Hierarchical Qualitative Descriptions of Perceptions for Robotic Environments

E. Muñoz, T. Nakama and E. Ruspini
Collaborative intelligent agents Lab, European Centre for Soft Computing, C/ Gonzalo Gutiérrez Quirós, Mieres, Spain

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Abstract: The development and uptake of robotic technologies, outside the research community, has been hindered by the fact that robotic systems are notably lacking in flexibility. Introducing humans in robot teams promises to improve their flexibility. However, the major underlying difficulty in the development of human-robot teams is the inability of robots to emulate important cognitive capabilities of human beings due to the lack of approaches to generate and effectively abstract salient semantic aspects of information and big data sets. In this paper we develop a general framework for information abstraction that allows robots to obtain high level descriptions of their perceptions. These descriptions are represented using a formal predicate logic that emulates natural language structures, facilitating human understanding while it remains easy to interpret by robots. In addition, the proposed formal logic constitutes a precisiation language that generalizes Zadeh's Precisiated Natural Language, providing new tools for the computation with perceptions.

1 INTRODUCTION

Multi-robot teams are successfully employed in a broadening range of application areas. However, purely robotic systems are rather unflexible and have difficulties adapting to unexpected changes in the environment. Introducing humans in robotic teams can alleviate these problems, adding the required flexibility and adaptability. Especially when humans and robots collaborate as peers, in contrast to scenarios where humans use robots as mere tools.

Despite the advantages offered by human-robot teams, some challenging problems need to be addressed to favor their development and uptake, primarily concerning human-robot interaction and coordination. Humans can easily share information and coordinate due to their ability to abstract and aggregate salient information about complex objects and events. Nonetheless, these abilities have not been matched by robots yet. It is necessary to provide robots with these capacities to support their integration in human-robot teams.

To a large extent robotic limitations are caused by an unsuitable choice of tools to represent knowledge. In most cases robots rely on technologies that emphasize precision and detail, failing to recognize major features, themes and motifs ("not seeing the forest because of the trees"). These techniques have been designed historically for computational convenience rather than to facilitate understanding of the nature and behavior of complex systems. Employing perceptions, as defined by Zadeh (Zadeh, 2001), we can overcome this problem, favoring the abstraction and summarization of information at various levels.

Perceptions can be considered clumps of values drawn together by some similarity measure, whose boundaries are unsharp or fuzzy (Zadeh, 2001). Conceiving perceptions as fuzzy-granules, or f-granules, helps to avoid emphasis on detail and precision that is detrimental to the obtaining of high-level abstractions, and makes it possible to imitate the ways in which human concepts are created, organized and manipulated (Dubois and Prade, 1996; Zadeh, 1997).

In this paper we establish a framework that, employing perceptions as a base, permits the abstraction of the information obtained by robots, and its communication through a quasi-natural language. We define a formal logic to effectively define perceptions. In formal logic each sentence is assigned a truth value (in two valued logic, for example, it is either *true* or *false*). In our framework a multi-valued logic is used, and sentences can be assigned a truth value in the interval $[0,1]$. These truth values are computed using what we have called perception functions, which are inspired by f-granular definition of perceptions. This paper is an extension of our previous work (Nakama

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et al., 2013b), which introduced a formal logic to describe and specify robotic tasks. More details about this framework can be also found in the companion article (Nakama et al., 2013a), which discusses the semantics of the formal logic.

We have chosen a formal logic as a middle-ground between natural language used by humans and low level data and instructions used by robots. A formal logic can produce an indefinite number of sentences, but avoids natural language ambiguity, and can be easily interpreted and produced by robots. In addition, humans can also easily understand this logic, since we adapt its syntax to the syntactic structures frequently observed in natural language (Halliday and Matthiessen, 2004). In particular, we aim to make it accessible for naive users with a limited experience in robotics.

The framework is organized following a hierarchy of perception functions, where higher-level functions are built combining lower-level ones. Using a simple procedure, perception functions can be easily translated into sentences from the formal logic.

The proposed formal logic is also a first step towards the establishing of an operative precisiation language. A precisiation language (Zadeh, 2001; Zadeh, 2004) is a subset of natural language that consists of propositions that can be precisiated through translation into a formal language, whose propositions can be used to compute and deduce with perceptions.

The remainder of this paper is organized as follows. Section 2 discusses related work. The proposed approach is presented in Section 3. Section 4 presents a formal predicate logic to describe perceptions. A methodology for defining perception functions is defined in Section 5. A mechanism to translate perception functions into logic sentences is shown in Section 6. Section 7 presents the research conclusions.

2 RELATED WORK

In human robot interactions, humans have traditionally played the role of teleoperators or supervisors (Tang and Parker, 2006). Nonetheless, the improvement in the capabilities of robots has favored the development of teams where humans and robots collaborate as true peers. This kind of teams, in contrast to human supervised teams and fully autonomous teams, allow humans and robots to support each other in different ways as needs and capabilities change throughout a task (Marble et al., 2004), overcoming the different disadvantages of the other approaches.

However, the development of this kind of teams has been hindered by robotic limitations that prevent a fluent communication between humans and robots. In particular, robots' inability to successfully abstract salient information from perceived data is a flaw that should be overcome to improve such communication. This problem has been frequently studied in other fields, particularly in computational intelligence, but consistently ignored in robotics.

Notable among the approaches dealing with information abstraction are Qualitative Object Description methods (Zwir and Ruspini, 1999), which summarize and abstract key qualitative features in a complex computational object. These methods rely on combinations of fuzzy logic, evolutionary computation, and data mining techniques. They have been successfully applied in a variety of fields, notably in molecular biology (Romero-Zaliz et al., 2008) and time series analysis (Zwir and Ruspini, 1999).

This problem has been also addressed in the field of linguistic summarization (Yager, 1982). This approach, based upon the theory of fuzzy sets, uses templates to summarize big sets of data, and has been succesfully employed in time series (Wilbik, 2010) and assistive environments (Anderson et al., 2008). Other approaches include that of Fogel (Fogel, 2002), using methods for the learning and detection of semantic features in complex systems, or the one proposed by Martin et al. (Martin et al., 2006), who generated fuzzy summaries by means of fuzzy associative rules.

However, the approaches above mainly proposed ad-hoc methods particularly developed to address concrete problems. In contrast, in this paper we propose a general framework that facilitates the creation of summaries and abstractions.

In addition, the introduced predicate logic can work as a precisiation language, allowing computation, manipulation and deduction using perceptions. We extend and generalize precisiation language, which has been initially defined to represent relations in the form

$$X \ isr \ R,$$

where X denotes a constrained variable, R denotes the constraining relation, and r identifies the modality of the constraint (Zadeh, 2001; Zadeh, 2004). The formal logic introduced in this paper extends these relations to include more complex sentences. Furthermore, we illustrate how to implement computation with perceptions, which has not been previously done.

3 THE APPROACH

In this Section we introduce a framework that facilitates the expression of perceptions in a way easily

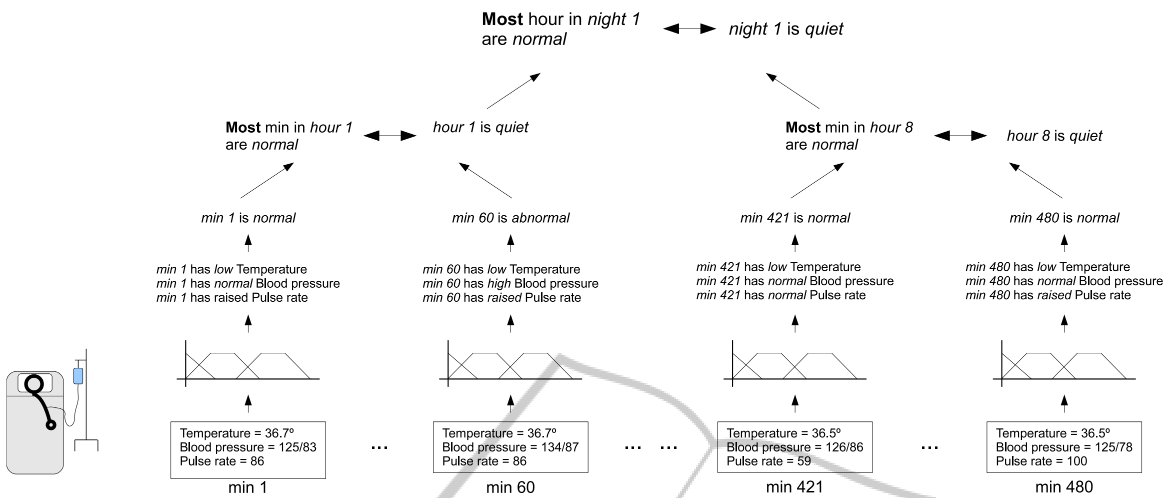

Figure 1: An example of the hierarchy.

comprehensible for both humans and robots. Perceptions are employed to describe an object or set of objects. We define object as any element relevant to the problem being addressed, whose characteristics need to be described. Some examples of objects, in a robotic environment, may include: boxes, reports of the state of a patient, people or other robots.

Perception descriptions abstract raw data obtained by robot sensors using perception functions, which are based on fuzzy set theory. Fuzzy sets are a natural choice to represent perceptions as f-granules. Employing this tool we can define high level concepts as functions that evaluate the raw observations that describe an object, and indicate to what degree the object is represented by the concept. Perception functions are defined and described using a formal predicate logic. Utilizing predicate logic we can construct well formed sentences that have an unambiguous meaning, facilitating robot interpretation, and a structure similar to natural language, easing human understanding. Furthermore, the degree of membership obtained from the perception function represents the truth value associated to a sentence, and allows computing with them.

Perception functions are organized following a double hierarchy, with a first hierarchy, called local hierarchy, that describes single objects and a second one, named global hierarchy, that characterizes sets of objects. In both hierarchies, high-level perception functions are built combining lower level perception functions. Using a hierarchical structure we can produce abstract concepts at an appropriate level for the targeted listener, for example depending on its background, or on the amount of information she prefers to deal with. In addition, we can easily explain high level perceptions using those perceptions that were used to define them.

At the bottom of the local hierarchy we find descriptions of individual objects that can be directly obtained from observations. Their meaning is grounded, because they can be directly mapped into measurements of the perceived objects. Combining them we can obtain more elaborated local perception functions, conforming the second level of the hierarchy, which can be combined analogously obtaining third level, and so on.

If the number of objects is high, descriptions that concern just one object may not be sufficient. For this reason, It is necessary to define perception functions that describe groups of objects aggregated according to a significant grouping, the so-called global perception functions. Global perception functions that constitute the first level of the global hierarchy are obtained combining local perception functions from the top-most level of the local hierarchy. Successively, second level global perception functions are created combining global perception functions from the first one. This process can be iteratively applied until an adequate level of aggregation is reached.

Figure 1 shows an example of the proposed idea, where a robot monitors the state of a patient at periodic intervals of one minute. Using its sensors the robot can measure the values of certain attributes, like blood pressure, body temperature or pulse rate. As a first level of abstraction we define fuzzy sets that partition and describe those attributes. Next we combine those simple concepts to create more elaborated concepts that describe each time interval. These perception functions represent the local hierarchy. Since the patient is monitored for a long period of time it is necessary to aggregate the obtained descriptions. This is done aggregating observations at intervals of one hour, and defining perception functions that describe those intervals. This process can be repeated, for instance, joining hour observations in eight hours intervals, as shown in the example.

4 A FORMAL LOGIC TO DESCRIBE PERCEPTIONS

In this section we introduce the predicate logic employed to describe perception functions in quasi-natural language. To facilitate naive users' understanding, sentences follow a syntax that seems closer to propositional logic, where predicates are represented using quasi-natural language syntactic expressions (*box is red*), instead of functions ($is(box, red)$). It should be noted, however, that sentences belong to a predicate logic, where the predicate is the verb and the rest of components of the sentence are constants, variables, quantifiers, qualifiers or operators. Instead of propositional logic, we chose predicate logic because of its ability to deal with more complex sentences that include quantifiers and variables, which, in our opinion, are necessary to describe perceptions.

Due to space restrictions we cannot fully formalize the predicate logic, but we will introduce its syntax. In a previous work (Nakama et al., 2013b) we fully characterized a propositional logic to describe robotic tasks. The formal logic introduced here extends that approach to deal with perceptual information.

4.1 Components of Well formed Sentences

We start by defining the sets of components that can compose a sentence. Such sets are called component sets. We consider the following sets:

- Q denotes the set of quantifiers that can bound a variable. For instance, we can consider $Q = \{All, Most, Some\}$.
- N indicates the set of object constants that can be described using perceptions, where *constant* is defined as a term that has a well determined meaning that remains invariable (traditional definition of constant in formal logic). For example, $N = \{Box\ 1, Minute\ 1\}$.
- R denotes the set of object variables that can be described using perceptions, with a *variable* being a term with no meaning by itself and whose value can be substituted by any constant (traditional definition of variable in formal logic). For example, $R = \{Boxes, Minutes\}$.
- A denotes the set of aggregation sets, which represent boundaries for variables. For instance, we can consider $A = \{Room\ 1, Hour\ 1\}$.
- P specifies the set of prepositions that can be used to link variables to aggregation sets. For instance, $P = \{in\}$.
- S denotes the set of objects and aggregations of objects that can be described using perceptions, it can include constants, variables and bounded variables. Hence $S = N \cup R \cup (R \times P \times A)$. Members of this set constitute the subjects of well formed sentences.
- V denotes the set of verbs or predicates employed to characterize objects. For instance, $V = \{be, have\}$.
- C specifies the set of complements that can describe objects, being these complements typically perception functions. For instance, we can have $C = \{red,\ blue,\ big,\ small,\ high,\ low\}$.
- T denotes the set of object attributes. For example, $T = \{Color,\ Size,\ Pulse\ rate\}$.
- O indicates the set of available operators to combine perceptions. As a first step, we will just keep basic logic operators. Hence, we have $O = \{and,\ or,\ not\}$.

These elements are combined in a specific way to form valid sentences. Table 1 summarizes the types of sentences allowed in the framework.

4.2 Atomic Valid Sentences

An atomic valid sentence is defined to be a tuple that consists of elements in the component sets. Each admissible tuple structure is specified in the form of a cartesian product of component sets. To develop linguistic object descriptions, we employ tuple structures that reflect syntactic structures observed in natural language. We can distinguish two different types of atomic valid sentences, copulative sentences and attribute sentences.

4.2.1 Copulative Sentences

In linguistics a copulative sentence is a sentence where the verb acts as a nexus between two meanings. Such verbs are called copulative verbs, and have practically no meaning, acting as a copula between subject and complement. The complement is the most important word in the sentence, while the verb expresses time, mode and aspect. In English, the most common copulative verb is the verb *to be*. Other examples include to appear or to become.

Table 1: Summary of sentence types.

	Atomic Sentence (AS)		Compound Sentence
Type	Copulative	Attribute	
Basic Structure	$Q \times S \times V \times C$	$Q \times S \times V \times C \times T$	$AS \times O \times AS$
Example	Some Minutes in Hour 1 are Normal	Most Minutes in Hour 1 have Low Pulse rate	Minute 1 has Low Pulse rate **and** Minute 1 has High Temperature

Our framework emulates copulative sentences as QSVC clauses, meaning that they can take values from the cartesian product $Q \times S \times V \times C$ (where Q, S, V, C, stand for quantifier, subject, verb and complement). Adding a "null element" to Q, we can also have sentences in the form SVC. Bellow we show some examples:

- $\frac{null}{Q}\ \frac{Min\ 1}{S}\ \frac{is}{V}\ \frac{Normal}{C}.$
- $\frac{Most}{Q}\ \frac{Hours}{S}\ \frac{are}{V}\ \frac{Abnormal}{C}.$
- $\frac{Some}{Q}\ \frac{\frac{Minutes}{R}\frac{in}{P}\frac{Hour\ 1}{A}}{S}\ \frac{are}{V}\ \frac{Normal}{C}.$

4.2.2 Attribute Sentences

While copulative sentences describe objects characteristics, we sometimes need to describe a specific attribute. For example, *Most Minutes have Normal Heart rate*. In some occasions this expressions can be transformed into a copulative sentence. However, in some others such transformation is not natural. For that reason, we introduce *attribute sentences*. These sentences are QSVCT clauses (where Q, S, V, C, T, stand for quantifier, subject, verb, complement and attribute), with an admissible sentence structure $Q \times S \times V \times C \times T$. Q includes the "null element" in order to allow the creation of SVCT clauses. The following examples show valid attribute sentences:

- $\frac{null}{Q}\ \frac{Minute\ 1}{S}\ \frac{has}{V}\ \frac{High}{C}\ \frac{Pulse\ rate}{T}.$ To simplify the notation we will omit instances of the null element. Thus, this sentence will be expressed as $\frac{Minute\ 1}{S}\ \frac{has}{V}\ \frac{High}{C}\ \frac{Pulse\ rate}{T}.$
- $\frac{All}{Q}\ \frac{Minutes}{S}\ \frac{have}{V}\ \frac{High}{C}\ \frac{Temperature}{T}.$
- $\frac{Some}{Q}\ \frac{\frac{Minutes}{R}\frac{in}{P}\frac{Hour\ 1}{A}}{S}\ \frac{have}{V}\ \frac{Low}{C}\ \frac{Pulse\ rate}{T}.$

4.3 Compound Sentences

Copulative and *attribute* sentences constitute what we call atomic sentences. Employing them we can create many sentences, which are easy to specify and understand for humans. Meanwhile, the structural and lexical constraints substantially limit the diversity and flexibility of everyday language, ensuring that the resulting summaries can be effectively interpreted and created by robots.

However, in certain occasions, particularly when it is necessary to define complex perception functions, we may need to combine atomic sentences obtaining more complex sentences, called compound sentences. A compound sentence consists of multiple atomic sentences combined using operators from the set O. Some examples may include:

- $\frac{\frac{Minute\ 1}{S}\ \frac{has}{V}\ \frac{Low}{C}\ \frac{Pulse\ rate}{T}}{Atomic\ sentence}\ \frac{and}{O}\ \frac{\frac{Minute\ 1}{S}\ \frac{has}{V}\ \frac{High}{C}\ \frac{Temperature}{T}}{Atomic\ sentence}.$
- $\frac{\frac{Some}{Q}\ \frac{\frac{Minutes}{R}\frac{in}{P}\frac{Hour\ 1}{A}}{S}\ \frac{have}{V}\ \frac{Low}{C}\ \frac{Pulse\ rate}{T}}{Atomic\ sentence}\ \frac{and}{O}\ \frac{\frac{Most}{Q}\ \frac{\frac{Minutes}{R}\frac{in}{P}\frac{Hour\ 1}{A}}{S}\ \frac{have}{V}\ \frac{High}{C}\ \frac{Temperature}{T}}{Atomic\ sentence}.$

compound sentences are the key mechanism that allows the combination of perceptions to build the double hierarchy.

5 PERCEPTION FUNCTIONS

5.1 Example

Before formalizing perception functions we illustrate them by means of an example, where a robot recognizes boxes while navigating through a building. Using its sensors the robot obtains a set of measurements concerning some relevant attributes. In particular, each box has six attributes, height, width, length and the three RGB color coordinates. For each attribute we define fuzzy sets identifying level-0 local perception functions. In this example we focus on size attributes and employ the partitions shown in Figure 2, where *low* and *high* refer to height, *narrow* and *broad* to width, and *short* and *long* to length. These partitions were specifically designed for this example in a subjective way. However, in many cases, in order to design these partitions the help of an expert or the use of more sophisticated tools will be necessary, as explained in Section 5.5. To obtain a more sophisticated description we can combine these three

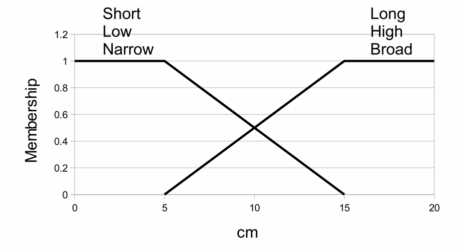

Figure 2: Fuzzy sets describing height, width and length.

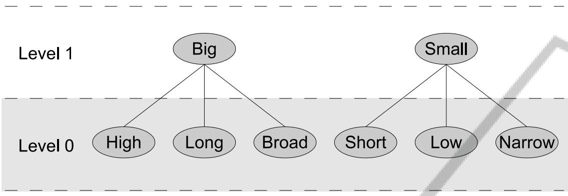

Figure 3: Simple hierarchy of local perceptions.

attributes, creating the concept of size, and the perceptions big and small. *box is big* could be defined as *box is high* **and** *box is broad* **and** *box is long*, on the other hand, *box is small* could be defined as *box is low* **and** *box is narrow* **and** *box is short*. In this way we have created a simple hierarchy of local perceptions as the one showed in Figure 3.

Using these local perception functions we start building the global hierarchy, which defines concepts concerning more than one object. We group boxes depending on their location and define global perceptions that describe sets of boxes present in a room. Such perceptions are obtained combining top-most perceptions from the local hierarchy. For instance, using fuzzy quantifiers we define *Most boxes in Room are Big*, where most is a proportional quantifier as shown in Figure 4. These fuzzy quantifiers were subjectively defined trying to be as general as possible. However, these concepts can be application dependent and it could be necessary to use techniques as those shown in Section 5.5 to define them. Following the same procedure we can describe other global perceptions functions as *Few boxes in Room are Big*, *About half boxes in Room are Small*, and so on.

At a higher level it can be necessary to regroup boxes, for example joining all boxes found in the

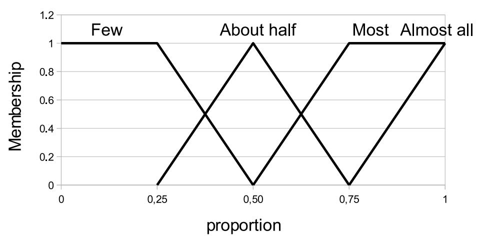

Figure 4: Fuzzy sets describing quantifiers.

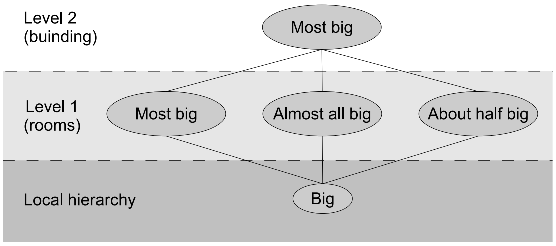

Figure 5: Simple hierarchy of global perceptions.

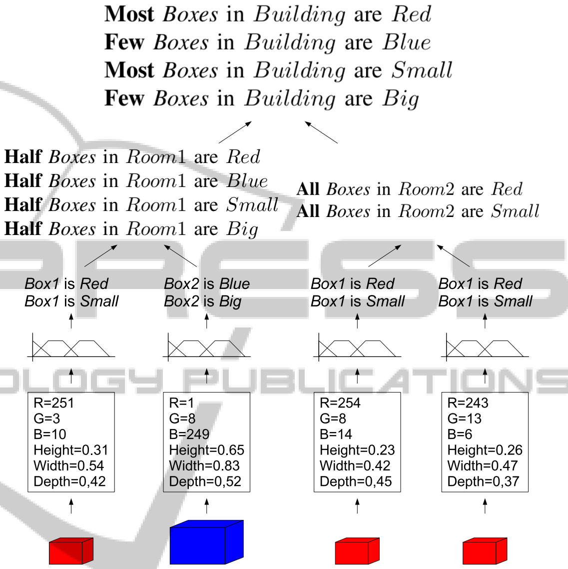

Figure 6: An example of the obtained perceptions.

same building. If the building is just composed of *Room 1* and *Room 2*, this is the same as joining the boxes from *Room 1* and *Room 2*. For instance, we can define more elaborated global perceptions as *Most boxes in building are big* as a combination of perceptions from the first level. In particular, we can define it as *(Most Boxes in Room1 are Big* **and** *Most Boxes in Room2 are big)* **or** *(Almost all Boxes in Room1 are Big* **and** *About half Boxes in Room2 are Big)*. In a similar way we can characterize other global perception functions as *Few Boxes in building are big*, *About half boxes in building are Big*, *Almost all boxes in building are Big*, and so on. Figure 5 shows the part of the global hierarchy concerning the global perception function *Most boxes in building are Big*.

Figure 6 shows an example of the kind of abstractions obtained by a robot. In particular, the robot observes four boxes present on a building with two rooms, and employs the previously defined perception functions to abstract data. Only those abstractions that obtained a high membership value are shown.

5.2 Fuzzy Sets, Fuzzy Quantifiers and Perceptions

In this section we introduce some common concepts used in fuzzy sets theory and necessary to fully understand this paper.

Let X be the universal set, or the set of all elements of concern in a given context. In traditional *crisp* sets, the function that defines a crisp set assigns each element in the universal set a membership value of either 0 or 1, therefore discriminating between members and nonmembers. In contrast, fuzzy sets generalize this function in such a way that the values assigned to the elements of the universal set fall within a specified range and indicate the membership grade of these elements in the set in question (Klir and Yuan, 1995). Larger values denote higher degrees of set membership. Such a function is called *membership function*.

Nonetheless, in order to obtain functions that represent complex concepts, single fuzzy sets are not enough. Therefore it is necessary to combine different fuzzy sets. This can be done using fuzzy operations of complement, union and intersection.

The complement of a fuzzy set is specified in general as $c : [0,1] \to [0,1]$, and represents the degree to what an element does not belong to a fuzzy set. The complement has to satisfy the following axioms (Klir and Yuan, 1995):

- $c(0) = 1$ and $c(1) = 0$.
- $\forall a,b \in [0,1], if a \leq b$, then $c(a) \geq c(b)$.

And it is desirable that satisfies these axioms:

- c is a continuous function.
- c is involutive, which means that $c(c(a)) = a$ for each $a \in [0,1]$.

Sugeno class complements (Sugeno, 1977) are a widely used family of involutive complements.

The union of two fuzzy sets is specified in general as $u : [0,1] \times [0,1] \to [0,1]$, and has to satisfy the following axioms:

- $u(0,0) = 0; u(0,1) = u(1,0) = u(1,1) = 1;$
- $u(a,b) = u(b,a);$
- If $a \leq a'$ and $b \leq b'$, then $u(a,b) \leq u(a',b');$
- $u(u(a,b),c) = u(a,u(b,c)).$

A function that satisfies these axioms is usually called a triangular conorm or t-conorm. One of the most commonly used t-conorms is *max*, however, many others have been proposed (Klir and Yuan, 1995).

On the other hand, the intersection of two fuzzy sets is specified in general as $i : [0,1] \times [0,1] \to [0,1]$, and has to satisfy the following axioms:

- $i(1,1) = 1; i(0,1) = i(1,0) = i(0,0) = 0;$
- $i(a,b) = i(b,a);$
- If $a \leq a'$ and $b \leq b'$, then $i(a,b) \leq i(a',b');$
- $i(i(a,b),c) = i(a,i(b,c)).$

A function that satisfies these axioms is usually called a triangular norm or t-norm. One of the most commonly used t-norms is *min*, however, many others have been proposed (Klir and Yuan, 1995).

Along with these fuzzy operators it is necessary to use linguistic or fuzzy quantifiers to define complex functions. A quantifier is a logic operator that limits a variable specifying its quantity. Zadeh (Zadeh, 1983) introduced fuzzy quantifiers, representing them as fuzzy sets. We can distinguish two general classes of quantifiers: absolute and relative. Absolute quantifiers are defined as fuzzy subsets of $[0,+\infty]$ and can be used to represent statements like, *about six* or *less than twenty*. Relative quantifiers are defined as fuzzy subsets of the interval $[0,1]$ and can express concepts like *most*, *about half* or *almost all*.

5.3 Formalizing Perception Functions

Let us suppose that we are observing a set of objects $O = \{1,2,\dots\}$, where every object is described by a set attributes $A = \{a_1,\dots,a_n\}$, whose domains are $A_1,\dots,A_n$, being n the number of attributes.

After observing an object $o \in O$ we obtain a measurement $m_o \in \times A_i$, which specifies the values measured in the object for each attribute. We call $M = \{m_o : o \in O\}$ the set of all measurements, where for each object $o \in O$ we have exactly one measurement.

5.3.1 Local Perception Functions

We define local perception functions as functions $L_j^k : \times_{i=1}^n A_i \to [0,1]$ that describe individual objects, where k indicates the level of the function in the hierarchy, and j is an index to identify each function. If $k = 0$, then $L_j^k(M_o)$ represents a fuzzy membership function. On the other hand, when $k > 0$ $L_j^k(m_o)$ is defined as a combination of local perception functions from level $k-1$, using fuzzy union ($\wedge$), intersection ($\vee$) and negation ($\neg$). For example, L_1^1 can be defined as $L_1^1(m_o) = (L_1^0(m_o) \wedge L_2^0(m_o)) \vee \neg L_5^0(m_o)$. This is a process analogous to that followed in the example to define function *Big*.

Note that we can take advantage of the fact that every $L_j^k(M_o)$ is defined as a function of local perception functions from level $k-1$ to save computational effort, by calculating truth values in ascending order.

5.3.2 Global Perception Functions

Global perception functions describe groups of objects called aggregations. At each level of the global hierarchy the set of measurements is partitioned obtaining a set of aggregations, or aggregation set, that will be recursively defined. We will use a superscript to specify the level of the aggregation set in the global hierarchy. Let $S^0 = M$, then for each level $v \geq 1$ we define a partition S^v of S^{v-1}; $S^v = \{s_1^v, s_2^v, ...\}$, $\forall i, j; i \neq j; s_i^v \cap s_j^v = \emptyset$, $\bigcup s_l^v = S^{v-1}$. These partitions are used to group measurements in sets from which we will obtain global perceptions. In the example shown in Section 5.1, aggregation sets correspond to the groupings of boxes, for instance, boxes in room 1.

The domain induced by an aggregation set S^v is referred to as $D^v = (\times_{i=1}^n A_i)^{|s_l^v|_{max}}$. Where $|\cdot|_{max}$ indicates the maximum number of measurements m_o that a $s_l^v \in S^v$ can contain. We characterize the $r-th$ global perception function from $v-th$ level of the global hierarchy as $G_r^v : D^v \to [0,1]$. Such functions describe groups of objects, indicating to which degree they present a given characteristic. When $k \geq 1$, the $r-th$ global perception function, G_r^v, is obtained as a combination of global perception functions from level $v-1$, using $\wedge$, $\vee$, $\neg$ and fuzzy quantifiers. When $k = 0$ G_r^{v-1} are substituted by local perception functions of the top-most level of the local hierarchy. For instance, we can define $G_1^3(s^3) = Q\ s_i^2\ in\ s_j^3\ are\ G_1^2(s_i^2)$, where Q is a fuzzy quantifier.

In the example proposed in Section 5.1, perceptions *Most Big* (level 1 and 2), *Almost all Big*, *About half Big* are examples of global perception functions, which use diverse fuzzy quantifiers.

Since global perception functions are organized as a hierarchy, where functions in the higher levels are obtained as combinations of functions of lower levels, we can easily simplify their domains. In this way, the domain of G_r^v can be reduced to $[0,1]^x$, where x represents the number of perception functions from level $v-1$ that compose G_r^v.

5.4 Partition of the Set of Measurements

In order to create global perception functions it is necessary to define adequate partitions of the set of measurements M. In particular, one partition per hierarchy level. These partitions are crucial to obtain meaningful descriptions of the data, and consequently, it is necessary to define them carefully. We distinguish two methods to define partitions, space-driven and data-driven.

Sometimes the space where observed objects can be found induces partitions in an intuitive or natural way. For instance, in the example of the robot monitoring a patient, it was natural to group measurements indicating activity in minutes, hours, and so on. Analogously, in the example of the robot exploring a building, observations where intuitively grouped depending on where they took place, a room, or a building. We call these partitions space-driven partitions.

In certain occasions, however, the partition of the set of measurements is not so immediate. Particularly when perception functions are designed to find specific or special structures among objects. In such cases it is necessary to analyze data looking for those specific patterns, and we cannot arbitrarily partition the set of objects according to the structure of the space. We need to group objects taking into account the information they present and the defined perception functions. This process can be complex and may require the use of approximate tools like genetic algorithms. For instance, Zwir (Zwir and Ruspini, 1999) and Romero-Zaliz (Romero-Zaliz et al., 2008), used genetic algorithms together with fuzzy definitions of structures to describe time series and DNA sequences, respectively. Since these partitioning processes depend on the actual data and perception functions, we call them data-driven partitions.

5.5 Defining Perception Functions

Perception functions are the core of the proposed framework, and thus, they have to be carefully specified. In most cases they can be defined with the help of domain experts, who know which features are more interesting or relevant. For example, in the medical scenario previously introduced, experts like doctors or nurses can indicate which information is more relevant to detect potential problems. Many previous efforts use this approach (Zwir and Ruspini, 1999; Martin et al., 2006; Anderson et al., 2008).

In other areas, however, defining perception functions is not so automatic and it is necessary to discover them from historical data. For instance, a robot used for elder care may need to learn what can be considered the *normal* behavior of its owner, in order to discover uncommon behavior patterns that may indicate health problems. In these cases the use of unsupervised learning strategies, as fuzzy clustering, can be very helpful. This approach has been used by Wilbik et al. (Wilbik et al., 2012) and by Romero-Zaliz et al. (Romero-Zaliz et al., 2008).

6 FROM PERCEPTION FUNCTIONS TO SENTENCES

In this section we specify how perception functions can be translated into valid sentences from the formal logic and vice versa. To explain the process we establish a mapping between component sets and the elements used to build perception functions.

We assume that each object is represented by a logic constant and has a unique identifier or name, being all object names included in component set N. Each attribute is also given a unique name and component set T contains all attribute names. Each local perception function is also given a unique name, the set of all names of local perceptions is added to component set C. In addition, for each local perception function it is necessary to indicate if it should be worded as a copulative or an attribute sentence.

Local perception functions worded as attribute sentences need one more step when their level is 1 or more. In particular, a new artificial attribute has to be created and added to T. For example, when we recognize objects, the color is perceived with three different attributes R, G, and B, and the attribute *color* is artificial, as it is obtained combining these three attributes.

Furthermore, the fact that level n, with $n > 0$, local perception functions are obtained using fuzzy operators makes it possible to *explain* the meaning of the perception function, obtaining a compound sentence that includes all the level $n-1$ local perception functions that compose it. Such sentences are combined using the operators in $O = \{and,\ or,\ not\}$.

When local perception functions are combined to obtain global perception functions, the process to obtain sentences is slightly different. First, in this case the unique name is optional, since some of the functions may only specify aggregations with no individual meaning. For instance, in the patient monitoring example, we can specify that a night in which *Most hours in night are quiet* can be also explained as *night is quiet*. However, in the box aggregation example, a sentence *Some boxes in Room 1 are Blue*, has no equivalent copulative sentence. In any case, if they are given a name, they follow a treatment similar to level n local perception functions, where we have to specify if they are copulative or attribute sentences. In the last case, it is also necessary to indicate the name of the artificial attribute and add it to T.

Obtaining an *explanation* for global perception functions is a bit more complicated than for local, given the fact that they may include quantifiers and variables, in addition to logic operators. Quantifiers treatment requires the definition of a unique name for each quantifier. The set of all names of the available quantifiers constitutes component set Q. Regarding variables, it is necessary to define one variable name per level in the hierarchy. Starting in level 1 with a variable name for the domain of the objects, and continuing with each subsequent level. For instance, in the patient monitoring example, since minutes constitute the objects in level 1, we have *minutes* as level 1 variable name, *hours* as level 2 variable name, and so on. On the other hand, in the boxes example, the variable name for every level is *boxes*. Component set R includes all variable names. In addition, all the elements included in aggregation sets need unique identifiers to allow their use as a subject or as a bound for variables, and each one of these names has to be included in component sets N and A. For instance, we may obtain the following summaries, *Hour 1 is quiet* and *Most minutes in Hour 1 are quiet*, in which *Hour 1* is the name of an element of level 2 aggregation set that is used as a subject, in the first sentence, and as a bound, in the second. With respect to combinations of perception functions using logical operators the process is equivalent to that used for local perception functions.

Once this mapping has been established we can easily translate perception functions into sentences and vice versa, obtaining a language that is both easily interpretable for humans and robots. Table 2 summarizes the mapping between component sets and the elements used to define perception functions.

7 CONCLUSIONS

In this paper we present a general framework to provide robots with information abstraction and aggregation capabilities. This framework allows robots to obtain high-level summaries and descriptions of complex objects, events, and relations in terms that are easy to comprehend by both humans and robots.

In order to obtain such abstractions we rely on what Zadeh has described as perceptions (Zadeh, 2001), which group observations into fuzzy granules. This approach changes the traditional standpoint, which emphasizes detail and precision. By doing so we expect to overcome the problems shown by traditional methods, which fail to recognize major features, themes and motifs.

In addition, perceptions are translated into expressions easy to interpret by humans and robots. We have defined a predicate logic that acts as a middle-ground between natural language and low-level commands, which limits the diversity and flexibility of everyday language. Nonetheless, logic sentences syntax emulates syntactic structures frequently observed in nat-

Table 2: Mapping between component sets and perception functions.

Component set	Perception function element
Q	Fuzzy quantifiers
N	Object names, names of elements in aggregation sets
R	variable names defined per level
A	names of elements in aggregation sets
P	purely linguistic, it does not depend on the perception function, initially we will only use *in*
S	$N \cup R \cup (R \times P \times A)$
V	verbs that can be used, initially to be and to have
C	local and global perception functions names (for those global that have a name)
T	names of objects attributes and *artificial attributes*
O	and, or, not

ural language, facilitating human interpretation, even for naive users.

Perception functions, and their associated linguistic descriptions, are organized following a hierarchy. This structure permits the creation of appropriate summaries that change the level of detail depending on the targeted user. It also provides an easy way to explain high-level perceptions, navigating through the hierarchy, and favors computational efficiency.

In addition this framework is a first step towards obtaining an operative precisiation language that allows us to compute with perceptions. Such language makes it possible to represent the meaning of a proposition drawn from a natural language. And consequently, provides a basis for a significant enlargement of the role of natural languages in scientific theories.

As future work we plan to extend the framework, incrementing the number of available structures. Some possibilities include:

- The use of linguistic hedges to annotate complements/perception functions.
- The introduction of new types of declarative sentences.
- Permitting the qualification of subjects. Like in the sentence *Most* Red *boxes are Big*.
- Allowing the use of compound complements. Like in the sentence *Most boxes in Room 1 are Red and Big*.

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