Evaluation of Physical Activities Recommendation Methodology for Blood Glucose Level Regulation

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ABSTRACT

Providing patients with convenient health facilities at a low cost has always been a great challenge for health service providers. Moreover, the fast changing life style of the modern world and the problem of aging society pose an urgent need to modernize such facilities. The emphasis has to be paid on providing health monitoring in out-of-hospital conditions for elderly people and patients who require regular supervision, particularly in remote areas. This paper presents a recommendation algorithm, which incorporates collaboration and classification techniques in order to generate recommendations and suggestions for the physical activities that the users should carry out in order to improve their health. The algorithm has been evaluated using generic data and considering the daily food intake. The results of the experimental evaluation show that the algorithm is robust and could suggest the physical activities that might compensate the influence of the food intake over the blood glucose level.

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1. INTRODUCTION

In general, terms "telemedicine" or "telehealth" encompass a wide range of services that use electronic and telecommunications technologies to either provide care, or support care provided electronically over a geographic distance. The clinical conditions that are most commonly addressed by telehomecare and remote monitoring programs include: asthma, diabetes, chronic obstructive pulmonary disease, chronic heart failure, mental health (anxiety and depression) and wound care. Measurements such as capillary blood glucose, blood pressure, respiratory peak flow rate and weight allow patients to self-administer appropriate amounts of medication in response to dietary and activity variations [1], meaning many wireless mobile devices have been developed to monitor people's health and wellbeing [2].

Use of information technologies enables different ways to improve public health and healthcare systems by reducing costs, saving time and money[3]. Patient-centered development process is useful for healthcare information system in order to reduce system complexity and increase the usability [4]. In the past few years there are plenty of papers that propose different solutions for better health care of patients [2, 5, 7, 8]. Although all proposed solutions have similarities, they are all different and have own unique features. However, these systems do not consider collaborative value that can be provided with matching gathered data.

The collaborative health care system model (COHESY) [12] gives a new dimension in the usage of novel technologies in the healthcare. This system model uses mobile, web and broadband technologies, so the citizens have ubiquity of support services where ever they may be, rather than becoming bound to their homes or health centers. Broadband mobile technology provides movements of electronic care environment easily between locations and internet-based storage of data and allows moving location of support.

Main components and advantages of COHESY, which differentiates it from other health care systems, are the usage of the social network and its' recommendation algorithm. The social network allows connecting users with same or similar diagnoses, sharing their results and exchanging their opinions about performed activities and received therapy. At the same time, collaborative algorithms generate average values based on filtering large amounts of data about concrete conditions as are geographical region, age, sex, diagnosis, etc. In this way, recommendation algorithm gives recommendations to the users for performing a specific activity that will improve their health.

The algorithms implemented in COHESY are designed to have as low complexity as possible, to be efficient and provide instant feedback to users. These algorithms are also flexible and can easily be adapted to deal with different problem variations. There is also a possibility of generating more specific recommendations by exploring the information provided with each activity.

2. COHESY – COLLABORATIVE HEALTH CARE SYSTEM MODEL

Food and physical activity are factors that have a major impact on health.

Improper diet can disrupt health parameters and cause imbalance in the human body. Food is made up of carbohydrates, protein, and fat, and all of these have some effect on users' health parameters like blood glucose or blood pressure. On the other hand, these health parameters are very important for management of diseases such as diabetes (prediabetes) or chronic heart failure. For example, blood glucose level is affected differently depending on whether the food contains carbohydrates, proteins, fats, or a combination of these three. Carbohydrates will cause blood glucose to rise the most and the most quickly. Liquids that contain carbohydrates will cause blood glucose to rise faster than solids that contain carbohydrates. Generally, the meals during the day influence the blood glucose as shown on Figure 1. As one may observe the meals rich with carbohydrates increase the amplitude compared to the carbohydrate-low meals [13].

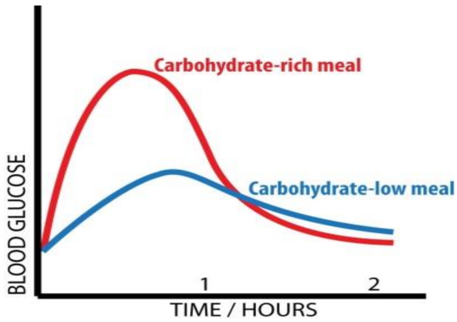

Figure 1. Blood glucose changes due to carbohydrate-rich and low meals.

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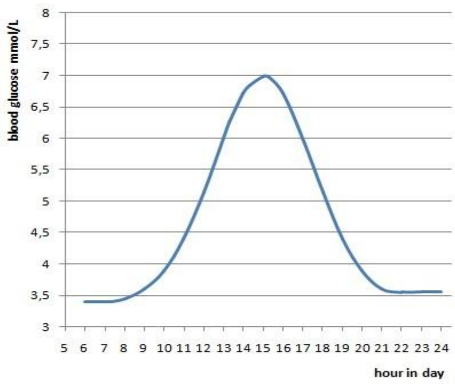

Figure 2. How food intake during the day influences the blood glucose

Considering three main daily meals and other food intakes during the day, we may describe the influence of the food intake over the blood glucose during the day, with a single cumulative function as the one shown on Figure 2

Unlike improper diet, physical activities affect the improvement of health parameters. Moderate physical activity (specified by type and duration) is recommended for almost all chronic diseases.

There are number of studies that have shown that increased physical activity and diet modification, independent of other risk factors, has a protective effect against the development of chronic diseases (e.g. diabetes) [6, 7]. Life style with moderate eating habits and increased physical activity plays a key role in disease management. So, many people with chronic diseases can control their health condition by executing their diet plan, exercise program and taking oral medication on time [8]. Guidance and interactive training regarding appropriate choices of diet and exercise plans combined with encouragement and monitoring of progress, can empower patients to make beneficial lifestyle modifications [9].

Self-monitoring of blood glucose, heart rate, blood pressure, weight is considered a tool for guiding patient and healthcare provider actions regarding dietary changes, physical activity, and pharmacologic therapy. Self-monitoring can give more power to patients by encouraging greater involvement in self-care and by doing so, generate more equal partnerships between patients and health professionals [10].

According to [11] currently there is no reliable system available to objectively monitor and manage their physical activity, calories spent and food consumed on an ongoing basis. These are the reasons why we consider our system model COHESY as assistance needed for people and chronically ill patients. What we want to achieve is to integrate these two factors (food intake and physical activity) within one tool. COHESY is system model that takes into account the effects of food and physical activity on health parameters, and based on prior knowledge recommend physical activity that will improve the users' health.

COHESY has simple graphical interfaces that provide easy use and access not only for the young, but also for elderly users. It has more purposes and includes use by multiple categories of users (patients with different diagnoses). Some of its advantages are scalability and ability of data information storing when communication link fails. This model is interoperable system that allows data share between different systems and databases.

COHESY is deployed over three basic usage layers. The first layer consists of the bionetwork (implemented from various body sensors) and a mobile application that collects users' bio data and parameters of physical activities (e.g. walking, running, cycling). The second layer is presented by the social network which enables different collaboration within the end user community. The use of a social network allows communication between users with same or similar condition and exchange of their experiences. The third layer enables interoperability with the primary/secondary health care information systems which can be implemented in the clinical centers and different policy maker institutions. The data information in this system are: users' personal data (name, age, height, diagnosis, therapy), data from users' bionetwork (weight, heart rate, blood pressure, blood-sugar level), realized and recommended activity (type of activity, path length, time interval, average speed), food intake, weather conditions, recommendation and suggestions. Different data information are exchanged between different layers of COHESY.

COHESY is an infrastructure that enables various personal healthcare scenarios. It enables matching of performed user activity, by combining various data, including: length of path crossed, duration, speed of movement, medical condition of the user (heart rate, blood pressure - before and after, blood sugar level - before and after performed activity), food intake, weather conditions (atmospheric pressure, humidity, temperature), what is the medical diagnosis or therapy of the user (if there are any) and it can generate recommendation when certain patient should perform walk, with what pace and duration.

There are many possible scenarios. For example, the user switches on the application on her/his mobile phone and connects to the social network. The user is suspecting that she/he has diabetes. The algorithms deployed on the social network checks her/his profile, compares her/his health and physical parameters with the average results of the other users with diagnosed diabetes (obtained from the social network). The social network gives notification to the user that her/his health data matches with the average data gathered from people having this condition (diabetes), as stated by medical institutions and other users with similar profile. The system can confirm potentional matches for diagnose and advice her/him to talk to physician.

3. RECOMMENDATION ALGORITHM IN COHESY

Recommendation systems are used extensively by sites which want to give users better experience and they do this by giving suggestions to users about items they may like. But before giving the recommendation, the site first needs to learn user's preferences and it does that by examining the items he already said that he liked or by directly asking the user about his preferences.

There are few definitions for recommendation systems. According to the authors of [7] “Recommender Systems are software tools and techniques providing suggestions for items to be of use to a user. The suggestions provided are aimed at supporting their users in various decision-making processes, such as what items to buy, what music to listen, or what news to read.”

The recommendation algorithm is part of the second level, the social network, in COHESY. The main purpose of this algorithm is to find the dependency of the users’ health condition and physical activities they perform. The algorithm incorporates collaboration and classification techniques in order to generate recommendations and suggestions for the physical activities that the users should carry out in order to improve their health. To achieve this we consider datasets from the health history of users and use classification algorithms on these datasets for grouping the users based on their similarity.

Our recommendation system is not very similar with the most popular recommen-dation systems used in different context. In our context, we talk about physical activities and their influences on the change of the health parameters instead of talking about items and their attributes.

In the proposed algorithm we can distinguish four different phases. The four phases are explained in the following text, but more detailed description can be found in [12].

The first phase is categorization of users according to their diagnosis. There is information supplied by a doctor about the diagnosis of all users. We use this information in order to group users that have similar diagnosis. Users from the same group have the same set of permissible activities and this is the main reason why we perform categorization. For each user and for each possible diagnosis we assign a value that indicates whether the user has the particular diagnosis. We choose a subset of users and an expert should assign category to each of the users from this subset. This training set is used to build a classification model that will assign categories to other users. We do not use manual categorization because the number of different users might be very big and an expert might not always be available. When we want to generate recommendations to the active user, first we need to find the users that belong to the same category with the active user. All other users are ignored in the next steps of the algorithm.

In the second phase we use a similarity metrics in order to find the most similar users to the active user according to their medical history. We can define health profile as the combination of the parameters’ values at a particular moment. For each user we keep a history of health profiles. Health profiles are generated at regular time intervals. However, we do not need to save all the health profiles of the user, but only those which are different enough from each of the saved profiles from his current history.

We assume that if two users had the same combination of parameter values in the past, there is bigger probability that similar latent factors affect their health condition. If some user has at least one health profile similar enough (according to some metrics such as Euclidean distance) to the current health profile of the active user, then we declare this user as similar to the active user and his data are used in the next phase of the algorithm. If there are many users that are declared as similar, we can select only top k most similar users. For each user from the set of similar users we keep the details about the physical activities he performed and the measurements of his health parameters.

In the third phase we use only data from the active user and from the users most similar to him. This is the most important phase of our algorithm because we calculate the usefulness of each type of physical activity. First, the current health condition of the active user is analyzed. If some of the health parameters’ values are not in the normal range, we want to discover useful activities that could potentially improve those values. We analyze the history of activities and measurements of each user and we want to find the type of influence of each type of activity on each of the health parameters. For this purpose two measurements are selected for each activity – the most recent measurement before the execution of the activity and a measurement performed a particular time period after the execution of the activity (for example this period could be one or two weeks). We don’t choose the first measurement after the activity because a time is needed for the activity to show its effect. The difference between the next and the previous measurement approximates the influence of the activity on the parameter change.

In the fourth phase we use the information about the usefulness of each activity in order to generate recommendations. For each user from the set of similar users (plus the active user) we obtain the most useful activity that could potentially improve his health condition. The activity which is declared as the most useful to most of the users is recommended to the active user.

4. EVALUATION OF THE ALGORITHM

In our previous research work we have evaluated the proposed recommendation algorithm using a model of an activity influence to the global paramether change. Our purpose was to test whether our algorithm is successful in recommending the correct activity if only two types of activities with opposite directions of influence are present in the model. Additional evaluations with increased data uncertainty were also performed. The results have shown that the algorithm is robust and promising. In this evaluation we have improved the model in order to deal with more realistic scenarios.

4.1. Methodology

In our model we assume that the health parameter is blood glucose and the factors that influence on its change are food intake and the activities. We used a function shown on Fig. 2 to model the influence of the food intake for entire day. We can notice that in absence of activities at the end of the day the value of the blood glucose is increased. This is a realistic presumption because we need everyday activities in order to normalize the blood glucose. We have also used two types of activities in our model and both of them have inhibitory effect. The first type of activity has bigger inhibitory effect than the second type (Fig. 3 and Fig. 4).

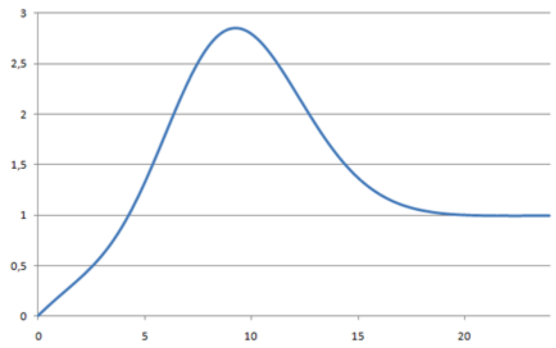

Figure 2. Function that models the food intake (hours are shown on x axis)

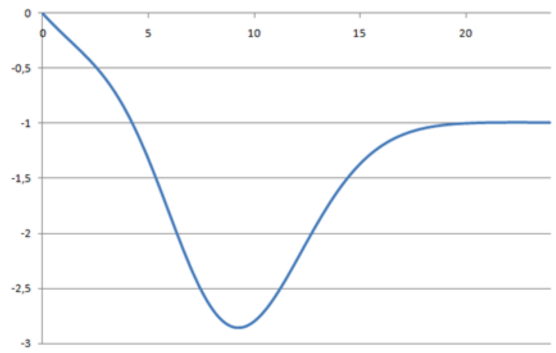

Figure 3. Function that models the influence of the first type of activity with bigger inhibitory effect (hours are shown on x axis)

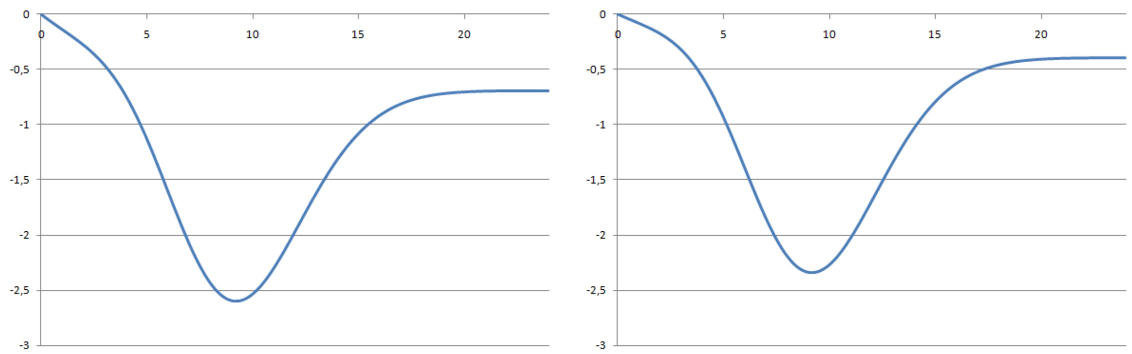

Figure 4. Two function that model the influence of the second type of activity with smaller inhibitory effect (hours are shown on x axis)

We have chosen the length of the simulation in days and in this simulation we have generated the same number of activities from both types at random times, but keeping in mind that the expected global parameter value change after sufficiently long time is equal to zero. At the end of the simulation we applied our recommendation algorithm in order to test which type of activity has bigger influence on the global parameter change. If the algorithm correctly recommends the first type of activity, then we say that this trial is a “success”. We perform a series of trials and at the end of our experiment we analyze them. Our goals are to test the accuracy of the proposed algorithm using the previously defined model and to evaluate its behaviour when the second type of activity has bigger and smaller inhibitory effect, when we change the number of measurements present in the system and when we change the algorithm parameter which determines whether closer measurement made after the activity will be preferred over more distant one and vice versa as most relevant representatives of the activity influence. On Fig. 5 we can see the global parameter change during one simulation.

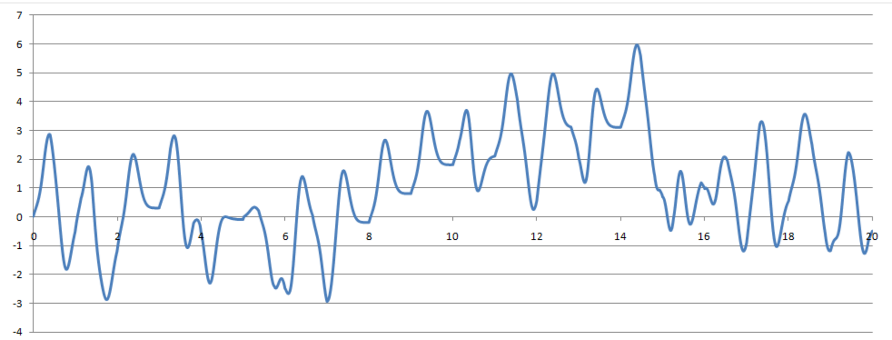

Figure 5. Global parameter change during one simulation (x axis – days)

4.2. Results and Analysis

First we have performed simulations when the first type of activity decreases the global parameter value for 1 unit and the second type of activity decreases the global parameter value for 0,4 units. Let's define the random event A: "The type of activity that produces bigger decrease of the parameter value is recommended as the most useful activity by the recommendation algorithm" and let p=P(A). We have made 100000 trials and the algorithm recommended the correct type of activity 72696 times. We test the hypothesis:

$$H_0: p = 0.7$$

against the alternative hypothesis:

$$H_1: p > 0.7$$

with significance level $= 0.01$. For testing we use the following z-statistics:

$$z_0 = \frac{\hat{P} - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}}$$

z_0 should be bigger than $z_\alpha = 2.3263$ in order to reject the null hypothesis and accept the alternative one. From our experiments we found that $z_0 = 18{,}604$ so we conclude that $p = P(A) > 0.7$ with significance level of 1%. The results from this experiment show that our algorithm gives relevant recommendations when the model includes the food intake information and under our assumption of the shape of the activity influence.

The algorithm finds the most relevant measurement performed after the activity using a validation function. Before we apply the algorithm we need to set the parameter which determines the moment after the activity in which we expect that the activity influence reaches the peak. It is not easy to determine this moment, and the most obvious solution would be to take a training set, to try different values and to choose the best value. In our next experiment we want to inspect how the accuracy of the algorithm changes when we change the time after the activity in which we expect the biggest activity influence. We also observe the change of the accuracy when the second activity decreases the global parameter value for 0.7 and 0.4 units. Additionaly, we compare the results obtained when we have 30 and 100 measurements present in the simulation.

On Fig. 6 we can see how the accuracy of the recommendation algorithm changes when we increase the time after the activity when we consider the measurements as the most relevant. At the beginning we notice rapid increase of the accuracy and after that we notice constant decline. For our model we should choose the time to be 2 days in order to get the most accurate recommendations. This time depends on the factors influencing the global parameter change and in our case: the food intake and the activities (represented by the function that models their influence and their appearances).

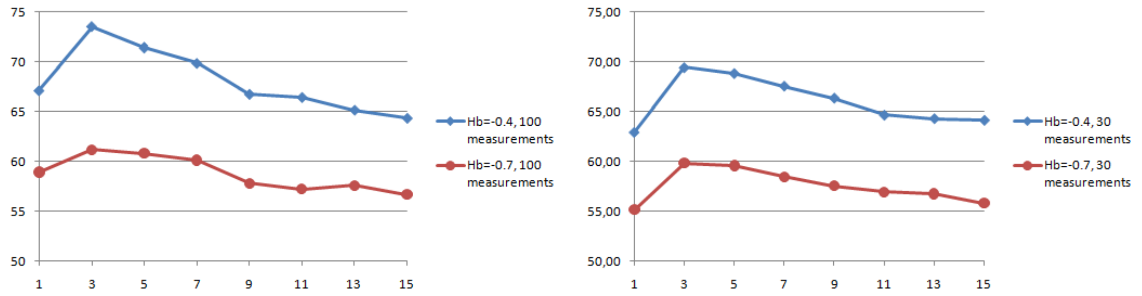

Figure 6. Accuracy of the recommendation algorithm as a function of the time after the activity (in days) when we consider the measurements as the most relevant (we compare results from simulations with the same number of measurements and different influence of the second type of activity)

From Fig. 6 we notice that the recommendations are more accurate when the types of activities have influences that differ a lot (for example H_a=-0.1 and H_b=-0.4 vs. H_a=-0.1 and H_b=-0.7) because it is easier for the algorithm to determine the type of influence for each activity.

As we decrease the number of measurements available to the recommendation algorithm, we notice decrease of the accuracy, but this decrease is not with big magnitude. This means that even small number of measurements is sufficient to get relevant recommendations. On Fig. 7 we notice that the selection of the time after the activity when we consider the measurements as the most relevant is very important and must be carefully determined because in other case we cannot get improvement of the accuracy by increasing the number of measurements available to the algorithm. In our case we cannot significantly improve the accuracy of the recommendation algorithm if we chose the time to be 9 days or more.

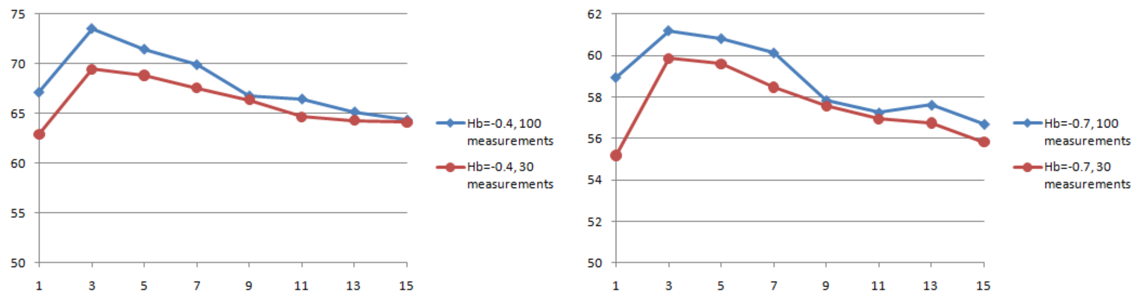

Figure 7. Accuracy of the recommendation algorithm as a function of the time after the activity (in days) when we consider the measurements as the most relevant (we compare results from simulations with the same influence of the second type of activity and different number of measurement)

5. CONCLUSION

This paper presents an algorithm capable to generate recommendations considering the dependency beteween the users' health condition and physical activities he/she performs. This algorithm is designed as a part of the developed collaborative health care system model – COHESY. COHESY provides data about the users' health condition and set of knowledge derived from the health and physical activities history of the user and users like him/her. Based on this information, the developed recommendation algorithm gives the users recommendations for performing a specific activity that will improve their health.

In this paper we have considered a realistic scenario where the food intake and activities affect the change of the blood glucose. The evaluation proved that the algorithm generates correct recommendations. The accuracy of the recommendations depends on the amount of available measurements, but even a small number of measurements (30) is enough to generate relevant recommendations. The time after the activity when we consider the measurements as the most relevant is also very important factor that affects the accuracy. This parameter for the algorithm was determined by experiments and the method should also be used when the algorithm is applied to different scenarios and models. It could be easily determined by expecting the visualized results. The results show that the algorithm is very robust and promising. It was also shown that the developed algorithm can be easily adapted and applied to different models and scenarios.

The recommendations suggested by the algorithm should help the user to adapt and align his/her physical activities, their frequency and intensity in order to suppress the negative influence of the food intake over some biological parameters. This way while improving his/her health condition the user will be fully aware to take self-care.

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