Toward the evaluation of Case Base Maintenance policies under the belief function theory

Safa Ben Ayed[1,2], Zied Elouedi[1], and Eric Lefevre[2]

[1] Université de Tunis, Institut Supérieur de Gestion de Tunis, LARODEC, Tunis, Tunisia
safa.ben.ayed@hotmail.fr, zied.elouedi@gmx.fr

[2] Univ. Artois, EA 3926, Laboratoire de Génie Informatique et d'Automatique de l'Artois (LGI2A), 62400 Béthune, France
eric.lefevre@univ-artois.fr

Abstract. The life cycle of Case-Based Reasoning (CBR) systems implies the maintenance of their knowledge containers for reasons of efficiency and competence. However, two main issues occur. First, knowledge within such systems is full of uncertainty and imprecision since they involve real-world experiences. Second, it is not obvious to choose from the wealth of maintenance policies, available in the literature, the most adequate one to preserve the competence towards problems' solving. In fact, this competence is so difficult to be actually estimated due to the diversity of influencing factors within CBR systems. For that reasons, we propose, in this work, an entire evaluating process that allows to assess Case Base Maintenance (CBM) policies using information coming from both a statistical measure and a competence model under the belief function theory.

Keywords: Case-Based Reasoning · Case-Base Maintenance · Competence Evaluation · Uncertainty · Belief Function Theory · Combination

1 Introduction

Case-Based Reasoning (CBR) is a methodology of problem solving that reuses past experiences to solve new problems according to their similarities [1]. Every new solved problem by a CBR system is retained in a memory structure called a Case Base (CB) to serve for future problems resolution. Although the incremental learning of CBR systems presents a strong point, it is not free of drawbacks. In fact, this evolution can be uncontrollable, caused by the retention of redundant and noisy cases which conduct to the degradation of systems' problem-solving competence and performance. For those reasons, the Case Base Maintenance (CBM) field presents the key factor's success of CBR systems. As has been defined in [2], *"Case-base maintenance implements policies for revising the organization or contents (representation, domain contents, accounting information, or implementation) of the case base in order to facilitate future reasoning for a particular set of performance objectives"*. During the last five decades [4],

a wide range of CBM policies have been proposed, even in Machine Learning or CBR communities, that aim to update CBs content in such a way to be performer and more competent to make high quality decisions. Different attempts to classify them have been proposed in different papers [5, 6, 9, 10]. One of the simplest categorizations consists at regrouping CBM policies by their ability for uncertainty management (*hard and soft*). *Condensed Nearest Neighbor* (CNN) [11] and *Reduced Nearest Neighbor* (RNN) [12] present the baseline of the CB maintenance task. For the *soft* CBM policies, less work have been proposed, where two are implemented within the framework of the belief function theory which are *Evidential Clustering and case Types Detection for CBM* (ECTD) [6] and *Dynamic policy for CBM* (DETD) [13].

After performing a maintenance task, the question that arises is whether the original CBR is better, tantamount, or worse than the maintained one. The intuitive answer to this question is to measure the competence of the CB before and after maintenance. Therefore, this allows us to estimate the support degree of the CBM policy as well as its adequacy to be applied. However, estimating the real competence of a given CBR system in problem-solving is a very complex task since this competence depends on many affecting factors, such as statistical and problem solving properties [3]. To deal with these problems, available research are even measuring the accuracy of the CBR system using a statistical measure [6, 7] or estimating their competence using a competence model [8, 3]. Some of them are aware of the great importance of managing uncertainty within such knowledge since they reflect real-world situations. Consequently, we aim, in this work, to evaluate CBM policies by offering a support/adequacy degree through combining information coming from an accuracy measure and a competence model. To offer high quality aggregation with managing conflict within both sources' information, and to deal with uncertainty within case knowledge, we use one among the most powerful tools for uncertainty management called the belief function theory.

The rest of the paper is organized as follows. In the next Section, we overview the key factors that affect CBs competence and the two used ways for CBR evaluation. Section 3 presents, then, the basics of the belief function theory, as well as the used tools. Throughout Section 4, our CBM evaluating process is detailed to indicate the adequacy of the used CBM policy and estimate its support degree. In Section 5, we elaborate the experimental study on different CBM policies and using different CBs. Finally, Section 6 concludes the paper and proposes some future work.

2 Case Base Competence Evaluation

The competence (or coverage) of a CBR system presents the range of problems that it can successfully solve [3]. Actually, this criterion cannot be well estimated when we use a simple metric due to the diversity of influencing factors (Subsection 2.1). In the literature, this competence is even estimated using statistical

measure such as the accuracy (Subsection 2.2), or using some competence model such as CEC-Model [14] (Subsection 2.3).

2.1 Key factors affecting CBs competence

Estimating the competence of a CBR system needs an awareness regarding the set of elements that may affect it. Actually, we note that the statistical properties of cases within a CB is highly influencing its ability in covering the problem space. Besides, problem-solving properties are an intuitive influencing factor of CBR systems competence. As done in [3, 14], we can enumerate these factors as follows: CB size*, cases distribution*, density of cases*, cases vocabulary*, Similarity*, and adaptation knowledge[3].

2.2 Statistical Measures for CBR evaluation

Some works mention that the precision or the accuracy presents a kind of true competence [3] with some limitations. Actually, the competence of a CBR system can be recognized as input problem solving capability with the right solutions. The most common and straightforward practice consists at using a test set from the original CB and applying a classification algorithm[4] to solve problems. By this way, we can estimate the competence of the CBR system using statistical measures such as the accuracy as the percentage of correct classifications, the specificity as the true negative rate, and others [15].

Actually this kind of measures have to be taken into account when measuring the competence of a CB. However, it is not sufficient since it does not cover several affected factors. Hence, competence models are also used for this matter.

2.3 Competence Models for CBR evaluation

Various competence models have been proposed to take into account different influencing factors. For instance, we find Case Competence Categories Model [16] which consists at dividing cases into four types so as to fix a maintenance strategy to be followed. However, it is not able to tangibly and mathematically quantify the global competence of the entire CB. Besides, we find Coverage model based on Mahalanobis Distance and clustering [17], that uses a density-based clustering method to distinguish three types of cases on which the overall CB competence depends. However, we cannot well estimate this competence without deeply studying the relation between cases. Although Smyth & McKenna model [3] is able to deal with different influencing factors, it suffers from its disability to manage the uncertainty within the real stored situations. Hence, the Coverage & Evidential Clustering based Model (CEC-Model) [14] has been proposed in a preliminary work to tackle the problem of uncertainty management while regrouping cases and measuring similarities. Its entire cycle is described in Figure 1. By this way, we use the latter mentioned CEC-Model [14], and the

[3] The factors identified with a star (*) are taken into account in the current work.
[4] The (k-NN) classifier is the most used within the CBR community.

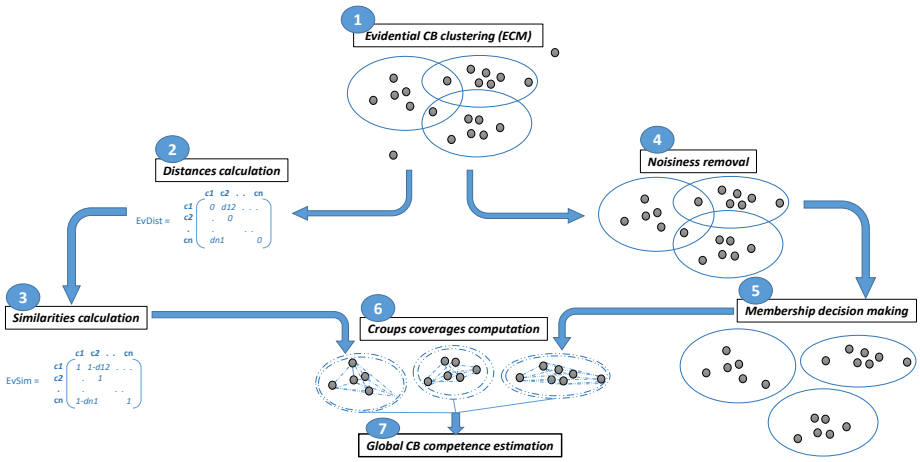

Fig. 1. CEC-Model's process

accuracy measure, during our proposed CBM evaluation process, where both of knowledge uncertainty and information fusion are taken into account under the belief function theory framework.

3 Belief Function Theory: Basic concepts

The belief function theory [18, 19], called also Evidence theory, is a mathematical framework for reasoning under partial and unreliable knowledge. This model is basically defined by a frame of discernment Ω which represents a set of a finite elementary events. The major strength of this theory is its ability to model all levels of uncertainty, from the complete ignorance to the total certainty, on a power set 2^{Ω} which contains all the possible subsets of Ω.

The key point of this theory is the *basic belief assignment (bba)* m which is defined as follows:

$$\begin{aligned} m : 2^{\Omega} &\rightarrow [0,1] \\ A &\mapsto m(A) \end{aligned} \tag{1}$$

with m is satisfying the following constraint:

$$\sum_{A \subseteq \Omega} m(A) = 1 \tag{2}$$

It aims at allocating to every set $A \in 2^{\Omega}$ a degree of belief to represent the partial knowledge about the actual value of y defined on Ω. A mass function is normalized if it assigns to the empty set partition null degree of belief ($m(\emptyset) = 0$). Contrariwise, the assigned amount of belief to the empty set reflects the flexibility to consider that the value of y may not belong to Ω. The latter situation has

usually been used during the evidential clustering to identify noisy instances [20, 21], where the frame of discernment Ω defines the set of clusters.

Actually, we often need to calculate the distance between two mass functions defined in the same frame of discernment. To do so, Jousselme Distance [22] presents one among the most used tools to measure distances between two pieces of evidence. It is defined as follows:

$$d(m_1, m_2) = \sqrt{\frac{1}{2}(\overrightarrow{m_1} - \overrightarrow{m_2})^T \underline{\underline{D}}\ (\overrightarrow{m_1} - \overrightarrow{m_2})} \tag{3}$$

where $\underline{\underline{D}}$ is a square matrix of size 2^K ($K = |\Omega|$), and its elements are calculated such that:

$$D(A, B) = \begin{cases} 1 & \text{if} \quad A = B = \emptyset \\ \frac{|A \cap B|}{|A \cup B|} & \text{otherwise} \end{cases} \tag{4}$$

In the framework of belief function theory, various combination rules of evidence have been proposed. The conjunctive rule of combination [23] is one of the most used ones to combine two pieces of evidence induced from two independent and reliable sources of information. When the normality constraint ($m(\emptyset) = 0$) is imposed, we may use the Dempster's rule of combination [18].

Ultimately, to make decision under the belief function theory, we may use the pignistic probability transformation, denoted $BetP$, which is considered as one of the best ways for decision making. If the mass function is normalized, then $BetP$ is defined as follows:

$$BetP(y) = \sum_{x \in A} \frac{m(A)}{|A|} \tag{5}$$

where $y \in \Omega$ and $A \subseteq \Omega$ contains y. Since m is normalized, $BetP(y)$ is independent of of the set A that contains y. Otherwise, a preprocessing step of normalization should be applied [23].

4 Evidential CBM Evaluating Process

In this Section, we propose an evaluation method for Case Base Maintenance policies that aims to estimate their support/adequacy degree for a given CBR system. Its main idea consists at combining two mass functions reflecting their adequacy. These mass functions are deduced from the improvement degree of competence, extracted respectively from the CEC-Model [14] and the accuracy criterion before and after applying the CBM policy. For the sake of clarity, a general depict of the proposed evaluating method is shown in Figure 2.

4.1 Two-level original CBR evaluation

First of all, we aim at measuring the competence of the original non-maintained CBR system using both the evidential competence model CEC-Model [14] to provide $\boldsymbol{Comp_O}$ and the accuracy criterion to provide $\boldsymbol{Acc_O}$.

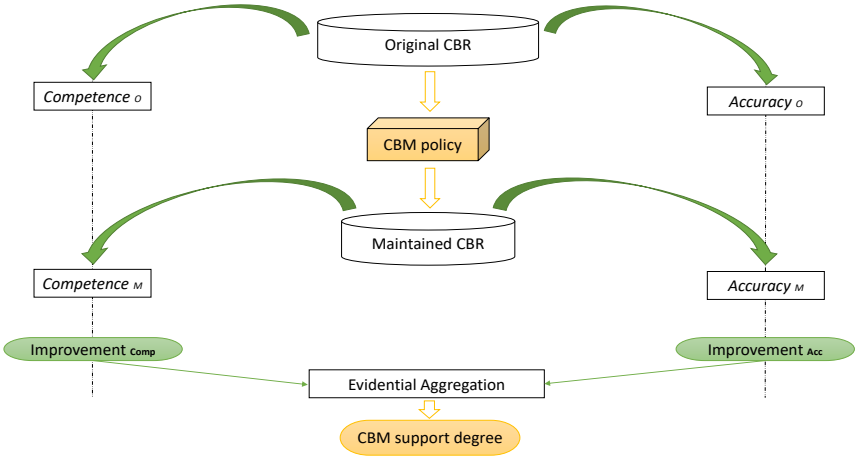

Fig. 2. The proposed CBM evaluating process

$Comp_O$ estimation: The original CB denoted CBR_O presents the input of CEC-Model. As shown in Figure 1, it applies the Evidential C-Means (ECM) [20] for cases clustering, Jousselme Distance [22] (Equations 3 and 4) for similarity calculation, and pignistic probability transformation (Equation 5) for cases membership decision. Finally, groups coverage and CB competence are estimated through the density and size properties. The output result is bounded in $[0, 1]$, where the more it is near to 1 the more CBR_O is considered as competent in solving problems.

Acc_O estimation: The accuracy criterion is studied using 10-fold cross validation and the k-NN as a classifier (we chose to take $k = 1$). To be measured, the original CB is divided into training set ($Tr = 0.8 \times CB$) and test set ($Ts = 0.2 \times CB$), where Tr plays the role of the entire CB and Ts contains the set of input problems to be solved from Tr. Acc_O is therefore calculated as follows:

$$Acc_O = \frac{\#Correct\ Classifications\ on\ Ts}{Size\ of\ Ts} \tag{6}$$

4.2 Case Base Maintenance application

After measuring the Original CB competence through the two previous identified sources (competence model and accuracy criterion), we perform on CBR_O the CBM policy to be evaluated. Actually, the main purpose of CBM policies is to detect the subset of cases that let a high problem-solving capability. In this step, we may consider the applied policy as a black box and we only focus on its input (CBR_O) and output, which is the maintained CB (CBR_M). By this way, any CBM policy, in the literature, may be applied at the aim to be evaluated, thereafter, by our evaluating process.

4.3 Two-level maintained CBR evaluation

Once the CBM policy completes its execution, our next step consists at measuring the edited CB competence using the same tools and settings as the first step to generate $Comp_M$ and Acc_M values.

$Comp_M$ estimation: As previously done, we evaluate the CB using the CEC-Model, whereas that time it is applied to assess the maintained CB (CBR_M) and provide $Comp_M$ between 0 and 1.

Acc_M estimation: The testing strategy of the accuracy after the maintenance task consists at dividing CBR_O into training set Tr and test set Ts. Then, the used CBM policy is applied on Tr to generate an edited training set Tr_M. Using 1-NN, the accuracy is measured through classifying Ts using Tr_M. Finally, Acc_M is obtained by averaging ten trials values using 10-fold cross validation.

4.4 Extracting CBM adequacy knowledge from statistical measure and competence model independently

Up to now, we have four different competence estimation values (in $[0, 1]$) that come from two sources: CEC-Model and Accuracy measure. The first is measuring the competence of CBR_O, and the second assesses the quality of the applied CBM task through CBR_M. During this step, we highlight the improvement of CBR_O against CBR_M, in terms of both competence and accuracy. Therefore, we define these two improvements (Imp_{Comp} and Imp_{Acc}) as follows:

$$Imp_{Comp} = Comp_M - Comp_O \tag{7}$$

and

$$Imp_{Acc} = Acc_M - Acc_O \tag{8}$$

Knowing that their offered values are in $[-1, 1]$, three distinguished situations arise regarding Imp_x, where x replaces even $Comp$ or Acc terms:

- If $Imp_x \simeq 1$, then a high degree of adequacy is assigned to the applied CBM policy for the CBR system.
- If $Imp_x \simeq -1$, then the used CBM policy is not adequate at all for the CBR system.
- If $Imp_x \simeq 0$, then we have no preference regarding the maintenance task.

4.5 Knowledge combination under the belief function theory

Based on the situations mentioned above, we build two mass functions on the same frame of discernment which contains two events. The first consists at indicating that the CBM policy is adequate to be applied on a given CBR system, and the second presents its complementary event. Hence, this frame is defined as follows:

$$\Omega = \{Adequate, \overline{Adequate}\} \tag{9}$$

By this way, the mass functions, defined on Ω, indicates the evaluation of the CBM policy. The first m_{Comp} describes the knowledge coming from the improvement in terms of competence, and the second m_{Acc} informs the knowledge originated by the improvement in terms of accuracy. Consequently, we similarly define them as follows:

$$m_{Comp} \begin{cases} m_{Comp}(\emptyset) = 0 \\ m_{Comp}(Adequate) = \begin{cases} Imp_{Comp} & If \;\; Imp_{Comp} \geq 0 \\ 0 & Otherwise \end{cases} \\ m_{Comp}(\overline{Adequate}) = \begin{cases} |Imp_{Comp}| & If \;\; Imp_{Comp} < 0 \\ 0 & Otherwise \end{cases} \\ m_{Comp}(\Omega) = 1 - |Imp_{Comp}| \end{cases} \tag{10}$$

and

$$m_{Acc} \begin{cases} m_{Acc}(\emptyset) = 0 \\ m_{Acc}(Adequate) = \begin{cases} Imp_{Acc} & If \;\; Imp_{Acc} \geq 0 \\ 0 & Otherwise \end{cases} \\ m_{Acc}(\overline{Adequate}) = \begin{cases} |Imp_{Acc}| & If \;\; Imp_{Acc} < 0 \\ 0 & Otherwise \end{cases} \\ m_{Acc}(\Omega) = 1 - |Imp_{Acc}| \end{cases} \tag{11}$$

Obviously, knowledge obtained from each source is not perfect. Hence, their aggregation presents an interesting solution to reach more relevant information. For that reason, we opt to synthesize the knowledge obtained in m_{Comp} and m_{Acc} by combining them using tools offered within the evidence theory. Since m_{Comp} and m_{Acc} present normalized mass functions that are defined in the same frame of discernment Ω and induced from two distinct information sources, which are considered to be reliable, we use the conjunctive rule of combination defined in [23] as follows:

$$(m_{Comp} \textcircled{\cap} m_{Acc})(C) = \begin{cases} \sum\limits_{A \cap B = C} m_{Comp}(A) m_{Acc}(B) & If \; C \neq \emptyset, \forall A, B \in \Omega \\ 0 & Otherwise \end{cases} \tag{12}$$

In the current work, we are not interested in making decision regarding whether the applied CBM policy is adequate or not, but we aim to estimate the adequacy support degree for the applied maintenance task. To do, we interpret this rate as the pignistic probability of the event "Adequate". Consequently, we measure this probability using Equation 5 in such a way that:

$$CBM \; support \; degree = BetP(Adequate) \tag{13}$$

5 Experimentation

The following experiments aim at projecting our proposal on the maintenance field within CBR systems and use it to evaluate this CBM policies adequacy. In this Section, we present used data and the followed settings during implementation and tests (Subsection 5.1). Offered results and discussion are then provided in Subsection 5.2.

5.1 Experimental setup

Our proposed evaluating process of the current work have been tested on five case bases from UCI Machine Learning Repository[5] to assess CBM policies available in the literature. These datasets are described in Table 1 in term of size, number of problems attributes, and number of classes or solutions.

Table 1. Case bases description

	Case base	**# instances**	**# attributes**	**# solutions**
1	Breast Cancer	569	32	2
2	Glass	214	9	6
3	Ionosphere	351	34	2
4	Indian	583	10	2
5	Sonar	208	60	2

For every CB, we estimate the support maintenance degree of four CBM policies. We have chosen CNN [11] and RNN [12] as the most widely used CBM algorithms, as well as ECTD [6] and DETD [13] as the two existing CBM policies under the belief function theory. These methods have been developed according to their default settings as described in their referenced papers.

5.2 Results and discussion

As regards to the study of results offered, in Table 2, by our proposed evaluating process, some particular situations should be pointed out. If the offered support degree is equal to 50%, then the applied CBM method was able to retain exactly the initial competence of the CBR system. The amount above 50 represents the capability rate of the CBM policy to improve that competence. Therefore, the higher this value, the more the CBM policy is adequate to be applied. On the contrary, the amount below 50 reflects the amount of competence degradation after maintenance. In Table 2, we note that almost all the offered CBM support degrees are in $[40, 60]$, which means that performed CBM policies slightly reduce or improve the CBR competence in problem-solving. Nevertheless, we remark that CNN and RNN algorithms are not adequate to be applied on some CBs

[5] https://archive.ics.uci.edu/ml/

such as "Ionosphere" and "Glass" datasets (25.74% and 29.98% with CNN, and 17.95% and 29.98% with RNN). In our sense, we may tolerate values in [45, 50] if other evaluation criteria are improved such as CBR performance and response time[6]. Ultimately, we note that the ECTD policy is the most supported

Table 2. Support degree results of some CBM policies applied on some CBs

CB	CBM	$Comp_O$ (%)	$Comp_M$ (%)	Acc_O (%)	Acc_M (%)	CBM support degree (%)
Cancer	CNN	83.44	81.52	59.39	71.45	55.08
	RNN	83.44	82.11	59.39	71.45	55.37
	ECTD	83.44	83.12	59.39	74.25	57.27
	DETD	83.44	83.06	59.39	70.12	55.18
Glass	CNN	55.86	54.24	87.38	48.33	29.98
	RNN	55.86	54.24	87.38	48.33	29.98
	ECTD	55.86	55.18	87.38	89.75	50.84
	DETD	55.86	54.26	87.38	73.81	42.52
Ionosphere	CNN	93.86	69.74	86.61	54.46	25.74
	RNN	93.86	68.88	86.61	34.46	17.95
	ECTD	93.86	89.17	86.61	86.61	47.66
	DETD	93.86	88.72	86.61	77.53	43.12
Indian	CNN	74.22	72.12	65.26	61.88	47.30
	RNN	74.22	71.03	65.26	61.75	46.71
	ECTD	74.22	73.68	65.26	67.15	50.68
	DETD	74.22	70.13	65.26	59.87	47.05
Sonar	CNN	78.11	73.87	81.28	64.22	39.71
	RNN	78.11	72.96	81.28	62.85	39.63
	ECTD	78.11	76.32	81.28	84.62	50.78
	DETD	78.11	76.01	81.28	78.55	47.31

CBM method to be applied on the different tested CBs, where it offers support values equal to 57.27% with "Breast Cancer", 50.84% with "Glass", 47.66% with "Ionosphere", 50.68% with "Indian", and 50.78% with "Sonar". These values indicate that maintenance task applied by ECTD improves the performance of almost all the original tested CBs.

6 Conclusion

In this paper, a process for evaluating Case Base Maintenance policies is proposed. Its main idea consists at applying a given CBM policy and measuring the CB competence before and after maintenance using both of an evidential competence model and the statistical accuracy measure. The output of these two sources are modeled and aggregated within the belief function framework to offer a high-quality CBM support degree estimation. During the experimentation,

[6] Forthcoming research work will carry out with other evaluation criteria.

this process has been performed on different CBM policies and using different datasets. As future work, we opt to intervene on the opposite sense by setting parameters of some CBM policies at the aim of maximizing the support degree offered by the proposed evaluation process.

References

1. Aamodt. A., Plaza. E.: Case-based reasoning: Foundational issues, methodological variations, and system approaches. *In Artificial Intelligence Communications*, pp. 39-52 (1994)
2. Leake. D., Wilson. D.: Categorizing case-base maintenance: dimensions and directions, *In Advances in Case-Based Reasoning*, pp. 196-207 (1998)
3. Smyth, B., McKenna, E.: Modelling the competence of case-bases. *In: Smyth, B., Cunningham, P. (eds.) EWCBR. LNCS, vol. 1488*, pp. 208-220. Springer (1998)
4. Juarez, J. M., Craw, S., Lopez-Delgado, J. R., Campos, M.: Maintenance of case bases: current algorithms after fifty years. *In proceedings of the International Joint Conferences on Artificial Intelligence*, pp. 5458-5463 (2018)
5. Smiti, A., Elouedi, Z.: Overview of Maintenance for Case based Reasoning Systems. *In International Journal of Computer Applications*, pp.49-56 (2011)
6. Ben Ayed. S., Elouedi. Z., Lefevre. E.: ECTD: Evidential Clustering and case Types Detection for case base maintenance. *In proceedings of the 14th International Conference on Computer Systems and Applications (AICCSA)*, pp. 1462-1469, IEEE (2017)
7. Ben Ayed. S., Elouedi. Z., Lefevre. E.: Exploiting Domain-Experts Knowledge Within an Evidential Process for Case Base Maintenance. *In proceedings of the International Conference on Belief Functions*, pp. 22-30, Springer, Cham (2018)
8. Smiti, A., Elouedi, Z. SCBM: soft case base maintenance method based on competence model. *In Journal of Computational Science, 25*, pp. 221-227 (2018)
9. Lupiani, E., Juarez, J. M., Palma, J.: Evaluating case-base maintenance algorithms. *In Knowledge-Based Systems, 67*, pp. 180-194 (2014)
10. Chebel-Morello, B., Haouchine, M. K., Zerhouni, N.: Case-based maintenance: Structuring and incrementing the case base. *In Knowledge-Based Systems, 88*, pp. 165-183 (2015)
11. Hart, P.: The condensed nearest neighbor rule. *IEEE transactions on information theory, 14(3)*, pp. 515-516 (1968)
12. Gates, G.: The reduced nearest neighbor rule. *IEEE transactions on information theory 18 (3)*, pp. 431-433 (1972)
13. Ben Ayed, S., Elouedi, Z., Lefevre, E.: DETD: Dynamic Policy for Case Base Maintenance Based on EK-NNclus Algorithm and Case Types Detection. *In proceedings of the International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pp. 370-382. Springer (2018)
14. Ben Ayed, S., Elouedi, Z., Lefevre, E.: CEC-Model: A New Competence Model for CBR Systems Based on the Belief Function Theory. *In International Conference on Case-Based Reasoning*, pp. 28-44, Springer, Cham (2018)
15. Mosqueira-Rey, E., Moret-Bonillo. V.: Validation of intelligent systems: a critical study and a tool. *In Expert Systems with Applications 18 (1)*, pp. 1-16 (2000)
16. Smyth, B., Keane, M.T.: Remembering to forget: a competence-preserving deletion policy for CBR systems. *The Thirteenth International Joint Conference on Artificial Intelligence*, pp. 377-382 (1995)

17. Smiti, A., Elouedi, Z.: Modeling competence for case based reasoning systems using clustering. *In proceedings of the 26th International FLAIRS Conference, the Florida Artificial Intelligence Research Society*, pp. 399-404 (2013)
18. Dempster. A. P.: Upper and lower probabilities induced by a multivalued mapping. *Ann. Math. Stat. 38*, pp. 325-339 (1967)
19. Shafer. G.: A Mathematical Theory of Evidence. *Princeton University Press*, Princeton (1976)
20. Masson, M. H., Denœux, T.: ECM: an evidential version of the fuzzy c-means algorithm. *Pattern Recognition 41 (4)*, pp. 1384-1397 (2008)
21. Antoine, V., Quost, B., Masson, H. M., Denœux, T.: CECM: Constrained evidential c-means algorithm. *Computational Statistics & Data Analysis*, pp. 894-914 (2012)
22. Jousselme, A.L., Grenier, D., Bossé, E.: A new distance between two bodies of evidence. *Inf. Fusion 2(2)*, 91-101 (2001)
23. Smets, P.: Application of the transferable belief model to diagnostic problems. *In International journal of intelligent systems, 13(23)*, pp. 127-157 (1998)