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A CBR System to New Product Development: An Application for Hearing Devices Design

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Abstract—Nowadays, quick technological changes force companies to develop innovative products in an increasingly competitive environment. Therefore, how to enhance the time of new product development is very important. This design problem often lacks the exact formula for getting it, and highly depends upon human designers' past experiences. For these reasons, in this work, a Case-based reasoning (CBR) system to assist in new product development is proposed. When a case is recovered from the case base, the system will take into account not only the attribute's specific value and how important it is. It will also take into account if the attribute has a positive influence over the product development. Hence the manufacturing time will be improved. This information will be introduced as a new concept called "adaptability". An application to this method for hearing instrument new design illustrates the proposed approach.

Keywords—Case based reasoning, Fuzzy logic, New product development, Retrieval stage, Similarity.

I. Introduction

The request of rapid product design is becoming stronger while the product life cycle is getting shorter in the market. Therefore reducing manufacturing time for new products is needed. Case-based reasoning (CBR) is a well-known technique in Artificial Intelligence (AI) which has been applied successfully in many domains like [1]–[5] and for this problem it seems very promising to provide a solution for rapid product design if a library of design cases is available [6]–[8]. CBR is based on: "similar past experiences can guide the new experiences". Therefore, the new product can be used as a help, if the old product has some features in common with the new one. It will allow us to save manufacturing time, costs and also improve the delivery of this product. A CBR system is commonly described by the CBR-cycle [Fig1] which comprises four activities (the four-REs) [9]:

1) *Retrieve* similar cases to the problem description
2) *Reuse* a solution suggested by a similar case
3) *Revise* or adapt that solution to better fit the new problem if necessary
4) *Retain* the new solution once it has been confirmed or validated

The CBR system should be developed as close as possible to the scheme shown in Fig.1.

Retrieval is a very important stage because if the retrieved case is not the most relevant, the rest of the process will

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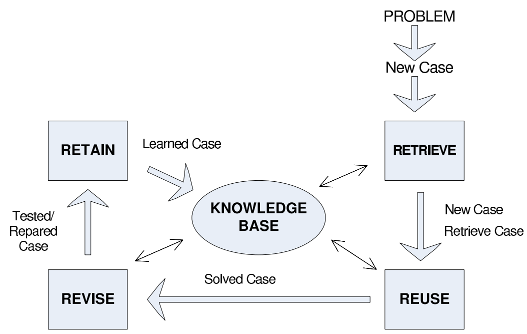

Fig. 1. CBR-Cycle.

not provide any useful results or information. Retrieval is therefore one of the major research areas in CBR systems. Many researchers have worked in this domain and various retrieval techniques have been developed. These techniques range from classical methods, such as the famous k-NN [10] or Fish and Shrink [11], to more sophisticated methods that mix neural networks [12] or fuzzy logic [13]. In previous works [14]–[16] how the success of retrieval stage was influenced by the suitability of the solution of the retrieved case to solve our problem was showed, which was measured, with regard to each attribute, by the Local Risk variable. After, this concept was extended to the entire case [17].

By including Local Risk in the retrieval stage, good results were obtained. Therefore, this technique could be useful for new product development. In order to use this technique in this context, the Local Risk definition will be adapted to the specific problem. It will be called "Local Adaptability". This variable will quantify if the considered attribute is or not suitable for developing the new design. It will save time both to make and to train staff for its manufacture. Thereby, product delivery time and cost is improved.

The most common methods for new product development does not use artificial intelligence. These methods use statistical models which provide the relationship between the input parameters and resulting properties involved in the design problem. When the need for developing new product properties arises, it becomes the sole responsibility of the human designer to make a new design that can provide those properties. Instead of starting from scratch for developing the new design, design engineers rely on their past experiences and expertise for quality design. Many researches have been made in this [18]–[20]. However, this human-based approach often lacks a consistent and systematic procedure for designing new products and as result might lead to poor design with unnecessarily higher production cost and late delivery to customer. The aim of this research is to alleviate the difficulties of product development, in order to make it a CBR method is suggested. A CBR system can assist the development process in many ways. By using the "local adaptability" information and fuzzy logic in the retrieval stage, a similar case to the new design problem can be found and the characteristics used in the old case might be directly applied to the design or at least they can provide useful information for adaptation the new components. Using the local adaptability information, the incompatibilities between attributes are deleted and both staff training and product cost are reduced. Therefore the product development process is reduced, thus competitive in the market will be increased. Finally, an application of this approach for developing new hearing instrument is proposed.

The rest of this paper is organized in three more sections. Section 2 defines Local risk and Local Adaptability and also presents presents the fuzzy inference system composed of 19 rules, which assign global similarity, based on Local Adaptability. In Section 3, an application of the proposed approach to a new product development is illustrated. The conclusions of our research study are given in Section 4.

II. Adaptation of Local Risk for Developing New Product: Local Adaptability

Quick changes in market force companies to develop new products constantly. These products have to adapt to new technologies, for this reason, they will be more complex and therefore more difficult to make. This means more time for manufacturing and for staff training will be needed. Consequently production is delayed.

In this section how to adapt the local risk concept to obtain a CBR system for new products development is explained. When a new product is developed, the most similar case or cases from the case-base are recovered. After, the new concept "local adaptability" helps to choose the most suitable case which minimizes time, cost and the incompatibilities between new product characteristics.

A. Local Risk and Local Adaptability

1) Local Risk: In real-life, there are two different kinds of problems: *i) Risk-problems*, they are problems where to make a decision is involved by risk, for example: health problems, in these kind of problems to consider whether the solution is dangerous for the patient is really important, because the patient's life cannot take a risk and *ii)Non-Risk-problems* where risk is zero or very little. The aim of the model was not to waste the information provided by the risk when Risk-problems were being solved. For this reason the risk concept was introduced. A formal definition of Local Risk can be found in *Definition 1*.

Definition 1. *The Local Risk variable, R_i, for* i*th attribute is defined as, the suitability of applying the solution of C^{Mem} when the* i*th attribute of C^{New} takes the value A_i, where A_i is the actual attribute value, C^{Mem} the case in memory and C^{New} the target case.*

2) Local Adaptability: In order to take advantage of the good results that were obtained using Local Risk in Risk-problems, this concept has been adapted for developing new products.

Definition 2. *The Local Adaptability variable, LA_i, for* i*th attribute is defined as, the positive influence of the* i*th attribute over the New Product, when $Cost/U_i$ and $Hour/U_i$ take the values X, Y respectively for the* i*th attribute.*

A_i is the actual ith attribute value, $Cost/U_i$ is cost per unit for ith attribute (it is measured in Euros) and $Hour/U_i$ are the hours per unit for making the ith attribute (it is measured in minutes).

By using this information, the attributes which are not important or incompatible for developing the new product are going to be deleted. Therefore, time in manufacture will be saved. Both Local risk and Local Adaptability are putted into the similarity measure through a fuzzy inference system.

B. A New Similarity Measure Based on Local Adaptability

The new variable, Local Adaptability, is introduced using a fuzzy inference system. This system has been chosen because it is useful and efficient for dealing with imprecise, rough information and also as it is able to provide to the measure with linear and non-linear information which improve the retrieval. In order to build this system, the formula of the overall similarity will be modified, making it dependent on the local adaptability (LA_i), $Cost/U_i$ cost per unit and $Hour/U_i$ hour per unit. They only intervene in the fuzzy inference system and not in the calculation of the similarity.

$$Sim(C^{Mem}, C^{New}) = \frac{\sum_{i=1}^{n} f(LA_i, Cost/U_i, Hour/U_i)}{n} \tag{1}$$

where n is the number of the attributes. The function $f(\cdot)$ is implicitly obtained with a fuzzy inference system and is calculated as a weighted average of the outputs from all the rules. The fuzzy inference system used in Equation 1 can be viewed as a direct application of the TSK model [21]. This inference system for the ith attribute contains 19 rules.

Rule 1. If LA_i is *high* and $Cost/U_i$ is *high* and $Hour/U_i$ is *high*, then v_i=$2 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 2. If LA_i is *high* and $Cost/U_i$ is *high* and $Hour/U_i$ is *medium*, then v_i=$2.25 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 3. If LA_i is *high* and $Cost/U_i$ is *high* and $Hour/U_i$ is *low*, then v_i=$2.5 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 4. If LA_i is *high* and $Cost/U_i$ is *medium* and $Hour/U_i$ is *high*, then v_i=$2.25 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 5. If LA_i is *high* and $Cost/U_i$ is *medium* and $Hour/U_i$ is *medium*, then v_i=$2.5 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 6. If LA_i is *high* and $Cost/U_i$ is *medium* and $Hour/U_i$ is *low*, then v_i=$2.75 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 7. If LA_i is *high* and $Cost/U_i$ is *low* and $Hour/U_i$ is *high*, then v_i=$2.75 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 8. If LA_i is *high* and $Cost/U_i$ is *low* and $Hour/U_i$ is *medium*, then v_i=$2.75 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 9. If LA_i is *high* and $Cost/U_i$ is *low* and $Hour/U_i$ is *low*, then v_i=$3 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 10. If LA_i is *medium*, then $v_i = sim(A_i^{Mem}, A_i^{New})$.

Rule 11. If LA_i is *low* and $Cost/U_i$ is *high* and $Hour/U_i$ is *high*, then v_i=$0.2 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 12. If LA_i is *low* and $Cost/U_i$ is *high* and $Hour/U_i$ is *medium*, then v_i=$0.25 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 13. If LA_i is *low* and $Cost/U_i$ is *high* and $Hour/U_i$ is *low*, then v_i=$0.25 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 14. If LA_i is *low* and $Cost/U_i$ is *medium* and $Hour/U_i$ is *high*, then v_i=$0.3 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 15. If LA_i is *low* and $Cost/U_i$ is *medium* and $Hour/U_i$ is *medium*, then v_i=$0.3 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 16. If LA_i is *low* and $Cost/U_i$ is *medium* and $Hour/U_i$ is *low*, then v_i=$0.3 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 17. If LA_i is *low* and $Cost/U_i$ is *low* and $Hour/U_i$ is *high*, then v_i=$0.35 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 18. If LA_i is *low* and $Cost/U_i$ is *low* and $Hour/U_i$ is *medium*, then v_i=$0.35 \cdot sim(A_i^{Mem}, A_i^{New})$.

Rule 19. If LA_i is *low* and $Cost/U_i$ is *low* and $Hour/U_i$ is *low*, then v_i=$0.5 \cdot sim(A_i^{Mem}, A_i^{New})$.

In these rules, the linguistic terms (*low, medium, high*) are defined on LA_i, $Cost/U_i$ and $Hour/U_i$, respectively; v_i $i = 1, \ldots, 19$ is the similarity measure adjusted by the system under the condition prescribed in the premise of the *i*th rule.

The reason for the design of this fuzzy inference system is that the rules increase or decrease the influence of the local similarity on the overall similarity, depending on the local adaptability, cost per unit and hour per unit values. For example, there is three-unit increase in *Rule 9* since not only is there high risk but also low cost and hour per unit, that is the perfect situation, a feature which has positive influence and low cost and manufacture time. *Rule 10* is neutral on the local similarity, because if the local adaptability is medium, it is not important enough in the manufacture process. This simplifies the work.

The fuzzy inference system (or equivalently, the calculation of $f(LA_i, Cost/U_i, Hour/U_i$ is inferred in two steps. First, the firing strength g_j, $j = 1, \ldots, k$ is calculated where k is the number of fired rules. The firing strength of each rule is determined by aggregating the truth-values, i.e. membership values of all the linguistic terms through the "*and*" operator. In this paper, the operation of "*and*" is defined as an algebraic product. For instance, the firing strength of the first rule is obtained as follows:

$$g_1 = \mu_{high}(LA_1) \cdot \mu_{high}(Cost/U_1) \cdot \mu_{high}(Hour/U_1) \quad (2)$$

For all the rules with the exception of *Rule 10*, the firing strength is calculated using Equation 2. For the tenth rule (which is a special rule), the firing strength is calculated using Equation 3.

$$g_{10} = \mu_{medium}(LA_{10}) \quad (3)$$

Then the output of the system is calculated

$$f(LA_i, Cost/U_i, Hour/U_i = \frac{\sum_{j=1}^{k_j^i} v_j^i \cdot g_j^i}{\sum_{j=1}^{k_j^i} g_j^i} \quad (4)$$

where k_j^i is the number of fired rules for the *i*th attribute, v_j^i is the output of the *j*th rule fired for the *i*th attribute and g_j^i is the firing strength of the *j*th rule for the *i*th attribute. Finally, the overall similarity is calculated using Equation 5.

III. Case study: An Application for Hearing Aids New Design

Challenges in the design of new products are caused not only by strict design, but also by business and market requirements. Shrinking life-cycles and time-to market concerns, together with the drive for competitiveness constantly create the need for higher quality, higher functionality and cheaper products. As many companies are scaling down, leaving fewer resources, design team members and support staffs available, the task of product design becomes even more difficult. All these problems are presented by Beltone. Beltone is an international company which works on developing new hearing instruments. Its office in Spain (www.beltone.es) was contacted by us. This office is a lab where they make both old and new designs. The manufacture of a hearing aid is a delicate process which requires skilled staff. Their customers frequently request new designs that can adapt to market trend and satisfy their expectation in time. In this paper a CBR system approach is presented to effectively store and apply the past experiences and expertise of human designers for developing new hearing instrument. Within our approach, the process has to main parts: formal case representation and case retrieval.

- *Formal Case Representation*

Let us see in detail, how case-base has been organized. It was made with an expert help from Beltone. The company has a portfolio of 350 models. The expert defined a case, C, like a set of attributes $C = (A_1, \ldots, A_n)$. An attribute, A, is the two-dimensions vector $A = (P,N)$, where P is a specific device feature and N the pair of values Cost/U (cost per unit for the P characteristic) and Hour/U (hours per unit for the P characteristic). The expert recommended to us to take these 16 characteristics into account: Volume Control(VC), Push Button (PB), Trimmers (TR), Removal Cord (RC), Switch (S), Wax Protection (WP), Reference Dot (RD), Bluetooth (B), Telecoil (TL), Dual (D), Remote Microphone (RM), Receiver Into the Ear (RIE), Battery Size (BS), Cost per device (C/Dev) is measured in Euros, Hours per device (H/Dev) is measured in hours and Delivery Time (DT) is measured in days.

- *Problem Description*

The new design is a hearing aid with a hybrid circuit which makes unnecessary the use of Volume Control (VC) and Push Button (PB). The new model is called *Hybrid Model*, it has these two features in one. By reducing two features in one making the device lighter and portable and therefore to have the device installed in the ear canal is more comfortable, and this is a benefit for customer. Table I shows the attributes of the New Product.

TABLE I
Attribute values of the New Product.

Attributes	*VC*	*PB*	*TR*	*RC*	*S*	*WP*	*RD*	*B*
Values	?	?	No	No	No	Yes	No	No
Attributes	TL	D	RM	RIE	BS	C/Dev	H/Dev	DT
Values	Yes	Yes	No	No	S312	650	1.5	3

Now, the development team leader has to decide how to make this new model with the lowest effort in order to save time and human resorts.

- *Case Retrieval*

In this step, how our proposed method works and how it can be useful for developing the new device will be explained. Firstly, the similarity between the cases in memory in relation to the current case, *New Model* is calculated. In order to do it, is possible to choose between a lot of measurements, as followings studies [22], [23] show. Heterogeneous Euclidean-Overlap Metric (HEOM) [24]will be used in this study. This measurement returns the distance between two input cases C^{Mem} and C^{New}. It is defined as follows:

$$Sim(C^{Mem},C^{New}) = 1 - \sqrt{\frac{\sum_{i=1}^{n} sim_i^2(A_i^M,A_i^N)}{n}} \qquad (5)$$

where n is the number of attributes, A_i^M and A_i^N are the ith attribute of C^{Mem} and C^{New} respectively. The function $sim_i(A_i^M,A_i^N)$ uses one of two functions defined in Equation 6 depending on whether the attribute is nominal or linear.

$$sim_i(A_i^M,A_i^N) = \begin{cases} 1 & if\ A_i^M\ or\ A_i^N\ is\ unknwn \\ overlap(A_i^M,A_i^N) & if\ ith\ attrbt\ is\ nminl \\ rn-diff_i(A_i^M,A_i^N) & if\ ith\ attrbt\ is\ linear \end{cases} \qquad (6)$$

Unknown attribute values are handled by returning an attribute distance of 1 (i.e., a maximal distance) if either of the attribute values is unknown. The function *overlap* and the range normalized difference *rn-diff* are defined as:

$$overlap(A_i^M,A_i^N) = \begin{cases} 0 & if \quad A_i^M = A_i^N \\ 1 & if \quad A_i^M \neq A_i^N \end{cases} \qquad (7)$$

$$rn-diff_i(A_i^M,A_i^N) = \frac{|A_i^M - A_i^N|}{range_i} \qquad (8)$$

The value $range_i$ is used to normalize the attributes, and is defined as, $range_i = max_i - min_i$, where max_i and min_i are the maximum and minimum values, respectively, observed in the training set for ith attribute.

Table II shows the attributes of the most suitable models with regard to New Model and Table III the global similarity value, using Equation 5. In order to see to see all models, please contact with Beltone.

TABLE II
Cases Retrieval.

	VC	*PB*	*TR*	*RC*	*S*	*WP*	*RD*	*B*
Reach RCH35	No	Yes	No	No	No	Yes	No	No
Identity(IDT35)	Yes	Yes	No	No	No	Yes	No	No
Reach 35VC	Yes	Yes	No	No	No	Yes	No	No
Identity (IDT45)	Yes	No	No	No	No	Yes	No	No
	TL	*D*	*RM*	*RIE*	*BS*	*C/Dev*	*H/Dev*	*DT*
Reach RCH35	No	Yes	No	No	S13	625	1.75	3
Identity(IDT35)	Yes	Yes	No	No	S312	650	1.5	3.5
Reach 35VC	Yes	Yes	No	No	S312	600	1.5	3.25
Identity (IDT45)	Yes	No	No	No	S312	650	1.8	3

TABLE III
Similarity between cases in memory and New Model.

	Similarity
Reach RCH35	0.8619
Identity(IDT35)	**0.8916**
Reach 35VC	**0.8915**
Identity (IDT45)	0.8749

Table III shows the most similar cases, they are *Identity(IDT35)* and *Reach 35VC*, At first sight they look like the most suitable to make the New Model because they have both properties (Volume Control and Push Button), but they are not. The expert told us that if a model with VC was chosen the new product will be more expensive than if a model without this feature was chosen. VC is one of the most expensive features and the most difficult to make. Let us see what happen if the Local Adaptability information is used.

Now, the Local Adaptability is assigned independently to each attribute. Let us see some examples with model *Reach RCH35*. Local Adaptability will be just assign to the following features: Volume Control(VC), Push Button (PB), Trimmers (TR), Removal Cord (RC), Switch (S), Wax Protection (WP), Reference Dot (RD), Bluetooth (B), Telecoil (TL), Dual (D), Remote Microphone (RM), Receiver Into the Ear (RIE) and Battery Size (BS). Local adaptability is not assigned to the other three attributes because they do not take part in manufacture process.

First attribute: *Volume Control*
LA_1(*VC=No* and $Coste/U_1 = 60$ and $Horas/U_1 = 50$)= *High*. Because VC is a expensive and difficult feature and is better

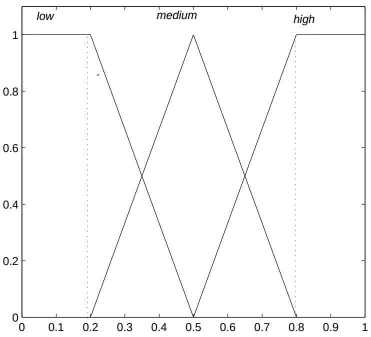

Fig. 2. Membership function.

to start the Hybrid Model without it, therefore the attribute *VC=No* has a important positive influence in New Product.

Second attribute: *Push Button*

LA_2(*PB=Yes* and $Coste/U_2 = 30$ and $Horas/U_1 = 10min$)= *High*. In this case is because this is a cheap feature and it is useful for Hybrid Model. *PB=Yes* has a important positive influence in New Product.

Third attribute: *Trmmers*

LA_2(*PB=Yes* and $Coste/U_2 = 20$ and $Horas/U_1 = 10min$)= *Medium*. It does not take part in the manufacture process.

The procedure with the other models and the other attributes are repeated. Table IV shows the value of the local adaptability of each attribute in each model. In this table L i low, M is medium and H is high.

TABLE IV
The Local Adaptability Assignment Table showing the critical values of the attributes.

	VC	*PB*	*TR*	*RC*	*S*	*WP*	*RD*	*B*
Reach RCH35	H	H	-	-	-	L	H	-
Identity(IDT35)	L	H	-	-	-	L	H	-
Reach 35VC	L	H	-	-	-	L	H	-
Identity (IDT45)	H	H	-	-	-	L	H	-
	TL	*D*	*RM*	*RIE*	*BS*	*C/Dev*	*H/Dev*	*DT*
Reach RCH35	L	-	-	-	-	-	-	-
Identity(IDT35)	L	L	-	-	-	-	-	-
Reach 35VC	-	L	L	-	L	-	-	-
Identity (IDT45)	L	L	-	-	-	-	-	-

This table does not show all the results because in practice just critical cases are interesting. Critical cases are cases which present high or low Local Adaptability values. It should be remembered that these values are dependent on an expert's opinion, and another human expert might consider other different values in the same situations.

Now the linguistic labels for cost per unit and hour per unit are assigned in order to infer on the fuzzy inference system. In this case, it is not necessary to assign a linguistic label to local adaptability as this has been assigned linguistically rather than as a numerical value. This is not a restriction because if the local adaptability were a numerical value, the process would be the same which was made for the other features. The Fig.2 shows the membership functions of cost per unit and hour per unit.

Now, let us see how the rules are fired: first, one case from the case base is chosen, for example, *Reach RCH35* , and after an attribute for this case is also chosen, e.g. *VC*, $Coste/U_1 = 60$ and $Horas/U_1 = 0.30$. The linguistic terms for $Coste/U_1 = 60$ and $Horas/U_1 = 50min$ are shown in Fig.2 and they are *high* and for both. Local Adaptability for the attribute is High. With these values, the fired rules are: Rule1 and Rule5.

The fired strength of the rules is calculated using Equation 2 for all the rules except for the tenth rule where Equation 3 must be used. Finally, the following results are obtained:

TABLE V
Similarity between cases in memory and New Model using Local Adaptability.

	Similarity
Reach RCH35	**0.9876**
Identity(IDT35)	0.7654
Reach 35VC	0.7432
Identity (IDT45)	0.9111

Now the model with the higher similarity is Reach RCH35, which is the best option because does not has VC and it has PB.

IV. Conclusion

The competitiveness on the market has increased hence many companies have to reduce resources, to be able to continue obtaining benefits. In this situation is difficult to develop new product. In this work a CBR system to help in new product development is presented. This approach uses the expert's experience to help in this task. The human-experience will be stored and it can be used at anytime. A real application for hearing device is showed. In this application how the Local Adaptability concept help in the development process can be seen. We shall continue working on this line of research by studying how to implement this method in Beltone.

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