Fuzzy Based Model to Detect Patient's Health Decline in Ambient Assisted Living

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Abstract: Detecting a decline in the health condition of a patient may still be considered a challenge in Ambient Assisted Living (AAL) since the concept of 'decline' is vague and imprecise. In this context, Fuzzy Logic comes as an excellent alternative for AAL systems. This paper presents a model based on Fuzzy logic reasoning in order to identify a possible decline in the patient health condition. In order to achieve this goal, the model considers relevant situations that may somehow impact the patient. To evaluate the model, a case study was developed, showing that the developed model can simulate the human reasoning and be used in an AAL system.

1 INTRODUCTION

Fuzzy logic (Bai; Wang, 2006) is present in our daily lives. Some concepts used in everyday life, such as *tall*, *cold*, *young*, among others, may be vague and difficult to be clearly defined without generating ambiguity. For example, a person may say that a 28-year-old person is young, but another may not agree with this point of view.

Fuzzy logic is an extension of the classic Boolean logic that, by introducing the concept of degree, makes it possible to present much more precise results when dealing with uncertainty and vagueness.

This logic aims at formalizing the human reasoning in a much more natural way than it would be done by just applying 0's or 1's, values known by machines. Lately, this kind of reasoning has been applied in complex systems (Marro et al., 2010) such as expert systems and systems that deal with artificial intelligence or human behaviour.

Ambient Assisted Living (AAL) (Pieper; Antona; Cortés, 2011) is a field that, most of time, has to interpret the human behavior. AAL applies technology in order to assist elderly people in their daily lives aiming at providing a safer environment and, consequently, improve their life quality.

AAL also has as its goal to provide more independence for the patient, making it possible for the elderly person to live longer in his/her residence, many times, without the need of the presence of a caregiver.

However, despite all technology provided, it is common that some patients present a natural decline in their health condition, what should be perceived by AAL systems. Nonetheless, *'detecting a decline'* can be seen as a very vague idea since it is hard to define and describe what exactly means a decline. A patient's decline can be defined differently by two different doctors, for example.

Additionally, another important aspect to be noticed is the fact that the data obtained through sensors may be imprecise and, many times, incomplete. In this context, Fuzzy Logic can be applied aiming to present a much more reasonable solution, since its main goal is the computational modeling of the human reasoning, which is imprecise and vague (Marro et al., 2010).

This paper defines a model that considers relevant situations for a patient in an AAL environment in order to detect whether he is presenting a decline in his health condition.

Considering the fact that detecting a situation (health decline, in our case) presents a considerable level of uncertainty summed to the feature of

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human-like language of the Fuzzy logic, this work will facilitate caregivers' work in an AAL. Our model aims at achieving a result closer to what would be achieved by human reasoning and can be implemented allied with other already published reasoning models in AAL. In addition, since an AAL environment presents multiple applications and sensors, a new application making use of this model can be easily introduced to the environment.

This paper is structured as follows: Section 2 presents a background of the concepts used in this work. In Section 3, related works are presented. The developed model is presented in Section 4 followed by Section 5 that presents a case study demonstrating the use of this model in a case study. Finally, in Section 6, the conclusions and future works are presented.

2 BACKGOUND

In order to make the reader more familiar with the model developed in this paper, this section explains the concept of Fuzzy Logic and the three steps of its process (fuzzification, inference, deffuzification). We also present the main concepts related to AAL systems and its main goals.

2.1 Fuzzy Logic

The concept of Fuzzy logic was introduced in 1965 by Lotfi Zadé. According to Zadé (Zadé, 1965), terms such *'fast'* and *'hot'* can be created and implemented only by human beings. In other words, computers are not capable of reasoning on such terms, because they only interpret the meaning of 0 and 1 (Bai; Wang, 2006). He also highlights that such way of expressivity exerts an important role on the logic and human reasoning.

In this way, Fuzzy logic introduces the concept of degree instead of getting limited to only *'true'* or *'false'*. In Fuzzy logic everything can present a degree that is represented by a word or by a numeric value (usually the interval 0...1 is used), indicating the degree of veracity of the information.

The Fuzzy processing is a crisp-Fuzzy-crisp process (Bai; Wang, 2006). It means that (i) input values are crisp (classical logic), (ii) in order to be processed, these values are converted to Fuzzy, and (iii) the result is converted back to crisp.

The most well-known method for achieving the Fuzzy inference process, is the Mandami method (Marro et al., 2010). According to Mandami, the three necessary steps to implement Fuzzy logic in an application consist of: fuzzification, process of Fuzzy inference and defuzzification.

2.1.1 Fuzzification

In order to make it possible for machines to process vague information, it is necessary to convert the input and output data, so far crisp (numeric), to linguistic variables with Fuzzy components. To achieve this goal in the Fuzzification process, first, the *membership functions* ($\mu(x)$) are defined to every possible input or output variable.

Membership functions (George; Bo, 2008) indicate the degree that an element belongs to a given set. For example, given an input variable *'temperature'*, three membership functions are defined: '*cold*' (0-20), '*normal*' (10-30) and '*warm*' (20-40). After this definition, the input values (usually obtained through sensors, other systems, etc.) are calculated identifying what is known as the *membership degree* to each membership function defined. Supposing that the input value for temperature is 12°, the membership function will identify a membership degree greater than 0 for '*cold*' and '*normal*', but 0 for '*warm*'.

2.1.2 Fuzzy Inference Process

In this step, the membership degrees are combined with *inference rules* (Bai; Wang, 2006) in order to obtain a Fuzzy output value. The inference rules are generated based on the human knowledge and experience over the application domain. These rules are known as *if-then* rules, representing what action should be taken or what information is obtained based on the input value. An example related to temperature is given below:

```
IF temperature IS high
THEN reduceSpeed.
```

(Vieira, 1999) highlights that there is not a mathematical formulation to generate these rules. They are usually defined by an expert and must be very intuitive (Bai; Wang, 2006) (Vieira, 1999), presenting as aspect to be easy to understand and comprehend when read by humans.

2.1.3 Defuzzification

This step consists in an inverse process in relation to Fuzzification. In other words, the result obtained is converted from linguistic back to crisp (numeric) and, then, can be applied in an application or system. There are different methods available that can be applied in this process. However, Center of Gravity (COG) (Dernoncourt, 2011) is the most commonly used method.

Due to the characteristic of the use of natural language, Fuzzy logic suits well in technologies that deal with human reasoning and behaviour. Expert systems and Ambient Intelligence are examples of technologies that present meaningful research and works implementing Fuzzy logic (Marro et al., 2010). Ambient Assisted Living is also a field that, many times, has to interpret vague and imprecise concepts and, also, try to reproduce the human reasoning. This field is better described in the next section.

2.2 Ambient Assisted Living (AAL)

Ambient Assisted Living (AAL) is a field within Ambient Intelligence (AmI) that focuses on the use of ubiquitous or pervasive technology in elderly's residences (Aarts; Wichert, 2009). This field has been widely explored in several researches in the field of Computer Science (Pieper; Antona; Cortés, 2011).

AAL aims at creating a safe environment able to improve elderly's autonomy and to assist them in daily activities, making it possible at the same time, to preserve their independence (Sun et al., 2009). One of its main goals is to extend the time that the elder will be able to continue living in his/her residence without the need of the care of a third part.

Some examples of technologies (Rashidi; Mihailidis, 2013) in AAL are: applications capable of alerting the patient to the correct use of his medicine; sensors that detect possible falls; and robots able to help with simple routine tasks, such as sweeping the floor or washing dishes.

In other words, AAL covers concepts, products and services that connect new technologies to the patient's own environment, being it possible to be used in the prevention, cure and improvement of his health condition as well as of his wellbeing.

3 RELATED WORK

It is possible to find many works in the literature that aim at contributing to detect and/or avoid unwanted situations in AAL. Many of these works report the inconvenience of devices that require some attention of the user to operate.

In (Storf et al., 2009), for example, an approach was described for detecting situations in an AAL environment in order to act in a proactive way and avoid emergencies. Their approach focused on the use of non-obtrusive devices and this was achieved by the use of information obtained from sensors in the environment and by the analysis of daily and historical data of the patient.

Based on the fact that many times an undesired situation may occur as a result of some other previous situations or actions mistaken by the patient, (Machado et al., 2017) presented an approach that makes use of Bayesian Networks and aims at an early detection of these undesired situations in order to avoid them. With this, this work presented the importance of mechanisms that act not only reactively, but also proactively in AAL.

When it comes to the use of Fuzzy Logic in AAL, we can give as an example the system proposed by (Nefti; Manzoor; Manzoor, 2010). Their work consisted of a "*multi-agent system based application used to assess the risk level in different situations to patient*", which goal is to monitor patients suffering from dementia. Fuzzy logic was applied to predict the risk assessment, as it can simulate human-like decisions to determine the best course of actions to be taken.

By the analysis of works like the mentioned ones, we can see the importance of detecting situations in order to avoid future unwanted ones.

Another aspect to be considered is, since Fuzzy logic makes use of a very human-like language, we realize that Fuzzy logic makes it possible to users who are not information systems experts to reconfigure the system. This would not be achieved in a trivial way by the use of Bayesian Networks, for example.

(Walley, 1996) compares some measures that are used when dealing with uncertainty in expert systems. Since he describes and compare general features on Fuzzy Logic and Bayesyan Probabilities (among others), his comparison can also be applied to the context of this paper.

Walley highlights the contribution of the Fuzzy Logic to expert systems due to the design of natural language reasoning and the introduction of possibility measures models. According to him, Fuzzy logic has the advantage of handling well the aspect 'imprecision', since it is one of its main goals. In addition, it also addresses well the aspect 'assessment', since it makes it possible to the users of the system to use natural language when describing the uncertainty on the domain.

One advantage of Bayesian probabilities is that they guarantee consistency in their rules, what may be different in Fuzzy Logic (Walley, 1996). However, they do not handle well aspects such as uncertainty in natural language and incomplete information. Also, Bayesian probabilities are not satisfactory when it comes to modeling vague terms or vague probabilities as, for example, 'Mary is probably young'. Bayesians demand precise probability models and lack in the aspect 'imprecision' being, therefore, not suitable for our work.

The model presented in this paper does not intend to replace neither put in question any other work previously published. Instead, it creates the possibility of joining some different existing models in order to achieve a more specific goal in AAL (to detect a decline). Such feature was not attended by any of the previously mentioned researches and was even being ignored by the execution of actions that avoid undesired situations but do not identify a cognitive decline.

The next section presents the model developed in this work.

4 FUZZY BASED MODEL FOR AAL

Within the set of vague concepts that cannot be simply identified with a 'true or false' value without generating ambiguity or the need for further explanation, is the concept of '*health decline*'. In order to make it possible to a system to achieve a result closer to a human being reasoning in this vague context, we developed a model based on Fuzzy logic to detect a possible health decline of a patient in an AAL environment.

The model considers that a decline degree can be achieved after the defuzzification of the impact degree obtained from different situations considered relevant for the patient. More specifically, we establish that a health decline is influenced by the occurrence of situations that affect negatively the patient, the impact that they have on his wellbeing, and it is aggravated by the recurrence of these situations within a certain period of time (Figure 1).

For the concept of situation, we adopted the concept used in (Machado et al., 2017) that describes a situation as a set of active entities and the interactions between them in a frame of time. In other words, a situation has a start and an end time, is composed of entities, their attributes and the relations between these entities. In the AAL context, some examples of situations can be: *Patient felt*, *Patient had a heart attack* and *Patient forgot taking a medicine*.

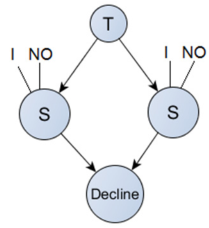

Figure 1: Health decline model. T: time interval, S: situation, I: impact degree, NO: number of occurrences.

It is important to point out that every patient may present different relevant situations, identified in the model as linguistic variables to be considered. For example, for some patients it is important to consider possible falls, however, for a patient in a wheelchair this information may have no relevance.

This work does not detect these situations, our focus is on the detection of a possible health decline. Therefore, in order to identify the relevant situations, some related works can be applied as, for example, the framework presented in (Machado et al., 2016). This framework makes use of a Multi-Entity Bayesian Network (MEBN) and presents an ontology network in order to predict unwanted situations in smart environments.

Our Fuzzy based model (c) depends on a database (a) containing data about the patient (usually obtained from sensors or other systems) and a rule base (b) (may be specified by an expert in the domain or by machine learning). After the fuzzy reasoning, the information obtained is available to be used by any external system (d). Figure 2 illustrates the model (c) and its external connections (a, b and d).

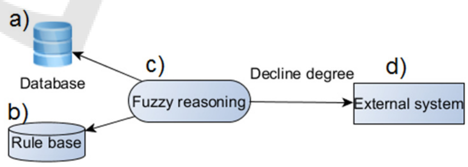

Figure 2: Fuzzy based model and its external connections.

The model developed is composed of 3 stages (Figure 3). These stages are described in the sequence:

4.1 Stage 1

In the first stage, all relevant input linguistic variables (*a.1, b.1, ... , n.1*) should be detected presenting the corresponding membership functions. These variables correspond to situations faced by the patient that present some risk to his wellbeing

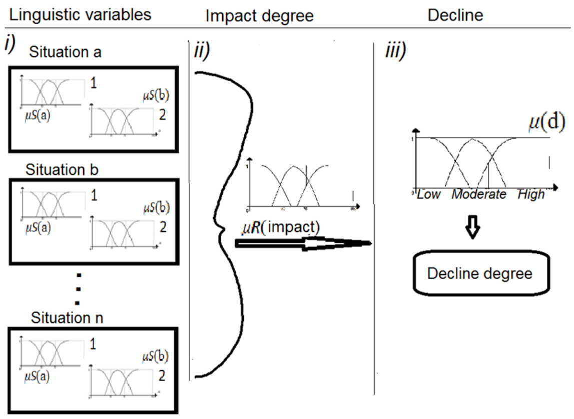

Figure 3: Fuzzy model.

impacting in a health decline. For each linguistic variable, a membership degree (μ(S)=x) must be identified, which is the input used to achieve the impact degree in the fuzzy controller.

As mentioned before, the situations may be different for each patient and can be obtained from different sources. Besides the framework cited, other examples of sources are experts and ontologies. Nonetheless, the membership degree should be defined by an expert or it can be the output originated from the processing of previous linguistic variables in a Fuzzy controller.

For example, let us suppose that one of the variables that is being considered is the level of forgetfulness of a patient over his medicines (*level_forget*: {*low, moderate, high*}). Detecting this level, may not be possible without, among other relevant coefficients, analysing the importance of the medicine (*medicine_relevance*:{*notMuch, moderate, important*}) and for how long the medicine was forgotten (*medicine_forgot*: {*shortPeriod, moderatePeriod, longPeriod*}. These data could have been pre-processed by a Fuzzy controller being, therefore, *level_forget* value the defuzzificated output of it.

Associated to each linguistic variable defined, there must be a second linguistic variable (*a.2*) that defines the number of occurrences (*num_occurrences*) of this situation in some interval of time defined according to the need. The membership functions defined for *num_occurrences* in this model are 5, being labeled as: *never*, *few*, *moderate*, *many*, *always*. Its bounds vary according to the interval of time defined. This leads us to conclude that there must exist a database containing historical data obtained from sensors or applications available for this patient.

4.2 Stage 2

Impact degree (*impact_degree*) is also defined as a linguistic variable (output), being its membership degree (μ(I)=x) the output resulting from the execution of the inference rules applied to the membership functions of the linguistic variables previously defined. This process must happen in each input linguistic variable identified.

The possible source for retrieval of the inference rules could be: an expert; machine learning; a base of rules previously defined in the system; another system or model that makes use of methods as the one presented by (De Campos; Moral, 1993).

The membership functions for the variable *impact_degree* are labeled as: *low* (0-4), *moderate* (1-9), *high* (6-10).

Again, it is important to remember that the linguistic variable related to the number of occurrences must be always considered in an inference rule. For example:

```
IF level_forget IS high
AND num_occurrences IS many
THEN risk IS HIGH

IF level_falling IS moderate
AND num_occurrences IS moderate
THEN risk IS HIGH
```

4.3 Stage 3

After having the membership degree values for *impact_degree*, it is finally possible to figure out whether or not a decline in the patient's health condition is happening. Basically, in this stage, after aggregating the membership degrees for *impact_degree* and identifying the resulting fuzzy set for *decline_level* (*low, moderate, high*), there will happen the process of defuzzification. Further studies should be realized in order to identify the most recommended defuzzification technique to be applied in this model. Meanwhile, we recommend to use COG, the most commonly used one.

We consider that for a result with *'0'* value means that there is absolutely no decline in the patient situation, however the *'10'* value means that there is a *'complete'* decline and some providence should be taken as fast as possible. For any different value in the interval 0-10, the application using this model should decide how to proceed.

5 CASE STUDY

In order to demonstrate the use of the presented model, we defined a fictitious scenario of a patient living in an AAL environment. The Fuzzy controller tool available in Matlab (*Fuzzy Logic toolbox*) was used to process the data.

Let us consider the following scenario: *"Mr. Miller is a 77 year old retired citizen who lives in an AAL residence and has some aging-associated diseases such as memory disorders, hypertension and Parkinson's disease (what can increase the risk of falls). Because of his condition, he takes different kinds of controlled medicines. Each medicine presents a different impact and relevance in his treatment in case of omission. Considering that Mr. Miller's current health situation is defined as stable, he does not need the constant presence of his caregiver. However, in the AAL residence, there is a middleware (Machado et al., 2017) that uses the given Fuzzy based model and constantly monitors his health situation in order to identify a decline and possible need of a full-time caregiver."*

Considering the scenario described and the model defined in the previous section, the following activities must be identified in order to implement the model:

5.1 Identification of Possible Risky Situations

With the help of Mr. Miller's physician and a database containing a history of his situation from the last two months (falls, medicine's usage, hospitalizations, among others), two situations are identified as possibly offering some risk to his treatment: *falls* (situation A) and *forgetfulness of medicine usage* (situation B). In this context, the two linguistic variables defined are:

(a) **Falls_Level**: Represents a history of falls of the patient. The membership functions are labelled as *light_fall* (when there was no injury and the patient straightened up by himself; interval: 0-3.5), *moderate_fall* (the patient needed help to stand up and there may be an injury; interval: 2.5-5), *heavy_fall* (the patient was injured and possibly hospitalized; interval: 4-10);

(b) **Forgetfulness_Level**: represents a historical of the patient's forgetfulness of the usage of his medicines. The membership functions are labelled as *low* (0-3.5), *moderate* (3-6), *high* (5-10).

Considering the registers contained in the database, we suppose that both situations are first processed in a Fuzzy controller in order to achieve a value that will be used as the input value in our model. In other words, the membership degrees for both linguistic variables are the result of the output of another Fuzzy reasoning.

In situation A, for example, all registers of falls were analysed considering their gravity (resulted in injury or not), whether someone had to be contacted, etc. Then these registers were processed in a Fuzzy controller and the value 4.2 was obtained. Similarly, the registers for medicines usage were analysed considering whether the medicine was taken late or it was not taken, the relevance of the medicine, its acceptable delay, among other factors.

Table 1 shows the input values identified, as well as the membership degree for the variable *num_occurrences* of each of these variables.

Table 1: Input values.

Situation	Value	Number of occurrences
A	4.2	6
B	3.8	18

The number of occurrences considers all registers, independently of their level/degree. As the period considered is two months, the bounds for the membership functions in *num_occurrences* are defined in days as follows: never (0-5), few (4-15), moderate (10-25), many (18-55), always (53-60).

Finally, we have the four input variables (Figure 4) that will be used in our Fuzzy controller, which will have as output *'impactA'* for the impact level identified.

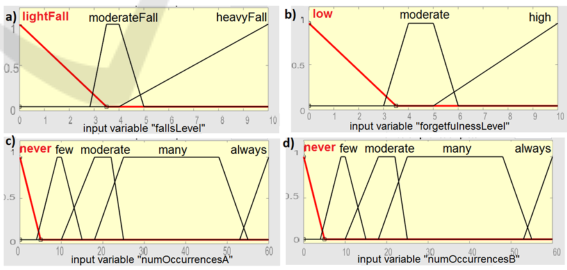

Figure 4: Input linguist variables. (a) *fallsLevel*, (b) *forgetfullnessLevel*, (c) *numOccurrencesA*, (d) *numOccurrencesB*.

5.2 Identify the Membership Degree of Impact for Each Defined Linguistic Variable

To define the inference rules, it is required a high level of knowledge about the situation in order to get a good approximation to human reasoning. In this case, we consider that the rules were derived according to the knowledge of Mr. Miller's physician. The inference rules are illustrated in the matrices in Figure 5.

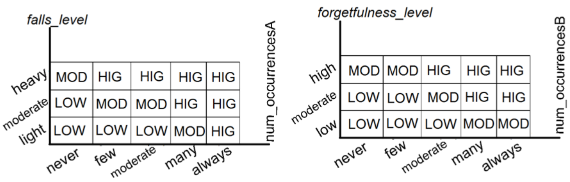

Figure 5: Inference rules matrices.

Based on these matrices, it is possible to describe linguistically the inference rules as, for example:

```
IF falls_level IS light
AND num_occurrencesA IS always
THEN impact IS high

IF forgetfullness_level IS high
AND num_occurrencesB IS few
THEN impact IS moderate.
```

Notice that the impact value increases (is aggravated) as the number of occurrences also increases.

5.3 Identifying Possible Decline

By applying the inference rules to our input variables, impact membership degrees are obtained and then aggregated in order to identify the resulting Fuzzy set (Figure 6(d)).

Then, the defuzzification method COG is applied and we, finally, have a result that identifies a possible decline in the health condition of Mr. Miller (Figure 6(b)).The result obtained in this case study was 5.04, what represents a significant decline in the health situation of the patient. Supposing that an application that makes use of this model considers that for any value above 4 means that the patient needs the attention of a caregiver, this is the moment that the application would alert Mr. Miller's health provider. A physician analysing the data provided summed to his knowledge about the context, would probably achieve the same conclusion – there is a significant decline. In this way, we achieve the goal for this model - the result obtained simulates the human reasoning using vague concepts.

Another advantage of the use of a system using this model is the possibility of, when a decline is identified, the caregiver/doctor can verify what is influencing it in an easy to understand language. For example, if the system makes it available the inference rules and a graphic view of the inference, the person analysing it will be able to identify the linguistic variables (falls, medicine forgetfulness, among others) and easily comprehend it. With that, the routine or environment of the patient can suffer adaptations in order to be improved.

Summarizing, the application of the model in the case study made it possible to determine the health decline of the patient involved in the scenario by using vague concepts. In this way, the use of this model allied with other reasoning models for AAL (Maran et al., 2015) could be efficiently used by AAL systems.

6 CONCLUSIONS

Ambient Assisted Living (AAL) is a field that deals with people, their actions, behaviour, and even

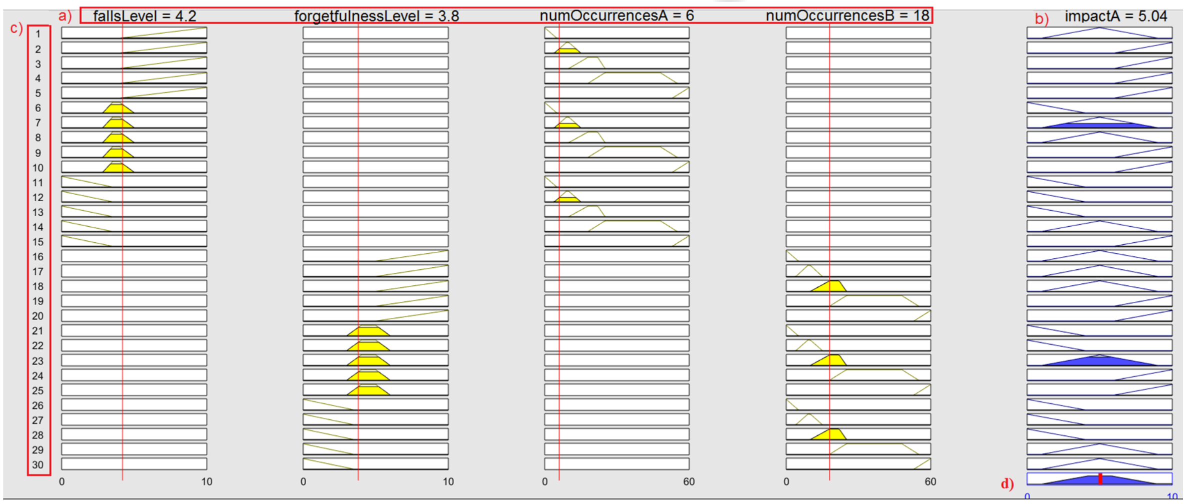

Figure 6: Fuzzy inference. (a) crisp input values, (b) crisp final result, (c) Fuzzy rules applied, (d) Fuzzy resulting set.

emotions. None of these aspects is very precise being it, many times, hard to define a yes or no, black or white. Considering that detecting a decline in the health situation of a patient in an AAL may be vague and difficult, this paper presented a model that makes use of Fuzzy Logic to achieve this goal.

To detect a health decline, our model considers as input values daily situations that are faced by the patient and may offer some risk to his wellbeing. The impact of each situation is processed in a Fuzzy controller and, finally, a value for the decline is obtained. In order to better explain our model, we presented a case study with a fictitious scenario.

We are aware that the model presented in this paper is not the only possible way to detect a decline in the health situation of a patient. Many other methods can be applied, however, one of our goals in this work is, through the use of Fuzzy logic (since it deals with vagueness, uncertainty and aims to reproduce human decisions), to achieve a result much more close to the reality being it similar to a result that could have been obtained if the situation of the patient was being analysed by a human being (expert, physician, among others) and not by a computer limited to 0 and 1s.

As future work, we aim to elaborate an approach that identifies automatically the situations that may offer some risk to the patient generating, also automatically, the membership degree to be used as input in this model. We also aim to apply the model in a system with real data in order to develop further studies to determine the accuracy of the model developed.

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