

Using Fuzzy Logic to Monitor the State of an Ubiquitous Robotic System

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Received 22 July 2007; Accepted 27 December 2007

Abstract

A trend is emerging in the fields of ambient intelligence (AmI) and autonomous robotics, which points in the direction of a merger between these two fields. The inclusion of robotic devices in AmI system, sometimes named *ubiquitous robotics*, makes one of the hard problems in this field even harder: how can we provide a comfortable, natural interface between the everyday user and a complex system which consists of a large multitude of highly heterogeneous devices? In this paper, we address a specific, important aspect of this problem: to enable the user of an ubiquitous robotic system to monitor the state of this system in a natural way. The solution that we propose is based on two mechanisms: an *expression-based semantics* to represent in a uniform way the status of heterogeneous devices; and a *common interface point* to aggregate the information from all devices into a summary status presented to the user. For both mechanisms, we propose to use the tools of fuzzy logic. We justify this choice by arguments grounded in the semantics and formal properties of fuzzy logic. We also illustrate our approach on a specific type of ubiquitous robotic system called *Ecology of Physically Embedded Intelligent Systems*, or PEIS-Ecology.

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Keywords: ambient intelligence, ubiquitous robotics, network robot systems, human-robot interaction, cooperative systems, robot ecology

1 Introduction

There is a marked tendency today toward the embedding of many ubiquitous, intelligent, networked robotic devices in our homes and offices. This tendency is witnessed by the growing interest in the field of ambient intelligence and smart homes, as well as by the new emerging fields of intelligent spaces [17] and ubiquitous robotics [14, 20, 29]. The development of these ubiquitous domestic systems is often motivated by the desire to improve the quality of life of citizens in general, and in particular of those citizens with special needs like elderly people or people with disabilities [25, 10]. In this context, it is essential that this development is accompanied by the development of suitable *interfaces* that ensure the usability and acceptability of these systems [24, 10].

The problem of interfacing with an ubiquitous domestic system is different from, and more complex than, the conventional human-computer interface problem [9, 30]. Although a typical ubiquitous system consists of a collection of heterogeneous, inter-connected devices, it should be perceived by the user as one system and the interaction should obey one set of rules — as close as possible to the interaction rules which are natural to the user [1]. This entails two major challenges. First, the user should interact with all the devices according to a uniform model, thus hiding the *heterogeneity* of the devices [35, 16]. Second, this interaction should happen through one and the same virtual interface point, thus hiding the underlying *complexity* of the whole system [31].^a

In this paper, we address a specific, important case of this interface problem: to enable the everyday user of the ubiquitous (AmI or robotic) system to monitor the state of the system. Even in this restricted case, we still need to address the heterogeneity and the complexity problems above. Figure 1 graphically illustrates our approach. First, the status information of each device in the system is translated to a *common representation*, endowed with a uniform semantics which is independent on the heterogeneous nature of the different devices. Second, the status information from all devices is *combined* into an overall status that

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^aAlthough the interface point is virtually unique, it should be possible to physically instantiate it at different locations and via different modalities, depending on the context [32, 24].

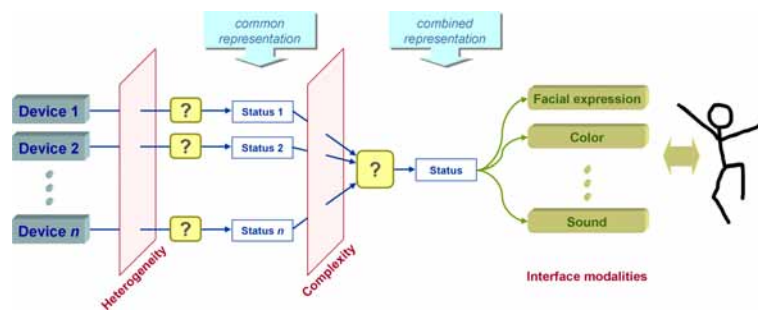


Figure 1: Schematic illustration of the approach presented in this paper, and of its two main challenges: how to represent the status of heterogeneous devices in a uniform way; and how to combine the status of each device into an overall status according to a possibly complex combination pattern.

gives a summary view of the entire system, abstracting the underlying complexity. This overall status can be presented to the user via a suitable choice of modalities, including facial or bodily expressions of synthetic actors, sounds, lights, colors, and so on. The question marks in figure 1 highlight the two main challenges that need to be addressed in order to apply this approach: how to find an adequate common representation, and how to combine information into a summary assessment.

In the work presented here, we use fuzzy logic techniques to address the two challenges above: to represent status information, we use fuzzy values under a desirability interpretation [26, 27]; and to combine individual items of status information into a summary one, we use fuzzy propositional calculus. In addition, we associate fuzzy (desirability) values with human-understandable expressions, like ‘sad’ or ‘happy’, which are visualized to the human user via an animated character. Although fuzzy logic has been applied previously to ambient intelligence settings [3, 28, 8, 13], we are not aware of other uses of fuzzy logic to provide a uniform way to encode, combine and visualize the status of an ambient intelligence or an ubiquitous robotic system.

In the rest of this paper, we present our proposed approach in the above direction. Our approach is in principle applicable to any heterogeneous distributed system. For concreteness, however, in this paper we consider a specific system for ubiquitous robotics, named *Ecology of Physically Embedded Intelligent Systems*, or PEIS-Ecology. The next section provides a reminder on PEIS-Ecology. In Section 3 we describe our use of fuzzy logic to represent the status of each device by what we call an *expression-based semantics*. Section 4 deals with the problem of how to combine the status information from different devices into one overall status using the mechanisms of fuzzy logic. Section 5 discusses our sample implementation of the ideas in this paper, and shows a simple illustrative example, and Section 6 concludes.

2 The PEIS-Ecology Approach

The concept of PEIS-Ecology, originally proposed by Saffiotti and Broxvall [29], combines insights from the fields of ambient intelligence and autonomous robotics, to generate a new approach to the inclusion of robotic technology into everyday environments. In this approach, advanced robotic functionalities are not achieved through the development of extremely advanced robots, but rather through the cooperation of many simple robotic components. The concept of a PEIS-Ecology builds upon the following ingredients.

First, any robot in the environment is abstracted by the *uniform notion* of a PEIS (Physically Embedded Intelligent System), which is any device incorporating some computational and communication resources, and which is capable of interacting with the environment via sensors and/or actuators. A PEIS can be as simple as a toaster and as complex as a humanoid robot. In general, we define a PEIS to be a set of inter-connected software components, called PEIS-components, residing in one physical entity. Each component may include links to sensors and actuators, as well as input and output ports that connect it to other components in the same or another PEIS.

Second, all PEIS are connected by a *uniform communication model*, based on a distributed tuple-space [12]. This model allows the exchange of information among PEIS, and can cope with their joining and leaving the ecology dynamically, while hiding the heterogeneity between PEIS and in the physical communication layers.



Figure 2: A simple PEIS-Ecology consisting of a vacuum cleaner, a tracking system, and a plant.

Third, all PEIS can cooperate using a *uniform cooperation model*, based on the notion of borrowing functional components: each participating PEIS can use functionalities from other PEIS in the ecology in order to complement its own. We define a *PEIS-Ecology* to be a collection of PEIS which are all embedded in the same physical environment and adhere to the above models.

As an illustration, consider the autonomous vacuum cleaner (PEIS) in figure 2. By itself, this simple device can only use basic reactive cleaning strategies, because it does not have enough sensing and reasoning resources to assess its own position in the home. But suppose that the home is equipped with an overhead camera-based tracking system, itself another PEIS. Then, we can combine these two PEIS into a simple PEIS-Ecology, in which the tracking system provides a global localization functionality to the vacuum cleaner. Suppose then that the vacuum encounters a plant, and that the plant is equipped with a micro-PEIS (e.g., a mote) able to communicate its properties — e.g. size, humidity, and type of support (static or wheeled). Then, the vacuum can use these properties to decide whether or not it can push the plant away and clean under it.

In our realization of a PEIS-Ecology, the PEIS rely on a distributed middleware to communicate and cooperate, called the PEIS-middleware. The PEIS-middleware implements a distributed tuple-space on a dynamic P2P network: PEIS exchange information by publishing tuples and subscribing to tuples, which are transparently distributed by the middleware. By stipulation, each PEIS also publishes a set of standard tuples, e.g., to announce its physical appearance or to advertise the functionalities that it can provide. More details on the PEIS-middleware can be found in a number of technical papers [4, 5], available from the PEIS-Ecology project web site [22].

3 Expression-Based Semantics

The first of the two challenges listed in the Introduction is how to address the *heterogeneity* problem: that is, how to represent in a uniform way the status information about different, heterogeneous devices in the ubiquitous system — in our case, about different PEIS in a PEIS-Ecology.

For most PEIS, the PEIS has an internal status from which we can distinguish “normal” and “abnormal” conditions. Different PEIS, however, have different ways to represent their status, and different variables and physical quantities are involved in these normal or abnormal conditions. For instance, in the above scenario, the plant may need watering, or the cleaning robot may be running out of batteries: the relevant measures are, respectively, the ground humidity and the battery voltage.

In order to provide a uniform way to treat these conditions, we consider an abstract notion of “satisfaction”, and we encode the degree of satisfaction of each PEIS by a fuzzy predicate with values in the $[0, 1]$ interval. In our example, both the plant and the vacuum cleaner would have associated fuzzy predicates, say *plant-ok* and *vacuum-ok*, whose values range from total dissatisfaction (0) to total satisfaction (1). This use of fuzzy predicates is compatible with the semantic interpretation of fuzzy logic in terms of desirability proposed by Ruspini [26, 27] after the seminal work by Rescher [23]. According to that interpretation, the degree of truth, in a given state s , of a fuzzy predicate (e.g., *plant-ok*) measures the degree by which state s is *desirable* from the point of view expressed by that predicate (i.e., that the plant is ok). The latter corresponds precisely to the degree of satisfaction, in state s , of the PEIS associated to that predicate (i.e., the plant).

In general, the desirability of a state for a given PEIS may depend on several factors. In the vacuum cleaner example, a state may be desirable if in that state the battery is charged, and the vacuum dust-bag is not full. For each one of these factors, we introduce an atomic fuzzy predicate of the relevant variables. For instance, the fuzzy predicate $\text{fullbattery}(v_b)$ represents the degree of satisfaction of the vacuum cleaner from the point

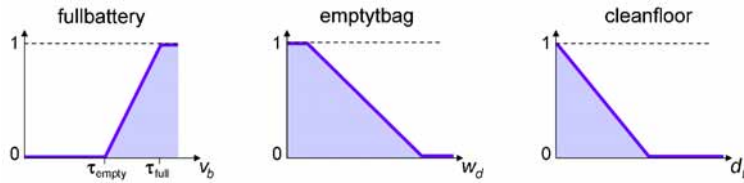


Figure 3: Fuzzy satisfaction predicates for the vacuum cleaner.

of view of having a charged battery. The truth value (degree of satisfaction) of $\text{fullbattery}(v_b)$ depends on the battery voltage v_b , as shown in figure 3 (left), where τ_{empty} and τ_{full} are voltage thresholds corresponding to the conditions of the battery being fully empty and fully charged, respectively. In a similar way, the fuzzy predicate $\text{emptybag}(w_d)$ represents the degree of satisfaction of the vacuum cleaner from the point of view of having an empty dust-bag. Its truth value depends on the dust-bag fill level w_d , as shown in figure 3 (middle). (The other predicate in the figure will be discussed in the next section.)

The overall satisfaction of the vacuum cleaner, represented by the fuzzy predicate vacuum-ok , is obtained by a suitable combination of the atomic predicates that represent the different factors that contribute to its satisfaction. How the combination is done will be discussed in the next section. What we wish to emphasize here is that the use of fuzzy predicates allows us to represent in a uniform way the satisfaction status of any PEIS in a PEIS-Ecology, irrespective of the internal details of the PEIS and on the physical quantities which this status relates to.

Since our goal is to convey the satisfaction status to the user, we endow the satisfaction predicates with what we call an *expression semantics*. We associate the truth value of these predicates to human-understandable expressions. This semantics is informally defined by the following stipulations:

- the value 0 is associated to a ‘sad’ expression;
- the value 1 is associated to a ‘happy’ expression; and
- for any $x, y \in [0, 1]$, if $x > y$ then the expression associated to the value x is ‘happier than’ the expression associated to the value y .

Expressions can be communicated to the human user via a suitable interface modality (e.g., sound, light, gestures) provided that this modality can comply with the above semantic stipulations. In particular, it should be possible to define a ‘sad’ and a ‘happy’ expression, and it should be possible to define what it means for an expression to be ‘happier than’ another one. Said differently, a suitable interface modality should be able to generate a set of expressions that are totally ordered with respect to ‘happiness’, and that have a top and a bottom element. In our prototype implementation, we use facial expressions of a simple animated character. These expressions are generated by changing the geometric parameters of the face, and cover a continuous range from fully sad (0) to fully happy (1). Figure 4 shows three expressions corresponding to three different degrees of satisfaction.

The fact that different modalities can be used to represent status information is a consequence of the uniform nature of expression semantics. In particular, this semantics is not only uniform with respect to the heterogeneity of the devices being monitored, but it is also uniform with respect to the interface modality used to convey information to the user. For instance, we could modulate the color of a given artifact (e.g., a lighted sculpture) to convey expressions, provided that we have an intuitive mapping between colors and perceived expressions — or the corresponding emotions. Mappings of this type are studied in psychology and design [33, 19]. The possibility offered by the expression semantics of rendering the same status using different modalities is especially interesting in an ubiquitous or ambient intelligence setting: in general, the choice of the most adequate modality depends on several contextual conditions, including the user’s current location and activity, ambient light, noise level, and so on. The development of techniques to automatically select the most adequate modality would be an interesting extension to the study presented in this paper.

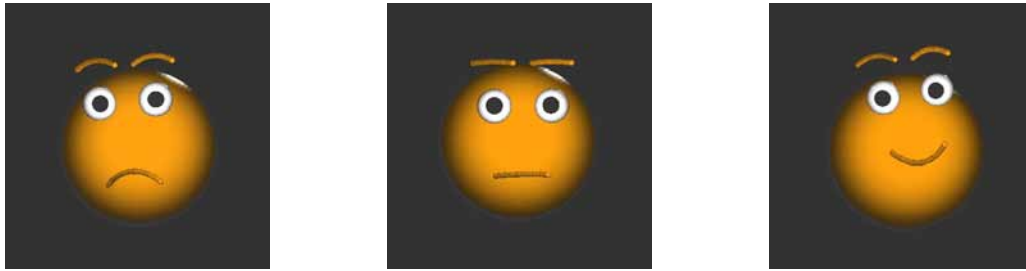


Figure 4: Visualization of the satisfaction status for three different values. Left: 0.2 (rather sad, serious problems encountered). Middle: 0.6 (slightly concerned, minor problems encountered). Right: 1.0 (fully happy, everything is fine).

4 Common Interface Point

Now that we are able to represent in a uniform way the satisfaction status of each individual PEIS in a PEIS-Ecology, we can turn our attention to the second challenge listed in the Introduction. How can we combine all this information into one single, overall item of information that gives the user an overall view, at a glance, of the status of the entire PEIS-Ecology? Three factors contribute to complicate this problem.

- (a) The combination can be more complex than simply taking the average (or minimum) of all the individual values of satisfaction. For instance, the fact that the batteries in the vacuum cleaner are discharged indicates a problem if the floor needs to be cleaned, but it does not if the floor is already clean.
- (b) It should be possible to compute this combination in a modular and decentralized way, to account for the distributed nature of a PEIS-Ecology.
- (c) It should be possible to trace back the source of a low satisfaction status, and present this to the users in order to help them to identify the origin of a problem and possibly correct it.

The fact that we use fuzzy predicates to represent satisfaction values allows us to use the mechanisms of fuzzy logic to combine these values. In this section, we show that doing that allows us to properly address all the three aspects above.

4.1 Encoding complex combination patterns

In our framework, we encode combinations of satisfaction conditions by using propositional formulas in fuzzy logic, built upon the fuzzy predicates that we used to encode the individual satisfaction conditions. We then evaluate the overall satisfaction degree by computing the corresponding degree of truth of that formula.

Consider again our vacuum cleaner. This PEIS includes the following PEIS-components: a *battery-manager*, which manages the battery and monitors the current voltage v_b ; a *dustbag-sensor*, which determines the fill level w_d of the dust-bag using an internal sensor, and stops the vacuum if the bag is full; and a *dirt-sensor*, which senses the amount of dirt under the vacuum and maintains a cumulative value d_t of the total dirt encountered over the last n minutes of operation. Correspondingly, the vacuum cleaner includes three fuzzy satisfaction predicates: $\text{fullbattery}(v_b)$ and $\text{emptybag}(w_d)$, discussed above, and $\text{cleanfloor}(d_t)$, true if no remaining dirt was detected on the floor. Figure 3 above shows a possible definition of these fuzzy predicates. The overall satisfaction of the vacuum cleaner, then, can be represented by the fuzzy predicate vacuum-ok defined by the following logical formula

$$\text{vacuum-ok} = (\text{fullbattery} \wedge \text{emptybag}) \vee \text{cleanfloor}, \quad (1)$$

where we omit for simplicity the arguments of the predicates. According to (1), the vacuum cleaner is satisfied if it is in good operating conditions (battery charged and dust-bag not full), or if there is no remaining dirt to clean.

The use of fuzzy logic formulas to represent satisfaction conditions can be extended to the case of multiple PEIS. Suppose that the plant in our small ecology is a PEIS which includes two PEIS-components, one that measures the humidity and one that measures the temperature. Then, we can define two corresponding fuzzy

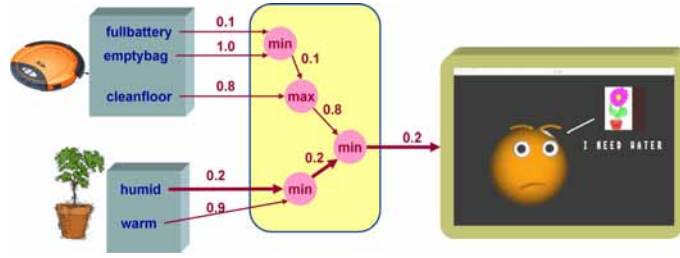


Figure 5: Computing the overall state of a simple ecology from the state of each individual component. An icon of the main culprit of the low satisfaction state is shown to the user.

predicates, respectively named *humid* and *warm* with the obvious meaning of measuring the satisfaction status of the plant from the point of view of having enough water and of being at the right ambient temperature, respectively. (The definitions of these predicates clearly depend on the type of plant, and on the best humidity and temperature levels for it [6].) The satisfaction of the plant, then, can be represented by the fuzzy predicate *plant-ok* defined by the following logical formula

$$\text{plant-ok} = \text{humid} \wedge \text{warm}. \quad (2)$$

We can now define the overall satisfaction Φ of our simple PEIS-Ecology by the formula:

$$\Phi = \text{vacuum-ok} \wedge \text{plant-ok} \quad (3)$$

$$= ((\text{fullbattery} \wedge \text{emptybag}) \vee \text{cleanfloor}) \wedge (\text{humid} \wedge \text{warm}) \quad (4)$$

The satisfaction degree of our ecology at time t , then, is obtained by computing the truth value of Φ at time t , which we denote $\llbracket \Phi \rrbracket_t$. This is computed from (4) according to the usual rules of fuzzy logic:

$$\llbracket \Phi \rrbracket_t = (((\llbracket \text{fullbattery} \rrbracket_t \otimes \llbracket \text{emptybag} \rrbracket_t) \oplus \llbracket \text{cleanfloor} \rrbracket_t) \otimes (\llbracket \text{humid} \rrbracket_t \otimes \llbracket \text{warm} \rrbracket_t)) \quad (5)$$

where: \otimes is any T-norm; \oplus is the corresponding T-conorm [34, 15]; and the truth values of the individual fuzzy predicates at time t depend on the value, at time t , of the corresponding state variables: e.g., $\llbracket \text{fullbattery} \rrbracket_t = \text{fullbattery}(v_b(t))$.

Figure 5 shows an example of this computation, using the min/max pair for \otimes/\oplus . At the current time t , the battery level $v_b(t)$ is approaching the empty-battery threshold τ_{empty} . Correspondingly, we have $\llbracket \text{fullbattery} \rrbracket_t = 0.1$. However, the cumulative dirt count w_d computed over the last few minutes is rather low, which gives us $\llbracket \text{cleanfloor} \rrbracket_t = 0.8$. Hence, the overall level of satisfaction of the vacuum cleaner is 0.8. For the plant, however, the humidity sensor is measuring an insufficient level of humidity, which causes $\llbracket \text{humid} \rrbracket_t = 0.2$. This results in a low level of satisfaction of the overall ecology: $\llbracket \Phi \rrbracket_t = 0.2$.

The use of fuzzy propositional logic to encode combinations of satisfaction conditions has three advantages. First, it allows us to address desideratum (a) above, since we can use the full expressive power of propositional calculus to represent complex combination patterns. Second, we have a wide variety of \otimes/\oplus operators to choose from, depending on which behavior we want to model. For instance, if having two PEIS with low satisfaction values should be regarded as worse than having just one, we should use a strict T-norm (e.g., product), so that the combination of two low values would be even lower. Third, for any operator choice, we are guaranteed that the values computed are semantically consistent with our interpretation of the satisfaction values, since this interpretation is consistent with the desirability interpretation of fuzzy logic [26]. That is, if each atomic predicate in a combination represents a degree of satisfaction, then the combined value also represents a degree of satisfaction — the one of the corresponding logical combination.

4.2 Distributed computation

Turning now to desideratum (b) above, we notice that in general a PEIS-Ecology has a hierarchical structure. In fact, each PEIS consists of a set of more elementary PEIS-components: in our example, the vacuum cleaner

PEIS has three components, and the plant PEIS has two components. Moreover, PEIS in the ecology might be grouped into sub-ecologies according to some structure. An obvious grouping can be induced by the structure of the environment, e.g., all the PEIS in the kitchen can form the kitchen sub-ecology, and all the sub-ecologies in the house can form the overall house PEIS-Ecology. Notice that membership to sub-ecologies may change dynamically: for instance, the vacuum cleaner may exit the kitchen sub-ecology and enter the bedroom one during its operation. A similar hierarchical and dynamic structure may characterize most other systems of ubiquitous robotics and ambient intelligence.

In practice, it is unrealistic to assume that the overall equation Φ is represented and computed at one single place in the PEIS-Ecology — that is, at the interface point. This would require that the interface point has access to the status of each individual PEIS-component in the PEIS-Ecology; and that the representation of the Φ formula inside the interface point is updated every time a PEIS joins or leaves the ecology. A more efficient and modular solution is to distribute the representation of the Φ formula in the PEIS-Ecology. In our implementation, we keep the formula that combines the satisfaction status of all the PEIS-components of a given PEIS inside that specific PEIS. The truth value is computed locally inside the PEIS, and the result is propagated outside to be further combined. For example, Φ in equation (3) above is computed by first evaluating the truth value of `vacuum-ok` and `plant-ok` separately inside the respective PEIS, and then combining these values at the interface point:

$$\llbracket \text{vacuum-ok} \rrbracket_t = (\llbracket \text{fullbattery} \rrbracket_t \otimes \llbracket \text{emptybag} \rrbracket_t) \oplus \llbracket \text{cleanfloor} \rrbracket_t \quad (6)$$

$$\llbracket \text{plant-ok} \rrbracket_t = \llbracket \text{humid} \rrbracket_t \otimes \llbracket \text{warm} \rrbracket_t \quad (7)$$

$$\llbracket \Phi \rrbracket_t = \llbracket \text{vacuum-ok} \rrbracket_t \otimes \llbracket \text{plant-ok} \rrbracket_t \quad (8)$$

It is worth to emphasize that the ability to freely distribute the computation across PEIS comes from the fact that T-norms and T-conorms are associative and commutative. If we used operators outside the scope of fuzzy logic (for instance, arithmetic average), distribution might not be possible.

4.3 Tracing the source of a problem

The last desideratum above (c) can also find a simple solution using fuzzy logic. Assuming that we use the min/max pair for \otimes/\oplus ,^b the formula Φ that encodes the overall status of the PEIS-Ecology can be put in Disjunctive Normal Form [11]:

$$\Phi = \bigvee_{i=1}^n \left(\bigwedge_{j=1}^{k_i} l_{ij} \right) \quad (9)$$

where l_{ij} are literals. Then, we can find the literal which can be regarded as the main “culprit” of a low overall value of satisfaction by: (1) finding the clause i with the highest truth value, and (2) finding the literal with the lowest truth value inside that clause. If there is only one such literal, say l_{ij} , we take it to be the most direct cause of the low desirability of Φ . This literal is such that $\frac{\partial \Phi}{\partial l_{ij}} > 0$, that is, increasing the satisfaction of l_{ij} would immediately result in an increase in the overall satisfaction Φ . The “culprit” PEIS-component, then, is taken to be the one associated to that literal. If there is more than one literal with the lowest value in the clause, all the corresponding PEIS-components share responsibility for the unsatisfactory situation.

In practice, the literal (PEIS-component) with the lowest value can be found by following the lowest values backward in the computation tree. In the example in figure 5, the path leading to the low 0.2 satisfaction value is marked by thick arrows, and the culprit is the `humid` predicate in the plant PEIS. In our implementation, each PEIS has an associated graphical icon, and each of its components has an associated text that gives an explanation of why it would be unsatisfied. This icon and text are visualized in the graphical interface in order to give the user an immediate indication of what is going wrong: in figure 5, the artificial character is visualizing the plant’s icon with the explanatory text “I need water”.

The above procedure is simplistic, and it may lead to counter-intuitive results in some cases. While some heuristics can be added to this procedure to improve culprit identification, a more thorough treatment of this problem should probably address it using more sophisticated reasoning methods, including qualitative reasoning [21] or fuzzy abductive inference [18].

^bThis assumption is not strictly needed, but it simplifies the computation described below.

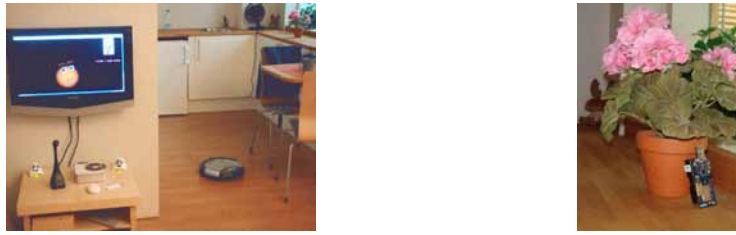


Figure 6: Two views of the experimental testbed. Left: the expressive face interface shown on a TV screen. Right: A MoteIV Tmote used to monitor temperature and humidity of a plant.

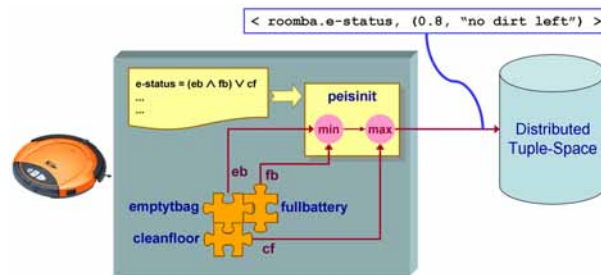


Figure 7: Each PEIS computes its local satisfaction status in its “peisinit” component.

5 An Experimental System

In order to verify the viability of the ideas presented above, we have performed a few simple experiments in the framework of our PEIS-Ecology testbed [22]. This is a small bachelor apartment (about 25 m²), which we call the PEIS-Home (see figure 6). The PEIS-Home has a living room, a bedroom, and a kitchen. It is equipped with a number of PEIS, including mobile robots, a smart refrigerator, ceiling cameras, a media center, and others. These PEIS can communicate and cooperate using the PEIS-middleware introduced in section 2 above. The PEIS-Home also includes a few everyday objects which have been converted into PEIS by the inclusion of small computing and communication devices [4]. Figure 6 (right) shows a plant equipped with a MoteIV “Tmote Sky” mote that incorporates temperature and humidity sensors, and can exchange tuples with all the PEIS in the PEIS-Ecology.

Each PEIS produces its satisfaction information by regularly publishing tuples in the PEIS-Ecology distributed tuple-space. These tuples have as key the reserved key **e-status**, and as values the current satisfaction value (an arbitrary float between 0 and 1) together with an explanatory text (a string). The **e-status** tuples are generated inside the PEIS by a special component, called **peisinit**, which is responsible for the initialization, maintenance, and configuration activities for that PEIS. We have extended **peisinit** to also: (a) combine the satisfaction values provided by the components inside the PEIS into an overall value, according to a given combination formula, like formula (1) above; (b) generate an explanatory string derived by the culprit component, determined as above; (c) publish a **e-status** tuple that contains that value and that string. Figure 7 shows the above elements for the vacuum cleaner PEIS. The combination formula and the explanation strings are currently pre-compiled into the PEIS, but we plan to eventually specify them as parameters using standardized languages like XML or FML (fuzzy markup language) [2]. As for T-norm and T-conorm, we currently use the min/max pair.

To visualize the status of the PEIS-Ecology, we have implemented a simple interface point that subscribes to all the **e-status** tuples, combines them into an overall satisfaction value, and visualizes this value by a facial expression. If the satisfaction value is below a given threshold, the icon and the explanatory text of the “culprit” are also visualized as explained above. Figure 6 (left) shows the interface visualized on the PEIS-Home TV set. In our future work, we plan to explore the use of other modalities to realize expressions (e.g., a user interface pet-robot [7]).

6 Conclusions

Expression-based semantics provide a uniform way to represent status information across a highly heterogeneous distributed system, to summarize this information, and to convey it to the user. In this paper, we have shown that fuzzy logic provides an adequate set of tools to convert expression-based semantics in an effective and well-founded computational framework. While we have used our PEIS-Ecology testbed as an illustrative example, we believe that the principles and techniques introduced in this paper can be applied to any system of ubiquitous robotics, ambient intelligence, or pervasive distributed computing.

The study of expression-based semantics has just started, and many issues remain to be investigated. Among the most urgent ones: How can we weight the satisfaction values to take into account the user's needs, priorities and preferences? How can we convey "expressions" using other modalities, like sound or color? Can we extend the expression-based semantics by adding more dimensions, corresponding to other types of states, like danger or surprise?

Acknowledgments

This work was partly supported by ETRI (Electronics and Telecommunications Research Institute, Korea) through the project "Embedded Component Technology and Standardization for URC (2004-2008)". We are grateful to Mathias Broxvall and Jayedur Rashid for their help with the implementation of the experimental system.

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