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EXPLORING THE POWER OF FAILED EXPERIENCES IN CASE-BASED REASONING FOR IMPROVED DECISION MAKING

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Abstract. Case-based reasoning (CBR) is a popular approach for problem-solving and decision-making that involves using previous cases as a basis for reasoning about new situations. While CBR has shown promise in many domains, it is not immune to errors and failures. One limitation of the approach is that it tends to focus primarily on successful cases, ignoring the potential value of failed cases as a source of learning and insight. While many studies have focused on the role of successful cases in CBR, less attention has been given to the value of analyzing failed cases. In this paper, we explore the benefits of reasoning from both successful and failed cases in CBR. We argue that by examining both types of cases, we can identify patterns and insights that can help to refine CBR methods, improve their accuracy and efficiency, and reduce the likelihood of future failures. Using a combination of theoretical modeling and empirical analysis, we demonstrate that failed cases can provide valuable insights into identifying potential solutions that might otherwise be overlooked. To illustrate our approach, we present a case study in which we apply our reasoning methodology to a real-world problem in the field of energy management. Our analysis demonstrates that by considering both successful and failed cases, we can identify new and more effective solutions to the problem at hand.

Keywords: Case-based reasoning · adaptation · successful case · failed case.

1 Introduction

Case-based reasoning (CBR) is certainly the most intuitive approach of artificial intelligence to solve a problem since it mimics human behavior in problem-solving. A CBR system looks in its memory represented by a base of previously solved experiments called source cases, for cases having similar problems to the target problem to be solved by adapting their solutions if necessary. The target solution is revised to make sure of its adequacy to solve the target problem and finally the base of cases is enriched following the new experiment of resolution of the target case. Each step of the reasoning process is supported by a process of

acquiring the necessary knowledge to perform this step. It is worth highlighting the close connection between the knowledge of the different stages of the CBR approach.

Of the four principal stages of the reasoning process, adaptation is a crucial stage since the quality of the solution heavily depends on its performance. Its focus is on fitting the solutions of similar source cases to meet the specific requirements of the target problem. This is particularly important since the source problems usually do not match the target problem, and as a consequence, without this step, the CBR system cannot ultimately generate an appropriate solution to the target problem. Awareness of the pivotal role that adaptation plays was noted from the early days of CBR systems, as a result, there is a large number of studies exploring various approaches to acquiring adaptation knowledge to improve its performance.

Existing adaptation approaches focus exclusively on cases whose solutions are deemed relevant to the corresponding problems (hereafter these cases are referred to as successful cases and are denoted by $C+$). The appreciation of success is subjective to the application domain, e.g., in the context of the CBR application in the elaboration of an energy management system in a building, a successful case would correspond to a scenario satisfying the user's comfort while minimizing the energy expenditure. However, there are also failed cases. A failed case (noted hereafter $C-$) is a case having an unsatisfactory solution to the problem to solve, in particular, these are cases proposed by the adaptation process but rejected during the validation stage. Moreover, the adaptation process often involves the acquisition of the knowledge required to generate the adaptation rules. Usually, such knowledge is strongly dependent on the application domain, making the acquisition process complex and challenging to understand and grasp.

Surprisingly, despite a large number of research studies and an increased interest in the adaptation issue, few works are concerned with the challenge of proposing a domain-independent adaptation approach. Even less studies consider adaptation from the solution quality perspective, i.e., addressing both failed and successful cases. These cases are seldom used by the CBR systems even though they constitute potentially useful source of knowledge.

In this work, we propose a novel perspective on the adaptation process of the CBR paradigm, based on a fully domain-independent approach and drawing on both successful and failed cases. In particular, the present study proposes a new approach to the acquisition of adaptation knowledge exploiting both successful cases and failed ones. The approach takes its inspiration from studies in the planning of the path of a robot moving towards a destination in an unknown and insecure environment (includes obstacles). The originality of this approach consists in applying artificial forces to the solution to be proposed to move away from failed source solutions and move closer to successful source solutions.

The rest of this paper is arranged as follows. Section 2 introduces an illustration of motivation and the background of this work. Section 3 details the contribution to harnessing failed and successful cases for a new adaptation ap-

proach. An evaluation of the proposed approach is presented and discussed in Section 4, before drawing conclusions about this work and outlining some guidelines for future work in Section 5.

2 Motivating example and preliminaries

A CBR-based energy management system (EMS) in a building is a representative case study of the systems relevant to the scope of this study. The objective of an EMS is to fulfill the user's desire for thermal comfort, air quality, etc. while minimizing the energy consumption in the building. Indeed, a building is a complex system whose potential to save energy depends on several factors with dependencies difficult to identify [3], such as climate, building materials, geographical position, and energy rate, but also the occupant of the building exercises a major influence. Findings of earlier work [7] has already highlighted the advantage of acquiring adaptation knowledge in improving the performance of a CBR-based EMS. Furthermore, due to the growing awareness of environmental issues, several studies have focused on the correlation between energy consumption in a building and the comfort of its occupants, leading to the definition of standards [5,1,2] to estimate the comfort of users. Thanks to the norms defined in these standards, the revision process can gauge the quality of the target solution proposed by the adaptation process, allowing the retention process to label this solution as a successful case $C+$ or a failed one $C-$.

In the CBR-based EMS proposed in [3], the objective is to make the user conscious of the influence of his actions on the energy behavior of the building. For this, the system guides the user in his actions by advising him on a set of actions aiming at decreasing the energy waste while considering his comfort. A case describes the energy management scenario of a building for one day. The actions retained in the system case base are the actions effectively carried out by the building occupant, so there is no guarantee that they are actions that generate satisfactory effects for the occupant. For this reason, the system is provided with a function to evaluate the performance of the actions stored in the case base, allowing to label the corresponding cases with the appropriate labels ($C+$ or $C-$).

2.1 Founding notions and notations about CBR approach

The memory of a CBR system is made of a set of source cases C_{sr} which constitute a case base CB.

Case description. Let $\mathbb{C}$, $\mathbb{A}$, and $\mathbb{E}$ be three mutually disjoint sets. A case is a triplet $(\mathscr{C}, \mathcal{A}, \mathcal{E}) \in \mathbb{C} \times \mathbb{A} \times \mathbb{E}$ where:

- $\mathscr{C}$ is an element of the context domain $\mathbb{C}$, i.e., the imposed elements of the problem over which one cannot exert control. For instance, in a CBR-based disease treatment system, the context data can be the different physiological measures of the patient (blood pressure, glycemic rate, etc.).

- $\mathcal{A}$ is an element of the action domain $\mathbb{A}$, i.e., elements that can be controlled to achieve the relevant outcomes. It represents the solution proposed by the system. For instance, the names and the protocol for administering the drugs prescribed in a CBR-based disease treatment system.
- $\mathcal{E}$ is an element of the effect domain $\mathbb{E}$, i.e., elements describe the state of the system after applying action $\mathcal{A}$ to context $\mathscr{C}$. For instance, the patient's physiological measures after the treatment.

A target context $\mathscr{C}_{tg}$ is a context for which the CBR system tries to predict target actions $\mathcal{A}_{tg}$ to generate target effects $\mathcal{E}_{tg}$ and thus elaborate a target case C_{tg}. Formally, the resolution of a problem in the CBR paradigm is defined by Equation (1).

$$\begin{aligned} \text{CBR system: } (CB, \mathscr{C}_{tg}) &\longmapsto \mathcal{A}_{tg} \\ C_{tg} &\triangleq (\mathscr{C}_{tg}, \mathcal{A}_{tg}, \mathcal{E}_{tg}) \end{aligned} \tag{1}$$

With CB – the case base.

Retrieving and adaptation. A full presentation of the reasoning process is beyond the focus of this paper, but due to the particular connection between adaptation and retrieving knowledge, it is usually necessary to present the adaptation process in conjunction with the retrieval process. Indeed, the reasoning process modeled by Equation (1) is made up of two main steps.

- *retrieval process*: Given a threshold σ for the distance between the context variables of the source cases and the target context, the retrieval process consists of identifying the source cases having a context similar to the target context. The profile of the retrieval function is given in Equation (2).

$$\text{Retrieve:} \quad \mathscr{C}_{tg} \longmapsto \{\forall\, C_{sr} \in CB / Distance(\mathscr{C}_{tg}, \mathscr{C}_{sr}) \leq \sigma\} = \mathcal{S}_{\mathcal{C}_{tg}} \tag{2}$$

  Where $Distance(\mathscr{C}_{tg}, \mathscr{C}_{sr})$ – a metric that computes the distance between the context variable $\mathscr{C}_{tg}$ and the context variable $\mathscr{C}_{sr}$.
  No constraints are imposed on the type of distance to use since it permits handling the context variables. For instance, the Minkowski metric can be used to calculate the context distance in a CBR-based EMS since the context variables are real values.
- *adaptation process*: Since the source contexts usually do not match the target context, it is required to define a function to adapt the source actions to satisfy the requirements of the target context. The profile of the adaptation function is defined by the Formula (3).

$$\begin{aligned} \text{Adaptation: } \forall\, C_{sr} \triangleq (\mathscr{C}_{sr}, \mathcal{A}_{sr}, \mathcal{E}_{sr}) \in \mathcal{S}_{\mathcal{C}_{tg}}, \\ (\{(\mathscr{C}_{sr}, \mathcal{A}_{sr}, \mathcal{E}_{sr})\}, \mathscr{C}_{tg}) \longmapsto \mathcal{A}_{tg} \end{aligned} \tag{3}$$

  Where $\mathcal{S}_{\mathcal{C}_{tg}}$ – the set of similar source cases as defined by Equation (2).
  Note that Equation (3) does not impose any constraints on the number of similar cases considered in the adaptation process, thus we are dealing with a compositional adaptation (whose single case adaptation is a particular case),

where solutions from several source cases are combined to yield a target solution. Indeed, the experiment indicated that retaining a single case often gives less accurate results [9]. This is explained by the fact that frequently only a part of the problem of the similar source case is relevant for the target problem, which makes the task of adaptation complicated (if not impossible).

2.2 Collisionless path planning

Robot path planning study focus on the path planning of an autonomous robot moving in an unknown environment, i.e., guide the robot in its movement from an initial position to a target position by calculating the optimal but moreover the safest path to avoid obstacles that can occur along the path towards the target.

Several approaches were proposed to tackle this challenge, in particular, the Artificial Potential Field (APF) approach originally proposed in [6] is extensively adopted in robot guidance. The APF approach can cope with the reality of the current environment of the robot displacement by considering both the objectives to be reached and the obstacles to be avoided while moving. The key idea of this approach is to consider the robot as a point evolving in a 2-dimensional space (in the basic scenario) subject to the field influences of targets to reach and obstacles to avoid. Consequently, the robot is subjected to two kinds of forces, including an attractive one $\mathbb{F}_{at}$ generated by targets and a repulsive one $\mathbb{F}_{rp}$ generated by obstacles to move the robot further away.

Whereas repulsive forces are disproportional to the distance between the robot and the obstacles, i.e. they are strongest close to the obstacles and are less influential at distance, attractive forces are proportional to the distance between the target and the robot. The combined (total) of all the forces $\overrightarrow{\mathbb{F}} = \overrightarrow{\mathbb{F}_{at}} + \overrightarrow{\mathbb{F}_{rp}}$ applied to the robot defines the movement direction of the robot and its speed whilst avoiding collisions with obstacles. For the sake of simplification, the principle of this method for a robot traveling in a 2-dimensions environment is depicted in Figure 1.

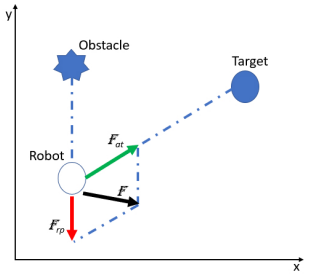

Fig. 1: Artificial potential field.

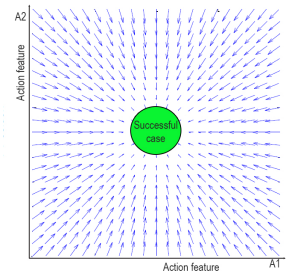

Fig. 2: CBR attractive force

3 Reasoning from successful and failed cases

3.1 Problem formalization

The adaptation problem considering failed and successful cases can be formalized as follows. Given the following observations:

- the case base CB is divided into two partitions of failed cases $CB\_$ and successful cases CB_+. So, $CB = CB\_ \cup CB_+$.
- by misuse of language, we refer to a target case as the elements of a target context for which we are looking for a solution. The case structure is not completely defined as the elements representing the actions and therefore, the effects are unknown.

Finding a solution for a target case (thus under construction) is to infer, from source cases having similar context, a set of target actions that best satisfy the target context, which leads to the definition of the target effects, and thus to building an effective case containing the three elements: context, actions, and effects.

Similar source cases should be handled differently depending on whether they are failed (member of $CB\_$) or successful (member of CB_+) and on their degree of similarity to the target case. The method to be proposed should provide mechanisms to move towards the solutions of successful similar source cases and away from failed similar source cases while taking into account that the closer the source case to the target case the more influence its solution has on the target solution.

3.2 Principle

The principle of our approach to considering failed cases in the adaptation process is inspired by navigation algorithms originating from the literature on the programming of autonomous robots, in particular, based on the artificial potential field presented in Section 2.2.

Before describing the details of our approach in the next section, to ensure the successful implementation of an artificial potential field-like concept in the context of this work, some assumptions are formulated:

- while the labeling process falls outside the scope of this study, we assume that previous experiences (source cases) are already labeled as successful or failed cases. Furthermore, we suppose that the CBR system is given a quality function $\mathcal{Q}$ which scores the efficacy of the actions applied to the context. The highest scores are the best. This implicitly defines a threshold value $\mathcal{P}_s^{\mathcal{E}_i}$ for each effect feature $\mathcal{E}_i$ according to Equation (4).

$$\forall\ C_i \in CB\ ,\ \mathcal{Q} : \mathcal{E}_i \longmapsto \mathbb{R}$$
$$\mathcal{L}(C_i) = \begin{cases} C_i+ & \text{if } \mathcal{Q}(\mathcal{E}_i) \geq \mathcal{P}_s^{\mathcal{E}_i}\ ,\ \forall \mathcal{E}_i \in \mathbb{E} \\ C_i- & \text{otherwise.} \end{cases} \tag{4}$$

With $\mathcal{L}$ – the labeling function, $\mathcal{E}_i$ – an effect feature of case C_i.

– classical CBR methods retrieve a defined number of neighboring cases from the case base CB regardless of an optimal number of similar ones regarding the target case. This KNN-like approach poses some issues since the target cases do not necessarily have the same number of similar neighbors, while some target cases should have more similar cases, others less. Furthermore, the configuration where much more source cases with equal distance from a target case than the predefined number, must be handled. In this work, we assume the existence of a retrieval approach that adjusts the number of source cases similar to the target case C_{tr} by dynamically defining a similarity threshold $\sigma_{C_{tr}}$ for the context distance between C_{tr} and the neighboring source cases. For instance, the work presented in [3], provides a method to define this threshold by combining a statistical approach and a genetic algorithm.

The key idea of the approach proposed in this work is to map the type of source cases available in the case base, i.e., successful and failed cases, to the type of objects handled in the context of robot moving, i.e., target and obstacles. Therefore, failed cases are assimilated into obstacles and successful cases into targets. While cases $C_i+ \in \mathcal{S}_{\mathcal{C}_{tg}}$ with good performances should generate an attractive force $\mathbb{F}_{at}$ that pulls the target solution towards them, the bad cases $C_i- \in \mathcal{S}_{\mathcal{C}_{tg}}$ should produce a repulsive force $\mathbb{F}_{rp}$ that pushes away the solution from them.

The successful and failed source cases are considered to be sources for generating a potential field representing the properties of the target solution. As in the robotic potential field method, the CBR potential field is still composed of two fields. For instance, regarding the attractive potential field, an attractive force is produced from the target solution to the source solutions of the successful cases by the configuration of the latter, which allows to pull the target solution towards the solutions of these cases.

To illustrate this concept, let's consider, for the sake of presentation, a system with domain knowledge containing only 2 action variables, the attractive potential field generated by any successful case looks like Figure 2, where at each point of the context space representing the target context, the force vectors are directed towards the successful source case. Concerning the repulsive potential field, a pushback force is generated by the configuration of the failed case towards the target solution, which allows to pull the target solution away from the solutions of these cases. Figure 3 depicts the CBR repulsive force in a similar configuration to the example illustrating the CBR attractive force.

Ultimately, the configuration of the target solution, i.e., the position of the target solution in the space of solutions (actions), is determined by summing all repulsive and attractive forces generated by neighboring failed and successful cases respectively. For the simple case of only two neighbors, a successful case and a failed case, the total potential field has the shape shown in Figure 4.

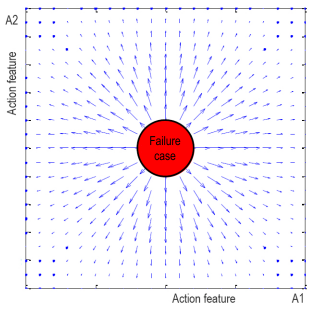

Fig. 3: CBR repulsive force

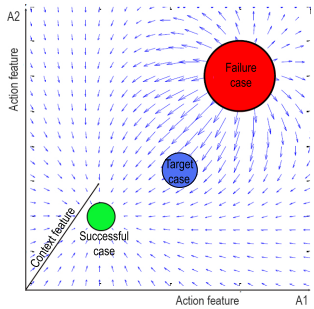

Fig. 4: CBR total potential force

3.3 Local prediction of the target solution

Although we are inspired by the potential artificial field method, its application in the context of this work as applied in the robotics context does not permit determining the solution for many reasons:

- the potential total force in the robotic context depends exclusively on the distance between the goal/obstacles and the robot. In the CBR context, the magnitude of the attraction and repulsion forces are not dependent only on the distance between the target context and the neighboring source contexts but also on the performance (quality solution) of the neighboring source contexts.
- within the robotics context, unlike the attractive force, the magnitude of the repulsive force is at its highest value close to the obstacle and decreases proportionally when moving away from it. Within the context of CBR applications, the magnitude of the two forces should be proportional to the performance of the source solutions but disproportional to the distance between the source contexts and the target one.
- there is usually only one goal to reach in robotic applications, but in the case of a multi-goal environment, one looks for a path that goes through all these goals in sequential order by optimizing some criteria. For CBR systems, the aim is to combine the knowledge of all the neighboring source cases to infer the target solution.
- while the purpose of the robotic potential artificial field is to find the safe path to the goal, its purpose in the CBR application is to acquire new knowledge that guides the adaptation process in the construction of the target solution, i.e., to orient the reasoning process towards the most useful solutions (closest and best-performing cases) and away from the worst cases (farthest away or bad performance).

It is, therefore, necessary to adapt the approach of the artificial potential field to take into consideration the specificities of the CBR adaptation process. To do so, our approach defines the target solution (actions) $\mathcal{A}_{tg}$ by the vectorial sum of all attractive forces ($\mathbb{F}_{at}^{C_i+}, \forall\, C_i+ \in \mathcal{S}_{\mathcal{C}_{tg}}$) and all repulsive forces ($\mathbb{F}_{rp}^{C_i-}, \forall\, C_i- \in \mathcal{S}_{\mathcal{C}_{tg}}$) as described in Equation (5).

Table 1: Summery of evaluation results.

TEST SET / APPROACH	S1			S2			S3			S4			S5			GLOBAL		
	METRICS			METRICS			METRICS			METRICS			METRICS			METRICS		
	PER (%)	*APR(%)*	*TIR(%)*	*PER*	*APR*	*TIR*	*PER*	*APR*	*TIR*	*PER*	*APR*	*TIR*	*PER*	*APR*	*TIR*	*PER*	*APR*	*TIR*
$CBR-S$	16.73	59.13	59.13	17.85	48.57	48.57	19.53	60.12	60.12	20.48	56.07	56.07	18.79	64.48	64.48	18.68	57.67	57.67
$CBR-B$	18.27	57.51	57.51	15.36	63.90	63.90	22.85	59.69	59.69	24.23	65.52	65.52	21.10	662.71	62.71	20.36	61.87	61.87
$CBR-P$	22.62	42.26	57.10	18.54	48.85	63.71	20.14	50.21	60.10	22.48	52.92	70.19	23.47	39.86	60.09	21.45	46;82	62,24
$CBR-R$	-2.56	32.18	49.75	9.12	29.89	51.19	14.71	43.07	64.24	17.45	39.52	57.74	12.04	41.26	62.84	10.15	37.18	57.15
$CBR-APF$	**34.68**	**100**	**100**	**28.85**	**99.76**	**99.76**	**33.91**	**100**	**100**	**31.27**	**100**	**100**	**38.73**	**99.88**	**99.88**	**33.49**	**99.92**	**99.92**

$$\forall\ C_i+, C_i- \in \mathcal{S}_{\mathcal{C}_{tg}},\ \sum_{C_i} \mathbb{F}^{C_i} \overrightarrow{\mathcal{A}_{tg}\mathcal{A}_i} = \sum_{C_i+} \mathbb{F}^{C_i+}_{at} \overrightarrow{\mathcal{A}_{tg}A_{C_i+}} + \sum_{C_i-} \mathbb{F}^{C_i-}_{rp} \overrightarrow{\mathcal{A}_{tg}A_{C_i-}} = 0 \tag{5}$$

As already mentioned earlier, the magnitude of the repulsion and attraction forces depends both on the distance of the target context from the context of the similar source case and on the performance of the latter. From Equation (5), the metric $\mathbb{F}^{C_i}$ defines the magnitude and direction of the associated force to the case C_i. We propose in Equation (6) a formula to estimate its value.

$$\forall\ C_i \in \mathcal{S}_{\mathcal{C}_{tg}}, \mathbb{F}^{C_i} = \begin{cases} \left(1 - \frac{\mathcal{D}_C(C_{tg}, C_i)}{\sigma_{C_{tg}}}\right) \times (\mathcal{Q}_i - \mathcal{P}_s) & \text{if } \mathcal{Q}_i \neq \mathcal{P}_s \\ 1 - \frac{\mathcal{D}_C(C_{tg}, C_i)}{\sigma_{C_{tg}}} & \text{else} \end{cases} \tag{6}$$

With $\sigma_{C_{tg}}$ – the context distance threshold, $\mathcal{Q}_i$ – the performance of the case C_i, $\mathcal{P}_s$ – the performance threshold, $\mathcal{D}_C(C_{tg}, C_i)$ – the context distance between C_{tg} and its neighbor C_i.

From Equation (6), one can observe that whatever the type of force, its magnitude progressively decreases at the expense of an increasing context distance until it becomes null when the context distance equals the similarity threshold $\sigma_{C_{tg}}$. Besides defining the magnitude of the force, the operand $\mathcal{Q}_i - \mathcal{P}_s$ specifies the type of the force. When $\mathcal{Q}_i \geq \mathcal{P}_s$, then $\mathbb{F}^{C_i} \geq 0$, and the case C_i generates an attractive force else, it should be a repulsive force.

In this manner, the actions to be proposed $\mathcal{A}_{tg}$ have to satisfy:

$$\mathcal{A}_{tg} = \frac{1}{\sum_{C_i} \mathbb{F}^{C_i}} \sum_{C_i} \mathbb{F}^{C_i} \mathcal{A}_i\ ,\ \forall C_i \in \mathcal{S}_{\mathcal{C}_{tg}} \tag{7}$$

Where $\mathcal{S}_{\mathcal{C}_{tg}}$ – set of similar cases to the target case C_{tg}.

4 EVALUATION

The present section provides an empirical evaluation of our approach. The objective of the evaluation is twofold, i) study the potential impact of considering both failed and successful cases on improving the performance of the CBR system; ii) assess the performance of the artificial potential field approach, this is referred to as CBR-APF in the following, compared to other adaptation approaches.

4.1 Experimental setup

As mentioned in Section 2, the approach is implemented in an EMS whose objective is to make the user aware of the impact of his actions on the energy use in a building. Concretely, the EMS proposes to the occupant a series of actions to improve the comfort while consuming less energy.

To evaluate our approach, we conducted an experiment using semi-synthetic data generated from real-data presented in [4]. The case base contains 15,948 cases, where each case is composed of: 1) the effect variables which represent the temperature and air quality in the building; 2) the action variables which model the opening of the door and window; 3) the context variables which are weather conditions. Each variable is described by a 24-value vector corresponding to one day. We adopted a 5-fold cross-validation where the original case base is randomly split into five equal-sized subsets: $S1$, $S2$, $S3$, $S4$, and $S5$. A single set is selected as a test set CB^T (target cases) while the remaining four sets are used as a learning set CB^L (source cases). The cross-validation procedure is performed five times, each of the five sets being used once as a test set. The results of the metrics adopted to evaluate the performance are averaged to provide a final estimate.

To evaluate case performance we used functions that assess the user's dissatisfaction with the effects of the actions, as presented by Formula (8). To simulate the effects following the application of the proposed actions, a physical model of the building involved in the experiment was developed.

$$\mathcal{S}_T^h(T) = \begin{cases} 0 & \text{if } T \in [21, 23] \\ \frac{T-23}{26-23} & \text{if } T > 23 \\ \frac{21-T}{21-18} & \text{if } T < 21 \end{cases}, \quad \mathcal{S}_C^h(C) = \begin{cases} 0 & \text{if } C \leq 500 \\ \frac{C-500}{1500-1000} & \text{if } C > 500 \end{cases} \tag{8}$$

With $\mathcal{S}_T^h(T)$ – the dissatisfaction with the temperature in the office, $\mathcal{S}_C^h(C)$ at hour h – the dissatisfaction with the air quality in the office at hour h.

4.2 Baselines and metrics

Several baselines are considered in the evaluation process:

1. the approach proposed in [4], denoted CBR-S in the following, exploits failed and successful cases but with a null adaptation process as the latter consists in making a vote among the similar cases solutions to select the solution with the best performance (maximizes the quality function) by applying it directly to the target case. The choice of this baseline is to check the relevance of using several source cases to establish the adaptation process.
2. a standard barycentric approach that combines solutions from the set of successful and failed similar source cases without artificial forces, noted CBR-B hereafter. The goal is to validate the efficiency of the artificial forces in improving the adaptation process.
3. a modified variant denoted CBR-P of our approach is tested, it considers only positive cases and thus uses only attractive forces. The objective is to

illustrate the advantage of considering both negative and positive cases w.r.t only positive cases.
4. the approach proposed in [8] is used as a further baseline. This approach referred to as CBR-R, is based on a KNN approach to select similar source cases from which a generalized case is generated. Similar cases are used also to train a linear regression model, which is applied to the generalized case to predict the target case solution.

Note that in the experiment, the performance evaluation of all tested approaches is performed by comparison against a reference which is the actions carried out by the user without assistance according to three measures:

- *Performance Enhancement Rate (PER)*: The PER consists of comparing, for each test case C_i, the average of the thermal performances $\mathcal{Q}_T^*$, the air quality performances $\mathcal{Q}_C^*$, and the global performance $\mathcal{Q}^*$ of the proposed actions to the corresponding values $\mathcal{Q}_T^r$, $\mathcal{Q}_C^r$, and $\mathcal{Q}^r$ of the actions already recorded in the case base. The PER_{C_i} related to the test case C_i, if any, is given by the (9).

$$PER_{C_i} = \frac{\mathcal{Q}^* - \mathcal{Q}^r}{\mathcal{Q}^r} \tag{9}$$

- *Approach Efficiency Rate (APR)*:The APR is defined as the average of the ratio of the number of test cases whose performance is improved by applying the actions recommended by this approach to the total number of test cases.

$$APR = \frac{Z^+}{Z} \tag{10}$$

  With $Z = |CB^T|$ – the set of test cases, $Z^+ = \left\{C_i \in CB^T \,/\, PER_{C_i} > 0\right\}$
- *True Improvement Rate (TIR)*: This measure is the average of the ratio between the number of test cases whose performance is improved by applying the actions recommended by the approach and the total number of the test cases for which the approach successfully proposed a solution (improving or degrading performance compared to the user's actions).

4.3 Results and analyse

Whatever the adaptation approach applied in a CBR system, its performance depends partially on the retrieval process. However, analyze the latter goes beyond the scope of the present paper. We use the approach given in [4] to estimate the similarity and define the similar source cases in the training set. It follows that each target case from the test set has at least one similar source case from the training set.

Table 1 summarizes the results of the 5-fold cross-validation of our approach against the four baselines considered. Some important findings from this experiment are:

- while the value of the TIR metric corresponds to the value of APR for the CBR-S, CBR-B, and CBR-APF approaches, the APR value is less than that of TIR for the CBR-P and CBR-R approaches, which is due to the ability of the first three approaches to computing a solution even with a similar set of cases consisting exclusively of failed cases.

- regardless of the test set, our CBR-APF approach is clearly better in performance than all other baselines with also better APR and TIR.
- the number of similar source cases has a significant influence on the quality of the adaptation process, a compositional adaptation systematically gives a better PER, as illustrated by the comparison between PERs of CBR-APF which is a compositional approach and CBR-S which uses a single similar case.
- attraction and repulsion forces have an important impact on the results of the adaptation process. Given the same number of similar cases, by using these forces, our CBR-APF approach outperforms the CBR-B baseline, which does not use them. CBR-APF is 1.64 times more performing than CBR-B regarding the improvement of the cases performances (global PER= 33.49% versus 20.36%) and 1.61 times more efficient according to the number of cases for which it manages to find a solution (CBR-APF improves the performance of the solutions proposed by the user without assistance for 99.92% of cases against 61.87% for CBR-B).
- using failed cases in case-based reasoning significantly influences the performance of a CBR system. By exploiting both successful and failed cases, the system improves the results of the reasoning process. Comparing the performance of the CBR-APF approach with that of the CBR-P and CBR-R approaches (both do not use failed cases in their reasoning), the TIR results show that the CBR-APF approach outperforms the other baselines. CBR-APF approach is more than three times more efficient than CBR-R and more than 1.5 times more than CBR-P in improving the performance (PER).

5 CONCLUSION

This paper proposed a new approach to the adaptation process in the CBR paradigm by looking at both failed and successful source cases instead of the traditional practice of considering only successful source case. We found inspiration in the studies on planning safe paths for a robot moving in an unknown environment. The concept is that both successful and failed cases generate attraction and repulsion forces respectively on a likely barycentric solution to drive the reasoning towards the best performing solutions and away from the failed ones. The experimentation of this approach in the context of an EMS showed a significant improvement in the system performance by considering both successful cases and failed ones.

In this work we have developed and evaluated an approach considering the whole set of successful and failed similar cases, it would be interesting to perform a deeper evaluation taking into account the number of neighboring successful and failed cases considering only the n cases with the best performances and the m cases with the worst performances. Another line of future research for this work would be to explore the possible impact of a failed case on the domain ontology (if any). It could be useful to suggest new necessary conditions to add to the domain ontology that would avoid the reappearance of such a negative case in the future.

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