Possibilistic Medical Knowledge Representation Model

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Medical Decision Support Systems involve two main issues: medical knowledge representation and reasoning mechanisms adapted to the considered representation model. This paper proposes an approach to construct a new medical knowledge representation model, based on the use of possibility theory. The major interest of using the possibility theory comes from its capacity to represent different types of information (quantitative, qualitative, binary, etc.), as well as different forms of information imperfections such as uncertainty, imprecision, ambiguity and incompleteness. Starting from the description, realized by an expert of the medical knowledge, describing the relationship between symptoms and diagnoses, the proposed approach consists on building a possibilistic model including the Medical Knowledge Base. Moreover, the proposed approach integrates several possibilistic reasoning mechanisms based on the considered knowledge. The validation of the proposed approach is then conducted using an Endoscopic Knowledge Base. The proposed representation, reasoning model and the obtained validation results show a real interest in order to realize various goals of Medical Decision Support Systems such as classification, similarity estimation, etc.

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1. INTRODUCTION

Physician is the direct responsible for health and life of his patients. Therefore, diagnosis delivering is an extremely critical, although difficult task. Furthermore, diagnosis delivering is an error-prone task [3]. Medical Decision Support Systems such as Knowledge Based Systems, Case Based Reasoning Systems, Machine Learning Systems and Medical Data Mining Systems, have been constructed in order to reduce diagnosis error risks, as well as to help physicians making high quality and reliable medical decisions [4]. These systems involve two main issues: the medical knowledge representation and adapted reasoning mechanisms. The medical knowledge, in general terms, has to be considered from two points of view: Expert Knowledge related to the physician's description of different relationships between symptoms and diagnoses, symptoms and symptoms, and diagnoses and diagnoses. Patient Information is collected from each patient (patient data collecting and structuring). The first is crucial in order to establish Medical Knowledge Base, while the second leads to establish the patient database (i.e., Medical Case Base). Experts use their own experience of the medical cases as well as references knowledge sources to define the structure of the medical knowledge base.

Medical knowledge often suffers from different forms of information imperfections (i.e., uncertainty, imprecision, ambiguity, etc.). In addition to the different types of information imperfections, the information can be quantitative (numerical or binary) or qualitative (nominal and ordinal) [17, 29]. Thus, the heterogeneity and imperfection of medical knowledge must be taken into consideration while the construction of a Medical Decision Support System. In other words, Medical Decision Support System has to be able to deal with heterogeneous and imperfect knowledge.

In [27] R. Seising et al. defined the Medical knowledge as follows:

> "*The certain information about relationships that exist between symptoms and symptoms, symptoms and diagnoses, diagnoses and diagnoses and more complex relationships of combinations of symptoms and diagnoses to a symptom or diagnosis are formalizations of what is called medical knowledge*."

The term "symptom" is used for any information about the patient's state health (anamnesis, signs, laboratory test results, etc.).

According to the previous definition, the term "medical knowledge" will be considered in this study to represent the relationship between symptoms and diagnoses, (Symptom)–(Diagnosis). This relation is generally expressed in a probabilistic way based on the use of a linguistic term, referring to the expert's assessment of the occurrence of a given symptom related to a given diagnosis.

In order to be exploited in Medical Decision Support Systems, this Medical Knowledge has to be modeled (translated into a model understandable by the system) using one of representation's approaches such as probabilistic, fuzzy, possibilistic, etc.

In [4] and [18], theory about clinical decision supports system is presented. The probabilistic approach is one of the first model that can be proposed, regarding the probabilistic nature of the linguistic term. The following probability, $\mathrm{pr}(\mathbf{D} \mid B)$ (where $\mathbf{D}$ and B represent respectively a diagnosis and a symptom), should be computed for each diagnosis. This value is obtained by the Bayes' formula:

$$\mathrm{pr}(\mathbf{D} \mid B) = \frac{\mathrm{pr}(B \mid \mathbf{D}).\mathrm{pr}(\mathbf{D})}{\mathrm{pr}(B)}. \tag{1}$$

In this formula we need two types of information:

—$\mathrm{pr}(B \mid \mathbf{D})$ which is available

—$\mathrm{pr}(\mathbf{D})$ which is difficult to be known, but it can be estimated by a statistic approach.

In our case, we suppose that the only available information is $\mathrm{pr}(B \mid \mathbf{D})$. For this reason the probabilistic representation approach is not adequate in our context.

Fuzzy sets theory, introduced by Zadeh [33] has several interesting properties that make it suitable for formalizing the imperfect information upon which medical diagnosis is usually based on. Firstly, it allows the definition of inexact and/or ambiguous medical entities as fuzzy sets. Secondly, it offers the possibility of using linguistic variables in addition to crisp numerical variables. Finally, fuzzy logic (i.e. mathematical logic allowing the manipulation of fuzzy sets) offers reasoning methods adequate for approximate inferences drawing. Fuzzy sets as a framework representation and fuzzy logic as a reasoning mechanism have been successfully applied to different Medical Decision Support Systems [1, 5, 21, 22, 26].

Progress in this field was characterized by the introduction of the possibility theory as an alternative approach of the inexact reasoning. Although the possibility theory is an extension of the fuzzy sets theory, it has many advantages over to make it more suitable as well as more efficient [24, 35]. In fact, possibility theory provides an approach to formalize subjective uncertainties of events, that is to say means of assessing to what extent the occurrence (realization) of an event is possible and to what extent we are certain of its occurrence, without having the possibility to measure the exact probability of this realization because we lake similar events to be referred to, or because the uncertainty is the consequence of observation instruments reliability absence. It also offers the advantage of decision making based on two set-based measures called the possibility and the necessity measures. At the level of information fusion, the possibility theory uses simple mathematical operations (min, max, etc.). Several studies proved the successful using of possibility theory as a representation framework and as a reasoning mechanism in Medical Decision Support Systems [9].

In this document, we propose the use of the possibility theory [10] as a global framework in our Medical Decision Support System. After studying the existing possibilistic approaches, we can note that these works neglect the issue of the medical knowledge representation, and concentrate their contribution only on the issue of possibilistic reasoning (for instance see [10]). In other words, there is no algorithm describing the phase concerning the transition from the medical description (i.e. the linguistic term expressing the medical knowledge (Symptom)–(Diagnosis)) into a possibilistic description (i.e. numerical value in the interval $[0,1]$ expressing the occurrence possibility degree of Symptom with a given Diagnosis).

The important contribution of this work is to answer the question concerning the issue of medical knowledge possibilistic representation. Furthermore, this work proposes an algorithm describing, in details, the construction of Possibilistic Knowledge Base (in which the relation (Symptom)–(Diagnosis) is represented by possibilistic value belonging to the interval $[0,1]$) from Medical Knowledge Base (in which the relation (Symptom)–(Diagnosis) is represented by linguistic term).

This document is organized as follows: Section 2 details a knowledge representation model allowing physicians to express their medical knowledge. Main aspects of possibility theory are briefly introduced in Section 3. Section 4 is devoted to the detailed description of the proposed approach to construct a new possibilistic model of medical knowledge and to the use of this model in order to build Possibilistic Knowledge Base. In Section 5, the evaluation of the reliability of the constructed model will be conducted by realizing several tasks accomplished by Medical Decision Support Systems. The particular Endoscopic Knowledge Base allowing the validation of proposed possibilistic model, obtained results and the comparison with prior ones are detailed in Section 6. Finally, Section 7 presents conclusions concerning the proposed model as well as some propositions for further developments.

2. MEDICAL KNOWLEDGE AND REPRESENTATION (EXPERT VISION)

The objective of the medical knowledge base construction is to perform a reliable information modeling of the medical knowledge description, expressed by physicians, according to a predefined knowledge representation scheme. The knowledge representation schemes had been classified by Carter [6] into four categories: logical, procedural, graph/network and structural. In this paper, we adopt the structural model that has been used by Cauvin [4] in order to construct the Endoscopic Knowledge Base, which represents our medical application. According to this structural model, this section is devoted to present the description of:

—Diagnoses in the medical knowledge base;

—Patient-cases in the medical case base.

From here, we will use the term "feature" to represent the name of symptom, and the term "modality" to represent the value of symptom. For example, the

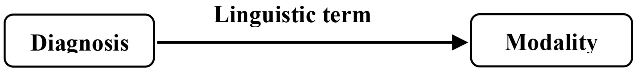

Fig. 1. Qualitative description using linguistic term.

Fig. 2. Example of qualitative description using linguistic term.

TABLE I
Example of Physician Description in a Medical Knowledge Base

	$\mathbf{P}_1$			$\mathbf{P}_2$	
	v_1^1	v_2^1	v_3^1	v_1^2	v_2^2
$\mathbf{D}_1$	always	never	never	rare	usual
$\mathbf{D}_2$	rare	usual	usual	never	always
$\mathbf{D}_3$	exceptional	usual	usual	never	always

feature "Temperature" can take one of three modalities *low*, *normal*, *high*.

2.1. Medical Knowledge Base

The Medical Knowledge Base is assumed to encapsulate the expert knowledge related to the different considered diagnoses. A diagnosis is represented by physicians, using all potential modalities of the predefined features, through describing the relationship between modalities and diagnoses. This relationship expresses the occurrence, assessed by physicians, of a given modality for a given diagnosis.

2.1.1. (Modality)–(Diagnosis) Relationship

From a probabilistic point of view, the ideal representation of this relation is to attribute to each couple (Modality)–(Diagnosis), it's exact occurrence probability value. Nevertheless, these values are rarely known by physicians in terms of exact values. For this reason and in order to express this imprecise/ambiguous knowledge of the probabilistic values, physicians use a qualitative description by means of natural language [2]. This description mode offers physicians the opportunity to express their uncertainty by using linguistic terms more indicative than numerical ones used in possibility or probability theories. The form of the qualitative description using these linguistic terms is shown in Fig. 1. In this form, the linguistic term belongs to the scale $\{$*never*,…,*always*$\}$. For instance, if the relation between a given diagnosis *Flu* and a given modality *fever* is described by the linguistic term *habitual* as shown in Fig. 2, then we can read: the modality *fever* occurs *habitually* with the diagnosis *rheum*.

2.1.2. Medical Diagnosis Representation

Let $\mathbf{D} = \{\mathbf{D}_1, \ldots, \mathbf{D}_M\}$ denote the set of M diagnoses, $\mathbf{P} = \{\mathbf{P}_1, \ldots, \mathbf{P}_G\}$ denote the set of G features used for the description of diagnoses. In this description, each feature is considered independently from the others. Each feature $\mathbf{P}_g$ can assume one of K_g potential modalities defined by the set $\mathbf{V}_g = \{v_1^g, v_2^g, \ldots, v_{K_g}^g\}$. The diagnosis $\mathbf{D}_m$, $m = 1, \ldots, M$, is thus represented in the medical knowledge base by the following model:

$$\mathbf{D}_m = \{(\mathbf{P}_g, v_j^g, R(v_j^g, \mathbf{D}_m));\ g = 1, \ldots G;\ j = 1, \ldots, K_g\} \quad (2)$$

where

- $\mathbf{P}_g$ denotes the feature "g";
- v_j^g is the jth modality ($j = 1, \ldots, K_g$) of the feature "g";
- $R(v_j^g, \mathbf{D}_m)$ represents the linguistic term (defined by physicians) that expresses the occurrence of jth modality related with the given diagnosis $\mathbf{D}_m$;
- $\mathbf{Q} = \{q_1, \ldots, q_L\}$ represents the predefined set of linguistic terms.

Table I shows an example of an expert description in a medical knowledge base [4]. In this example, the physician describes a set of three diagnoses (diseases) $\mathbf{D} = \{\mathbf{D}_1, \mathbf{D}_2, \mathbf{D}_3\}$ using two features: $\mathbf{P}_1$ (with three modalities: $\mathbf{V}_1 = \{v_1^1, v_2^1, v_3^1\}$) and $\mathbf{P}_2$ (with two modalities: $\mathbf{V}_2 = \{v_1^2, v_2^2\}$). Five linguistic terms are used: $\mathbf{Q} = \{q_1 =$ *never*, $q_2 =$ *exceptional*, $q_3 =$ *rare*, $q_4 =$ *usual*, $q_5 =$ *always*$\}$.

2.2. Patient-Case Representation

The Medical Case Base is assumed to encapsulate the recorded data collected from different patients. An expert standardizes the description such that a case has a unique description and is structured to be used by a computer-aided system [4].

A patient-case is described by physicians using the same set of G features ($\mathbf{P}_g$, $g = 1, \ldots, G$) used in the description of diagnoses. Each feature $\mathbf{P}_g$ can assume one and only one of its potential modalities included in its corresponding feature modalities set $\mathbf{V}_g$, or it can assume the value "0" in the case where this feature is not evaluated (i.e., a missing data) or if the feature is impossible to be observed or to be evaluated.

Let $B = \{B_1, \ldots, B_N\}$ denote a medical case base containing a set of N patient-cases. A patient-case B_n, $n = 1, 2, \ldots, N$, is thus represented in the medical case base by the following medical model:

$$B_n = \{(\mathbf{P}_g, x^{g,n}), \mathbf{D}_n\} \quad (3)$$

where

- $x^{g,n}$ is the value of the feature $\mathbf{P}_g$ such that $x^{g,n} \in \mathbf{V}_g \cup \{0\}$, $g = 1, \ldots, G$;
- $\mathbf{D}_n$ is the diagnosis associated with the case B_n, $\mathbf{D}_n \in \mathbf{D} = \{\mathbf{D}_1, \ldots, \mathbf{D}_M\}$, ($\mathbf{D}$ contains all possible diagnoses).

In this model, only a discrete set of modalities is involved, it means that an expert divides each continuous modality in intervals.

An illustrative example of an Endoscopic Medical Case Base is shown in Table II. In this example,

TABLE II
Example of Physician Description in an Endoscopic Case Base

	$\mathbf{P}_1$ = Object Type	$\mathbf{P}_2$ = Origin	Diagnosis
$\mathbf{B}_1$	Not Homogenous Simple	Parietal	Tumor
$\mathbf{B}_2$	Homogenous	Parietal	Spot
$\mathbf{B}_3$	Not Homogenous Multiple	Luminal	Food

three cases B_1, B_2, B_3, are described using two features: $\mathbf{P}_1$ = "Object Type" with three modalities {*Homogenous*, *Not Homogenous Simple*, *Not Homogenous Multiple*} and $\mathbf{P}_2$ = "Origin" with two modalities {*Parietal*, *Luminal*}. The associated diagnosis is respectively given as {$\mathbf{D}_1$ = *Tumor*, $\mathbf{D}_2$ = *Spot*, $\mathbf{D}_3$ = *Food*}.

3. POSSIBILITY THEORY

3.1. Possibility and Necessity Measures

Possibility Theory, introduced by L. Zadeh in 1978 [34] and then developed by Dubois and Prade in 1988 [13], offers an interesting tool allowing to deal with different forms of information imperfections (ambiguity, imprecision, incompleteness, etc.).

The possibility theory constitutes the basis of several recent studies in medicine [11]. The obtained results in these studies confirmed the efficacy of the use of possibility theory as a tool for medical knowledge representation, as well as for the medical diagnostic decision.

Let $\mathbf{\Omega} = \{x_1,\ldots,x_N\}$ denote an exhaustive and exclusive Universe of discourse that means the list of the possible alternatives. At the semantic level, the basic function in possibility theory is the *possibility distribution* denoted as $\pi : \Omega \to [0,1]$ which assigns to each possible alternative x_n from Ω a value ranging within the interval $[0,1]$. This possibility distribution represents the possibility occurrence degree of x_n, the basic alternative, decision, diagnosis, etc. If, for some x_n, $\pi(x_n) = 1$, then x_n is said to be a *totally possible* alternative; and if $\pi(x_n) = 0$, then x_n is said to be an *impossible* alternative. Based on a possibility distribution, the information concerning the occurrence of an event $A \in \mathcal{P}(\Omega)$ ($\mathcal{P}(\Omega)$ is the power set of Ω) is represented by means of two set functions: a *Possibility Measure* denoted as $\mathbf{\Pi}(.)$ and a *Necessity Measure* denoted as $\mathbf{N}(.)$.

The *possibility measure* $\mathbf{\Pi}(.)$ is defined as follows [11]:

$$\begin{aligned}&\Pi : \mathcal{P}(\Omega) \to [0,1]\\ &\qquad A \to \Pi(A) = \max_{x_n \in A}(\pi(x_n))\end{aligned} \tag{4}$$

and satisfying the following requirements:

$$\Pi(\Phi) = 0 \qquad \text{and} \qquad \Pi(\Omega) = 1 \tag{5}$$

$$\Pi\left(\bigcup_{j\in J} A_j\right) = \max_{j\in J} \Pi(A_j) \qquad \forall A_j, \quad j \in [1,J] \tag{6}$$

where J represents the number of elements of the set $\mathcal{P}(\Omega)$.

If the possibility measure of an event $A \in \mathcal{P}(\Omega)$ is equal to the unity (i.e., $\Pi(A) = 1$, then A is said to be *totally possible* event. If $\Pi(A) = 0$ then, A is said to be totally *impossible* event.

Reciprocally, the possibility distribution can be defined from the possibility measure, by affecting the possibility measure of the subset $A = \{x_n\}$ to the alternative x_n: $\pi(x_n) = \Pi(\{x_n\})$.

The second measure, called the *necessity measure* $\mathbf{N}(.)$, is defined as follows [11]:

$$\begin{aligned}&N : \mathcal{P}(\Omega) \to [0,1]\\ &\qquad A \to N(A) = 1 - \max_{x_n \in A}(1 - \pi(x_n)) \qquad \forall A_j, \quad j \in [1,J]\end{aligned} \tag{7}$$

and satisfying the following requirements:

$$N(\Phi) = 0 \qquad \text{and} \qquad N(\Omega) = 1 \tag{8}$$

$$\Pi\left(\bigcap_{j\in J} A_j\right) = \min_{j\in J} N(A_j) \qquad \forall A_j, \quad j \in [1,J]. \tag{9}$$

If the necessity measure of an event $A \in \mathcal{P}(\Omega)$ is equal to the unity (i.e., $N(A) = 1$, then A is said to be *totally certain*; and if $N(A) = 0$, then A is said to be *totally uncertain*.

Several duality relations link the possibility measure and the necessity measure:

$$A \in \mathcal{P}(\Omega) : 0 \leq N(A) \leq \Pi(A) \tag{10}$$

$$\text{If} \quad N(A) > 0, \quad \text{then} \quad \Pi(A) = 1 \tag{11}$$

$$\text{If} \quad \Pi(A) < 1, \quad \text{then} \quad N(A) = 0 \tag{12}$$

$$N(A) = 1 - \Pi(A^c). \tag{13}$$

3.2. Joint and Conditional Possibility Distribution

Within the application studied here, the expert expresses medical knowledge as the possibility of modality occurrence given a diagnosis. This type of knowledge can be modeled using the conditional possibility concept.

Given two reference sets X and Y where $X = \{x_1,\ldots,x_M\}$ and $Y = \{y_1,\ldots,y_N\}$, a joint possibility distribution $\pi(x_m, y_n)$ where $x_m \in X$ ($m = 1,\ldots,M$) and $y_n \in Y$ ($n = 1,\ldots,N$) can be defined on the Cartesian product $X \times Y$ in order to express the joint occurrence possibility of the singletons $x_m \in X$ ($m = 1,\ldots,M$) and $y_n \in Y$ ($n = 1,\ldots,N$) [34]. The joint possibility distribution provides information on each reference set X and Y individually as two marginal possibility distributions, obtained by retaining the largest value of joint possibility distributions relative to the reference set as it is explicated in the following definitions.

Definition 1 Starting from a given joint distribution π, the *marginal possibility distributions* are defined on the two reference sets X and Y as follows:

$$\forall x_m \in X : \pi(x_m) = \sup_{y \in Y} \pi(x_m, y) \tag{14}$$

$$\forall y_n \in Y : \pi(y_n) = \sup_{x \in X} \pi(x, y_n). \tag{15}$$

The reciprocal influence among the reference sets can be studied through the degree to which an element y_n of Y is possible, knowing that the element x_m of X is considered. In other words, the conditional possibility which is defined as follows:

Definition 2 There is not a unique definition of the *conditional possibility distribution* $\pi(y_n \mid x_m)$ measuring the occurrence for an element y_n from Y knowing that the element x_m from X has occurred [6], but all proposed definitions in the literature [31] are based on the following general formula linking the conditional possibility with the joint and marginal possibilities:

$$\pi(x_m, y_n) = \pi(y_n \mid x_m) * \pi(x_m) \qquad \forall x_m \in X, \quad \forall y_n \in Y \tag{16}$$

where, "*" is a combination operator which can be considered as the *minimum* or the *product* fusion operator.

The decision made by humans, is usually taken based on information fusion of different types and assigned various forms of imperfection: uncertain information, possibilistic information, binary information, ambiguous information, etc. To address these different types of information into a single framework, a transformation from one type to another is fundamental. An important facet of the theory of possibilities lies in the ability to transform probabilistic information in possibilistic information in carrying out the projection of probability distributions to possibility ones. Indeed, this transformation is a useful operation when dealing with heterogeneous information. Several transformations of a probability distribution into a possibility distribution and conversely have been proposed in this direction. In this study, we will adopt Dubois-Prade transformation [13, 15]:

Dubois-Prade transformation procedure:

Given a reference set $X = \{x_1, \ldots, x_M\}$, in which each element x_i is associated with its probability $\mathrm{pr}_i = \Pr(\{x_i\})$, $i = 1, \ldots, M$. In order to perform the transformation from the given probability into a possibility distribution, first, the probability values are arranged in a decreasing order so that $\mathrm{pr}_1 \geq \mathrm{pr}_2 \geq \ldots \geq \mathrm{pr}_M$; then, the following possibility degrees are computed $\forall i$, $i = 1, \ldots, M$:

$$\begin{aligned} \pi_1 &= 1 \\ \pi_i &= \Pi(\{x_i\}) = \sum_{j=1}^{M} (\mathrm{pr}_j) \qquad \text{if} \quad \mathrm{pr}_{i-1} > \mathrm{pr}_i \\ &= \pi_{i-1} \qquad\qquad\qquad\quad \text{otherwise.} \end{aligned} \tag{17}$$

4. POSSIBILISTIC MEDICAL KNOWLEDGE REPRESENTATION MODEL

In Section 2, we have shown the Medical Knowledge Base, and how physicians qualitatively describe, using linguistic terms, the medical knowledge considered mainly as a relationship (Modality)–(Diagnosis).

In order to be exploited in Medical Decision Support Systems, this Medical Knowledge Base has to be modeled using one of representation approaches. Furthermore, the linguistic term, expressing the relationship (Modality)–(Diagnosis), has to be translated into a model understandable by the system.

This section is devoted to present our proposed approach in order to represent this kind of relationships by means of possibilistic model.

4.1. Possibilistic Knowledge Base Construction

Assume that a Medical Knowledge Base (as described in Section 2), containing a set $\mathbf{D}$ of M diagnoses, is available. Each diagnosis in this base $\mathbf{D}_m$, $m = 1, \ldots, M$, is characterized using a set $\mathbf{P}$ of G features. Each feature $\mathbf{P}_g$, $g = 1, \ldots, G$, can assume one of K_g possible modalities grouped in a set $\mathbf{V}_g$. The diagnosis D_m is thus expressed using the model given in (2). The expert will indicated the modality frequency for each diagnosis in using a qualitative scale $\mathbf{Q}$ of L linguistic terms $\mathbf{Q} = \{q_1, \ldots, q_L\}$ running from "*never*" to "*always*" as follows: $q_1 = \textit{never}, \ldots, q_L = \textit{always}$. The expert doesn't know the exact probability but only an approximation.

The objective here is to translate the Medical Knowledge Base established by the Expert into a possibilistic model exploitable by medical decision support systems. In other words, we want to build the following possibilistic model of diagnosis $\mathbf{D}_m$, $m = 1, 2, \ldots, M$, in which the relationship (Modality)–(Diagnosis) is represented as a possibility value:

$$\mathbf{D}_m = \{(\mathbf{P}_g, v_j^g, \pi(v_j^g \mid \mathbf{D}_m));\ g = 1 \ldots, G;\ j = 1, \ldots, K_g\}. \tag{18}$$

The proposed approach to realize reach this target consists on performing the following steps:

Step 1 Transforming the qualitative scale of linguistic terms $\mathbf{Q} = \{q_1, \ldots, q_L\}$ into a quantitative one of numerical values $\boldsymbol{\alpha} = \{\alpha_1, \ldots, \alpha_L\}$ where $\alpha_i \in [0,1]$, $\alpha_1 = 0, \ldots, \alpha_L = 1$, and $\forall j \in [0, L-1] : \alpha_j < \alpha_{j+1}$, so that $\forall i \in [1, L]$ there is $q_i \equiv \alpha_i$.

Step 2 Substituting each $R = q_i \in \mathbf{Q}$ in the Medical Knowledge Base by the corresponding numerical value α_i. Therefore, the representation of a given diagnosis $\mathbf{D}_m$ will be as follows:

$$\mathbf{D}_m = \{(\mathbf{P}_g, v_j^g, \alpha(v_j^g \mid \mathbf{D}_m));\ g = 1 \ldots, G;\ j = 1, \ldots, K_g\}. \tag{19}$$

In fact, the distribution of numerical values at the level of given feature $\mathbf{P}_g$, cannot called a probability distri-

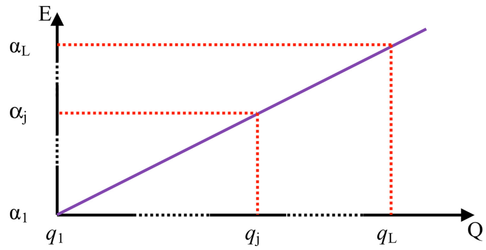

Fig. 3. Projection d'une échelle qualitative en une échelle numérique.

TABLE III
Linguistic Term Substitution by Numerical Ones

	P		
	$v_1^{\mathbf{P}}$	$v_2^{\mathbf{P}}$	$v_3^{\mathbf{P}}$
$\mathbf{D}_1$	always	never	never
$\mathbf{D}_2$	rare	usual	usual
$\mathbf{D}_3$	exceptional	usual	usual
$\mathbf{D}_4$	usual	exceptional	never

bution because the normality condition is not satisfied (i.e., $\sum_{j=1}^{K_g} \alpha(v_j^g \mid \mathbf{D}_m) \neq 1$). For this reason, a normalization operation at the level of feature is necessary.

Step 3 Normalizing the numerical values α at the level of feature, in order to have a conditional probability distribution:

$$\mathbf{D}_m = \{(\mathbf{P}_g, v_j^g, \mathrm{pr}(v_j^g \mid \mathbf{D}_m));\ g = 1\ldots,G;\ j = 1,\ldots,K_g\} \tag{20}$$

so that:

$$\mathrm{pr}(v_j^g \mid \mathbf{D}_m) = \frac{\alpha(v_j^g \mid \mathbf{D}_m)}{\alpha(v_1^g \mid \mathbf{D}_m) + \cdots + \alpha(v_j^g \mid \mathbf{D}_m) + \cdots + \alpha(v_{K_g}^g \mid \mathbf{D}_m)}. \tag{21}$$

For $j = 1,\ldots,K_g$.

Step 4 Applying the Dubois-Prade transformation on the probability distributions in order to construct the conditional possibility distributions. Once the transformation is performed, we obtain the model presented in (18) of $\mathbf{D}_m$.

4.2. Illustrative Example

In order to illustrate the construction of the Possibilistic Knowledge Base, let us consider the following example: Assume that we have a set of four diagnoses $\mathbf{D} = \{\mathbf{D}_1,\mathbf{D}_2,\mathbf{D}_3,\mathbf{D}_4\}$ described using one feature $\mathbf{P}$ of three potential modalities grouped in a set $\mathbf{V}_P = \{v_1^{\mathbf{P}}, v_2^{\mathbf{P}}, v_3^{\mathbf{P}}\}$ (Table III), and the occurrence of these modalities is represented by means of the qualitative scale $\mathbf{Q} = \{q_1 = \textit{never},\ q_2 = \textit{exceptional},\ q_3 = \textit{rare},\ q_4 = \textit{usual},\ q_5 = \textit{always}\}$.

TABLE IV
Substituting Linguistic Terms by Numerical Ones

	P		
	$v_1^{\mathbf{P}}$	$v_2^{\mathbf{P}}$	$v_3^{\mathbf{P}}$
$\mathbf{D}_1$	1	0	0
$\mathbf{D}_2$	0.25	0.75	0.75
$\mathbf{D}_3$	0.1	0.75	0.75
$\mathbf{D}_4$	0.75	0.1	0

TABLE V
Resulting Probability Distribution

	P		
	$v_1^{\mathbf{P}}$	$v_2^{\mathbf{P}}$	$v_3^{\mathbf{P}}$
$\mathbf{D}_1$	1	0	0
$\mathbf{D}_2$	0.14	0.43	0.43
$\mathbf{D}_3$	0.06	0.47	0.47
$\mathbf{D}_4$	0.88	0.12	0

In order to construct the possibilistic model of these four diagnoses following the proposed approach, steps from 1 to 4 must be applied as follows:

Step 1 The projection of the qualitative scale $\mathbf{Q}$ (having five linguistic values), onto a numerical scale $\boldsymbol{\alpha}$ (also having five empirical numerical values), will produce $\boldsymbol{\alpha} = \alpha_1,\alpha_2,\alpha_3,\alpha_4,\alpha_5\}$ where $\alpha_i \in [0,1]$, $\alpha_1 = 0,\ldots,\alpha_5 = 1$, and $j \in [1,4] : \alpha_j < \alpha_{j+1}$, so that: $\forall i \in [1,5]$ we obtain $q_i \equiv \alpha_i$ as follows:

—$q_1 = \textit{never} \rightarrow \alpha_i = 0$,
—$q_2 = \textit{exceptional} \rightarrow \alpha_2 = 0.1$,
—$q_3 = \textit{rare} \rightarrow \alpha_3 = 0.25$,
—$q_4 = \textit{usual} \rightarrow \alpha_4 = 0.75$,
—$q_5 = \textit{always} \rightarrow \alpha_5 = 1$.

Step 2 Substituting each linguistic term q_i in Table III by the corresponding numerical value α_i, leads to Table IV.

We note that the sum of numerical values at the level of the feature $\mathbf{P}$ doesn't equal to 1 (for example, $\sum_{j=1}^{3} \alpha(v_j^{\mathbf{P}} \mid \mathbf{D}_2) = 0.25 + 0.75 + 0.75 = 1.75 \neq 1$). For this reason, a normalization operation at the level of feature is necessary.

Step 3 The conditional probability value for each modality according to a given diagnosis is computed according to (21) and shown in Table V. For example, the conditional probability value of modality $v_2^{\mathbf{P}}$ for a given diagnosis $\mathbf{D}_2$ is calculated as follows:

$$\mathrm{pr}(v_2^{\mathbf{P}} \mid \mathbf{D}_2) = \frac{\alpha(v_2^{\mathbf{P}} \mid D_2)}{\alpha(v_1^{\mathbf{P}} \mid \mathbf{D}_2) + \alpha(v_2^{\mathbf{P}} \mid \mathbf{D}_2) + \alpha(v_3^{\mathbf{P}} \mid \mathbf{D}_2)} = \frac{0.75}{0.25 + 0.75 + 0.75} = 0.43.$$

TABLE VI
Conditional Possibility Distribution (Possibilistic Knowledge Base)

	$\mathbf{P}$		
	$v_1^{\mathbf{P}}$	$v_2^{\mathbf{P}}$	$v_3^{\mathbf{P}}$
$\mathbf{D}_1$	1	0	0
$\mathbf{D}_2$	0.14	1	1
$\mathbf{D}_3$	0.06	1	1
$\mathbf{D}_4$	1	0.12	0

The transformation of the probability distribution into a possibilistic one, will be realized by applying the Dubois-Prade's transformation (Step 4), which will finally produce the possibilistic model of this base containing four diagnoses (Table VI). For example, the probability distribution associated with the diagnosis $\mathbf{D}_4\{\mathrm{pr}(v_1^{\mathbf{P}} \mid \mathbf{D}_4) = 0.88;\ \mathrm{pr}(v_2^{\mathbf{P}} \mid \mathbf{D}_4) = 0.12,\ \mathrm{pr}(v_3^{\mathbf{P}} \mid \mathbf{D}_4) = 0\}$ will be transformed according to Dubois-Prade as follows:

—Ranking the probability distribution as follows: $\mathrm{pr}_1 = \mathrm{pr}(v_1^{\mathbf{P}} \mid \mathbf{D}_4) = 0.88 > \mathrm{pr}_2 = \mathrm{pr}(v_2^{\mathbf{P}} \mid \mathbf{D}_4) = 0.12 > \mathrm{pr}_3 = \mathrm{pr}(v_3^{\mathbf{P}} \mid \mathbf{D}_4) = 0$;

—According to (17), we obtain:

$$\pi_1 = \pi(v_1^{\mathbf{P}} \mid \mathbf{D}_4) = 1,$$

$$\pi_2 = \pi(v_2^{\mathbf{P}} \mid \mathbf{D}_4) = \sum_{i=2}^{3} \mathrm{pr}_i = \mathrm{pr}_2 + \mathrm{pr}_3$$

$$= \mathrm{pr}(v_2^{\mathbf{P}} \mid \mathbf{D}_4) + \mathrm{pr}(v_3^{\mathbf{P}} \mid \mathbf{D}_4) = 0.12 + 0 = 0.12$$

$$\pi_3 = \pi(v_3^{\mathbf{P}} \mid \mathbf{D}_4) = \sum_{i=3}^{3} \mathrm{pr}_i = \mathrm{pr}_3 = \mathrm{pr}(v_3^{\mathbf{P}} \mid \mathbf{D}_4) = 0.$$

This table is defined for each feature. If G is the number of features, then we have G tables.

5. POSSIBILISTIC REASONING

Once Possibilistic Knowledge Base is constructed, as detailed in the previous section, the reliability of the possibilistic modeling should be evaluated. This evaluation has to be performed in terms of the quality of different tasks conducted by medical decision support systems. In this paper, we will study the exploitation of our possibilistic model in medical decision support systems adopting the Reasoning by Classification. This reasoning type is based on the comparison of the available information acquired from a patient with the medical a prior knowledge formulated by physicians (i.e., Expert Medical Vision) with the aim to assign potential diagnoses facing this particular patient-case.

Given a new case with an unknown diagnosis B which its description is as follows:

$$B = \{(\mathbf{P}_g, x^g);\ g = 1,\ldots G;\ x^g \in \mathbf{V}_g \cup \{0\}\} \quad (22)$$

where

- $\mathbf{P}_g$ represents the feature 'g';
- x^g represents the observed modality of the feature 'g'. If the feature is observed, then x^g take one and only one value from the set of possible modalities $\mathbf{V}_g = \{v_1^g, v_2^g \ldots, v_{K_g}^g\}$, and it takes the value 'zero' otherwise (i.e., the feature $\mathbf{P}_g$ is not observed or it is missing data).

In order to classify this case B (i.e., finding its corresponding diagnosis), we have to compare it with all diagnoses included in the knowledge base, through calculating the similarity between this case and each diagnosis, and then ranking the set of obtained potential diagnoses according to the maximum similarity.

The similarity between B and $\mathbf{D}_m$, $m = 1,\ldots,M$, is represented in our approach by the possibilistic couple $[N(\mathbf{D}_m \mid B), \Pi(\mathbf{D}_m \mid B)]$ of similarity which can be estimated by performing the following steps:

Step 1 Estimation of the local conditional possibility (i.e., at the level of feature), $\pi(\mathbf{D}_m \mid \mathbf{P}_g)$, $m = 1,2,\ldots,M$ and $g = 1,2,\ldots,G$. Here, we distinguish two cases:

- The feature $\mathbf{P}_g$ is observed and produced in the case B as the modality x^g: in this case, the local conditional possibility $\pi(\mathbf{D}_m \mid \mathbf{P}_g = x^g)$ will be estimated from the possibilistic knowledge $\pi(x^g \mid \mathbf{D}_m)$ which is available in the possibilistic knowledge base (as we will see later).
- The feature $\mathbf{P}_g$ is not observed or it is a missing data: in this case, the local conditional possibility is considered equal to the unity, $\pi(\mathbf{D}_m \mid \mathbf{P}_g = 0) = 1$. This means that the diagnosis $\mathbf{D}_m$ is considered as possible solution for a given feature $\mathbf{P}_g$.

Step 2 Estimation of the global conditional possibility (i.e., for the set of all features), $\pi(\mathbf{D}_m \mid B)$, $m = 1,\ldots,M$, by performing a conjunctive fusion of local conditional possibilities. Indeed, the choice of the conjunctive as a fusion type is justified by the fact that if the diagnosis D_m is impossible to produce as a potential solution, at least for one feature (i.e., $\pi(\mathbf{D}_m \mid \mathbf{P}_g) = 0$), then the diagnosis has to be rejected as an impossible solution to the target case B (i.e., $\pi(\mathbf{D}_m \mid B) = 0$). For example, using the conjunctive operator min, we obtain:

$$\pi(\mathbf{D}_m \mid B) = \min_{g=1}^{G} \pi(\mathbf{D}_m \mid \mathbf{P}_g). \quad (23)$$

After this step, we obtain the conditional possibility distribution defined on the set of diagnoses: $\{\pi(\mathbf{D}_1 \mid B), \ldots, \pi(\mathbf{D}_M \mid B)\}$.

Step 3 Using the previous possibility distribution to calculate the conditional possibilistic couple $[N(\mathbf{D}_m \mid B), \Pi(\mathbf{D}_m \mid B)]$, $m = 1,\ldots,M$, according to the following formulas:

$$\Pi(\mathbf{D}_m \mid B) = \max_{n=m}(\pi(\mathbf{D}_n \mid B)) = \pi(\mathbf{D}_m \mid B) \quad (24)$$

$$N(\mathbf{D}_m \mid B) = 1 - \Pi(\overline{\mathbf{D}_m} \mid B) = 1 - \max_{\substack{n=1 \\ n \neq m}}^{M}(\pi(\mathbf{D}_n \mid B)). \tag{25}$$

It is clear that the possibilistic couple estimating is essentially based on the availability of the local possibility value, $\pi(\mathbf{D}_m \mid x^g)$ (i.e., more precisely, the possibility value $\pi(\mathbf{D}_m \mid v_j^g)$, $j = 1,2,\ldots,K_g$). However, the real challenge lies in the fact that this value is not available in the possibilistic knowledge base. Indeed, the available information is the local possibility $\pi(v_j^g \mid \mathbf{D}_m)$ (i.e., the possibility of observing a given modality of a certain feature, since the diagnosis $\mathbf{D}_m$). For this reason, the essential question that arises is:

"*How can calculate the conditional possibility $\pi(\mathbf{D}_m \mid v_j^g)$ where the information available in the possibilistic knowledge base is the conditional possibility $\pi(v_j^g \mid \mathbf{D}_m)$, $m = 1,2,\ldots,M$, $g = 1,2,\ldots,G$, $j = 1,2,\ldots,K_g$?*"

In order to answer to this question, we use the formula (16) that defines the conditional possibility distribution. From this formula, we can write:

$$\pi(\mathbf{D}_m, v_j^g) = \pi(v_j^g \mid \mathbf{D}_m) * \pi(\mathbf{D}_m) = \pi(\mathbf{D}_m \mid v_j^g) * \pi(v_j^g). \tag{26}$$

From this formula, we notice that:

—The estimating of the conditional possibility $\pi(\mathbf{D}_m \mid v_j^g)$ is based on, beside to the conditional possibility $\pi(v_j^g \mid \mathbf{D}_m)$ which is known, the availability of marginal possibilities $\pi(v_j^g)\pi(\mathbf{D}_m)$ which are unknown.

—Also, this relation does not provide a unique opportunity to build the conditional possibility $\pi(\mathbf{D}_m \mid v_j^g)$.

For these reasons, various rules are proposed in the literature to interpret the relation between the conditional and joint possibility distributions, as well as to define the conditional possibility (i.e., *Zadeh's rule*, *Hisdal's equation*, *Ramer's rule*, etc.) [31].

After having analyzed these rules, two of them can be exploited, *Zadeh's rule* and *Nguyen's rule*, thanks to their good properties and their relevance to the process of medical diagnostic reasoning, because of its capability to estimate the conditional possibility $\pi(\mathbf{D}_m \mid v_j^g)$ using only the conditional possibility $\pi(v_j^g \mid \mathbf{D}_m)$ without any other information as the marginal possibility. In this study, we adopt *Zadeh's rule* defining the conditional possibility as equal to the joint one as follows:

$$\pi_{ZA}(y_n \mid x_m) = \pi_{ZA}(y_n, x_m) = \pi_{ZA}(x_m \mid y_n), \quad \forall x_m \in X \quad \text{and} \quad \forall y_n \in Y. \tag{27}$$

6. MEDICAL APPLICATION AND RESULTS

6.1. Endoscopic Application

The Medical Knowledge Base used in this study is an Endoscopic Knowledge Base [8, 19]. This Base consists of a set of 89 endoscopic findings (diagnoses). Each diagnosis is described using a set of 33 features corresponding with 206 global modalities. The qualitative scale used to express the relationship (Modality)–(Diagnosis) by the physicians consists of the following linguistic values {*never*, *exceptional 2*, *exceptional 1*, *rare 2*, *rare 1*, *usual 2*, *usual 1*, *always*}. Furthermore, the linguistic value *doubtful* that is intermediate between *never* and *exceptional*, is added when the expert has an ignorance about the reality of the modality observation. It is important to notice that there are two importance levels for the three variables *exceptional*, *rare*, and *usual*.

The case base used in this study has been developed in the framework of an endoscopic image analyzes system [19]. It is a decision support system of the diagnosis of endoscopic findings. These findings are described by the physicians, from the endoscopic images, through symbolic terms, which are defined by the Minimal Standard Terminology of the SEGE (European Company of Gastro-enterology). A case (or an object) in the base represents a description of the image (using a set of 33 features, 24 features to describe an object and 9 features to describe a potential sub-object) of an endoscopic lesion.

6.2. Experiments and Results

Before analyzing the results of the proposed approach on the global case base, and in order to have a simple and clear representation of the obtained results, we propose to analyze, as an illustrative example, the classification of a small subset of three cases (i.e., endoscopic lesions), $\mathbf{CB} = \{B_1, B_2, B_3\}$, where the "known" diagnoses of these cases are respectively: *Normal Esophagus*, *Dilated Lumen*, and *Ring*.

The compatibility between each case B_f, $f = 1,2,3$, and each diagnosis $\mathbf{D}_m$, $m = 1,2,\ldots,M$, predefined in the knowledge base, will be estimated according to our possibilistic approach (presented in Section 5). In this approach, the diagnosis $\mathbf{D}_m$ is considered as a potential solution for the case B_f, if the conditional possibilistic couple $[N(\mathbf{D}_m \mid B_f), \Pi(\mathbf{D}_m \mid B_f)]$ is not $[0,0]$.

The results obtained by our approach will be compared with that obtained by the fuzzy approach. In the fuzzy approach, $\mathbf{D}_m$ is considered as a potential solution for the case B_f, if the conditional membership degree $\mu(\mathbf{D}_m \mid B_f)$ is not zero.

Fuzzy Theory uses one measure for uncertainty whereas Possibility Theory uses two measures (i.e., the possibility and necessity measures). So, in order to realize the comparison of our possibilistic approach with other one, we must build one measure Ψ which combine the possibilistic couple $[N, \Pi]$ as follows [24]:

$$\Psi(\mathbf{D}_m \mid B) = \frac{N(\mathbf{D}_m \mid B) + \Pi(\mathbf{D}_m \mid B)}{2}. \tag{28}$$

So, according to this measure, the diagnosis $\mathbf{D}_m$ is considered as a potential solution for the case B_f, if the conditional possibilistic measure $\Psi(\mathbf{D}_m \mid B_f)$ is not zero.

The ranking of the potential solutions will be performed according to: the maximal conditional membership degree in the fuzzy approach, and the maximal measure Ψ in possibilistic approach.

Two types of comparison between these two approaches will be realized: comparison in terms of potential diagnoses ranking, and comparison in terms of decision quality. As an evaluation index of the taken decision quality, we propose the use of the distance between the first two potential solutions, if this distance is great, then the decision is of quality, because the discrimination between the potential solutions is easier.

The obtained results are presented in Table VII. This table shows the first two potential diagnoses proposed for each case B_f, as well as the measure "Dist." which represents the evaluation index of taken decision quality according to the considered decision criteria.

To facilitate the comparison and analysis of results presented in this table, we made a graphic representation in Fig. 4. This figures show a representation of the first two potential diagnoses according to the three approaches as well as the distance Dist., for respectively the cases B_1, B_2, B_3. In these figures, the two potential diagnoses obtained by each approach, are presented in the same color (i.e., the colors green, and blue represent respectively the potential diagnoses obtained by the Fuzzy, and Possibilistic Approach).

By analyzing the table and the figure, we note that:

In terms of potential diagnoses ranking:

- For the case B_1, the two approaches gave the true diagnosis (i.e., diagnosis of the studied case) as the first potential solution.
- For the case B_2, the proposed approach gave the true diagnosis as the unique potential solution, whereas the fuzzy approach gave an additional solution as a second potential solution.
- For the case B_3, the proposed approach gave the true diagnosis as the first potential solution, whereas the fuzzy approach gave two diagnoses as two first potential solutions having the same compatibility degree.

In terms of decision quality:

- For the three cases, the distance between the first two potential solutions obtained by possibilistic approach is greater than that obtained by fuzzy approach.
- For the case B_3, the fuzzy approach could not distinguish between the two potential solutions.

After presenting an illustrative example, we will realize a comparison between two approaches on the global case base containing 4450 cases (lesions). As presented in the previous example, the comparison will be realized in terms of the potential diagnoses ranking, and in terms of the taken decision quality.

In order to realize the comparison in terms of the potential diagnoses ranking, we can distinguish four groups:

—**Found:** represents the number of cases for which the right diagnosis is classified as a potential solution.

TABLE VII
Potential diagnoses of the set **CB** according to two approaches (Fuzzy, Possibilistic)

	Fuzzy Approach	Dist.	Possibilistic Approach	Dist.
	$\mu(\mathbf{D}_m \mid \mathbf{B}_f)$		$\Psi(\mathbf{D}_m \mid \mathbf{B}_f)$	
$\mathbf{B}_1$	$\mathbf{D}_1$ = Normal Esophagus: 0.5 $\mathbf{D}_2$ = Spot: 0.37	0.13	$\mathbf{D}_1$ = Normal Esophagus: 0.94 $\mathbf{D}_2$ = Spot: 0.06	0.88
$\mathbf{B}_2$	$\mathbf{D}_1$ = Dilated Lumen: 0.45	0.45	$\mathbf{D}_1$ = Dilated Lumen: 1	1
$\mathbf{B}_3$	$\mathbf{D}_1$ = Ring: 0.49 $\mathbf{D}_2$ = Web: 0.32	0.17	$\mathbf{D}_1$ = Ring: 0.84 $\mathbf{D}_2$ = Web: 0.15	0.69 2

—**Sole:** represents the number of cases for which the right diagnosis is classified as a unique potential solution.

—**First:** represents the number of cases for which the right diagnosis is classified as the first potential solution.

—**Other:** represents the number of cases for which the right diagnosis is classified as a potential solution, but not the first.

We note that the recognition rate associated with diagnostic group called "Found" is always 100% for both fuzzy and possibilistic approaches. This shows that the correct diagnosis still occurs as a potential solution to the target case considered.

For other groups, we note that the results obtained by the proposed approach are better than those obtained by the fuzzy approach, because the greater recognition rate is devoted to the group First, while this rate is divided in the possibilistic approach for the two groups "Unique" 61.24% and "First" 30.76%.

In order to realize the comparison in terms of the taken decision quality, we apply the following algorithm:

For each approach: *Possibilistic* and *Fuzzy* ***Do***

From $n = 1$ ***To*** $n = 4450$ ***Do*** (n: means the considered target case)

1. Calculate the possibilistic couple $[N(\mathbf{D}_m \mid B_n), \Pi(\mathbf{D}_m \mid B_n)]$ for all the diagnoses, $\mathbf{D}_m$, $m = 1, \ldots, M$;
2. Ranking the set of cases according to the maximum similarity measure;
3. Identify all cases where the correct diagnosis (i.e., the true diagnosis of considered target case) is the first potential diagnostic obtained by each approach;
4. Calculate, for each case obtained by the previous step, the distance between the two first potential diagnoses (the true diagnosis and the next diagnosis).

End

End

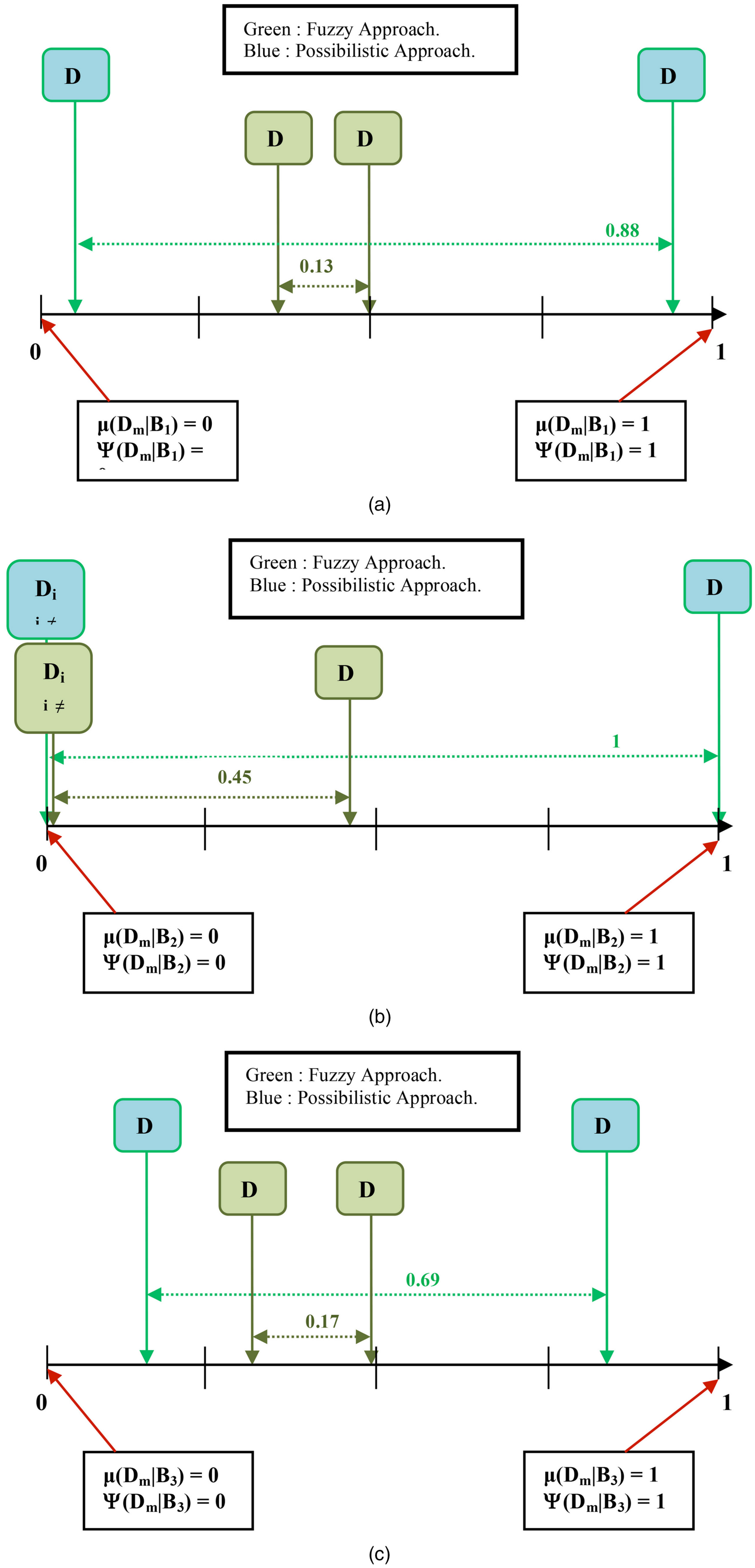

Fig. 4. Distance Representation. (a) Case B_1. (b) Case B_2. (c) Case B_3.

TABLE VIII
Comparaison Between the Two Approaches

	Fuzzy Approach	Possibilistic Approach
	$\mu(\mathbf{D}_m \mid \mathbf{B}_f)$	$\Psi(\mathbf{D}_m \mid \mathbf{B}_f)$
Found	100%	100%
Sole	0.2%	61.24%
First	91%	30.76%
Other	8.8%	8%

TABLE IX
Result Obtained by the Possibilistic Approach

	Distance
Superior (Possibilistic > Fuzzy)	3678/4031 = 91.24%
Equal (Possibilistic = Fuzzy)	3/4031 = 0.08%
Lower (Possibilistic < Fuzzy)	129/3207 = 8.68%

After applying the above algorithm, the distances obtained by the possibilistic approach are compared with those obtained by one of the fuzzy approach. Three groups can be distinguished:

—**Superior:** represents the number of cases for which the distance calculated by the possibilistic approach is greater than that calculated by the fuzzy approach.

—**Lower:** represents the number of cases for which the distance calculated by the possibilistic approach is lower than that calculated by the fuzzy approach.

—**Equal:** represents the number of cases for which the distance calculated by the possibilistic approach is equal to that calculated by the fuzzy approach.

We note that the highest rate is dedicated to the group "Superior." This means that the distance characterizing the quality of the solutions obtained by the proposed approach is higher than that obtained by the fuzzy approach.

7. CONCLUSION AND PERSPECTIVES

In this paper, the use of the possibility theory as a global framework is proposed to construct the medical knowledge representation model. This possibilistic model is applied, as a knowledge representation approach, to represent the relationship (Modality)–(Diagnosis), as well as in the construction of the medical knowledge base. Possibilistic reasoning mechanisms are also developed in order to support the case classification by the physician.

This possibilistic representation transforms the expert linguistic knowledge into a model useable by a decision support system. To tackle the case classification issue, the compatibility (based on necessity and possibility measures) has been defined between the target case and different potential diagnoses.

The proposed approach has been applied in the context of Digestive Endoscopic Image Analysis where the medical expert knowledge was successfully modeled with results in full coherence with the expert's expectation.

In this study, we have considered the complete case description (i.e., all features that should have been described by the expert are considered as fulfilled and present). Nevertheless, an important decision making difficulty has not been tackled; this concerns the partial description context where some features, considered by the user (not the expert) as less important, are not filled. This situation makes some the application of decision support systems very difficult, even to the extent of blocking. In the proposed framework, and due to the use of the possibilistic distance, a decision proposition can always be suggested to the user associated with a pertinence value. In a further research work, this pertinence value will be upper and lower bounded allowing thus to improve user confidence in the employed system.

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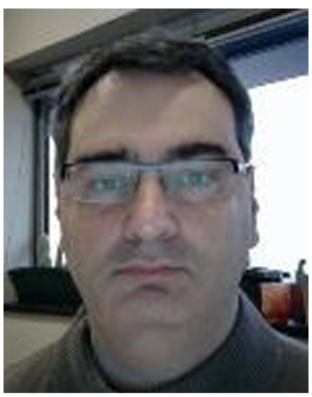

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