Expert Systems with Applications 39 (2012) 10479–10488

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A Fuzzy Temporal Rule-based System for handling the Nursing Process on mobile devices

J. Medina *, M.D. Ruiz-Lozano, M. Delgado, A. Vila

School of Computer Science, University of Granada, Department of Computer Science and Artificial Intelligent, C/Periodista Daniel Saucedo Aranda s/n, E-18071 Granada, Spain

ARTICLE INFO

Keywords:
Nursing Theory
Ubiquitous computing
Fuzzy controller
Fuzzy Temporal Rules

ABSTRACT

Nowadays, mobile devices offer new methods to retrieve information everywhere. In the nursing area, this technology is highly suitable due to the ubiquity in this profession. In this paper, we present a new version of Medea, a mobile system that provides storing the evolution of patients from handheld devices using the nursing viewpoint. Medea is relied on the Need Theory of Virginia Henderson, as patient valuation model, and the nursing taxonomies of NANDA, NIC and NOC, as patient care plan. In addition, the vital signs of patients have been integrated in the mobile application. The main complementary innovation of Medea is an expert system based on fuzzy temporal rules, which suggests diagnoses, interventions and outcomes from the patient valuation and the vital signs. This model takes into account the importance of the data and temporal dimension in the patient symptoms. Furthermore, the complexity of the nursing domain has been synthesized in a few concepts, which make possible the creation of rules in an easy way.

1. Motivation

Nursing work is capital in health care systems. However, the tasks carried out by nurses are not usually recognized properly. This fact is due to the lack of written evidence about nursing cares, which is known as *nursing invisibility*. In order to solve this invisibility, we have focused our research to computerize the nursing tasks with a dual purpose: (1) to record the nursing work that is put into practice in each patient and (2) to assist the nurse in the decision making process.

In recent years several studies have been conducted in the nursing area, but most of them focus on organizing or planning nursing schedules (Tsai & Li, 2009; Yeh & Lin, 2007) in order to solve the multi-objectives nurse or minimizing patients queue time in emergency environments. Thus, nursing knowledge on patient outcomes in the hospital is not reflected. There is a real demand for applications that use a theoretical framework for the Nursing Process and makes it possible to record the work of nurses.

In other hand, the design of intelligent systems for medical diagnosis has been one of the most prolific areas. Numerous Model-Based Diagnosis techniques have been proposed and applied in this area (Fox, Glasspool, & Bury, 2001; Montani et al., 2007). However, nursing diagnosis reasoning systems are less studied, despite the work of a nurse is very important for the evolution of patient in hospital.

In general, the development of knowledge-based systems for diagnosis in medicine is still a hard process. Mainly, the difficulties that arise are: the domain complexity on knowledge, the relevance of the context and the importance of the temporal dimension. These three problems have been studied by the academic world, and many proposals have been made in several application fields (Dubois, Lang, & Prade, 1994, chap. 3; Fox et al., 2001; Marn and Navarrete, 2003; Montani et al., 2007; Pani, 2001), but most of the proposed solutions do not cover all three items. In Juarez, Camposa, Palma, and Marin (2008), a general framework is proposed for the development of Context-Dependent Temporal Diagnosis architectures to solve each of the problems cited.

In the state of the art, we can read papers about the impact of handheld devices in nursing, such as Prgomet, Georgiou, and Westbrook (2009), Rodriguez et al. (2003), and Shneyder and Pharm (2002). Even, some approaches such as Choi et al. (2004), Yang, Yang, Su, and Xue (2009), Keplar and Urbanski (2003), and Wu and Lai (2009) have been developed. Unfortunately, there is a large lack in the mobile proposals because they do not include basic concepts of Nursing Theory and neither, they do not introduce any Decision Support System.

Thus, our objective is the development of a tool where the Nursing Theory can be handled by nurses to store the values from the valuation of patients, the nursing care plan and any other relevant data. This system is called *Medea*. A previous versions of the system where presented respectively in Delgado, Medina Quero, Ruiz Lozano, and Vila (2007) and Medina Quero and Ruiz Lozano (2006). In this paper, Medea has been expanded in order

* Corresponding author. Tel.: +34 958 244019; fax: +34 958 243317.
E-mail address: javiermq@decsai.ugr.es (J. Medina).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2012.02.062

to help nurses in decision-making stage. So, we propose a Fuzzy Temporal Rule-based System for the Nursing Process, which offers nurses a set of possible nursing diagnoses, interventions or outcomes of patients. One of our goals is to provide the theoretical ground of model of Fuzzy Temporal Rules that make possible the study of the patient evolution in the complex domain of the nursing.

We want to emphasize that our aim is to computerize the Nursing Process to improve the efficiency and to communicate the knowledge of this work, without hindering the daily tasks. In order to provide a handy tool, we have developed a mobile system that integrates the Nursing Process, since the handheld devices can be carried inside a pocket and can be handled in the patient room in real time. In addition, it is essential that the system suggests and assists the nurses in decision making, guiding and facilitating their tasks.

The paper is organized as follows. In Section 2 is described the Nursing Process theoretical framework, on which we based this work. In Section 3 we present our approach. In Section 4 we describe in a detailed way our main contribution: a Fuzzy Temporal Rule-based System for the Nursing Process. It is a recommender system that suggests diagnoses, outcomes and interventions after analyzing the patient symptoms and guide nurse when choosing a care plan for patients. Finally in Section 5, we present the conclusions and future work.

2. Introduction: Nursing Process

Theory can be defined as *an internally consistent group of relational statements (concepts, definitions and propositions) that present a systematic view about a phenomenon and which is useful for description, explanation, prediction and control* (Chittty, 1993).

Nursing theories are used to describe, develop, disseminate, and use present knowledge in nursing. These theories provide a framework for nurses to systematize their nursing actions: what to ask, what to observe, what to focus on and what to think about. Thus, Nursing Theory is used to: define commonalities of the variables in a stated field of inquiry; guide nursing research and actions; predict practice outcomes; and predict client response.

There are several nursing theories for the patient cares. In this research, we have relied on models that have been put into practice successfully worldwide. Specifically, we refer to the Need Theory of Virginia Henderson (Luis, Fernandez, & Navarro, 2005) (as patient evaluation model) and the Nursing taxonomies for Nursing Diagnosis Classification (NANDA) (Nanda International, 2008), Nursing Interventions Classification (NIC) (Bulechek, Butcher, & McCloskey Dochterman, 2007) and Nursing Outcomes Classification (NOC) (Moorhead, Johnson, Maas, & Swanson, 2008).

Next, we are going to describe briefly the *Nursing Process* that reflects nurse task in the hospital. This process consists of cares carried out by the nurse to the patient. In the Nursing Process theoretical framework, we can differentiate and emphasize the following concepts: nursing valuation, nursing care plan and assessment of vital signs.

2.1. Nursing valuation

The first step, before submitting the patient to any care, consists of realizing a descriptive valuation of patient. Thus, the valuation is carried out by the nurse to assess the first contact between nurses and patients. The valuation is an essential process because it detects and delimits the disease problems. In general, the valuation reflects the physical and the psychological aspect of patient and it changes gradually depending on the state of health. As mentioned above, there are diverse valuation models that have been standardized. We have chosen the valuation model proposed by Virginia Henderson (Luis et al., 2005), who divides the valuation in fourteen basic needs:

- Physiological
  - Oxygen (breathe normally).
  - Nutrition (eat and drink adequately).
  - Elimination (eliminate body wastes).
  - Move and maintain desirable postures.
  - Sleep and rest.
  - Select suitable clothes – dress and undress.
  - Maintain body temperature within normal range by adjusting clothing and modifying the environment.
  - Keep the body clean and well groomed and protect the integument.
  - Avoid dangers in the environment and avoid injuring others.
  - Communicate with others in expressing emotions, needs, fears, or opinions.
  - Learn, discover, or satisfy the curiosity that leads to normal development and health and use the available health facilities.
- Spiritual
  - Worship according to the faith.
- Sociological
  - Work in such a way that there is a sense of accomplishment.
  - Play or participate in various forms of recreation.

The valuation will change little by little during the evolution of the patient in the hospital.

2.2. Nursing care plan

The main phase of the Nursing Process is diagnosing the diseases and complications of the patients. In nursing theoretical framework, a *nursing diagnosis* is a clinical judgment about individual, family, or community responses to actual or potential health problems/life processes. Nursing diagnoses provide the basis for selection of nursing interventions to achieve outcomes for which the nurse is accountable, which are identified and treated independently by nurses. The main organization that has developed the nursing diagnosis is NANDA (201 nursing diagnoses) (Nanda International, 2008).

After the patient valuation, nurses consider a set of diagnoses based on the obtained information. Each diagnosis links with several *nursing interventions*. The interventions represent actions that nurses carry out on the patient during the stay in hospital with the purpose of improving the disease. The official classification for the interventions is maintained by NIC (433 nursing interventions) (Bulechek et al., 2007).

Finally, the targets are represented by the *nursing outcomes*, which are used to establish the goals and objectives in nursing cares. NOC is an official classification for the outcomes (260 nursing results) (Moorhead et al., 2008).

Nurses use these concepts (diagnoses, interventions and outcomes) to prepare the patient plan. First, they establish a series of diagnoses that the patient demonstrates. Second, they assign an interventions set for each diagnosis. These interventions will carry out by the nurse on the patient. Third, nurses assigned a set of outcomes for each diagnosis. The outcomes are improvements that they expect to obtain in the patient after applying interventions.

2.3. Vital signs

One of the most important tasks for nurses is monitoring the vital signs of patients (temperature, breathing frequency, heart frequency, arterial pressure, ...) Nurses annotated periodically the status of these signs to be taken into account at the diagnosis detection process.

3. Our approach: Medea

Our approach, *Medea*, has a dual purpose: (1) to record all the work of nursing and (2) to assist the nurse in the decision making process. Medea is a mobile system that integrates the concepts based on Nursing Theory, such as the valuation model of patients proposed by Virginia Henderson and the taxonomies NADA, NIC and NOC (mentioned above).

From the mobile devices, the nurses acces to system by identified way (login and password). Medea shows a list of assigned patients of each nurse in the current day. Nurse can select a concrete patient and access to the related information with the patient. Medea divides the Nursing Process into several stages. We have integrated these stages differentiating the nursing tasks in five items: valuations, care plans, nursing activities (which are related to the interventions – an intervention consists of several activities), nursing indicators (which are related to the outcomes – an outcome consists of several indicators) and vital signals. These items are showed in different tabs in the application and are described in more details in Medina Quero and Ruiz Lozano (2006). In this paper, we show it briefly.

In Medea, nurses can store changes and consult the evolution in the valuations of patients through a user-friendly mobile interface. If any valuation exists previously, it will be downloaded into the mobile device. So, nurses can complete it and determine the values depending on the changes of the patient symptoms. The nursing professional can consult and update the valuations component by component. An example of patient valuation is showed in Fig. 1, where we can see the valuation corresponding to two needs.

On the other hand, the nurse annotate the measurement of the vital signs of patients using Medea. Thus, vital signs can be queried and recorded comfortably around the bedside of patient thanks to mobile devices. Medea integrates several kinds of vital signs:

- Temperature.
- Breathing frequency.
- Heart frequency.
- Arterial pressure.
- Veined pressure.

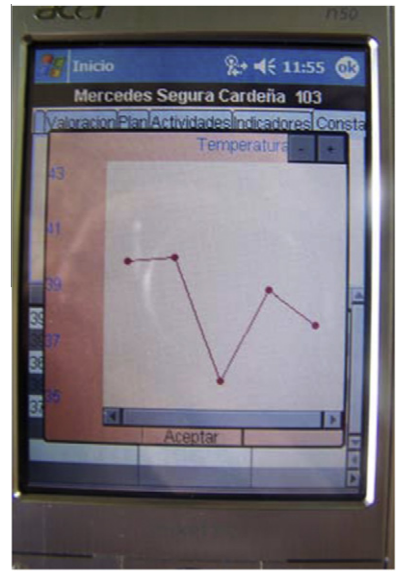

Fig. 2. Evolution of vital signs.

For all vital signs, Medea provides a table that illustrates the time, the value and the nurse who introduced it. In addition, we show the data of this table in a graphic way and nurses will be able to see the state and progress for each signal (see Fig. 2).

Nurses use the data from the patient valuation and the vital signs to prepare the *patient care plan*. After a study about Nursing Theory, we have based our approach on Clinical Disease Tables (CDTs). A CDT is a structure that consists of one diagnosis, several interventions and several outcomes. Thanks to this, the main nursing taxonomies are related and united in a unique concept. In this way, nurses assign to each diagnosis a set of interventions and results that they consider beneficial for the patient. Medea integrates our CDT model for the patient plan, as we detail in Fig. 3.

With the aim of assisting the nurse to choose manually the different diagnoses, interventions and outcomes, we have developed a search assistant. This assistant makes planning easier for the nurse. In the assistant, the nurse can look for diagnoses, interventions and results. Each searcher makes possible querying by name (alphabetical order), code (numeric order), and also restricting the search space specifying the domain, class, or class and domain. The

Fig. 1. Nursing valuation in mobile devices.

Fig. 3. Diagnoses, interventions and outcomes of Nursing Theory.

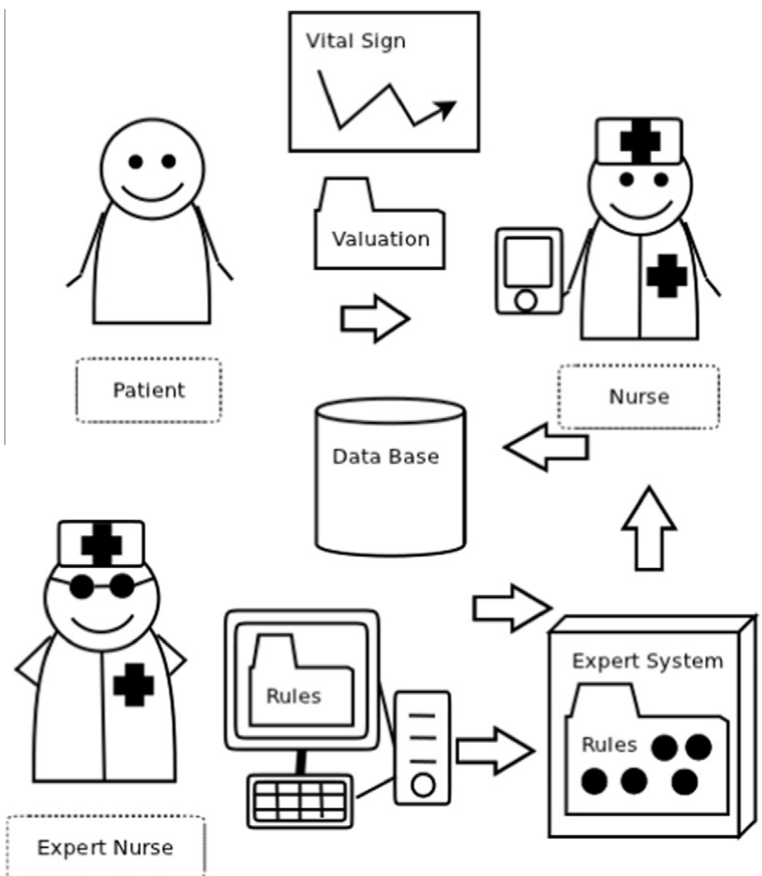

Fig. 4. Scheme of Medea.

diagnoses, the interventions and the outcomes are good classified by domains and classes. This makes it possible to classify, operate and restrict the search space in queries.

In addition, the main novelty in Medea is the Recommendation System presented in this work. In order to guide the nurse when choosing a care plan for the patients, we have designed an expert system that suggests diagnoses, outcomes and interventions based on the patient valuation and the state of vital signs. The system is based on fuzzy logic rules, which are described by expert knowledge using a friendly language. As we detail in Section 4, we apply a fuzzy process to the different fields of the valuation and the vital signs. So, we can match nursing fuzzy values with fuzzy rules obtaining possible diagnoses, outcomes and interventions. The proposed model takes into account the importance of the temporal dimension in the patient symptoms.

The rules of the system can be specified by expert nurses in a friendly language, indicating the elements of the valuation and vital signs that determine a series of care, (see Fig. 4).

Thus, the system suggests information when nurses establish the care plan of patient. In this way, the proposed system is a helpful tool to detect the nursing diagnosis, interventions or outcomes. The nurse can select or reject the proposed result when they design the Patient Care Plan.

4. Expert fuzzy system

In order to guide the nurses when choosing a diagnosis, an intervention or an outcome, we have developed a fuzzy control system that helps them in decision-making. This process is critical because, as we mentioned in Section 2, there is an extensive list of taxonomies, which cannot be known fully by nurses. Through this system, the novice nurses begin to become familiar with taxonomies thanks to the expert knowledge integrated into the decision system.

As we show below, our system takes as input data the valuation and the vital signs of the patient. In the first place, these data are fuzzified in the system (see Section 4.2) using fuzzy concepts and temporal adverbs. The results obtained after this fuzzification process are used to evaluate system rules (see Sections 4.3 and 4.4).

4.1. System inputs

The input values of the expert system are the data corresponding to the patient health status, which have been observed and recorded by nurses. Specifically, this controller studies two types of information:

- *Valuation fields*. On the one hand, we analyze the data recorded in the assessment of patient. As mentioned above, in this work we have based on the Need Theory of Virginia Henderson, which considers 14 components of basic nursing care. Each component comprises several fields (discrete attributes) that are evaluated in an instant of time:
  <*attribute*, *discrete value*, *date*, *time*>, such as
  <*disorientation*, *spatial*, 10/07/2011, 20:54> or
  <*incontinence*, *occasionally*, 11/07/2011, 16:32>

  They represent the qualitative assessment of patients.
- *Vital Signs*. On the other hand, we evaluate the state of the vital signs of patient: temperature, blood pressure, tension, ... Each sign is defined by a continuous value in an instant of time:
  <*attribute*, *continuous value*, *date*, *time*>, such as
  <*temperature*, 38.2, 09/07/2011, 12:00> or
  <*tension*, 11.2, 09/07/2011, 12:10>

  They represent the quantitative analysis of patients.

These data will be fuzzified in order to be integrated as antecedent of fuzzy rules, which consequents are a nursing taxonomy (a diagnosis, an intervention or an outcome). In addition, we propose the use of fuzzy temporal rules because they integrate a great expression to quantitative or qualitative fields in a temporal way. So, we analyze the input information on the health of the patient to offer nurses a set of possible nursing diagnoses, interventions or outcomes. For each one of them, the system will provide a degree of belief, which represents the relevance between them.

The fuzzification process of quantitative and qualitative data is detailed in Section 4.2, where we explain how to apply the fuzzification process for the valuation (see Section 4.2.1), and the vital signs (see Section 4.2.2), according to a fuzzy concept. There, we propose a model where all discrete fields are evaluated homogeneously by four concepts (none, presented, high and incessant) and the continuous values, by three concepts (low, normal and high). Thus, the values of the valuation and the vital signs become fuzzy and they are represented with the following pattern <evaluated data, fuzzy label, degree of belief, date, time>. Some examples are:

<*incontinence*, *presented*, 0.75, 11/07/2011, 16:32> or
<*tension*, *low*, 0.95, 09/07/2011, 12:10>

Moreover, the fuzzification according to temporal modifiers in time intervals is described in Section 4.2.3. In this case, we evaluate the data set that comprises the interval based on four temporal adverbs (ever, frequently, promptly, never). Thus the fuzzy label may be accompanied by an temporal adverb evaluated in a time interval. In this way, several values from the time interval are evaluated by one vague concept. The new pattern to follow is:

<evaluated data*, *fuzzy label*, *time interval*, *temporal adverb*, *degree of belief>

For example:

<*incontinence*, *presented*, *from* 2 *days*, *frequently*, 0.65> or
<*tension*, *low*, *to*1 *day*, *promptly*, 0.8>

Theses final fuzzified inputs are evaluated on the antecedents of the rules.

The complete process is summarized in Fig. 5, where we distinguish the three important parts in the fuzzy control system: a fuzzifier module, the Knowledge Framework and the Inference Engine.

4.2. Fuzzifier module

As the input data of the system can be discrete or continuous, we propose two fuzzification processes according to these types of information. We will apply them depends on whether the data are quantitative or qualitative. In next subsections, we describe the fuzzification process of the nursing evaluation and the vital signs in a separate way.

4.2.1. Fuzzifying the nursing valuation

In order to compute the nursing valuation, the first step is to apply a fuzzification process in the valuation model of Henderson. As we have explained previously, each one of the fourteen basic needs contains several fields. These fields are crisp attributes-values observed in a subjective interpretation, such as:

- Insomnia (*yes, not*).
- Need help (*stand-alone, partial, total*).
- Vomiting (*none, by excess, by defect*).
- Immobility (*none, device need, individual need, person and device need*).
- Disorientation (*none, mild spatial, mild temporal, spatial, temporal, spatial and temporal*).
- Play or participate in various forms of recreation (*none, occasionally, always*).
- Etc.

The main problem to apply a fuzzification process to the evaluation is that it exits a total of 53 fields, where each field contains one or several linguistic labels. We can see that is the valuation domain is complex and varied to systematize. In order to work with the linguistic labels used in the valuation model homogeneously, we have normalized the data obtaining a value between 0 and 1 from each valuation field. Thus, we can apply the same concepts to all data without having to learn different concepts for the 53 fields. This process has been called *numerical recodification*. We distinguished three groups of recodification in function of the valuation fields:

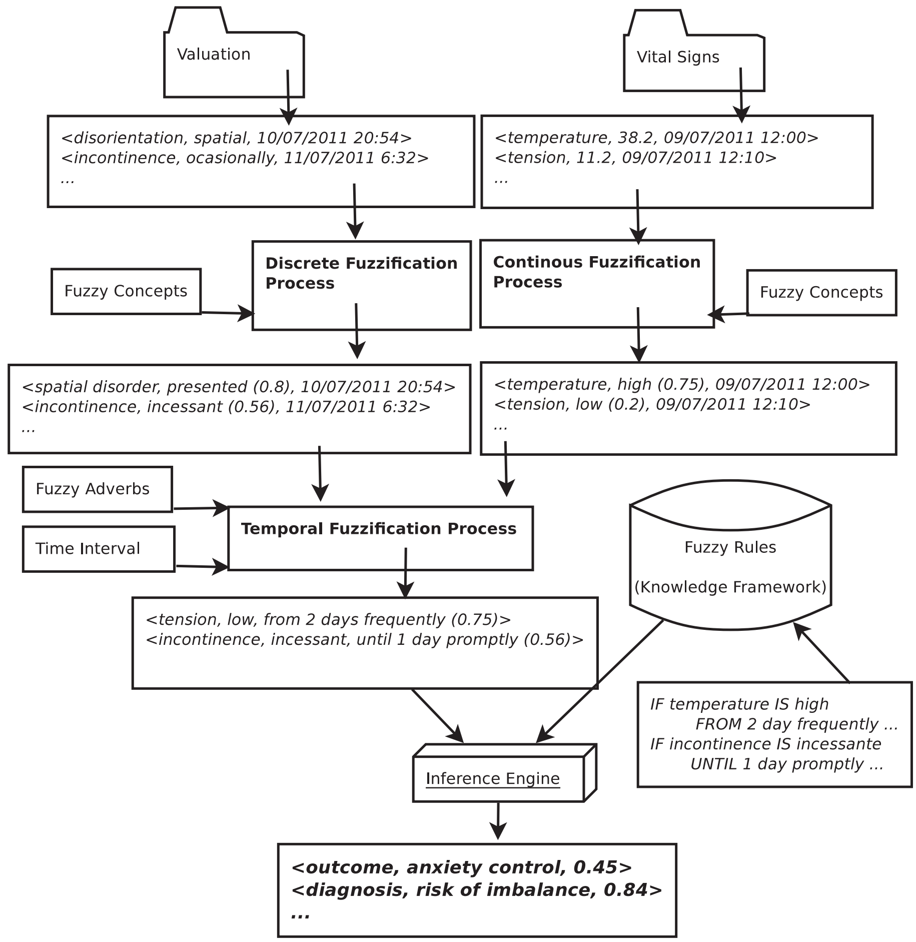

Fig. 5. Fuzzy control system.

- True–false fields, such as *insomnia*, *diarrhea* or *constipation*, which are translated to 0 and 1, respectively.
- Progressive fields, such as *incontinence*, *immobility* or *Play or participate in various forms of recreation*, which are translated between 0 and 1 according to a progression of the values.
- Multiple linguistic fields, such as vomiting or disorientation, which are translated between 0 and 1 according to the progression of the values in different fields. In this case, the source field is divided in several target fields.

In order to represent the numerical recodification, each field has a correspondence matrix that maps the crisp value with one or more numeric values. Some examples are described in Table 1.

Once we have obtained the normalized values from valuation, we have defined four fuzzy concepts to evaluate these values:

- *None*, if the measure is not observed.
- *Presented*, when the measure is partially presented.
- *High*, when the measure is significantly observed.
- *Incessant*, if the measure is always present.

Thanks to the recodification of the values, we can use these four concepts in all fields. We have proposed four functions that indicates the degree of membership to the fuzzy concepts: *none*, *presented*, *high* and *incessant*. Using this functions, we can determinate the degree of membership (w) of a normalized value (x) with respect to the fuzzy concepts. In Fig. 6, we show the functions that represents the membership to the studied fuzzy concepts.

Table 1
Examples of correspondence matrix.

True–false example		
Diarrhea		Diarrhea
False		0
True		1
Progressive field example		
Immobility		Immobility
None		0
Device need		0.5
Individual need		0.75
Person and device need		1
Multiple linguistic example		
Disorientation	Spatial disorientation	Temporal disorientation
None	0	0
Mild spatial	0.25	0
Mild temporal	0	0.25
Mild spat. and temp.	0.25	0.25
Spatial	1	0
Temporal	0	1
Spatial and temporal	1	1

4.2.2. Fuzzifying the vital signs

On the other hand, the vital signs are represented by values of continuous range; such as temperature, respiratory rate, heart rate or blood pressure. We have defined three fuzzy concepts to evaluate the continuous values:

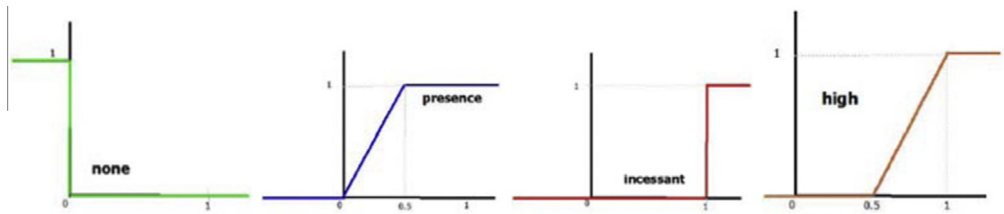

Fig. 6. Fuzzy concepts in nursing valuation.

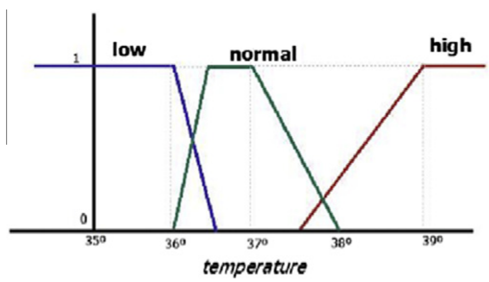

Fig. 7. Fuzzy concepts in temperature.

- Low, if the vital sign is a value below the acceptable range.
- Normal, if the vital sign is a value between the optimum range.
- High, when the vital sign exceeds the acceptable range.

So, we propose three functions that represent the degree of membership to the fuzzy concepts: low, normal and high. Using this functions, we can determinate the degree of membership (w) of a vital value (x) with respect to the fuzzy concepts *low*, *normal* and *high*.

Obviously, in the case of vital signs, the parameters and limits of each function are adjusted according to the range of each vital constant. For example, in Fig. 7, we show the functions of the temperature sign.

4.2.3. Fuzzifying the time interval

In the previous sections, we have detailed how to apply a fuzzy process for discrete and continuous values. Then, we discuss how to reference a data set based on a time interval fuzzily. A time interval can be represented by:

- Two temporal points (a, b). We recover the data whose time occurs between a and b. It corresponds to the expression *FROM a TO b*.
- One temporal point (a) and an order (< or >). If the order is >, we recover the data that occur after a. By contrary, if the order is <, we recover the data prior to a. They correspond to the expression *FROM a*, or *TO a*, respectively.

In a classical data time recovery, the main problem is that there exists data out of range but close to it, which can be relevant to evaluate the interval. In order to solve this problem, we have applied a fuzzy process to the time intervals that evaluate the data close to a fuzzy border. Thus, we have defined a function that determines the degree of membership within the time interval as a fuzzy value between 0 and 1. This degree represents the temporal weight of the data in the interval.

From a interval [a, b], we define the function as:

$$w(t) = \begin{cases} 0 & t < a + a/4 \\ -t/(4a) + 5/4 & t \geqslant a + a/4, t < a \\ 1 & t \in (a, b) \\ 4t/(b) - 3t \geqslant b, t < b - b/4 & \\ 0 & t > b - b/4 \end{cases}$$

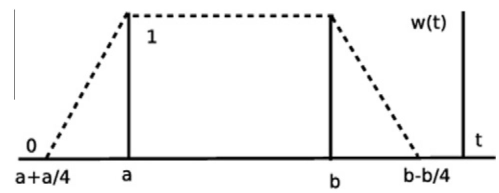

Fig. 8. Fuzzy concept of temporality.

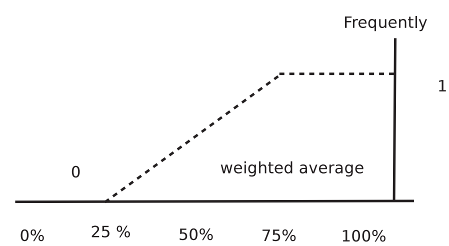

Fig. 9. Function that represents the fuzzy concept $\widetilde{frequently}$.

We can observe the function graphically in Fig. 8.

At this point, each time value (*attribute*, *value*, *time*) has been processed to a fuzzy time value ($attribute, \tilde{x}, \tilde{w}$). For example:

$$< tension, 9.2, 09/07/2011\ 12:10 >$$
$$\rightarrow < tension, low(0.85), from\ 2\ days\ (0.5) >$$

In order to the expert can express the behavior of the data over time, we have defined four fuzzy adverb (ever, frequently, promptly, never). These adverbs make it possible to know properties about the contained data in the fuzzy temporary interval and take values between 0 and 1. The temporal adverbs are:

- *Ever* represents that the value $\tilde{x}$ is continually presented. So, we propose the time-weighted average as the membership function to the fuzzy adverb.

$$\widetilde{ever} = \widetilde{x(t)} = \frac{\sum x_i \cdot w(t_i)}{\sum w(t_i)}$$

- *Frequently* denotes that the value $\tilde{x}$ is observed most of the time. In order to represent this concept, we analyze the time-weighted average, which maximum value is $\sum w(t_i)$. This value represents 100% of the value of x in t. We propose a function that represents the membership to frequently based on the percentage of the time-weighted average. If the average is below the first quartile ($25\% = \sum w(t_i)/4$), the value is 0. On the other hand, if the average is higher than the third quartile ($75\% = \sum w(t_i) \cdot 3/4$), the value is 1, see Fig. 9. Between the two quartiles, the value is increasing from 0 to 1. So, the function is:

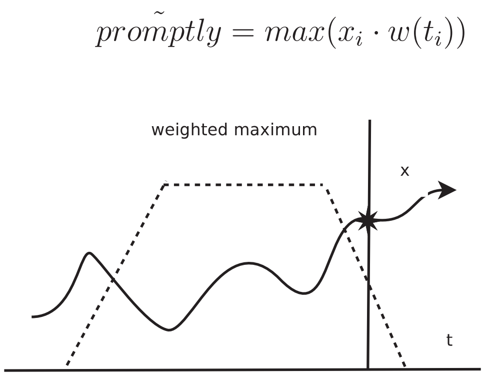

Fig. 10. Time-weighted maximum function.

$$\widetilde{frequently} = \begin{cases} 0 & \widetilde{x(t)} < q1 = \sum w(t_i) \cdot 0.25 \\ \frac{0.5+2\widetilde{x(t)}}{\sum w(t_i)} & \widetilde{x(t)} \in (q1, q3) \\ 1 & \widetilde{x(t)} > q3 = \sum w(t_i) \cdot 0.75 \end{cases}$$

- *Promptly* suggests that the value $\tilde{x}$ is presented at least once in the time interval. We propose the use of the time-weighted maximum function to represent this concept because it obtains the highest peak of the function considering the fuzzy interval, see Fig. 10. So, if the maximum has a high value, the concept has occurred at least once significantly.

$$\widetilde{promptly} = max(x_i \cdot w(t_i))$$

- *Never* denotes that the value $\tilde{x}$ is not presented. As *never* is the complementary of *always*, we have proposed the use of the complementary time-weighted average.

$$\widetilde{never} = \neg\widetilde{x(t)} = \frac{\sum(1 - x_i) \cdot w(t_i)}{\sum w(t_i)}$$

4.3. Knowledge Framework

The Knowledge Framework is composed of the observed information on the health of patient (nursing valuation and vital signs) and the Rule Base.

Previously, we explain how to obtain the degree of membership to the fuzzy concepts of the nursing valuation and the vital signs in a fuzzy temporal interval, which represent the patient health state. Next, these values will be computed as conditions of antecedents in fuzzy rules. The consequent of these rules are diagnosis, outcomes or interventions. In this way, the system analyzes the valuation and the vital signs of the patients and may propose diagnosis, outcomes and interventions that nurses could use.

Each rule condition is defined by a valuation fields or a vital signs, and also, by a fuzzy concept. For example: *spatial disorientation is incessant* or *temperature is high*. The language of the rules is very intuitive for the human operator, since you need to use only four fuzzy concepts from the valuation and three concepts from vital signs.

Thus, the Rule Base has the following proposed pattern:

R_i: If x_1 is A_{i1} in T_1 B_{i1} and ... and x_n is A_{in} in T_n B_{in} Then $\langle Z, y_i \rangle$ (y_i = F ($w_1, \ldots, w_n$)).

where:

- x_k ($k \in [1..p]$) is any valuation field or vital sign,
- A_{i1} ($i1 \in [i1..im]$) is a fuzzy concept,
- T_1 is a time interval $[a, b]$, where both parameters are optionals:
  - The interval $[a, b]$ represent *from a to b*.
  - The interval $[a,]$ represent *from a until now*.
  - The interval $[,b]$ represent *until b*.
- B_{i1} ($i1 \in [i1..iq]$) is a fuzzy temporal adverb,
- Z is a possible diagnosis, outcomes and intervention of the Nursing Process,
- w_1 is the degree of fulfillment of the condition x_1 *is* A_{i1} in T_1 B_{i1},
- ...
- w_n is the degree of fulfillment of the condition x_n *is* A_{in} in T_n B_{in},
- y_i is the degree of belief associated to the possible Z and is in function of degree of fulfillment of the rule antecedent, $F(w_1, \ldots, w_n)$ = AND $(w_1, \ldots, w_n)$.

This rule model can be viewed as a variant of Takagi–Sugeno model (Takagi & Sugeno, 1985), where the output of the system is in function of the system input values.

Some examples of this type of rules are:

- **R1**: IF
  spatial disorientation IS *incessant* FROM *7 days* frequently
  AND
  temperature IS *normal* FROM *2 days* promptly
  THEN
  THE *diagnosis* IS *risk of imbalance*
- **R1**: IF
  insomne IS *presented* UNTIL *1 days* ever
  AND
  heart rate IS *high* FROM *2 days* promptly
  THEN
  THE *outcome* IS *anxiety control*

Considering the pattern of the fuzzified input data (<*evaluated data*, *fuzzy label*, *time interval*, *temporal adverb*, *degree of belief*>), the parameters of an *j*-antecedent in an *i*-rule "x_j is A_{ij} in T_n B_{ij}" corresponds to:

- x_j is the "evaluated data" (any valuation field or vital sign).
- A_{ij} if the "fuzzy label" (which represents a fuzzy concept).
- T_n if the "time interval".
- B_{ij} if the "temporal adverb".

4.4. The inference engine

The inference engine models the human reasoning process, using the Rule Base, and its function is to extract conclusions from the analyzed data. This module evaluates all the rules conditions and to apply the actions defined in the consequents.

The conditions of the antecedent are concatenated with the logical AND operator, in this case we use the MIN function. So, the antecedent is evaluated with a value (W_{Ri}) in the interval [0, 1], which corresponds to the degree of fulfillment of the rule.

$$\text{AND}(w_1, \ldots, w_n) = (w_1 \wedge_{min} \ldots \wedge_{min} w_n),$$

where w_k is the degree of fulfillment of the *k*-condition of assessed rule antecedent.

If $W_{Ri} > 0$, the conditions are true and the diagnosis, outcome or intervention should be proposed with a degree of belief W_{Ri}.

It is important to emphasize that the same consequent can be retrieved by different rules. In this case, we must increase the degree of relevance of the consequent. The possibility that a diagnosis, intervention or outcome is present is cumulative. Several rules influence in the detected level or degree of presentation. For this reason, we apply the probabilistic OR: *a OR b* = $a + b - a \cdot b$ to the values $W_{Ri}..W_{Rn}$ of the consequents obtaining the final value of relevance.

Thus, each consequent of the rule is evaluated with the MIN function of the conditions of the antecedent. In addition, we propose an additive model using the probabilistic OR, which accumulates the relevance of those consequents that are recovered by several rules (W_{Ri} OR..OR W_{Rn}). This rule model has been proposed by the authors in Castro, Delgado, Medina, and Ruiz-Lozano (2011) to detect intrusions in surveillance areas.

Finally, the true diagnosis, outcomes and interventions are ordered by the relevance value in order to present first the most important results. The proposed values are queried by nurses when they configure the care plan that they will put into practice on the patient, choosing between the proposed results, or other diagnosis, outcomes and interventions.

4.5. Evaluation

In this subsection, we present qualitative result about the performance of the system. The main problem for carrying out the evaluation is that Medea is currently experimental and it has not yet been implanted in a Hospital. For this reason, we performed several test to eight care nurses in a simulated session where they had to manage the mobile tool and to evaluate the diagnostic, outcomes and interventions proposed by the expert system.

The first test was designed to assess the management of the mobile tool. The test is composed by a user survey, which measures the nursing experience with the user interfaces, the interference and the importance of the nursing visibility (Fig. 11). The mobile devices that we used for the test have a screen between 3 in. and 4 in. As can be seen, top marks were produced by larger devices. This stems from the fact that there exist extensive data that integrates the Nursing Process, which are not recommended for managing daily in small devices. Therefore, in future work we will port and test the application to tablets.

The second test analyzes the performance of the expert system. In this case, the simulated scenario were composed by an expert nurse and eight care nurses. The expert nurse identified several rules for the study of one virtual hemodialysis patient.

In a first way, the eight care nurse, based on their experience, completed the standard data of the hemodialysis patient (nursing valuation and vital signs). Later, they analyzed interventions, diagnoses and results suggested by the expert system. In order to assess their satisfaction with the expert system and the human expert nurse independently, we show the rules written by the expert nurse. Thus, they could demonstrate their compliance with the system and/or the human expert, see Fig. 12. The data show that cases with a low valuation of the expert system are accompanied by a disagreement with the rule of the expert. Therefore, we see that satisfaction of the expert system depends intrinsically on the quality of knowledge that is introduced by the expert nurse. Finally, we have found that fuzzy temporal adverbs seem more indefinite than fuzzy concepts, due to the subjective perception of time.

In future work, we want to implement and test the expert system in real care centers. So, we will conduct the evaluation with

User	Screen size	Is it easy to use?	Does it not interfere in your daily work?	Does it give visibility of your work?
U1	3	2	3	3
U2	3	2	2	4
U3	3	3	2	5
U4	3,7	4	3	5
U5	3,7	3	3	4
U6	3,7	4	3	5
U7	4	5	4	5
U8	4	3	3	4
		3,25	2,875	4,375

Fig. 11. Qualitative evaluation of mobile tool.

User	The suggestions are appropriate?	Do you agree with the expert human rule?	The data relevance is right?	The time relevance is right?
U1	5	4	5	4
U2	4	4	4	3
U3	2	2	4	3
U4	4	5	3	2
U5	5	4	3	3
U6	3	4	4	3
U7	2	1	3	2
U8	5	4	4	3
	3,75	3,5	3,75	2,875

Fig. 12. Qualitative evaluation of expert system.

several nursing experts that will introduce the system rules. In this way, it will be really interesting to measure the agreement of the care nurses whit each expert nurses, because we could evaluate not only the system, but the quality of the expert human knowledge.

5. Conclusions and future work

In order to improve the recognition of nursing in the health sector, the nursing work must be stored by the computer systems. However, computers or laptops hinder the daily nursing activity, due to mobility of the tasks. In order to solve it, we present a mobile application for the Nursing Process, which is called Medea. It can be used in the room of patients and it can be kept in pockets. The main advantage compared to other mobile systems is that it incorporates the Need Theory of Virginia Henderson (Luis et al., 2005) (as patient evaluation model) and the Nursing taxonomies of NANDA, NIC and NOC in the care plan.

The mobile system is complemented by an expert system based on fuzzy temporal rules that proposes diagnoses, interventions and outcomes using as input the patient valuation and the state of vital signs to guide nurses when they diagnose. The highlight of the approach is that the all the valuation fields can be evaluated with only four fuzzy concepts and all the vital signs with only three fuzzy concepts. Furthermore, we take into account the importance of the temporal dimension in the patient symptoms. As we show in the evaluation, the satisfaction of the expert system depends intrinsically on the quality of knowledge that is introduced by the expert human nurse.

In future works, the authors focus in extracting the expert system rules from real stored data in hospitals. Currently, this stage has not been developed because it would be necessary to implement the system in a real environment with several nurses where we should obtain a long database. This future work would be very interesting also for nurses, which will reassess the theory based on the practice results. Also, we will port the application to tablets as we have found that a larger screen enhances the satisfaction of nurses with the mobile tool.

References

Bulechek, G., Butcher, H., & McCloskey Dochterman, J. (2007). *Nursing interventions classification (NIC)*.

Castro, J. L., Delgado, M., Medina, J., & Ruiz-Lozano, M. D. (2011). Intelligent surveillance system with integration of heterogeneous information for intrusion detection. *Expert Systems with Applications, 38*(9), 11182–11192.

Chitty, K. (1993). *Professional nursing: Concepts and challenges*. Philadelphia: W.B. Saunders Co.

Choi, J., Chun, J., Lee, K., Lee, S., Shin, D., Hyun, S., et al. (2004). MobileNurse: Handheld information system for point of nursing care. *Computer Methods and Programs in Biomedicine, 74*(3), 245–254.

Delgado, M., Medina Quero, J., Ruiz Lozano, M. D., & Vila, A. (2007). Architecture for databases access and consultation through handheld devices. In *2nd International symposium on ubiquitous computing and ambient intelligence, September, 2007* (pp. 75–82). Zaragoza (Spain), Thomson, Madrid.

Dubois, D., Lang, J., & Prade, H. (1994). Possibilistic logic. In C. H. D. M. Gabbay, J. Robinson (Eds.), *Handbook of logic in artificial intelligence and logic programming*.

Fox, J., Glasspool, D., & Bury, J. (2001). Quantitative and qualitative approaches to reasoning under uncertainty in medical decision making. In *Artificial intelligence medicine: Eighth conference on AI in medicine in Europe. AIME 2001. LNCS* (Vol. 2101). Springer-Verlag.

Juarez, J. M., Camposa, M., Palma, J., & Marin, R. (2008). Computing context-dependent temporal diagnosis in complex domains. *Expert Systems with Applications, 35*, 9911010.

Keplar, K. E., & Urbanski, C. J. (2003). Personal digital assistant applications for the healthcare provider. *The Annals of Pharmacotherapy, 37*(2), 287–296.

Luis, M. T., Fernandez, C., & Navarro, M. T. (2005). De la teora a la practica. In *El pensamiento de Virginia Henderson en el siglo XXI*. Edit, Masson, Barcelona.

Marn, R., & Navarrete, I. (2003). Temporal constraint satisfaction problems. *Inteligencia Artificial, 20*, 111120.

Medina Quero, J., & Ruiz Lozano, M. D. (2006). Medea, sistema para la informatizacin del Proceso Enfermero. In *VI International Simposium of Nursing Diagnoses, May 2006* (pp. 231–235). Proyecto Sur. Industrias Grficas S.L. Granada (Spain). (ISBN: 84-611-0010-7).

Montani, S., Magni, P., Bellazzi, R., Larizza, C., Roudsari, A., & Carson, E. R. (2007). Integrating model-based decision support in a multimodal reasoning system for managing type 1 diabetic patients. *Artificial Intelligence in Medicine, 29*, 131151.

Moorhead, S., Johnson, M., Maas, M., & Swanson, E. (2008). *Classification nursing outcomes classification (NOC)* (4th ed.).

Nanda International. Nursing Diagnoses: Definitions and Classification, 2009–2011. (2008).

Pani, A. (2001). Temporal representation and reasoning in artificial intelligence: A review. *Mathematical and Computer Modelling* (34), 5280.

Prgomet, M., Georgiou, A., & Westbrook, J. (2009). The impact of mobile handheld technology on hospital physicians' work practices and patient care: A systematic review. *Journal of the American Medical Informatics Association, 16*(6), 792–801.

Rodriguez, N. J., Borges, J. A., Soler, Y., Murillo, V., Coln-Rivera, C. R., Sands, D. Z., & Bourie, T. (2003). PDA vs. Laptop: A comparison of two versions of a nursing documentation application. In *Proceedings of the 16th IEEE symposium on computer-based medical systems*.

Shneyder, Y., & Pharm, D. (2002). Personal digital assistants (PDA) for the nurse practitioner. *Journal of Pediatric Health Care, 16*(6), 317–320.

Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics, 15*(1), 116–132.

Tsai, Chang-Chun, & Li, Sherman H. A. (2009). A two-stage modeling with genetic algorithms for the nurse scheduling problem. *Expert Systems with Applications, 36*, 95069512.

Wu, C. -C., & Lai, C. Y. (2009). Wireless handhelds to support clinical nursing practicum. *Educational Technology* & *Society*, *12*(2), 190–214.

Yang, H., Yang, Y., Su, X., & Xue, X. (2009). A mobile nursing system based on barcode. *Computer Knowledge and Technology*, *16*, 114–115.

Yeh, Jinn-Yi, & Lin, Wen-Shan (2007). Using simulation technique and genetic algorithm to improve the quality care of a hospital emergency department. *Expert Systems with Applications, 32*, 10731083.