being dealt with a stochastic environment (because there is a lot of uncertainty when sensing the robot surroundings), it is appropriate to choose a classifier based on probabilistic methods.

Regarding the activity type, the classification task is a sequential activity, performing a single classification at a time but considering the previous state. This activity is performed, clearly, in a dynamic environment, since is changing constantly as the robot is patrolling within different areas.

For the sake of efficiency, the environment can be considered as discrete, since it is made an abstraction of the "real world" in a finite number of clearly defined possible states.

Regarding the type of data present, it was interesting to have a structured architecture which supports relations between the different entities of an environment to better classify it (relational databases, knowledge-based learning,

ontologies, etc.). Maybe in the second step of sub-classification this will be useful (future work). Regarding this dissertation, a factored representation is present, which support probabilities and uncertainty but doesn't support relations or hierarchy between the set of variables (in order reduce complexity).

In the scope of this master dissertation, the more suitable technique for classification lies is supervised learning (classification field), more particularly a Bayes classifier (Bayes network). It seemed to be a good starter since it has good performances, even with less training data, is highly scalable, can adapt to a wide variety of classification tasks and is appropriate for a factored representation of data. It was decided to start with a more basic classifier to get some sense of the collected data (labeled) and then train it properly.

Step-by-Step Classifier Implementation

There are some basic workflow when working with ML techniques according to [45]: Firstly prepare the data, choose an algorithm, fit a model, choose a validation method, examine fit and update until satisfied and finally use fitted model for predictions. These steps were very useful and followed when doing the final classifier.

Preparing the data

When preparing the input data, each row should correspond to an observation and each column represents a variable (it can also be referred as attributes or features). Each row of observable data should have a response/output class to make a pre-classified training set and therefore build the model [45].

Relation: ENVIRONMENT

No.	LIGHT Nominal	GPS_SAT Nominal	TEMP_WEB Nominal	TEMP_SENSED Nominal	HUMIDITY_WEB Nominal	HUMIDITY_SENSED Nominal	FLOOR Nominal	TIME Nominal	SOUND Nominal	PREVIOUS_STATE Nominal	**OUTPUT** Nominal
1	VERYH...	HIGH	VERYHOT	VERYHOT	DRY	DRY	CONC...	DAY	COMF...	OUTDOOR	OUTDOOR
2	VERYH...	HIGH	VERYHOT	VERYHOT	DRY	DRY	CONC...	DAY	COMF...	OUTDOOR	OUTDOOR
3	HIGH	HIGH	HOT	HOT	HIGH	COMFORTABLE	PAVE...	DAY	COMF...	OUTDOOR	OUTDOOR
4	HIGH	HIGH	HOT	HOT	HIGH	COMFORTABLE	PAVE...	DAY	COMF...	OUTDOOR	OUTDOOR
5	HIGH	HIGH	HOT	HOT	HIGH	COMFORTABLE	PAVE...	DAY	COMF...	OUTDOOR	OUTDOOR

Figure 3.20 - Dataset sample using weka arff visualizer

In Figure 3.20 it is presented a sample of our dataset and the chosen attributes can be viewed. It is believed that those are the relevant attributes to this classification task (light, gps satellites, temperature from webservice, sensed

temperature, humidity from webservice, sensed humidity, floor type, time of the day, sound level and previous state). The reason why there is a temperature and humidity from a webservice is further discussed. Although it's known that typically temperature and humidity are relatively constant in indoor environments like home of office (as it was proved by the line chart in Figure 3.21), but for the purpose of this application this is not useful, since a moving robot typically doesn't stand enough time on the same location to foresee if the temperature or humidity will remain constant for hours. To solve that problem, the measured values of temperature and humidity are compared to the values of a local (nearest) PWS (Personal Weather Station) by the means of a webservice. Those PWS provide accurate data (humidity, temperature, wind speed, pressure, precipitation, etc.) from time to time (typically 10 in 10 minutes) in an outdoor environment as close as possible to the robots location. For this dissertation, a wunderground nearest station is used to provide outdoor data (using a wunderground java API). For example, if the measured values match the announced, the output must be "outdoor" with a lot more confidence.

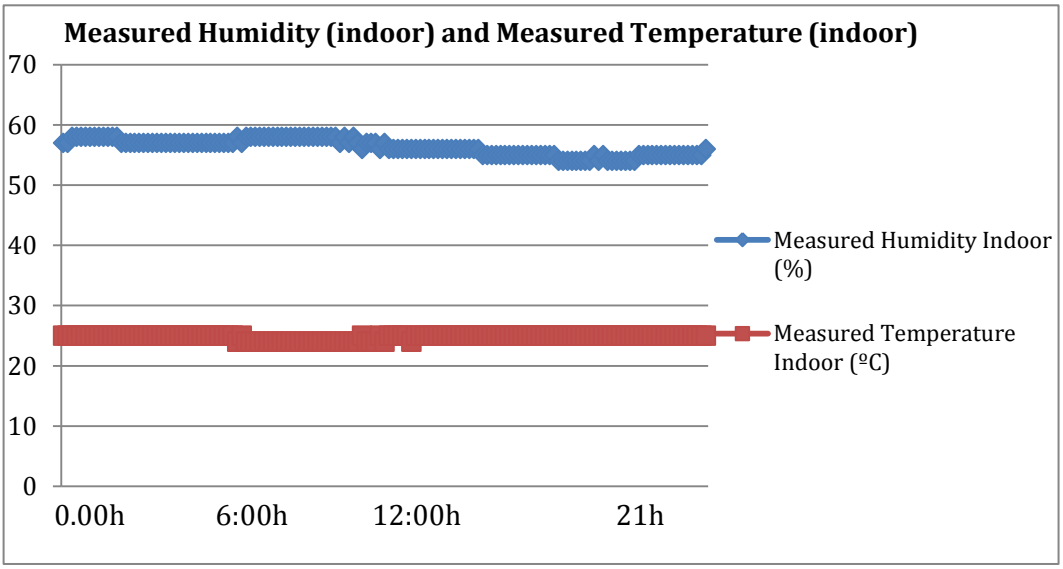


Figure 3.21 – Measured temperature and humidity indoor for 24hours

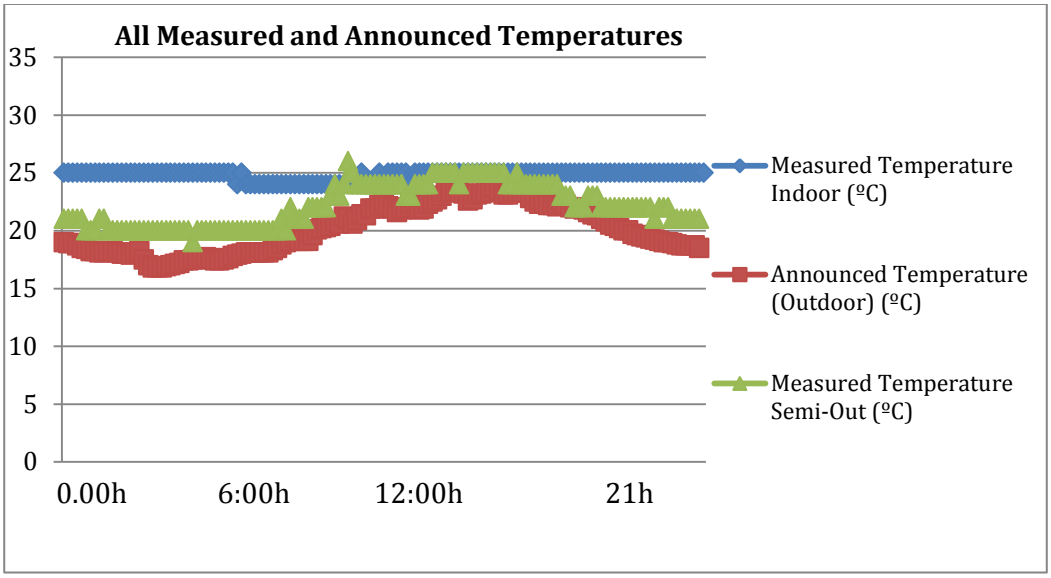


Figure 3.22 – All measured temperatures from indoor and outdoor

As can be concluded from Figure 3.22, the measured temperature in a semi-outdoor environment (in an opened window) follows the trend line announced by the outdoor webservice (green and red, respectively). Still, the measured temperature indoor remained roughly constant during the entire test.

As obvious, this deviation from indoor to outdoor (in terms of temperature) is more pronounced during the night. During the day (some days) this deviation can be too narrow, which means that sometimes this attribute is not clear.

Concerning humidity, it was noticed in our measures that this attribute is very unpredictable, and can vary much from the announced value (as can be seen on Figure 3.23). This is due to the high variation and sensitivity to the specific local that is measured. At this point it was considered to discard this attribute. Further on, this adjustment will be justified using an attribute evaluator, from the weka framework).

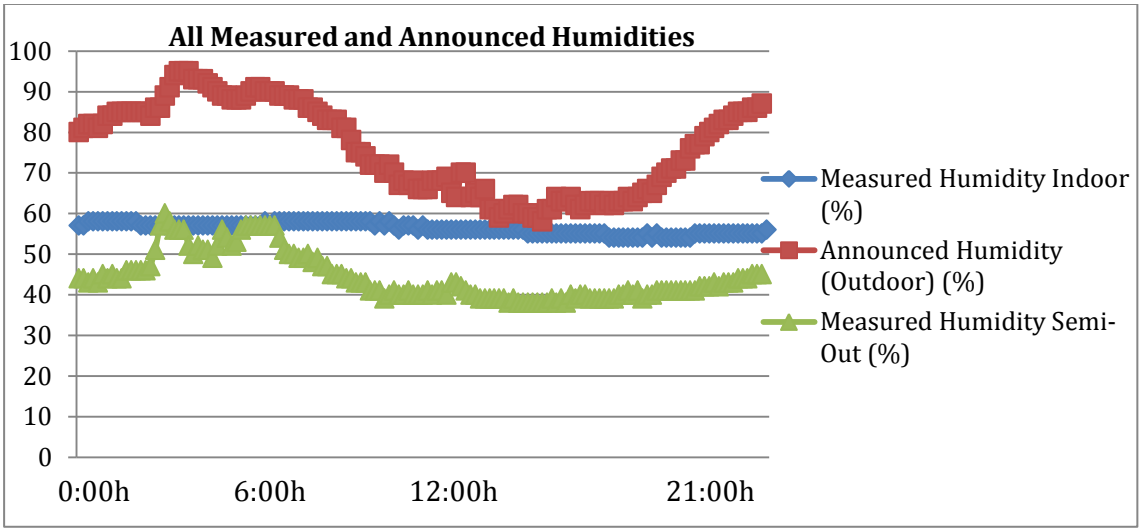


Figure 3.23 – All measured and announced humidities

The previous state was added because there can be occasions where the robot leaves an indoor environment and it may take some time for the GPS to collect satellites data. That can generate mistaken classifications, since typically there is GPS signal available outdoors.

Unfortunately, it was not possible to include a wind speed sensor (anemometer) in this classification system.

Choosing an algorithm and fitting the model

Next it's time to choose the algorithm. As been said in section 3.4.3, a Bayes network classification was chosen.

In order to fit the model (train the classifier with the dataset), validate it (test the classifier) and to make predictions, the support from weka framework was used. The results are shown further, on chapter 3.5.

After getting the model is time to perform a feature selection, using the attribute evaluator from weka, in order to identify how well and which attributes alone can predict the desired class.

After some GUI tests and model selection, it was implemented the classifier in our project (java code) along with the fuzzy sets, sensors from the Arduino (ROS nodes) and also from a nearest wunderground weather station.

3.4.4 Software hierarchy

Below it is presented the overall software project hierarchy.

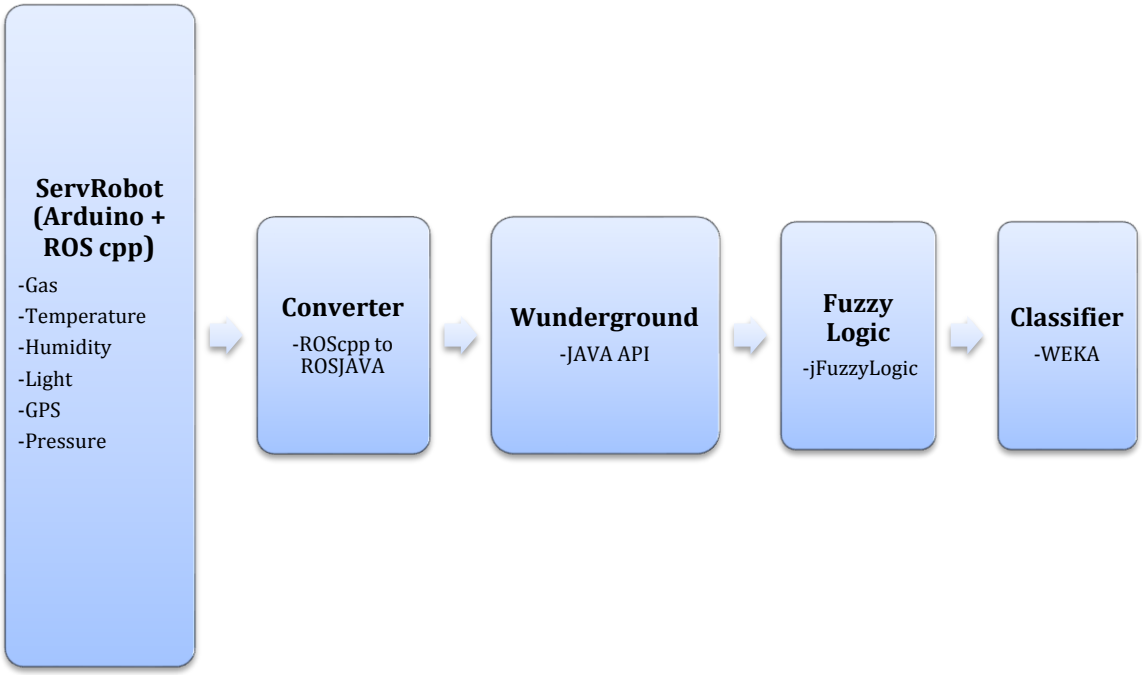


Figure 3.24 - Overall software project hierarchy

First, the sensory information is gathered on the Arduino (within ServRobot ROS node). This node has several topics constantly publishing sensor data. The node Converter was covered in chapter 3.4.1. The next three boxes refer to a main node that contains the remote weather station information (Wunderground), Fuzzy Logic and the Classifier. This main node subscribes the Converter node, performs the classification task and outputs the final context classification.

The hierarchy concerning ROS nodes and topics, obtained by the command tool "rqt_graph" is presented in Figure 3.25.

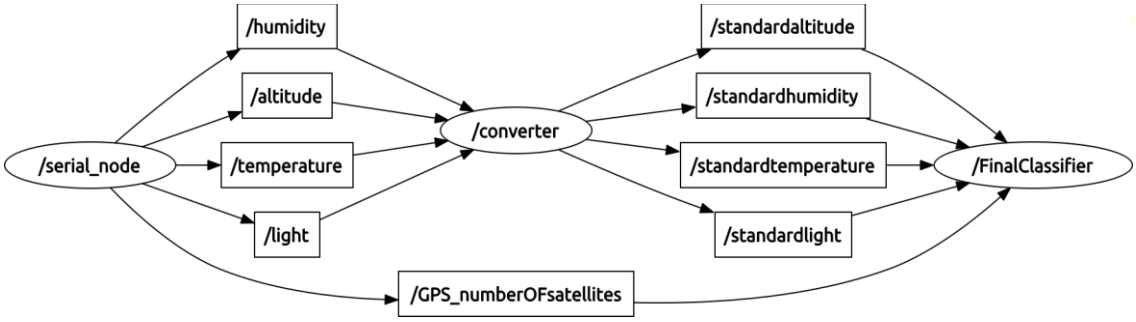


Figure 3.25 - ROSgraph representing nodes and topics

GUI

After the development of the classifier, a GUI was made in order to simplify the management and interaction with the system. This module turned to be very convenient during the field tests.

In Figure 3.26, a screenshot of the designed GUI is shown and its main features are:

- Connect to ROS;
- Running options (run once or continuously);
- Display the predicted label and the number of classified instances so far;
- Choose the training and testing dataset;
- Possibility of training the classifier (exporting its model) or testing the classifier (importing its model);
- Log for debug purposes.

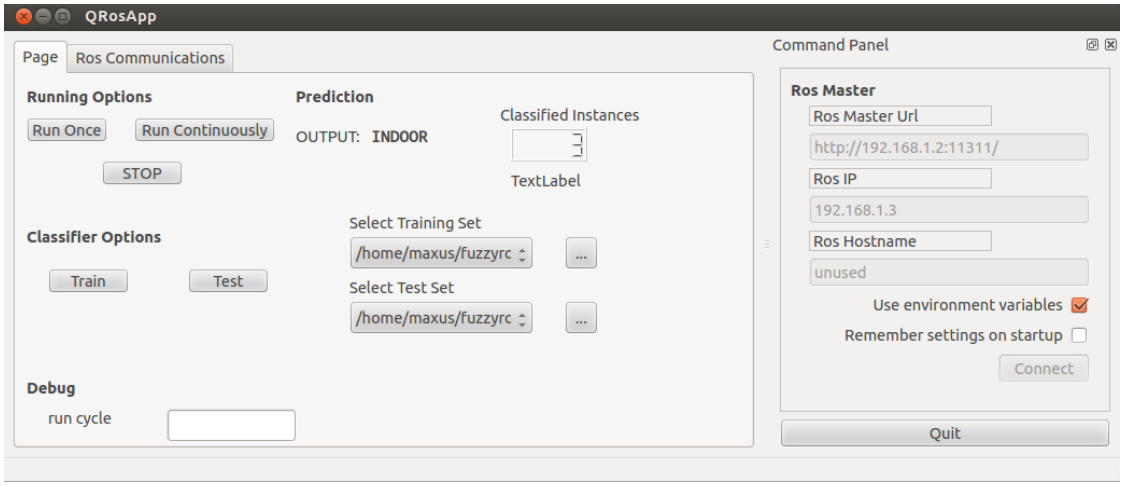


Figure 3.26 - GUI form design

3.5 Field tests and experiment results

For the initial field tests and data collection, the Madan park corridors (for indoor tests) and the Madan park exterior (for outdoor tests) were chosen.

In Figure 3.27 it is presented the building's plan with the corresponding path (indoor) performed by the classification system (attached to the ServRobot).

In this first data collection on the main corridor, all the numbered stages were correctly classified as indoor. Numbers 1, 2, 7, 8 and 9 are the main troubled spots because there are large windows (very high light intensity and chance to catch some GPS satellites). This data was collected during the late afternoon (18:50pm) with an average sunlight.

Figure 3.27 – Holos indoor testing path

Regarding Figure 3.28, the path from 1 to 9 represents an open space between walls (outdoor), causing a lot of shadows (especially in the morning). These walls can also break the line of sight with some GPS satellites. Still, all the steps were correctly classified as outdoor.

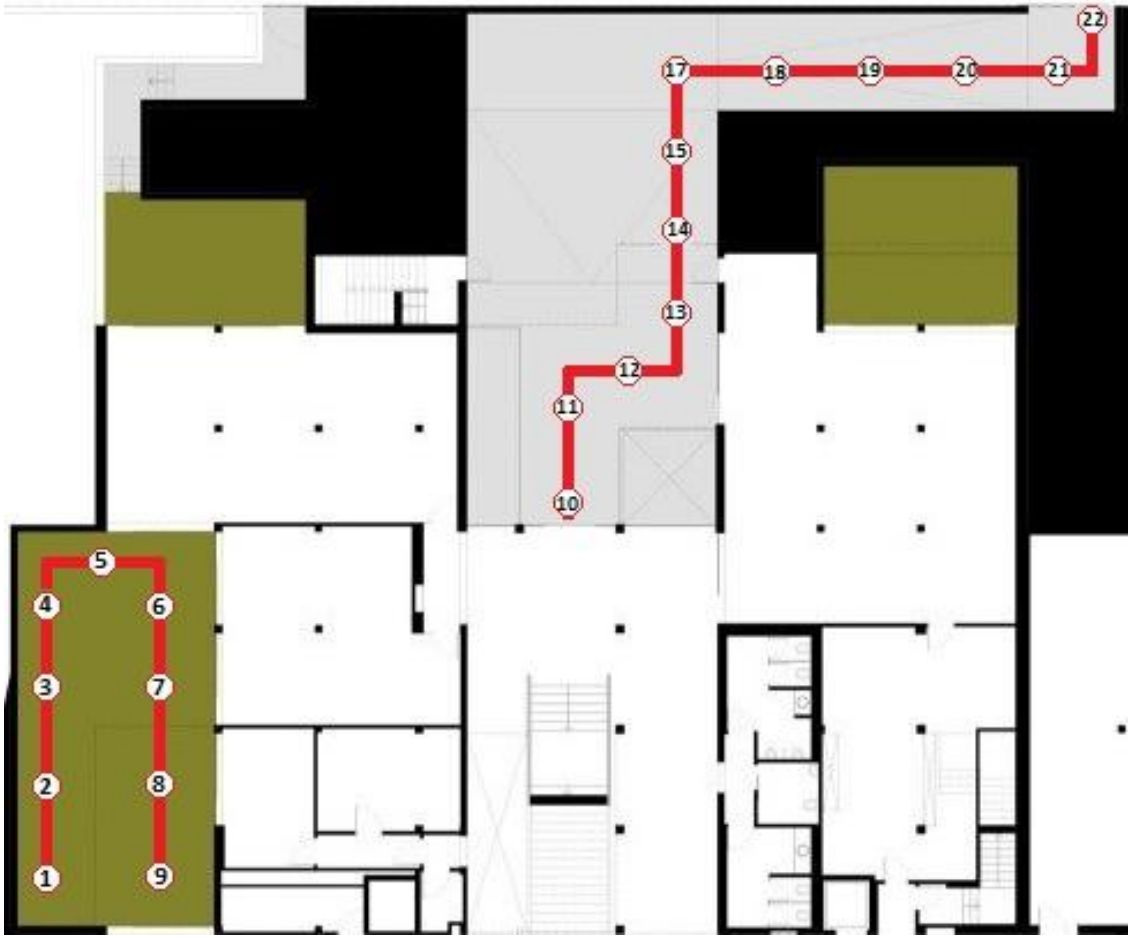


Figure 3.28 – Holos outdoor testing path

As expected, the fact from section 3.4.1 was observed during the experiments, even with no direct sunlight (cloudy/rainy day and shadows) the light measurements outdoor were very high, due to the sunlight spectrum in visible light.

From the first dataset collected, it was obtained 87.5% of correctly classified instances, using a 10-fold cross-validation evaluation on the training dataset (CV).

Further on, a detailed description of the overall systems accuracy is presented, obtained with the help of WEKA framework.

Table 3.3 - Classification statistics (CV)

Correctly Classified Instances	133 (87.5%)
Incorrectly Classified Instances	19 (12.5%)
Total Number of Instances	152

Table 3.4 – Confusion Matrix (CV)

Indoor	Outdoor	Classified as
119	2	Indoor
17	14	Outdoor

The confusion matrix represents TP (true positives), FP (false positives), FN (false negatives) and TN (true negatives) in the following order:

Table 3.5- Confusion matrix labels

TP	FN
FP	TN

From Table 3.4 and Table 3.5, it can be understood that 119 instances were correctly classified as "indoor" out of a total of 121 indoor instances (true positives). A more detailed accuracy table is presented below (Table 3.6).

Table 3.6- Detailed performance measures (CV)

TP Rate	FP Rate	Precision	Specificity	F-Measure	ROC Area	Class
0.983	0.548	0.875	0.452	0.926	0.909	INDOOR

TPR (True Positive Rate) also known as *sensitivity* (in biomedicine) or *recall* (in machine learning). Measures the proportion of positives which are correctly classified as such and it is calculated by:

$$TPR = \frac{\text{proportion classified as class X}}{\text{Actual total in class X}} = \frac{TP}{TP+FN} = 0.983 \quad (1)$$

FPR (False Positive Rate), also known as *false alarm rate* or *fallout. I*t's the complementary with the specificity (1-specificity) and can be calculated by:

$$FPR = \frac{\text{proportion incorrectly classified as class X}}{\text{Actual total of all classes except X}} = \frac{FP}{FP+TN} = 0.548 \quad (2)$$

Precision (represents the positive predictive values):

$$Precision = \frac{\text{Proportion of the examples which truly have class X}}{\text{total classified as class X}} = \frac{TN}{TN+FN} = 0.875 \quad (3)$$

Specificity (also known as TNR – True Negative Rate) measures the proportion of negatives which are correctly identified as such (complementary of FPR), and it is calculated by:

$$Specificity = \frac{\text{Proportion of the examples which truly have class X}}{\text{Actual total of all classes except X}} = \frac{TN}{FP+TN} = 0.452 \ (4)$$

F-measure (a combined measure for precision and recall):

$$Fmeasure = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} = 0.926 \quad (5)$$

A perfect classifier should be 100% specific and 100% sensitive.

Besides confusion matrix, another way to examine the performance of classifiers is trough ROC (Receiver Operating Characteristic) analysis. The area under the ROC curve characterizes the quality of a forecast system by describ-

ing the system's ability to anticipate correctly the occurrence (or not) of events [91]. ROC is created by plotting the fraction of TP out of the TPR versus the fraction of TN from FPR. An ideal classifier will have ROC area values approaching 1, with 0.5 being comparable to random guessing.

In Figure 3.29 it is presented the ROC curve, being X-axis the FPR and Y-axis the TPR.

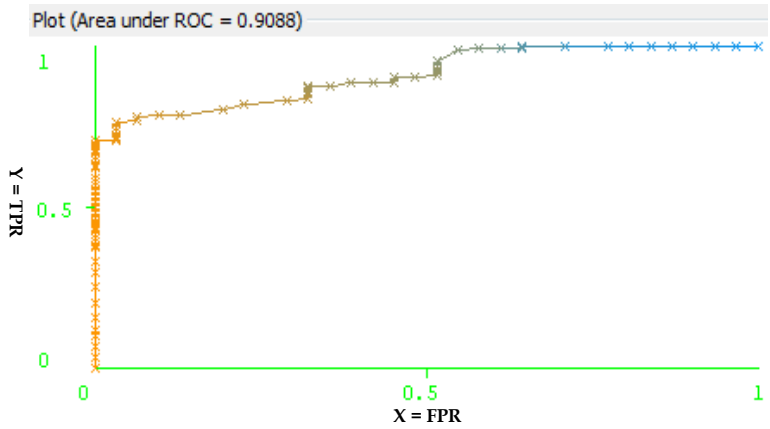


Figure 3.29 - ROC curve for class INDOOR

In Figure 3.30, the Bayes network model of this work is presented. As it can be noticed, the "floor" attribute has no effect on the classification (not connected to any node), because the datasets collected so far in Holos all have "concrete" on the floor type (outdoor and indoor). As a larger dataset is collected, this issue will be solved.

Another evaluation was made (10-fold cross validation) without considering humidity and the results weren't improved, so it was decided to consider it in the classification, at least until new (larger) datasets are collected and retrained.

As expected, the number of GPS satellites is the most relevant attribute, although all other attributes are needed to increase systems consistency and accuracy.

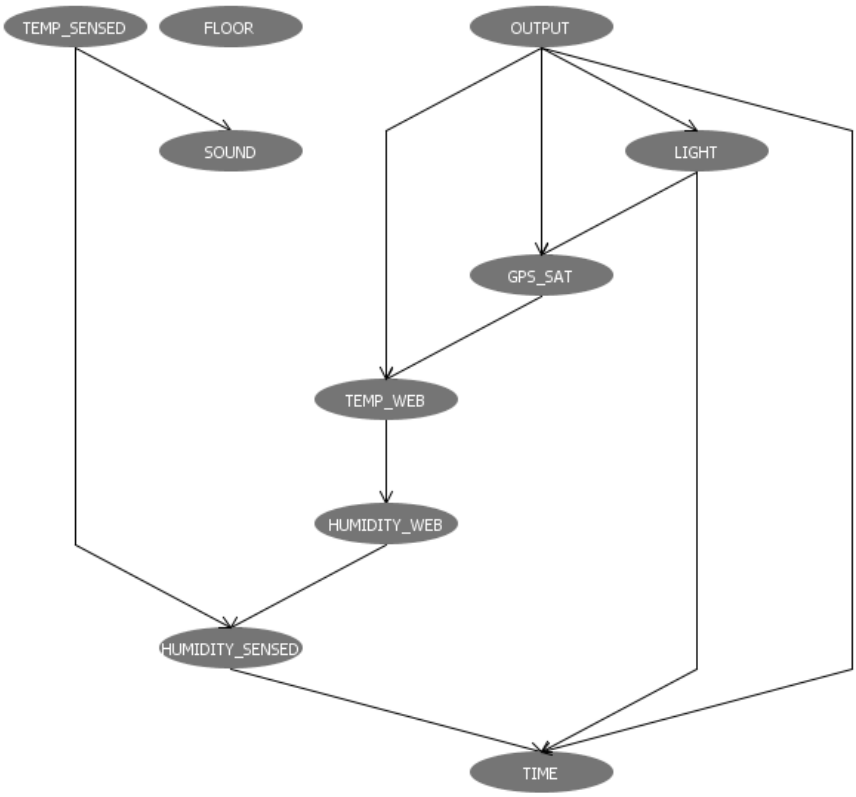


Figure 3.30 – Bayes Network

Table 3.7 exhibits the (conditional) probability distribution table for the node GPS_SAT (number of GPS satellites). As can be seen, there is a high probability (93.4%) of "indoor" events that have "none" gps satellites and a "very low" light. That illustrates a typical indoor environment (e.g. home corridors/rooms).

Table 3.7- Probability distribution table for node GPS_SAT

OUTPUT	LIGHT	NONE	LOW	MEDIUM	HIGH
INDOOR	VERYLOW	0,934	0,007	0,051	0,007
INDOOR	LOW	0,75	0,05	0,15	0,05
INDOOR	MEDIUM	0,289	0,026	0,658	0,026
INDOOR	HIGH	0,038	0,038	0,885	0,038
INDOOR	VERYHIGH	0,31	0,071	0,595	0,024
OUTDOOR	VERYLOW	0,038	0,038	0,885	0,038
OUTDOOR	LOW	0,167	0,167	0,5	0,167
OUTDOOR	MEDIUM	0,045	0,045	0,864	0,045
OUTDOOR	HIGH	0,25	0,25	0,25	0,25
OUTDOOR	VERYHIGH	0,042	0,042	0,875	0,042

These presented tests don't include the "previous state" attribute yet. Some initial experiments were made later on with this feature and the overall accuracy (correctly classified instances) was increased to 93.42% (performing a 10-fold cross-validation on the training set).

With all the theoretical tests made and the classifier validated, it's time to test it on a mixed environment, in order to evaluate the system's consistency in its real application scenario. In Figure 3.31, a mixed testing path is presented. The indoor path is represented in blue color, the outdoor path is represented in red color and the transition areas are represented in orange.

Figure 3.31 – Holos mixed testing path

These experiments were performed in different daytimes and weather conditions (mostly cloudy/rainy and sometimes sunny), were traveled in about 8 minutes from step 1 to 26 (11 times) and the previous state attribute was taken into account. Those were very challenging experiments, since despite the different daytimes and weather conditions, the outdoor temperature was always around the comfortable zone, the floor type was always concrete, the sound

level was considered to be constant and there were large windows in the transition zones (as well as porches, that decrease GPS signal strength), making more difficult to distinguish indoor from outdoor class.

It was observed that the most troubled zones were in step 5, 6, 17 and 18, as expected. Next, in Table 3.8, the obtained confusion matrix is presented.

Table 3.8 – Confusion Matrix from the mixed testing path

Indoor	Outdoor	Classified as
119	19	Indoor
2	146	Outdoor

From Table 3.8 it's easily extracted the number of correctly classified instances: $119 + 146 = 265$ from a total of 286 instances classified, which corresponds to 92.66% of overall accuracy. Regarding the incorrectly classified instances: $19 + 2 = 21$ from a total of 286 instances classified, which corresponds to 7.34%. Of those incorrectly classified instances, the 2 FP cases ("indoor" classified as "outdoor", false positives) are located on step 6 of the Figure 3.31 and they occurred due to the presence of a glass wall in the room. Near the glass wall, the classifier can be deceived (e.g. with high intensity light and GPS satellites present). Regarding the 19 FN cases ("outdoor" classified as "indoor", false negatives), 2 of them occurred on the step 5 of the path (Figure 3.31), which is the transition step (expected), 6 of them occurred in step 18 (due to the presence of a porch, which attenuates the light intensity and the GPS signal intensity and the fact that the GPS attribute is slower to acquire satellites when moving from indoor to outdoor environments) and the majority of the FN cases (11) occurred in step 17, which is another transition step. In Figure 3.32, this transition step (17) from the mixed path is shown.

Figure 3.32 – ServRobot performing a classification near a transition zone

Based on the previous formulas (1), (2), (3), (4) and (5) it's possible to re-make all the calculations, this time for the real application scenario. In Table 3.9, those calculations are presented.

Table 3.9 – Detailed performance measures

TP Rate	FP Rate	Precision	Specificity	F-Measure	Class
0.862	0.014	0.885	0.986	0.873	INDOOR

Regarding the results from Table 3.9, very good results were achieved in specificity and sensitivity (TPR) as well as a pronounced decrease in the FPR (false alarm rate).

Considering the "previous state" attribute in the classification and all the datasets collected so far, a new Bayes network was generated and presented in Figure 3.33. As can be seen, the "output" class is directly connected to some of the most relevant attributes, which now are: "light, "GPS satellites", "previous state" and "temperature web".

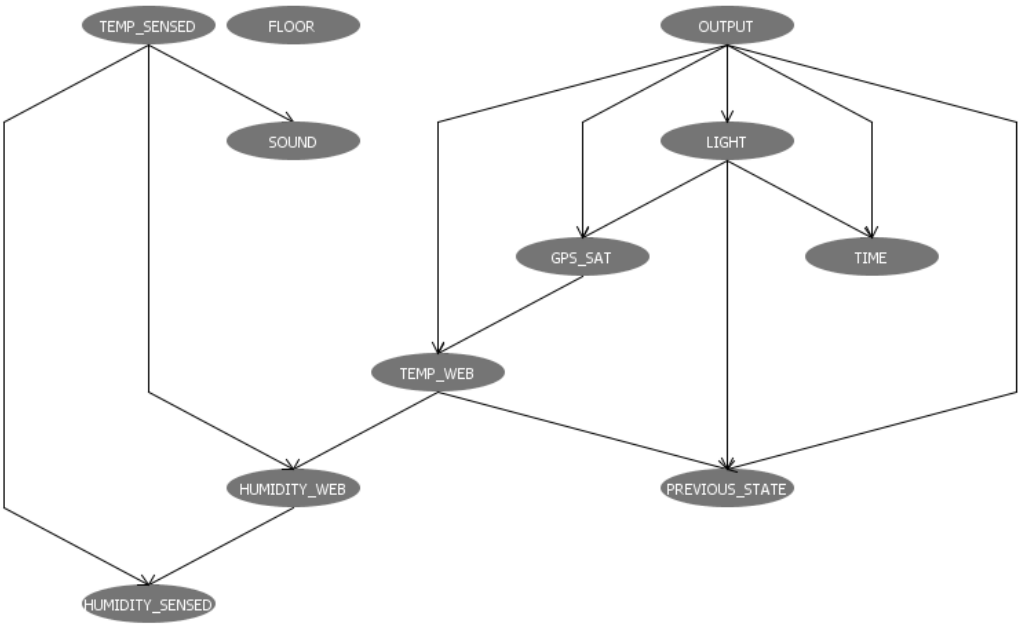


Figure 3.33 – Bayes network with "previous state"

The obtained results for this particular real world application scenario were similar to the simulated ones using a 10-fold CV on the training set (considering the "previous state" attribute). This occurrence is due to the dataset improvement.

4. Conclusions and Future Work

This chapter completes and summarizes the work performed so far along this dissertation. It also proposes future work that can be done considering this project to further progress towards the goals.

4.1 Conclusions

Independently of the application, whether it is social, entertainment, service, educational, security, etc. robotic systems need to have the notion of its context in order to behave appropriately and provide useful information to users and applications that depend on that information. There are several context models, techniques and frameworks. From all of those possibilities the ones based on ontologies seem to be the ones with most widespread use (often used to support ML techniques). From all existing frameworks and for the intent of this architecture, machine learning techniques, particularly Bayesian networks, seemed to be the more appropriate method for solving the systems classification problem. This assertion was verified by the good results achieved by this system. Nevertheless, another future experiments should be considered with more linguistic terms in the fuzzy sets (for example, "morning", "afternoon", "late afternoon" or "night" instead of just "day" or "night" for the time attribute). Increasing the attribute information (more levels) can add a valuable improvement in the overall performance. However, increasing the number of at-

tributes (more sensory information) doesn't necessarily improve the systems accuracy.

In conclusion, it is believed that a good performance level was reached (92.66%) regarding this system, that compared with the precisions observed from other systems state of the art was, in some cases better. As stated before, there is still a lot of room for improvement of this architecture, giving confidence that these good results may be improved.

Although limited to an indoor or outdoor classification, this architecture is scalable to include a broader range of contexts.

In the robotics field there are, at this point, already some applications but it seems that context classification can be an added value to others. In this sense a new application scenario is presented as well as the architecture to support it in the reliability field.

4.2 Future Work

In the scope of this dissertation, there is more to be done. It is believed that a good base and starting point was made to a more complex and detailed classification. As it's known if the robot is indoors or outdoors with a very good accuracy, it can now be sub-classified, in more detail, what sub-type of environment is present (office, manufacture, etc.). To do that, another classifier should be created and trained with proper datasets (that comprise all the intended environments to be classified). Once the type of environment and context present could be classified in more detail, this dissertation will further contribute to a more accurate reliability assessment.

Since reliability is tightly coupled with the hazard rates of the several components (constants) and also with influence of variable factors (time, terrain type, etc.), knowing the robot's operating time in different environments will surely provide a valuable item for its calculations.

Below it is presented the reliability expression considering the two existing variable factors (time and terrain).

$$R = e^{-\lambda \cdot \pi \cdot t} \quad (5)$$

Where R is the reliability, λ is the module hazard rate, π is the terrain factor and t is the time. The terrain factor can be calculated by:

$$\pi = \pi_{tx} \times t_{tx} \quad (6)$$

Where $\pi_{tx}$is the terrain factor asserted to terrain x and t_{tx} is the total percentage of the operating time in terrain x.

Another variable factor will be added to this reliability calculation, regarding the type of context present. The more different context types (more different factors), the more accurate is the its reliability forecast.

Scientific Contributions

Some of the concepts covered in the introduction and state of the art of this document were result of an intensive research that resulted in a publication and it's referenced below:

- F.Miranda, T.Ferreira, J.Pimentão, P.Sousa, "Review on Context Classification in Robotics", *Rough Sets and Intelligent Systems Paradigms*, pp. 269-276, 2014.

Also, part of the implementation steps and experiment results has produced another paper, referenced below:

- T.Ferreira, F.Miranda, P.Sousa, J.Barata, J.Pimentão, "Context Classifier for Service Robots", *Technological Innovation for Cloud-based Engineering Systems,* Apr .2015.

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