A Fuzzy Inference Algorithm for Personal Bio-Informatics Fusion in Home-care System

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Abstract *In the real world, people may not always clearly understand what the other people mean when they communicate. This holds true as well whenever changes occur in their individual health conditions. The same situation is present in the judgment of multiple bio-signals because a similarly fuzzy situation exists. If personal bio-signals are collected, we can judge that a bio-signal overtakes its thresholds. In this research, we applied the fuzzy theory to fuse multiple bio-signals. In addition, we were able to identify the weak patients in a group. In this study, a fuzzy inference algorithm for fusing multiple bio-signals and referring to a person's health was proposed, as a result of which, the weaker persons in the same group were easily identified. Moreover, the inference results were outputted by semantic representations such as high, median, or low. The boundary values of degrees were also defined through special test cases. Furthermore, the degree range was divided into parts to differentiate between the healthy levels of patients.*

Keywords: Fuzzy Inference, Bio-signals Fusion, Health Promotion, Bio-signals Repository

1. Introduction

In the real world, human thought, language representation and feeling are all fuzzy phenomena. Generally, fuzziness is inaccurate, uncertain, and has multiple meanings. Language purpose is mostly judged from people's subjective feelings [1]. Everybody has a different interpretation of one particular sentence. People may not clearly understand what other people mean, more so with the changes that their own health's undergo. Hence, a fuzzy situation also exists in judging multiple bio-signals. If personal bio-signals are collected, we are not only able to determine that any bio-signal overtakes its threshold limit value; moreover, we are able to fuse bio-signals to be fuzzily analyzed.

In this study, we applied the fuzzy theory to fuse bio-signals and to identify weaker persons in the same group. In Section 2, the fuzzy theory is briefly discussed. In Section 3, a fuzzy inference system is first introduced. The main functionalities in the system are to collect, transmit, fuse, and analyze bio-signals. A fuzzy inference algorithm is bundled in the system. The algorithm is described in Section 4. Likewise, one practicable example is illustrated. In Section 5, the experimental results are evaluated and discussed. Finally, brief summaries are presented in Section 6.

2. Related Works

Fuzzy sets are sets whose elements have degrees of membership. Fuzzy sets have been introduced by L. A. Zadeh (1965) as an extension of the classical notion of set. Lee et al. proposed a genetic fuzzy agent for meeting scheduler system [2]. Delen and Pratt designed an intelligent decision support system for manufacturing [3]. Wang applied the concept of agent-based control theory in traffic and transportation management [4]. Yan *et al.* proposed a perception-based medical decision support system for the diagnosis of heart diseases [5]. Grossklags and Schmidt studied how software agents affect the consumer's behaviors for human traders [6]. Gerla [7] proposed fuzzy set based on quantitative analysis of people's thought. It is similar to the models of people's thought. Each element in the fuzzy set can be expanded into two-value logic as well as into multi-value logic. The fuzzy degree that assembles the fuzzy set would lie between 0 and 1. The degree value is given by a function, which we named as the membership function. Owing to the difference among every individual's subjective consciousness, the degree value is also definitely different for each individual.

Generally, the degree value is decided based on the knowledge of the domain experts. There are various formulas of membership function for a user's defined function. Nonetheless, it is possible to deduce four kinds of membership functions: z-type, lambda-type, pi-type, and s-type [8]. If an inference is judged based on the fuzzy theory, they call it fuzzy inference. By comparing with the traditional logical inference, fuzzy inference could match adaptive rules by the fuzzy degrees. Even if the inferable degrees do not exactly match the rules, the inference can also approximately apply the most suitable rules.

It is suggested that the best time when personal health should be initially promoted is when people are basically healthy. In medical science, this concept is called preventive medicine. People would like to find methods to maintain and promote their health. Nowadays, information and communication technology (ICT) have greatly advanced. Personal bio-signals can be easily measured and immediately delivered to even remote locations. A remote server could thus analyze bio-signals to quickly judge a person's physiological status. Lee [9, 10] proposed the use of fuzzy inference architecture to filter the image noises. Their inference rules were optimized through an iterative learning. In this study, we adapted this architecture to fuse multiple bio-signals and to infer personal physiological status.

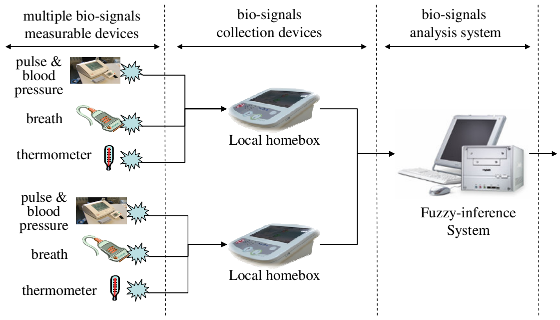

Figure 1. *FIS* system architecture

3. Fuzzy Inference System

The fuzzy inference system (*FIS*) is designed to manipulate multiple bio-signals. Its main functions in the *FIS* are to collect, transmit, fuse, and analyze bio-signals. Bio-signals include pulse, blood pressure, blood oxygen, blood sugar, breath, and body temperature among others. The applicable domains of *FIS* are chronic home-care, leisure treatment, and health promotion among others [11]. The various bio-signals represent their own specific features, which need to be artificially determined and interpreted by medical doctors.

However, numerous bio-signals need to be recorded over a significant period of time. Doctors and nurses cannot always stay near the patients to interpret the meaning of their bio-signals. In this situation, a real-time response could not be performed without the information system. We designed the *FIS* to cover these gaps between the providers and consumers. The *FIS* could automatically determine and interpret the incoming bio-signals. Thereafter, it could prompt adaptive actions to related persons through its service processes. The *FIS* and its algorithms can immediately provide utilities protection and alert patients, hence reducing the manual operational cost.

In the scope of the *FIS* deployment, if the patient is in a public area, he could be first identified through an RFID tag or ZigBee module. This has been predefined in the database. Thereafter, the patient could measure his own bio-signals by using measurable devices in the public bio-station. The patient could even set up his own configuration after being identified. If the patient is in private area such as his room, he could then directly measure the bio-signals and check up on them by himself. He could naturally set up his own configuration in a private area. After collecting multiple bio-signals from an identified patient, the local homebox is able to converge and fuse the bio-signals. The homebox would then transmit personal data to the *FIS* for fuzzy-inferred analysis. The transmission is performed in a secure and private protocol. Likewise, the system architecture of collection and analysis bio-signals is shown in Figure 1. If any unusual signal is detected in the analytic results, the system would alert the related persons, such as the patient, family members, or local nurses. In the scope of *FIS* deployment, the local nurses could also actively monitor and adapt the patients' activities through the collected and analyzed results.

For fusion and fuzzy-reference of multiple bio-signals, the system requires identification, static personal profile, and dynamic bio-signals. However, local nurses in most environments are not enough. It is quite difficult to manually manipulate these jobs. Therefore, the fuzzy inference system has been designed to solve these issues. In the system infrastructure, homogeneous bio-signals could be handled through international standard, such as Health Level 7. The messages are transmitted in a secure and private mechanism on a service-oriented architecture ([11], [12]). In this infrastructure, the bio-signals are ready to be analyzed. We thus have to focus on designing an analytic algorithm in the system. The details would be described in the next section.

4. Proposed Fuzzy Inference Algorithm

The fuzzy inference algorithm (*FIA*) in *FIS* was designed to identify the weaker persons in the same group. Through the identified information, local nurses or caregivers could pay more attention on the patients who were physiologically weaker. In the same algorithm, *FIA* could also identify persons who were healthier than others. The healthy levels of all patients could also be drawn out. The multiple bio-signals were collected by sensors, which were deployed in the environment. The patients' bio-signals would first be fused into fuzzy set.

Thereafter, these data would be granularly computed in the fuzzy inference architecture. The inference results would thus be outputted by semantic representations, such as high, median, or low. These representations could be sent to pertinent medical professionals to alert them once it is needed. We define the *FIS* and *FIA* in the following section.

Let the *FIS* system = {*U*, *A*}, where *U* is a set of patients' bio-signals. Let set *U* = {P_1, P_2, P_3 … P_n}, where P_i represents the specific features of one patient's various bio-signals. Set *A* presents various bio-signals. If A = {*h*, *w*, *blood*, *pulse*, *spo2*, *breathe}*, set *A* thus represents the generic features of *height*, *weight*, *blood*, *pulse*, *spo2,* and *breath*. Let the group of bio-signals $V = v^m$, where *m*=1, 2, 3… 6. The fuzzy set was defined to correspond with fuzzy semantic presentations, such as [*low*, *median*, *high*]. Let the features of a membership function *f*(*P*) = [*begin_support*, *begin_core*, *end_core*, *end_support*]. The pi-type of the *f*(*P*) is represented in Figure 2.

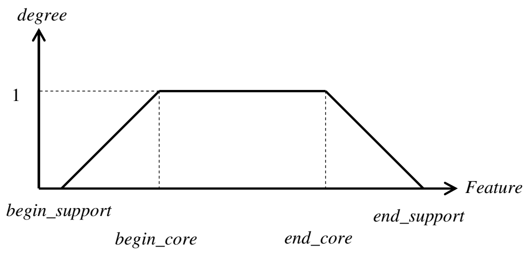

Figure 2. The pi-type of the *f*(*P*)

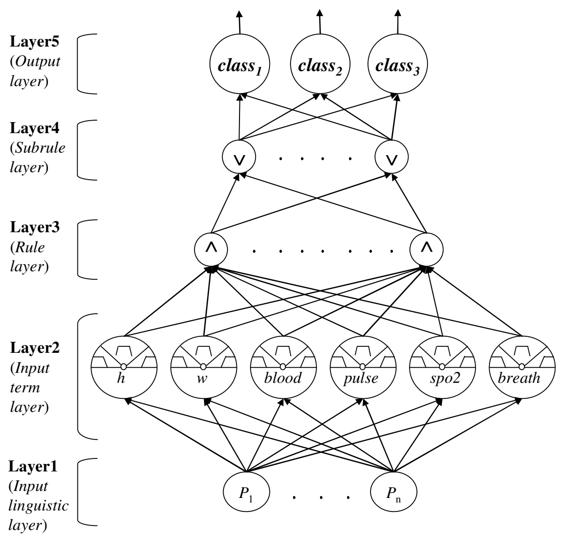

Figure 3. Granular computing in fuzzy inference algorithm

The granulation of *FIA* is designed into layers. Personal bio-signals would be computed by these granulations in each layer. There are five layers defined in the *FIA* architecture, namely, *input linguistic layer, input term layer,* r*ule layer, sub-rule layer,* and o*utput layer.* The architecture of *FIA* is shown in Figure 3. The definitions of layers are described as follows:

Layer 1 (*Input Linguistic Layer*): Input of layer 1 is {P_1, P_2, P_3… P_n}; Output of layer 1 is
$\mu_{ij} = P_{ij}$, *i*=1… *n*, *j*=1… 6. (1)

Layer 2 (*Input Term Layer*)**:** Input of layer 2 is ((P_{11} … P_{16})… (P_{n1} … P_{n6})); Output of layer 2 is $\mu^2_{ijk} = f_{jk}(P_{ij})$, *i*=1… *n*, *j*=1… 6, *k*=1, 2, 3. (2)

Layer 3 (*Rule Layer*)**:** Input of layer 3 is
$((f_{11}(P_{11}) \cdots f_{13}(P_{11}))\cdots(f_{61}(P_{n6}) \cdots f_{63}(P_{n6})))$;
Output of layer 3 is μ^3_{ik}, where $r \in \Re^{3,4}$ and,
$\mu^3_{ik} = \min\{f_{1k}(P_{i1}), f_{2k}(P_{i2}),..., f_{6k}(P_{i6})\}$,
i=1… *n*, *k*=1, 2, 3. (3)

Layer 4 (*Sub-rule Layer*)：Input of layer 4 is μ^3_{ik}; Output of layer 4 is μ^4_d，d = 1, 2, 3, where $r \in \Re^{4,5}$ and,
$\mu^4_{ik} = \max\{R_k(\mu^3_{11}),...,R_k(\mu^3_{ik})\}$, *i*=1… *n*, *k*=1, 2, 3 (4)
When $R_k(\mu^3_{ik})$ = the value of the k^{th} semantic rule of the μ^3_{ik}.

Layer 5 (*Output Layer*): The degree is computed by employing all the values from layer 4. Input is μ^4_{ik}. Output is

$$\mu^5_k = \frac{1}{n}\sum_{i=1}^{n}(\mu^4_{ik}), \; i=1\ldots n, k=1, 2, 3 \quad (5)$$

In the following section, we present *pulse* and *breath* as examples to evaluate whether one patient in his group is comfortable or not. The *breath* is depicted in the y-axis in Figure 4, while the *pulse* is depicted in the x-axis. The ranges of the x-axis and y-axis are separated by the fuzzy semantic presentation ([*low*, *median*, *high*]). Moreover, the whole area is divided into nine sub-areas. One distribution example of *pulse* and *breath* is presented in Figure 4.

The rules $\Re^{3,4}$ between layers 3 and 4 are defined in Table 1. On the other hand, the rules $\Re^{4,5}$ between layers 4 and 5 are defined in Table 2. For example, three compositions of all the inferable rules are listed in Table 2. Their referred results correspond to $class_1$, $class_2$, and $class_3$. For instance, the inferable architectures of *the classes* are shown in Figure 5. $Class_1$ covers the union of $Rule_1$, $Rule_2$, and $Rule_4$. $Class_2$ covers the union of $Rule_2$, $Rule_3$, $Rule_5$, and $Rule_7$. $Class_3$ covers the union of $Rule_3$, $Rule_6$, $Rule_8$, and $Rule_9$.

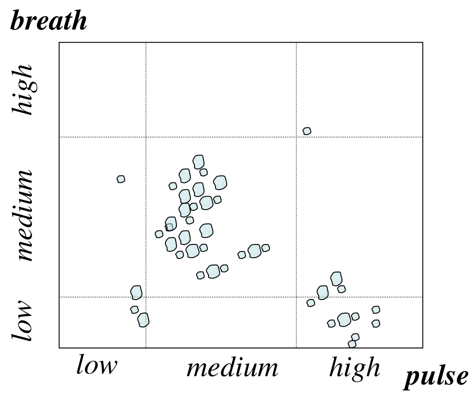

Figure 4. One distribution of breath and pulse

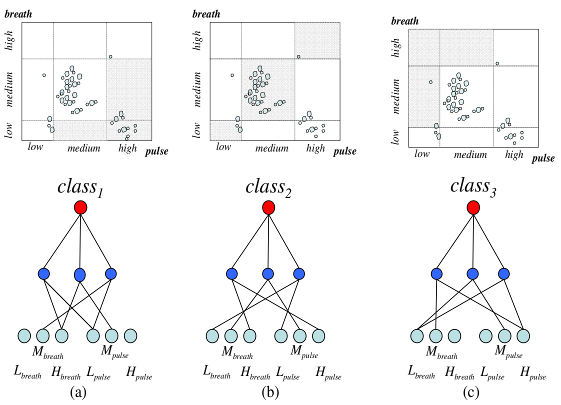

Figure 5. Architectures of the referred classes

Table 1. Rules $\Re^{3,4}$ between layers 3 and 4

$Rule_1 \leftarrow high_{breath} \wedge low_{pulse}$
$Rule_2 \leftarrow high_{breath} \wedge median_{pulse}$
$Rule_3 \leftarrow high_{breath} \wedge high_{pulse}$
$Rule_4 \leftarrow median_{breath} \wedge low_{pulse}$
$Rule_5 \leftarrow median_{breath} \wedge median_{pulse}$
$Rule_6 \leftarrow median_{breath} \wedge high_{pulse}$
$Rule_7 \leftarrow low_{breath} \wedge low_{pulse}$
$Rule_8 \leftarrow low_{breath} \wedge median_{pulse}$
$Rule_9 \leftarrow low_{breath} \wedge high_{pulse}$

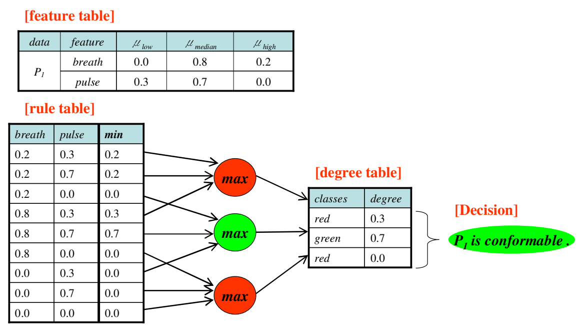

Figure 6. Referred result example

Table 2. Rules $\Re^{4,5}$ between layers 4 and 5

$class_1 \leftarrow Rule_1 \vee Rule_2 \vee Rule_4$
$class_2 \leftarrow Rule_3 \vee Rule_5 \vee Rule_7$
$class_3 \leftarrow Rule_6 \vee Rule_8 \vee Rule_9$

Table 3. Basic values in fuzzy set

Input Terms	Low	Median	High
SBP	80,80,110	95,130,160	150,200,200
DBP	40,40,65	60,75,90	85,100,100
Pulse	50,50,70	60,80,100	90,110,110

The feature degrees of a patient's breath and pulse are shown in the *feature table* of Figure 6. Subsequently, we could induce *rule table* based on the *feature table* and the rules in Table 1. The values in the *degree table* are computed through the *min* column in the rule table. Likewise, we could obtain that the degrees of *classes* (*class*$_1$, *class*$_2$, and *class*$_3$.) are 0.3, 0.7, and 0.0, respectively. Thus, we can infer that the patient is conformable in his group.

5. Experimental Evaluations

In the experimental design, the membership function *f(x)* could be displayed as a triangle shape (lambda-type), given that we defined *begin_core* = *end_core*. The *f(x)* was formally defined as follows:

$$f(x)=\begin{cases} 0, & x \le Begin\_\sup port \\ (x - Begin\_\sup port)/(Begin\_core - Begin\_\sup port), & Begin\_\sup port < x < Begin\_core \\ 1, & x = Begin\_core \text{ or } x = End\_core \\ (End\_\sup port - x)/(End\_\sup port - End\_core), & End\_core < x < End\_\sup port \\ 0, & x \ge End\_\sup port \end{cases}$$

A manometer with three input terms was chosen as a bio-signal device. It could measure systolic blood pressure (SBP), diastolic blood pressure (DBP), and pulse. The initial values in the fuzzy set are presented in Table 3. In addition, they corresponded with the semantic presentation.

In this experiment, one semantic presentation went along with one fuzzy linguistic term hedge (FLTH) of the fuzzy set. The const parameter δ was defined to modify the range of the fuzzy set. Their relationships are listed in Table 6. We set three fuzzy hedges by changing the value of δ. Furthermore, three hedges with their semantic presentations are listed in Table 4.

Table 4. δ setting of fuzzy hedges

fuzzy hedges	Low(δ)	Median(δ)	High(δ)
Hedge 1	1	1	1
Hedge 2	2	0.5	2
Hedge 3	0.5	2	0.5

In Figure 7, we were to deduce that fuzzy hedges were affected by the value of δ. The inferred results were depended on the hedge settings. By comparing the hedges in Figure 7, hedge 2 had more significant differences than others. Specifically, the inferred results of hedge 2 would be more precise than the others.

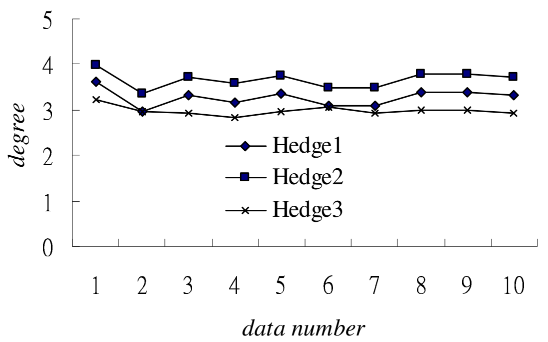

Figure 7. Hedge comparisons

Table 5. Special test case

Input [SBP, DBP, Pulse]	Output degree
[80,40,30]	0.67
[200,100,110]	0.0
[130,75,65]	4.5

The boundary values of degrees were also defined by special test cases. This is shown in Table 5. The worst degree is 0, while the best degree is 4.5. If the degree range is equally divided into three parts, the range of the healthy persons is from 3.0 to 4.5. In contrast, the range of the weak persons is from 1.5 to 2.9, while the range of the critical persons is from 0 to 1.4. However, a large amount of data samples is required to accurately define the boundaries before the algorithm is used in specific domains.

6. Conclusions and Future Works

In the real world, people may not always clearly understand each other's thought. Likewise, they also find it difficult to understand the changes in each other's health conditions. We could judge one bio-signal whenever overshoots its thresholds, that is, generic or personal. In this study, a fuzzy inference algorithm for fusing multiple bio-signals and determining a person's health was proposed. We applied the fuzzy theory to fuse multiple bio-signals and to identify weaker persons in a group. In the experimental results, the weaker persons could be successfully identified by semantic representations. Likewise, the boundary values of degrees were defined. The degree range could be divided into parts to differentiate the patients' health levels and could be used in specific domains.

In the future, we will apply *FIA* in specific domains, such as computer officers and leisure health promoters. The initial values of fuzzy set have to be defined by the specific domain experts. The best value of fuzzy hedge will be adapted if *FIA* is used in different users' domains.

Acknowledgments

This research was supported by the Applied Information Services Development and Integration project of the Institute for Information Industry (III) and sponsored by MOEA, Taiwan R.O.C.

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Table 6. Relationship between FLTH and δ

FLTH(δ=*2*) : Very	FLTH(δ=*1*) : Normal	FLTH(δ=*0.5*) : More or Less