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Practical Causal Analysis for Biomedical Sensing Based on Human-Machine Collaboration

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1. Introduction

In general, human understand phenomena by considering causalities when they face any problem. In fact, many causal-based applications and solutions have been proposed in keeping with theoretical development.

For instance, in industrial domain, Furuta et al. proposed a training support system for plant operation in which trainee's knowledge is represented as two-layered model of task hierarchy and qualitative causality (1998). In medical domain, Thang et al. proposed a medical diagnosis support system based on oriental diagnosis knowledge (2006). In their approach, the causality among some subject's symptoms and their diagnostic outcome is described by using RBF neural network. Nakajima et al. proposed a generic health management framework named *Human Health Management Technology* which is applied to not only human being but also manufacturing process, energy consumption management, and so forth (2008b). In addition, Hata et al. suggested a concept named *Human Health Care System of Systems* which focus on health management, medical diagnosis, and surgical support. In the concept, the human health management technology is discussed from view point of system of systems engineering (2009). Thus, causality acquisition and its utilization among complex systems has a quite important role in optimal management.

On another front, from a viewpoint of theoretical development, lots of causal analysis theories have been proposed (Bishop, 2006). Bayesian network describes statistical causality among phenomena observed from certain managed systems, and the statistical causality provides inference and reasoning functions (Pearl, 2001). Graphical model visualizes causality among components in complex systems (Miyagawa, 1991). Fuzzy logic helps intuitive representation of causality which is experts' tacit knowledge (Zadeh, 1996).

As mentioned above, causal analysis theories and their applications and solutions in many domains have been improved for long time. However, causal analysis for designing sensors is not discussed enough yet. Thus, in this chapter, a role of causal analysis in biomedical sensing is discussed.

In the rest of this article, in section 2, the importance of human-machine collaboration in causal analysis is described. In the section, problems which we address in this chapter is defined. In section 3, a human-machine collaborative causal analysis is proposed. Then, in section 4 and 5, two kinds of biomedical sensing which employ the human-machine collaborative causal analysis are demonstrated, that is, visceral fat measurement and heart rate monitoring.

2. Problem definition and related works

In this section, the importance of human-machine collaboration in causal analysis is discussed from a viewpoint of requirements for practical biomedical sensing. And, problem definitions are discussed.

2.1 Requirements for biomedical sensing from a viewpoint of practical use

Considering practical usage, biomedical sensing has to be easy to use. In addition, it should be non-invasive, low-intrusive, and unconscious regarding consumers' home usage. For instance, X-ray CT is not available at home because of its X-ray exposure.

In addition, biomedical sensing is required to have not only measurement accuracy but also transparent measurement theory because it provides users with feeling of security besides informed consent (Marutschke et al., 2010). However, measurement accuracy becomes worse while measurement theory becomes too simplified. Thus, the satisfaction of accuracy and transparency should be considered while experts design certain biomedical sensing equipments.

Regarding the above-mentioned problem, a new designing process of biomedical sensing is proposed which employs causal analysis based on human-machine collaboration. In the next section, the human-machine collaboration is discussed, and its importance described.

2.2 Human-machine collaboration

As means for representing causality, many theories have been proposed, that is, Bayesian networks, graphical modeling, neural networks, fuzzy logic, and so forth. Additionally, as means for modeling cause-effect structure, lots of learning theories have been studied considering the characteristics of each theory (Bishop, 2006; Zadeh, 1996). Particularly, Bayesian network and graphical modeling are utilized for a variety of applications in the broad domain, due to transparency of the causality (Pearl, 2001).

These previous works show two primary approaches to causality analysis: one for generating causality based on experts' knowledge and then optimizing the causalities by using actual datasets, and the other for automatically processing a measured dataset and then modeling causalities based on the trend and statistics from the data. The former is based on experts' knowledge and has an advantage in understandability of the causality, but needs sufficient knowledge on a certain target system and much more efforts for modeling such a system with many components. Conversely, the latter provides subjective causality obtained from datasets and has an advantage of not requiring any knowledge from experts, but sometimes has difficulty in understanding the causality. Here, there could be another approach that makes use of benefits of both in order to effectively model causalities by using experts' knowledge during working with machines. This idea is considered an effort to achieve goals through human-machine collaboration (Tsuchiya et al., 2010).

2.3 Problems to be solved and related works

According to the above discussion in section 2.2, the causal representation process and its framework for causality acquisition based on human-machine collaboration has an important role in practical causality acquisition. Regarding causality acquisition process and its framework based on human-machine collaboration, a similar study has been shown in Knowledge Discovery in Databases (KDD) processes (Fayyad et al., 1996). KDD defined the process of knowledge discovery and data mining techniques. Nadkarni has proposed a

learning method with causal maps which is practically applicable in Bayesian networks, and then dividing the cause-effect structure into D-maps and I-maps considering independency among the causality (2004). Gyftodimos represented causality in a hierarchical manner and proposed a set of frameworks regarding the representation and inference for understandable relationships (2002). Tenenbaum et al. showed that a following process is effective for learning and inference in the target domain; treating the fundamental principle of the domain as something abstract, structuring it, and fitting the structure into the final measured data (2006). The authors proposed that hierarchical representation of causality among components which are obtained from certain target systems (Tsuchiya et al., 2010). These studies have indicated that conceptualization of components is effective for acquiring significant causality. Thus, in the following section, an effective causal analysis process for practical biomedical sensing is proposed.

3. Practical causal analysis for biomedical sensing

To solve the problems which defined in the previous section, the proposed process represents a causality of target components with a conceptual model and evaluates the independency of the conceptual causality by employing experts' knowledge. Then, feature attributes and cause-effect structure are prepared in each independent subset of the causality. Finally, whole cause-effect structures of each subset are integrated, and the integrated cause-effect structure is fitted to the actual dataset. These process is executed via human-machine collaboration.

In the following, the detailed steps of the above causal analysis are determined.

Step 1. Illustration of conceptual causality based on measurement principle

The intuitive causality among components in the target system is represented by a directed graph based on experts' knowledge. The represented intuitive causality is determined conceptual causality.

Step 2. Causal decomposition based on experts' knowledge

The conceptual causality defined in Step 1 is decomposed into independent subsets by employing experts' knowledge including design information about the target system.

Step 3. Practical cause-effect structure formulation via human-machine collaboration

Firstly, in each subset of the conceptual causality, feature extraction is executed by combining components, multiplying by itself, and so forth. In the next, cause-effect structure among the prepared feature attributes is formulated. Then, the cause-effect structures are integrated according to the conceptual causality. And feature selection is conducted if necessary. At last, components in formulated cause-effect structures are optimized by using actual dataset.

In the following section 4 and 5, the proposal causal analysis process is applied to two kinds of biomedical sensing.

4. Visceral fat measurement by using bioelectric impedance

In the 21st century, declining birth rate and growing proportion of elderly people develop into more serious social problems in advanced nations. Not only solving the labor power reduction but also extending healthy life expectancy are the important challenge which human beings should address. In terms of the issue, primary prophylaxis has got lots of attention as an important activity to prevent lifestyle-related diseases.

According to such a social problems, metabolic syndrome has been recognized in advanced nations. Currently, the waist circumference, blood pressure, blood sugar, and serum lipid are evaluated for the primary screening whether the person is diagnosed with metabolic syndrome at the medical checkups. Here, the purpose of waist circumference is for screening visceral fat accumulation since it is well known that visceral fat area at abdominal level is strongly related to lifestyle-related diseases (Matsuzawa, 2002). However, the waist circumference reflect not only visceral fat but also subcutaneous fat, organs, and so forth. Thus, more accurate screening method is desired. On another front, in major hospitals, X-ray CT image processing at abdominal level is the gold standard (Miyawaki et al., 2005). However, X-ray CT has a serious problem of X-ray exposure.

Thus, non-invasive and low-intrusive visceral fat measurement is desired.

4.1 Measurement principle

Fig. 1 shows a X-ray CT image at abdominal level, and the visceral fat is located in the light grey area in Fig. 1. Therefore, the objectives of visceral fat measurement is to estimate the square of the light grey area.
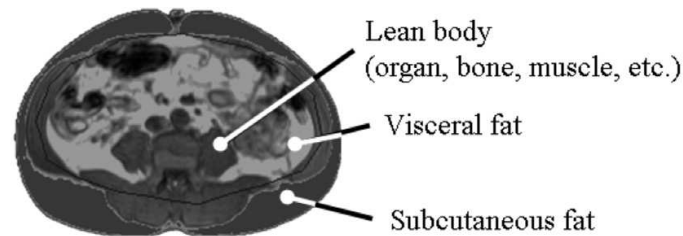

Fig. 1. Body composition at abdominal level

To measure the visceral fat area non-invasively, biomedical impedance analysis (BIA) has been employed (Gomi et al., 2005; Ryo et al., 2005; Shiga et al., 2007). BIA is famous for its consumers' healthcare application, that is, body composition meters, and has been studied by lots of researchers (Deurenberg et al., 1990; Composition of the ESPEN Working Group, 2004).

Considering each body composition in Fig. 1, the impedance of lean body is low since muscle comprised in lean body involves much water, and the impedance of visceral fat and subcutaneous fat are high. Thus, each area of body composition could be estimated independently by taking advantage of the impedance characteristics of each body composition.

The basic idea of visceral fat measurement via BIA is that the visceral fat area (VFA) S_v is estimated by reducing subcutaneous fat area (SFA) S_s and lean body area (LBA) S_l from abdominal cross-section area (CSA) S_c. This idea is illustrated in Fig. 2, and is formulated in equation (1).
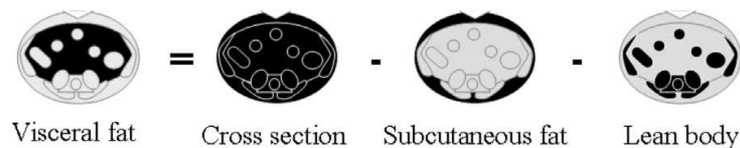

Fig. 2. Visceral fat measurement principle

$$S_v = S_c - S_s - S_l \qquad (1)$$

where S_v, S_c, S_l are visceral fat area, subcutaneous fat area, and lean body area respectively.

4.2 System configuration

In accordance with the measurement principle, the visceral fat measurement equipment is implemented. The equipment obtains human's body shape and two kinds of electrical impedance at abdominal level.

At the beginning of measurement, the equipment measures human's body shape as shown in Fig. 3 and 4. Obtained a and b are body width and depth at abdominal level respectively.
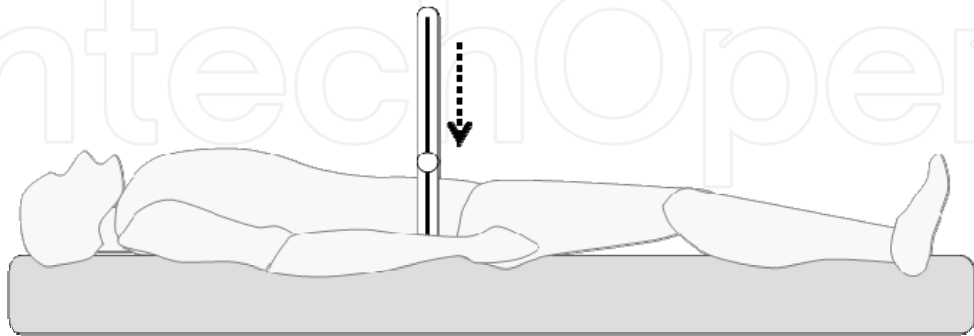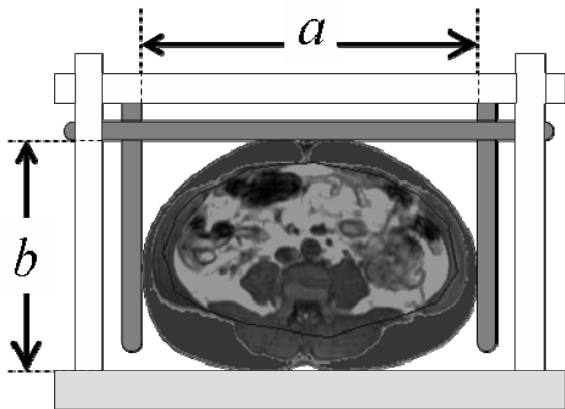

Fig. 3. Body shape measurement procedure

Fig. 4. Body shape information

In the next, the equipment measures two kinds of electrical impedance at abdominal level. Eight paired electric poles are placed on surroundings of the abdominal as shown in Fig. 5. And an weak current, 250 µA with 50 kHz, is turn on between subject's wrist and ankle as shown in Fig. 6. Then, eight impedances are obtained via eight paired poles, and their average is determined as Z_t.
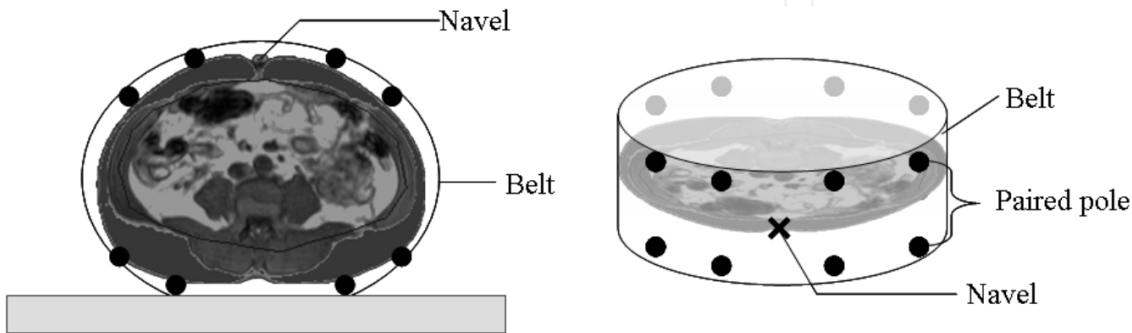

Fig. 5. Eight paired electric poles placed on surroundings of abdominal

After that, in the same manner, an weak current is turn on subject's surface at abdominal level via eight paired poles. And, eight impedances are obtained via eight paired poles as shown in Fig. 7, and their average is determined as Z_s.
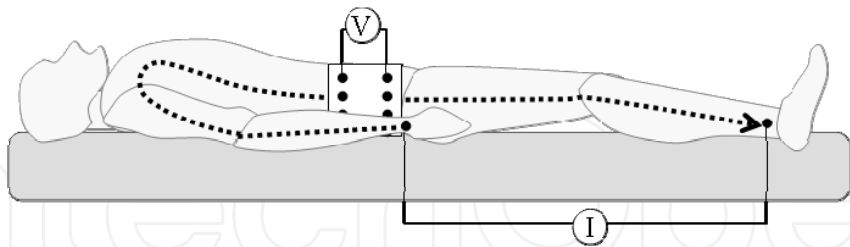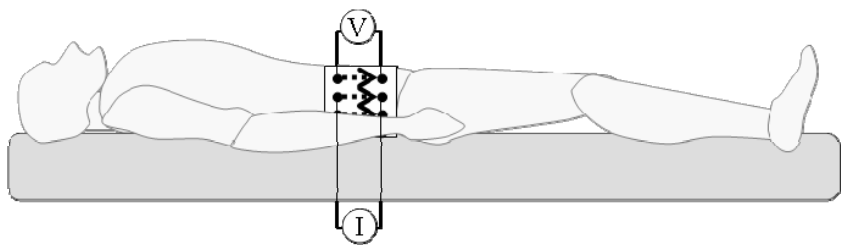

Fig. 6. Impedance Z_t measurement procedure

Fig. 7. Impedance Z_s measurement procedure

As a result, body shape a and b, two kinds of impedance Z_t and Z_s are acquired by using the implemented equipment.

4.3 Causal analysis via human-machine collaboration

Firstly, the actual dataset of 196 subjects was prepared before the following causal analysis. The dataset consists of 101 males and 95 females at age 49.0 ± 11.3 for males and 49.6 ± 11.3 for females. Two kinds of impedance Z_t, Z_s and body shape information a and b are calculated by using the visceral fat measurement equipment. In addition, VFA S_v, LBA S_l, SFA S_s, and CSA S_c are obtained by X-ray CT image processing as reference.

Step 1. Illustration of conceptual causality based on measurement principle

According to measurement principle and the equipment system configuration, the relationship among the set of obtained four components a, b, Z_t, Z_s and three kinds of body composition S_l, S_s, S_c is illustrated with a conceptual causality as shown in Fig. 8.
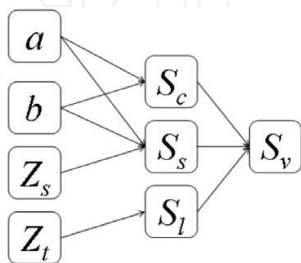

Fig. 8. Conceptual causality in visceral fat measurement

Step 2. Causal decomposition based on experts' knowledge

At first, according to the measurement principle, the causality among body composition is independent from four component obtained via the equipment. Thus, the subset consist of body composition is decomposed from conceptual causality. In the next, since S_c doesn't

affect a and b directly, the subset consist of S_c, a, and b is decomposed from conceptual causality. In the same manner, the subset related to S_s and S_l is decomposed respectively. As a result, the conceptual causality is decomposed into four subsets in Fig. 9.
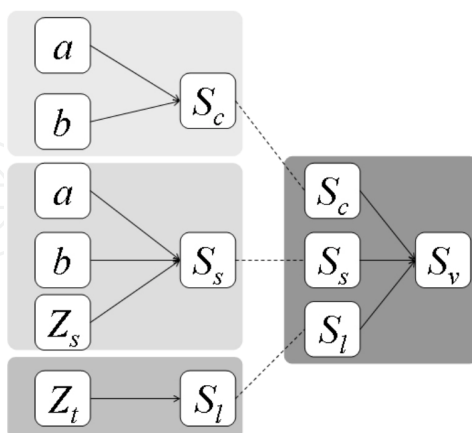

Fig. 9. Decomposed conceptual causality in visceral fat measurement

Step 3. Practical cause-effect structure formulation via human-machine collaboration
According to equitation (1) and the decomposed conceptual causality in Fig. 9, the cause-effect structure is formed in equation (2).

$$\tilde{S}_v = \alpha_1 f_c(a,b) + \alpha_2 f_l(Z_t) + \alpha_3 f_s(a,b,Z_s) + \varepsilon \tag{2}$$

Then, by assuming that the body shape at abdominal level is ellipse, feature attributes a^2, b^2, ab, $(a^2 + b^2)^{1/2}$, $1/Z_t$, $Z_s a^2$, $Z_s b^2$, and $Z_s(a^2+b^2)^{1/2}$ are prepared (Yoneda et al., 2008). By replacing the corresponding terms in equation (2) with these attributes, the following cause-effect structure can be acquired as shown in equation (3).

$$\tilde{S}_v = \beta_1 ab + \beta_2 1/Z_t + \beta_3 Z_s a^2 + \beta_4 Z_s b^2 + \beta_5 Z_s(a^2 + b^2)^{1/2} + \varepsilon \tag{3}$$

where β_i are regression coefficients and ε is an error term. However, considering the complexity in the shape of the abdomen, it is not always true that employing all of the feature attributes included in equation (3) could result in over estimation. Thus, from the statistical viewpoint, we perform feature selection by employing Akaike Information Criterion (Akaike, 1974). As a result, the cause-effect structure in equation (4) is obtained.

$$\tilde{S}_v = \gamma_1 ab + \gamma_2 1/Z_t + \gamma_3 Z_s b^2 + \gamma_4 Z_s ab + \varepsilon \tag{4}$$

where γ_i are regression coefficients and ε is an error term.

4.4 Experimental result and discussion
To compare performance, a experts' knowledge-based measurement model is prepared (Shiga et al., 2007), and is fitted to the sample dataset which is described in the previous section.
Table 1 shows comparison of accuracy of visceral fat measurement. In Table 1, *EM* and *ESD* indicate the mean of absolute errors and the standard deviation of estimated errors respectively, and *R* is the correlation between the X-ray CT reference and the estimated value.

According to the results, the improved estimation model provides higher performance in *EM* by 3.73 cm², in *ESD* by 5.03 cm², and *R* by 0.063. Thus, the proposed causality analysis process is proven to have enough performance to model a practical cause-effect structure.

	EM [cm²]	ESD [cm²]	R
Experts' knowledge-based model	20.369	26.702	0.826
Human-machine collaboration	16.638	21.676	0.889

Table 1. Visceral fat estimation performance comparison

5. Heart rate monitoring in sleep by using air pressure sensor

Among vital-signals, heart rate (HR) provides important information of humans' health transit such as an early stage of cardiac disease (Kitney & Rompelman, 1980). In addition, HR variability provides information of autonomic nerve activity (Kobayashi et al., 1999). Considering such values, continuous HR monitoring would have a quite important role in daily life. Thus, it is pretty important for us to measure our HR continuously to know its changes in our daily life.

Considering human's activities of livelong day, sleep has a high proportion. In addition, human being is in resting state in sleep. Thus, wealth of heart rate variability in sleep provides much information about human's health condition.

Currently, in a medical domain, an electrocardiography (ECG) is the gold standard for measuring HR variability accurately. However, ECG restricts human's free movement since many poles are put on body. Thus, ECG is hard to be used in sleep.

Thus, a low-intrusive and non-invasive continuous heart rate monitoring in sleep on lying on the bed is desired.

5.1 Measurement principle

To solve such a problem, HR monitoring equipment by using an air pressure sensor (APS) has been developed (Hata et al., 2007; Yamaguchi et al., 2007; Ho et al., 2009; Tsuchiya et al., 2009). Considering sleep condition, heartbeat causes pressure change of back. Thus, the basic idea of measuring heart rate monitoring is to extract heartbeats from pressure change of back. However, pressure change of the body is caused not only heartbeat but also roll-over, respiration, snore, and so forth. Thus, a new method to extract heartbeats from pressure change on back is required.
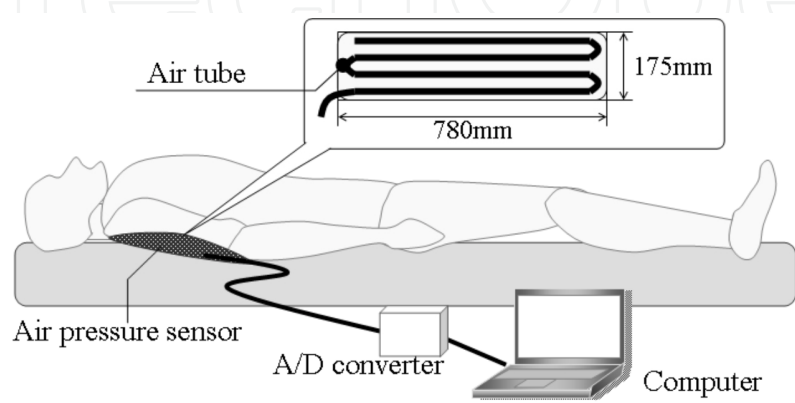

Fig. 10. Heart rate monitoring equipment

5.2 System configuration

The HR monitoring equipment measures body pressure variability x_{APS} via an APS to extract HR variability from the obtained pressure variability. Fig. 10 shows the configuration of the equipment. The APS composed of air tube, and is set under human's back on the bed. The characteristics of APS is drawn in Fig. 11. APS record pressure change at 100Hz, and quantizes pressure change into 1024 level via A/D convertor.
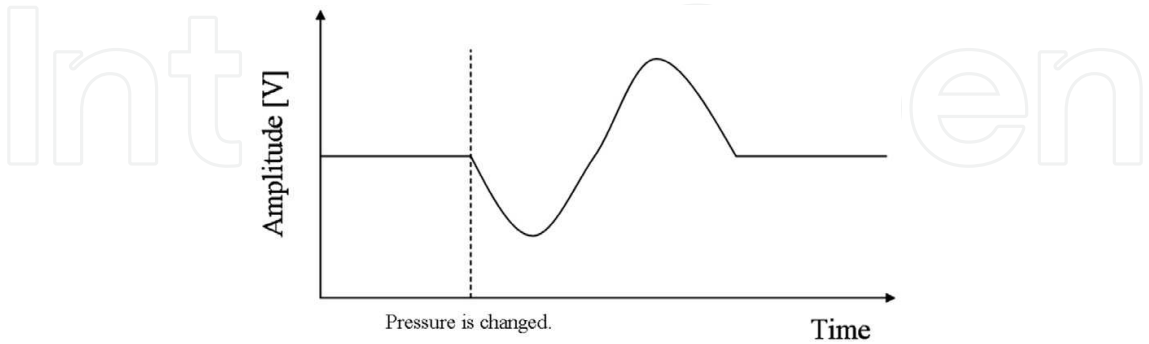

Fig. 11. Air pressure sensor characteristics

In HR monitoring, the heartbeats are detected and the HR variability x_{HR} is extracted from heartbeat intervals.

5.3 Causal analysis via human-machine collaboration

Firstly, the actual dataset of 8 subjects was prepared before the following causal analysis. The detailed profile of each subject is shown in Table 2.

Subject	Age [yrs]	Height [cm]	Weight [kg]	Gender
A	23	175	76	Male
B	23	171	68	Male
C	23	165	50	Male
D	25	171	56	Male
E	22	180	92	Male
F	22	172	55	Male
G	23	170	62	Male

Table 2. Profile of subjects

Each subject lied on bed for 10 minutes, and ECG is obtained for each subject while HR monitoring equipment measured pressure change of back.

Step 1. Illustration of conceptual causality based on measurement principle

According to the measurement principle, the conceptual causality among heartbeat x_{HB}, body movement x_{MV}, respiration x_{RSP}, obtained air pressure x_{ASP}, and heart rate x_{HR} is illustrated in Fig. 12.

In addition, according to the knowledge on heart rate that heart rate is defined by the interval of heartbeat, the conceptual causality is modified as shown in Fig. 13. It shows that HR variability is calculated from R-R interval τ_{RR} like ECG when R-waves τ_{R}.

Step 2. Causal decomposition based on experts' knowledge

Since the HR extraction from τ_{R} is generalized, the causality shown in Fig. 13 is decomposed into two parts as shown in Fig. 14. They consist of the causality for generalized HR extraction, and the causality for τ_{R} extracted from x_{ASP}.
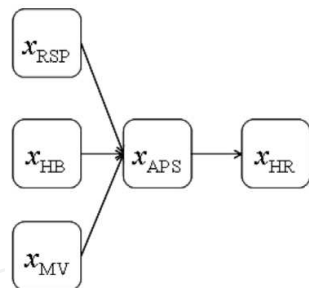
Fig. 12. Conceptual causality in heart rate monitoring via air pressure sensor
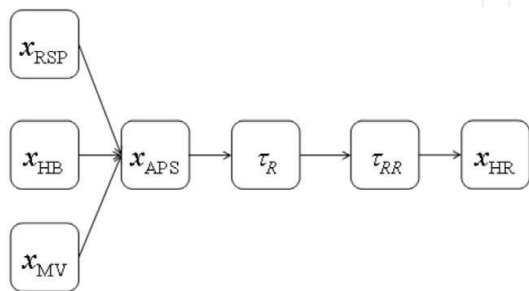

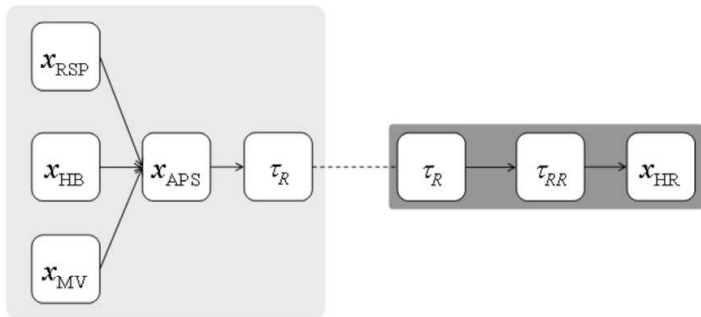Fig. 13. Conceptual causality in heart rate monitoring

Fig. 14. Decomposed conceptual causality in heart rate monitoring

Step 3.   Practical cause-effect structure formulation via human-machine collaboration

As for τ_R extraction from pressure change, the pressure change involves not only heartbeat but also respiration and body movement. Because of the nature of the signals, it could be difficult to determine the precise position of R-waves τ_R by autocorrelation function and peak detection method. In this study, fuzzy logic is employed to formulate the knowledge about heartbeat.

Firstly, full-wave rectification is applied to x_{ASP}, and the result signal is determined as x_{FRA}. Then, the fuzzy logic based on the knowledge about τ_{RR} is applied to the pre-processed pressure changes. These fuzzy rules are described in the following.

Knowledge 1 : The large pressure change is caused by heartbeat.
Knowledge 2 : Heartbeat interval does not change significantly.

According to the knowledge on heartbeat characteristics, the fuzzy rules are denoted in the following.

Rule 1 : IF x_i is HIGH, THEN the degree of heartbeat point μ_{Amp} is HIGH.
Rule 2 : IF t_i is CLOSE to $\overline{T}$,THEN the degree of heartbeat point μ_{Int} is HIGH.

Where $\mu_{Amp}(i)$ is the membership function of Rule 1, x_i is pre-processed pressure change, t_i is the sampling point of obtained pressure change, $\overline{T}$ is the average of heartbeat intervals that calculated by using previous ten heartbeats, and $\mu_{Int}(i)$ is the membership function of Rule 2. Then, the membership functions respond to the fuzzy rules are illustrated in Fig. 15 and 16, and formulae are equations (5)–(7) and (8), (9).

Fig. 15. Membership function for evaluating degree from viewpoint of amplitude

$$\mu_{Amp}(i) = \begin{cases} 0 & \text{if} \quad x_i < x_{min} \\ \dfrac{x_i - x_{min}}{x_{max} - x_{min}} & \text{if} \quad x_{min} \le x_i \le x_{max} \\ 1 & \text{if} \quad x_i > x_{max} \end{cases} \tag{5}$$

$$x_{min} = \min(x_{FRA}) \tag{6}$$

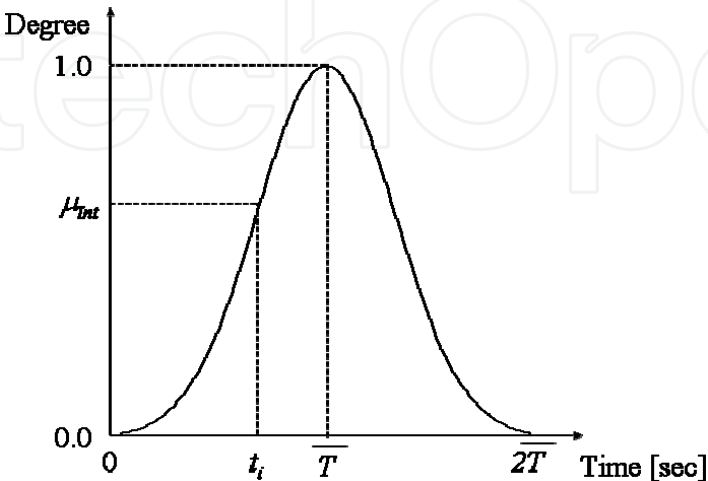$$x_{max} = \max(x_{FRA}) \tag{7}$$

Fig. 16. Membership function for evaluating degree from viewpoint of heartbeat interval

$$\mu_{Int}(i) = \exp\left(\frac{-(t_i - \overline{T})^2}{2\sigma^2} \right) \tag{8}$$

$$\sigma = \overline{T} / 3 \tag{9}$$

Finally, μ_i is calculated by multiplying μ_{Amp} and μ_{Int} and the location with maximum μ_i is determined as heartbeat x_{HB} as formulated in equation (10).

$$\mu(i) = \mu_{Amp}(i) * \mu_{Int}(i) \tag{10}$$

5.4 Experimental result and discussion

In this experiment, the proposed heart rate monitoring based on human-machine collaboration is compared with conventional typical method that is based on autocorrelation functions and peak detection and one with proposed method by using fuzzy logic. Table 3 shows correlations between HR changes obtained from the ECG and those obtained from the heart rate monitoring equipment.

The results indicate that the method of fuzzy logic achieved higher performance for all of the subjects. In particular, the correlation to ECG for the subject A and E is over 0.97, which is extremely high.

Subject	R	
	Human-machine collaboration	Autocorrelation functions-based
A	0.973	0.703
B	0.807	0.389
C	0.754	0.621
D	0.872	0.699
E	0.972	0.658
F	0.844	0.677
G	0.737	0.346
Avg	0.851	0.585

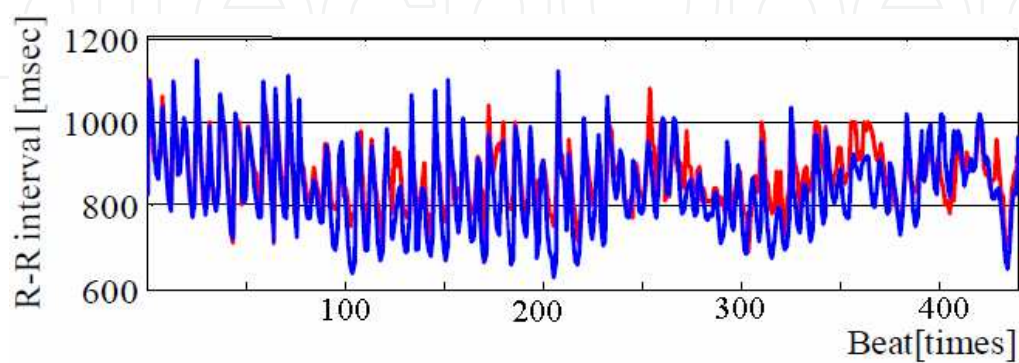Table 3. HR monitoring performance comparison

Fig. 17. Heartbeat count vs. R-R interval against subject B

In the following, the some of detailed HR monitoring results are discussed.

Fig. 15-18 shows the result for subject B and E where horizontal axis and virtual axis are heartbeat count and R-R interval respectively, and the blue line and red line is the R-R interval variability obtained by using the HR monitoring equipment and ECG respectively.

According to the results for subject B and E, the result of HR monitoring is quite similar to ECG's one. In addition, in Fig. 17, the HR monitoring could detect the significant R-R interval occurred around 200 beats.
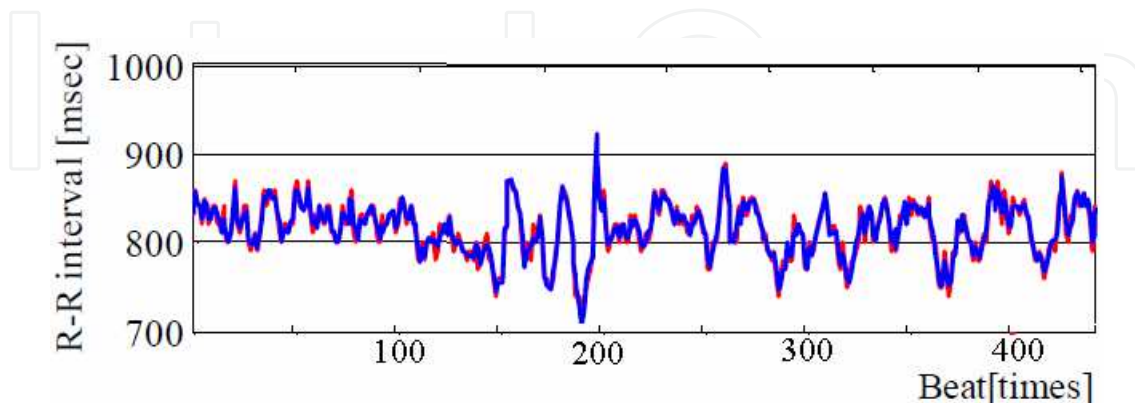

Fig. 18. Heartbeat count vs. R-R interval against subject E

6. Summaries and conclusions

This chapter has introduced a causal analysis based on human-machine collaboration for practical biomedical sensing. In the proposed method, the cause-effect structure is actualized in three steps. Firstly, experts illustrate the conceptual causality among components which are obtained from sensing target. In the next step, the conceptual causality is decomposed into independent subset by employing experts' knowledge. Then, feature attributes are prepared by using components, and each subset is formulated. At last, the formulae of each subset is integrated and optimized by using actual dataset obtained from sensing target.

Additionally, two applications of practical biomedical sensing have been presented; visceral fat measurement based on bioelectrical impedance analysis and heart rate monitoring by air pressure sensor.

In the case of visceral fat measurement, the conceptual causality was constructed by using experts' knowledge of the relationship among two kinds of bioelectrical impedance, body shape and body composition and the cause-effect structure was realized by fitting 196 subjects' dataset. According to the comparative experimental results, the measurement accuracy was improved in keeping with its measurement transparency.

In case of heart rate monitoring, the conceptual causality among air pressure sensor, R-wave, R-R interval and heart rate was constructed by using experts' knowledge on electrocardiograph. Then, the conceptual causality is decomposed into two subset, that is, the causality which describes heart rate extraction from heartbeat and the one among air pressure sensor, heartbeat, respiration, and body movement. According to the experimental result, the accuracy improvement was confirmed by comparing with the typical heart rate extraction used in the electrocardiograph.
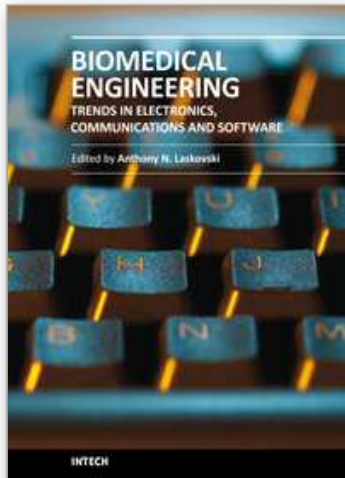
According to the above two application, the proposal causal analysis based on human-machine collaboration is useful to realize practical biomedical sensing.

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