Similarity Measure in the Case-Based Reasoning Systems for Medical Diagnostics in Traditional Medicine

Odilon Yapo M. ACHIEPO[1], Behou Gérard N'GUESSAN[2], Konan Marcellin BROU[3]

[1]Laboratory of Mathematics and New Information Technologies, National Polytechnic Institute (INP-HB) Yamoussoukro, BP 1093, Ivory Coast

[2]Laboratory of Computer Science and Telecommunications, National Polytechnic Institute (INP-HB) Abidjan, 08 BP 475, Ivory Coast

[3]Department of Mathematics and Computer Science, National Polytechnic Institute (INP-HB) Yamoussoukro, BP 1093, Ivory Coast

Abstract

The Case-Based Reasoning (CBR) is a problem solving paradigm based on the reuse of past experiences stored in a cases base. The CBR has been used in many industrial systems to solve problems in various fields including medical diagnosis. In CBR systems, the concept of similarity is very important because it is the basis for the entire system. However, the effectiveness of similarity measures used depends on the problem being addressed. In this paper, we propose a measure of similarity for the development of CBR systems automatically diagnose diseases appropriate to the field of traditional medicine

Keywords: *Case-Based Reasoning, medical diagnostics, traditional medicine, similarity measures*

1. Introduction

Knowledge-based medical diagnosis used in aid systems has predominantly occupied the computerized world for a certain moment in time. It is for this reason that the teaching of traditional medicine couldn't remain indifferent in this technological evolution. Traditional medicine is the gathered traditional knowledge based on the use of medicinal plants [1]. According to OMS, it is the total sum of knowledge, practical and competences that rationally or not rests on the theories, believes and real experiences of a culture and which are used in taking care of the health of human beings, thus, to prevent, diagnose, treat and heal the physical and mental diseases.

In the case of disease diagnosis, real cases are not uniform and are subjectively left to the practitioner. Thus, these practitioners have resulted in their former experiences in conducting and diagnosing as well as prescribing treatments. It is evident that effected diagnoses as well as proposed treatments are subject to intrinsic limitations to the human cognitive capacity, notably concerning remembrances in the human memory. In this context, a bigger aid in the remembrance capacity of these practitioners is the more accurate guarantee of effectiveness. To do this, the Case-Based Reasoning systems will help traditional medical practitioners to improve the quality of benefits, reduce sanitary error-risks for patients and to serve as a basis of learning this medical science in plain upswing in numerous countries notably in Africa.

The CBR technique has almost nearly never been experimented in traditional medicine; its use necessitates the acknowledgement of the specificity of this domain. Now, the CBR systems are adapted to different realities through the measure of used similarities. It is for this, that our work is concentrated on the development of such measure for traditional medicine. In effect, the measure of similarities used in the medical domain in general is complex. We find there some numerical variables, qualitative variables and textual variables. The domain of traditional medicine being less structured, these three types of variables must co-exist in the CBR systems that will be developed. However, the form of collaboration must be well specified for an appropriation of a well-paced technology.

This paper makes firstly a brief preview of the methods on from the Case-Based Reasoning. Then, enumerates some preview works in the medical domain. Finally, describe the similarity measure we propose for the traditional medicine through the construction methodology and some mathematical properties and concludes.

2. Literature Review

2.1. The Case-Based Reasoning approach

Introduced by Minsky and Schank at the end of the 70's, the Case-Based Reasoning has been the object of several research works. The theory developed by Minsky presents the notion that corresponds to a recollected structure that must be adapted to correspond to the reality of a newly met situation. In the same shuttle, [03] proposed an approach called CBR420SD based on reasoning from these cases. His approach, thus, permits the ability of going against the discovery of semantic web services. This would permit new clients to be able to determine their functional and non-functional needs. According to [04] [06], a decisional mechanism based on the Case-Based Reasoning is proposed.

This mechanism, thus, permits to resolve complex maintenance problems more particularly to the collaborative mechanisms problems faced by experts. Elsewhere, [07] [08] propose a helping instrument in decisions resting on capitalized expertise in the maintenance of all performers in preserving their knowledge and know-how. On the contrary [09], developed a method of qualitative diagnosis to know an oriented system resembling a classification and a system of oriented knowledge diagnosis, notably oriented-experiences. This brings us to choose the formalization instrument in the field of experience. [10] is based on the cycle of CBR to put in exergue a tool of EIAH. This instrument will permit the learner to be able to acquire some methods founded on the classification of problems and their resolving instruments. Bur [11] conceives a computerized instrument in the name of TELEOS for surgical formation. This instrument rests on habitual surgical expertise to improve its intervention. In view of all these works and evolution, we think it well that it is time traditional medicine familiarizes itself with a CBR systems describe below:

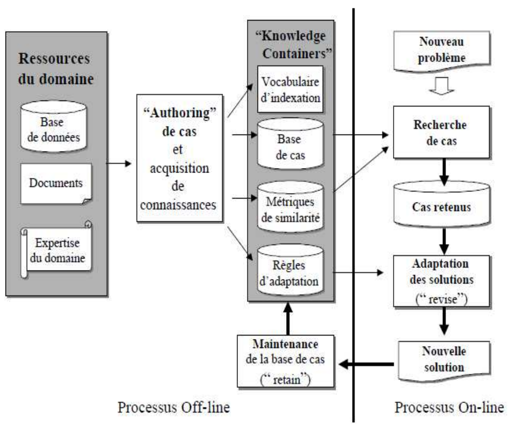

Fig. 1: Architecture of a CBR system

The reasoning from the CBR case is a reasoning model exploiting the experience of problem resolution to solve new ones. These experiences are knowledge from a particular situation and it isn't in first sight to generalize this knowledge for other situations [12].

The on-line part comprises of the cycle phases of CBR. The off-line part connotes the used resources and the acquisition phase and the representation of knowledge as well as the knowledge container. The case of the construction part and the acquisition of knowledge guide the initial structuration of the cases base and some other knowledge of the system from different resources such as documents, database or expert domain. We are particularly showing interest in this model in which we exploit knowledge containers as well as the cycle phases of CBR.

2.2. The measure of similarities

The reasoning approach behind the CBR systems is a model of reasoning that exploits the experience from problem resolution to solve the new. These experiences are knowledge of a particular situation. A CBR system must solve, in a particular field, new problems in adopting pre-existing solutions that were previously used in resolving old problems. The remembrance of case sources (already-solved problems) to find a solution to new target case (new problem) is the focal point of the CBR cycle. In effect, The CBR systems use different techniques to compare a description of a target case with one of the already known case sources. The user gives a description of the new problem and the system search it's data of cases the source of which the description is most similar to the description of the new problem. Afterwards, through a session of consultation of questions and responses of case sources, the system returns the candidates cases, which permits the user to select the case that seems to be the most appropriate or can be adapted to solve the new problem.

All the CBR System is based on a similarity measure and the quality of the system depend on the quality of the similarity measure used. A measure of similarity in the Case-Based Reasoning system must possess the following properties.

- Reflexivity: A case being, in principle, similar to itself, the measure of similarity must be necessarily reflexive.
- Symmetry: If a case A is similar to similar to another case B then it is necessary that the case B is also similar to the case A in using the measure of similarities.
- Non-transitivity: A measure of similarity must not necessarily be transitive. Consequently, if a case A is similar to a case B; and if the case B is similar to a case C, it isn't imperative that the application of the measure of similarities permits do deduce that the case A is forcibly similar to C.

The non-exigency of the transitivity comes from the fact that the characteristics that define the similarities between A and B and between B and C are not necessarily the same.

3. Diagnostic similarity modeling

Let $\mathscr{C} = (C_i)_{i \in I}$ be the set of I diagnosed patients, treated and healed by a traditional medical practitioner. These individuals constitute case sources and form the basis of the case. Each case can be decomposed into a pair $C_i = (S_i, \Gamma_i)$ where S_i is the set of symptoms shown by the patient is and Γ_i represents the medical sequence given to the symptoms observed on the patient by the traditional practioner. This sequence is the set $\Gamma_i = (M_i, T_i)$ of which M_i represents the principal diagnosed sickness and T_i the treatment prescription to the patient and having brought about his recovery. Let's note again:

- $\mathscr{S} = (X_1, \ldots, X_S) = (X_j)_{1 \leqslant j \leqslant S}$ the set of S clinical signs considered in the patient, and the confounded sicknesses.
- $\mathscr{M}$ the set of M registered sick individuals having had a remedy to traditional medicine.
- $\mathscr{N}$ the set of N numerical clinical signs (temperature, arterial pressure, tension, etc)
- $\mathscr{Q}$ the set of Q categorical clinical signs (fever, migraine, etc)
- $\mathscr{T}$ the set of T various text descriptions of different non standard signs.

We can write that $\mathscr{S} = \mathscr{N} \cup \mathscr{Q} \cup \mathscr{T}$ (1)
And we have $S = N + Q + T$ (2)

Let $I_s \in \mathscr{C}$ a source case and I_c a new patient to traditional medicine called the target case in CBR context. If we denote it $Sim(.)$, the measure of similarities between these two patients and Φ a re-writing of $Sim(.)$, we get :

$$\begin{aligned}
&Sim(I_s, I_c) = Sim(C_s, C_c) \\
&= Sim(\{S_s, \Gamma_s\}, \{S_c, \Gamma_c\}) \\
&= Sim(\{S_s, S_c\}, \{\Gamma_s, \Gamma_c\}) \\
&= Sim(S_s, S_c) \\
&= Sim(\{\mathscr{N}_s \cup \mathscr{Q}_s \cup \mathscr{T}_s\}, \{\mathscr{N}_c \cup \mathscr{Q}_c \cup \mathscr{T}_c\}) \\
&= \Phi(\{(\mathscr{N}_s, \mathscr{N}_c), (\mathscr{Q}_s, \mathscr{Q}_c), (\mathscr{T}_s, \mathscr{T}_c)\}) \\
&= \Psi(\alpha(\mathscr{N}_s, \mathscr{N}_c), \beta(\mathscr{Q}_s, \mathscr{Q}_c), \gamma(\mathscr{T}_s, \mathscr{T}_c)) \\
&= \Psi(\alpha(I_s, I_c), \beta(I_s, I_c), \gamma(I_s, I_c)) \qquad (3)
\end{aligned}$$

The functions α, β, γ are the distances between two vectors of numerical, qualitative and textual variable respectively. It applies to each uniform part of the vectors. According to the function Ψ , it shows the final mathematical expression of the measure of similarity.

4. Data type-based metrics

4.1 The α function

α being a distance between two vectors of numerical variables, it seems to be a natural to define it using the Minkowski distance. Consequently, we have:

$$\alpha(I_s, I_c) = \sqrt[p]{\sum_{X_k \in \mathscr{N}} (X_{ks} - X_{kc})^p} \qquad (4)$$

We can limit ourselves to $p = 2$ which corresponds to the Euclidean distance. Thus, we take as interval between the numerical variables, the definite function by:

$$\alpha(I_s, I_c) = \sqrt{\sum_{X_k \in \mathscr{N}} (X_{ks} - X_{kc})^2} \qquad (5)$$

The α metric such as defined possesses reflexivity properties and hope symmetry. In effect, we have:

- $\alpha(I_s, I_s) = \sqrt{\sum_{X_k \in \mathscr{N}} (X_{ks} - X_{ks})^2} = 0 \qquad (6)$
- $\alpha(I_s, I_c) = \sqrt{\sum_{X_k \in \mathscr{N}} (X_{ks} - X_{kc})^2}$

$$= \sqrt{\sum_{X_k \in \mathscr{N}} (X_{kc} - X_{ks})^2}$$
$$= \alpha(I_c, I_s) \qquad (7)$$

4.2. The β function

β being the distance between two vectors of qualitative variables, it seems natural to consider the distance of Chi Square. Yet, there are other qualitative variables. We propose then the construction of a Chi Square distance using each qualitative variable, then to make their sum weighted by the inverse of the degrees of freedom. To do that, let define $\mathscr{C}^c$ and $\mathscr{C}^s$ as:

$$\begin{aligned}
\mathscr{C}^c = \mathscr{C}_{s \leftarrow c} &= \{\mathscr{C} \setminus \{I_s\}\} \cup \{I_c\} \\
&= \complement^I_{I_s} \cup \{I_c\} \qquad (8)
\end{aligned}$$

$$\mathscr{C}^s = \mathscr{C}_{c \leftarrow s} = \{\mathscr{C}^c \setminus \{I_c\}\} \cup \{I_s\} = \mathscr{C} \qquad (9)$$

$\mathscr{C}^c$ represent the modified cases base in replacing the source case I_s by the target case I_c and $\mathscr{C}^s$

is the cases base obtained by the inverse operation. Constructively, we have:

$$Card(\mathscr{C}^c) = Card(\mathscr{C}^s) = Card(\mathscr{C}) = S \quad (10)$$

$\forall X_k \in \mathscr{Q}$, noting N_k the number of modalities to the qualitative variable X_k and x_{kj} the j^{th} modality of X_k. We note too:

- $N_{kj}^E = Card(\{I_i \in E \mid X_k = x_{kj})$ (11)
- $\chi_k^2(I_s, I_c) = \sum_{j=1}^{N_k} \frac{(N_{kj}^{\mathscr{C}^s} - N_{kj}^{\mathscr{C}^c})^2}{(N_{kj}^{\mathscr{C}^s} + N_{kj}^{\mathscr{C}^c})}$ (12)
- $\omega_k = \frac{1}{ddl(X_k)} = \frac{1}{N_k+1}$ (13)

Using Eq. (11), Eq. (12) and Eq. (13), The β metric is defined by:

$$\beta(I_s, I_c) = \sum_{k=1}^{k=Q} \omega_k \chi_k^2(I_s, I_c)$$
$$= \sum_{k=1}^{k=Q} \sum_{j=1}^{N_k} \frac{(N_{kj}^{\mathscr{C}^s} - N_{kj}^{\mathscr{C}^c})^2}{(N_k+1)(N_{kj}^{\mathscr{C}^s} + N_{kj}^{\mathscr{C}^c})} \quad (14)$$

The metric β as defined possesses reflexivity properties and hoped symmetry. In effect, we have:

- $\beta(I_s, I_s) = \sum_{k=1}^{k=Q} \omega_k \chi_k^2(I_s, I_s)$
  $= \sum_{k=1}^{k=Q} \sum_{j=1}^{N_k} \frac{(N_{kj}^{\mathscr{C}^s} - N_{kj}^{\mathscr{C}^s})^2}{(N_k+1)(N_{kj}^{\mathscr{C}^s} + N_{kj}^{\mathscr{C}^s})} = 0$ (15)
- $\beta(I_s, I_c) = \sum_{k=1}^{k=Q} \omega_k \chi_k^2(I_s, I_c)$
  $= \sum_{k=1}^{k=Q} \sum_{j=1}^{N_k} \frac{(N_{kj}^{\mathscr{C}^s} - N_{kj}^{\mathscr{C}^c})^2}{(N_k+1)(N_{kj}^{\mathscr{C}^s} + N_{kj}^{\mathscr{C}^c})}$
  $= \beta(I_c, I_s)$ (16)

4.3. The γ function

The γ function is the distance between two vectors of textual variables. To define it, we consider the distance to be called "Kernel string". Because we have many variables in play, we propose to construct a kernel string distance per variable then to make their sum weighted by the relative proportion of words using only words common to all variables.

$\forall X_k \in \mathscr{T}$, we note Δ_{ks} and Δ_{kc} the couple relative to the textual variable X_k corresponding to the case source I_s and to the target case I_c from the same sequences of linguistic operations, in particular the same tokenization process. In the case of traditional medicine, we advice on the operations in putting texts in minuscule, deleting of white spaces, deleting numerical values, deleting punctuations, deleting stop words and tokenizing using the tri-grams algorithm.

The use of the tri-grams algorithm for tokenization is really advised. Once the text tokenization is effectuated, the set of tri-grams of X_k common to the case source I_s and of the target case I_c is given by $\Delta_k = \Delta_{ks} \cap \Delta_{kc}$ (17)

Noting $\tau_{kj} \in \Delta_k$ a tri-gram met δ_j^{ks} times in Δ_{ks} and δ_j^{kc} times in Δ_{kc}. The number of times that the tri-gram τ_{kj} is met in Δ_k is $\delta_{kj} = Min(\delta_j^{ks}, \delta_j^{kc})$ (18)

The corresponding cosine distance between the source case and the target case can be defined by:

$$cosine_k(I_s, I_c) = \frac{<X_{ks}, X_{kc}>}{\|X_{ks}\|.\|X_{kc}\|}$$
$$= \frac{\sum_{j=1}^{card(\Delta_k)} \delta_j^{ks}.\delta_j^{kc}}{\sqrt{\sum_{j=1}^{card(\Delta_k)} \delta_j^{ks}}\sqrt{\sum_{j=1}^{card(\Delta_k)} \delta_j^{kc}}} \quad (19)$$

Considering the weights $\lambda_k = \frac{Card(\Delta_k)}{\sum_{k=1}^{k=T} Card(\Delta_k)}$ (20)

We obtain:

$$\gamma(I_s, I_c) = \sum_{k=1}^{k=T} \lambda_k \mid ln(cosine_k(I_s, I_c)) \mid$$
$$= \frac{1}{\sum_{k=1}^{k=T} Card(\Delta_k)} \sum_{k=1}^{k=T} Card(\Delta_k) \mid ln\left(\frac{\sum_{j=1}^{card(\Delta_k)} \delta_j^{ks}.\delta_j^{kc}}{\sqrt{\sum_{j=1}^{card(\Delta_k)} \delta_j^{ks}}\sqrt{\sum_{j=1}^{card(\Delta_k)} \delta_j^{kc}}}\right) \mid \quad (21)$$

By construction, the γ metric as defined possesses reflexivity properties and hoped symmetry. In effect, we have:

- $\gamma(I_s, I_s) = \sum_{k=1}^{k=T} \lambda_k \mid ln(cosine_k(I_s, I_s)) \mid$
  $= \sum_{k=1}^{k=T} \lambda_k \mid ln(\frac{<X_{ks}, X_{ks}>}{\|X_{ks}\|.\|X_{ks}\|}) \mid = 0$ (22)
- $\gamma(I_s, I_c) = \sum_{k=1}^{k=T} \lambda_k \mid ln(\frac{<X_{ks}, X_{kc}>}{\|X_{ks}\|.\|X_{kc}\|}) \mid$
  $= \sum_{k=1}^{k=T} \lambda_k \mid ln(\frac{<X_{kc}, X_{ks}>}{\|X_{kc}\|.\|X_{ks}\|}) \mid = \gamma(I_c, I_s)$ (23)

5. Global similarity measure

5.1. The Ψ function

The α, β and γ are the distances. To deduce the measure of similarities, we'll use a polynomial interpolation of Lagrange on the interval $[0,1]$. In effect, if we note d_α, d_β and d_γ, the normalized values of α, β and γ and $v \in \{\alpha, \beta, \gamma\}$, we can pose :

$$d_v = 1 - \frac{1}{1+v} \quad (24)$$

And $\mu = \frac{d_\alpha + d_\beta + d_\gamma}{3} = 1 - \frac{\frac{1}{1+\alpha} + \frac{1}{1+\beta} + \frac{1}{1+\gamma}}{3}$ (25)

Constructively, we have $\mu \in [0,1]$ (26)

We want to construct the Ψ function to a sort that $\Psi(0) = 100$ $\Psi(\frac{1}{4}) = 75$, $\Psi(\frac{3}{4}) = 25$ and $\Psi(1) = 0$. We have then, a set of five geometric points $(x_i, y_i)_{1 \leqslant i \leqslant 5}$ in the plan. The Lagrange polynomial interpolation using the coordinates of each point (x_i, y_i) is given by $l_i(X) = \prod_{j=0, j\neq i}^{j=5} \frac{x - x_j}{x_i - x_j}$ (27)

The application of the equation Eq. (27) permits to get the polynomial function that respects the conditions which is:

$$\Psi(x) = \sum_{i=1}^{i=5} y_i l_i(x) = 100(1-x) \quad (28)$$

5.2. The global similarity measure

If we conform to the defined notations in 3, 4 and 5.1, we can take as a measure of global similarity, the definite quantity by:

$$Sim(T_s, T_c) = \Psi(\mu(T_s, T_c))$$
$$= 100\left(1 - \frac{\frac{1}{1+\alpha(T_s,T_c)} + \frac{1}{1+\beta(T_s,T_c)} + \frac{1}{1+\gamma(T_s,T_c)}}{3}\right) \quad (29)$$

Where $\alpha(I_s, I_c)$, $\beta(I_s, I_c)$ and $\gamma(I_s, I_c)$ are those define respectively in Eq. (5), Eq. (14) and Eq. (21).

The similarity measure, as is defined is decreasing with the divergence of the target case with respect to the case sources, reflexive, symmetric and bounded between 0 and 100. In effect:

- $Sim(I_s, I_s) = 100\left(1 - \frac{\frac{1}{1+\alpha(I_s,I_s)} + \frac{1}{1+\beta(I_s,I_s)} + \frac{1}{1+\gamma(I_s,I_s)}}{3}\right)$
  $= 0$ (30)
- $Sim(I_s, I_c) = 100\left(1 - \frac{\frac{1}{1+\alpha(I_s,I_c)} + \frac{1}{1+\beta(I_s,I_c)} + \frac{1}{1+\gamma(I_s,I_c)}}{3}\right)$
  $= 100\left(1 - \frac{\frac{1}{1+\alpha(I_c,I_s)} + \frac{1}{1+\beta(I_c,I_s)} + \frac{1}{1+\gamma(I_c,I_s)}}{3}\right)$
  $= Sim(I_c, I_s)$ (31)

The values of the similarity measure $Sim(I_c, I_s)$ is bounded between 0 and 100. In effect, the maximum of $Sim(I_c, I_s)$ is obtained if we have the conditions below:

$$\alpha(I_c, I_s) = \beta(I_c, I_s) = \gamma(I_c, I_s) = \infty \quad (32)$$

In that case, the value (minimum value) of the similarity is:

$$Sim(I_c, I_s) = 100(1-0) = 100 \quad (33)$$

The condition to obtain the minimum of $Sim(I_c, I_s)$ is:

$$\alpha(I_c, I_s) = \beta(I_c, I_s) = \gamma(I_c, I_s) = 0 \quad (34)$$

In that case, we have the following minimum value:

$$Sim(I_c, I_s) = 100(1-1) = 0 \quad (35)$$

6. Conclusions

The application of the Case-Based Reasoning (CBR) to traditional medicine seems very complex. In effect, the distance of classic similarities doesn't permit to take into consideration textual information. Moreover, taking into consideration qualitative data is limited to the presence or the absence table with an increasing number of zero values increasing with the number of modalities of each variable. It was, thus, necessary to propose a measure of similarity that takes into account the diversity of the types of information that we can take for each patient.

The interest of the measure of similarity proposed in this article is double. From one part, It takes into consideration the diversity of data generally given in the framework of traditional medicine (numerical, qualitative and textual), but it gives the advantage to keep the two base theory properties of such an indicator type to know the reflexivity and the symmetry. Besides, it's bounded character between the values 0 and 100permits to confer a practical interpretation in terms or percentage, being that the exact sense of this interpolation must deserve to be studied in future works.

It must also be noted that this article is concentrated on the problem of the development of a similarity measure. It is important in perspective of future research, to confront this metric to the empirical data before measuring the full scope. These data could permit a more accurate analysis of eventual mathematical properties of this similarity measure. We shouldn't lose the final objective view which is to develop the reasoning systems using the Case-Based Reasoning approach in the realm of traditional medicine. Also, the integration of this metric to tools permitting to construct the CBR system is a problem which must be regarded.

Finally, through its global nature, the similarity measure developed can be use outside the framework of CBR especially in the fields of Multidimensional Statistics, Machine Learning, Data Mining and Data Science. In these domains, the variety of the data types is a fundamental characteristic.

References

[01] Mobyen Udding Ahmed, Shahina Begum, Peter Funk, Ning Xiong, Bo Von Shéele, Case-based Reasonning for Diagnosis of Stress using Ehanced Cosine and Fuzzy Similarity, Transactions on Case-Based Reasonning for Multimedia Data Vol.1, No 1, 3-19, 2008.

[02] B. Maadjou, D. S. Ténin, D. Hawa, K. A., C. Selly and S. Saténin "stratégie national et plans d'action sur la diversité biologique" volume 2: plan d'actions pour la conservation de la diversité biologique et l'utilisation durable de ses ressources (GUINEE/ PNUD / FEM Conakry Avril 2001)

[03] I. E. BITAR "CBR4WSD : Une approche de découverte de services Web par Raisonnement à Partir de Cas ", Artificial Intelligence. Ecole Mohammadia d'Ingénieurs - Université Mohammed V de Rabat - Maroc, 2014. French.

[03] Rainer Koschke, Georg Schied, Jean-François Girard, A Metric-based Approach to Detect Abstract Data Types and State Encapsulations, Published in Proceedings of the Conference on Automated Software Engineering, 1997.

[04] P. P. Ruiz, D. Noyes and B. K. Foguem, "Raisonnement collaboratif à partir de cas dans la résolution de problèmes en maintenance", 9th International Conference on Modeling, Optimization et SIMulation, Jun 2012, french.

[05] Cindy MARLING, Jay SHUBROOK, Frank SCHWARTZ, Toward case-based reasoning for diabetes management: A preliminary clinical study and decision support system prototype, study and decision support system prototype, Computational Intelligence, Volume 25, Number 3, 2009

[06] D. Dhouib : "Aide multicritère au pilotage d'un processus basée sur le raisonnement à partir de cas", Engineering Sciences. Université Paris VIII Vincennes-Saint Denis, 2011. French

[07] Ivana Rasovska "Contribution à une méthodologie de capitalisation des connaissances basée sur le raisonnement à partir de cas: Application au diagnostic dans une plateforme d'e-maintenance.", HAL https://tel.archives-ouvertes.fr/tel-00257893 Submitted on 20 Feb 2008

[08] F. Bandou, A. H. Arab, K. Bouchouicha and N. Zerhouni: "Diagnostic de pannes d'un système de pompage photovoltaïque", Revue des Energies Renouvelables Vol. 14 N°3 (2011)

[09] Mohamed Karim Haouchine "Remémoration guidée par l'adaptation et maintenance des systèmes de diagnostic industriel par l'approche du raisonnement à partir de cas.", https://tel.archives-ouvertes.fr/tel-00466560 Submitted on 24 Mar 2010

[10] N. Duclosson: "Représentation des connaissances dans l'EIAH AMBRE-add", Technologies de l'Information et de la Connaissance dans l'Enseignement Supérieur et l'Industrie, Oct 2004, Compiègne, France. Université de Technologie de Compi_egne, pp.164-171,

[11] V. Luengo, M. Dubois, L. Vadcard and J. Tonetti, "Le projet TCAN TELEOS: Technology enhanced Learning in orthopaedic surgery". TELEOS: Technology enhanced Learning in orthopaedic surgery. 2006

[12] J. Cojan. "Application de la théorie de la révision des connaissances au raisonnement à partir de cas", Artificial Intelligence. Université Henri Poincaré - Nancy I, 2011.

Odilon Yapo M. ACHIEPO Is a statistician-economist Engineer (ENSEA Abidjan, Ivory Coast) and has a Master degree in Computer Science with specialization in Artificial Intelligence and Business Intelligence (Polytechnic School of Nantes, France). He is a Ph-D student in Mathematics and Information Technologies (EDP-INPHB Yamoussoukro, Ivory Coast). He is also a Teacher-researcher in University of Korhogo (Ivory Coast), International Senior-Expert Consultant, member of the international resilience research group (UMI Resilience, IRD) and is a member of the Laboratory of Computer Sciences and Telecommunications (INP-HB) Abidjan, Ivory Coast. His centers of interests are Computational Mathematics, Multidimensional Statistics, Artificial Intelligence, Machine Learning, Data Mining and Data Science. He also is the author-creator of the Resilometrics, a modeling discipline which consists on developing and applies computational models for measure, analyze and simulate social resilience process.

Behou Gérard N'GUESSAN Is in third year of thesis (PhD) at the university Nangui Abrogoua, member of the Research Laboratory in Computer Sciences and Telecommunications of Houphouët Boigny National Polytechnic Institute (INP-HB), Abidjan, Ivory Coast. His interests of the research include the mathematical modeling, the engineering of the media, the traditional medicine, and inventor of applications. His works are centered on their research of the method of training the traditional medicine

Konan Marcellin is a Doctor in Computer Science and Teacher researcher at the Houphouët Boigny National Polytechnic Institute (INP-HB) de Yamoussoukro (Ivory Coast). He is the Director of the Department of Mathematics and Computer Science. He is a Member of Laboratory in Computer Sciences and Telecommunications (INP-HB) Abidjan Ivory Coast. His interests are information systems, database and programming languages.