Development of a novel recommendation algorithm for collaborative health – care system model

Igor Kulev[1], Elena Vlahu-Gjorgievska[2], Vladimir Trajkovik[1], and Saso Koceski[3]

[1]Faculty of Computer Science and Engineering, University "Ss Cyril and Methodious", "RugjerBoshkovikj" 16, P.O. Box 393 1000 Skopje Macedonia
{igor.kulev,trvlado}@finki.ukim.mk

[2]Faculty of administration and information systems management, University "St.KlimentOhridski", Bitola, Macedonia
elena.vlahu@uklo.edu.mk

[3]Faculty of Computer Science, University "GoceDelcev", bul. KrsteMisirkov bb. 2000 Stip, Macedonia
saso.koceski@ugd.edu.mk

Abstract. The recent trend in healthcare support systems is the development of patient-centric pervasive environments in addition to the hospital-centric one. Pervasive health care takes steps to design, develop, and evaluate computer technologies that help citizens participate more closely in their own healthcare, on one hand, and on the other to provide flexibility in patients' active everyday life with work, family and friends. This paper presents the mathematical model of a novel algorithm that generates recommendations and suggestions for preventive intervention instead of emergency care and hospital admissions. The main purpose of this algorithm is to find the dependence between users' health condition and performed physical activities. In this way, the proposed algorithm generates recommendations that will help the user to adapt his physical activities in order to improve his own health. These recommendations also encourage users to lead an active life filled with physical activities and thus become direct participants in maintaining their own health care. The proposed algorithm has been validated using generic data. The results of this validation are presented and conclusions are derived.

Keywords: personal healthcare, recommendation algorithm, fuzzy-discretization.

1. Introduction

Implementation of the information system in healthcare institutions improves their efficiency, productivity and work quality, evaluates work, eliminates repetition of data and enables more comprehensive data use. On the other

Igor Kulev, Elena Vlahu-Gjorgievska, Vladimir Trajkovik, and Saso Koceski

hand, general characteristic of the social computing technologies is collaboration - users collaborate to add contents, semantics and models.

The recommendation algorithm, presented in this paper, is part of the Collaborative health care system model called COHESY [1]. This system model enables the user to contact other people with similar condition and exchange their experience. In that way COHESY improves quality of care and life to its users, by offering freedom to enjoy life with the confidence that a medical professional is monitoring theirs health condition.

The main concept of the proposed recommendation algorithm is the impact of the performed physical activity on users' health parameters. What we want to achieve is to find how physical activity, determined by its characteristics (type, duration, path length, etc.), affect the improvement of the users' health condition.

The algorithm generate recommendations using a variety of data: data from users' bionetwork, data of user's physical activities (saved by a mobile application or a social network), the user's health records (obtained from medical centers), data from the users' social network profile and prior knowledge gained on the basis of previous experiences of other users of the social network that have similar characteristics with the considered user.

The main purpose of this algorithm is to find the dependence between users' health condition and performed physical activities. To achieve this in the proposed recommendation algorithm we apply classification and filtering algorithms in order to group users with similar characteristics. Such use of classified data provides relevant recommendations based on prior knowledge of users with similar health conditions and reference parameters.

Description of the recommendation algorithm is in the fourth section. Validation of the algorithm is covered in the fifth section. The sixth section contains conclusion and future work.

2.   Related work

There are many researches working on solutions for better health care of patients and systems that will help to have continuous monitor of the health of the patients. Although all proposed solutions have similarities, they are all different and have own unique features.

Lee et al. [2] propose an intelligent mobile healthcare information system with alert mechanism. Proposed system provides constant monitoring of patient's health parameters along with professional medical support. The system consists of three components: medical server, mobile device and reading device for health parameters. Its architecture allows the simplicity of hardware design, high flexibility of the architecture and the opportunity to expand the system functions. The alert mechanism supports different urgency levels and provides different priorities to multiple healthcare providers. Thus, it automatically notifies the right persons at the right time, which could ensure the accuracy of information and the completeness of notification. This can

save the medical resource without sacrificing any need of healthcare to the patient.

Jog Falls system [3] is an end to end system to manage diabetes that blends activity and energy expenditure monitoring, diet-logging, and analysis of health data for patients and physicians. This is an integrated system for diabetes management providing the patients with continuous awareness of their diet and exercise, automatic capture of physical activity and energy expenditure, simple interface for food logging, ability to set and monitor goals and reflects on longer term trends. Its backend interface gives physicians comprehensive and unbiased visibility into the patients' life styles with respect to activity and food intake, as well as enabling them to track their progress towards agreed upon goals. The main emphasis authors place on its novel method for fusing heart rate and accelerometer data that improves the accuracy of energy expenditure estimation (a key feature in enabling weight loss).

The papers [2], [3] include detailed research of systems that cover only parts of our system model COHESY. These systems have no social network and collaborative algorithms, which enables gathering data for different users. The social network and collaborative algorithms are the main advantages of our system COHESY.

Personal healthcare provides an opportunity to achieve proactive treatment by which problems can be addressed and prevented at the earliest possible stage. Therefore is developed system MediNet [4] which personalizes the process of healthcare by sending personalized messages to the patients. The system offers messages customization at two levels. The first level of personalization is done on the basis of a group of patients who have the same disease and common features, while the second level is based on features that are specific to a particular patient. MediNet uses a reasoning engine to generate a personalized message to a patient based on current and previous readings from monitoring devices connected to the patient, patient's profile, location, and the content and purpose of medical treatment. Messages are formatted according to several different types of forms and structures depending on the need. Using personalization as an important aspect in the process of medical treatment is the main advantage of MediNet compared to other systems.

In COHESY besides monitoring of health parameters, physical activities are also monitored, which is not a case in MediNet [4]. Although the both systems (COHESY and MediNet) generate recommendations, there is substantial difference in these recommendations. MediNet generate messages based on current and previous information that is known about the patient, without using any collaboration. Opposite of this, COHESY generate recommendation for a specific activity that user should perform in order to improve his health. The recommendation in COHESY is based on users' given health condition and set of knowledge derived from the history of the user and users like him.

In the paper of Cortellese et al. [5] authors present two different approaches (static and dynamic clustering) to personal diagnosis, for the

provision of innovative personalized services. The presented case study describes a service for physical activity support, where (diabetic) patients receive motivational feedbacks to improve their performances. In that way motivational messages are sent to the patients, with the aim to give feedback on the performance and to motivate the patients to improve, giving advice to support their walking activity. Their proposal for the second approach (dynamic clustering) is to apply the choice - which message to be sent to the user. In this approach, two recommendation services are possible: the patient will be provided with messages similar to the ones that worked better in the past or the patient will be provided with messages that worked with people with similar characteristics and preferences in the past.

Despite differences in the recommendations/messages that are generated in both systems (e.g. COHESY recommend different activities with different intensity and duration) the essential difference is the evaluation of the recommendation. Unlike the model in [5] where the validation is done only on the basis of whether the activity is carried out or whether the user has updated the data, it is not the case in COHESY. In COHESY evaluation is done based on the improvement of the health parameters after performing physical activity by the user. This actually is major input parameter in the process of generating recommendations by the COHESY algorithm.

3. A Brief Overview of COHESY

COHESY is deployed over three basic usage layers. The first layer is consisting of the bionetwork (composed of various body sensors) and mobile application that collects users' bio data during various physical activities (e.g. walking, running, cycling) and users' health parameters (e.g. weight, blood pressure, blood-sugar level and heart rate) (Fig.1).

The second layer is presented by the social network implemented as a web portal which enables different collaboration within the end user community. The communication between the first and second level of Cohesy is implemented within the framework of SportyPal mobile collaborative system [9] which also includes active social network available at SportyPal.com [9] with more than 450000 active users. The social network at SportyPal.com additionally allows users to analyse their results, to compare them with the results of other users or to comment all results.

The third layer should enable interoperability with the primary/secondary health care information systems which can be implemented in the clinical centers and different policy maker institutions. We have defined the communication and data exchange protocols between the third and previous two layers, with emphasis on personal data privacy and security. Currently the access to patients' medical records is not available because the communication with the information systems used in institutions of primary and secondary health care is still not established.

Fig.1. Mobile application displaying details (current values of the parameters) related to the current user's exercise

In COHESY, mobile technologies are used to support and enable collaboration. It not only offers the possibility of sending an emergency call for sudden deterioration of user medical condition, but also gives opportunity for the users not to be restricted in their movements or their location. By using their mobile phone (the installed application) they have access to the medical personnel at any time. Mobile application can connect to a remote server (clinical center) through TCP/IP, GPRS (whichever is available in the area or the least costly in case of multiple services availability) and transfer the data to it. The remote clinical center will receive the data, invoke process to perform analysis of data, and provide feedback to the user cell phone notifying the decision given by the clinical center.

At the same time, the user individual data can be compared with average data obtained, using different collaborative filtering techniques in the social network. Namely, mobile application give opportunity to send data received from sensors to social network (if previously the user have agreed with conditions,security and privacy statements of the social network), while user has the possibility to choose which of them will send, but with no option to edit them and when to send.

Social network can provide interface and use data from a variety of medical databases and environmental databases (temperature, wind speed, humidity). For example, it enables matching of performed user activity, combining this various data: length of path crossed, duration, speed of movement, medical condition of the user (heart rate, blood pressure, occurrence of arrhythmia), weather conditions (atmospheric pressure, humidity, temperature), what is the medical diagnosis or therapy of the user (if there are any) and can generate recommendation when certain user should perform walk, with what pace and duration. Social network allows direct communication between users (if approved by the user and stored in the user profile), sharing their results and

exchange their experience. Even more important, the social network can learn from recommendation (given to the user from medical personnel) and generate notifications and recommendation based on the most successful scenarios.

This complex structure of data from a social network along with the data arriving from different clinical centers can be used by different medical databases for further analysis and research.

COHESY creates the opportunity for increasing user health care within their homes by 24 hour monitoring on the one hand, and increasing medical capacity of health care institutions on the other hand. This results in reducing the overall costs for users and hospitals and improves the user's quality of life [6]. It provides a better health care allowing suggestions and recommendations based on knowledge from other users, cases and experience.

4. Recommendation Algorithm

The recommendation algorithm is part of the second level of COHESY (the social network). It is implemented as a web service and its main purpose is to recommend the physical activities that the users should carry out, in order to improve their health.

This web service uses the data read by the bionetwork, the data about the user's physical activities (gathered by the mobile application), user's medical record (obtained from 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 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 users and use classification algorithms on these datasets for grouping the users based on their similarity. Use of classified data when generating the recommendation provides more relevant recommendations, because they are enacted on knowledge for 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, geographic region, 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 modelled 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 modelling. Therefore, in

our 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 parameter, several discretization intervals are considered. Each person has a corresponding membership factors for each of those intervals, depending on his/her parameter value. For example, if parameter P is described with three discretization intervals A, B and C, a person's membership factors for this parameter are (a, b, c) where a, b and c are values in the range [0, 1] and they represent how strong the person belongs to the corresponding interval.

At this stage we decided to take into account the health parameters such as blood pressure and blood sugar levels.The value of these parameters can be measured by the user using non-invasive methods. Currently there are devices [10, 11] capable of reading the value of users' blood pressure and blood sugar levels and loading them directly into the mobile device. That allows easier, faster and more efficient reading of the values of users' health parameters. In our further work, other health parameters, such as cholesterol level, can be taken into account. Values of these parameters can be read from the user's medical health records.

In our approach, the user's feature vector is defined with four parameters: body mass index, age, blood pressure and blood sugar levels. Moreover, the location of the user and his heart rate are also considered. The heart rate is used as an indicator for the intensity of the activities that should be performed by the user. While the user's location is used in the process of finding the most similar users that are geographically closer to the analysed one.
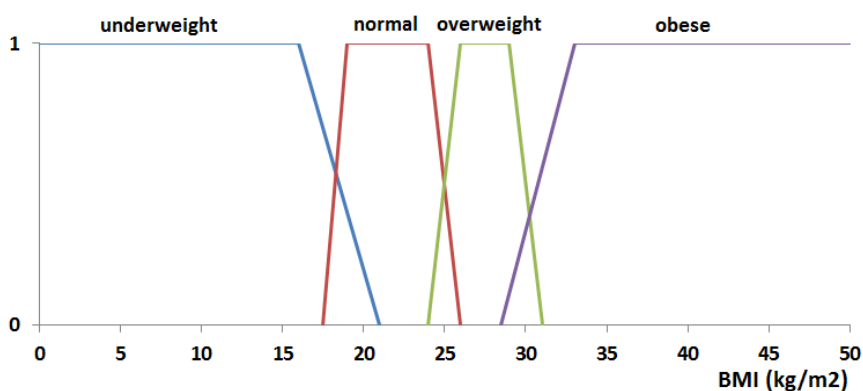

Fig.2. Discretization functions for BMI.

BMI. BMI (body mass index) is a height-weight indicator for obesity (body fat) of the individual. This indicator is defined as the ratio of the weight of the individual and the square of his height as Eq.(1).

$$BMI = \frac{mass\,[kg]}{(height\,[m])^2}$$

. (1)

BMI discretization intervals are defined as: underweight, normal, overweight, obese. These intervals are taken by the classification obtained from the World Health Organization [7]. The correspondent membership functions are presented in the Fig. 2.

AGE. The discretization intervals of the user's age are defined as: child, teenager, young adult, middle-aged, senior and elderly and the membership functions are presented in Fig. 3.
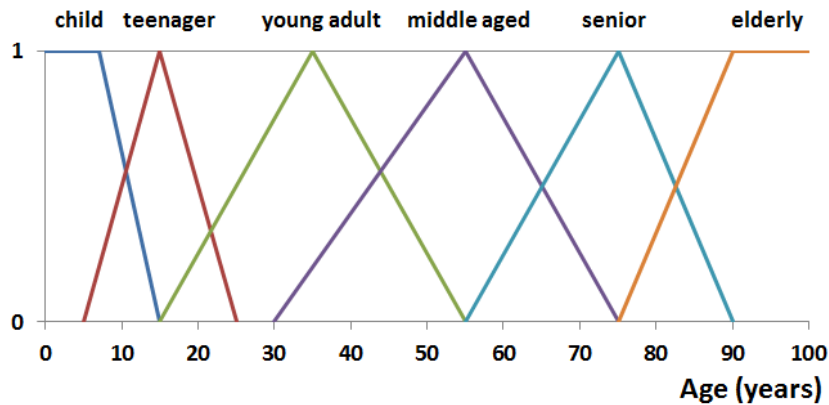

Fig.3. Discretization functions for age
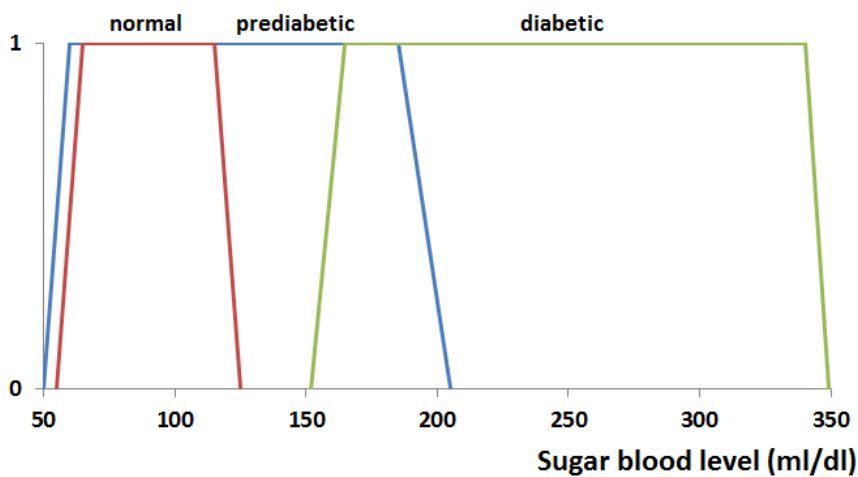
Fig.4. Discretization functions for sugar blood level

BLOOD PRESSURE. The discretization intervals of the value of the users' blood pressure are: optimal blood pressure, normal blood pressure, normal systolic value, mild hypertension, moderate hypertension and severe hypertension/high blood pressure. In the discretization process the value of both, systolic and diastolic, blood pressures are taken into account.

SUGAR BLOOD LEVEL. The discretization intervals of the users' sugar blood level are defined as: normal, pre-diabetic and diabetic [8], and the membership functions are shown in Fig. 4.

Reading of the parameters is performed at certain intervals. While each reading is performed, all read parameters are written in the memory in the form: *parameter (parameter code), value, date / time (or number of reading).*

The classification of users is done at regular intervals (e.g. once a week) and the recommendation of the activities is done according to the following algorithm:

STEP 1. All the users with a certain diagnosis (e.g. people with increased sugar level) as the user u_* are filtered out. The other users will not be considered in the next steps of the recommendation algorithm.

$$U' = filterUsers(U, u_*), U' \subseteq U \quad . \tag{2}$$

STEP 2. Find *M* most similar (neighbour) users, for an active user based on the similarity of the respective membership factors for all parameter values and the closeness of their geographical location.

$$P' = parametersForEstimatingSimilarity(P), P' \subseteq P \quad . \tag{3}$$

The similarity coefficient between the given user u_* and any other user u_i of the set *U'* is calculated as in Eq.(4).

$$d_{*,i} = \sum_p^{p'} t_p \cdot normalize(\sqrt{\frac{\sum_l^{Lp}(MV_{*,p,l} - MV_{i,p,l})^2}{num(L_p)}}) \quad . \tag{4}$$

Where *Lp* represents the set of classes for parameter p, $MV_{u,p,l}$ represents the membership value for user u, class l of parameter p, the function *num(*)* gives the number of elements in given set, function *normalize(x)* returns a normalized value in the interval [0, 1] and the coefficient t_p define the weight of each parameter i.e. its contribution to the similarity. The set of M similar users *U"* to the active one are chosen to be those with the smallest value for $d_{*,i}$.

STEP 3. Filter the activities that may harm the user or which do not have a positive effect on the user. The set of feasible activities A' is calculated using the user's data for certain parameters:

$$P'' = parametersForFilteringActivities(P), P'' \subseteq P \quad . \tag{5}$$

$$A' = filterActivities(u_*, A, P'') \quad . \tag{6}$$

STEP 4. Find the benefits of performing activity *a* to improve parameter *p* for the user *u*. The benefit of performing activity *a* by the user *u* for parameter *p* is calculated by Eq.(7).

$$V_{u,a,p} = \frac{importance_p \cdot \sum_{i=1}^{Nu,a} \left(\frac{\left| \frac{PVnew(u,o,a_{i,u}) - PVold(u,o,a_{i,u})}{uLimit_p - lLimit_p} \right|}{\ln(period_{a_{i,u}})} \cdot dir_{p,a_{i,u}} \cdot validitya_{i,u} \cdot intensity \right)}{Nu,a} \tag{7}$$

.

$N_{u,a}$ is the number of reviewed readings of activity per user. $PV_{old,u,p,aiu}$ is the previous and $PV_{new,u,p,aiu}$ is the next read value of the parameter, in time closest to activity $a_{i,u}$. $limit_{lower,p}$ and $limit_{upper,p}$ represent the range of the value of the parameter. $Period_{aiu}$ is the time interval between the two readings of the parameter. *Intensity* is the value of the intensity of performed activity and it's calculated by an appropriate formula. *Importance*$_p$ represents the importance of this parameter for a monitored user (the bigger importance of the parameter for the health of the user - the higher its coefficient is). The activity can be beneficial for the user if it causes change of the parameter value towards its optimal value. When the change of the parameter's value is beneficial $dir_{p,aiu} = 1$ and in the other case $dir_{p,aiu} = -1$. *Validity*$_{aiu}$ is a boolean function (0/1) that presents the impact of the examined activity on the given parameter. Namely, if the activity is performed in short time interval before the reading of the parameter than that activity does not affect the parameter change. Impact of the activity is also negligible when the activity is performed much earlier before the reading of the parameter. Thus the impact of a certain activity on a given parameter can be modelled using a function whose shape is similar to a Poisson probability mass function.

STEP 5. Make matrix of useful activities per user. First, the benefit of performing activity *a* by the user *u* is calculated by Eq.(8).

$$V_{u,a} = \sum_{p}^{p''} V_{u,a,p} \quad \forall u, u \in U'', \forall a, a \in A', \forall p, p \in P''. \tag{8}$$

u is chosen from the set of similar users *U''* to the given user *u*$_*$ for whom a recommendation should be generated. Activity *a* is chosen from the set of feasible activities *A'* for the user *u*$_*$. Using these values we form the matrix (Eq.(9)) of useful activities per user.

$$M = \begin{matrix} & \begin{matrix} A_1 & \cdots & A_r \end{matrix} \\ \begin{matrix} U_1 \\ \vdots \\ U_m \end{matrix} & \begin{bmatrix} V_{1,1} & \cdots & V_{1,r} \\ \vdots & \ddots & \vdots \\ V_{m,1} & \cdots & V_{m,r} \end{bmatrix} \end{matrix} \tag{9}$$

.

*STEP 6.*Considering the activities that have the biggest usefulness value for each user, a new vector Eq.(11) is formed according to the criteria presented in Eq.(11).

$$UA = \left[UA_1 .. UA_m\right].$$
(10)

$$\forall i = 1,...,m \ UA_i = k \ where \ V_{i,k} = \max_{j=1,..r} V_{i,j}.$$
(11)

UA_i is the number (code) of activity that has the greatest usefulness for user *i=1,..,m*.

*STEP 7.*The activity that has the biggest usefulness for the most of the users is selected and recommended to the observed user.

$$\forall k \in A' \ count(k) = \sum_{i=1}^{m} \begin{cases} 1, k = UA_i \\ 0, k \neq UA_i \end{cases}$$
$$RA = u \ where \ count(u) = \max_{k \in A} count(k).$$
(12)

5.   Validation of the recommendation algorithm

Our recommendation algorithm tries to find the usefulness of each type of activity on the bio-medical parameter change. Activity is considered useful if it changes the global parameter value towards the desired one. The change of a parameter value might be influenced by many factors. It is impossible to make a mathematical model that takes into account all these factors, so we tried to make a model for the parameter change, under the influence of the activities performed, that is simple and as closer to the reality as possible. We assume that each performed activity has some influence on the parameter change and that the parameter change is influenced only by the effect of the activities (pharmacological influence is neglected). Various activities show the maximum of their effect in different time intervals from their beginning.

We model a single activity influence to the global parameter change by a function whose shape is similar to a Poisson probability mass function (Fig.5). In our model, it depends on several variables: type of activity, the time moment at which the user starts to practice a certain activity, activity's duration, intensity and frequency.

The peak of the model function can have either positive or negative amplitude depending on whether it has a stimulatory or inhibitory effect correspondingly. The influence of all other parameter is modelled by adding a Gaussian noise to the curve whose standard deviation at a certain point is proportional to the absolute value of the function at that point.
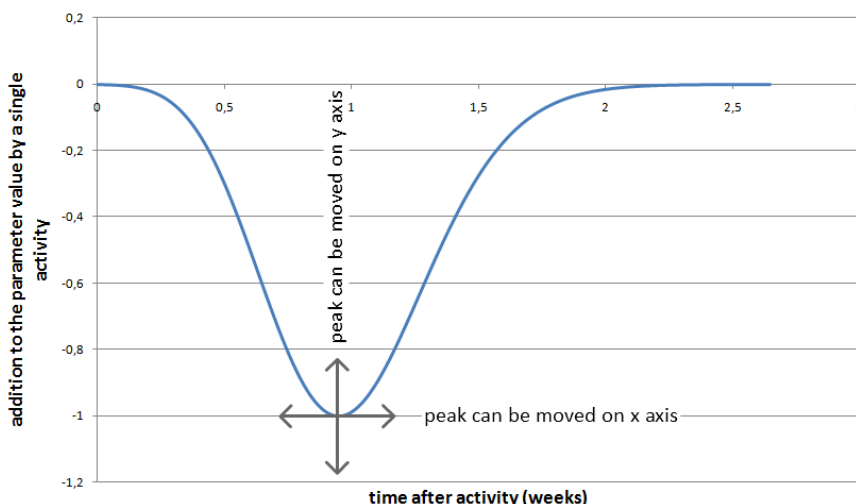
Fig.5. Influence by a single activity on the global parameter change

When multiple activities from different type are performed, each of them influences the value of a certain parameter in a given moment. So, the parameter value at each moment of time can be defined by the expression in Eq.(13).

$$f(t) = \sum_i h(a_i, timeOfStart_i, duration_i, \mathrm{int}\, ensity_i\, frequency_i, t) \qquad (13)$$

In order to test the recommendation algorithm we generate many activities uniformly at random. We also take measurements uniformly at random. Noise is also added to the global parameter function. On Fig. 6 and Fig. 7 we can observe two global parameter functions, the first one without noise and the second one with noise.

The simplest case to test the correctness of our algorithm is to use two types of activities which are symmetrical. The first one has positive peak amplitude and the second one has negative peak amplitude. Our algorithm should "guess" which activity increases the parameter value and which doesn't. If we flipped a coin we could guess with 50% accuracy which activity has more usefulness (in our experiment we assume that activity is useful if it increases the global parameter value). In our simulator we use these parameters:
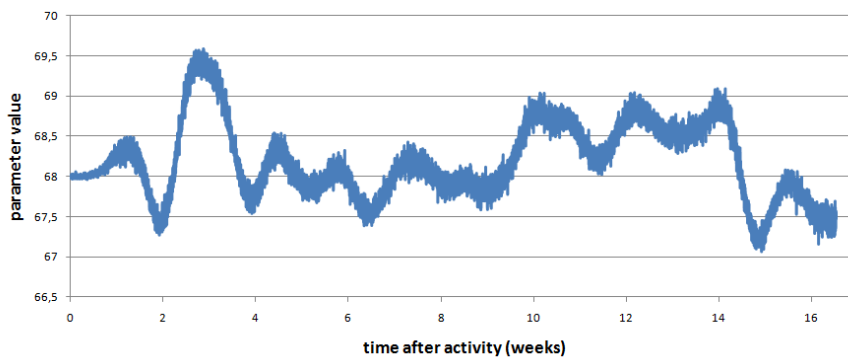
- Duration of the simulation

- Average time between consecutive activities

- Average time between consecutive measurements

- X coordinate of the peak

- Y coordinate of the peak

- Standard deviation of the peak (x coordinate)

- Standard deviation of the peak (y coordinate)

- Standard deviation of the Gaussian noise (single influence)

- Standard deviation of the Gaussian noise (global parameter function)
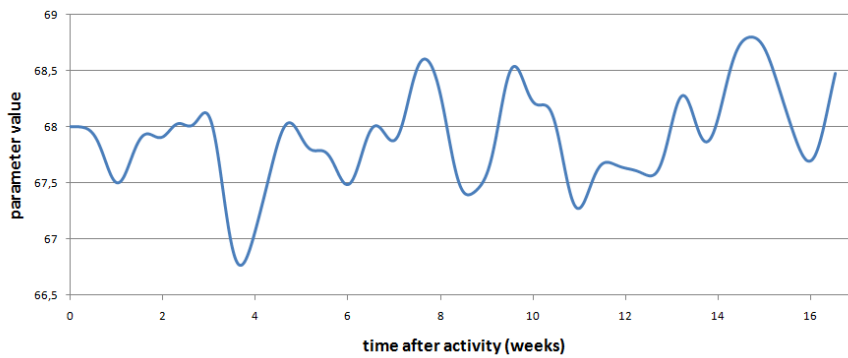

Fig.6. Global parameter function without noise

Fig.7. Global parameter function with noise

We expected that by increasing the standard deviation we would get lower accuracy, but by increasing the duration of the simulation and the average

time between consecutive activities we would get higher accuracy. Longer duration of the simulation means more activities and more data and longer average time between consecutive activities means that it could be easier to distinguish between consecutive activities by observing the global parameter function. On the other side, longer average time between consecutive measurements means that we will have less data for our recommendation algorithm and less accurate recommendations. We applied our recommendation on generic data and we obtained correct results when we didn't have standard deviation of the peak and of the noise. We wanted to know how the algorithm behaves when we change the parameters of the simulation. We were especially interested how the accuracy of the recommendation algorithm changes in the border cases (Fig. 8 and Fig. 9).
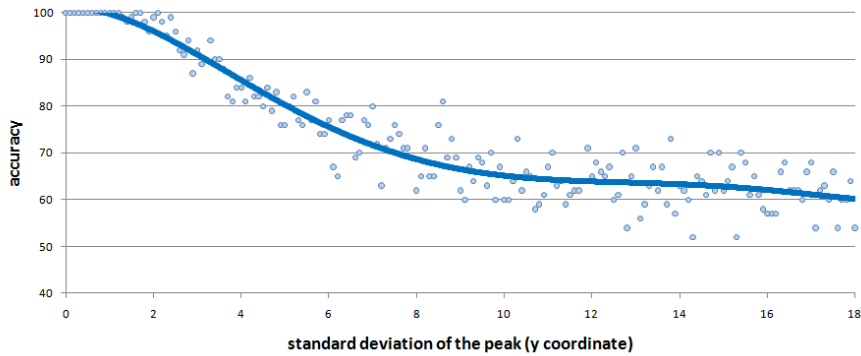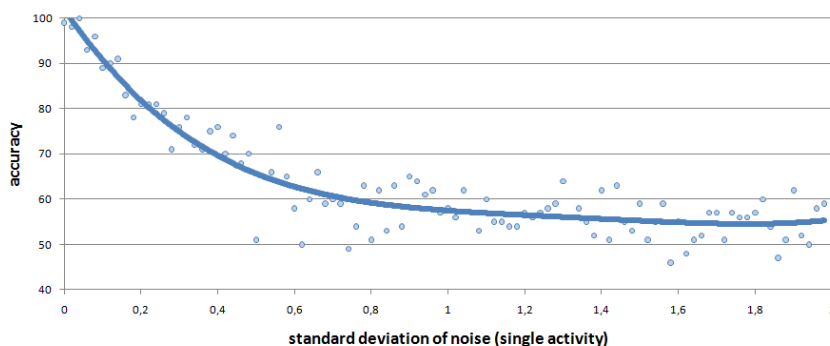

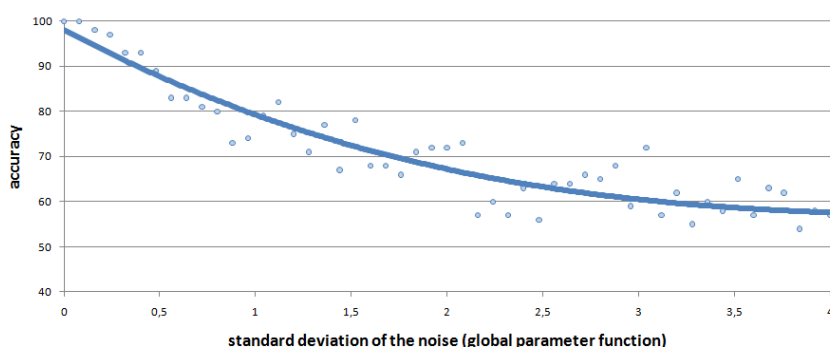**Fig.8**. Accuracy as a function of the standard deviation of the peak (y coordinate)
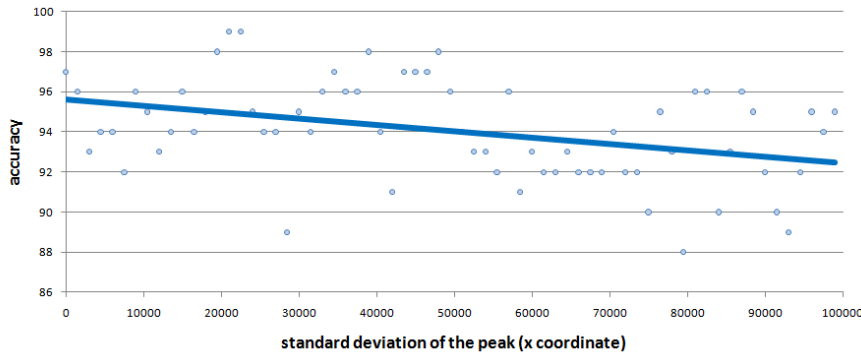
Fig.9. Accuracy as a function of the standard deviation of the peak (x coordinate)

Fig.10. Accuracy as a function of the standard deviation of the noise (single activity)

Fig.11. Accuracy as a function of the standard deviation of the noise (global parameter function)

We chose a set of values for the parameters of the simulator in order to see more clearly the way the accuracy changes. We tried to define a curve that fits the results we obtained. In the first case, when we observed the accuracy as a function of the standard deviation of the peak (y coordinate) we noticed that there is some threshold after which the algorithm gives bad results, however, this threshold is relatively big comparing to the amplitude of the peak. Surprisingly, the increasing of the standard deviation of the peak (x coordinate) didn't cause significant worsening of the results.

The increase of standard deviation of the noise caused exponential decline of the accuracy. This is shown on Fig. 10 and Fig. 11.

6.   Conclusion and Future work

In this paper we present a recommendation algorithm as a part of collaborative health care system model - COHESY. The main purpose of this algorithm is to find the dependency of the users' health condition and physical

activities he/she perform. To achieve this we consider datasets from the health and physical activities history of users and use classification algorithm on these datasets for grouping the users based on their similarity.

Recommendation algorithm gives to the user recommendation for performing a specific activity that will improve his/her health. This recommendation is based on users' given health condition and set of knowledge derived from the health and physical activities history of the user and users like him/her.

To evaluate the proposed recommendation algorithm a model of an activity influence to the global parameter change was used. The experiments conducted with generic data show that the algorithm increased with the duration of the observation i.e. with the number of activities observed and the amount of data obtained. We have also evaluated the behaviour algorithm on the increased data uncertainty. The results show that the algorithm is very robust and promising.

The generated recommendations should allow the user to adapt and align his/her physical activities, while improving his/her health condition and overall way of rehabilitation, meaning to be fully able to take self-care and professional concern about his/her health.

We would like to emphasize that one of the advantages of Cohesy, its recommendation module, although developed and available, is still not integrated in the SportyPal system. However, we are convinced that in our further work, we will be able to integrate the module for generating recommendations based on the recommendation algorithm that we have proposed, and will succeed to evaluate its functionality and benefits through the SportyPal system.

References

1. Vlahu-Gjorgievska, E., Trajkovik., V.: Towards Collaborative Health Care System Model – COHESY. In Proceedings of the 2011 IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WOWMOM '11), IEEE Computer Society, Washington, DC, USA, 1-6. (2011)
2. Lee, R.G., Chen, K.C., Hsiao, C.C., Tseng C.L.: A Mobile Care System With Alert Mechanism. Transactions on Information Technology and Biomedicine, Vol.11, No.5, 507-517. (2007)
3. Nachman, L., Baxi, A., Bhattacharya, S., Darera, V.: Jog Falls: A Pervasive Healthcare Platform for Diabetes Management. Pervasive Computing, Vol. 6030, 94–111.(2010)
4. Mohan, P., Marin, D., Sultan, S., Deen, A.: MediNet: Personalizing the Self-Care Process for Patients with Diabetes and Cardiovascular Disease Using Mobile Telephony. In Proceedings of 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vancouver, Canada, 755-758. (2008)
5. Cortellese, F., Nalin, M., Morandi, A., Sanna, A., Grasso, F.: Personality Diagnosis for Personalized eHealth Services. In Kostkova, P.(ed.):Electronic Healthcare. Lecture Notes of the Institute for Computer Sciences, Social

Informatics and Telecommunications Engineering, Vol.27. Springer, Berlin Heidelberg, 173–180. (2010)

6. Zimmerman, T., Chang, K.: Simplifying home health monitoring by incorporating a cell phone in a weight scale. In Proceedings of1st international conference on PErvasive Technologies Related to Assistive Environments, ACM Press, New York, 1-4. (2008)

7. http://apps.who.int/bmi/index.jsp?introPage=intro_3.html [Accessed September 2012]

8. http://diabetes.co.in/blood-sugar-levels/ [Accessed September 2012]

9. http://www.sportypal.com [Accessed September 2012]

10. Wayner, P.: Monitoring Your Health With Mobile Devices, The New York Thimes, published Fevruary 22, 2012. (http://www.nytimes.com/2012/02/23/technology/personaltech/monitoring-your-health-with-mobile-devices.html?_r=0)

11. http://www.diabetes.co.uk/blood-glucose-meters/smallest-blood-glucose-meters.html [Accessed September 2012]

Igor Kulev is a junior teaching and research assistant at the Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University, Skopje, Macedonia since 2011. He received Master degree in Computer Science in 2013 at the Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University. His research interests include algorithms and data structures, collaborative computer systems, machine learning and data mining.

Elena Vlahu-Gjorgievska received the PhD degree from the Faculty of Computer Science and Engineering at the "Ss. Cyril and Methodius" University in Skopje, in 2013. She is currently an Assistant Professor at the Faculty of administration and information systems management at the University "St.KlimentOhridski" in Bitola, R. Macedonia. Her research interests include information systems, e-Health and collaborative algorithms.

Vladimir Trajkovik received Ph.D. degrees 2003. He joined the Ss. Cyril and Methodious University, Skopje, R .Macedonia, in December 1997. His current position is the Associate Professor and the Vice Dean for Science at the Faculty of Computer Science and Engineering. He is currently responsible for several courses at undergraduate level, and "Mobile and Web Services", "Collaborative Systems" and "Innovative Technologies" at postgraduate level. He is an author of more than 100 journal and conference papers.

Saso Koceski obtained his PhD in robotics and artificial intelligence in 2009 from the University of L'Aquila, Italy. Currently he is an assistant professor at the Faculty of Computer Science, University "Goce Delcev"-Stip, Macedonia and head of the Institute of Computer Science at University "Goce Delcev"-Stip. He is an author or co-author of more than 60 refereed journal and conference papers and book chapters. He serves as an editor and reviewer in several SCI journals. His current research interests are focused in the field of bioengineering, robotics and artificial intelligence, bioinformatics, HCI and medical imaging.