Application of Fuzzy Rough Temporal approach in Patient Data Management (FRT-PDM)

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***Abstract*—**Management of fuzzy and vague information has been a research problem for computer scientists, particularly in artificial intelligence, relational and temporal databases. Fuzzy set theory has been widely used to cater this problem. Rough set theory is a newer approach to deal with uncertainty. After many years of rivalry between the two theories, many researchers have started working towards a hybrid theory. In this paper we have discussed the fundamental concepts of fuzzy and rough set theories as well as their application in temporal database model. We have also presented a conceptual model of fuzzy rough temporal data processing along with a case study.

***Keywords*—** Temporal relational model, fuzzy rough sets, imprecise data, fuzzy rough temporal model.

I. INTRODUCTION

RELATION algebra forms the foundation of the relational database model (RDM) [1] which has been extensively used for a period of time to store and maintain huge amount of data. Many extensions have been proposed and implemented to the RDM in order to fulfill the increasing demands of users. However, RDM doesn't fulfill all the requirements [2]. For example, the capability of handling time is of immense importance in many real world problems but relational database doesn't offer much support in this regard. It only records the current state of the real world usually referred as a snapshot. Many applications such as insurance systems, online reservation systems, medical management information systems, decision support systems, CRM applications and HR applications require past information in addition to the most recent state.

In the earlier era of relational database development, the management of temporal data was handled with the help of adhoc methods or through application programs. Extensive research has been conducted and dozens of temporal models have been proposed [3] [4]. An important survey of temporal database models was conducted by [2].

Imprecise information is another issue that has bothered the database designers for a long time. Many proposals have been put forth for managing the inherent imprecision that accompanies the data from real world [5]. Fuzzy set theory is the approach that has been widely adopted to manage imprecise or vague data in the relational database environment [6] [7]. Since its introduction, the fuzzy set theory has had a significant impact on the way we represent vague information. Of late, it has become an important constituent of soft computing, a paradigm that adheres closer to human mind and real world than conventional hard computing techniques [7] [8]. During the last few decades, new theories have been put forward that generalize the original fuzzy set theory.

In this paper we have focused the fuzzy rough set theory. Rough set theory [9] is another approach to deal with uncertain data. It is a mathematical approach to represent vague knowledge that provides a framework for construction of approximation of concepts in case of incomplete information. It uses equivalence relations to compute lower and upper approximations of sets that are based on the "indiscernibility" or "indistinguishability" of elements. Rough sets have found many applications in the area of classification, web mining, finance, banking, databases, expert systems and knowledge acquisition and decision analysis. After many years of rivalry between fuzzy and rough set theories, many researchers have started working towards a hybrid theory (e.g. [10], [11], [12], [13], and [14]). In doing so, the focus has moved from elements' indiscernibility (objects are dissimilar or not) to their similarity (objects are similar or not), represented by a fuzzy relation [8]. As a result, the objects are categorized in soft boundaries based on their similarity to one another and the transition from "belongs to" to "not belongs to" becomes gradual rather than abrupt (as in case of classical sets.)

We have also provided a case study regarding the application of fuzzy rough approach in dealing with temporal data.

The rest of the paper is organized as follows: Section II introduces the model of development that we have proposed. Section III, IV and V provide review of the temporal databases, fuzzy set theory and rough set theory respectively. Section VI discusses fuzzy rough approach and section VII contains the case study. In section VIII we have provided some database queries for the fuzzy rough temporal model while the detailed records of the database tables have been listed in the appendix.

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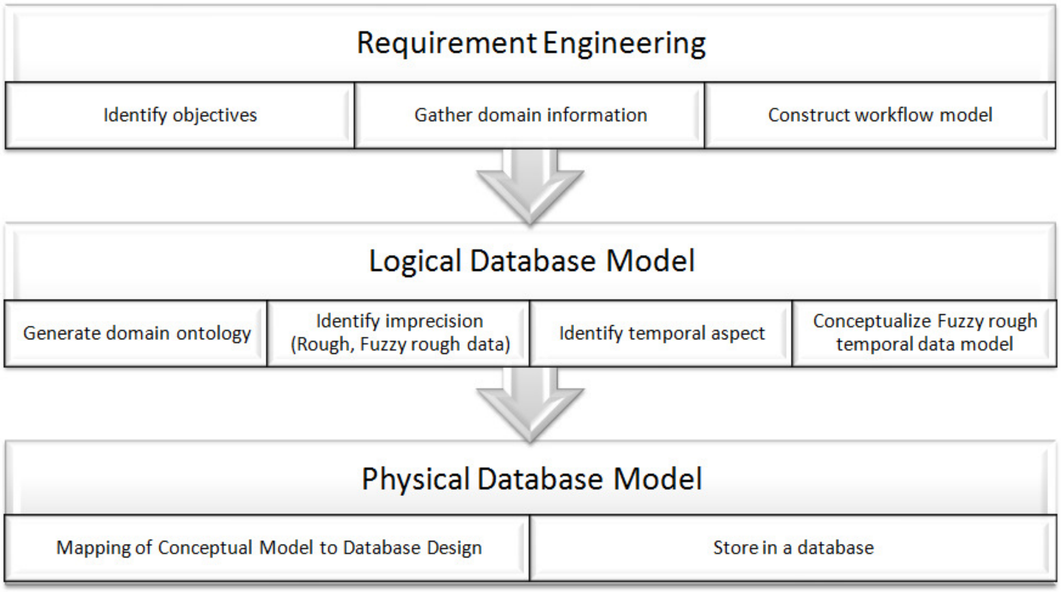


Fig. 1 Conceptual model for FRT-Database

II. PROPOSED MODEL

Our proposed conceptual model of fuzzy rough temporal database development is represented in Fig. 1. The model is an extension of our previous model presented in [10]. Before building an information system for the patient data, we should clarify the main objectives of the system in the requirement engineering phase. This will provide us a thorough understanding of the system and enable us to gather the relevant domain information. Once we have built the mini-world (domain definition, requirements) we can move on to build the requirement workflow model that represents the flow of data in the system. A variety of models such as UML Use cases, Data flow diagrams, Event flows etc can be used for this purpose. The requirement engineering phase leads us to the development of logical database model. This step starts with building the domain ontology for patient data. An important concern here is the identification of imprecision and temporal aspects in the system. The gathered data can be temporal, non-temporal as well as being rough, crisp or rough temporal. For instance, treatment given to a particular patient may vary with time therefore it is classified as temporal. Safety and care are vague concepts and must be treated using rough, fuzzy or a combined approach. A detailed classification of patient data is provided in [6] and [7]. This classification will help us to conceptualize the fuzzy rough temporal data model. Lastly, the conceptual model will be mapped to a physical database model that will consist of physical constraints, relationships, table definitions, indexes and other elements needed for physical data storage. The information system can then be stored on database software that can handle the elements incorporated in the logical and the physical data model.

III. TEMPORAL DATABASES

A. *Time Domain*

Jensen [2] defines a time domain as “An ordered pair (T ; ≤) is where T is a non-empty set of time instants and ’≤’ is total order on *T*”. A time domain is referred to as “discrete” if all elements other than the last has an instant successor, and all elements other than the first has an instant predecessor.

B. *Time Granularity*

Partitioning of the time-line into a finite set of smaller segments called granules. Each non-empty subset $G(i)$ is called a granule of the granularity [3]. For e.g. date of hiring is stored in time granularity of days, interview timings are stored in hours and flight schedules in minutes.
Bettini [15] defines granularity as
“A mapping G from the integers (the index set) to subsets of the time domain such that If $i<j$ and $G(i)$ and $G(j)$ are non-empty, then each element of $G(i)$ is less than all elements of $G(j)$; If $i<k<j$ and $G(i)$ and $G(j)$ are non-empty, then $G(k)$ is non-empty.”
Mixed granularities are important for modeling real-world temporal data; however, they create problems such as semantics of operations with operands at differing granularities, or conversion from one granularity to another, etc.

C. *Time points and time intervals*

Three common approaches of time representation are a single time point, an interval and a set of time intervals. In few models time is expressed using single time points called as events [15]. Most of the temporal models use time intervals to represent time. A detailed study of point and interval based temporal database models was published by Bohlen [16].

D. Temporal Logic

The term temporal logic is widely used to represent temporal information in a rational framework. Prior [17] is of the point of view that "temporal logic refer specifically to the modal-logic type of approach introduced as tense logic". It is an extension of propositional logic that contains special operators that can manage time. Detailed review has been provided by the authors in [4] and [18].

IV. FUZZY SETS

Fuzzy logic in contrast with the binary logic provides the possibility of intermediate values instead of rigid and crisp boundaries. For instance, in the health management system, the patient condition can be normal, stable, critical and severe or how close to these values. In binary logic there are no middle values either the patient is stable or unstable. Fuzzy logic deals with uncertain and imprecise information in a much flexible manner [19] [20] [35].

A. Fuzzy sets and membership functions

If X is a collection of objects denoted generically by x, then a fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{ (x, \mu_A(x)) \mid x \in X \} \quad (1)$$

where $\mu_A(x)$ is called a membership function (MF) for the fuzzy set A. This membership function maps each point in X onto the real interval [0.0, 1.0]. As the value of MF approaches 1.0 the membership grade increases and it decreases when MF approaches 0.0.

Fuzzy sets [20] are a natural outgrowth and generalization of crisp sets. Fuzzy set theory offers a new angle to investigate the relationship among sets and its elements. This investigation is different from the traditional "Black and White" way. It goes beyond the "belongs to" and "not belongs to" way.

A fuzzy set is completely characterized by its membership function. It provides a transition from region completely outside a fuzzy set to a region completely inside. Although fuzzy sets have greater expressive power than classical crisp sets, their effectiveness depends on the construction of appropriate membership functions. A membership function can be designed in variety of ways such as

Triangular MFs:

A triangular membership function is specified by three parameters {a, b, c} as

$$f(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \quad (2)$$

Trapezoidal MFs:

A trapezoidal membership function is specified by four parameters {a, b, c, d} as

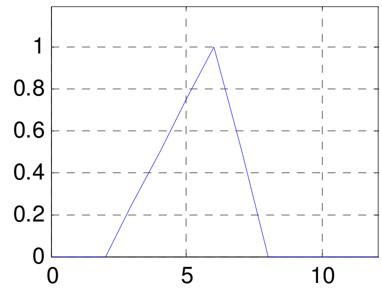
$$f(x; a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \quad (3)$$

Gaussian MFs:

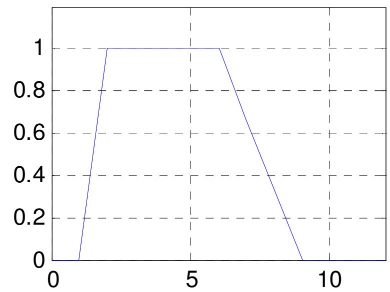
A gaussian membership function is specified by two parameters $\{c, \sigma\}$ as

$$guassian(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (4)$$

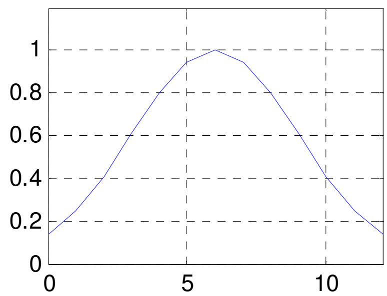
The graphs are shown in Fig. 2



(a) Triangular MF (tri_mf(x, [2, 6, 8])



(b) Trapezoidal MF (trap_mf(x, [1, 2, 6, 9])



(c) Gaussian MF (gauss_mf(x, [6, 3])

Fig. 2 Graphs of fuzzy membership functions

B. Support

The support of a fuzzy set A is the set of all points x in X such that $\mu_A(x) > 0$:

$$\text{Support}(A) = \{\mu_A(x) > 0\} \quad (5)$$

C. Core

The core of a fuzzy set A is the set of all points x in X such that $\mu_A(x) = 1$:

$$\text{Core}(A) = \{\mu_A(x) = 1\} \quad (6)$$

D. Crossover points

A crossover point of a fuzzy set A is a point $x \in X$ at which $\mu_A(x) = 0.5$:

$$\text{Crossover } (A) = \{x \mid \mu_A(x) = 0.5\} \tag{7}$$

These basic concepts of MFs are shown in Fig. 3.

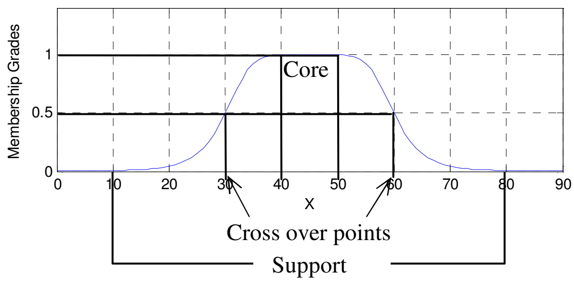


Fig. 3 Core, Support, and Crossover points

E. α-cut, strong α-cut

The α-cut or α-level set of a fuzzy set A is a crisp set defined by

$$A_\alpha = \{x \mid \mu_A(x) \geq \alpha\} \tag{8}$$

Strong α-cut or strong α-level set are defined similarly:

$$A'_\alpha = \{x \mid \mu_A(x) > \alpha\} \tag{9}$$

F. Similarity diagram

A suitable representation of fuzzy similarity between two sets is possible using Sagittal diagram. Each of the sets X, Y is represented by a set of nodes in the diagram; nodes corresponding to one set are clearly distinguishable from nodes representing the other set (bipartite graph) [22] [23]. An example of the Sagittal diagram of a temporal binary fuzzy relation R (X,Y) together is shown in Fig. 4. In the diagram X and Y are two timestamps with three states Critical(C), Severe(S), Stable(T) {C, S, T} that represent the patient condition at any instant of time.

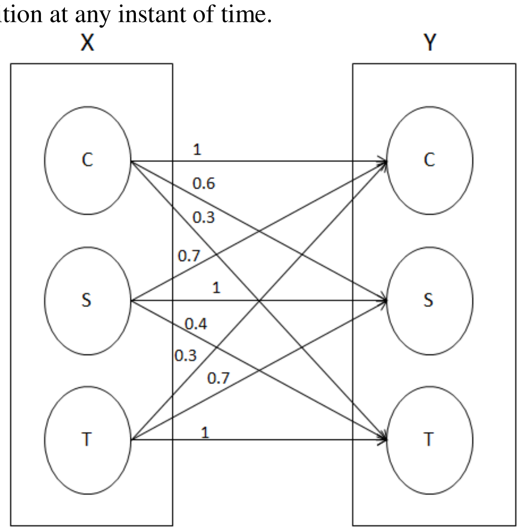


Fig. 4 Sagittal diagram for Temporal Fuzzy relationship

V. ROUGH SETS

Rough set theory [9] [24] is an extension of the conventional set theory that supports approximations in decision making. It complements the Dempster-Shefar theory of evidence [25] and fuzzy set theory [20]. Rough set is a useful means for studying delivery patterns, rules and knowledge in data. It is used to estimate a vague concept by a pair of specific notions called lower and upper approximations [26].

For instance, if our area of interest is set S that contains some elements. We want to define S in terms of its attributes. The membership of objects with respect to some subset of domain may not be definable. This fact leads us to the description of S in terms of lower and upper approximations. The lower approximation consists of those objects that certainly belong to subset of interest whereas the upper approximation may or may not belong to the subset. Any subset defined in terms of lower and upper approximations is known as a Rough set [26].

A. Information and decision system:

An information system is a data table that contains objects (in form of rows) and attributes (in form of columns). For example, in Patient Management Systems [6] [7] [10] [13] [35] patients are represented as objects whereas measurements such as blood pressure, blood sugar, pulse rate etc. serve as attributes.

Formally, "$I = (U, A)$ is an information system where U is non-empty set of finite objects (Universe of discourse) and A is a finite set of attributes such that $a: U \rightarrow V_a$ for every $a \in A$."

Decision systems are similar to information systems with the exception that they contain a *decision attribute* as well. They are stored in rectangular form as Table (C, D) where C represents condition attributes, while D represents decision attributes with $C \cap D = \emptyset$ [28].

B. Formal Definition

Feng [29] states that "Let U denote a finite and nonempty set called the universe and $\theta \subseteq U \times U$ represent an equivalence relation on U. The pair $apr = (U, \theta)$ is called an approximation space. The equivalence relation θ partitions the set U into subsets that are all disjoint. Such a partition of the universe is denoted by U/θ".

If two elements in the universe U belong to same equivalence class, we say that both are identical.

If we consider some arbitrary set X such that $X \subseteq U$, it will not be possible to express X accurately using the equivalence classes of θ. In this scenario, one a pair of lower and upper approximations can be used to characterize X. These approximations are stated as

$$\underline{X}_\theta = \bigcup\{[x]_\theta : [x]_\theta \subseteq X\} \tag{10}$$

$$\overline{X}_\theta = \bigcup\{[x]_\theta : [x]_\theta \cap X \neq \phi\} \tag{11}$$

where $[x]_\theta = \{\, y \in U \mid x\theta\, y \,\}$ is the equivalence class that contains *x*. The pair $\left(\underline{X}_\theta, \overline{X}_\theta\right)$ is referred as the rough set with respect to *X* as shown in Fig. 5.

"The lower approximation $\underline{X}_\theta$ is the union of all the sets which are subsets of *X*, and the upper approximation $\overline{X}_\theta$ is the union of all the elementary sets which have a nonempty intersection with *X*. An element in the lower approximation necessarily belongs to *X*, while an element in the upper approximation possibly belongs to *X*." [29]

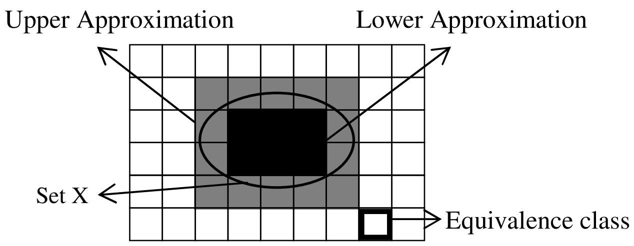


Fig. 5 Rough Set [9]

C. Properties

Some of the basic properties of rough sets as discussed in [24] are as follows:

(i) $\underline{B}(X) \subseteq X \subseteq \overline{B}(X)$

(ii) $\underline{B}(\phi) = \overline{B}(\phi) = \phi,\ \underline{B}(U) = \overline{B}(U) = U$

(iii) $\underline{B}(X \cap Y) = \underline{B}(X) \cap \underline{B}(Y)$

(iv) $\overline{B}(X \cup Y) = \overline{B}(X) \cup \overline{B}(Y)$

(v) $X \subseteq Y$ implies $\underline{B}(X) \subseteq \underline{B}(Y)$ and $\overline{B}(X) \subseteq \overline{B}(Y)$

(vi) $\underline{B}(X \cup Y) \supseteq \underline{B}(X) \cup \underline{B}(Y)$

(vii) $\overline{B}(X \cap Y) \subseteq \overline{B}(X) \cap \overline{B}(Y)$

(viii) $\underline{B}(-X) = -\overline{B}(X)$

(ix) $\overline{B}(-X) = -\underline{B}(-X)$

(x) $\underline{B}(\underline{B}(X)) = \overline{B}(\underline{B}(X)) = \underline{B}(X)$

(xi) $\underline{B}(\overline{B}(X)) = \overline{B}(\overline{B}(X)) = \overline{B}(X)$

D. Accuracy of approximation

Rough sets can be characterized numerically by the accuracy of coefficient $\alpha_B(X)$ [24] defined as

$$\alpha_B(X) = \frac{\left|\underline{B}(X)\right|}{\left|\overline{B}(X)\right|} \tag{12}$$

where $|X|$ represents the cardinality of set *X*. Accuracy of approximation remains in the close interval [0, 1] i.e. $0 \le \alpha_B(X) \le 1$. If $\alpha_B(X)$ = 1, then X is crisp with respect to B and otherwise if $\alpha_B(X)$ < 1 then X is rough with respect to B.

E. Rough membership function

In classical set theory, either an element belongs to a set or doesn't belong to a set. The corresponding membership function has a value of 1 or 0, respectively. In case of rough this concept is different. The *rough membership function* [30] quantifies the degree of overlap between set *X* and the equivalence class to which *x* belongs. It is defined as

$$\mu_x^B(x): U \to [0,1] \text{ and } \mu_x^B(x) = \frac{\left|[x]_B \cap X\right|}{\left|[x]_B\right|} \tag{13}$$

F. Example

The example in Table 1 is adapted from [10] for a health care information system:

Patient	Loss of Appetite	Fatigue	Muscle ache	Hepatitis
A	No	No	Yes	Yes
B	Yes	Yes	No	No
C	Yes	Yes	Yes	Yes
D	No	No	Yes	No
E	No	Yes	No	Yes
F	Yes	Yes	No	No

Table 1 Patients with attributes

Condition Attributes: {Loss of appetite, Fatigue, Muscle ache}
Decision Attribute: {Hepatitis}

Columns of this table are the symptoms observed in the set of patients represented as rows. The entries are the values of attributes corresponding to each patient. For instance, patient *D* in the table is characterized by the following attribute value set (Loss of appetite, No), (Fatigue, No), (Muscle ache, Yes), (Hepatitis, Yes).

In the table, patient *A*, *D* and *E* are indiscernible as regards to attribute loss of appetite, patient *B*, *E* and *F* are similar as regards to attributes fatigue and muscle ache whereas patient *B* and *F* are indiscernible with respect to loss of appetite, fatigue and muscle ache. Hence, the attribute fatigue generates two elementary sets {*A*, *D*} and {*B*, *C*, *E*, *F*} whereas loss of appetite and fatigue form elementary sets as follows:
R = {Loss of appetite, Fatigue}
Indiscernibility(*R*) = {{*A*, *D*}, {*B*, *C*, *F*}, {*E*}}

Patient *A* suffers from hepatitis whereas patient *D* doesn't suffer from the disease even though they have same attribute values for loss of appetite, fatigue and muscle ache. Therefore, hepatitis cannot be fully characterized by loss of appetite, fatigue and muscle ache. Moreover, it can be stated that *A* and *D* are boundary line cases with respect to the available information. The patients *B* and *F* can be classified with certainty as not suffering from hepatitis, whereas patients *C* and *E* as suffering from hepatitis. Patient *A* and *D* cannot be excluded as suffering from hepatitis in view of the displayed symptoms. If X_1 represents patients suffering from hepatitis then

X_1 = {x | Hepatitis(x) = yes} = { *A*, *C*, *E* }

$\underline{R}X_1 = \{ C, E \}$

$\overline{R}X_1 = \{ C, E, A, \mathbf{D} \}$

Thus, lower approximation of the patients suffering from hepatitis is {C, E}, the upper approximation is {A, C, E, D}, and patient A and patient D form the boundary. Similarly, sets for "Not suffering from hepatitis" can also be formed as

X_2 = {x | Hepatitis(x) = no} = { B, D, F}

$\underline{R}X_2 = \{ B, F \}$

$\underline{R}X_2 = \{ B, F, D, \mathbf{A} \}$

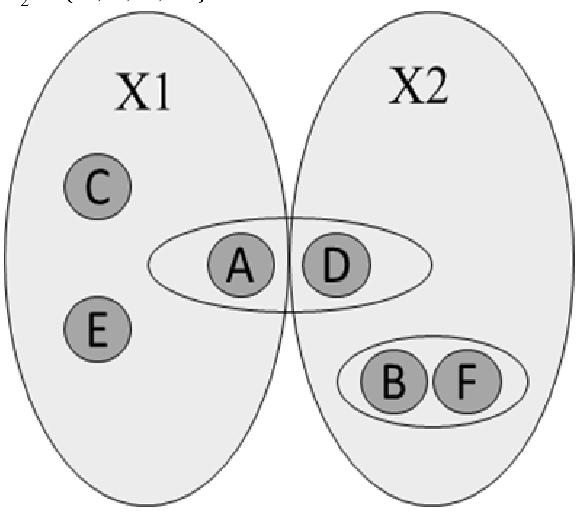


Fig. 6 PDM using rough sets

Another important aspect of data analysis using rough sets is discovering the dependency between attributes. This helps in determining whether some data (attributes) can be removed from the table without affecting its basic properties i.e. whether a table contains some superfluous data. This can be accomplished by finding out the degree of dependency using calculations provided by several authors [9] [24].

VI. FUZZY ROUGH APPROACH

The application of fuzzy and rough sets has led the researchers to study various approaches to combine both theories [8] [12] [13] [14] [31]. Most of them have concluded that both the theories are not equivalent, in fact complementary and can be used in combination. The advantage of introducing fuzziness in rough sets is that it allows us to quantify the level of roughness in the boundary regions by using fuzzy membership values. Thus, the lower and upper approximation sets are no longer crisp but fuzzy. Moreover, all elements present in the lower approximation or the positive region have a MF value of one whereas the elements beyond the upper approximation have a membership value of zero. The elements that lie in the upper approximation but are not in the lower approximation region, i.e., elements of the boundary region, are assigned a membership value of between zero and one. Rough set definitions of union and intersection were modified so that the fuzzy model would satisfy all the properties of rough sets [31].

A. Definition

Let *U* be a universe, *X* is a rough set in *U* then a fuzzy rough set *Y* in *U* is a membership function $\mu_Y(x)$ which associates a grade of membership from the interval [0, 1] with every element of *U* where all elements of the positive region have a membership value of one and elements of the boundary region have a membership value between zero and one [31].

$$\mu_Y(\underline{R}X) = 1 \tag{14}$$

$$\mu_Y(U - \overline{R}X) = 0 \tag{15}$$

$$0 \leq \mu_Y(\overline{R}X - \underline{R}X) \leq 1 \tag{16}$$

VII. CASE STUDY

The example we present in this section is database that can be used in the critical care section of a health facility to monitor the vital signs (such as blood pressure, pulse rate, blood sugar etc.) of a patient under observation or treatment. The information system stores only the basic information of patient such as name and emergency contact. For the sake of simplicity, only a small section of the database has been presented here. The case study illustrates the need of incorporating uncertainty, together with temporal aspect, in relational databases.

The critical care ward of a health facility maintains an information system that monitors that blood pressure of the patients all the time. The blood pressure measurement is converted to a description using a predefined mechanism in the information system. Based on this description, appropriate medication is provided to the patients by the healthcare personnel on duty. The medication provided varies with age of the patient; hence 'Age of patient' is also stored in the information system. One important consideration here is that the age of the patient is stored as description such as CHILD, ADULT, or ELDERLY, for example. This is because the exact age of the patient isn't available instantly. To manage such a situation, health care personnel on duty are responsible for classifying the patient to a particular age group. However, a problem may arise if multiple observers are recording the patient data. For instance, YOUTH and TEEN may be used by two different observers for classification of same age group. Therefore, the age attribute is rough having indiscernible attribute values.

The ER-diagram our database is shown in Fig. 7. The diagram used is generated using MS SQL Server 2000 diagramming utility. There are five tables namely Patient, PatientBP, BPrange, BPgroup and Indiscernibility. Attributes that may contain indiscernible (similar) values are handled in the Indiscernibility table.

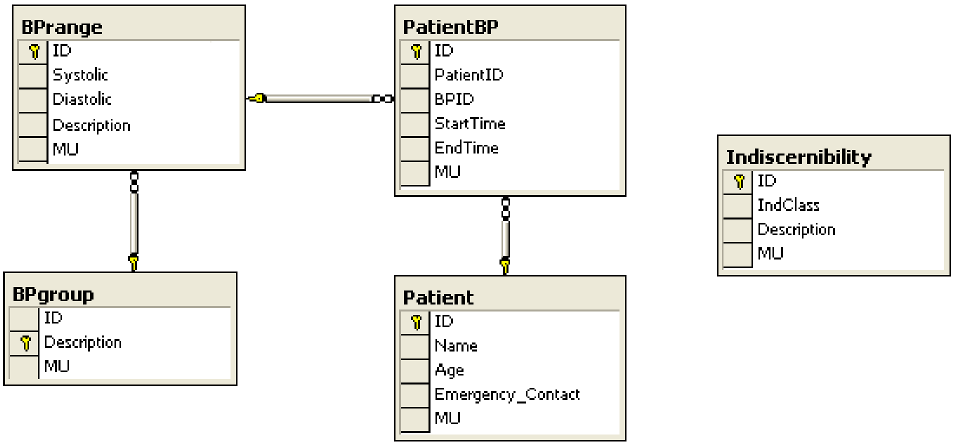


Fig. 7 ER-diagram for FRT-Database

The table is not actually the part of the relation database design, but inherent in the fuzzy rough approach. The fuzziness of the relation is handled using the membership function attribute (MU). Moreover, if there is no fuzziness in any particular indiscernibility relation then value of MU will be 1.

A brief description of the table follows whereas detailed records are listed in the appendix:

A. Indiscernibility table

The Indiscernibility table has attributes ID, IndClass, Description and membership value. All the attributes that are similar to one another are placed in an indiscernibility class and thus have the same value for the attribute IndClass. For example, Moderate BP or very high BP belongs to the indiscernibility class 6.

B. BPgroup table

The BPgroup table has attributes ID, description and membership value. This table is used to assign an ID to different levels of blood pressure.

C. BPrange table

The BPrange table has attributes ID, Systolic, Diastolic, Description, MU. This table quantifies the description of the blood pressure level set in BPgroup table in terms of possible values of Systolic and Diastolic pressure (in mm of Hg). The membership value is to cater 'Description' attribute. The different combination of systolic and diastolic blood pressure is an arbitrary generated range and the corresponding description has been provided by the authors based on information available in [33] [34]

D. Patient table

The Patient table has attributes ID, Name, Age, Emergency Contact, MU. The membership value is to manage the attribute 'Age'.

E. PatientBP table

The PatientBP table has attributes ID, PatientID, BPID, StartTime, EndTime, MU. This is the major table of the database that has indiscernibility, ambiguity as well temporal aspect at the same time. The table stores the BP level of a patient along with the table interval for which that level was valid. The medication administered to the patient is on the basis of the trend shown by table.

For instance, Patient ID 1000 who is a middle aged elderly person, had moderate blood pressure (Systolic: 160, Diastolic: 100) on 3-March-2012 between 14:30 to 16:30. Similarly, Patient ID 1001, a middle aged adult had a high normal blood pressure (Systolic: 130, Diastolic: 85) on 3-March-2012 between 14:30 to 17:30.

VIII. FUZZY ROUGH TEMPORAL QUERIES

Another important advantage of integrating fuzzy rough approach to temporal databases is that it will allow us to write queries in a language that is much closer to natural language as opposed to the trivial query languages. A query language that caters for fuzzy, rough and temporal aspect, once developed, will allow for direct mapping of natural language statements to database queries, thus providing much accurate results. Some of the queries are presented below:

(i) List age groups of the patients that have severe blood pressure today.

(ii) List the patients whose blood pressure was normal yesterday.

(iii) List the blood pressure of patient 1001 between 14:30 to 16:30 on 3-March-2012.

(iv) Retrieve the list of all elderly patients whose blood pressure remained severe during last two days.

A query language that supports such constructs will produce SQL like result sets for all the queries listed above. Such language will be based on rough and fuzzy rough relation algebra as well as contain operators to handle the temporal aspect of the database. A detailed discussion and overview of such language and operators has been provided in [18] [31] [35].

APPENDIX

Table A: BPgroup

ID	Description	MU
1	Low	1
2	low normal	1
3	normal	1
4	high normal	1
5	Mild	1
6	Moderate	1
7	severe	1
8	very severe	1
9	very low	1

Table B: BPrange

ID	Systolic	Diastolic	Description	MU
1	225	130	very severe	1
2	215	125	very severe	0.9
3	205	120	very severe	0.8
4	195	115	very severe	0.7
5	185	110	very severe	0.6
6	175	105	severe	0.85
7	165	100	severe	0.75
8	160	100	moderate	0.95
9	155	95	moderate	0.9
10	150	95	moderate	0.85
11	140	90	mild	0.7
12	130	85	high normal	0.9
13	125	80	high normal	0.85
14	120	80	normal	0.95
15	110	70	normal	0.85
16	105	70	normal	0.8
17	100	65	low normal	0.95
18	90	60	low normal	0.85
19	85	55	low	0.75
20	75	50	low	0.85
21	70	50	low	0.9
22	65	45	very low	0.8
23	55	40	very low	0.95

Table C: Indiscernibility

ID	IndClass	Description	MU
1	1	low	1
2	1	below normal	1
3	2	slightly below normal	1
4	2	low normal	1
5	3	far far too high	1
6	3	very severe	1
7	3	too too high	1
8	4	slightly above normal	1
9	4	high normal	1
10	5	mild	1
11	5	high	1
12	6	moderate	1
13	6	very high	1
14	7	child	1
15	7	pre teen	1
16	7	young	1
17	8	youth	1
18	8	teen	1
19	8	teenager	1
20	9	adult	1
21	9	grown up	1
22	10	sr adult	1
23	10	middle aged	1
24	11	elderly	1
25	11	old	1

Table D: Patient

ID	Name	Age	Emergency Contact	MU
1000	Ahmed	{middle aged, elderly}	0300-1234565	0.8
1001	Ali	{Adult, Middle age}	0333-9543212	0.6
1002	Salman	Adult	0346-2654855	1
1003	Najam	Elderly	0332-3054468	1
1004	Ameen	{Adult, Sr Adult}	0300-2386132	0.55

Table E: PatientBP

ID	PatientID	BPID	StartTime	EndTime	MU
500	1000	8	03/03/12 14:30	03/03/12 16:30	1
501	1000	9	03/03/12 16:30	03/03/12 20:30	1
502	1001	12	03/03/12 14:30	03/03/12 17:30	1
503	1001	11	03/03/12 17:30	03/03/12 22:30	1
504	1004	16	03/03/12 14:30	03/03/12 15:30	1
505	1004	15	03/03/12 15:30	03/03/12 18:30	1
506	1004	17	03/03/12 18:30	03/03/12 21:30	1

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