Fuzzy Reasoning for Medical Diagnosis-based Aggregation on Different Ontologies

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Abstract—The paper discusses reasoning application for decision making in medical diagnosis. This is to reason on medical concepts that are viewed on two types of ontologies; namely physical and mental. We highlighted in this position paper issues on fuzzy reasoning by aggregating two types of ontologies that are used to formalize a patient state: mental ontology reflecting the patient mental behavior due to certain disorder and physical ontology reflecting the observed physical behavior exhibited through disease. Similarity matching is used to find the similarity between fuzzy set reflected to mental fuzzy ontology, and physical fuzzy ontology. The alignment is projected on medical ontology to rank attributes for decision making. We apply aggregate function for ranking attributes related to physical object. In the same time, we apply harmonic power average aggregate function for ranking attributes related to mental objects. The alignment of these two aggregate function produce weighted ranking order fuzzy set for medical decision making for diagnosis. The paper highlights these issues as new challenges extending intelligence reasoning of VDS.

Keywords- Medical diagnosis, fuzzy reasoning, cognitive model, human interaction, aggregate function

I. INTRODUCTION

Medical diagnosis is important practice and is related to optimization evaluation. However, the task is complex due imprecise and fuzzy alternatives involved in decision making. Medical diagnostic process involves a complex mental exercise and a state space search of medical knowledge, which could become complicated as variables involved are many and patients symptoms are fuzzy with many relates alternatives. Also, patients are not precise in expressing their situation in practicable mathematical manner. As they use ambiguous terms and language to express their health parametric situation mixed aligned with different views (context). Also, human doctors due to different background and experiences they may interpret in different manner patient symptoms, putting scattering priorities on alternatives.

This conundrum is compounded when a particular pathological process presents with ambiguous symptoms that are similar to those of other conditions, as in the case of fever, or in situations when expert medical practitioners are in short supply and pressured [20]. In order to improve the possibility of early and accurate diagnosis of sickness, there is the need for the application of artificial intelligence or other decision support systems in the diagnostic process, because these are known to improve practitioner performance, reduce costs and improve patient outcomes.

A number of expert technology oriented systems have attempted to mitigate these challenges, and have attempted to address the subjects of knowledge acquisition, representation, and utilization in medical diagnosis. However, the problem of managing imprecise knowledge still exists. Clinical decision support systems utilize patient’s data and some inference procedures to generate case specific advice and suggestions to the practitioner [22].

Virtual Doctor System (VDS) is reported in [2][8][9][6] is related to design avatar that resemble a real human doctor and act to interact with patient user to establish a diagnosis scenarios. The system outline and related experiments is outlined in SISY [6].

We have created a related technology, reflecting the state of art on creating a program that resembles the user mental psychological behavior through a face. This concept we called is mental cloning [1][2][3][9][10]. The mental cloning is used to collect on the built avatar reflecting a real person, the animated real-time images created in real-time on this avatar resembling the emotional behavior of that person articulated through this avatar in the same manner the real person interact with certain world in similar invocation. This is represented by using that person ego state [3][10].

In this paper the system is extended to reflect on reasoning issues that the VDS can use to interact with human patient for medical diagnosis. The interoperability is represented by utilizing the medical diagnosis cases of medical doctor, and represented in machine executable fashion based on human patient interaction with virtual
avatar resembling a real doctor. The avatar or VDS is working as a 1st glance diagnosis to classify patients based on the criticality, emergence related to examination parameters and diagnosis scenarios outcome for decision making. In this paper we discuss aspects on using fuzzy techniques for realizing multi criteria in decision making for medical diagnosis. The PhO ontology and MeO ontology is extended to have fuzzy index terms (relation) governed by fuzzy logic that is used to do decision making based on medical diagnosis.

II. VDS SYSTEM OUTLINE

This section is outlining the experimental system called a VDS. The medical scenarios used in medical diagnosis are defined on general guidelines formalization, and customization according to the subject doctor experience and related specialization on the course of medical practices. This system is to help the real doctor by filtering the outpatient (when they come to the hospital) who waiting to see the real doctor. The virtual doctor sees patients by interacting with them and issues a decision making for simple cases and non-simple cases categorical based on criticality issues. Criticality issues are estimation of the outpatient sickness state. This is based on his/her mental and physical reasoning that is achieved (i.e., reached) collectively (inferred) by the VDS. We have constructed two concepts that the system uses to do reasoning. One is called Physical Ontology, and the other is called Mental Ontology. We define the concept of “pain” as part of mental ontology. The two represented ontologies are merged to yield a third ontology called Medical ontology, representing the diagnosis processor in Fig. 1. The action processor is the decision making that use fuzzy reasoning, that define the membership of index terms to do decision making and analysis. The simple medical case in our context; is defined as the case that usually medical doctor reaches through medical diagnosis, and is considered by medical Doctor namely A, as a state that the outpatient can be recovered by taking a rest, or simple medical supplement, a case resulted from stress, heavy work or tiredness or else. The simple case treatment is in most cases is to ask the patient to rest and come back after few days if the recovery is not achieved.
accordingly direct the action processor to select the best scenarios that would readout the selected diagnosis fitting to the patient instance, in the same manner as the real doctor does. On [10] we appended several video that demonstrate how the VDS interacts with the patient and how the system’s camera is eyeing on patient face to extract values to reason through on patient state as shown in Fig. 2. This link [13] has demo files and news available for download.

III. REASONING FRAMEWORK

There are several parts related to the VDS interaction parts that have already reported in published work related face emotional recognition [4][5][6] and voice emotional recognition [9][13]. We have built a concept we call it as mental cloning [1] we could collect user emotion and mentality reflected through face and voice to understand the mental state of the user. These are used for creating output for the avatar and input data due to user emotional change (engagement) with the avatar [2] (Fig. 2). This paper is discussing the reasoning framework related to VDS application for diagnosis based on fuzzy reasoning. The context of the engagement is defined in advance. In this paper the context is medical diagnosis based on Doctor A (expert). So collecting the user mental state is to have the system adapt to changes that would have the user be engaged with the system in a positive manner.

The avatar in our system that we built as experimental is virtually constructed to resemble real Doctor objectified for subjective human patient to interact with. We have a mask face model for real doctor practicing his/her medical provision in hospital in our town [2][1]. Such face (system) will interact with the user in emotional based manner [10]. The face would act in emotional manner according to the context and engagement style of the user. The face mental background resembling an ego state reflected through the egogram resembled person (medical doctor) and represented in the system as a program [10]. The face states are the primitive states that the system would select interactively according to the user engagement as cognitive state. The user ego state is also collected from the best match from the database based on what we called universal template. A set of egograms is stored in the system and indexed according to universal templates [3].

These stored classified egogram are to work as templates to test user ego states (emotion). User observed ego state is measured through a set of universal templates. The measurement of face parts movements are referenced (computed) to indexed templates collected from many Japanese subject (people) contributed in our experiment [3][5][6][10]. On [13] you can view (download to view) the movies showing how the system works and also for public news on the project, (in Japanese media).

The system would test the mental states of the user based on these ego grams, and interact with the user based on instantiation of observed changes on the face parts collected due to emotional reasoning based engagement. Also, the same is done on the voice as well. The voice emotional features are examined to reflect the patient voice sound features like soaring throat related sound feature, or related expression to pain or else. The same also, is for expressing the dialogue with patient by doctors with emotional voice to patient synchronized with their mental situation. We have built the system that ensemble a medical doctor interacting with the patient based on the framework mentioned above,
to do diagnosis on patient at clinic in Japan. These two instances of MD style of reasoning (diagnosis) are examined and represented in the VDS system based on provided instances of simple cases medical practices data that have fuzzy nature.

IV. REASONING BASED ON FUZZY ONTOLOGY

The conceptual reasoning framework is based on representing two types of ontologies, reflecting patient (user) physical conceptual status as seen by the VDS, as shown in Fig. 3. We have used a combination of fuzzy techniques, to do decision making on simple case diagnosis. The target of the system is identifying the patient case as simple, with weight. (Simple ?), where? is: High, medium and low, or not-simple. By ranking the symptoms based on attribute that has fuzzy membership to ontology. In [6] we have defined two types of ontologies (Fig. 3).

Physical Ontology definition: PhO.
Mental Ontology Definition: MeO.

Each ontology represents causal relation articulated from physical view analysis, and mental view analysis. In [6] we have used Probabilistic model to reference and infer to doctor diagnosis. It is taking use of alignment of the two defined ontologies, and do diagnosis based on probabilistic type calculation to compute values that would be used to make the decision related to special cases, this is modeled on Bayesian network. We have used the Bayesian network [6] (as belief network) aligned and reflected on these two ontologies. Logical and probabilistic approaches were applied to the diagnosis for Decision Making (DM). However, Due to uncertainty of human cognition it is not easy to provide suitable numerical values for the criteria needed to make appropriate (optimal or reasonable) DM. We need to provide linguistic fuzzy attributes for decision making as these are provided by medical doctors or experts. Medical knowledge represents symptoms on patients in fuzzy manner, like high Temperature, and young, very young and so on. There are many attributes involved in decision making. These attributes are represented in fuzzy logic and aggregate function [24].

The weights are used to represent the relative importance that the DM gives to different individual distance. The distance is to find the difference between two alternatives (object), based on similarity matching using Minkowski distance.

Fuzzy logic models are generalization of the conventional set theory and a mathematical way to represent the vagueness of parameters. The basic idea in fuzzy logic is that statements are not just ‘true’ or ‘false’, but sometimes “partial truths” or “partial falses”. Fuzzy logic exhibits complementary characteristics by offering a good framework for approximate reasoning. Fuzzy systems are capable of acquiring knowledge from domain experts, and attempt to model the human reasoning process.

The meanings of metadata based on (gender, egogram, age, history) of User (patient) situation are classified [2]. These are alternatives, acting as fuzzy values that in a collective manner classify the medical scenarios articulated on the ontologies representation. These alternatives are ranked fuzzy logic to reflect on the aligned mental ontology and physical ontology according to the observed fuzzy values. Medical cases are examined in two hospitals. Different cases are collected from Medical doctors who are
participated to provide values that are used to define the attributes and its membership fuzzy values. The both are aligned to articulate to the status of the outpatient observed alternatives: (Fuzzy mental, fuzzy physical). All alternatives are ranked based on ranking of attributes represented by two types of aggregate functions. One aggregate function related to physical ontology for decision making to related attributes. The other aggregate function is related to mental ontology for decision making on mental attributes for mental decision making. Similarity matching for decision making is relative to Positive ideal solution [24] provided by experts on each ontology represented as weighted ranked attributes of the two ontology aligned on medical ontology. The scoring of expertise knowledge used in such calculation is used for retrieving Knowledge related to medical cases. (Fig. 3)

How to produce the membership values:
- From diagnosis document and medical guidelines.
- From experience with patient and nurses, (human experts).

Linguistic fuzzy variables are reflecting quantified attributes, like body temperature, weights and etc. This is appropriate representation in PhO. The linguistics terms in the value scale as fuzzy intervals that for a fuzzy partition of the prescribed unit interval. The decision specifies properties among these intervals. This called as granulation of unit interval. So the aggregations of medical criteria are represented using: “fuzzy if-then rules”. These are diagnosis fuzzy rules based on fuzzy linguistic variables, eg., BMI(), etc. The knowledge base is fuzzified as power ordered weighted geometric aggregation in ascending manner. This linguistic knowledge is represented as quadratic fuzzy numbers, and is used to compute the weight vector of attributes and rank it for decision making based on similarity computation.

Pho related attributes fuzzy relation matrix is computed based on Ordered Weight Average (OWA) similarity to determine the weight orders or priorities.

\[ OWA(a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} w_i a_{in(i)} \]

where \( in \) is an indexing function such that \( in(i) \) is the index of the \( \text{ith} \) largest attribute, \( w_i \) is weight of attribute.

Power Order Weighted Geometric (POWG):

\[ POWG(a_1, a_2, \ldots, a_n) = \prod_{i=1}^{n} a_{in(i)} \]

POWG is used to compute the similarity index to aggregate attributes to the medical argument in the knowledge base. The attributes related to decision making on patient having temperature is related to the POWG of attributes to physical ontology aggregation and mental ontology aggregation.

**Symptoms type Physical**: Are those symptoms observed on the patient by devices or previous documented data. In our system, we have the patient be seated on a chair with three types of devices that read: The body weight, temperature distribution on the face, and blood pressure. There are also other data that can be collected from previous history or document, referencing to previous physical state and articulates on the new state, (Fig. 4)

**Symptoms type Mental**: These are the observed behavioral patterns on the patient face, articulated through templates to reflect to the mental state of the patient, if she/he is in a pain or a sort of situation (Fig. 5)

However, in MeO this is not the case. As most of the attributes values computed by the mental interaction are qualitative values based on aggregate values collected from the parts of the face and cognitive models that in total contribute to estimate the mental state of the patient. We need to provide a sufficient linguistic granularity to the attributes that are related to qualitative values attributes computed through the MeO reasoning process. Most Medical doctors in diagnosis use qualitative values for attributes on their observation on patients. We have suggested using 5 linguistic terms for simplicity. \( T = \{t_0=N, t_1= VL, t_2=L, t_3=M, t_4=H \} \)

These 5 terms membership functions are reflected from advices received from medical doctors.

The semantics are represented by fuzzy number in the interval [0,1] as membership function using triangular fuzzy numbers. For example:

\( N= (0, 0, 0.2), VL= (0, 0.2, 0.40), L= (0.2, 0.40, 0.60), M=(0.4, 0.6, 0.80), H=(0.6, 0.8, 1.0), \)

Fig. 6: Fuzzy based reasoning outline
For each alternative, we need to combine all attributes in complete manner. We think the model of 2-tuples fuzzy [29] linguistic hierarchical structure may improve the aggregation processes of multi granular linguistic information as projected on MeO. However, we have used the Bonferroni mean aggregator operator to aggregate attributes on MeO. MeO is reflected on attributes ordered as Bonferroni Mean power average aggregation function. The Bonferroni mean (BM) is a mean type aggregation technique, which is developed to deal with situation that has correlations between the aggregated arguments. BM can capture the interrelationship of the input arguments, which makes it very useful in decision making [30]. BM is a kind of combined \textit{and} and \textit{averaging} operator represented as [30]:

\[
BM^{p,q}(a_1, a_2, \ldots, a_n) = \left(1 - \frac{1}{n-1} \sum_{j=1}^{n} a_j^q\right)^{\frac{1}{p+q}}
\]

Where \(a_n\) are attributes related to MeO. Each is composition of decision making. Stress \((x, y, z)\) is concluded from aggregation of six attributes, represented as \textit{Happy}(x,y,z), \textit{Sad}(x,y,z) and so on. These are related to six Ekman states plus neutral. This is the model we used to instantiate the mental state of a patient. The same also is related to ego state of the patient. Ego \((x,y,z)\). All these are represented using trapezoidal fuzzy numbers, and reasoned using decision making related to the knowledge of experts. Such knowledge is represented as trapezoidal membership function. Such linguistic hierarchy is provided by the MeO model, as a set of attributes with qualitative values reflected from subject patient on different granularity level.

As the medical diagnosis in concern the symptoms observed on patients are computed using facial and sound recognitions provided as membership function that is fuzzified linguistic value. The fuzzification is based on PhO and MeO views are collected from medical doctors. Physical variables, \(PH=(ph_1, ph_2, \ldots, ph_n)\) and mental variables \(ME=(me_1, me_2, \ldots, me_n)\). There PH, ME are vectors of fuzzy attributes, Pain \([PH, ME]\) represents discrete fuzzy set of five values related to membership function.

The aggregate functions (contingent) specify a set of attribute with contingent ranked feature. This is from medical data analysis. Example Linguistics fuzzy variables

\begin{itemize}
  \item \textit{Age (years)}={YONG, MEDIUM, OLD}
  \item \textit{BMI (kg/m2)}={L, M, H}
\end{itemize}

(Other fuzzy variables)

The aggregate function specifies diagnosis symptoms attributes, as a set of aggregate function reflected on each ontology (Fig. 7). MeO={\{aggregate function\}. It is a set of fuzzy values reflected as membership functions. These are to assess the importance of the positive and negative effects on decisions. It is predisposition intermediate decisions as complete order or complete disorder (as weighted to certain situations). This is treated as subjective to the doctor decision criteria predisposition on patient fuzzy mental attributes (qualitative values) and physical fuzzy attributes (quantitative values).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig7.png}
\caption{Aggregation of attributes}
\end{figure}

We have proposed to provide a set of preferences and ranking for term index on aligned ontologies. We also have studied issues on presenting the memberships function of the attributes in Mental Ontology by bipolar fuzzy logic. The Fuzzy bipolar are used for representing the membership attributes for MeO objects to capture the positive and negative effect. It makes the triangular fuzzy number to be nested.

On the other side PhO attributes are reformed as pair wise comparison matrix used to compute the ranking of alternatives [17] based on the aggregation that can be used to measure the distance for related decision making based on concepts similarity in medical cases.

This is suitable in spatial reasoning application like in medical application on MeO. The semantics of “opposite” captures a notion of symmetry rather than a strict complementation. In particular, there may be membership of attribute positions which are considered neither to the positive side nor to the negative side of certain reference object.

For each point \(x\), \(u(x)\) defines the membership degree of \(x\) (positive information). Since the positive concept information; models what is possible, preferred, observed or experienced.

Let \(U, V\) be two non-empty universes. A fuzzy set \(R \subseteq F(U, V)\) of the universe \(U \times V\) is called a fuzzy relation from \(U\) to \(V\). In general, for any \(u \in U, v \in V\), the degree of the membership \(R(u,v)\) denotes the degree of the relations of \(u\) and \(v\). If \(U = V\), the fuzzy relation \(R \subseteq F(U \times V)\) will be called a fuzzy relation on \(U\).

Let \(U\) is the set of patients who have symptoms \(U\). If \(u \in U\),
S is a subset of V, and S represents the symptoms \( \{v_i\} \) reflected on Physical ontology and mental ontology. As each sickness is a combination of different symptoms reflected on Physical ontology and mental ontology. S is a subset of V, and S represents the symptoms \( \{v_i\} \) reflected on a certain sickness S. We can derive different relations defined in relation ordered power mean.

On the other hand we have used power ordered weighted geometric for representing member function on Fuzzy physical Ontology and determine the ranking of attributes based on fuzzy PhO framework presentation.

The multi-criteria decision analysis (MCDA) method that uses mathematical algorithms to transform qualitative subjective judgments into quantitative data, which produces a computational model that serves as input into the evaluation of decision alternatives. It uses judgments from a group of decision makers along with hierarchical decomposition of a problem to derive a set of ratio-scaled measures for decision alternatives. With such approach we can determines the relative priorities consistent with overall objectives. The variables involved in medical diagnosis are numerous; as such, their combinatorial analysis may become explosive, and lead to a decay of the medical expert’s preference. When the variables under consideration are so many, pairwise comparison reduces this problem associated with comparing many variables at the same time. However, AHP fails to achieve multiple criteria decision support (MCDS) due to its non-linear nature in case we need to have prioritization on attributes [23].

In medical diagnosis and due to our investigation we argued that uncertainty is the central and critical fact about decision making in general, and medical reasoning, in special. Uncertainty and imprecision therefore should characterize the sources of information available to medical expert systems. Such sources include the patient, physician, laboratory and other technical methods of evaluation, and mathematical models that simulate the diagnostic process. This culminated in the utilization of fuzzy logic (FL) to resolve the problems of imprecision and uncertainty in medical diagnosis. This is because of the ability of fuzzy logic to handle vague information to mathematically model unstructured information. Therefore we have studied related solution from ontological representation of different domain medical knowledge aligned in pair-wise manner for decision making.

Criteria depend on alternatives. The properties for the criteria are judgments relation to pairwise comparison. However, judgment evaluation on criteria can be made after carefully examine the alternatives. For example, in a headache health decision where one of the criteria is type of headache and another is location; one might have a pre-conceived idea that type of headache is the most important criterion. But after actually checking the location and seeing its impact on its related alternatives in relation to its impact on health, we may achieve better precise decision on diagnosis. What has happened is that after studying the properties of the actual alternatives, of headache, the importance of the criteria changed. This approach makes it clear how to determine the priorities of criteria, tangible and/or intangible, by considering their dependence on the alternatives [23].

As stated “alternatives are derived from paired comparisons and the resulting values are not linearly related” [23]. Ontology of different domain knowledge can be categorized, so we think providing ontology alignment can provide a solution to produce linear evaluation to the multi-criteria decision making (Fig. 3).

Ontology alignment can provide a hierarchical structure for the knowledge contents that can support data contents models so that we can build on top of fuzzy models (to tackle issue related to imprecise knowledge for appropriate decision making). To handle the uncertainty problems in decision making especially in heterogeneous systems that are reflecting different medical knowledge of expertise. We have focused in this research on semantic interoperability between ontologies to achieve dynamic alignment. This is to organize knowledge base into classes that can be aligned based on concept specialization using similarity computation. We assume that the best configuration should be maximizing the summation of class similarities. Similarity between two classes is computed by not only class labels but also features extracted from the instances. We have investigated several techniques for semantic analysis for dynamic alignment. Term feature is specified by set of patients symptoms that are articulated on each ontology to produce a set of features that are used for dynamic binding (pair wise) related to a set of merged attribute aligned for reasoning on different knowledge-bases. The alignments between heterogenous ontologies are a set of pairs of concepts as equivalence or subsumption among heterogeneous ontologies. Such approach, we believe produce prioritization for attributes that can help to make reasoning aggregation achieved in linear space manner. We need to prove this in real practices using medical domain problems. The alignment process itself is interoperable among different heterogeneous ontologies.

The user profile ontology is reflected as Fuzzy cluster that is suitable in constructing ontology-based user preferences because some information is not forced to fully belong to any one of user profiles. Fuzzy clustering methods may allow some information to belong to several user profiles simultaneously with different degrees of accuracy. Fuzzy c-means is best algorithm available to construct fuzzy clusters. A patient user profile can be represented by different ontologies. It can be represented as set of cluster of different features.

The patient preference computation matrix:
The patient preferences are not static. They express emotions indifferent patterns in relation to a set of symptoms. The medical cases are stored on KB have fuzzy values in relation to user physical and mental attribute to emerged symptoms. These are categorized based user preferences.

For DM in Fuzzy PhO,

The most commonly used fuzzy numbers are triangular and trapezoidal fuzzy numbers. Triangular fuzzy numbers (TFNs) are often used in applications because of their calculation easiness and features. TFNs are used to represent the linguistic variables.

In TOPSIS (Technique for order Performance by Similarity to Idle Solution) the alternative orders are calculated by measuring the distances to both the fuzzy positive-ideal solution (FIPS): optimistic

The linguistics preferences for alternatives are converted to fuzzy numbers [27]. In order to rank the alternatives (attributes) reflected to the collected input of the VDS projected on ontology, we compute the fuzzy relation matrix. Then from the fuzzy relation matrix we compute the fuzzy relation strength that finally can produce the rank properties of the alternatives. The ranking computation is carried on using quality function deployment (QFD) [27]. The fuzzy relation matrix is constructed to link the attributes of the diagnosis requirements to the related diagnosis projected on the KB through similarity computation. The i-th attributes related to j-th diagnosis by weight; wj. In such style the integrated fuzzy relation matrix is constructed. All the attributes on each ontology is computed based on similarity degree for related diagnosis in weight values representation.

This is based on medical doctors KB medical cases estimation. PheO related attributes fuzzy relation matrix is computed based on similarity to determine the weight orders or priorities. The Bonferroni mean aggregation is used for MeO. The fuzzy relationship strength would compute the final decision aligned on the total summation of all triangular fuzzy values. Then after the defuzzification [26] we can obtain the attributes priorities reflecting to the relevance of the diagnosis query.

Similarity and distance measure are important in decision making using the weight function provided by the Fuzzy ontology analysis mentioned above.

The alternatives are those values defined by the PhO and MeO views. These fuzzy alternatives set are any values between 0 and 1. These values are representing the temperature in relation to threshold values (representing normal situation articulated on user situation). The total weight is the sum of these values and should be one.

Symptoms type Physical: Are those symptoms observed on the patient by devices or previous documented data. In our system [6], we have the patient be seated on a chair with three types of devices that read: The body weight, temperature distribution on the face, and blood pressure. There are also other data that can be collected from previous history or document, referencing to previous physical state and articulates on the new state.

Symptoms type Mental: These are the observed behavioral patterns on the patient face, articulated through templates to reflect to the mental state of the patient, if she/he is in a pain or a sort of situation.

These above two situations each are reflected and represented on medical ontology for diagnosis. The Symptoms reflected on Physical ontology are those reflected on mental ontology and are mutually independent. The medical ontology represents the conceptual (abstract) view of medical diagnosis. The view is specialized by the doctor type, and reflected as a specialization model, of the both PhO and MeO in diagnosis. The simple case is defined in conceptual view and generalized form, the specialization due to the type definition of simple cases according to the doctor experiences, and is represented on medical ontology. The style of reasoning diagnosis is also relative to the doctor diagnosis ontology (as a specialization to medical ontology).

The variables outcome would infer to the medical cases and invoke certain scenarios. These scenarios are explained to the outpatient as question or comments, expressed by the VDS in the same manner the real doctor does.

Ontology is a set of concepts related to set of attributes on to each concept, and set of relationship among these concepts. All variables values (relationship or attributes) are computed based on mental and physical observation in the model. Variables are computed and collected by initiating scenarios with outpatient to collect these causes’ values (probabilistic) for decision making.

With these medical doctors help we have established several cases resembling different types of configuration of variables. These configurations can resemble different types of simple cases. We could create more complicated configuration in the same manner, however this would make the Bayesian network more complicated. At the moment our interest is to build the system and test it in these two hospitals. There are several issues that need to be examined from real experiment. Not only the inference complexity, but the practicality on having such system in medical practices for simple case scenarios needs also, to be investigated.

The fuzzy weight of each symptom is calculated with weights representing the importance of that variable. All variables in the PhO, MeO have classified weight reflecting the structure of medical knowledge. The knowledge base is categorized and classified base on these variables importance as part of the two defined ontologies. The evaluation is not numerical but subjectively qualitative and oracle. The PhO, is mapped with related aspect collected from fuzzy attributes to related aspect from the MeO, The alignment is articulated on MedO through causal relation based on fuzzy based decision making which is proved to be
useful in reasoning on imperfect knowledge like these related to medical diagnosis on patient. The medical alignment ontology is a conceptual view of simple medical case that is defined in terms of PhO and MeO aligned on medical diagnosis.

Patients come to the hospital and fill a forms of questionnaire that specify their egogram which is done by touch panel monitor. These egograms are stored in patient profile database associated with properties and restrictions according to the patient state as part of patient concept. Physical data on patient states are automatically collected. The reasoner creates the ranked fuzzy attributes corresponding to the two ontologies (explained, and accordingly, creates the classification as specialization for the simple case for such patient. The system computes through the simple case senarios the decision on a set of fuzzy attributes related to fuzzy physical ontology and a decision to fuzzy mental ontology on the 1st pass then another question that articulates the special case to construct the mapping classification and the network to compute the 2nd pass using again fuzzy decision making for the 2nd pass simple case diagnosis.

The confidence in selecting the related set of inter_concepts is related to associating rules mining in the related ontology, as either the MeO, or the PheO represented fuzzy membership values. Related concepts can produce cluster that is reflected as alignment and pairing of cluster reflected on Medical ontology, as goal ontology.

Feature can be computed by information gain reflected through patient profile feature and collected from the physical and mental decision making related features ranking.

$$\text{Entropy}(f) = - \sum_{i=0}^{O_c} p(i|\text{feature}) \log_2 p(i|\text{feature})$$

Feature reflected on either type of ontology, $p(i|\text{feature})$ is the fuzzy value for the $i$-type user related feature $\text{feature}$. $O_c$ is the ontology as either MeO or PheO related set of coherent set concepts related to the feature $\text{feature}$ and patient type $i$. Concepts gathered in relation to feature are weighted according to degree of entropy and the similarity of concepts calculated. The higher the weight is the better concepts reflecting the patient related diagnosis collection of concepts. Concepts are aggregated to two types, mental concepts and physical related concepts. Each concept is an aggregation to patient feature, patient patterns[15]. The similarity is computed as weighted nearest neighbor [16]. Concepts are class with related feature that is reflected as query vector. The set of concepts C1 is aligned with query keywords on other concepts class (C2). The semantic similarity measurement is utilized to produce weighted content information by taking similarity among concepts related to ontology (PhO, or MeO), reflected by features collected from input. $a_j$ is the $j$-the medical case with $i$ feature.

MeO related ranked fuzzy attributes and Physical related fuzzy attributes are aligned (Pair wised) for decision making. The alignment paired set of concepts is reflected as set of key words inquiry to search for best fit for medical diagnosis case using normalized Euclidian distance measure

$$\text{similarity}(a_1,a_2) = \sum_{i=1}^{n} w_i * \text{sim}(a_{1i},a_{2i}) / \sum_{i=1}^{n} w_i$$

$a_{ni}$ is medical case, 1 for feature $i$ of fuzzy weight $w_i$, and $a_{nj}$ medical case 2, for feature $i$ of fuzzy weight $w_j$. The weight represents the relative importance that the DM gives to different individual distance. The similarity is computed on related medical case that is pairwise collection of merged weighted feature reflected from medical knowledge retrieving (deriving) related similar cases.

In this position paper we have presented concepts and guidelines on reasoning issues in VDS based on fuzzy set from the prospective of defining membership function based on doctor experience in diagnosis related to set of fuzzy based attributes for decision making. Like YONG attributes repressed by the fuzzy membership. WIGHT, BLOOD PRESSURE and other attributes are part of the PhO. The expert fuzzy model used to rank fuzzy modeled attributes is the above fuzzy aggregate model that is proposed to be used for ranking the attributes in either ontology according to their feature to medical case. The other fuzzy attributes related to the MeO is modeled also by Harmonic membership function producing aggregate function related to Mental Ontology variables. The aggregate function used to model these fuzzy attribute is used to rank these attributes and define the corresponding weights to rank these attributes. We ranked attributes will be aligned to medical ontology using rule provided by the medical doctor.

**ACKNOWLEDGMENT**

This research is supported by the Ministry of Internal Affairs and Communications of Japan under the Strategic Information and Communications R&D Promotion Programme (SCOPE). We would like to give our gratitude to the Medical Doctors Committee board of VDS of SCOPE project as the medical application board advisory of this research, who have provided experience and advises on their medical analysis on patients diagnosis, and simple cases outline senarios.

**REFERENCES**
