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Validation of the Collaborative Health Care System Model COHESY

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Abstract. Collaborative health care system model COHESY allows monitoring of users’ health parameters and theirs physical activities. This system model helps its users to actively participate in their health care and prevention, thereby providing an active life in accordance with their daily responsibilities at work, family and friends. Recommendation algorithm, which is part of the social network of the proposed model, gives recommendations to the users for performing a specific activity that will improve their health. These recommendations are based on the users’ health condition, prior knowledge derived from users’ health history, and the knowledge derived from the medical histories of users with similar characteristics. In this paper we give validation of the proposed model by using simulations on generic data.

Keywords: Personal healthcare systems, recommendation algorithms

1 Introduction

Advances in communication and computer technologies have revolutionized the way health information is gathered, disseminated, and used by healthcare providers, patients and citizens. The collaborative health care system model COHESY [1] 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 [2]. Broadband mobile technology provides movements of electronic care environment easily between locations and internet-based storage of data allows moving location of support [3]. The use of a social network, in COHESY, allows communication between users with same or similar condition and exchange of their experiences.

COHESY has simple graphical interfaces that provide easy use and access not only for the young, but also for elderly users. It has many 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. COHESY is interoperable system that allows data share between different systems and databases.

The recommendation algorithm, which is part of the social network in COHESY, is based on the dependence between the values of the health parameters (e.g. heart rate, blood pressure, arrhythmias) and the users' physical activities (e.g. walking, running, biking). The basic idea is to find out which physical activities affect change (improvement) of the value of health parameters. This dependence continues to be used by the algorithm to recognize the same or similar health situations found in another user with similar characteristics. If there is information in the users' history that after performing some physical activity their health condition has improved, the algorithm accepts this knowledge and proposes the activity to other users with similar health problems.

The usage of the social network and its recommendation algorithm are the main components and advantages of COHESY which differentiates it from other health care systems. These components provide a new perspective in the use of information technologies in pervasive health care and make this system model more accessible to users. COHESY bridges the gap between users, clinical staff and medical facilities, strengthening the trust between them and providing relevant data from a larger group of users, grouped on the basis of various indicators.

2 Collaborative Health Care System Model COHESY

Simple overview of COHESY is shown in Fig.1. System model 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 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 communication between the first and the second layer is defined by the users' access to the social network where the user can store their own data (e.g. personal records, healthcare records, bionetwork records, readings on physical activities). The social network allows communication between users based on collaborative filtering techniques, thus connecting the users with the same or similar diagnoses, sharing their results and exchanging their opinions about performed activities and received therapy. Users can also receive average results from the other patients that share the same conditions in a form of notifications. These notifications can vary from the average levels of certain bio data calculated for certain geographical region, age, sex, to the recommendation for certain activity based on the activities of other users. Collaborative filtering can be used to achieve different recommendations in these contexts.

The communication between the first and the third layer is determined with the communication between patient and health care centers. The patient has 24 hour access to medical personnel and a possibility of sending an emergency call. The medical personnel remotely monitors the patient's medical condition, reviewing the medical data (fatigue, blood pressure, heart rate) and responds to the patient by suggesting most suitable therapy (if different from the one that is incoded in the mobile application) as well as sending him/her various notifications (e.g. tips and suggestions) regarding his/her health condition.

The second and the third layer can exchange data and information regarding a larger group of patients, grouped by any significant indicator (region, time period, sex, type of the activities) which can be later used for research, policy recommendations and medical campaign suggestions.

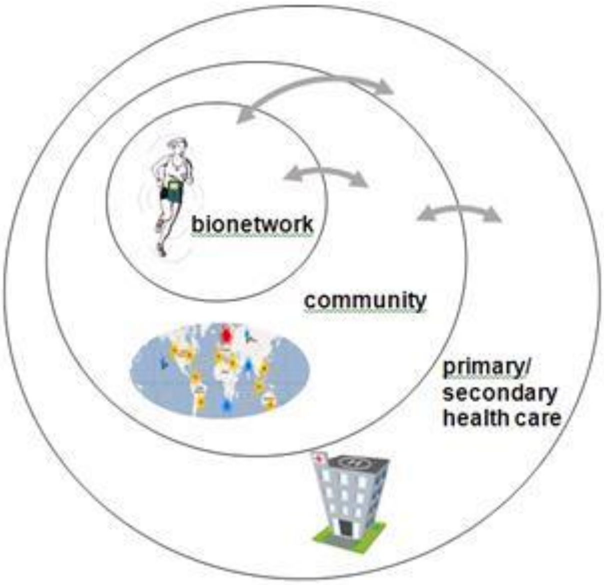

Fig. 1. System Layers

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COHESY uses different techniques and protocols that guarantee security and privacy of users' data [4, 5, 6]. It has own security and privacy statements that explain how the system protects the users' privacy and confidentiality and the way in which their personal information will be treated. Every user can choose which information can be private or public. The user can choose his records to be public: (a) for medical purposes, (b) to all visitors of the Social network, (c) to the users in his category, (d) to none. In order to have medical support the user has to agree to share personal information with clinical centers and medical databases, whose data are also protected. According to user’s agreement policy, those data information would be exchanged through the system.

2.1 Recommendation algorithm

The recommendation algorithm is part of the second level in COHESY (the social network). It is implemented as a web service and its purpose is to recommend the physical activities that the users should carry out in order to improve their health. The algorithm uses the data read by the bionetwork, the data about the user’s physical activities (gathered by the mobile application), the user’s medical record (obtained from a clinical centre) and the data contained in the user profile on the social network (so far based on the knowledge of the social network).

The main purpose of this algorithm is to find the dependency of the users’ health condition and the physical activities they perform. The algorithm incorporates collaboration and classification techniques in order to generate recommendations and suggestions for preventive intervention. To achieve this, we consider datasets from the health history of the users and we use classification algorithms on these datasets to group the users by their similarity. The usage of classified data when generating the recommendation provides more relevant recommendations because they are enacted on knowledge from users with similar medical conditions and reference parameters.

There are a number of parameters that might be used to characterize a person such as: body mass index, age, blood pressure, heart rate, blood sugar levels. All these characteristics are essentially continuous variables and they are measured with (near) continuous resolution. On the other hand, the bio-medical parameters and phenomena are often too complex and too little understood to be modeled analytically. Because of its continuous nature, the fuzzy systems are very close to the medical reality and at the same time, fuzzy sets allow natural description of bio-medical variables using symbolic models and their formalisms, avoiding the analytical modeling [7]. Therefore, in this algorithm, fuzzy sets and fuzzy discretization are considered as a suitable approach that can bridge the gap between the discrete way reasoning in the IT systems and the continuity of biomedical parameters. For every health parameter, several discretization intervals are considered. Each person has a corresponding membership factors for each of those intervals, depending on his/her parameter value.

This algorithm uses three levels of filtering, as shown in Fig.2. The first step is classification. All users belong to some diagnosis class (normal diabetes, heart problems). All users with different diagnosis from the diagnosis of the given user are filtered out. This step is important because some activities may be harmful for a particular group of people e.g. running may have much different effect on people with heart problems as opposed to people which are physically active.

The second level of our recommendation algorithm is the collaborative filtering. Every user has its own history of health conditions (health profiles) and it is important to find similar users to the given user which at some point of time in the past had similar health condition to the health condition of the given user at the moment. The technique that is used here can be considered as a collaborative filtering technique where items are equal to health profiles.

When the similar users are chosen, we use all their health condition history and the history of performed activities to find the influences of each activity on the change of the health parameters. Now we come with a fairly good approximation of the potential effect of the activity on the health condition for the given user. Here we use the characteristics of the activities in order to get good recommendations. In other words, we explore the content of the activities and use content-based filtering techniques to find the best matching activities. User preferences in our context are the desired values for the health parameters (normal range). The chosen activities would potentially improve the health condition of the given user towards the desired values.

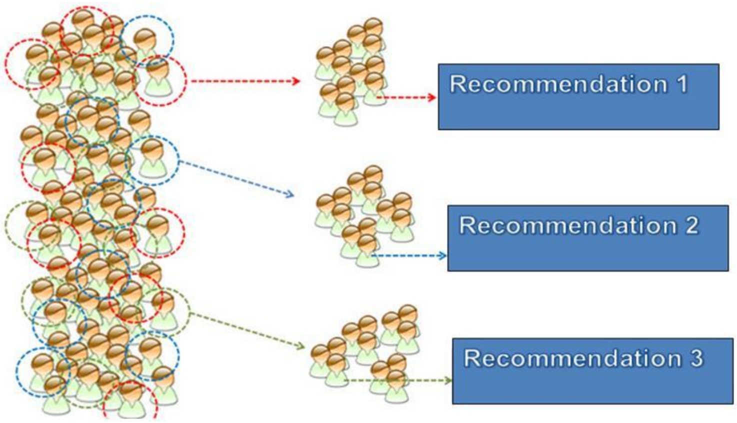

Fig. 2. Levels of filtering in COHESY recommendation algorithm

3 Simulation results and discussion

In this section we give a validation of the proposed model by using simulations on generic data. Three simulations are made and in all of them, two types of activities are generated: a positive activity (activity whose performance increases the value of a given parameter) and negative activity (activity whose performance reduces the value of a given parameter). Each activity has individual influence to the global parameter change and it is presented by a function whose shape is similar to a Poisson probability mass function. The graphs of the influences of the positive and negative activities in the time period [0, 3000000] are shown on Fig.3.

In the first simulation 25 activities were generated. Each activity begins at a randomly chosen time point between 0-th and 3000000-th second and it is positive or negative by a random choice.

Each activity carried out before a certain point in time affects the value of the parameter at that point. Our assumption is that the maximum impact of the activity takes place in a relatively short time after its execution. There are 25 generated activities that begin and end at different time points and they all affect the global parameter change. The global parameter change is a sum of all (25 generated activities) individual influences and it is presented in Fig.4.

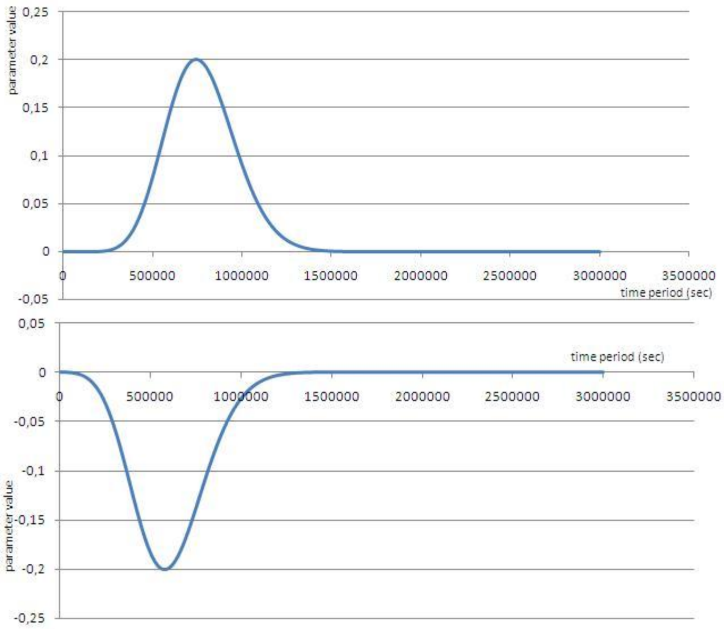

Fig. 3. Graphs of the influence functions for a positive and a negative activity

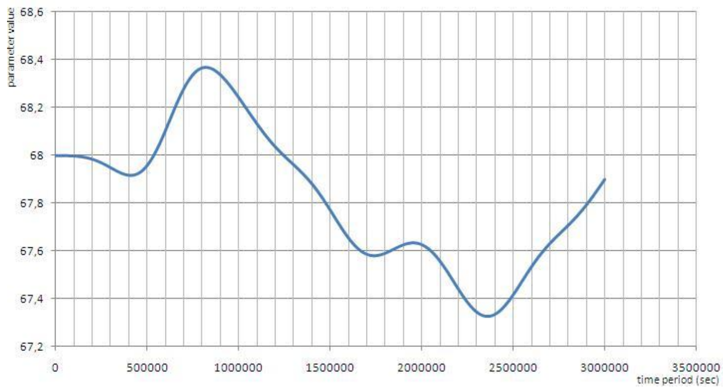

Fig. 4. Graph of the global parameter change in the first simulation

To evaluate the effectiveness of the COHESY using the proposed recommendation algorithm, in the first simulation 28 recommendations in 28 different (random) time points were generated.

In the second simulation 56 activities were generated. Each activity begins at a randomly chosen time point between 0-th and 5000000-th second. The graph of the global parameter change in the second simulation is presented in Fig.5. In this simulation, 45 recommendations were generated in 45 different (random) time points

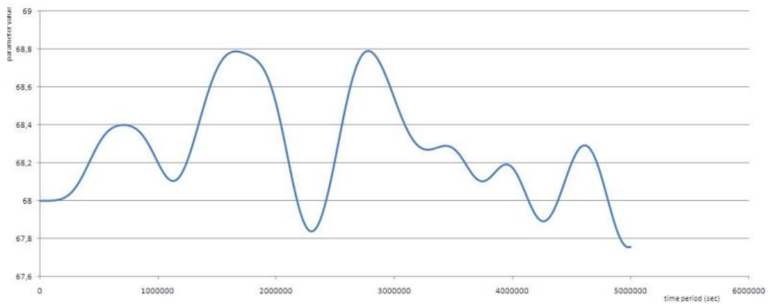

Fig. 5. Graph of the global parameter change in the second simulation

Seventy activities were generated in the third simulation. In this simulation, each activity starts at a randomly chosen time point between 0-th and 7500000-th second. The graph of the global parameter change in the third simulation is presented in Fig.6. In this simulation, 58 recommendations were generated.

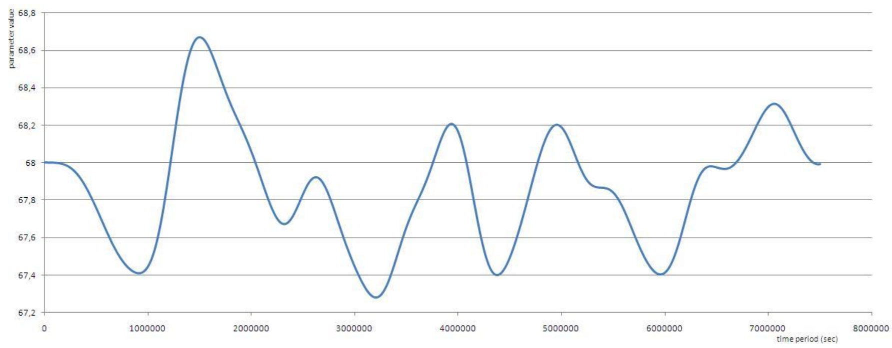

Fig. 6. Graph of the global parameter change in the third simulation

To avoid borderline cases when the value of the parameter is in the normal range, the normal range value of the parameter in the simulations is from 85 to 95. From the presented graphs in Fig.4, Fig.5 and Fig.6 we can see that the value of the parameter in all simulations ranges from 67.2 to 68.8 which is much below the lower limit of the normal value of the parameter. So, the algorithm generates the appropriate recommendations only if the recommendation relates to a positive activity.

From the results we can conclude that the recommendation algorithm in the first simulation generated appropriate recommendations with 82.14% accuracy. In the second simulation, the accuracy of the generated appropriate recommendations is 84.44%, while the percentage of appropriate recommendations generated in the third simulation is 91.38%.

These percentages show that as the number of activities increases and the time period extends, so does grow the percentage of appropriate recommendations generated by the algorithm.

Analyzing the results obtained in all the three simulations, it can be concluded that the time periods, during which the algorithm generates inappropriate recommendations, correspond to the initial period. Because all three simulations use the same algorithm and the same types of activities, it is expected that the time of adaptation or learning period of the algorithm is roughly the same in the three simulations. But while in the first and the third simulation the period in which improper recommendations are generated is about the same length, that period is almost as twice as long in the second simulation.

To discover the reason for the varying length of the period in which inappropriate recommendations are generated, we have analyzed the number and the type (positive and negative) of generated activities in the simulations individually.

Table 1. Percentage of generated activities by type (positive and negative)

	I simulation			II simulation			III simulation		
	no. a.	% p.a.	% n.a.	no. a.	% p.a.	% n.a.	no. a.	% p.a.	% n.a.
1/3 of activities (33%)	8	62,50	37,50	19	73,68	26,32	23	39,13	60,87
1/2 of activities (50%)	13	46,15	53,85	28	71,43	28,57	35	40,00	60,00
2/3 of activities (66%)	17	35,29	64,71	37	70,27	29,73	47	40,43	59,57
total activities	25	40,00	60,00	56	62,50	37,50	70	45,71	54,29

Table 1 illustrates the percentage of positive and negative activities for the three simulations by periods of generating activities. Considering the number and the type of the top 33%, top 50% and top 66% generated activities for each simulation.

The analyses show that in the initial period in the second simulation mostly positive activities are generated, while the number of generated negative activities is significantly lower. In the first and in the third simulation, the number of generated positive and negative activities is not much different. So, it can be concluded that if the number of generated positive and negative activities in the beginning of the simulation is not approximately the same, the period in which inappropriate recommendations are generated increases. This is the case in the second simulation where the period in which inappropriate recommendations are generated is almost twice longer than in the first and third simulation.

Because in the initial period of all three simulations the algorithm generates inappropriate recommendations, the conclusion is that in the proposed algorithm the problem of a cold start occurs. This is a common problem in collaborative algorithms [8]. A possible solution to this problem is to generate prior knowledge before the following simulations. This will also avoid the elongation of the period which generates inappropriate recommendations as well as the issue of a cold start.

4 Conclusion and future work

In this paper a collaborative health care system model and its validation are presented. The proposed model COHESY represents a tool for personal health care by generating various recommendations, comments and suggestions to its users.

COHESY is a complex system composed of mobile application, social network, information systems that are used by the medical personnel, medical databases and additional services. It provides monitoring of health parameters and tracking of the users' physical activities, communication between users, automatic data transfer, data exchange between medical centers and databases. But what distinguishes the COHESY from the rest and its main advantage is the communication and exchange of data between the various components.

Validation of the proposed model is made by evaluating the effectiveness of the recommendation algorithm using generic data. The analysis of data obtained from the simulations of the recommendation algorithm on generic data show that the algorithm generates appropriate recommendations with an accuracy of 82% to 92%. As the time period and the number of activities extends, so does the percentage of appropriate recommendations generated by the algorithm increases.

However, the analyzes showed that the proposed model has deficiencies such as the *cold start* problem and the extension of the initial period in which inappropriate recommendations are generated, which should be treated with more attention in future.

The performed simulations are only an introductory step in the process of evaluating the effectiveness of the recommendation algorithm and the proposed model. In the future, the evaluations of the effectiveness of the proposed model should be done with simulations that will validate the behavior of the algorithm in different conditions (different values of the parameter, more types of activities) and with simulations with real data in order to make a quantitative and qualitative analysis of the behavior of the system.

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