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Fuzzy optimization to improve mobile wellness applications for young-elderly

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Abstract

Mobile applications and specifically wellness applications are used increasingly by different age-segments of the general population. This is facilitated by the large amount of data collected through various built-in sensors in the smartphone or other mobile devises, e.g. smart watches. Young-elderly cohort (60-75 year old individual) is probably one of the most potential user groups that would benefit from using mobile health and wellness applications, if their needs and preferences are precisely addressed. General knowledge is limited on understanding to what extent mobile wellness applications can and should provide precise recommendations which improve the users' health and physical conditions. To address this problem, the current study identifies the potential benefits of utilizing fuzzy optimization tools to design recommendation systems that can take into consideration the (i) imprecision in the data and (ii) the imprecision by which one can estimate the effect of a recommendation on the user of the system. The proposed approach, depending on the context of use, identifies a set of actions to be taken by the users in order to optimize the physical or mental condition from various perspectives. The model is illustrated through the example of walking speed optimization which is an important issue for the young-elderly.

Keywords: Possibilistic Optimization, Mobile Wellness Application, Young-Elderly, Chance Constrained Programming

1 Introduction

An important issue in modern society is to continuously improve health-related decision making. The needs and requirements of different age segments are not necessarily similar to each other. The use of mobile technology can greatly support users' health status if the underlying decision support tool can properly take into consideration the specific (and individual) requirements. An important and increasing segment of the population is young-elderly: the group of individuals aged between 60 and 75 years old (Haddon & Silverstone, 1996).

The number of senior people is constantly growing which has implications for many countries around the world (e.g., economic implications on the healthcare expenditures). Statistics Finland[1] reports that over 14% of the total population of Finland was between 65-79 years old and it is estimated that the total number of Finnish citizens aged 65 or over will be approximately 23% in 2020 and it will reach 25.6% in 2030. The growth rate in other EU countries shows a similar trend, for instance, it is estimated[2] that 25% of the Dutch population will be over 65 years old in 2038. Given the rapid growth in aging population and the latest advancement in mobile technology, one can argue that mobile health interventions and wellness applications could be solutions to expand the range of healthcare delivery options, reducing the healthcare expenditures and supporting health-related issues of aging adults.

For instance, it has been pointed out that physical activities on a regular basis could increase longevity and assist older adults to maintain their independence (Singh, 2002; Paterson, Jones & Rice, 2007). This is agreed on by Weuve et al. (2004) who show that regular walking can reduce stiffness and aid cardiovascular health and it is known as one of the most common and practical activities practiced by older adults to stay active. To help older adults to maintain and modify their walking pace, Qian et al. (2011) develop a mobile (wellness) application prototype which sends tactile feedback and auditory information to users to maintain their walking pace.

Fuzzy set theory has been introduced by Zadeh (1965) as an approach to deal with uncertainty different from randomness. In many real life situations, the available data cannot be specified either precisely or by relying on the tools of traditional probability theory. In these cases, the two most important sources of uncertainty present in a data relates to (a) the lack of available information to establish precise statement (imprecision) and (b) the uncertainty inherent in quantifying natural language and linguistic description of different phenomena (vagueness). In most of health-related decision making problems we have to deal with data that is imprecise (data collection methods with sensors, manual input by users) and user preferences that are unique for every individual. For example, a heart rate measurement for an individual: (i) provides an imprecise estimation of the actual heart rate and (ii) the same value for different individuals can indicate different health conditions.

In this article, we show how these two aspects can be incorporated into optimization models to be used in mobile wellness and health applications. We specify a general class of models based on imprecise information that can be tailored to specific wellness and health decision problems as a recommendation system. In the optimization model, the parameters and the variables are represented by fuzzy numbers reflecting the imprecise nature of wellness/health recommendations in the sense that they usually apply to "average" people, not to specific individuals. We formulate chance constrained

1 Population Structure 2013. http://www.stat.fi/til/vaerak/2013/vaerak_2013-2014-03-21_en.pdf
2 Population grows to 17,5 million in 2038,
http://www.cbs.nl/nl-NL/menu/themas/ bevolking/publicaties/artikelen/archief/2008/2008-085-pb1.htm

models using the specified fuzzy numbers. The use of the model is illustrated through the example of walking speed optimization by considering several health-related criteria.

The rest of the paper is structured as follows. First, we briefly discuss the literature related to mobile health and fuzzy sets. Next, we present an approach to personalized health and wellness decision support with smart-phones, and representation of health data using fuzzy sets; this is followed by the conceptual description of the optimization model. Then, we present a numerical illustration of the general approach in the case of a recommendations system for running exercises and in the final section the conclusion and future work is discussed.

2 Literature Review and Preliminaries

In this section, we summarize the most important contributions from the literature in health-related decision support systems focusing on two perspectives: (a) systems developed for mobile devices, specifically considering the young-elderly age segment, and (b) solutions utilizing fuzzy set theory. As we will see, one can find only a limited number of research articles in the intersection of these domains. Regarding fuzzy set theory applications, fuzzy optimization tools are practically absent from health decision support systems.

2.1 Mobile Health Intervention

Mobile health applications are being increasingly designed and developed to improve healthcare service delivery. These types of mobile technology-based health interventions provide support and services to (i) healthcare providers (e.g., support in diagnosis or patient management) as well as (ii) communicate between healthcare services and patients (e.g., appointment reminders and test result notification) (Free et al., 2013). There is a plethora of mobile health and wellness applications in the market, each of which has a range of functionalities and benefits. For example, to help people suffering from different types of Diabetes, Ajay and Prabhakaran (2011) argue that while, patients need to educate themselves on self-care practices such as blood-sugar monitoring, adherence to recommendations on diet, exercise and regular foot inspection, the existing mobile applications in Diabetes care provide benefits in three domains: (i) to health systems (e.g., remote patient monitoring and promoting evidence-based management through decision-support software applications); (ii) to physicians (e.g., tool for continuing medical education and receive guidelines and advice); (iii) to the patients (e.g., tool for self-management and reminders for drug intake and follow-up visits).

In an attempt to maintain and improve the older adults' walking behaviour through tactile signals and multimodal feedback, Qian et al. (2011) develop a prototype using mobile technology to amplify vibrations which enables older adults to monitor and improve their walking habits. The authors conclude that, redundant auditory information together with the tactile feedback help older adults to maintain a desired level of pace more consistently and improved their walking habits after the experiment.

Another important aspect is the usage of these types of services among this particular age group. Young-elderly are lagging behind in adopting and using mobile technology-based interventions such as wellness applications. Nikou (2015) has recently shown that the research in this domain is in its early stage and concluded that most of the current service and applications, if not all, have not been designed according to the specific needs of this particular age group. Unlike the younger generations who are the main users of mobile (smart) devices and technologies, young-elderly, due to specific physical and functional challenges has different needs and preferences with regard to using (advanced) mobile services. Although they are more likely to experience different health issues such as high blood pressure and hearing loss, followed by more natural but negative health issues like memory loss, Alzheimer's, and Parkinson's, recent advances in mobile technology-based interventions can be used to the advantage of this age group to support their health conditions by making, for instance, simple lifestyle changes in their daily routines and start using mobile wellness applications on a regular basis. Ahtinen, Huuskonen and Häkkilä (2010) claim that mobile wellness applications by providing tracking or sharing the personal data can motivate people to exercise and perform more physical activities. By leveraging the existing built-in sensors in smart phones, a mobile wellness application which records various personal data such as the level of activity, heartbeats of a user and body temperature can provide personalized recommendations to the users.

2.2 Fuzzy sets for health-related decision making

One of the main application areas of fuzzy logic and fuzzy set theory concerns decision making problems in the presence of imprecise or vague information. A typical situation of this type is when the decision has to be performed by relying on the evaluations provided by an expert or a set of experts. This is typically the case in medical decision making: doctors rely on their extensive experience when making a diagnosis. A typical example of utilizing fuzzy logic in medical decision making is presented by Yao and Ya (2001), where the authors propose models that utilize different fuzzy relations (symptoms disease, patient-symptoms). In general, different mathematical approaches based on fuzzy sets have been extensively used in medical decision making problems (Abbod et al., 2001; Mahfouf, Abbod & Linkens, 2001). In the following we look at these applications mainly from the perspective of the employed methods.

The most traditional approach in applying fuzzy logic in general and specifically in medical problems is through approximate reasoning. Originating mainly from control theory, this approach captures the general behaviour of a complex system (the human body) through a set of IF-THEN rules with the antecedent and consequent conditions represented as imprecise quantities. These so called rule-based systems have been extensively applied in different diagnostic problems. For example, Oad et al. (2014) proposed a rule-based system to estimate the risk level of heart diseases.

A significant part of the applications making use of fuzzy rules considers the information gained from the system as a basis for classification. An important advantage of this method, as pointed out by Nauck and Kruse (1999), is that linguistic rules are easy to interpret by the user. User can be the doctor but also a patient who is using a medical or wellness recommendation system on a mobile device.

A different type of application relies on different fuzzy clustering approaches. In contrast to traditional clustering methods, fuzzy clustering assigns every object to several clusters with different membership values. This approach is widely used in different pattern recognition problems, with image segmentation being the most important application in the medical context (c.f. Chuang et al., 2006). The most widely used model is c-means clustering that is applied for example in tumour classification. Moon et al. (2011) found that fuzzy c-means clustering provides a reliable tool to detect breast tumours.

Additionally to the variety of methods, we can also identify proposals utilizing different families of fuzzy sets (i.e., considering different types and levels of imprecision). Iakovidis and Papageorgio (2011) propose to use intuitionistic fuzzy cognitive maps to account for the hesitancy in the doctors' evaluation on the relationship between symptoms and possible diseases. Innocent and John (2004) developed a similar system using type-2 fuzzy sets and they found that accounting for this higher level of imprecision can improve the accuracy of diagnosis.

In the literature, we can identify very few contributions that offer insights on using fuzzy decision support systems in the context of health or wellness solutions for elderly. In one of the few examples, Zhang, Du and Sun (2010) have formulated a context-aware reminder system as a fuzzy decision making problem. To remind aging adults to perform certain activities in their daily routines, a reminder system which prompts an alert based on predefined (planned) activities can be used. However, planned activities may be interrupted by 'disruptive' activities which cannot be predicted in advance. To overcome these types of problems, Zhang et al. (2010) have proposed and used fuzzy logic to quantify the degree of the 'disruptive' activity and the urgency of the planned activity.

3 Personalized Health and Wellness Decision Support with Smartphones

3.1 Representation of Health Data Using Fuzzy Sets

In this section we will provide the necessary definitions and concepts from fuzzy set theory and fuzzy optimization in order to formulate mathematically the previously described problem. Our starting point is to consider a systems perspective on providing health and wellness tips and recommendations as well as a general motivation for using fuzzy logic in health-related decision making as it was outlined by Seising (2006). The most important philosophical underpinning of the use of fuzzy logic in the medical context is Sadegh-Zadeh's (2000) characterization of health, illness and disease as fuzzy concepts. For example, health can be understood as a fuzzy set, more precisely the complement of the fuzzy set 'patient-hood' which defines the extent to which a person can be considered as a patient.

In line with this approach, one can aim at providing suggestions to the user that can ensure the required results are obtained to an *acceptable* degree. For example, a mobile wellness application monitoring different activities of the user can recommend at a given time the necessity for taking a short walk but specifying the required distance, speed, location only in an imprecise manner, as these goals depend on several pieces of information that by themselves are imprecise.

Following Hudson and Cohen (1994), in the context of health and wellness related decision making, the following different types (or levels) of imprecision can be identified:

1. Numerical measurements that are approximately stable if we consider only a short time period (e.g., age or weight of the person).
2. Numerical measurements that can change significantly in a very short time period (e.g., blood pressure or blood glucose level).
3. Subjective modifier of the previous measurements (e.g., low blood pressure).

In addition to these types of imprecisions, Hudson and Cohen (1994) also identify symptoms that can be assessed only subjectively and difficult to measure numerically, for example the degree of sweating. The described three measurement types provide the motivation and interpretation of utilizing fuzzy logic for health-related decision problems. The first group of measurements can be described by using crisp values: age is 55 years or weight is 68 kilogram. Naturally, even during a short walk, the age of the person changes by few minutes and the weight by few grams, but the magnitude of these does not impact the outcome of a health or wellness recommendation significantly. Using set theoretical formalism, we can say that a person either belongs to the set of people who are aged 55 years (membership value 1) or does not belong (membership value 0).

To model the second type of attributes, we can make use of fuzzy sets. As the blood glucose level of a person can change significantly, already shortly after a measurement, the data collected provides an approximate, imprecise value of the real blood glucose level. Accordingly, we assign non-zero membership values not only to the actual measurement, but also values close to the observation. The most commonly used fuzzy sets are triangular fuzzy numbers; in the discussed example, we assign membership value 1 to the measured value, and using linear functions, assign memberships to numbers that are in the neighbourhood of the observation. The membership function of a triangular fuzzy number can be written as:

$$A(X) = \begin{cases} \dfrac{x-a}{b-a} & \text{if } a \le x \le b \\ \dfrac{c-x}{c-b} & \text{if } b \le x \le c \\ 0 & \text{otherwise} \end{cases}$$

where a ≤ b ≤ c, [a, c] is the support of the fuzzy number and b is the centre.

As for the third type of imprecision, linguistic modelling can be applied. We can make use of linguistic labels to model expressions such as high blood pressure or low blood glucose level. The linguistic labels are modelled as fuzzy sets with support in the unit interval and then applied on the interval of the feasible values of the specific health-related concept.

In the following, we describe how to use fuzzy optimization models to suggest an optimal course of action for the users in order to achieve their goals (i.e., improve their health and wellness from different perspectives). The main motivation behind this approach is that as the data is imprecise, the recommendation formulated based on this data should not be calculated in a definite way. This means that we require that the "possibility" of achieving a goal is sufficiently high, or equivalently we require that the "necessity" that an event happens is higher than a predefined threshold.

We propose to use possibilistic chance constrained programming models to make use of imprecise information in developing health-related decision support systems. Chance constrained programming was originally proposed in probabilistic environment (Charnes & Cooper, 1959) recognizing that as the input data is not precise, one can only provide a solution to a problem with keeping some level of uncertainty in the solution process. The extension of this approach using possibility and necessity measures was introduced in (Liu & Iwamura, 1998).

As we discussed above, the data encountered in health-related problems can be more classified as imprecise rather than random. According to this, in specifying the constraints of our optimization models, we only want to be confident enough (for example, to the degree of 0.9) that the heart rate will go down from 120 and stabilizes around 80. In this example the imprecisions that have to be taken into consideration are:

- 120 is measured imprecisely, we can just say it is approximately 120;
- optimal heart rate depends on the person: for some 120 is already a very high value as their average is around 70, for some it is only a medium level as their average is around 90;
- the threshold for the confidence level depends on the problem context; in some cases we require higher confidence (medical decision support), while in other cases a lower value is sufficient (wellness applications).

In the following, we provide a general approach on how the discussed concepts can be put together in a model, but we do not go into specific details as they can be very different in various applications. Rather we chose the case of identifying the optimal walking pace as a case to illustrate the use of the model in the next section.

3.2 The Model

As we discussed, the main goal of the model is to specify a set of actions to be taken by the user to optimize his/her physical or mental condition from different perspectives. One example is the case of optimizing walking habits. In the general case, the assumption is that there is a list of attributes describing the user of the wellness/health support system and also the context of use. This can include the height or weight of the user, blood pressure or heartbeat on the one hand, and temperature, type of physical activity performed or time of the day, on the other hand. The attributes can be of two main types:

- possible to be adjusted by the user immediately, for example the number of steps taken in one minute (or equivalently the walking speed);
- the user has no control (at least in a considered limited time interval), for example the temperature or the weight of the user.

The attributes belonging to the first class are used as variables of a recommendation system (e.g., how much the number of steps should be adjusted and what activity could be beneficial to perform). In the most extreme case, the system can recommend that the user should visit the doctor as the measured attributes indicate the possibility of a potential health problem.

The following general model can encompass both wellness and health-related recommendation systems (i.e., can be used as a personal trainer and a personal doctor).

In any application, the first task is to define the main objective of the system. In general, we assume that this objective can be written as finding a specification of the variable attribute(s) that minimizes the distance from an ideal state. The ideal state in turn is specified as a configuration of the attributes present in the model.

The parameters and the variables of the model are represented by triangular fuzzy numbers. As it can be observed from the definition of a triangular fuzzy number presented in the previous section, three values need to be identified: the centre (most likely value) and the upper and lower limit of the set of possible values. In practice, these parameters can be obtained as a combination of: (a) general recommendations based on some medical knowledge; and (b) user-specific values collected in the system. This way the system can provide individualized and personalized recommendations.

To specify the model, we need several notations. First, the parameters of the model are denoted as: $p_1, p_2, ..., p_m$; these parameters put constraints on the choice of optimal value for the variables, $x_1, x_2, ..., x_n$, and determine the ideal physical state for the user. Additionally, we denote by $x_1^0, x_2^0, ..., x_n^0$ the present values of the variables. The objective is then to identify new values for the variables that result in physical condition that is close to an ideal one, does not require too much effort from the user (in terms of change from the x_i^0 values to the x_i values) and satisfies constraints based on the parameter values. According to this, the objective function of the problem is the following weighted average:

$$\text{minimize } w_I \operatorname{dist}\big(I(p_1,...,p_m), A(x_1,...,x_n, p_1,..., p_m)\big) + w_E E(x_1,...,x_n, x_1^0, x_2^0,..., x_n^0) \quad (1)$$

The weights in this expression are also user-specific. In practice, these weights can be predefined for new users as the average value of weights for similar existing users. In later stages, by continuous data collection, the system can deviate from this general average and learn the individual weights of the user. The new values for the variables should be chosen by considering specific constraints on to what extent they affect the different attributes (parameters of the model). For every attribute, three things need to be specified in order to formulate the associated constraint:

- the acceptable range of the attribute;
- how the change in the variable(s) affect the value of the attribute;
- what is the required confidence level that is sufficient to achieve.

The acceptable range specified in terms of a crisp interval, $[p_i^l, p_i^u]$ (*l* stands for lower and *u* for upper), and the effect of the change in the parameter is realized through a predefined transformation function $f(x_j, x_j^o, p_i)$. Based on this, we specify two constraints for every attribute:

$$\begin{aligned} &\operatorname{Nec}\big(f(x_j, x_j^o, p_i) \geq p_i^l\big) \geq \eta_{i,j}^l \\ &\operatorname{Nec}\big(f(x_j, x_j^o, p_i) \leq p_i^u\big) \geq \eta_{i,j}^l \end{aligned} \quad (2)$$

where $\eta_{i,j}^l$ and $\eta_{i,j}^u$ can be considered as confidence values and are specified by the user and also based on some general medical knowledge; and *Nec* stands for the necessity measure. As $f(x_j, x_j^o, p_i)$ is a fuzzy number, if we denote its membership function by $f_{i,j}(x)$, the left-side of the two constraints can be rewritten as

$$\begin{aligned} \mathrm{Nec}\left(f(x_j, x_j^o, p_i) \geq p_i^l\right) &= 1 - \sup\left\{f_{i,j}(x) \mid x \leq p_i^l\right\} \\ \mathrm{Nec}\left(f(x_j, x_j^o, p_i) \leq p_i^u\right) &= 1 - \sup\left\{f_{i,j}(x) \mid x \geq p_i^u\right\} \end{aligned} \tag{3}$$

The same constraints need to be defined for all the parameters.

4 Numerical Illustration

In this section, we work out the details of the proposed general model in the case of a wellness recommendation system that helps the user to keep the optimal pace of the walking that corresponds to some predefined goals. Without loss of generality, we can assume that the range of all the variables and parameters is in the [0, 1] interval, with 1 indicating the best value of that attribute for the user and 0 indicating the worst. Naturally, this representation is not necessarily obtained through a linear transformation of the original values, for some variables, from the original range low and high values will correspond to 0 and medium values to 1. This data transformation can be done for example by asking for the opinion of doctors or estimating from previously collected data sets. The parameters in this specific application can include the following:

- *Weather (temperature and the intensity of rain and wind),*
- *Route (the slope and quality of the road),*
- *Age, weight and height of the user,*
- *Time elapsed from the last meal,*
- *Number of calories consumed during the day,*

The variable of the decision model is walking speed: the system provides recommendation to the user on increasing, decreasing or maintaining the actual speed. The parameters of the model (the attributes that are considered to be important for the user in this walking speed example) are heart rate, number of calories burnt per minute and physical fitness. The optimal solution in this example is simply obtained as the weighted average of the attributes. In practice, the weights can be determined based on the physical condition and preferences of the user in advance. We use the value (0.3, 0.4, and 0.3) for the weights of the three attributes. In Table 1, the actual values measured for the user as the basis for the recommendation and the ideal values (for that specific attribute and the specific individual using the system) are listed (the triplets represent triangular fuzzy numbers as defined in the previous section). The ideal values can be determined based on the data previously collected from the user or as a population average from the set of all users in lack of specific data. The actual speed of the user is (0.5, 0.6, and 0.7).

Attribute/value	Actual	Ideal
Heart rate	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)
Calories	(0.3, 0.4, 0.5)	(0.6, 0.7, 0.8)
Fitness	(0.8, 0.9, 1.0)	(0.5, 0.6, 0.7)

Table 1: Parameters of the Optimization Model

Naturally, increasing the speed would increase the heart rate (and keeping in mind that we have transformed values for the attributes, decreasing it on the [0, 1] scale), improves on the calories, and improves the physical fitness. For simplicity, we assume that change in speed affects all the attributes to the same extent: 1% change in speed results in 1 % change in the attribute value. The constraints are specified such that it is required (in any case with $\eta = 0.9$ confidence level), that the distance from the ideal attribute value should be not more than 25 %. In the objective function, the weight of the distance from the ideal point and the required effort to increase/decrease the speed are equal.

Attribute/value	Actual
Heart rate	(0.77, 0.89, 1.0)
Calories	(0.38, 0.51, 0.64)
Fitness	(1.0, 1.0, 1.0)

Table 2: Parameters based on the Optimal Recommendation

The optimization problem was implemented in Excel. The optimal solution was identified as 27% increase in the walking speed. This resulted in the attribute values listed Table 2. We can see that the heart rate increased but still close to the ideal, while the number of calories burnt is higher. In practice, the system informs the user regularly through the running exercises how he/she should adjust the running speed. This information also expressed in the form of linguistic terms ("Slightly increase your speed", "Slow down a bit"). Naturally, a suggestion such as "Increase the speed by 27%" would be completely impractical, but the choice of the appropriate linguistic term that corresponds to a speed increase of approximately 27% for the specific user would be the appropriate way for the system to communicate the results of the analysis.

5 Summary and Conclusions

In this paper we present a new way of looking at health-related data used in mobile health recommendation systems and apply it specifically in wellness applications as a basis for recommendation systems for young-elderly. The proportion of young-elderly in the population increases steadily which in the near future (or in some countries already presently) can cause significant increase in health-related cost. Using information and communication technology, most importantly mobile wellness and health applications, can help this age-segment to improve their health conditions resulting in lower healthcare expenditure. In this paper, we present an optimization model that can be utilized in wellness recommendation systems to identify the best course of action in a given situation that can help to improve (or simply maintain) the physical condition of the user. We reason why there is a need for models to incorporate imprecise information in health-related decision making problems and how fuzzy set theory provides a tool for decision support.

The main difference compared to traditional fuzzy models is that we do not rely on IF-THEN rules when determining recommendations but rather define ideal solutions that are unique for the user and identify optimal actions to be performed and: (i) minimizes a distance (in a possibilistic sense) from the ideal solution, while (ii) minimizes the effort necessary to perform the action. The main contribution of the paper is that it is one of the first approaches to (i) utilizing fuzzy optimization models in health-related decision making models and (ii) building wellness recommendation systems for young-elderly.

The main limitation of the paper, and also an important future research direction, is that the proposed model needs to be validated. In the future, we will perform user studies to test the model in different contexts to evaluate the performance. Additionally, as it is pointed out in the paper, in many practical situations we have to deal with different levels of imprecision: in the future we can improve the model by incorporating different families of fuzzy sets in the models.

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