Evolutionary Inspired Adaptation of Exercise Plans for Increasing Solution Variety

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Abstract. An initial case base population naturally lacks diversity of solutions. In order to overcome this cold-start problem, we present how genetic algorithms (GA) can be applied. The work presented in this paper is part of the selfBACK EU project and describes a case-based recommendation system that creates exercise plans for patients with non-specific low back pain (LBP). In selfBACK Case-Based Reasoning (CBR) is used as its main methodology for generating patient-specific advice for managing non-specific LBP. The sub-module of selfBACK presented in this work focuses on the adaptation process of exercise plans: A GA inspired method is created to increase the variation of personalized exercise plans, which today are crafted by medical professionals. Experiments are conducted using real patients' characteristics with expert-crafted solutions and automatically generated solutions. In the evaluation we compare the quality of the GA-generated solutions to null-adaptation solutions.

Keywords: Case-Based Reasoning, Similarity Assessment, Adaptation, Genetic Algorithm, Cold start problem

1 Introduction

Up to 80% in the adult population of Norway will experience low back pain during their lifetime, and a study showed that 50% of them had experienced pain during the last 12 months [18]. About 85% of these will experience non-specific low back pain, i.e., pain without a known pathomechanism [6]. As an example, back pain is the largest single cause of sickness leave in Norway, and it costs about 2% of the gross domestic product. Even though the amount of research in the area has increased, as well as the access to treatment and less physically demanding work, the costs have significantly increased over the last 30 years. General physical activity along with specific strength and stretching exercises constitute the core components in the prevention and management of non-specific low back pain.

CBR has been used in the domain of health science for a long time, because its method of using past experiences to solve a new problem lies very close to how clinical medicine is performed by specialists today. It is also a field where one often have the advantage of already having a collection of past cases to use when reviewing a new problem. The use of CBR in health sciences has proven to be so popular that over the past 10 years it has become a specialized sub-area within CBR research and application. There exist CBR-systems that are used commercially in the field of medicine, but it has still not become as successful here, in terms of successfully deployed applications, as in many other domains [5], [9].

The selfBACK project aims at creating a self-management tool for patients with non-specific low back pain, which will support them to self-manage their pain by obtaining personalized advice and continuous follow-up. After an initial screening of the patient using questionnaires, the patient gets access to a wearable and a smart phone app that is the interface to the decision support system. The wearable will be used to track activities and obtain objective measurements while the smart phone app displays feedback, shows progress in achieving the patient's goals, and obtains regular follow-up on pain, function and self-efficacy development. This includes for example whether the pain level decreases, the functionality increases and coping with pain improves. Figure 1 gives an overview of the architecture. A more thorough description of the CBR approach in selfBACK is given in [2]. This work focuses on how an adaptation phase can further improve the creation of exercise plans.

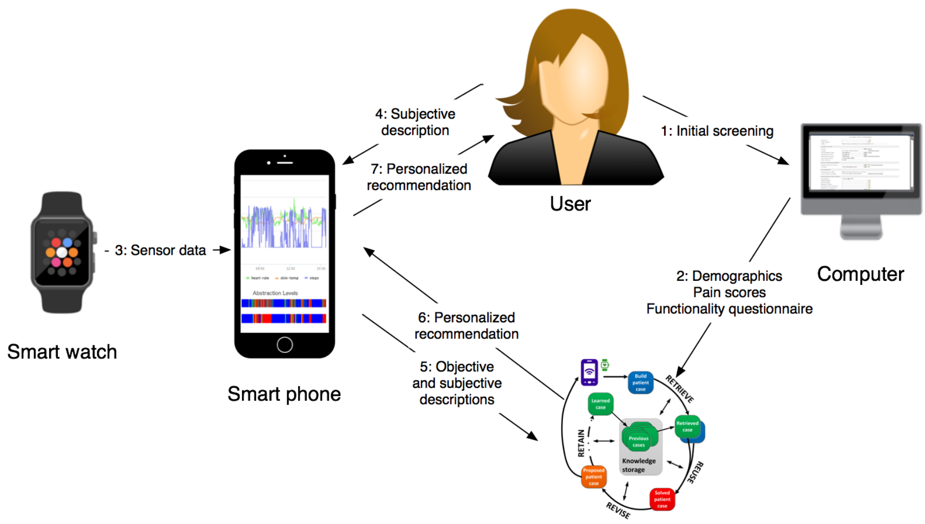

Fig. 1. The overall selfBACK architecture

1.1 Background

The adaptation part of CBR is one of most challenging issues for CBR systems in general as well as in the health sciences, where it has traditionally been carried out manually by experts of the domain. In recent years, however, the problem has been more focused. Several systems explore different approaches to automatic and semiautomatic adaptation strategies [4]. It has also been argued that the adding of adaptation is what makes the CBR system an artificial intelligence method, and that without it it can be seen as a simple pattern matcher [12]. The challenge with the adaptation phase is that it is hard to find a general strategy for case adaptation, and therefore the adaptation techniques generated are often domain specific. Adaptation is a challenge not only in the medical domain, but it is usually more complex here because cases often consist of a large number of features [22]. The reason for doing adaptation is because usually you can't reuse solutions of cases directly when you have a new case [8].

One of the reasons for the focus on adaptation in the work reported here is to deal with the cold-start problem in the beginning of the deployment of a CBR system. The cold-start problem describes the situation where the amount of cases is too low to create a good solution to the new problem [14]. Or, alternatively, if you want to introduce some variations of the solution to make a system more personalized or adaptive.

Retrieval-only Adaptation is not always necessary, and it is seen as a big challenge when creating a CBR system. Due to this, some authors skip the adaptation phase, referred to as retrieval-only. It can be justified by the fact that it is too complicated or even impossible to acquire adaptation knowledge in the given domain. Systems that are retrieval-only may just reuse the solution of the case that is closest to the problem case, or present the information of the most similar cases to the user. Some also point out important differences between the current case and similar cases. The system may present the most important information to an expert of the system, while the experts then manually will create the new solution for the current patient. This has been successfully used in systems in the field of image interpretation and organ function courses [22].

Another way to avoid the adaptation problem is to combine CBR retrieval with other reasoning methodologies [19]. The interest in these multi-modal approaches that involve CBR is increasing in different areas, including the medical domain. They can be combined in the same application, one reasoning process can be used to support the other, or the system can switch between the different reasoning processes. Rule Based Reasoning as well as reasoning form extended probabilistic and multi-relational models may be combined with CBR. A straight-forward combination is that rules and cases cooperate such that rules deal with reasonably standard or typical problems, while CBR faces exceptions, but they can be integrated in other ways [22]. Another example is to use rules or other generalized models an explanatory support to the case process [16].

Genetic algorithms Genetic Algorithms (GA) are adaptive heuristic search algorithms that are based on the natural process of evolution, known as the survival of the fittest. Systems that use GA are modeled loosely on the principles of evolution via natural selection through variation-inducing operators such as mutation and crossover. To have success you have to have a meaningful fitness evaluation and an effective GA representation. One reason to use this method is that it is capable of discovering good solutions in search spaces that are large, complex or poorly understood, where the domain knowledge is limited or the expert knowledge is difficult to encode in rules or other models. The use of GA may not find the optimal solution, but it usually comes up with a partially optimal solution [13].

1.2 Related Work

GAs have already been combined with CBR to optimise case retrieval, clean up case memory and create new and unique cases. They have also been used in the adaptation step, to achieve an adaptation technique that is not domain specific [12]. One of the most well known approaches for applying evolutionary algorithms to case adaptation is [11], in which the incremental evolution of solution candidates creates novel solutions. While this approach is general and knowledge independent, the work we are presenting in this paper includes domain knowledge from the case representation for guiding the evolution process.

Case-based reasoning is used in several health systems today, within a lot of different areas such as clinical diagnosis and treatment in psychiatry [21]. It has become a recognized and well-established method for the health sciences, and since the domain of health sciences is offering a variety of complex tasks which are hard to solve with other methods and approaches, it drives the CBR research forward. Since CBR is a reasoning process that works similarly to the reasoning of a clinician, with the use of previous experiences to solve the same or similar cases, it has become medically accepted and is also getting increased attention from the medical domain [4]. There are several advantages of using CBR in the medical domain, one is that with the use of CBR it is possible to find solutions to problems even though the complete understanding of the domain is not captured, or if the domain is very complex. The reuse of earlier solutions saves time since it is not necessary to solve every problem from scratch, and it allows learning from mistakes. The fact that cases hold a lot of information makes it usable for a number of different problem-solving purposes, compared to rules that can only be used for the purpose they were designed for [21].

Looking into previous work, we will now focus on relating our approach to existing CBR applications in the medical field and later on discuss how genetic algorithms come into play.

CASEY [17] is one of the earliest medical decision support systems that applied CBR, and it deals with heart failure diagnosis. It first retrieves similar cases, then looks at the differences between the current case and the similar case. If the differences are not too important it transfers the diagnosis of the similar case to the current one, and if the differences are too large it attempts to explain and modify the diagnosis. It falls back on a probabilistic network type of domain model if this does not work, or if no similar case can be retrieved.

Protos [3] is another well-known early medical CBR system. It addressed the problem of concpet learning and classification in weak-theory domains, such as medicine. It combined cases with a multi-relational network model used to explain case matching if features were syntactically different bu semantically related. Its domain was hearing disorders, and in the final testing it performed very well compared to clinical audiologists.

Another system that uses CBR deals with anterior cruciate ligament (ACL) injury [23], and it combines fuzzy logic with CBR. The system is not intended to interact directly with the user, but with experts such as sport trainers, coaches, and clinicians for multiple purposes in context of the ACL injury such as monitoring progress after an injury and predicting performance. It uses body-mounted wireless sensors to retrieve the input data for the case, while the solution part consists of recovery classification, treatment at different stages, as well as performance evaluation and prognosis. All the information is stored in the knowledge base with a profile of the patient and information about the recovery sessions.

One of the top fatal diseases in the world is cancer, and as part of their cancer treatment patients get diets to reduce the side-effects of the treatment, as well as making sure they get sufficient nutrition to boost the recovery cycle. This personalized diet recommendation system for cancer patients [13] makes use of the data mining techniques of CBR, and combines them with rule-based reasoning and a genetic algorithm. The CBR part of the system retrieves a set of diet plans from the case base, while the rule-based reasoning is used on this set to do further filtering of irrelevant cases. Then the genetic algorithm is used for the adaptation phase to make sure each diet menu is customized according to the patient's personal health condition. The solution part of this system consists of a menu recommendation that suggest dishes for the patient, as well as a list of specific nutritional values to be taken daily.

Radiotherapy treatment tries to destroy tumour cells with radiation, and radiotherapy treatment planning tries to make sure the radiation dose is sufficient to destroy the cells without damaging healthy organs in the tumour-surrounding area. The normal process of creating a solution to this problem can take everything from 2-3 hours to a few days, which makes it time-consuming, and it includes a group of experts in the area that you are dependent on. The Radiotherapy treatment planning CBR-system [21] was created to attempt to make the process faster and without the need to have several experts involved. The case base in the created system consists of cases made out of brain cancer patient descriptions as well as the plan used for the treatment. The treatment, i.e. the solution part, consists of the number of beams applied to the tumour and the angles of those beams. The system creates a new solution for the patient based on earlier patient cases and their treatment plans.

2 Case representation

The case representation is based on the selfBACK questionnaire, as this creates the basis for the data used in the experiments. The questionnaire describes the characteristics of a patient with non-specific low back pain. It covers areas such as the pain level, their quality of life despite the pain, functionality, coping capabilities and their physical activity level.

From the overall characteristics three different types of advice will be generated to support self-management:

- Goals for physical activity: number of steps/day, maximum of inactive periods during hours the patient is awake
- Education: Tailored list of educational exercises that support and reassure the patient in his/her self-management.
- Exercise: A customized list of exercises that combine clinical guidelines for low back pain with past cases into action items.

In the following, we will focus on the generation of exercise lists based on given cases. Therefore our case representation consists of two different concepts, the patient characteristics and the list of exercises at a given time. The patient characteristics are taken as problem description and the exercise are describing the solution part. These two different concepts are explained in further detail in section 2.1 and 2.2.

2.1 Patient concept

The patient concept consists of 44 attributes that describe different aspects of the patient's health. These attributes can be divided into different groups of information collected by 1) the selfBACK questionnaire, 2) a physical activity detecting wristband worn by the patient, and 3) an interaction module in the selfBACK app. The attributes collected by the questionnaire are a combination of important prognostic factors and outcome measures. Pain self-efficacy and beliefs about back pain have been shown to have great impact on the future course of low back pain [15]. Likewise, baseline pain and pain-related disability have strong influence on the course of low back pain but these attributes are also important outcome measures [7]. Quality of life at baseline may also influence the course of low back pain but this is mainly considered an important outcome measure [10]. An example of a patient concept can be seen in figure 2. The patient data in this case is made up, as data from real patients are confidential.

Demographics With a new patient it is necessary to know some simple demographics, such as height, weight, age and gender. These are the basis for each patient, and are all quite easy attributes to measure. All of these attributes may influence the solution, as all attributes can be an indication of how well a patient is able to perform and follow-up on a particular exercise plan. Young people are usually stronger and more fit than older people, men are in general stronger than women, and younger people are usually able to carry out more intense physical activity or exercises than older people. Obese people may need to focus on other exercises than normal weight people.

Quality of life The impact of low back pain on quality of life is another important measure of the severity and consequences of the back pain. As an additional measure, the patient also provides a score in his/her own health from 0 (worst) to 100 (best).

Pain self-efficacy and beliefs about back pain Scoring of pain self-efficacy indicates if the patient is confident that he/she can do various activities regardless of the pain and is therefore an important measure of how the patient copes with the pain. A related measure is fear-avoidance beliefs, i.e., to what extent the patient believes that physical activity will be harmful and exacerbate the back pain.

Physical activity and exercise Information about general physical activity is assessed by the selfBACK questionnaire and the physical activity detecting wristband. The attributes assessed by the questionnaire include work characteristics (i.e., physical work demands), physical activity limitations in everyday activities (work and/or leisure) due to back pain, and level of leisure time physical activity. Physical activity information that can be derived from the wristband data includes several attributes, such as step count (including intensity [i.e., step frequency] during walking/running), and distribution of active and inactive periods during wake time. The interaction module in the selfBACK app will ask the patient about accomplishment and adherence to the exercises prescribed in the self-management plan as well as a rating of whether the patient perceived the prescribed exercises as useful and enjoyable. All these attributes will say something about how active the patient is and the coping behaviour related to his/her low back pain.

Pain and pain-related disability Information about various aspects and characteristics of pain is relevant for the case, both because it can track progress and it provides an indication on how severe the case is. History of low back pain provides information about whether the patient has experienced similar problems before, if it is a recurrent problem, or if it is a long-lasting ('chronic') problem. Number of pain sites reported by the patient is important to assess musculoskeletal co-morbidity while the scoring of pain-related disability provide information about how the back pain influence function.

Exercise list To connect the two concepts, the patient has an attribute that is a list of all the exercises the patient has in his solution part. This consists of cases on the form of the exercise concept that is further described below.

2.2 Exercise concept

The exercise concept consists of four different attributes. An example of how the exercise concept looks like can be found in table 1 in the results section.

Description The descriptive name and type of the exercise. The type can be a strength, flexibility or pain-relief exercise. All patients are encouraged to perform strength and/or flexibility exercises each week, unless they are unable

Feature	Example
Gender	Male
Age	45
Height	1.89m
Weight	82
BMI	23
Quality of life (EQ5D)	90
Disability (RMDQ)	9
Pain (NPRS)	8
Work type	Mostly sitting
Self-Efficacy (PSFS) activity	Prolonged standing
Self-Efficacy (PSFS) Σ	8
FABQ Physical Activity	2
Pain medication	none
Pain history	none

Fig. 2. Patient example

because of strong pain. In general, strength and flexibility exercises are not recommended in the acute stage of a low back pain episode. By performing exercises regularly the patient will increase strength and improve flexibility, which over time will prevent relapse. In the acute stage or in case of a relapse, pain-relief exercises can be recommended to help the patient to relax and reduce the most intense pain. These exercises will mainly help to relieve acute pain but will have limited relevance when the patient is pain-free.

Level An exercise can have different levels. The strength exercises used in this project have up to six different levels, where each level is a new variation of an exercise that is more demanding than the former. The patient changes levels as he/she progresses, i.e., first by increasing the number of repetitions within a level before moving to the next level.

Repetitions Each exercise is performed in sets, with a given number of repetitions for each set. There are four levels of repetitions, 8,10, 12 and 15 repetitions respectively. When the patient is able to perform 12-15 repetitions per exercise the patient moves up a level in the exercise.

Set The set indicates the number of times the patient should perform the given repetitions for the exercise.

3 Experiments

In the experiments two different approaches are used, a no-adaptation and a genetic algorithm, to see how they compare in regard to solution variety as well as solution quality. Our hypothesis is that the GA inspired approach will produce better solution variety, but it will also have to produce solutions of good quality to be useful.

3.1 Case-set

The cases used for testing the algorithm are gathered from the selfBACK project, and consist of data from real patients who experience low back pain. A total of nine cases were created with an associated solution crafted by medical professionals.

3.2 No-adaptation

The first approach, and also one of the most used approaches, is the no-adaptation approach. This approach did not require any design choices as this solution was built out of the box from the myCBR workbench and an RestAPI for myCBR[3]. This approach is dependent on a comprehensive case base with a high case variation to be able to provide a good solution for all the different patients, as this does not evolve over time. The number of solutions will always be equal to or less than the number of cases you have, and this does not give enough room for patients having different needs and different baselines. In addition, this solution does not allow the patient to increase his or her level, nor the number of exercises or the frequency of the exercises.

3.3 Genetic Algorithm

A genetic algorithm was incorporated in the CBR cycle to perform an adaptation on the cases. The idea behind the genetic algorithm is to retrieve the two most fit cases, and combine them to create a new case. This approach is based on how nature evolves, and the assumption behind this approach is that the combination of the two best cases will give a satisfactory solution.

General algorithm structure A genetic algorithm consist of different parts. It has a fitness function, i.e. a function that helps you describe how good a given specimen is. It also has a crossover function, which creates a new solution based on the two fittest individuals. The algorithm is programmed to stop at a termination condition, where the new solution satisfies the given condition. In the genetic algorithm you also have a probability of a mutation to happen. This changes one of the attributes in the solution at random, to possibly create better solutions, and avoid getting stuck in local maxima.

Adapted algorithm The general structure of a genetic algorithm was adapted to fit the domain. The fitness function in the adapted algorithm is based on the similarity scores between the cases, and the two fittest individuals from the population are chosen by retrieving the two most similar cases to the new problem description from the case base. From these two cases we retrieve their solution, the exercise list, and we create a chromosome of the solutions that is used by the genetic algorithm. The chromosome is built up such that all exercises for the same muscle group are placed inside the same gene, as each gene represents a specific trait of an individual. An example of how this mapping is done can be seen in figure 3.

[3] https://github.com/kerstinbach/mycbr-rest-example

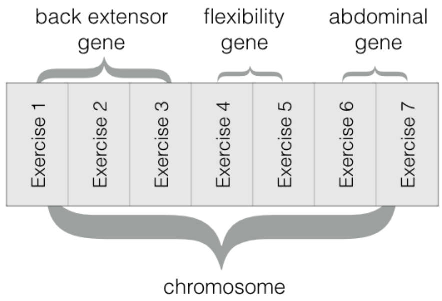

Fig. 3. The exercise list mapped to a GA chromosome

In figure 4 you see the description of the 4R cycle in this work with an adaptation example. Based on the patient description the two best matching cases are retrieved (C1 and C2). The two chromosomes representing the solution parts (S(C1) and S(C2)) are then sent to the crossover function. Here a new individual is created of the parent chromosomes, and it is done with a uniform crossover [24]. The mixing ratio is set to 0.5, since the solution is desired to have a close to equal mix of the parents' genes. The adapted algorithm finishes after one crossover at this moment as there exists no good measures to describe how well a patient will progress before they have executed the exercise plan. Measurements on progress will be added at later iterations, but in this work we only address the initial creation of plans.

The exercises also have a probability of 1,5% to have a mutation. These mutations are given some restrictions, such as that the type of exercise will be kept, but the level and the number of repetitions may alter by one level. The reason for such restrictions to the mutation is so that the algorithm should produce a solution that is feasible for the patient to fulfill and therefore not demotivating for the patient. Further the suggested solution should not be too easy and ensure the optimal progress for the patient.

3.4 Experimental Setup

Experiments were conducted in such a way that the solutions to the new problems created by the different approaches were compared to each other. Every unique solution was counted in order to check the increase in solution variety, and then the solution quality was checked. To define how good a solution is it was compared to the solution created by a medical professional. To be able to do this, the respective case to be tested was removed from the case base. The problem part of the case was fed as input to the system, and a new solution to the problem was generated. This solution, for both the no-adaptation and the GA systems, was in turn compared to the one that the medical expert had crafted. The comparison of the two solutions was done by using similarity measures to check how close the generated result was to the original solution. The

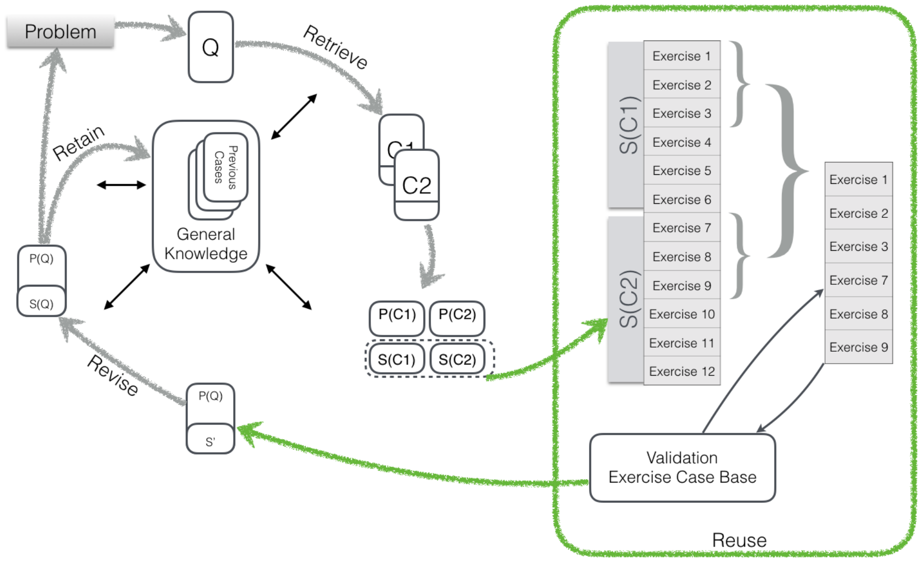

Fig. 4. Overview of the 4R cycle (based on [1]) including an adaption example of a result from a crossover between to chromosomes

no-adaptation method always creates the same solution, while the GA will return solutions that differ from each other. As a result of the fact that the GA will provide results with varied scores this approach was tested a total of five times to see how well it performed in terms of best case, worst case and average case.

3.5 Results

Regarding the cold-start problem the number of solutions in the case base will improve with the GA-approach, as hypothesized. In figure 5(a) the evolution of different solutions in the case base is presented. The number of different solutions of the no-adaptation method is, also as expected, staying constant, while for the GA the variation increases. It is expected that the GA-graph will converge with more iterations as the number of exercises to choose from is a finite number, as well as the specifications of level, repetitions and set. It still verifies that the GA-approach creates a greater solution variety when starting with a small case base.

While the GA clearly is a better solution for increasing solution variety, it only adds value to the user if the created solutions have an appropriate quality. To assure that the solutions are satisfactory they are compared to the ones created by the no-adaptation approach and the expert solutions. A textual example of the difference in results between the created solutions can be seen in table 1. Here none of the solutions created consists of exactly the same exercises. Some are the same on all three solutions, other exercises differ between the three solutions. The flexibility exercises recommended are for instance the same three variation of exercises in all three cases, while in the "strong in mid-position" exercise we see that the solution from the expert and the GA match and that the retrieval only solution has another suggestion. If we look at the first exercise-type suggested we can see that the expert solution suggests two exercises while the two other only suggest one and the same exercise, and the suggested exercise is neither one of the one's suggested by the expert.

Exercise description	**Expert solution**	**GA solution**	**Retrieval only solution**
Strength exercises for the back extensors	*Level:* 4 *Repetitions:* 10 *Set:* 2 *Level:* 5 *Repetitions:* 10 *Set:* 2	*Level:* 6 *Repetitions:* 10 *Set:* 3	*Level:* 6 *Repetitions:* 10 *Set:* 3
Strength exercises for the gluts and back extensors	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 2 *Repetitions:* 10 *Set:* 3
Strength exercises for the abdominal muscles	*Level:* 4 *Repetitions:* 10 *Set:* 3	*Level:* 4 *Repetitions:* 10 *Set:* 3	*Level:* 4 *Repetitions:* 10 *Set:* 3
Strength exercises for the oblique abdominals and rotator muscle in the back	*Level:* 3 *Repetitions:* 10 *Set:* 3	*Level:* 3 *Repetitions:* 10 *Set:* 3	*Level:* 3 *Repetitions:* 10 *Set:* 3
Strength Strong in mid-position	*Level:* 1 *Repetitions:* 10 *Set:* 3	6 *Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 2 *Repetitions:* 8 *Set:* 3
Flexibility	*Level:* 2 *Level:* 3 *Level:* 4	*Level:* 2 *Level:* 3 *Level:* 4	*Level:* 2 *Level:* 3 *Level:* 4

Table 1. Textual representation of different solutions: each solution has a level and most of them have the number of repetitions specified

The different suggested plans from both the no-adaptation and GA methods were scored against the exercise plan the medical expert created based on their similarity. Since the GA creates different solutions the results show how they scored in the best case, the worst case and the average case out of the five runs. The three different rankings are compared to the similarity scores for the no-adaptation result and can be seen in figures 5(b), (c) and (d). The results are sorted by the no-adaptation score as this will be similar in all figures, and therefore give a better impression of the differences between the measures. Both methods score quite well against the expert crafted solutions, which makes sense as all the solutions are built up with the same type of exercises. In the best case scenario for the GA it scores better or equal on eight out of nine cases which suggests that this method performs better than without any adaptation. The worst case scenario on the other hand gives another impression, and in this case only two cases are better on the GA approach while five actually give a worse solution with adaptation. The average case is still probably the best to look at to get a good impression on the performance of the two solutions. The average case shows that the GA performs better in five cases and worse in four. This makes the GA approach seem only somewhat better than without any adaptation, but it has another interesting trait to it. If you compare the similarity measures it shows that the solutions that scores higher with the GA have a larger benefit compared to no-adaptation, while the solutions that perform worse are quite close in scores. On average the solutions with the GA in fact score 4,8% better, which shows that in general the gain is larger with the use of this method.

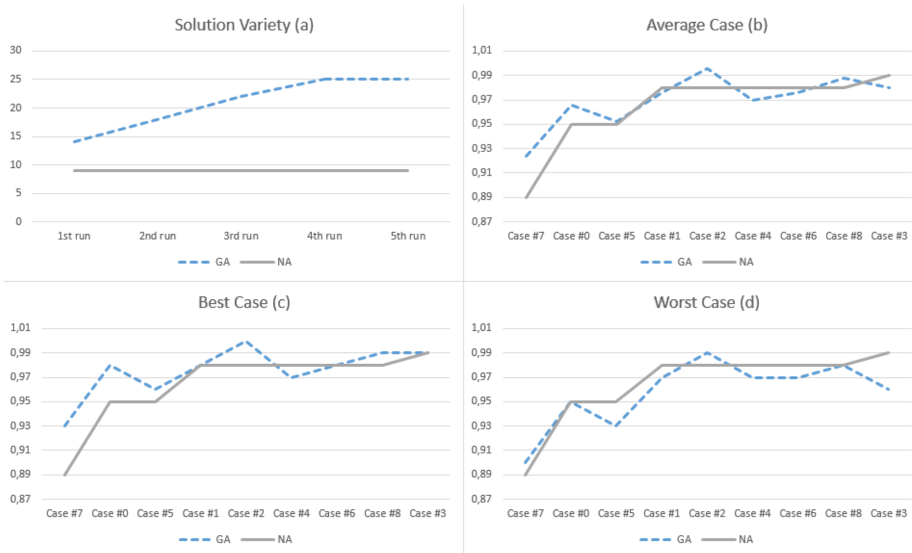

Fig. 5. The results from the experiments. Figure (a) shows the change in solution variety after testing nine different cases in five runs. The y-axis is the number of solutions created after each run. Figure (b), (c) and (d) show the quality of the exercise plans created in average case, best case and worst case respectively. Here the y-axis is the similarity score with an expert crafted solution.

4 Conclusion and Future Work

In this paper we have presented how to apply genetic algorithms for adapting cases in order to increase the solution variety, which might be necessary when deploying a new CBR system.

The results from the experiments show that the solutions created by the genetic algorithm copes better with the cold start problem since it creates a variation of solutions that are of good quality. With information obtained during the follow-up periods within the selfBACK project, we will gather more information on user preferences and outcomes in terms of pain and function.

This information will then allow us to create a better fitness function to further improve the results.

Within selfBACK this approach can be used for recommending behavioural change or educational sessions. More generally, the approach could fit applications where some degree of creativity is possible with user feedback available. This could, for example, be exercises for other rehabilitation programs, product recommendations, or meal planning.

In our further research, additional adaptation processes will be explored. First we would like to include adaptation rules based on clinical guidelines in order to see how they compare with the genetic algorithm. As part of our CBR research more generally, we have a focus on combining CBR with general domain models beyond rules, most recently by incorporating graphical models in the form of Bayesian networks [20]. This is a line of research that will extend our work on case adaption as well as other CBR processes within the selfBACK architecture. As a further study we also plan to extend the method presented here to become not only GA-inspired, but more GA-like, as mentioned in section 3.3. In order to incorporate direct feedback from patients, we plan to provide them with a web-application where they can rate the generated exercise lists.

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