Case Representation and Similarity Assessment in the selfBACK Decision Support System

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Abstract. In this paper we will introduce the selfBACK decision support system that facilitates, improves and reinforces self-management of non-specific low back pain. The selfBACK system is a predictive case-based reasoning system for personalizing recommendations in order to provide relief for patients with non-specific low back pain and increase their physical functionality over time. We present how case-based reasoning is used for capturing experiences from temporal patient data, and evaluate how to carry out a similarity-based retrieval in order to find the best advice for patients. Specifically, we will show how heterogeneous data received at various frequencies can be captured in cases and used for personalized advice.

Keywords: Case-Based Reasoning, Case Representations, Data Streams, Similarity Assessment

1 Introduction

Low back pain is one of the most common reasons for activity limitation, sick leave, and disability. It is the fourth most common diagnosis (after upper respiratory infection, hypertension, and coughing) seen in primary care [23]. Cost of illness studies in different countries indicate that the total annual cost of low back pain in Europe is between 85 billion EUR and 291 billion EUR (equals approximately 0.4-1.2% of the gross domestic product in the European Union) [3]. An expert group concluded that the most well-documented and effective approach to manage non-specific low back pain is to discourage bed rest, use over-the-counter pain killers in the acute stage if necessary, reassure the patient about the favorable prognosis, advise the patient to stay active both on and off work, and advise strength and/or stretching exercise to prevent a relapse [21].

Most patients (85%) seen in primary care with low back pain have non-specific low back pain, i.e., pain that cannot reliably be attributed to a specific disease or pathology. Self-management in the form of physical activity and strength/stretching exercises constitutes the core component in the management of non-specific low back pain; however, adherence to self-management programs is poor because it is difficult to make lifestyle modifications with little or no additional support. In the selfBACK project we will develop and document an easy-to-use decision support system to be used by the patient him/herself in order to facilitate, improve and reinforce self-management of non-specific low back pain. The decision support system will be conveyed to the patient via a smart-phone app in the form of advice for self-management. A recent study [22] identified 283 pain-related apps available in the main app shops App Store, Blackberry App World, Google Play, Nokia Store and Windows Phone Store. However, none of these apps had effects documented through scientific publications, and none included a decision support system. In contrast, we will conduct a randomized control trial to evaluate the effectiveness of the selfBACK decision support system.

1.1 Background

The selfBACK system will constitute a data-driven, predictive decision support system that uses the Case-Based Reasoning (CBR) methodology to capture and reuse patient cases in order to suggest the most suitable activity goals and plans for an individual patient. This will be based on data from two sources. One is a questionnaire, presented to the patient at suitable intervals, in order to capture general information and progress of symptoms (e.g. disability and pain). The other is a stream of activity data collected using a wristband. The incoming data will be analyzed to classify the patients current state and recent activities, and matched against past cases in order to derive follow-up advices to the patient. Two main challenges are to detect the activity pattern represented at a suitable level of abstraction, and to match that structure against existing patient descriptions in the case base. Combined with the patient profile data from the questionnaire, and the current goal setting, this should enable the system to suggest the best next activity goal and plan for the patient.

Stratified care for patients with low back pain, based on initial pain intensity, disability related to low back pain, and fear-avoidance beliefs have been shown to improve patient outcomes as well as being cost-effective [9]. The selfBACK system aims at further improving the stratified care approach by including data on the patients health and coping behaviour (i.e., the adherence to basic self-management principles) in order to support and prompt appropriate actions thereby empowering the patient to improve the self-management of their own low back pain. selfBACK incorporates existing knowledge to recommend advice that is personalized based on the information input by the patient. Figure 1 shows the overall architecture of the selfBACK system. The user initially uses a web page to sign up and provide answers to a set of screening questions (1), which are fed to the server (2) in order to initiate the smart phone app. All further interactions happen with the smart phone. It collects sensor data (3) from a wearable, subjective information from the user (4), pushes both the objective and subjective measurements (5) to the server and finally provides recommendations (6,7) to the user.

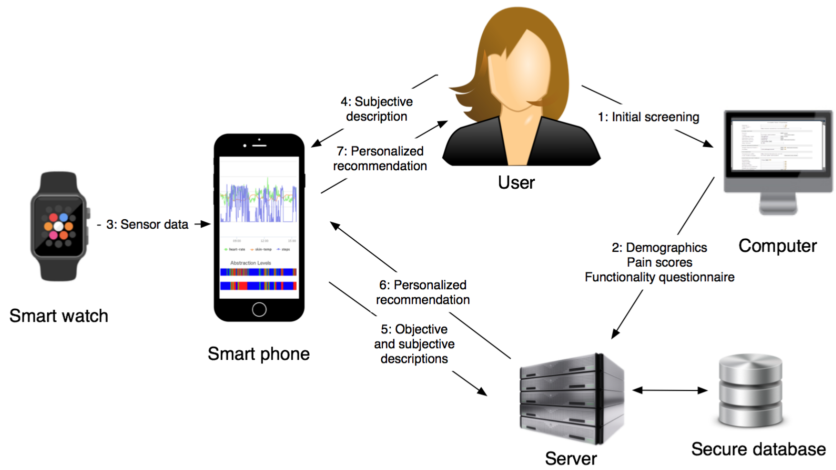

Fig. 1. selfBACK has a distributed architecture in which data collection and user interaction mainly is done on the mobile devices. The case-based recommendation is performed remotely on the server.

In what follows we will discuss related work, before we describe the case representation and case content in section 3. In section 4 we introduce the applied similarity assessment. We have conducted experiments using already existing data sets from the domain, and discuss these in section 5. The final section summarizes the paper and gives an outlook on future work.

2 Related Work

When reasoning with time in CBR, the temporal information can be dealt with at the feature level, the case level or a combination of these two. This idea was introduced by [15]. At the case level, history is described using temporally connected cases while at the feature level, the features of the cases contain temporal information. A combination of these two are temporally connected cases that contains temporal features. Temporal features could be of different types: 1) raw time series [18], 2) sequences of events [7,11], 3) graphs [10] and 4) piecewise interpretations of raw time-series [13].

The type of feature that represents temporal information directly influences the type of similarity metric that can be used to compare local similarity of the temporal features. In order to compare raw time series, the types of similarity metrics that are used include Euclidian Distance metrics, Fourier coefficient metrics, auto-regressive models, dynamic time warping, edit distance, time-warped edit distance and minimum jump cost dissimilarity metrics. See [20] for a review and empirical evaluation of these. Variants of these similarity metrics are used for both sequences and piecewise interpretations. [14] applies the Discrete Fourier Transform when comparing the similarity of time-series. In [13] time series are converted to temporal abstractions that describe the state or trend of a time-series. These temporal abstractions are organized in a tree based on the granularity of the abstractions, and similarity computations are conducted based on the distance in the tree structure. [4] compares the similarity of time-series using dynamic time-warping, and [7] uses edit distance on sequences of events. See [6] for a discussion on measuring the similarity of sequences of complex events.

Decision support systems that perform case-based reasoning on temporal data have been developed for a diverse set of domains that include weather prediction [8], buy and sell points prediction for stocks [2], oil well drilling [6] and fault diagnosis of industrial robots [17] among many others. One of the domains that has gotten the most attention is health care. Decision support systems that reason with temporal data in the medical domain include kidney function monitoring and prediction [19], long term follow up of stem cell transplantation patients [1], classification of respiratory sinus arrhythmia patterns [16], hemodialysis patient management [14], and Type 1 diabetes patient support [12]. The focus within selfBACK is to monitor the different factors (pain, function, activity, etc.) in order to compare patients based on summaries and abstractions from collected raw data. At this stage, cases contain temporal information at the feature level only, the temporal data is piecewise interpretations of time-series which are compared using edit distance. The temporal features are piecewise interpretations of the patient activity stream over a day. The overall progress of the patient over larger time spans will be solved through temporally connected cases at the case history level, but this is future work.

3 selfBACK Case Representation

Cases in selfBACK consist of different types of information representing the patient description and the personalized advice. Data for the patient description is acquired with various frequency patterns in the selfBACK life cycle, and the advice given through the app is updated accordingly. We can assume that the initial information, such as demographic data and information provided by the clinician, is somewhat static while other information is expected to change more frequently. At the extreme end of that scale is the continuous data stream from the wristband.

The case structure is shown in table 1. As earlier described, we differentiate between subjective and objective measurements of a patient's situation. The subjective measurements are obtained by asking the patient about their level of pain, degree of functionality, etc. A particularly relevant piece of information is the patient's self-efficacy, i.e. the patient's degree of belief in that the bad condition will improve and eventually vanish. These questions are based on standardized questionnaires and screening tools such as the Pain Specific Function Scale (PSFS), Roland Morris Disability Questionnaire (RMDQ), StartBACK, Pain Self Efficacy Questionnaire (PSEQ) or Quality of Life (EQ-5D). Further on questions are asked regularly on a weekly basis, which provide a time series describing the course of pain and functionality. All those measures are captured using standardized screening tools applied in common practice. This information is enhanced by the objective measurement of a patient's activity. The objective measurement is obtained via a wristband worn by the patient providing continuous readings of activity parameters such as sleep, number of steps, the duration time of sedentary (e.g. lying, sitting, standing), moderate (e.g. walking), and vigorous (e.g. running) activities.

	Case Part	Content	Update Frequency
Problem Description	Subjective Description	Demographics Quality of life Pain Level Functionality	weekly/biweekly
	Objective Description	Activity Stream	continiously
Solution	Advice	Activity Plan Exercise Plan	weekly

Table 1. Overview of the Case Content in selfBACK Cases

We are storing the raw data in a noSQL database and fetch it from there when cases are build or case matching is initiated. This approach allows us to keep a high level of detail, generate abstractions offline and extract from them on demand.

From research on non-specific low back pain, and the course of pain and functionality, we know that a severe episode of low back pain starts with an acute phase where a patient is in a lot of pain and basic movements are difficult. This phase can last from a few days up to four weeks. After that period one speaks about the sub-acute phase, followed by a chronic phase (pain lasts longer than 3 months), if the pain persists. In this paper we are focusing on the case content and similarity matching for patients in the acute phase.

3.1 Building Cases from objective and subjective measurements

When looking into existing data collections, the pain level and functionality level changes in the first weeks of an acute phase. As part of assessing a patient's degree of pain, the patient is asked to mark the pain level on a scale from 0 to 10, where 0 is no pain at all and 10 is described as the worst pain possible to imagine. The reported pain (as shown in figure 2) usually decreases over time, but the timing differs. As pain goes down, usually functionality increases. When looking at the course of pain in more detail, one can see that the pain levels out at a certain point (see levelling in figure 2) and from this point onwards the patient can start rehabilitating with light exercises and activities.

However, there are different journeys until the patient reaches a point from which s/he can start the recovery phase, and the goal of selfBACK in the acute phase is to provide suggestions to reach that point as fast as possible. In figure 2 we used the HUNT3 data set (described in section 5.1), which captures the patients' pain levels for a few weeks. The patients were asked twice about their current pain levels (week 2 and 6 in figure 2) as well as a summary on how their pain was the last two weeks (week 0 and week 4 in figure 2). This information gives us an overall indication that there are different courses of pain development, and also that these are not bound to the pain level a patient has in the very beginning of the treatment (baseline).

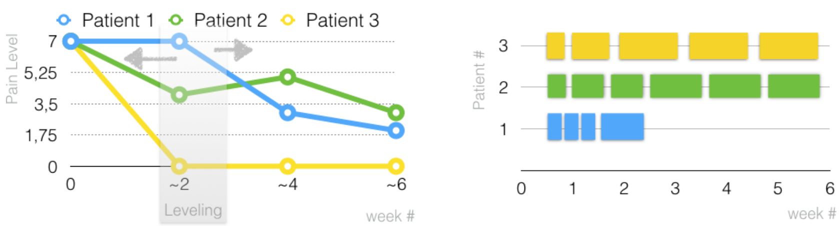

Fig. 2. Pain Leveling (left) and Data Collection Frequency for Acute Patients (right)

As *leveling* we describe the moment when the patient has reached a state, where the pain is bearable enough to start doing light strengthening and flexibility exercises. We aim at supporting the patient to reach that point as fast as possible by reusing successful advices from similar patients.

Driven by the reported pain in the selfBACK application, we expect cases to cover flexible time spans. While a patient has a lot of pain the advice is given on a short term (usually a day or two), while afterwards we are targeting at "reporting" weekly phases. On the right in figure 2 we show possible update frequencies for the aforementioned patients. Patient 1 stays at a high pain level, hence s/he is asked very frequently whether there has been a change until the pain level goes down and the time between re-asking becomes longer as well. Patient 2 and especially patient 3 have a much faster decline of their pain and therefore the length of capturing new subjective information is longer. We base this approach on the assumption that low back pain patients with high pain levels usually experience a change in perceived pain level within a few days, but with medium and low pain levels the change takes longer.

4 Similarity of Cases

To recapture, the selfBACK case contains objective and subjective data collected from one single patient and the advice given to that patient at specific timestamps (table 1).

The subjective problem description is mostly static and collected at baseline and updated weekly to monthly throughout the course of the raw data. The objective problem description is based on a continuous data stream, which is interpreted and contains the activity pattern of a patient. From initial experiments we have conducted, we have seen that the collected data from a wristband contains around 700 entities per week when abstracted to the activity level. We distinguish between four main types of activity: sleep, sedentary, moderate and vigorous activities. An activity is described in terms of this activity type, the start time stamp, and the end time stamp. Depending on the confidence and level of detail, the SELFBACK application will include more detailed activities such as lying, sitting, standing, walking, running or biking, which will result in even more timestamps. This means that the activity stream data may constitute more than 99% of the whole case content when stored.

4.1 Case comparison challenges

As mentioned, the case comparison uses the objective as well as the subjective problem description for case matching. Eventually, the SELFBACK application will reuse the personalized advice from the best matching case in order to produce a customized exercise and activity plan for the current patient. An exercise plan in this context is a set of stretching and strengthening exercises that build up gradually. Once an entry point is found, the patient is guided throughout specific workouts. An activity plan on the other hand sets goals for physical activities throughout a day or week such as reaching a specified number of steps/day or reducing continuous sitting time during the day to amount of minutes. The matching case may be a past case from the same patient or from another similar patient. The different characteristics of the problem descriptions require different approaches for similarity matching, hence we will compare the objective and subjective measurements.

Subjective measurements are matched by standard, simple similarity metrics for numerical and symbolic values. The activity stream, however, is converted into a string and several different string comparison methods are used. Each character in the string represents an activity the patient was doing at the n^{th} (n is here the position of the character in the string) second from the time the case was stored. For instance, the string "SSSSRRR" represents a period of 4 seconds standing (S) followed by a period consisting of 3 seconds running (R). If we were to use all of the described data as attributes summed in a global similarity function, our approach would suffer from several logistical weaknesses. Firstly, 99% of the data (the activity stream) would only be used for computing a few attributes in the global similarity function. Secondly, computing the similarity between those attributes is much more costly than computing the similarity between simpler and smaller data structures extracted from the questionnaire data. Therefore our next steps are to investigate which abstractions from the objective and subjective measurements are relevant for (a) predicting the course of a patient's convalescence and (b) which information is necessary for communicating the SELFBACK advice.

4.2 MAC/FAC model and the global similarity function split

To solve the problems described in section 4.1 we divide the retrieval of similar cases into two steps, as suggested by the MAC/FAC model [5]:

In the MAC phase, data from the subjective problem description is compared to the current situation of a selfBACK patient. Simple and computationally cheap similarity metrics are used. In the FAC phase the activity streams from the most similar results are extracted from the database and compared with use of more expensive sequence similarity metrics. By doing this, we extract considerably less data from the database, and we save significant amounts of time when computing the similarity scores between cases. Another advantage with this MAC/FAC approach can be seen when a selfBACK patient's MAC data remains unchanged (which often will be the case, because it mainly consists of reletively static data). If so, the whole retrieval from the MAC phase from last time can be reused.

One of the difficulties with the MAC/FAC model, is to ensure that the most similar cases retrieved after the FAC phase are indeed the most similar cases globally (during a retrieval when no cases are filtered out). Sometimes filters applied to cases in the MAC phase for selecting the globally most similar cases. Therefore, in our approach, we do not use metadata about the activity stream structure as a filter, but rather a part of the global similarity function itself. As we will see, this ensures that the case retrieved after the FAC phase is indeed the most globally similar one. Consider the properties (1) of a global similarity function which is a weighted sum of case attributes. Also assume that we are using it to compare cases containing n attributes:

$$sim_i(x_i, c_i) \in [0,1] \ , \qquad \sum_{i=1}^{n} w_i = 1 \ , \qquad \sum_{i=1}^{n} sim_i(x_i, c_i) w_i \in [0,1] \qquad (1)$$

Here $sim_i(x_i, c_i)$ is an attribute similarity function, that compares the i^{th} attribute from a case x to the i^{th} attribute of case c (for example a selfBACK patient case). The function returns a value between 0 and 1. Next, this value is multiplied by an attribute function weight w_i. Those weights reflect the importance of the attributes used in our case representation. In the current iteration of the selfBACK system, the values of those weights are not known. However, we know that their sum is equal to 1.

Finally, the sum of all the n attribute similarity functions multiplied with their corresponding weights constitutes the final global similarity function: the rightmost equation in (1). This function also returns a value between 0 and 1.

When these requirements are met, we can find a $k < n$ and rewrite the global similarity function, returning a similarity value z, into equation (2):

$$\sum_{i=1}^{k-1} sim_i(x_i, c_i) w_i + \sum_{i=k}^{n} sim_i(x_i, c_i) w_i = z \in [0,1] \qquad (2)$$

In the selfBACK system, all the inexpensive attribute comparisons are put into the leftmost sum of equation (2) and are computed during the MAC phase. The resulting sum, M, is then used as a filter for the FAC phase. Assume that the maximum value of the rightmost sum in equation (2) equals F_{max}. Suppose we compare a selfBACK patient case to cases stored in the selfBACK case base. However, instead of computing the whole global similarity function, we only compute the MAC phase sums (leftmost part of equation (2)). Let $M_{highest}$ be the highest such computed sum. To ensure that the retrieved most similar case after the FAC phase is also the globally most similar case, we have to consider all retrieved cases from the MAC phase for which M is:

$$M \geqslant M_{highest} - F_{max} \tag{3}$$

For every case with M satisfying equation (3), we compute the expensive FAC phase (F; rightmost sum in equation (2)). $M + F$ is then the global similarity of the compared case. Following this apporach the case with hte greatest similarity sum is also the most similar case overall. Splitting the global similarity function is only beneficial if F_{max} is less than 0.5 (half of the maximum overall similarity). We assume this to be true, as it is sufficient for clinicians today to only monitor attributes that are part of the subjective case description, described in table 2, for patient treatment.

5 Experiments and Results

In this section we will show that the suggested case representation can be used to describe patient cases that contain the development of pain, functionality and the activity of a patient. We will also show that the MAC/FAC approach can be used to carry out a similarity based retrieval on the given data sets.

Since this type of data collection is new, we do not have an existing data set to start experimenting. Therefore we use existing data sources which partially cover the SELFBACK target data in order to show how cases can be populated.

5.1 Case Base Population

In order to evaluate the applicability of the presented case structures within a CBR system, we created a data set from two already running projects, and we collected activity data from healthy people. The goal of the evaluation is (A) to test the representation of subjective measurements, and (B) to test the retrieval and similarity assessment of cases containing objective and subjective measurements.

The FYSIOPRIM data set has been created by a Norwegian medical research project focusing on capturing data about the treatments of musculoskeletal disorders in primary care[3]. A tablet app has been developed, which captures the status of the patient (while in the waiting area) along with the given treatments (inserted by the physiotherapist). The patients were also asked some of the questions again after a follow-up period. The project has finished its first phase including the development of the questionnaire and the app, as well as its

[3] http://www.med.uio.no/helsam/forskning/grupper/fysioprim/

Attribute name	SELFBACK	FYSIOPRIM	HUNT3	Example case
Gender	x	x	x	male
Age	x	x	x	45
Height	x	x	-	1.89m
Weight	x	x	-	82
BMI	x	x	-	23
EQ5D	x	x	-	90
RMDQ	x	x	-	8
NPRS	x	x	x	8
Work characteristics	x	x	x	mostly sitting
Sleep breaks	x	-	-	seldom-never
Sleep wake up	x	-	-	seldom-never
Sleep difficulty	x	-	-	seldom-never
Exercise frequency	x	x	x	2-3 times per week
Exercise intensity	x	x	-	I push myself
Exercise length	x	x	-	30-60 min
PSFS activity	x	-	-	prolonged standing
PSFS difficulty	x	x	x	8
StartBACK screening	x	-	-	2
Pain medication	x	x	x	none
Pain history	x	-	x	none

Table 2. Overview of the subjective problem description attributes currently captured in SELFBACK in comparison to the existing data sets from the FYSIOPRIM and HUNT3 study

integration in the electronic health record system. Since 2015 it is in the second phase of collecting data in different places in Norway. We have used 45 patient cases from the FYSIOPRIM pilot study to build cases. As shown in Table 2, this data set covers the target representation of SELFBACK pretty well. The only major part that is missing is subjective information regarding the sleep quality of a patient.

The HUNT3 data set: The HUNT3[4] data set we have used is a larger data set, which has been collected between 2006-2008. While HUNT3 is a cohort study within the larger area of Nord-Trøndelag in Norway, our data set comes from a spin-off study, which originates in a questionnaire for participants asking for more detailed information on musculoskeletal disorders if they indicated the occurrence of some type of shoulder, neck or back pain. After an initial questionnaire, they got asked follow up questions up until 5 times over a period of six months. This data set contains data from 219 patients.

Objective measurements of physical activity: In addition to the subjective case description, we collected objective measurements in order to achieve

[4] https://www.ntnu.edu/hunt/hunt3

a complete set of data in terms of data types. We collected activity data of a healthy person over a period of a few weeks for 24h per day. From that data we sampled out 27 days for this experiment focusing on the amount of data produced in one day. Figure 3 shows one of the recordings as well as the abstractions into the four main activity types included in the case representation. For the recording of the physical activity, we used the myBASIS Peak watch that provides the collected data as csv dumps. From these dumps we extracted 24h periods and used simple rules to differentiate between sleeping, sedentary, moderate and vigorous activity.

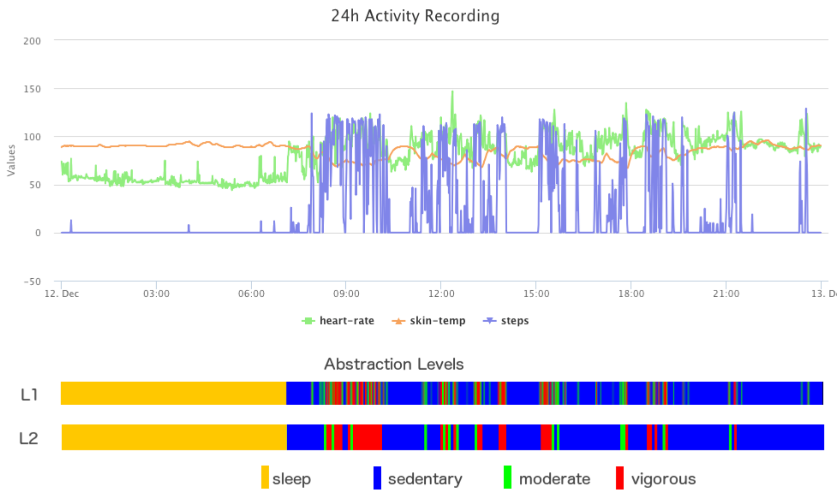

Fig. 3. Objective measurement and abstraction levels: on top you can see the first abstractions from accelerometer data: step counts together with heart rate and skin temperature measures. L1 and L2 show two abstraction levels for the activity recoding.

5.2 Similarity-based Case Retrieval: Subjective Measurements

We wanted to estimate how beneficial the use of the MAC/FAC model in our approach can be. Specifically, it is important to know how many of the cases can be filtered out before the costly FAC phase attribute comparisons. In order to do that, we investigated the similarity span when comparing the subjective problem description part of the SELFBACK cases populated with real data from patients with lower back pain. With similarity span we mean the difference in similarity between the most and least similar cases in a case base.

As shown in figure 2 in section 3.1, the frequency of data updates within cases depends on how often a patient is reassessed. For the evaluation, we choose to compare each set of collected data to the current SELFBACK patient during the case retrieval. This gave us the opportunity to create 90 FYSIOPRIM cases and 1095 HUNT3 cases. From the set of created cases from the FYSIOPRIM data set, we took one case out (the query case) and compared it to the rest. This was then repeated for every case in the set. The same procedure was applied to the HUNT3 cases. For this comparison all attributes were weighted equally. The results are shown in figure 4.

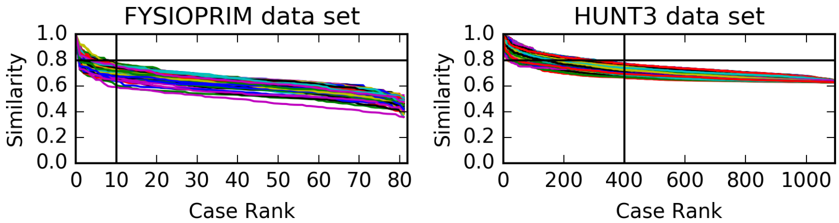

Fig. 4. MAC phase similarity decline within the FYSIOPRIM and HUNT3 data set.

Each colored line in figure 4 represents a MAC phase case retrieval. The cases matched with the query case (one query case for each colored line) are sorted by the similarity on the x-axis. This means that for every retrieval/line, the x-value does not represent a specific case, but rather the x^{th} case when sorted by similarity from greatest to lowest. The maximum value of the MAC phase part of the global similarity function, that will be used by the selfBACK system, is not yet known. Thus a simplification is made and the value is set to 1.0.

As we can see, by increasing the number of attributes, from eight attributes in the HUNT3 data set to eleven attributes in the FYSIOPRIM data set (see Table 1), the similarity covered by the cases on the y-axis in figure 4 (the similarity span) also increases. Since both the HUNT3 and the FYSIOPRIM data sets only uses a portion of the attributes that are planned to be included by the selfBACK system, it seems reasonable to assume that the similarity span would increase even further. The bigger the similarity span, the more cases will be filtered out by the MAC phase and the more beneficial will the usage of the MAC/FAC model be.

For example, take the maximum possible attribute similarity sum computed during the FAC phase in the final global similarity function, F_{max}, to be 0.2. We can see from the plots that we would only have to consider, in the worst case scenario (the colored lines at the top), 10 of the 95 FYSIOPRIM cases and only 400 of the 1095 HUNT3 cases during the expensive FAC phase. This is because only those cases satisfy equation (3) from section 4.2 ($M \geqslant M_{highest} - F_{max} = 1.0 - 0.2$).

5.3 Similarity-based Case Retrieval: Objective Measurements

It is important that the selfBACK system will be able to generate a meaningful retrieval based on comparing activity streams that are abstracted into strings.

In order to get a picture on how such a retrieval might look like, we filled 27 cases with collected activity stream data. During retrieval, we only computed the similarity resulting after the FAC phase. The result is shown in figure 5 where the query is at the bottom, and the matched activity streams are ordered from the most similar at bottom to the least similar at the top.

After converting the activity streams into strings, as described in section 4.1, twelve attributes were extracted when computing the similarity scores. For each of the four activities (see figure 3) we computed the percentage of each activity per activity stream and the number of distinguished periods (yielding eight attributes in total). Between each activity stream we computed the longest common sub-sequence, the sequence distance, the number of similar k-mers and the number of unique similar k-mers.

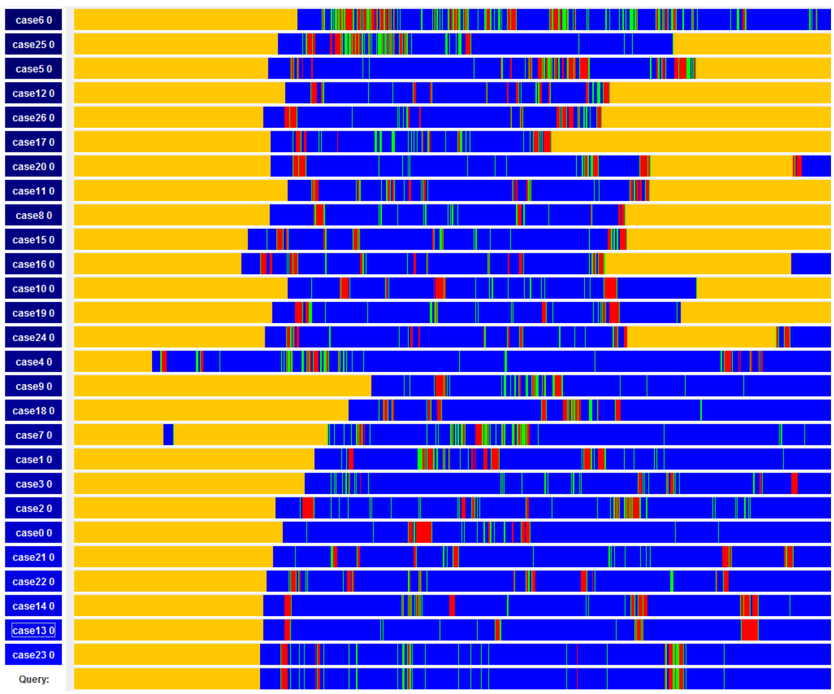

Fig. 5. Activity streams ordered by the FAC phase similarity to the query activity stream.

The number of distinguished periods per activity type is in figure 5 shown as the number of blocks having the same color (number of consecutive substrings containing the same character). The sequence distance is the Levenshtein distance which is the least number of single character insertions, deletions or substitutions that is required to transform one string into the other. A k-mer is a consecutive sub-string of length k. For the similarity calculations in figure 5, every 30-mers were extracted from the compared abstracted activity stream sequences. The resulting 30-mer sets were then compared based on their greatest common subset and uniqueness.

6 Conclusion and Future Work

In this paper we introduced the overall selfBACK system and how a case-representation that provide personalized advice to patients with non-specific low back pain can be designed. We focus on the case representation and similarity assessment within a temporal domain, because we base the advice on the course of pain, function, efficacy and activity. In order to evaluate the case representation and the accompanying similarity assessment we used existing data sets that match the target data in selfBACK and show that we can populate and match cases effectively. Next steps are: completing the case representation; performing a qualitative evaluation of the retrieval; and optimizing the interplay between the objective and subjective measurements.

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