Thinking eHealth:
A Mathematical Background of an Individual Health Status Monitoring System to Empower Young People to Manage Their Health

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ABSTRACT

This paper focuses on a mathematical background of an individual health status monitoring system to empower young people to manage their health. The proposed health status monitoring system uses symptoms observed with mobile sensing devices and prior information about health and environment (provided it exists) to define individual physical and psychological status. It assumes that a health status identification process is influenced by many parameters and conditions. It has a flexible logical inference system providing positive psychological influence on young people since full acceptance of recommendations on their behavioral changes towards healthy lifestyles is reached and a correct interpretation is guaranteed. The model and algorithms of the individual health status monitoring system are developed based on the composition inference rule in Zadeh's fuzzy logic. The model allows us to include in the algorithms of logical inference the possibility of masking (by means of a certain health condition) the symptoms of other health situations as well as prior information (if it exists) regarding health and environment. The algorithms are generated by optimizing the truth of a single natural "axiom", which connects an individual health status (represented by classes of health situations) with symptoms and matrices of influence of health situations on symptoms and masking of symptoms. The new algorithms are fairly different from traditional algorithms, in which the result is produced in the course of numerous single processing rules. Therefore, the use of a composition inference rule makes a health status identification process faster and the obtained results more precise and efficient comparing to traditional algorithms.

Keywords: *Classes of Health Situations, Composition Inference Rule, eHealth, Fuzzy Logic, Identification Process, Individual Health Status Monitoring System, Masking Symptoms, Mobile Monitoring Devices, Model and Algorithms, Recommendations, Symptoms*

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INTRODUCTION

The lifestyle-related illnesses (such as overweight and obesity) are among the top global healthcare challenges today (McGuire, 2012).

Overweight and obesity in young age is a disturbing predictor for obesity in adulthood, but also entails some other short term health complications in young population (Krebs, et al., 2007).

Knowing how to stay healthy is not enough to motivate young people to adopt healthy lifestyles (Prochaska & Velicer, 1997; Lenert et al., 2005; Krebs et al., 2010; Noar et al., 2011).

However, it is possible to motivate young individuals to change their behaviors towards healthier lifestyles using incentives delivered with a combination of processes and mobile technologies (Arnrich et al., 2010; Houshey, 2010; Mattila et al., 2010; Strasburger et al., 2010; Honka et al., 2011; Van Gemert-Pijnen et al., 2011).

This paper concentrates on a mathematical background of an individual health status monitoring system to empower young people to manage their health in order to prevent overweight and obesity. The individual health status monitoring system uses symptoms observed with mobile monitoring devices including wearable sensors and mobile phones and prior information about health and environment collected, for example, with multimedia diaries in order to identify individual physical and psychological status. We develop and improve a suggested in literature approach to constructing problem-independent diagnostic models based on the composition inference rule in Zadeh's fuzzy logic in order to create an individual health status identification model (Lokshina, 2002a; Lokshina, 2002b; Lokshina & Insinga, 2003).

The proposed identification model allows us to include in the algorithms of logical inference the possibility of masking (by means of a certain health condition) the symptoms of other health situations as well as prior information (provided it exists) regarding health and environment. The algorithms of logical inference are generated by optimizing the truth of a single natural "axiom", which connects an individual health status (represented by classes of health situations) with the symptoms and matrices of influence of health situations on symptoms and masking of symptoms.

Therefore, the proposed algorithms are quite different from traditional algorithms of logical inference, in which the result is produced in the course of numerous single processing rules; the use of a composition inference makes a health status identification process faster and the obtained results more precise and efficient comparing to traditional algorithms.

This paper is comprised of six sections, and is organized as follows. An individual health status monitoring system is described in the following section. The third section focuses on monitoring symptoms with a set of mobile monitoring devices during daily-life activities of young people in order to identify an individual health status. The fourth section concentrates on classification of health situations developed by healthcare experts. The fifth section describes development of model and algorithms of individual health status monitoring system based on the composition inference rule in Zadeh's fuzzy logic. Summary and conclusions are contained in the final section.

AN INDIVIDUAL HEALTH STATUS MONITORING SYSTEM

Knowing how to stay healthy is not enough to motivate young individuals to adopt healthy lifestyles. However, it is possible to monitor health status of young individuals by gathering multiple vital signs and parameters in order to provide them with recommendations, introducing personalized options for alternative physical exercise behaviors and healthier eating styles (Lenert et al., 2005; Krebs et al., 2010; Noar et al., 2011; Jonston & Papaioannou, 2013).

The advantages of creating a general model that can be used to identify an individual health status and facilitate providing feedback and recommendations, presenting personalized healthy options for alternative behaviors, are evident.

Let us assume that an individual health status is primarily settled on physical condition of the body structure (comprising body size and composition attributes), physiological condition (comprising metabolic parameters), and psychological condition (based on relevant characteristics of personality). The body structure and functionality are directly influenced by young individuals' behaviors in domains of alimentation and physical activity.

After that, an individual health status can be uniquely identified based on array of symptoms (i.e., individual physical, physiological, and psychological parameters), representing (or caused by) certain physical, physiological, and psychological conditions, and classified as normal situation or anomaly (e.g., problematic situation), given that classification of health situations has been developed by healthcare experts a priori.

A general formula of an individual health status monitoring in logic format can be given as (1):

$$C1 \wedge C2 \wedge C3 \rightarrow N \vee A \quad (1)$$

where:

C1 – physical condition
C2 – physiological condition
C3 – psychological condition
N – normal situation
A – anomaly

Accordingly, a formula of an individual health status monitoring based on physical and physiological conditions of young individuals is presented as (2):

$$C1 \wedge C2 \rightarrow N \vee A \quad (2)$$

where:

C1 – physical condition
C2 – physiological condition
N – normal situation
A – anomaly

A model of an individual health status monitoring system can be generated with use of the above formula. The model is developed as a table, with rows correspondent to arrays of symptoms that identify strictly certain classes of health situations. It is obvious that symptoms must be chosen in a way that makes it possible to differentiate classes of health situations.

MOBILE MONITORING DEVICES TO OBSERVE SYMPTOMS DURING DAILY-LIFE ACTIVITIES OF YOUNG INDIVIDUALS

In order to identify an individual health status based on physical, physiological and psychological conditions, a metabolic balance of young individuals has to be monitored.

The metabolic balance can be assessed based on individual food intake and energy expenditure. The food intake can be monitored through questionnaires and multimedia diaries, used to observe individual nutritional habits (Houshey, 2010; Mattila et al., 2010), while the energy expenditure should be estimated with a mobile multi-parameter sensing system (Bonato, 2010; Delgado-Gonzalo et al., 2014).

The following symptoms have to be observed in order to identify an individual health status based on physical and physiological conditions:

- Human kinetics
- Cardiac activity
- Respiratory activity
- Metabolic activity

The symptoms must be monitored during the daily-life activities. A typical day of young individuals along with related scenarios of using mobile monitoring devices can be described as follow: they sleep during the night, wake up in the morning, scale themselves, perform sport activities in the evening. They use Smartphone and wear a watch during the whole day.

Therefore, the symptoms should be observed with a set of mobile monitoring devices integrated into mobile multi-parameter sensing system, as shown in Figure 1:

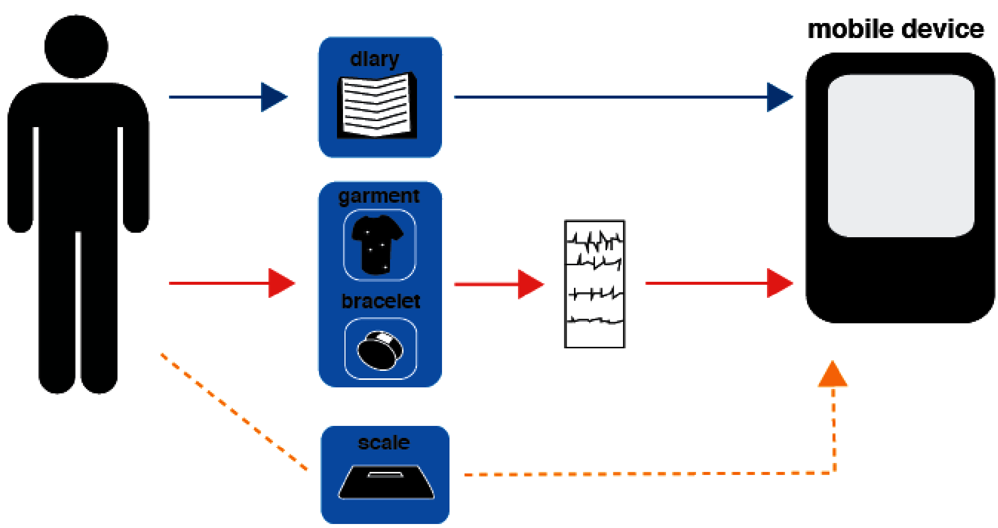
- A scale (or balance board) to monitor the body weight and composition (e.g., body structure). A balance board allows a frequent assessment of weight and can be used for directly measurable physical activities, also in a gaming context (with single or multiplayer modality);
- A Smartphone to monitor human kinetics;
- A smart garment to monitor human kinetics and cardiac/respiratory activity;
- A bracelet to monitor human kinetics (e.g., resting, walking slow/fast, running, swimming). Sensors embedded in a bracelet can give more precise measurements than the mobile phone and can be worn 24/7. They also can bear some form of identity;
- Specific sensors to monitor fitness activities. While in daily-life activities young individuals are expected to avoid wearing complex sensors, they might be willing to put on extra sensors when performing specific fitness activities (e.g., heart-rate sensors, etc.).

In order to obtain more precise assessment of the metabolic balance, the data, collected through mobile multi-parameter sensing system, should be complemented by other corresponding information, collected through multimedia diaries, as well as supported through some planned data redundancy.

The symptoms should be monitored through the mobile multi-parameter sensing system as described below:

- The human kinetics must be monitored with 3-axis accelerometers and gives information not only on motion of body and limbs as a function of time and level, but also on energy expenditure;
- The cardiac activity has to be monitored with dry electrodes integrated into smart garments providing a biopotential corresponding to an ECG derivation;
- The respiratory activity should be monitored with a strain gauge integrated into a smart garment and allows one to improve the cardiovascular monitoring by providing complementary information to heart rate;
- The body structure can be assessed using a commercial scale.

Figure 1. Monitoring devices integrated in mobile multi-parameter sensing system



The sensors, their location, observed signals, the estimations derived from observed signals, and scenarios of using mobile monitoring devices are summarized in Table 1.

Furthermore, two following processes are very important once producing arrays of symptoms: raw signal preprocessing and communication. Raw signals coming from sensors should be preprocessed, meaning that raw signals should be de-noised and appropriate information should be organized as arrays of symptoms used in the individual health status monitoring system. Additionally, a Smartphone must operate as both an aggregation platform and a bridging device, to transfer data from sensors to a raw signal preprocessing system.

CLASSIFICATION OF HEALTH SITUATIONS

Classification of health situations should be developed by healthcare experts a priori as a set of rules, connecting classes of health situations ($\{S_i\}$, $i=[1,m]$, $s_i=[0;1]$) with associated arrays of symptoms ($\{X_j\}$, $j=[1,n]$, $x_j=[0;1]$) with maximum truth of decision.

Healthcare experts are knowledgeable individuals from different disciplines, able to classify various health situations based on arrays of symptoms and develop recommendations on physical exercise behaviors and healthy eating styles in a way that full acceptance by young individuals can be reached and correct interpretation can be guaranteed (Krebs et al., 2010; Noar et al., 2011).

Therefore, the team of healthcare experts should include medical experts and psychologists, as well as experts in education.

DEVELOPMENT OF MODELS AND ALGORITHMS FOR AN INDIVIDUAL HEALTH STATUS MONITORING SYSTEM

This paper concentrates on a mathematical background of an individual health status monitoring system to empower young people to

Table 1. Sensors and their locations

Sensor	Location	Signal	Estimation	Scenario
3D accelerometer	Wrist (Water resistant bracelet)	X acceleration Y acceleration Z acceleration	Step count Stroke and lap count Swim speed & distance Run speed & distance Activity classification Energy expenditure	24 /7 Sport activities Fitness Swimming
3D accelerometer	Smartphone	X acceleration Y acceleration Z acceleration	Step count Activity classification Energy expenditure	Daily-life activities Sport activities Fitness
3D accelerometer	Torso (Smart garment)	X acceleration Y acceleration Z acceleration	Step count Stroke and lap count Swim speed & distance Run speed & distance Activity classification Energy expenditure	Sport activities Fitness
Dry electrodes	Torso (Smart garment)	Biopotential	Heart rate Recovery	Sport activities Fitness
Strain gauge	Torso (Smart garment)	Impedance	Breath rate	Sport activities Fitness
Scale	External device	Weight	Weight	At home

manage their health, based on the composition inference rule in Zadeh's fuzzy logic.

The proposed algorithms of an individual health status monitoring system are quite different from traditional algorithms of logical inference, in which the result is produced with the use of numerous single processing rules. An enhancement is achieved with the use of a composition inference rule, which makes a health status identification process faster and the obtained results more precise and efficient comparing to traditional algorithms.

The development of a traditional fuzzy inference model is occurred in several directions:

- The array of health situations Si and the array of symptoms Xj are introduced to the model: {Si}, i = [1,m], {Xj}, j=[1,n], si = v(Si) = [0;1], xj = v(Xj) = [0;1];
- The matrixes of minimum [Rij'] and maximum [Rij"] influences of symptoms onto health situations are introduced to the model instead of the matrixes of weights and relations:

$$[Rij] = v(Si \rightarrow Xj),\ i = [1,m],\ j = [1,n],\ rij = v(Si \rightarrow Xj) = [0;1]$$

$$[Rij'] <= v(Si \rightarrow Xj) <= [Rij'']$$

- The matrix of masking symptoms by health situations [Rij*] is introduced to the model:

$$[Rij^*] = v(Si \rightarrow Xj^*),\ i = [1,m],\ j = [1,n],\ rij^* = v(Si \rightarrow Xj^*) = [0;1]$$

- The prior information about health and environment is taken into account;
- The advanced expert information is taken into account;
- Fuzzy inference model connects the classes of health situations, symptoms, and matrixes of maximum and minimum influences of symptoms onto health situations.

The following auxiliary inference axioms are introduced to the health status identification model:

1. If the health situation doesn't cause the symptom appearing, the symptom doesn't appear, or its value is not true:

$$\neg\vee (Si \wedge (Si \rightarrow Xj)) \supset (\neg Xj \vee \neg TXj),\ 1 <= i <= m,\ 1 <= j <= n \quad (3)$$

2. If the health situation causes the symptom appearing and doesn't cause the symptom masking, the symptom does appear, or its value is not true:

$$\{\vee(Si \wedge (Si \rightarrow Xj))\} \wedge \{\neg\vee(Si \wedge (Si \rightarrow Xj^*))\} \supset (Xj \vee \neg TXj),\ 1 <= i <= m,\ 1 <= j <= n \quad (4)$$

3. Duo implications between health situations appear because of causal links between them:

$$(Si \rightarrow Sk)) \supset (Si \supset Sk),\ 1 <= i <= m,\ 1 <= k <= m \quad (5)$$

Let us denote the conjunctions of all n axioms of the first type with Ej; and the conjunctions of all n axioms of the second type with Fj; and the conjunctions of all n axioms of the third type with Hj.

A global axiom of the health status identification model is presented by the conjunction of above-mentioned axioms:

$$G \equiv \wedge (Ej \wedge Fj \wedge Hj),\ 1 <= j <= n \quad (6)$$

When causal links between situations are not very strong, the H-type axioms may be disregarded. However, in the health status identification model the causal links between the situations are rather strong and the H-type axioms are required.

The truth of decision, shown in (7-8) is a function of inter-logical distribution of symptoms and health situations (or, logical analogue of the maximum likelihood method in statistics):

$$v(G) = \varphi(s,x,r) \quad (7)$$

where:

$$v(Si) = si,\ v(Xj) = xj,\ v(Si \rightarrow Xj) = rij \quad (8)$$

Therefore, the following extreme tasks, given in (9-11) appear in the health status identification model find:

$$d(x) = \sup \varphi = \max \varphi\ (s,x,r) \quad (9)$$

$$si''(x) = \sup si(x) = \max \{si: \varphi\ (s,x,r) = d(x)\} \quad (10)$$

$$si'(x) = \inf si(x) = \min \{si: \varphi(s,x,r) = d(x)\} \quad (11)$$

Or, for a given array of symptoms $x=(x1,...,xn)$, $0<= xj <=1$, $1<= j <=n$:

- Define maximum value d, $0<=d<=1$, for which the system of max-min equations, shown in (12-13), has at least one decision $s = (s1,...,sm)$, $r = [rij]$ in interval $0< = si<= 1$, $rij' <= rij< =rij''$, $1<= i <=m$:

$$xj-(1-d)<= \text{maxmin}(si,rij''),\ 1<=j <=n,\ 1<=i<=m \quad (12)$$

$$\min \{\text{maxmin}(si, rij'), 1-\text{maxmin}\ (si,rij^*)\} <=xj + (1-d),\ 1<= j <=n,\ 1<= i <=m \quad (13)$$

- Define precise minimum $si'(x)$ and maximum $si''(x)$ values, which are correspondent to $d = dmax$.

Therefore, the proposed health status identification model allows us to include in the algorithms of logical inference the possibility of masking (by means of a certain health condition) the symptoms of other health situations as well as prior information (provided it exists) about existing health problems and environment. The algorithms of logical inference are generated by optimizing the truth of a single natural "axiom" which connects the health situations, symptoms and matrices of influence of health situations on symptoms and masking of symptoms. The use of a composition inference rule in the proposed algorithms makes a health status identification process faster and the obtained results more precise and efficient.

CONCLUSION

This paper focused on a mathematical background of an individual health status monitoring system to empower young people to manage their health. The proposed health status monitoring system uses symptoms observed with mobile sensing devices and prior information about health and environment (provided it exists) to define individual physical and psychological status. It assumes that a health status identification process was influenced by many parameters and conditions. It has a flexible logical inference system, providing positive psychological influence on young people since full acceptance of recommendations on their behavioral changes towards healthy lifestyles is reached and a correct interpretation is guaranteed.

The model and algorithms of the individual health status monitoring system are developed based on the composition inference rule in Zadeh's fuzzy logic. The model allows us to include in the algorithms of logical inference the possibility of masking (by means of a certain health condition) the symptoms of other health situations as well as prior information (if it exists) regarding health and environment. The algorithms are generated by optimizing the truth of a single natural "axiom", which connects an individual health status (represented by classes of health situations) with symptoms and matrices of influence of health situations on symptoms and masking of symptoms.

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