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Multimodal Medical Case Retrieval using Dezert-Smarandache Theory with A Priori Knowledge

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Abstract— In this paper, we present a Case Based Reasoning (CBR) system for the retrieval of medical cases made up of a series of images with semantic information (such as the patient age, sex and medical history). Indeed, medical experts generally need varied sources of information, which might be incomplete, uncertain and conflicting, to diagnose a pathology. Consequently, we derive a retrieval framework from the Dezert-Smarandache theory, which is well suited to handle those problems. The system is designed so that a priori knowledge and heterogeneous sources of information can be integrated in the system: in particular images, indexed by their digital content, and symbolic information. The method is evaluated on a classified diabetic retinopathy database. On this database, results are promising: the retrieval precision at five reaches 81.17%, which is almost twice as good as the retrieval of single images alone.

Keywords— Case based reasoning, Image indexing, Dezert-Smarandache theory, Contextual information, Diabetic Retinopathy.

I. INTRODUCTION

In medicine, the knowledge of experts is a mixture of textbook knowledge and experience through real life clinical cases. Consequently, there is a growing interest in case-based reasoning (CBR), introduced in the early 1980s, for the development of medical decision support systems [1]. The underlying idea of CBR is the assumption that analogous problems have similar solutions, an idea backed up by physicians' experience. In CBR, the basic process of interpreting a new situation revolves around the retrieval of relevant cases in a case database. The retrieved cases are then used to help interpreting the new one.

We propose in this article a CBR system for the retrieval of medical cases made up of a series of images with contextual information. Textbook knowledge about the contextual information are integrated in the proposed system. It is applied to the diagnosis of Diabetic Retinopathy (DR). Indeed, to diagnose DR, physicians analyze series of multimodal photographs together with contextual information like the patient age, sex and medical history.

When designing a CBR system to retrieve such cases, several problems arise. We have to aggregate heterogeneous sources of evidence (images, nominal and continuous variables) and to manage missing information. These sources may be uncertain and conflicting. As a consequence, we applied the Dezert-Smarandache Theory (DSmT) of plausible and paradoxical reasoning, proposed in recent years [2], which is well suited to fuse such sources of evidence.

II. DIABETIC RETINOPATHY DATABASE

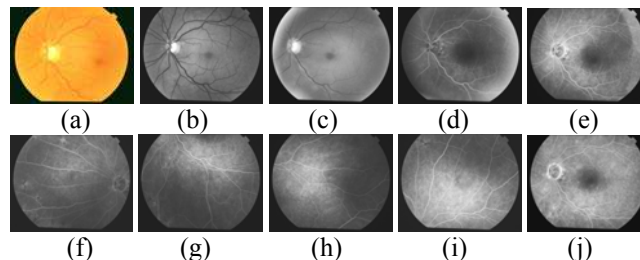


Fig. 1 Photograph series of a patient eye. Images (a), (b) and (c) are photographs obtained by applying different color filters on the camera lens. Images (d) to (j) form a temporal angiographic series: a contrast product is injected and photographs are taken at different stages (early (d), intermediate (e)-(i) and late (j)).

Diabetes is a metabolic disorder characterized by sustained inappropriate high blood sugar levels. This progressively affects blood vessels in many organs, including the retina, which may lead to blindness. The database is made up of 63 patient files containing 1045 photographs altogether. Patients have been recruited at Brest University Hospital since June 2003 and images were acquired by experts using a Topcon Retinal Digital Camera (TRC-501A) connected to a computer. Images have a definition of 1280 pixels/line for 1008 lines/image. The contextual information available is the patients' age and sex and structured medical information (about the general clinical context, the diabetes context, eye symptoms and maculopathy). Thus, at most, patients records are made up of 10 images per eye (see figure 1) and of 13 contextual attributes; 12.1% of these images and

40.5% of these contextual attribute values are missing. The disease severity level, according to ICDRS classification [3], was determined by experts for each patient.

Table 1 Patient disease severity level distribution

Disease severity	Number of patients
No apparent DR	7
Mild non-proliferative DR	11
Moderate non-proliferative DR	18
Severe non-proliferative DR	9
Proliferative DR	8
Treated / non-active DR	10

Twelve a priori rules about contextual information are available, including for instance: “After 12 years with diabetes type I, 90 to 95% of the patients have DR, among them, 40% have a proliferative DR.”

III. THE DEZERT-SMARANDACHE THEORY

The Dezert-Smarandache Theory allows combining any types of independent sources of information represented in term of belief functions. It generalizes the Dempster-Shafer theory. It is particularly well suited to fuse uncertain, highly conflicting and imprecise sources of evidence [2].

Let $\theta = \{\theta_a, \theta_b, \dots\}$ be a set of hypotheses under consideration for the fusion problem; θ is called the frame of discernment. A belief mass $m(A)$ is assigned to each element A of the hyper-power set $D(\theta)$, i.e. the set of all composite propositions built from elements of θ with \cap and \cup operators, such that $m(\{\}) = 0$ and $\sum_{A \in D(\theta)} m(A) = 1$.

The belief mass functions specified by the user for each source of information, noted $m_j, j = 1..N$, are fused into the global mass function m_f , according to a given rule of combination. Several rules have been proposed to combine mass functions, including the hybrid rule of combination or the PCR (Proportional Conflict Redistribution) rules [2]. It is possible to introduce constraints in the model [2]: we can specify pairs of incompatible hypotheses (θ_u, θ_v) , i.e. each subset A of $\theta_u \cap \theta_v$ must have a null mass, noted $A \in C(\theta)$.

Once the fused mass function m_f has been computed, a decision function is used to evaluate the probability of each hypothesis: the credibility, the plausibility or the pignistic probability [2].

IV. DEZERT-SMARANDACHE THEORY BASED RETRIEVAL

Let x_q be a case placed as a query. We want to rank the cases in the database by decreasing order of relevance for x_q . In that purpose, we estimate for each case x in the database the belief mass function for the frame of discernment $\theta_1 = \{Q, \bar{Q}\}$, where Q (resp. \bar{Q}) means “ x is relevant (resp. irrelevant) for x_q ” (Q and \bar{Q} are incompatible hypothesis). First, a mass function m_j is defined for each feature F_j , where F_j denotes either an imaging modality or a contextual attribute; m_j is based on the similarity between the values taken by x and x_q for F_j (see section IV.B below). Then, another mass function m_{apk} is derived from the A Priori Knowledge about contextual information (see section IV.C below). Finally, all the mass functions are fused to estimate the belief degree in Q (see section IV.D).

To define m_j , we first define a finite number of states f_{jk} for F_j and we compare the membership degree α_{jk} of x and x_q to each state f_{jk} . If F_j is a discrete variable, we associate a state with each possible value for F_j . If F_j is an image, the following procedure is applied.

A. Integrating images in the system

To define a finite number of states for an image feature F_j (an imaging modality), we follow the usual steps of Content-Based Image Retrieval (CBIR) [4]: 1) building a signature for each image (i.e. extracting a feature vector summarizing their numerical content), and 2) defining a distance measure between two signatures. Thus, measuring the distance between two images comes down to measuring the distance between two signatures. Similarly, to define variable states, we cluster similar image signatures (according to the defined distance measure) and associate a state of F_j for each image cluster.

In previous studies, we proposed to compute a signature for images from their wavelet transform (WT) [5]. These signatures model the distribution of the WT coefficients in each subband of the decomposition. The associated distance measure D [5] computes the divergence between these distributions. We used these signatures and distance measure to cluster similar images.

Any clustering algorithm can be used, provided that the distance measure between feature vectors can be specified. We used FCM (*Fuzzy C-Means*) [6], one of the most common algorithms, and replaced the Euclidian distance by D .

B. Estimating the mass functions

To compute the mass functions m_j for a given feature F_j , we first estimate a degree of match $dm_j(x, x_q)$ between x and x_q . We assume that the state of the cases in the same class are predominantly in a subset of states for F_j . So, in order to estimate $dm_j(x, x_q)$, we use a correlation measure S_{jkl} between two feature states f_{jk} and f_{jl} , regarding the class of the cases at these states. To compute S_{jkl} , we first compute the mean membership D_{jkc} (resp. D_{jlc}) of cases y in a given class c to the state f_{jk} (resp. f_{jl}):

$$\begin{cases} D_{jkc} = \beta \frac{\sum \delta(y, c) \alpha_{jk}(y)}{\sum \delta(y, c)} \\ \sum_{c=1}^C (D_{jkc})^2 = 1, \forall (j, k) \end{cases} \quad (1)$$

where $\delta(y, c) = 1$ if y is in class c , $\delta(y, c) = 0$ otherwise, and β is a normalizing factor. S_{jkl} and $dm_j(x, x_q)$ are given by equations (2) and (3), respectively.

$$S_{jkl} = \sum_{c=1}^C D_{jkc} D_{jlc} \quad (2)$$

$$dm_j(x, x_q) = \sum_k \sum_l \alpha_{jk}(x) S_{jkl} \alpha_{jl}(x_q) \quad (3)$$

Then, we define a test T_j on the degree of match: T_j is true if $dm_j(x, x_q) \geq \tau_j$ and false otherwise, $0 \leq \tau_j \leq 1$. The sensitivity (resp. the specificity) of test T_j represents the degree of confidence in a positive (resp. negative) answer to the test. Whether the answer is positive or negative, $Q \cup \bar{Q}$ is assigned the degree of uncertainty. The mass functions are then assigned according to equation (4) if T_j is true, or equation (5) otherwise.

$$\begin{cases} m_j(Q) = P(T_j | Q) = \text{sensitivity}(T_j) \\ m_j(Q \cup \bar{Q}) = 1 - m_j(Q) \\ m_j(\bar{Q}) = 0 \end{cases} \quad (4)$$

$$\begin{cases} m_j(Q) = 0 \\ m_j(Q \cup \bar{Q}) = 1 - m_j(\bar{Q}) \\ m_j(\bar{Q}) = P(\bar{T}_j | \bar{Q}) = \text{specificity}(T_j) \end{cases} \quad (5)$$

To calibrate the retrieval system, we learn τ_j from the database so that T_j is both sensitive and specific. As τ_j increases, sensitivity increases and specificity decreases. So, we set τ_j as the intersection of the two curves ‘‘sensitivity according to τ_j ’’ and ‘‘specificity according to τ_j ’’; these curves are built from each pair of examples in the database

(one playing the role of x and the other the role of x_q). τ_j is searched by the bisection method.

C. Integrating contextual a priori knowledge

The a priori knowledge about contextual information associates features with a severity level or a disjunction of severity levels: $L_0 = \{\text{no apparent DR}\}$, $L_1 = \{\text{mild non-proliferative DR, moderate non-proliferative DR, severe non-proliferative DR}\}$, $L_2 = \{\text{proliferative DR}\}$, $L_3 = \{\text{Treated DR}\}$. From these rules, we want to derive a degree of match between x and x_q . First, we define a second frame of discernment $\theta_2 = \{L_0, L_1, L_2, L_3\}$. For each case y considered (either x or x_q), we fuse the conclusion of all the rules r_i applying to that case as follows. For each rule r_i with conclusion $L^i \in \theta_2$, we define a mass function m'_i as in equation (6):

$$\begin{cases} m'_i(L^i) = \text{sensitivity}(r_i) \\ m'_i(\bigcup_{j=0}^3 L_j) = 1 - m'_i(L_i) \end{cases} \quad (6)$$

All the m'_i mass functions are then fused within θ_2 and the credibility $Bel(L_i)$ and plausibility $Pl(L_i)$ of each hypothesis $L_i, i \in \{0, 1, 2, 3\}$ are computed. We define a credibility vector $Bel(y) = (Bel(L_0), Bel(L_1), Bel(L_2), Bel(L_3))$ and a plausibility vector $Pl(y) = (Pl(L_0), Pl(L_1), Pl(L_2), Pl(L_3))$ for y . From these two vectors, evaluated for x and x_q , we derive an estimation $Bel(x, x_q)$ (resp. $Pl(x, x_q)$) of the credibility (resp. the plausibility) that x is relevant for x_q :

$$\begin{cases} Bel(x, x_q) = Bel(x) Bel(x_q)^T \\ Pl(x, x_q) = Pl(x) Pl(x_q)^T \end{cases} \quad (7)$$

Finally, these values are translated into a mass function m_{apk} for the frame of discernment θ_1 (defined in section IV). In that purpose, we used the two following equations, relating the belief functions and a mass function m within a frame of discernment with two exclusive hypothesis such as θ_1 :

$$\begin{cases} Bel(Q) = m(Q) \\ Pl(Q) = m(Q) + m(Q \cup \bar{Q}) \end{cases} \quad (8)$$

Applying equation (8) to $Bel(x, x_q)$, $Pl(x, x_q)$ and m_{apk} , we obtain the following mass function:

$$\begin{cases} m_{apk}(Q) = Bel(x, x_q) \\ m_{apk}(Q \cup \bar{Q}) = Pl(x, x_q) - Bel(x, x_q) \\ m_{apk}(\bar{Q}) = 1 - m_{apk}(Q) - m_{apk}(Q \cup \bar{Q}) \end{cases} \quad (9)$$

D. Retrieving the most similar cases

All cases in the database are processed sequentially. For each case x , the mass functions for the frame of discernment θ_i are computed for each feature F_j available for both x and the query x_q (see section IV.B) and for the contextual rules (see section IV.C). The sources available for x_q are then fused with the PCR5 rule [2] and the pignistic probability of Q , noted $betP(Q)$, is computed. The cases are then ranked in decreasing order of $betP(Q)$ and the topmost five results are returned to the user.

V. RESULTS

The mean precision at five (mp5) of the system, i.e. the mean number of relevant cases among the topmost five results, reaches 75.6%. As a comparison, the mp5 obtained by CBIR (when cases are made up of a single image), with the same image signatures, is 46.1% [5]. To evaluate the contribution of the proposed system for the retrieval of heterogeneous and incomplete cases, it is compared to a linear combination of heterogeneous distance functions, managing missing values [7], which is the natural generalization of classic CBR to the studied cases. Its extension to vectors containing images is based on the distance D between image signatures (see section IV.A). A mp5 of 52.3% was achieved by this method. The most significant mass functions are the m_j functions defined for each attribute F_j , as described in section IV.B; indeed, adding the mass function m_{cr} deriving from the contextual rules only leads to an increase of less than 2% of the mp5. To assess the robustness of the method regarding missing information, 1) we generated artificial cases from each case in the database by removing attributes, 2) we placed sequentially each artificial case as a query to the system and 3) we plotted on figure 2 the precision at five of these queries according to the number of available attributes.

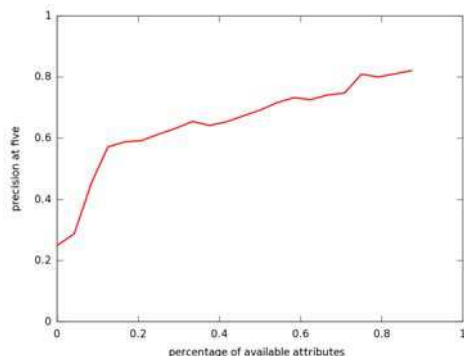


Fig. 2 Robustness regarding missing values.

VI. CONCLUSION

In this article, we introduce a method to include image series, with contextual information and contextual knowledge, in CBR systems. DSMT is used to fuse the output of several sensors (direct fusion) and of a priori knowledge (indirect fusion). On this database, the method largely outperforms our first CBIR algorithm (75.6% / 46.1%). This stands to reason since an image alone is generally not sufficient for experts to correctly diagnose the disease severity level of a patient. Besides, this non-linear retrieval method is significantly more precise than a simple linear combination of heterogeneous distances on the DR database (75.6% / 52.3%). This study suggests that the a priori knowledge about diabetic retinopathy is not very useful for the retrieval system, either because it is too vague or because the rules are already found by the learning procedure. Finally, if we use a Bayesian network to infer the missing values, prior to estimating the mass functions, the mp5 becomes 81.2%. It is thus a possible alternative to the decision tree based retrieval system we proposed previously [8] (showing a performance of 79.5% in mp5).

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