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A Personalized Approach for Predicting the Effect of Aerobic Exercise on Blood Pressure Using a Fuzzy Inference System

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Abstract—**Regular aerobic exercise is a recommended treatment for elevated blood pressure (BP). However, making permanent lifestyle changes is not easy. Having personally relevant information about the treatment, about its effects and importance, is a precondition for motivation. Thus, the first step towards a successful lifestyle change is appropriate education. This paper describes a Sugeno-type Fuzzy Inference System (FIS) that predicts the effect of regular aerobic exercise on blood pressure based on the exercise dose variables, exercise frequency and intensity, as well as demographics (age, gender, ethnicity), and the baseline BP of a person. Since BP response to exercise varies largely between individuals, the system takes an initial step towards personalized prediction. Hence, the system can be used to educate a person about the benefits of exercise on BP in a personally relevant way, providing more accurate information than traditional education materials. Furthermore, preliminary validation results of the performance of the FIS are promising. The predictions comply with the findings of medical research for populations, though the individual-level validation remains still to be done.**

I. Introduction

REGULAR aerobic exercise is one of the important non-pharmaceutical treatments of hypertension [1]-[4]. The role of lifestyle changes is especially central in controlling mild to moderate blood pressure (BP) elevations (systolic BP from 140 to 180 mmHg, diastolic BP from 90 to 110 mmHg) [3]. However, the variation in individuals' BP in response to exercise seems to be large. The average net change reported in several individual studies for mild to moderate hypertensive populations range from -20 to +9 mmHg and from -11 to +11 mmHg for systolic and diastolic blood pressure (SBP and DBP), respectively [3], [5]-[7]. Partly, this variation can be explained by varying study settings and intervention designs, but certainly the individual characteristics play a significant role. Approximately 75 % of individuals with hypertension have been found to benefit from exercise [3].

For treatments to be effective, patients need to comply with them. Lifestyle modifications can be especially hard to stick to, since fitting new routines in everyday life and changing existing habits can be difficult. [8]. Having correct, personally relevant information about the treatment, its effects and importance, is a precondition for motivation to develop [8]. Thus, the first step towards a successful lifestyle change is appropriate education.

This paper describes a Sugeno-type Fuzzy Inference System (FIS) that predicts the effect of regular aerobic exercise on blood pressure according to personal characteristics and exercise dose variables. The prediction model is constructed based on the knowledge available in medical literature. The purpose of the system is to concretize the exercise-induced BP related benefits of an individual by demonstrating the predicted BP change and the time frame required for it to take place with a personalized approach. By considering personal characteristics, the system takes an initial step towards narrowing the wide range of BP changes observed at the population level to an individual variation scale. Hence, the outcome of the model provides a person with personally relevant, more accurate information than the traditional medical education materials, which often use the same BP change range for all. In addition, the system is interactive, allowing the person to explore the influence of different exercise dose values on BP.

Fuzzy Inference Systems have the ability to deal with uncertainty and imprecision, since they are based on multi-valued logic where the interpretation of properties is not black and white [9], [10]. For instance, a 35-year old person can be interpreted to be young but close to middle-age. This resembles human reasoning, and like humans, fuzzy systems can make decisions based on these vague interpretations [10]. Therefore, they are capable of modeling complex phenomena, and with sufficient computational efficiency [9]-[11]. In addition, Fuzzy systems can be built based on human expert knowledge regarding the phenomenon in question [10].

We chose the fuzzy approach as an appropriate method to model the exercise - BP relation, since the material we had available for creating the model was acquired from medical literature, which is comparable to expert knowledge and characterized by uncertainty. Furthermore, the reasoning behind implementing a Sugeno-type system instead of Mamdani, the most commonly used inference method, is that the former are more compact and computationally more efficient in performance than the latter [9]. These properties make the implemented model compatible with adaptive techniques [9], which may allow for developing its personalized prediction capabilities further in the future.

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II. METHODS

In the following we outline the implementation of the exercise – BP fuzzy model. First, we describe the expert knowledge that determines its key components, namely the inputs and outputs, fuzzy subsets and the rule base. Then we shortly explain how we processed this knowledge to construct the fuzzy subsets and the rule base.

A. Expert knowledge

A literature review was conducted on clinical trials that study the effects of aerobic exercise on blood pressure. Reviews and meta-analyses of altogether 201 exercise intervention trials [3], [5]-[7], [12] and several individual clinical studies were included in the review (see [13] for a complete list of references regarding the literature review). Most of the study populations consisted of middle-aged, sedentary Asians or Caucasians, who were mildly or moderately hypertensive. The exercise intervention periods lasted from three to four months, involving regularly performed exercise sessions typically 35-40 min in duration.

The review provided information about the magnitude of average BP changes observed for different population groups and the personal characteristics that mediate the BP response to exercise. Baseline BP, gender, ethnicity, and age were identified as factors mediating the exercise-induced BP related benefits. In addition, the effects of the exercise dose properties, weekly frequency and session intensity (% VO_2max), were studied in the literature. Table I summarizes how these different factors were observed to influence the BP response.

B. Model structure

The model was implemented with MATLAB Fuzzy Toolbox (MATLAB v. R2009b; the MathWorks Inc; Natick, MA, USA). Based on the expert knowledge, 1) baseline SBP and DBP, 2) gender, 3) ethnicity, 4) age, 5) weekly exercise frequency and 6) exercise session intensity were selected as the input variables for the model. Systolic and diastolic BP changes are the output variables of the model.

For implementation simplicity reasons, the model is divided into several submodels or sub-FIS. The exercise-induced SBP and DBP changes are predicted in separate models, referred later to as SBP and DBP submodels, respectively. Separate submodels were constructed also for different ethnicity (Asian / Caucasian) and gender combinations. Hence, for the each type of populations *Asian women*, *Asian men*, *Caucasian women,* and *Caucasian men* there is a SBP and a DBP submodel to represent them.

TABLE I
FACTORS MEDIATING EXERCISE-INDUCED BP CHANGE AND THE TYPE OF INFLUENCES

Factor	Factor – BP relation
Exercise intensity	Mild to moderate intensity exercise reduces BP more than high intensity exercise.
Exercise frequency	Daily exercise reduces BP more than exercise performed three times per week.
Baseline BP	As the hypertension status increases from pre- to severe hypertension, the greater the BP benefits of exercise become. The BP benefits increase non-linearly: the increase gets larger as the hypertension status grows.
Gender	Women show greater BP reductions than men.
Age	Young people show slightly greater SBP reductions than elderly, but middle-aged people reduce SBP the most. DBP response to exercise decreases with age.
Ethnicity	Asians show greater BP reductions than Caucasians. Hypertensive Asians and Caucasians show similar DBP reductions, but amongst pre-hypertensives and normotensives, Asians reduce DBP more than Caucasians.

C. Fuzzy subsets

The linguistic terms used to describe the fuzzy subsets of the input variables are

- *zero*, *mild to moderate* and *high* for exercise intensity,
- *zero, three* and *most days* of week for exercise frequency,
- *normotensive,* and *pre-, mildly, moderately* and *severely* hypertensive for baseline BP,
- *young, middle-aged* and *old* for age.

These fuzzy subsets were fairly simple to derive from the expert knowledge, since the interpretations of the linguistic terms were mostly defined in the clinical trials. These interpretations were expressed as crisp sets, i.e. certain value ranges, which we used as references for the fuzzy subsets. We fuzzified these crisp sets with the commonly used triangular, trapezoidal, and Gaussian membership functions. The fuzzy subsets for the variables exercise intensity and baseline DBP are presented in Fig. 1. The ethnicity and gender inputs are only used to select the correct ethnicity-gender sub-FIS for prediction. Thus, they are not actual inputs for the sub-FIS and defining fuzzy subsets for them were not required, nor would it have been meaningful.

The submodels are zero-order Sugeno-type fuzzy models, which means that the membership functions for the output variables are constants. This allowed us to incorporate in the submodels the precise average BP reductions reported for different subgroups in the literature.

D. Rule base

Altogether 38 rules describing the relationships between the input fuzzy subsets and the output constants were formed for the SBP submodels. The rule base of the DBP submodels comprises 32 rules. To give a general idea on how the

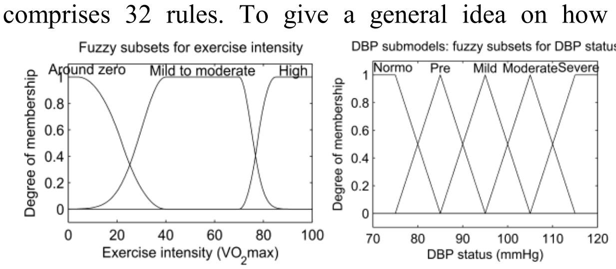

Fig. 1. Fuzzy subsets for the input variables *exercise intensity* and *baseline DBP* (labelled as DBP status). The baseline DBP is an input for the DBP submodels only, whereas exercise intensity is a common input for SBP and DBP submodels.

rules look like, we present here two rules from the *Caucasian women* submodels as examples, one for SBP and the other for DBP:

IF *intensity* is *mild* AND *frequency* is *three* sessions per week AND *baseline SBP* is *mildly* elevated AND *age* is *middle-aged,* THEN *SBP reduction* is *10.2* mmHg.

IF *intensity* is *mild* AND *frequency* is *three* sessions per week AND *baseline DBP* is *mildly* elevated AND *age* is *old,* THEN *DBP reduction* is *5.6* mmHg.

The imprecise input-BP relationships listed in Table I were processed further to more detailed forms. For instance, the mediating influence of age on SBP could be described more precisely as *Young and old people show 0.74-fold and 0.65-fold reductions in SBP, respectively, compared to the SBP reductions observed in middle-aged people.* These exact relationships were developed by comparing together the average BP reductions observed for the subgroups that differed by the property of interest. Furthermore, for each rule the average BP reduction (consequent) had to be derived for the different combinations of fuzzy subsets (antecedent). This was done based on the average BP reductions reported for different subgroups in the literature, the reported proportion of different individual properties appearing in the subgroups, and the constructed precise input-BP relationships.

III. Results

A. Outputs of the model

Based on the expert knowledge, the BP change predicted by the model should be achieved within 20 weeks after initiating a regular aerobic exercise habit characterized by the input exercise dose values and session durations of 30-45 min. The predicted BP change corresponds to the average change that should be observed in a population of sedentary people that have the individual characteristics given as inputs. The SBP/DBP change predictions range from -50/-30 mmHg to 0/0 mmHg depending on the input variables.

The model plots the time courses of the predicted systolic and diastolic BP reductions as outputs (Fig. 2). Two alternative time curve plots are generated: one for

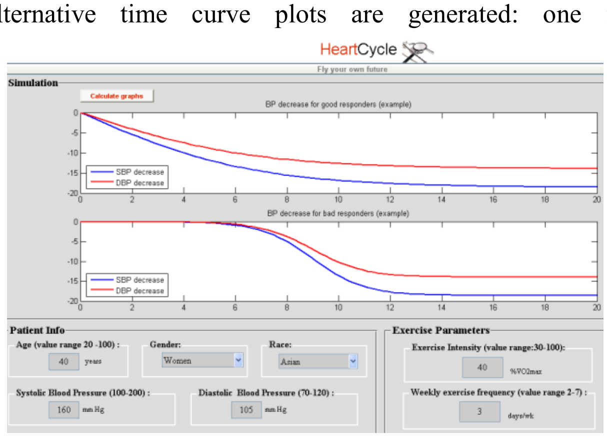

Fig. 2. Example outputs of the model and the corresponding inputs. The plots show the time curves of the predicted SBP (blue curves) and DBP (red curves) changes for fast (upper pane) and slow (lower pane) responders.

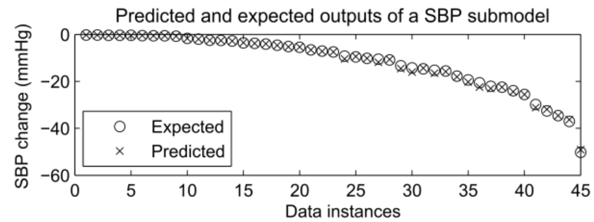

Fig. 3. The predicted and expected SBP changes generated with the Caucasian women submodel for the ideal input data set of 45 instances.

representing the BP change of individuals who are "fast" responders (exponentially decreasing curves) and another for "slow" responders (S-shaped curves). Since the literature review did not provide enough information to distinguish the individual characteristics that define the BP responder type of a person, the two scenarios are presented for any input set.

B. Model performance

Evaluations were conducted visually to assure that the model predicts according to the implemented rules and the input-BP relationships identified from the literature.

To ensure that the submodels predict as intended, an input data set was created, which included for each rule in a submodel, the ideal input values corresponding to the rule antecedent. An ideal value of a fuzzy subset is the element that obtains the highest membership degree in the subset. Each submodel was fed with the input data set and the resulting BP predictions were compared with the expected BP values, i.e. the values of the rule consequents. The predictions are well aligned with the expected values. Fig. 3 demonstrates this for the SBP submodel of Caucasian women.

Using the MATLAB GUI of the Fuzzy Inference Toolbox we could plot curves that describe the input-BP change relationships generated by the submodels. We compared the shapes of these curves to the input-BP relations derived from the literature (Table I) in order to evaluate the performance of the model. In general, the generated relationship curves follow the expert knowledge well. Fig. 4 demonstrates this for the age-SBP and exercise intensity-SBP relations predicted by the Caucasian women SBP submodel.

In addition to the described basic technical evaluations, a cardiologist was asked to verify the input-BP relations described in Table I as well as the processed, more precise

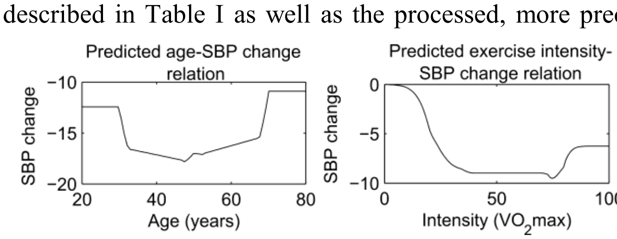

Fig. 4. The *age-SBP* and *exercise intensity-SBP* relations predicted by the Caucasian women SBP submodel: Middle-aged people show the greatest exercise-induced SBP benefits, whereas young people show slightly greater SBP benefits than older people. Mild intensity exercise is more effective in reducing SBP than high intensity exercise.

relations. He was also asked to verify the shapes of the time curves of the predicted BP change (Fig. 2), and the BP decrease ranges predicted for different individual and exercise dose properties. The feedback we received was positive, though he emphasized the individual variability in the BP related benefits of exercise. He agreed with the knowledge the model is based on and the model outcomes, and could imagine himself using the model to educate and motivate his patients.

IV. Discussion

We have introduced a Sugeno-type FIS that predicts the effect of regular aerobic exercise on blood pressure based on individual and exercise dose properties. Though the model is constructed based on medical literature where findings are reported at the group-level, considering individual characteristics is an initial step towards personalized prediction.

The available medical knowledge was not extensive enough to cover all the property combinations of the input variables. For instance, very little information was available for severely hypertensive subgroups and most of the study subjects were 30-70 years old. The incompleteness of age data appears in the depicted age-SBP relation generated by the model (Fig. 4). Furthermore, the subgroup characteristics were not fully reported in all the clinical trials. Due to these gaps in the knowledge, part of the FIS was constructed based on assumptions and generalizations. Therefore, some of the rules might not be completely reliable. However, in this paper we do not go into the details of the construction process of the rules, since it was multi-phased and tedious. The most valid rules are the ones involving fuzzy subsets for the terms *middle-age* and *mild hypertension*, since most of the clinical trials studied populations characterized by these properties. All in all, the preliminary validation results are promising in general, since the model predictions are well aligned with the overall expert knowledge, and also the feedback provided by a cardiologist was positive.

It remains to be studied how well the model predicts at the individual-level. Despite personalizing the predictions to individual characteristic, it will be difficult to produce accurate predictions for individuals due to individual variation as was also pointed out by the cardiologist. However, with our approach we should be able to at least narrow the wide range of BP changes observed at the population level to an individual variation scale. Furthermore, since thorough validation of the model would require an enormous data set with a sufficient number of instances for each combination of the input variable properties, utilizing the aggregated data from literature might still be the best approach to take, at least for initializing the model for individuals.

An advantage of the implemented Sugeno-type FIS is that it is compatible with data learning techniques and the output constant values are easy to update. Thus, if data were available, the performance of the model could be modified with a reasonable effort. Furthermore, the model could be developed further to be able to personalize the predictions automatically "on the fly" according to the exercise and BP measurements of an individual. However, the most obvious next steps to take for improving the model are to collect more feedback from health professionals and fine-tune the model accordingly if need arises. Moreover, the outputs of the model should be accompanied with confidence intervals to demonstrate the probable range of individual variation.

At the moment, whilst the predictions of the model (Fig. 2) might not be very accurate at the individual-level, we would like to emphasize that the model may be used for educational purposes only, for example, as a tool for doctors to educate patients on the probable effects of exercise on BP. Though the model provides only group-level predictions, it attempts to make them personally relevant and motivating by showing the individual characteristics the predictions are based on and allowing the users to interactively modify the exercise dose variables.

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