Case-Based Reasoning for Context-Aware Solutions Supporting Personalised Asthma Management

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Abstract. Context-aware solutions have the potential to address the personalisation required for implementing asthma management plans. However, they have limitations to aid people with asthma when their triggers and symptoms are poorly known or changing. Case-Based Reasoning can address these limitations as it can effectively deal with personal constraints in problems that involve evolving context adaptation. This research work proposes to use Case-Based Reasoning together with Context-Aware Reasoning to aid the personalisation of asthma management plans at specific stages of the condition when the triggers and symptoms are not completely known or evolving. The proposal was implemented and evaluated using historical weather and air pollution data, and two control cases that were defined based on a set of interviews. Finally, the benefits and challenges of the proposal are presented and analysed based on the results of the evaluation.

Keywords: Context-awareness · Case-Based Reasoning · Asthma · Personalisation

1 Introduction

Asthma is a heterogeneous respiratory condition characterised by an airway inflammation causing expiratory airflow limitation and respiratory symptoms that vary over time and intensity [21]. There is no cure for it, and its treatment is based on a self-management approach, whose aim is achieving control of the condition through pharmacological and non-pharmacological plans [20, 21]. The personalisation of these plans is important and challenging because of the high heterogeneity of asthma, which applies to the triggers provoking exacerbations and the symptoms shown when an exacerbation occurs [19]. This means that people with asthma may be susceptible to several triggers, but a specific trigger does not affect all people with asthma [20, 21]. Besides, people's triggers can change over the years, and their symptoms may even vary from nigth to day [23].

Context-aware solutions are promising tools to address the required personalisation of asthma treatments as, by definition, they are capable of adapting their features to the specific characteristics of each patient's asthma [2, 13, 19]. Unlike Dey's definition of context which goes from the system to the user, our person-centric approach goes from the user to the system, and the user defines what are the relevant *contexts*, that is "the information which is directly relevant to characterise a situation of interest to the stakeholders of a system". *Context-awareness* is then defined as "the ability of a system to use contextual information in order to tailor its services so that they are more useful to the stakeholders because they directly relate to their preferences and needs". Hence, personalised context-aware solutions can provide meaningful data to be used as input for more complex decision-making processes in asthma management [19].

Case-Based Reasoning (CBR) can be used together with Context-Aware Reasoning (C-AR) in order to build synergies in specific problem-solving situations involving multidimensional context-related data [14]. CBR is a type of Artificial Intelligence approach [1] that simulates the *"use of old experiences to understand and solve new problems"* [15]. It has been applied in several domains of the health sciences [8, 10], and one of the main directions is using CBR to adapt medical knowledge and reasoning strategies for personalising contextual information [16].

This research work studies the application of CBR together with C-AR for aiding the personalisation of solutions supporting asthma management. The benefit of this is related to the relevance of personalising asthma management plans. Recently diagnosed people are likely to know little about the triggers provoking their exacerbations, and they go through a trial and error process until finding out what sets off their symptoms [21]. In this scenario, although C-AR can help to monitor indicators associated with the triggers of a person with asthma (like temperature or pollen level), it cannot discover their triggers by itself. CBR can be used at this point with the aim of creating cases that will be used as a base in order to aid discovering the triggers affecting the person with asthma.

The paper is divided as follows. Section 2 summarises the state-of-the-art on the subject. Section 3 explains the methodology that led the research and the results of a questionnaire that was applied in partnership with Asthma UK. Section 4 describes the proposal, its implementation and evaluation. Section 5 and 6 present the discussion and the conclusions of the research work, respectively.

2 State-of-the-Art

The miniaturisation of electrical devices and the spread of wireless networks have allowed the creation of sensors that collect large amounts of data [3]. C-AR is crucial to interpret and understand this collected data as it aids in gathering meaningful information for specific purposes [18]. C-AR as part of Intelligent Environments has been applied to several areas [7], and the health care domain is a promising area in which C-AR can be used to enhance the quality of life [3].

A survey on C-AR in asthma shows a lack of solutions allowing personalised asthma management [19]. This means that users cannot choose the indicators to track nor the features to use according to the characteristics of someone's asthma. A more comprehensive way of framing the context of a person with asthma was proposed to address this personalisation issue [19]. It is suggested to use three types of indicators (Patient Indicators or PI, Indoor Environmental Indicators or IEI, and Outdoor Environmental Indicators or OEI) in order to allow personalisation and enhance decision-making of C-AR solutions supporting asthma management. This provides a basis for complex decision-making processes, and it can be used to apply CBR for asthma management personalisation.

CBR allows reusing information and knowledge from previous situations that are similar to the new problem to solve [1]. CBR problem-solving paradigm has found in the health science a promising application domain [10] because it can handle some issues better than other methods and techniques [11]. It has been used in the health sciences in tasks like diagnosis, classification, tutoring, treatment planning, and knowledge acquisition/management [8]. One future direction of CBR in the health sciences is adapting procedures and reasoning strategies to personal constraints described by the contextual information itself [16]. Asthma management fits under this category as recently diagnosed people need to discover their triggers and symptoms for adapting their plans to their personal constraints. This personalisation process can benefit from using CBR.

C-AR can be used together with CBR to solve problems that are not completely understood, like dealing with evolving context adaptation [14]. Asthma management corresponds to this issue as the condition evolves over time, which means that people with asthma are updating their triggers and symptoms while their condition develops. This evolution makes it challenging to create C-AR solutions supporting the personalisation of asthma management because they need to adapt considering that the indicators to monitor change over time.

CBR has been used to analyse symptoms of people with asthma in order to know their status and suitable care plans [22]. However, it has not been used to develop proactive solutions analysing triggers-related indicators for personalising preventive treatments and predicting risky situations. This paper reports on using CBR as a component of C-AR solutions supporting personalised asthma management. CBR is used to aid the discovery and adaptation of the indicators to monitor for a person with asthma, considering their triggers and symptoms.

3 Methodology

The research has been led by the User-Centred Intelligent Environments Development Process (U-C IEDP), whose basis is considering users as the heart of the development process in order to meet customers expectations as regards the required services [6]. The methodology is divided into 4 stages. The first one is a literature review that shows a lack of C-AR solutions supporting the personalisation of asthma management [19]. In the second stage four people with asthma, two health carers of people with asthma, and a physician expert in respiratory conditions were interviewed. Among other outcomes, this stage re-confirmed the necessity of solutions supporting the personalisation of asthma management [19].

A partnership with Asthma UK, a membership-based charity with a current membership of approximately 5,200 [5], was formed in the third stage. They distributed a questionnaire that was built based on the outcomes of the previous stages among their network of approx. 200 patient and carers representatives volunteers. A response rate of approx. 21% was accomplished (42 responses). Fig. 1 shows the results for the questions asking participants to rate from 0 (non-important) to 5 (most important) the following features of a solution supporting asthma management: alerting as regards triggers, alerting as regards symptoms, and reporting about the development of triggers and symptoms (T&S). Most of them (71%, 79% and 79%, respectively) rated these features with 4 and 5, what evidences a high concern for the triggers and symptoms of people with asthma.

The fourth stage focused on designing, implementing and evaluating the algorithm for the CBR. More details about this stage are shown in Section 4.

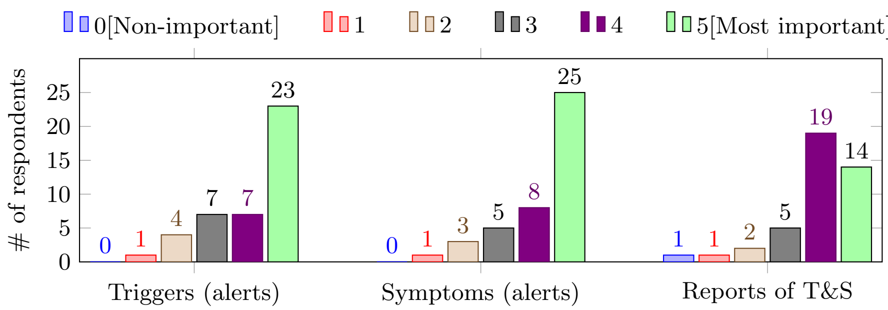

Fig. 1: Assessment of 3 features of solutions supporting asthma management

4 CBR for C-AR Solutions Supporting Personalised Asthma Management

CBR can aid the process of discovering the triggers of a person with asthma as it involves the use of multidimensional context-related data. A list of more than 25 potential triggers can be made using data provided by specialised organisations doing research on asthma [4,5,20,21]. A person with asthma has to narrow down this list until finding out what specific triggers affect them. CBR can also aid the context adaptation process. E.g. it can aid when someone's triggers change, or when they move to a new place with different environmental conditions.

A case for a CBR supporting asthma management (C_x) is made of a set of pairs indicator-value representing the context of a person with asthma (I_x), their predicted asthma health status (hsp_x) associated with I_x, and their real asthma health status (hsr_x) associated with I_x. The monitoring indicators can be PI (like heart rate or breathing rate), IEI (like temperature or humidity) or OEI (like temperature or pollen level). Equations 1 and 2 describe a case by a notation. This feature vector representation will ease the explanation of the similarity measurement process that is part of the CBR cycle explained below [9].

$$C_x = \{I_x, hsp_x, hsr_x\} \tag{1}$$

$$I_x = \{(i_1, v_{1x}), (i_2, v_{2x}), ...(i_m, v_{mx})\} \tag{2}$$

Fig. 2 presents how to use CBR for personalised asthma management. It has been adapted from the CBR cycle proposed by Aamodt & Plaza [1]. The *new problem* is a case (C_x) without its predicted health status (hsp_x) nor its real health status (hsr_x). The CBR then *retrieves* (from the database of *previous cases*) the case (C_s) that is most similar to C_x. If I_i and I_x are compared using the K-Nearest Neighbour (KNN) algorithm for a $k = 1$, the similarity between a case from the database (C_i) and C_x is $S_{ix} = \sqrt{\sum_{j=1}^{m}(v_{ij} - v_{xj})^2}$; and equation $S_{sx} = \min(S_{1x}, S_{2x}, ...S_{nx})$ defines the index (s) of the case to retrieve (C_s).

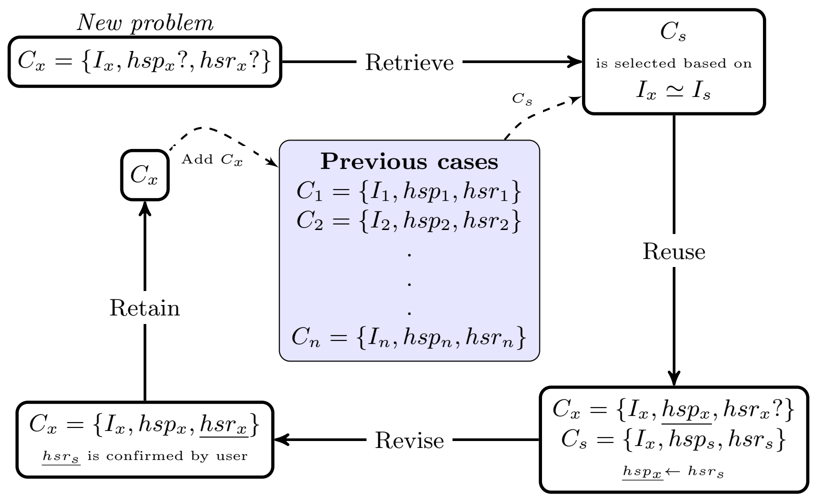

Fig. 2: CBR cycle adapted for personalised asthma management

Once C_s is selected, the CBR *reuses* its real solution (hsr_s) in order to attempt predicting the health status associated with C_x (hsp_x). The predicted solution is the predicted health status (hsp_x) of the person with asthma for the context to which s/he is exposed (I_x). Hence, $\underline{hsp_x}$ will get the value of the real health status associated with C_s (hsr_s). After this, the user determines their real health status ($\underline{hsr_x}$) through the *revision* phase, and C_x is completely defined. Finally, C_x is *retained* by being stored in the database of previous cases.

4.1 Implementation and Evaluation: A Case Study

The CBR was implemented and evaluated using two control cases that were defined based on the interviews held [19]: *Person A* (PA) whose trigger is low temperature, and *Person B* (PB) whose triggers are low temperature and pollen. Hourly data about weather and air pollution at Postcode NW10 0TH (London, UK) was gathered using World Weather Online[3] and London Air[4] APIs. The time frame of the data is from 01/01/2018 00:00:00 to 31/10/2018 23:00:00.

A case to be analysed by the CBR (C_x) partially represents the weather and air pollution scenarios for a specific day (*day x*). Hence, I_x is made of the minimum temperature ($minT$), the maximum temperature ($maxT$), the average feels like temperature (fl), the average temperature (t), the average humidity level (h), the average wind gust (wg) and the average values for ozone level (O_3), Particulate Matter 2.5 ($pm2.5$) and 10 ($pm10$) for *day x*.

The real health status for *day x* (hsr_x) is defined for *Person A* using equation 3, and for *Person B* using equation 4. The limit value for $maxT$ is based on the recommendations from Asthma UK [5], and the limit value for $pm10$ is taken from the guideline provided by the Committee on the Medical Effects of Air Pollutants (COMEAP) [12]. The case represented by *Person B* considers $pm10$ for defining hsr_x as it is the indicator mostly used to monitor pollen level.

$$f(maxT) = \begin{cases} 0 & \text{for } maxT \geq 10 \\ 1 & \text{else} \end{cases} \tag{3}$$

$$f(maxT, pm10) = \begin{cases} 0 & \text{for } maxT \geq 10 \land pm10 \leq 51 \\ 1 & \text{else} \end{cases} \tag{4}$$

The raw values of the indicators defining I_x have different scales. E.g. humidity values vary from 0% to 100%, and $pm10$ values vary from 0 ug/m^3 to more than 400 ug/m^3. This assigns different weights to the indicators as the differentials (for each indicator) to use to compare the cases will have different scales. Hence, the values of the indicators should be normalised to achieve a weightless comparison. It is important not to use weights in the *retrieval* as the aim is to aid people when they do not know their triggers yet. Thus, they must be equally aware of the potential triggers-related indicators that may affect them.

The normalisation for this case study is based on indicator $pm10$, whose values are transformed to a scale that goes from 1 to 10. This scale is proposed by COMEAP to simplify the explanation of the effects that $pm10$ has on people's health [12]. Hence, all the indicators were normalised to use a scale that goes from 1 to 10, and equations 3 and 4 were also adapted considering this normalisation.

The KNN algorithm was chosen to assess the similarity in the *retrieval* process as it is used to solve data classification problems [17]. Its simplicity and popularity [17] also aid the purpose of illustrating the application of the proposal. Thus, 304 cases (one for each day) were used for each control case and evaluated using the KNN algorithm for $k = 1$ and $k = 3$. The results are summarised in Fig. 3 - Fig. 6, where the accuracy (%) of the CBR is shown.

The final cumulative accuracies for $k = 1$ and $k = 3$ are similar (Fig. 3 and 4). The cumulative accuracy increases faster for $k = 1$, however using a $k = 3$ provides more stability when the CBR is fed with cases that are different from

[3] https://www.worldweatheronline.com/developer/api/
[4] https://www.londonair.org.uk/Londonair/API/

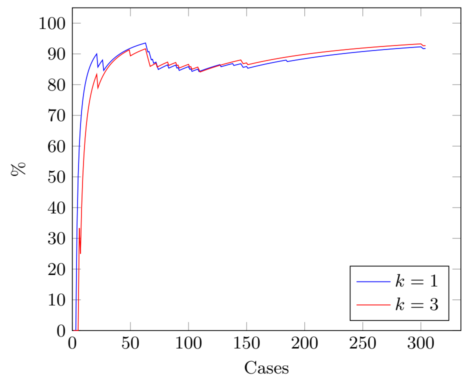

Fig. 3: PA: Cumulative accuracy

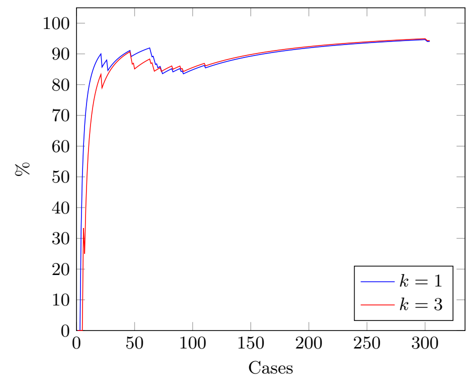

Fig. 4: PB: Cumulative accuracy

those that are stored. This is seen between cases 50 and 130 (approx.), and it is better illustrated in Fig. 5 and 6 that present the accuracy for the previous 20 cases that have been evaluated. These figures show the average accuracy for cases $C_{x-19}, C_{x-18}, ..., C_x$. Hence, a $k = 3$ makes the CBR has fewer low accuracy points when only the previous 20 cases are considered in the calculation.

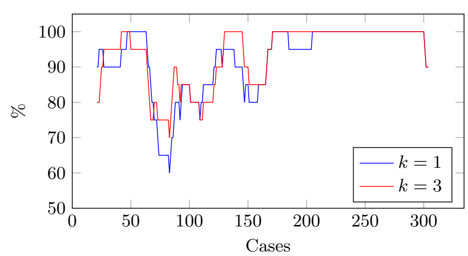

Fig. 5: PA: Previous 20 cases accuracy

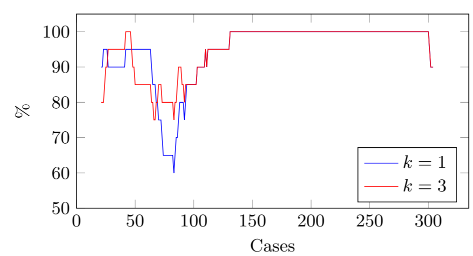

Fig. 6: PB: Previous 20 cases accuracy

Table 1 shows how the CBR behaves considering previous short-term cases for a $k = 3$. It is read by choosing an accuracy threshold (e.g. $> 70\%$) and a column (e.g. *Person A - Previous 10*). That number ($98,2\%$) represents the times that the CBR was at least 70% accurate considering the previous 10 cases in the calculation of its accuracy for *Person A*. In other words, it can be said for this example that the $98,2\%$ of the times the CBR was accurate in at least 7 out of the previous 10 cases. This is important because knowing the short-term accuracy of the CBR would allow defining a confidence level of the system at a specific moment. Thus, the system could tell users about its confidence level when it suggests an outcome, it could ask the user to confirm their real health status more often as it predictions may be less accurate, or it could prevent overloading users with false positive until its confidence level increases.

Table 1: CBR accuracy (%) distribution considering previous cases for $k = 3$

	Person A			Person B		
Accuracy	Previous 5	Previous 10	Previous 20	Previous 5	Previous 10	Previous 20
>10%	100%	100%	100%	100%	100%	100%
>20%	99.3%	100%	100%	100%	100%	100%
>30%	99.3%	100%	100%	100%	100%	100%
>40%	98.3%	100%	100%	98.3%	100%	100%
>50%	98.3%	99.7%	100%	98.3%	100%	100%
>60%	91.3%	96.9%	100%	93.9%	99.7%	100%
>70%	91.3%	92.8%	99.7%	93.9%	93.8%	100%
>80%	77.8%	81.5%	85.1%	82.8%	87.7%	92.6%
>90%	77.8%	66.1%	67.4%	82.8%	73.0%	75.2%
=100%	77.8%	66.1%	54.6%	82.8%	73.0%	62.0%

5 Discussion

The results of the experiment show that CBR can make reasonably accurate predictions when there is no explicit information to define control limits. It also shows that the CBR is more accurate and stable for *Person B* who has a set of two triggers instead of only one. Although this cannot be concluded as experiments with more complex cases should be made, it is expected CBR to have a good performance solving multidimensional problems, what is interpreted as dealing with more complex sets of triggers. This suggests that CBR can aid C-AR supporting personalised asthma management when there is not enough evidence to define the indicators to monitor or to set their control limits.

The proposal aids personalised asthma management in several ways. The interaction between CBR and C-AR helps when the triggers are not known or partially known. In the first case, the C-AR component gathers data about the potential triggers-related indicators and the CBR component analyses it considering previous situations. If the triggers are partially known, users define the indicators and its control limits (C-AR) according to what they know about their triggers, and the CBR analyses more data in order to find risky situations that users do not perceive yet. Further, this interaction can help people with asthma when their triggers change, and when they move to a different location with weather and pollution characteristics to which they were not exposed before.

Several challenges arise from the proposal. First, defining the frequency of bringing a *new case/problem* to be assessed by the CBR is relevant as it must consider technical and cognitive issues. For instance, if the CBR is implemented in a mobile application, concerns about processing/storage capacity, battery duration, and not overloading users with non-relevant tasks and information should be addressed. Another issue is about what to do if there is not enough data to complete the case to assess. This might happen because it is expected to gather data from different sources, what is always challenging [7,18]. Some possible solutions are (i) not assessing the incomplete case, (ii) assessing the incomplete case as any other case, or (iii) assessing the case telling the user it is not complete.

The algorithm to *retrieve* the most similar case influences in the time needed to improve and stabilise the accuracy of the CBR. This is particularly challenging in the asthma context because the algorithms may have different behaviours depending on several factors like the number of monitored indicators and the characteristics of someone's triggers. Finally, determining the real health status (hsr_x) for a specific I_x is crucial to complete the *revision* stage. This is an issue as there are no commercial sensors able to monitor the asthma health status of a person constantly. Thus, a human-in-the-loop approach is needed to determine hsr_x. This step is important because the hsr_x sets the ground truth to attempt the prediction of future cases, and confirms the accuracy of the predictions.

The team is currently working on implementing the proposal in a C-AR mobile application (prototype) aiding personalised asthma management. The prototype will be validated in partnership with Asthma UK that will facilitate the interaction with people with asthma and carers. Efforts are also being focused on studying the Human-Computer Interaction factor, testing other classification algorithms and using data from multiple locations to assess effectiveness.

6 Conclusions

C-AR can aid personalised asthma management. However, it cannot cope with situations in which the context of a person with asthma is not completely known or changing. This research work proposes to use CBR to support C-AR when there is not enough explicit information to recognise risky situations for people with asthma. CBR infers possible outcomes from similar contexts to which the person has been exposed. A CBR supporting personalised asthma management was implemented and evaluated, showing positive results. It is shown that the proposal can aid people with asthma with few or no knowledge about their triggers in recognising potentially risky situations, discovering their triggers and adapting their asthma management plans to their personal constraints.

7 Acknowledgement

We thank Asthma UK for spreading the questionnaire (Section 3), among their representative network of people with asthma and carers. The link to the questionnaire is https://figshare.com/s/9f6b5e8a677ebd223f4a. The Context and Context-awareness definitions in Section 1 were provided by J.C. Augusto.

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