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APPLICATIONS OF NEW BALLISTOCARDIOGRAPH SYSTEMS

-CONTINUOUS BLOOD PRESSURE ESTIMATION AND BIOMETRIC RECOGNITION

새로운 심탄도 계측 시스템의 응용

-연속혈압 추정과 생체인식

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노 승 우

Abstract

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Ballistocardiogram (BCG) is a recording of body movement, which is generated in synchronous with the heartbeats. Studies on BCG were a field of intense research in the past decades, since it could provide a non-invasive means to monitor cardiovascular activities.

However, such interests have slowly diminished after 1970's due to its impractical characteristics compared to the new technologies (i.e. echocardiography) that diagnose cardiovascular system.

Studies on BCG are now on its resurgence era, with advent of new sensors, microprocessor, and the signal processing techniques. Notable differences of today's BCG researches, compared to the past ones, are on the emergence of non-diagnostic applications of BCG. Sleep analysis, heartbeat detection and the estimation of pre-ejection time are the few examples of BCG applications that were previously non-existent.

Despite these advancements, however, practical usage of BCG has yet to become reality. One reason for this is in its difficulties in instrumentation. In a number of researches, BCGs are often recorded with a sensor attached to bulky objects, for example bed or chair. Also, a synchronously measured electrocardiogram (ECG) is required for the accurate analysis of BCG, therefore, increases the system complexity.

Morphological variability of BCG is another limiting factor. Waveforms of BCG are reported to vary among subjects and even in a same person. Such characteristics of BCG impose difficulties in its consistent interpretation and in drawing meaningful information.

In this dissertation, we first propose a sensor, namely BE-patch, which can record both the BCG and ECG using a ferro-electret film. As the sensor is thin and flexible and features reduced complexity, it suits for wearable applications in terms both of user compliance and power consumption.

The fabrication method of BE-patch and its application in blood pressure estimation is reported in Chapter 2. Using the time delay of R-peak of ECG and J-peak of BCG (so-called, R-J interval), which showed the negative relationship with changes in blood pressure, the beat-by-beat systolic blood pressure (SBP) is estimated. The mean error of the estimated SBP and its standard deviation were –0.16 and 4.12 mm Hg, respectively and their performance met both the Association for the Advancement of Medical Instrumentation and the British Hypertension Society guidelines.

In Chapter 3, the variable aspect of BCG is re-analyzed to develop a biometric application. Waveforms of BCG were described using features and their variability was separated to the inter-individual and the intra-individual variations by applying supervised learning algorithms. The result showed the potential utility of BCG as biometric signal, by achieving identification accuracy of 90.20% using only a cycle of BCG. Then identification increased to 98% when multiple beats were used, and reproducible with time and changes in heart-rates.

In Chapter 4, the thesis work is summarized, and future directions to further develop the proposed sensor and applications are discussed.

Keywords	Ballistocardiogram (BCG), Biometrics, Blood pressure, BE-patch
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Chapter 1

1. Introduction

1.1. History of BCG Research

Ballistocardiogram (BCG) is a record of body movements which is generated in synchronous to the cardiac activities. The first report on the BCG recording was made by Gordon in 1877 [1], where he observed that for a person "maintaining, as far as possible, perfect stillness, a rhythmic movement synchronous with the pulse" could be detected.

However it was Starr who pioneered the early era of BCG researches. He developed the "Ballistocardiograph" to measure BCG with a subject lying supine position. The earlier version of ballistocardiograph looks like Figure 1-1. It is basically a pendulum bed suspended from the ceiling, restricted with lateral motion using springs.

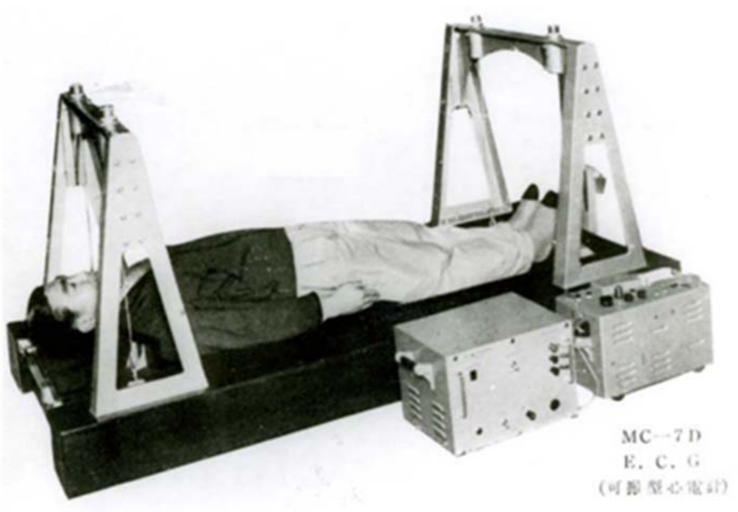


Figure 1- 1 The earlier version of ballistocardiograph

Image from [2]

The term “Ballistocardiograh” was coined using using two ancient Greek words “ballisto” and “graph”, meaning “to throw” and “a diagram”, respectively. As the name implies, the genesis of BCG is related to the repulsion of blood from the heart. More scientifically, shifts in the center of mass of blood during cardiac cycles [3, 4].

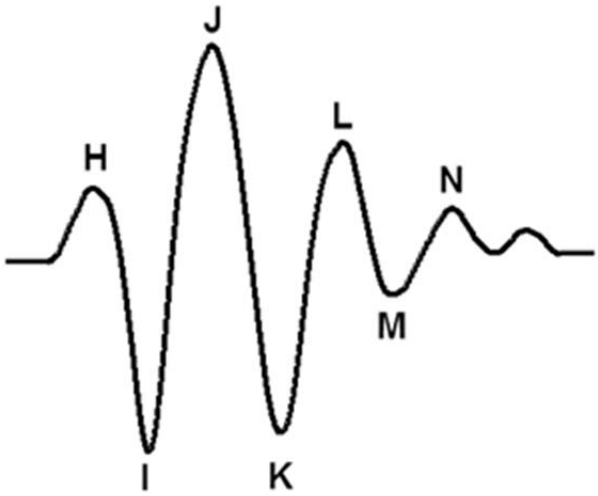


Figure 1- 2 Typical waveform of a BCG beat

A typical one-cycle waveform of BCG is depicted as Figure 1- 2 . It is composed of several sub-waves that are denoted with capitals from H to N. The largest component of BCG is the J-peak, which is believed to occur when the blood flow passes through the aortic arch during ventricular contraction.

The dominant methods that previously used to analyze BCG were the application of Newton's 3rd law of motion. Ideally, this simple rule is enough to fully understand this waveform, however, ironically, much of valuable findings about BCG are obtained empirically. Analysis of BCG with physiological basis is extremely challenging.

Although several articles that associate each sub-waves of BCG to the occurrences specific cardiovascular events can be found [2, 5-7], it seem that there is no established theory on this so far. (But general agreements -on the points that the systolic activities are represented up to K-waves and rests of them are related to the diastolic events- do exist).

The lack of standardized measurement method is the main culprit of this problem. As the BCG is the measurement of pulse wave mechanically propagated through the body and the measurement system, the coupling condition between the source and the sensor can affect the morphology of the captured signal. Therefore, different measurement system can produce significantly different signals (see, Figure 1-3).

Despite these difficulties, studies conducted in controlled environments revealed much of diagnostic values of BCG. For example, coronary artery diseases including myocardial infarction and angina pectoris could be detected with abnormalities in BCG [8]. Moreover, in some age groups, such deterioration of BCG showed more sensitivity to than that of ECG. A prospective study conducted on the patients with ischemic heart disease showed the prognostic value of BCG in predicting the subsequent infarction or sudden death [9-11].

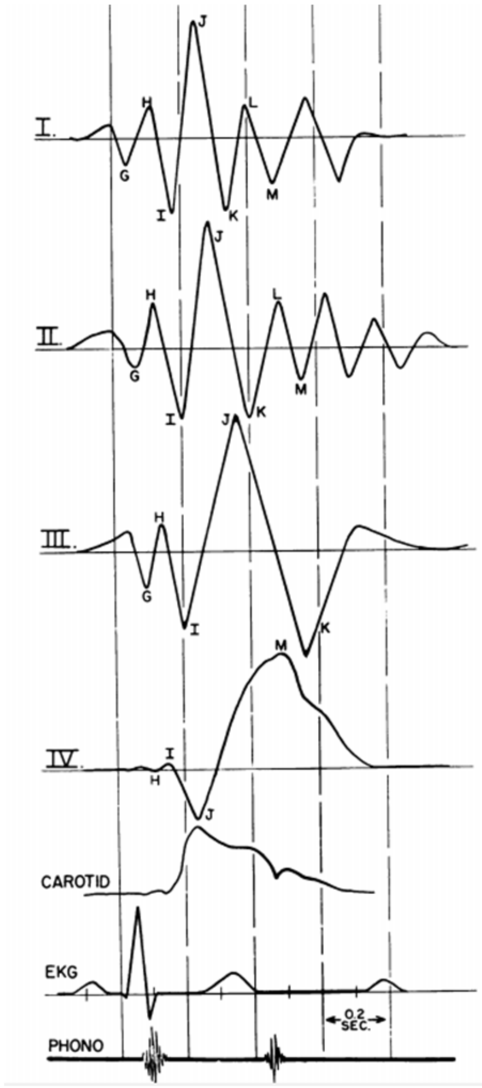


Figure 1- 3 Differences in BCGs according to the measurement systems

Image from [12]

Ⅰ: High frequency ballistocardiogram
Ⅱ: Direct body ballistocardiogram
Ⅲ: Low frequency ballistocardiogram
Ⅳ: High frequency ballistocardiogram

With all these findings, studies on BCG slowly diminished after 1970's. Emergence of echocardiography was the main reason for this leaving as it provided more simple and intuitive solution to diagnose or to assess the cardiovascular function, compared to the BCG. Figure 1-4 shows the number of books published with keywords using ballistocardiograph and echocardiograph during 1940 to 2000. The rises and falls of both technologies are clearly seen in the graph.

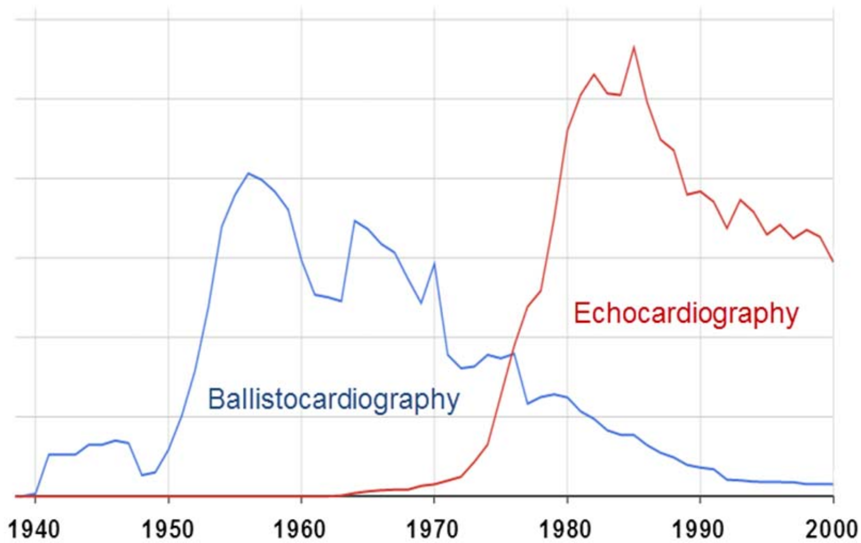


Figure 1-4 Google's Ngram results on BCG and echocardiogram

Unit of y-axis is arbitrary

1.2. Recent Advances

Studies on BCG are now on its resurgent era after 2000’s. Advent of new sensors, such as accelerometers, load cells and piezo-electric films, has enabled simple measurement of BCG with relatively cheap devices. Advancement in microprocessors and digital processing techniques also seem contributed to this revival. For more detailed explanation of this turn around can be found at [13]. To better understand and to withdraw more clinical relevance, scientists are now using computer simulations [14] and testing under micro gravity [15].

Though these approaches are new and meaningful, however, the most noteworthy differences of today’s BCG researches, compared to the past era, are on the new development of non-diagnostic applications of BCG. Sleep analysis is one representative non-diagnostic application of BCG that was previously non-existent. In this, BCG is used as an alternative of ECG to measure heartbeats. Compared to the ECG, BCG can be measured unobtrusively with no wires attached to human, and can provide information about the respiration and snoring without using additional sensors. Such information are used to estimate the sleep stage, and apnea detection, for instances.

New types of ballistocardiograph have been developed, also. Williams devised a weighing scale-based ballistocardiograph [16] after he noticed that the noise-like oscillations of the weighing scale are synchronized to the heartbeat. Shin et al. further developed this to measure ECG also, and utilized it in the measurement of blood pressure [17]. An ear-worn BCG measurement device has also been proposed [18]. The potential advantage of these technologies is that the important health parameters can be checked during daily life.

BCG can be used to estimate other hemodynamic parameters, also. For example, pre-ejection period (PEP), defined as the time delay from Q-wave of ECG to the timing of aortic valve opening, is a valuable parameter in assessing left ventricular functions. However, measurement of aortic valve opening time require impedance cardiograph or echocardiograph, both of them require either many electrodes attached on body or utilization of bulky devices. Usage of BCG enables simple and accurate estimate of PEP. The R-J interval, measured from the R-peak of ECG to the J-peak of BCG, are reported to be closely related to the pre-ejection period (PEP) [19]. Stroke volume could also be estimated using a set of features derived from BCG [20].

1.3. Goal of Thesis Work

Ballistocardiogram is a useful and information-rich bio signal. Compared to the ECG, BCG retains information not only about the heart, but also about the vascular system. In addition, BCG is more convenient to measure since it does not require electrical coupling to human body therefore can be recorded with clothes on.

Despite the recent advancements, however, practical usage of BCG has yet to become reality. One reason for this is in its difficulties in instrumentation. Common practices to measure BCG require bulky objects, for example bed or chair, with a sensor attached to them. Also, a synchronously measured electrocardiogram (ECG) is required for the accurate analysis of BCG. Figure 1-5 illustrates the need for ECG for the BCG interpretation. As the BCG has no distinctive mark like R-peak of ECG, a cycle of beat is hard to notice. Therefore, ECG is required as a timing reference. Extracting BCG cycles without ECG would be feasible, but this is another a topic in the field of BCG researches [21, 22]. Wearable BCG sensors have been proposed in literatures [18, 23, 24], however, they have limitations in embodiment of true wearable systems. Usage of chest belt reduces user compliance, and accelerometer-based ones are disadvantageous in terms of power consumption. Moreover, installation of additional sensors to measure ECG increases the system complexity and the cost.

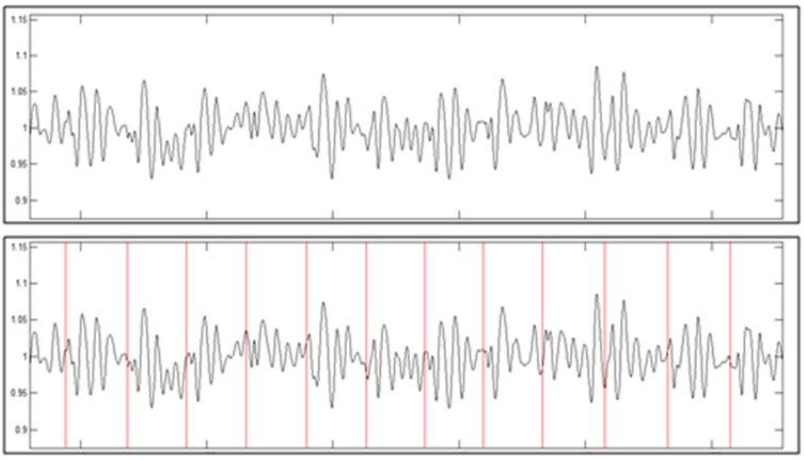


Figure 1-5 Comparison of BCG with and without using ECG as a timing reference

Morphological variability of BCG is another limiting factor. Waveforms of BCG are reported to vary among subjects and even in a same person. Such characteristics of BCG impose difficulties in its consistent interpretation and in drawing meaningful information. Figure 1-6 shows the examples of the morphological variations in BCG. Apparently, two subjects’ BCG are different (inter-subject variability), and beat-by-beat changes in one’s BCG are also seen.

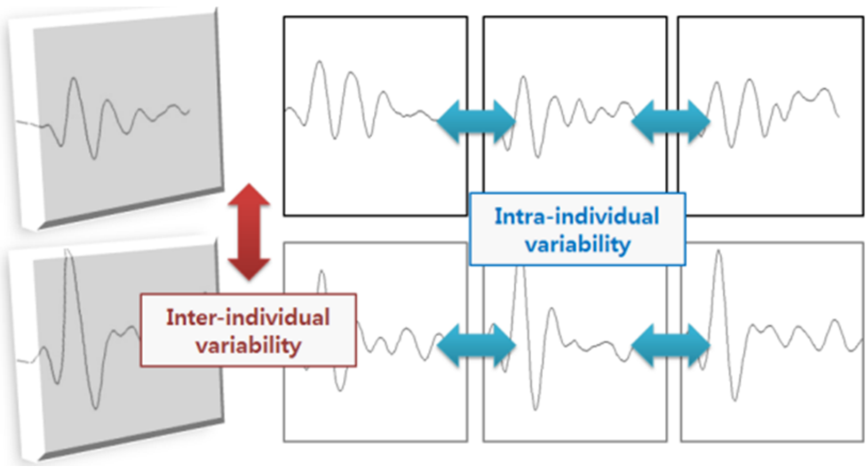


Figure 1- 6 Illustration of inter and intra-individual variability of BCG

In this thesis work, we first propose a sensor, namely BE-patch, which can record both the BCG and ECG using a ferro-electret film. As the sensor is thin and flexible and features reduced complexity, it suits for wearable applications in terms both of user compliance and power consumption. The fabrication method of BE-patch and its application on blood pressure estimation is reported in Chapter 2.

In Chapter 3, the variable aspect of BCG is re-analyzed to develop a biometric application. Waveforms of BCG were described using features and their variability was separated to the inter-individual and the intra-individual variations by applying supervised learning algorithms.

In Chapter 4, the thesis work is summarized, and future directions to further develop the proposed sensor and applications are discussed.

Chapter 2

2. Blood Pressure Estimation

2.1. Introduction

Close monitoring of blood pressure (BP) occupies an important niche in early diagnosis and treatment of hypertension. The golden standard to measure BP is the ausculatory method, where a specialist inflates a cuff around the arm, and uses a stethoscope to determine systolic blood pressure (SBP) and diastolic blood pressure (DBP). Oscillometric techniques are based on the same principle, but are intended for home use. Although the conventional auscultatory and oscillometry methods provide a reliable, noninvasive means to measure BP, usage of a cuff is inconvenient for continuous monitoring of BP.

BP can be estimated by the time delay between two dissimilar heartbeat signals. A well-known technique uses the pulse-transit time

(PTT) which is defined as the time interval for a blood pulse wave to travel from heat to the periphery [25]. The principle of PTT-based BP estimation is based on the fact that the speed of blood pulse is faster when the BP is elevated; assuming the elasticity of the arterial vessel remains constant for a period of time [26].

However, the timing when the blood leaves the heart is difficult to measure since its non-invasive recording is commonly accomplished with impedance cardiography (ICG). In practice, pulse arrival time (PAT) has been more widely used since it can be measured in a more convenient way, using the ECG and PPG. PAT is longer in time duration, compared to the PTT, since it included the pre-ejection time (PEP).

PEP is the time delay measured from the initiation of electrical stimulation to the actual ejection of blood with opening the aortic valve. PEP is also known to have negative correlation with BP [17, 27], however, it was not widely used in BP estimation since it required ICG to be measured, also. The chronological order of the mentioned cardiac timings is depicted in Figure 2- 1

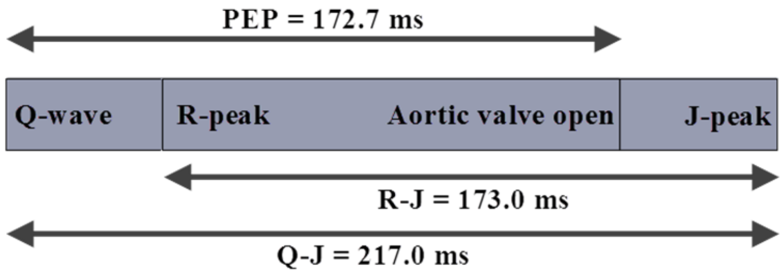


Figure 2- 1 Relative orders cardiac events used to define PAT, PTT and PEP

According to the recent findings, the R-J interval, which is computed from the R-peak of ECG and the J peak of BCG, has also been known to have a negative relationship with BP [17, 27]. The R-J interval is also known to be a good surrogate of PEP. On this principle, devices that can be used for unobtrusive estimation of BP have been introduced [28]. However, such devices incorporate separate sensors, such as biopotential electrodes, photoelectric sensors, accelerometers, and load cells to measure BCG or PPG together with ECG, which increases system complexity and power consumption. In this paper, a ferroelectret film–based patch-type sensor is proposed that features simultaneous measurement of BCG and ECG (BE-patch®) for continuous BP monitoring.

2.2. Principles of BP Estimation

It has been known that the speed of pulse wave of the blood vessels becomes faster at high level of blood pressure. There are number of literatures that relate time delay measured from two or more channels of heart signals to the blood pressure. The most widely used method uses pulse arrival time (PAT), which is the time delay between the R-peak of ECG and the initiation timing of photoplethysmogram (PPG). It is a measure of time required for a pulse wave to travel to the distal part (i.e. hand or foot) after its initiation by an electrical signal.

In practice, however, the pulse wave is generated just after the R-peak point. The time delay measured from this point is termed pulse transit time (PTT). The reason for the latency between the pulse wave and its electrical trigger is in fact due to the differences in pressure across the aortic valve. That is, isovolumic contraction time is needed for the left ventricular to increase its pressure to exceed that of in the aorta until the valve is opened (Figure 2- 2).

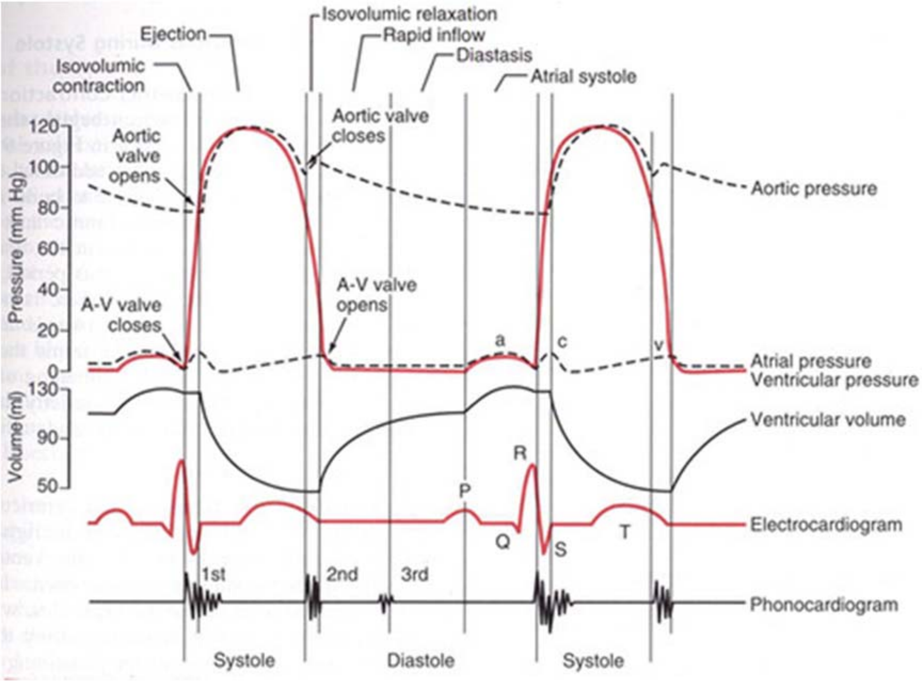


Figure 2- 2 Wiggers diagram to represent timings of cardiac events

Guyton's: Textbook of Medical Physiology
- 10th Edition. 2000. Chapter 9 - Page 99.

Meanwhile, for PAT, PTT and PEP to meet the relationship PAT = PEP + PTT, one should agree that the PAT is measured from the Q-wave of the ECG, not from its R-peak. The definition on the PEP is found in [29] as following:

PEP is defined as the time period from the beginning of the ECG's Q-wave, which marks the beginning of the ventricular depolarization, to the opening of the aortic valve, which marks the ejection of blood into the aorta.

Physiological understanding reveals, too, that the timing of R-peak is not related to the initiation any of cardiac events, and occurs during the process of ventricular depolarization (**오류! 참조 원본을 찾을 수 없습니다.**). Therefore, the reason for using the R peak in computation of PAT seems to reside much on signal process aspect, not on the solid physiological basis since the R-peaks can be located with much easy than Q-waves.

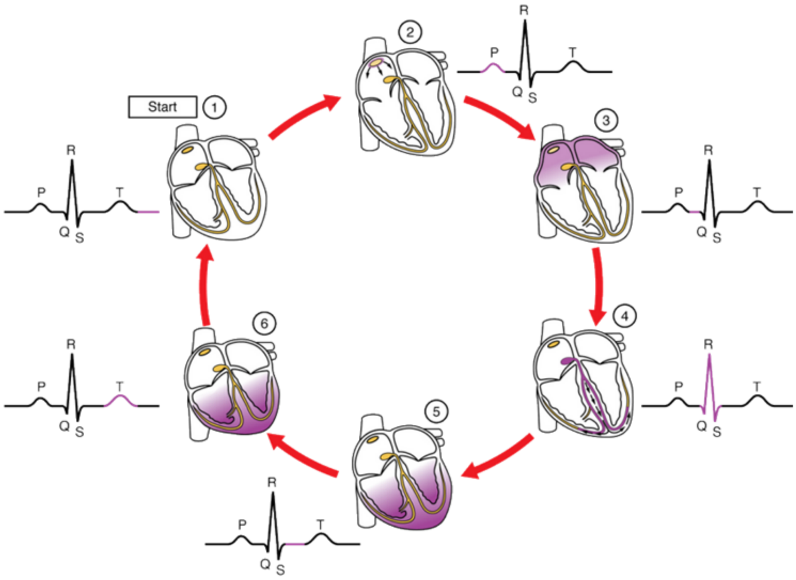


Figure 2- 3 Understanding of ECG waveform with electrical activity

OpenStax College. (2013, June 19). Cardiac Muscle and Electrical Activity. Retrieved from the OpenStax-CNX Web site: http://cnx.org/content/m46664/1.3/

A well-known theory regarding the blood pressure estimation using pulse wave propagation delay is the Moens-Korteweg equation. The equation assumes that the diameter of the blood vessel is constant and the pulse wave velocity measured from the inlet of the vessel to its outlet is formulated by the elasticity, radius and thickness of vessel and the viscosity of the blood. On the other hand, the pulse wave speed can be computed as the length of the vessel divided by PTT. Further development of this equation using Hughes equation, which describes the exponential relationship between the elasticity of the vessel and the blood pressure, blood pressure can note be estimated with measured PTT by assuming values of all other parameter do not vary within a relatively short period of time, where A and B are constants derived by each individual via calibration.

Estimation of blood pressure using the PTT can be found elsewhere [25, 30, 31]. For the use of PTT, one should measure when the aortic valve is opened. Impedance cardiography (ICG) has been widely used for this purposes, in which thorax impedance is monitored by injecting small amount of current to body. It is a type of plethysmography that uses four electrodes; two for current injection and another two for voltage pickup. Usually, ICG is interpreted using its first derivate signal, and the beginning of rapid overshoot of the signal is interpreted as the aortic valve is opening.

As the Moens-Korteweg equation was developed using the PTT, blood pressure estimation methods using PEP or PAT lack theoretical basis. However, it has been known that both the PAT and the PEP are also experimentally correlated with blood pressure with some degree of negative relationships. Moreover, in some literatures they are reported to be more reliable estimators of blood pressure than PTT.

In [27], researchers induced changes in blood pressure by exercise and compared the contribution of PAT, PTT and PEP in blood pressure estimation. Based on these results, the researchers concluded as following: When SBP was estimated using least-squares methods, the differences between the measured and predicted SBP using PEP, PAT and PTT were 0.0 ± 6.6, 0.0 ± 4.9 and 0.0 ± 9.3 mmHg, respectively. The findings suggested that PAT gives the best SBP prediction and PEP has some potential to predict blood pressure. The inclusion of PEP in the PAT measurement is necessary to facilitate accurate cuffless blood pressure prediction after exercise. Similar report on the effect of PEP during blood pressure estimation can be found in [32].

2.3. Methods

As a reference of continuous and real-time blood pressure, Finapres is one the most widely used device. Of course, the best accuracy is obtained when blood pressure is read via catheters placed, for example radial artery, but this is not suitable for many BP-estimation researches due to its invasive nature.

The core principle of Finapres is called 'volume-clamped method', in which unknown pressure in the chamber is read by exerting pressure outside of the chamber. For the Finapres, a servo system controls the pressure in a finger cuff, continuously counterbalancing the pressure in the arteries of the finger. This physically clamps volume oscillations of the arterial walls, canceling pulsations [33]. The arterial volume is measured using infrared sensor (so-called PPG), and the servo system capable of tracking up to 3500 mmHg/s of BP variation is utilized [34]. Detailed accounts of the original method and its subsequent development have been published [35, 36].

The proposed sensor was fabricated as a layered structure of a 90 × 50 mm-sized ElectroMechanical Film (EMFi, EMFIT LTD, Finland) with screen-printed electrodes and a flexible electronic circuit. EMFi has been commonly applied in vibration measurement, particularly BCG in physiological recordings, due to its piezoelectric characteristics. The ready-made EMFi sensors have conductive layers on both sides of the film for the signal pickup; however, we used a bare EMFi film to customize the patterns of those conductive layers. We segmented one conductive layer for simultaneous measuring of ECG as well as BCG signals by screenprinting conductive silver paste onto the EMFi film, as illustrated in Figure 2-4. For the ECG measurement, the potential difference between two ECG electrodes located in the bottom conductive layer was recorded with reference to the ground electrode. For the BCG measurement, the electric current produced by the EMFi film was measured at the BCG electrode located in the middle conductive layer with reference to the ground electrode. The pattern of the bottom-layer electrodes was heuristically determined to ensure maximum distance for the ECG lead while providing reasonable signal quality for both the ECG and BCG. A flexible electronic circuit was integrated as a top layer for conditioning ECG and BCG waveforms. In addition, an instrumentation amplifier and a charge amplifier were utilized for the amplification of ECG and BCG, respectively.

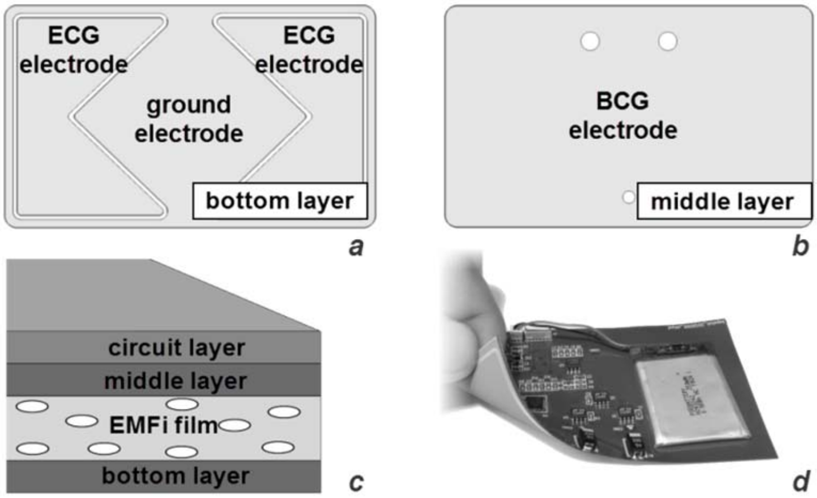


Figure 2- 4 Structure of the proposed sensor (BE-patch®)

(a) Bottom layer electrodes for ECG measurement

(b) Middle layer electrode for BCG measurement

(c) Cross-sectional view of the sensor

(d) Picture of the sensor (top view)

The developed sensor was tested on three human subjects with no history of cardiovascular disease (all males, 27–31 years old). The bottom layer of the sensor was tightly attached to the subject's chest using double-sided adhesive tape. To obtain a reference BP signal simultaneously, the FINOMETER® Pro (Finapres Medical Systems, Amsterdam, Netherlands) was used with a finger clip and a cuff worn on the arm of each subject.

The reference beat-to-beat BP signal and the ECG and BCG outputs of the developed sensor were synchronously recorded at a 1-

kHz sampling frequency using a signal acquisition system (BIOPAC MP-150, Biopac Systems Inc., Goleta, CA, USA). Subjects performed the Valsalva maneuver for 10 s to induce a BP change.

Normal physiological response to the Valsalva maneuver is characterized by a rapid BP increase when the strain is applied and a slow stabilization to normal BP when the strain is released. Each subject repeated the Valsalva maneuver six times, with a 5-min resting period between trials. The trials induced SBP changes from 103 to 176 mm Hg.

The functionality of the BE-patch® sensor could also be confirmed by observing the QRS complexes and J waveforms in the measured signals, which are distinctive for the typical ECG and BCG. Figure 2-5 shows an example of the obtained signals after releasing strain during the Valsalva maneuver.

A total of 395 R-J intervals occurring during the BP stabilization phases of the Valsalva trials were associated with the SBP by linear regression. The number of data points used for the regression varied depending on the subject, due to differences in the BP stabilization period.

In this study, we investigated only the systolic aspect of BP estimation using the RJ interval. Pulse arrival time–based BP estimation methods are commonly known to have limitations for diastolic BP monitoring [37].

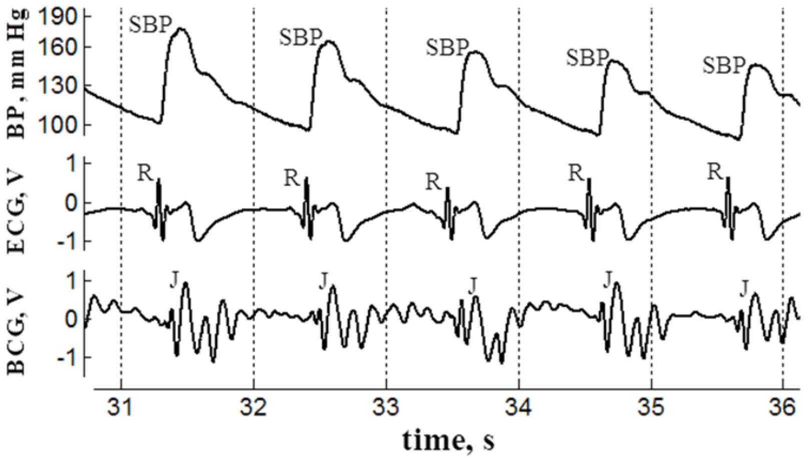


Figure 2- 5 ECG and BCG waveforms obtained using BE-patch® during induced BP change

2.4. Results and Discussions

The results of SBP estimation are shown in Figure 2-6 . Negative relationships between the RJ interval and the SBP were found in all subjects, and the Pearson’s correlation coefficients were 0.87, –0.89, and –0.73 (Figure 2-6 b to d).

These values are comparable to the previously reported RJ interval–based SBP estimation study that showed a range from –0.65 to –0.89 [17]. The estimated SBP (eSBP) showed excellent agreement with the reference SBP, by achieving an intraclass correlation coefficient (ICC) of 0.95 ($P<0.01$). Such agreement in SBP estimation was further analyzed using the Bland-Altman plot (Figure 2-6 (a)).

According to the U.S.-based Association for the Advancement of Medical Instrumentation (AAMI) criterion for the BP device, the mean error should be less than 5 mm Hg, and the standard deviation of the error should be less than 8 mm Hg. Furthermore, in the British Hypertension Society (BHS) guidelines [38], the BP monitor should meet class A or B for clinical use. The class A or B BP monitor should achieve at least 50, 75 and 90% cumulative estimation accuracy within 5-, 10- , and 15-mm Hg readings, respectively.

In this study, the mean error of the estimated SBP and its standard deviation were –0.16 and 4.12 mm Hg, respectively. Moreover, the cumulative percentage of error differences within 5, 10, and 15 mm Hg were 52, 85, and 97%, respectively. Therefore, the performance for SBP estimation of the developed BE-patch® sensor meets both the AAMI and the BHS guidelines

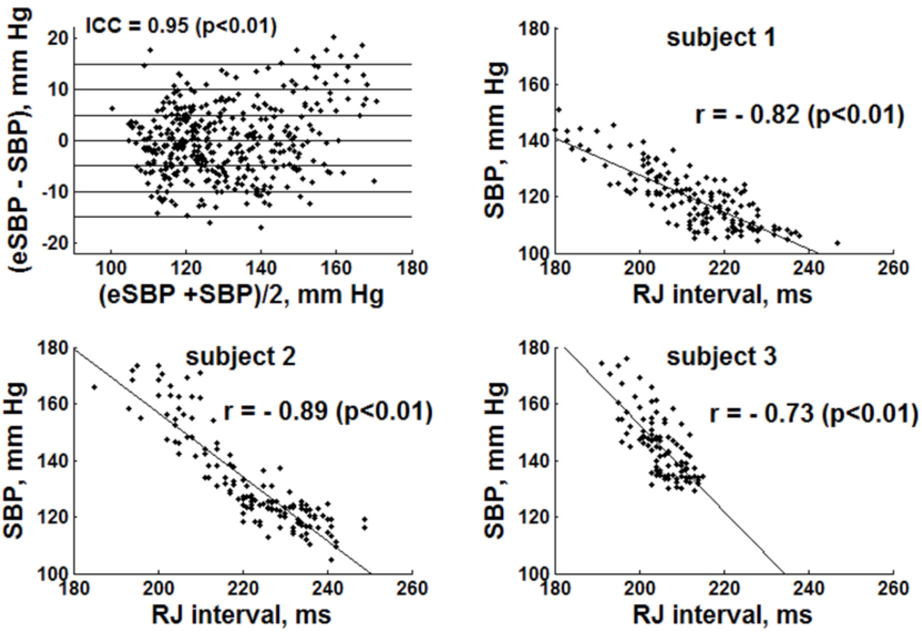


Figure 2-6 Results of SBP estimation using RJ interval measured using BE-patch® sensor

(a) Bland-Altman analysis of agreement between reference SBP and estimated SBP (eSBP)

(b)~(d) Linear regression of reference SBP values against RJ intervals for each subject

2.5. Conclusion

A patch-type continuous BP monitoring sensor is proposed that features single ferroelectret film–based simultaneous measurement of ECG and BCG. The results of the feasibility test showed that the SBP estimation performance using the developed sensor complied with both the AAMI and BHS guidelines for BP monitoring devices.

Further validation of the proposed sensor with more subjects, as well as for longer periods, will be conducted. The excellent wearability of this single patch-type unit and its ability to measure both BCG and ECG will greatly contribute to the development of a ubiquitous healthcare device for continuous monitoring of blood pressure and cardiac activity in daily life.

Chapter 3

3. Biometric Application

3.1. Introduction

Interpersonal differences in the ECG waveform had been reported as [39-42], however, it was Biel et al who first reported that such variability in ECG waveform can be used to identify human beings [43]. She discovered that the conventional ECG-derived diagnostic parameters, for example the onset and end timings, duration and amplitude of P, Q, R, S, T waves, could successfully be used as features to distinguish individuals through a series of pattern recognition algorithms.

The method was tested on the data collected from total of 20 subjects. The data collected for six weeks, repeatedly from each subject in order to confirm the time-varying characteristics. A small group of subjects underwent 10 times of repetition, and the rest of the subject underwent four to five times of repetition. In each measurements, six chest electrodes were attached and removed four to five times, to see the effect of electrode position (in fact, the diagnosis of the disease if affected by the positional variation of the chest electrodes) in reproducibility of ECG based biometric method.

ECG was measured with standard 12-lead configuration by using a commercially available ECG measurement device (SIEMENS Megacart). The machine automatically computes 30 diagnostic parameters for each lead; therefore, total 360 parameters are derived. Figure 3-１ below shows 30 ECG parameters.

No.	Features
1	P wave onset
2	P wave duration (ms)
3	QRS wave onset
4	QRS wave duration (ms)
5	Q wave duration (ms)
6	R wave duration (ms)
7	S wave duration (ms)
8	R' wave duration (ms)
9	S' wave duration (ms)
10	P+ wave duration (ms)
11	QRS wave deflection (ms)
12	P+ wave amplitude (μV)
13	P- wave amplitude (μV)
14	QRS wave peak to peak amplitude (μV)
15	Q wave amplitude (μV)
16	R wave amplitude (μV)
17	S wave amplitude (μV)
18	R' wave amplitude (μV)
19	S' wave amplitude (μV)
20	ST segment amplitude (μV)
21	2/8 ST segment amplitude (μV)
22	3/8 ST segment amplitude (μV)
23	T+ wave amplitude (μV)
24	T – wave amplitude (μV)
25	QRS wave area (μV * ms)
26	T wave morphology [-2,2]
27	R wave notch existence
28	Delta wave confidence [0,100] %
29	ST segment slope [-90,90] deg
30	T wave onset

Figure 3-1 Thirty ECG parameters computed from SIEMENS Megacart

However, not all of these 360 parameters were used for the recognition process. The correlation matrix on the parameters (however, the matrix was not shown in the paper) revealed that the parameters in every lead with same numbers are highly correlated each other. Therefore, parameters derived from limb-Ⅰ lead were used in recognition process, since limb-Ⅰ lead is advantageous in measurement (using both arms). The correlation matrix was then further reviewed and the some parameters having strong correlation with other parameters were removed to leave 12 features (however, the process or criterion of feature selection was not described). Total number of 12 features which includes three T-wave associated features and the ones described in Figure 3-2 were used in the recognition process.

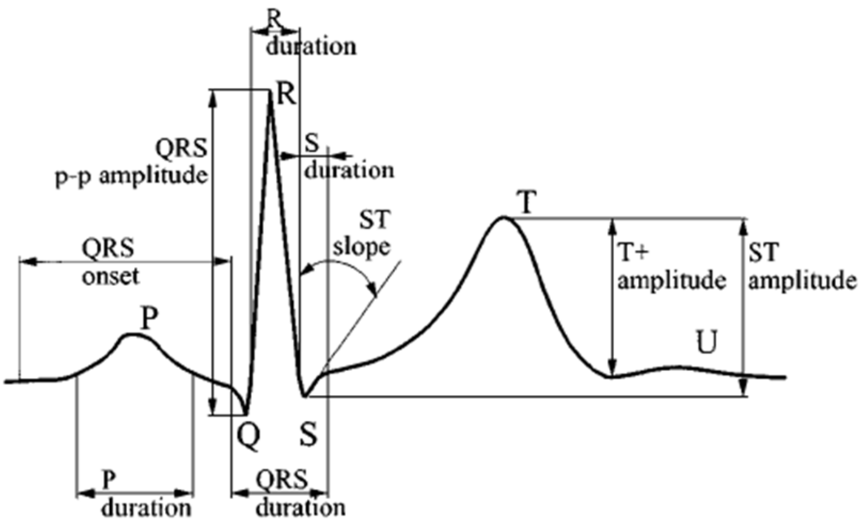


Figure 3-2 Features used by Biel et al to classify individuals

A type of supervised learning algorithm, so-called soft independent modeling of class analogy (SIMCA), was used as a classifier. The performance of the classifier was checked with 50 samples, after training it with 85 sets of data.

The performance of classification ranged from 90 to 100%, depending on the combination of the features. The best performance was achieved by using 10 features, not all of 12. This implies some redundancies in features and chances to improve performance by optimization process.

The origins on the inter-individual variability of ECG can be found Rudi Hoekema’s report [44]. In this, two groups of factors are described as potential sources of ECG variability. One is physiological factors, in which differences in Purkinje system, the heart muscle fiber orientation, and the electric conductivities of different parts of the heart and the activation can contribute to the morphological changes in ECG. Another one is geometrical factors, which includes all possible factors that affect the pathway between the electrical source (heart) and the electrode. Differences in heart position and orientation relative to the ribs, body habitus, sex, age, length, and weight of the subjects, and cultural characteristics are the examples. In addition to these, the electrode positions, other organs may also affect the morphology of ECG since they play a role in intrathoracic volume conduction of electrical signals.

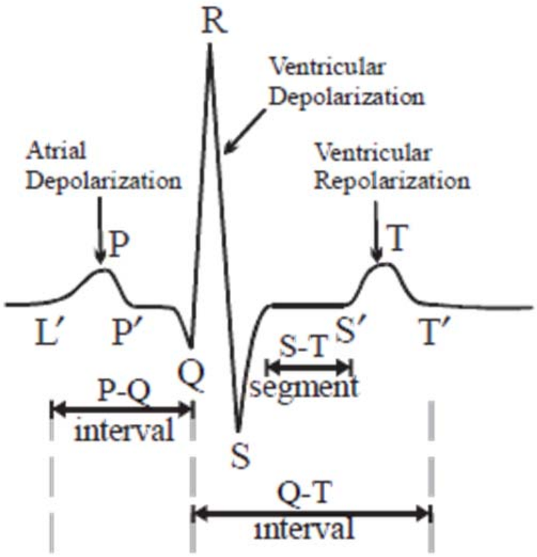
Test	No. of features	No. of correct classified (tot)
A	360	49 (50)
B	180 (chest leads)	49 (50)
C	180 (limb leads)	49 (50)
D	30 (I lead)	49 (50)
E	21 (zeros removed)	49 (50)
F	12	49 (50)
G	10 [1]	50 (50)
H	7	45(50)

Figure 3- 3 Human identification result using different feature sets

Israel et al pointed out that the researches on ECG-based biometric after Biel et al were not strict enough, and claimed that it needs be tested on various emotional state and electrode configurations, and require feature design supported by solid physiological understanding.

One session of his experiment was comprised of 7 different emotional states, which include 3 low stress conditions (baseline state, meditative, recovery), and 4 high stress conditions (reading aloud, mathematical manipulation, driving in virtual reality), with each 2 min of signal recording. Also, two channels of ECG were collected with electrodes attached at neck and chest. Total numbers of 41 sessions of experiments were done on 29 subjects (12 of them underwent two sessions of repetition).

Israel pointed that the previous studies used ad-hoc features to describe visual-traits of ECG, and claimed that features be designed to represent cardiac events [45]. In his opinion, only the temporal features should be used since the amplitude of ECG varies according to the lead configuration, electrode position and the emotional state. On the contrary, temporal features are at least irrelevant of lead configuration or electrode position, since the timings of specific cardiac events will remain same across the leads. He devised 15 temporal features as presented in Figure 3-４ using the fiducial points of ECG.



Extracted Attributes		
1. RQ	**6.** RT	**11.** ST
2. RS	**7.** RS'	**12.** PQ
3. RP	**8.** RT'	**13.** PT
4. RL	**9.** P width	**14.** LQ
5. RP'	**10.** T width	**15.** ST'

Figure 3- 4 Israel's temporal features used in ECG-biometric

The results showed 79 to 82% of heartbeat identification rate and 100% of individual identification rate when the training and the test of the classifier were done on the data collected from different positions. The tests on the different emotional states resulted in about 70% of heartbeat identification rate and 95% of individual identification rate (Figure 3-5).

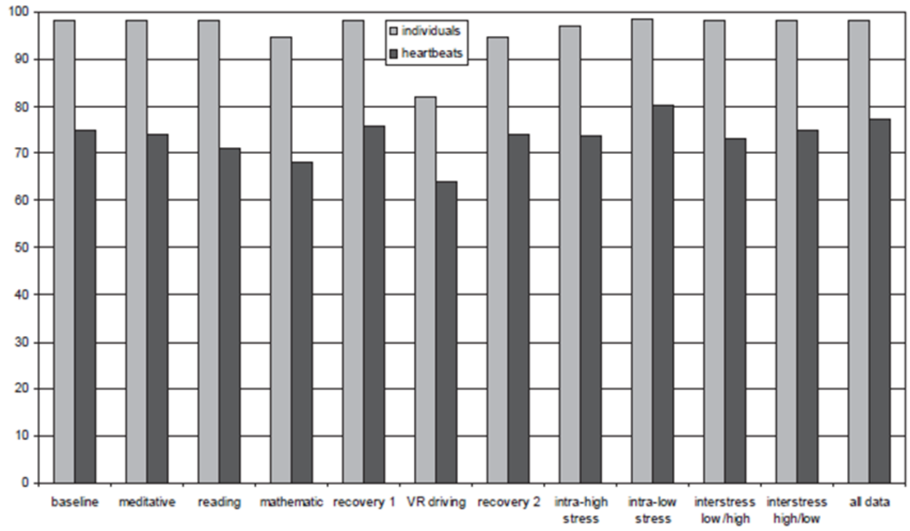


Figure 3-5 Result of human identification according to the emotional state

More than this, there have been intense researches to improve the performance of ECG-based biometric method. Various methods and algorithms were tested to the feature design, feature selection and the classifier design steps. Figure 3-6 found in [46] summarizes the ECG-based biometric researches regarding the algorithms used, number of subjects and the performance, etc. More recent reviews on ECG-based biometric method can be found in [47]. It is now generally accepted that the ECG-based biometric can achieve approximately 95% of subject identification rate. For example, Shen reported that 168 subjects could be classified with accuracy over 95% using 17 features [48], and Wang reported 100% of accuracy with 15 features when he tested his algorithm on PTB and MIT_BIH [49].

		Israel et. al	Biel et. al	Shen et. al	Wang et. al	Proposed method
Feature extraction	Fiducial detection	✓	✓	✓	✓	X
	Feature origin	Heart beats	Heart beats	Heart beats	Heart beats	ECG windows
	Feature specifics	Temporal	Temporal + amplitude + slopes	Temporal + amplitude	Temporal + amplitude + appearance	autocorrelation
	Extraction method	Automatic	Machine based	Automatic	Automatic	Automatic
Feature selection		Wilks' Lamda	Inspection of the correlation matrix	–	PCA or LDA	LDA
Classification		LDA and Majority voting	SIMCA model based on PCA	Prescreening and distance classification	Nearest centre, nearest neighbor, LDA	Nearest neighbor on Euclidean distance
Electrode orientation		Neck, chest	limb leads (I, II, III)	Lead I	Lead II	Lead II
Special experiments		(1) Electrode configurations	Different operators	Analysis of the effects of age, gender weight, height and BMI	Integration of analytic and appearance features	Arrhythmia scenarios
		(2) Anxiety conditions				
Performance	Subject rates	100%	100%	95, 30%	100%	96.42%
	Heart beat/window rates	82%	–	–	98, 90%	96.2%
	Number of subjects	29	20	168	13	56 (2905 windows)

Figure 3- 6 Summary of researches on ECG-based biometric methods

3.2. Methods

The biometric identification was carried out while the subjects were sitting, for example, on a car seat or an office chair. A highly sensitive (250 pC/N) mechanoelectric film (EMFi, EMFIT, Finland) was used as the BCG sensor and placed beneath the cushion of the seat. As a reference signal, the Lead-I electrocardiogram (ECG) was also measured using Ag-AgCl electrodes (3M Healthcare, Minnesota, USA) attached to the wrists and right leg of the subject. The BCG was amplified using a charge amplifier with a gain of 106, whereas the ECG was amplified using an instrumentation amplifier (INA118, Texas Instrument, USA) with a gain of 103. A second order 60 Hz twin-T notch filter was applied to both signals. The analog-to-digital conversion of the outputs of both amplifiers was done at a rate of 300 Hz using an off-the-shelf DAQ card (USB 6212, National instrument, USA) connected to a PC in which the digital data was saved in a file using an application program written in LabView (National Instruments, Texas, Austin, USA). Figure 3-７ shows the experimental setup to collect ECG and BCG.

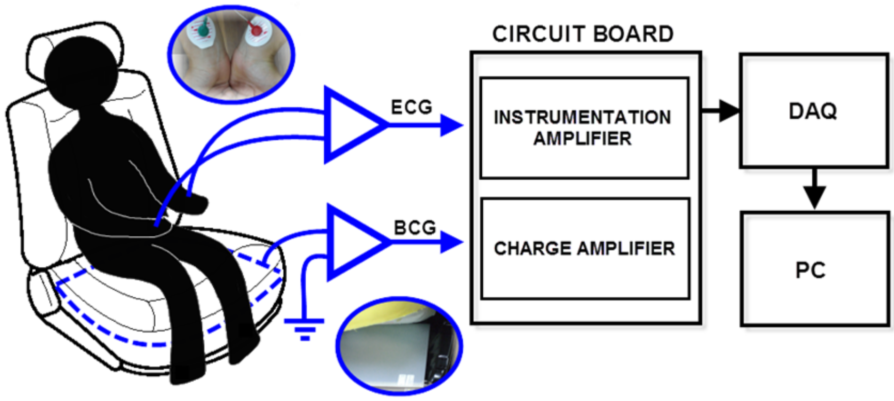


Figure 3- 7 BCG and ECG measurement setup

As mentioned in the Introduction section, morphology of BCG is dependent on the age and sex. For the proposed BCG-based biometric to occur, therefore, it is highly important to validate the methodology works to a clinical population. For this, we recruited total number of 35 subjects for the experiments, considering their age and sex to be uniformly distributed, as possible. However, it should be noted that we recruited only the healthy adult subject, since the morphological changes in BCG with the presence disease was beyond the scope this study. Therefore, subjects who had been diagnosed with any type of cardiovascular diseases were exempt in recruiting. Table 3-1shows the demographic statistics of the subjects recruited.

Table 3-1 Demographic statistics of the subjects recruited

		Male		Female	
Number		25		30	
		Mean	*S.D.*	*Mean*	*S.D.*
Height	[cm]	172.1	6.9	159.9	5.9
Age	[yr]	39.5	10.5	43.8	13.0
Weight	[kg]	70.9	10.1	56.5	8.0
BMI	[%]	23.9	2.4	22.1	2.9

In order to check the reproducibility of the BCG-based human identification, each subject underwent three times of experiments. Two experiments were conducted when the subject was in their normal heart-rate condition with an interval of minimum three days and another one experiment was done when the subject was in the elevated heart-rate condition. To make changes in heart-rate, subjects were asked to walk up the stairs of the 4-story building. Each subject went through approximately 3 min of signal recording while seated on the chair, and was instructed to refrain from moving and speaking and to maintain normal breathing. ECG was recorded simultaneously to use it as a timing reference in the BCG analysis, and three wet Ag-AgCl electrodes were attached to both arms the subject for this. This study protocol was approved by the Institutional Review Board of Seoul National University Hospital, and all the subjects agreed on the informed consent.

The goal of preprocessing of BCG signals is to prepare each beat ready for the feature extraction. Since BCG is highly susceptible to the motion artifact, and no distinctive peaks exist in their waveform, the preprocessing steps require some manual interventions but can be systemically performed following the steps below.

To eliminate noise components, a digital filter was applied to the original digital signal. Because the bandwidth of BCG is as much as 40 Hz and exhibits baseline wandering due to respiration, a second order Butterworth band-pass filter with a pass-band of 0.5-40 Hz was applied. The same digital filter was also applied to the ECG for stable detection of the R peaks and to equalize the filter output delay to that of the BCG.

The R peaks in ECG were detected using the well-known Tom-Pankins algorithm, limiting the minimum peak distances to 0.5 second. Peaks in BCG were found separately for the positive and the negative peaks, using the same algorithm, setting the minimum peak distance to 0.03 second. Details of Tom-Pankins algorithm can be found elsewhere. A cycle of the heartbeat in the BCG was defined as a segment of the BCG between two adjacent R peaks in a synchronously measured ECG, and was prepared for feature extraction (Figure 3-8).

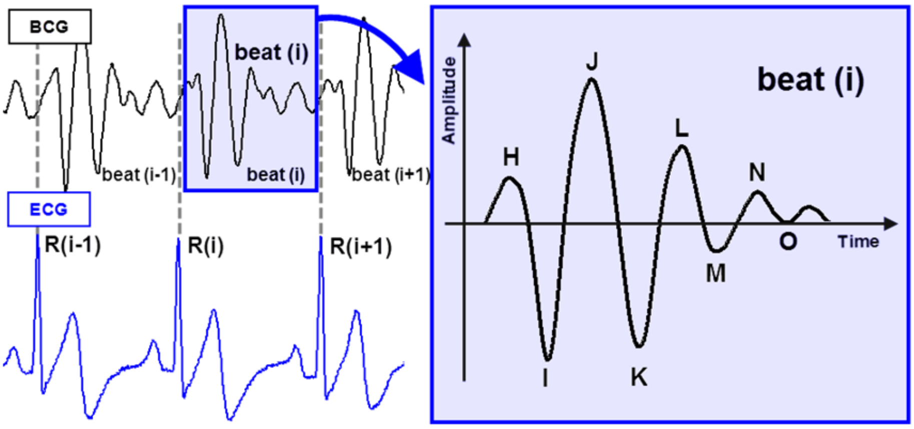


Figure 3-8 Definition of a cycle BCG and its preparation for feature extraction

The BCG beats with unclear fiducial points, corrupted by motion artifact, or corresponding to the ectopic beats of the ECG were eliminated using ‘BEpeakgram’ (Figure 3-9). The BEpeakgram is our novel technique to analyze BCG beats, which shows the positional distribution of the peaks inside the cycles of BCG, in the axis of relative time measured from each R peak. With the BEpeakgram, false-positive peaks are easily located as they are seen as non-arranged dots from the vertical lines. In addition, when BEpeakgram is analyzed in the form of histogram, normalized to the total number of beats, the usefulness of a certain peak as a reference point in feature generation step can be estimated. In this case, gaussianity, standard deviation, or area of its distribution can be used. Figure Figure 3-9 shows the example of BEpeakgram, its historgram, and a beat of BCG, collected from a subject for three minutes. Note that the BEpeakgrams are represented separately for the positive and the negative peaks.

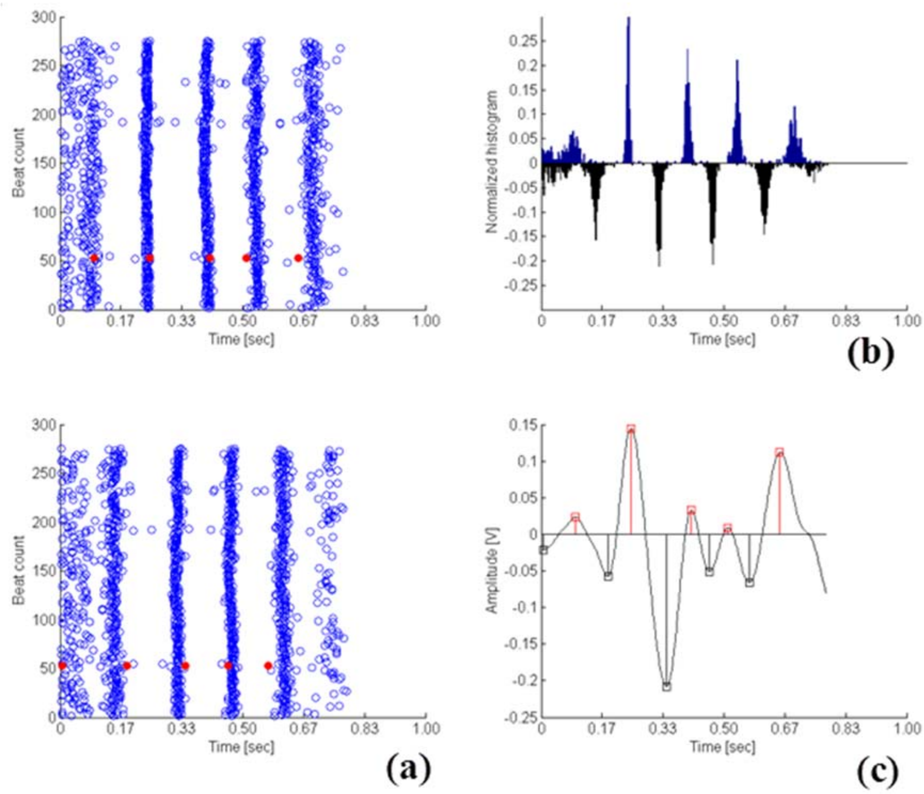


Figure 3- 9 Distribution of BCG peaks

(a) BEpeakgram for the positive and the negative peaks

(b) Histogram representation of peak positions

(c) A beat of BCG marked red in the BEpeakgram

Normalization was required because the duration and amplitude of the BCG beats varied even for a particular subject, which is undesirable for biometric applications. A simple normalization method is linear scaling, which was applied to the amplitudes by adjusting the amplitude between points I and J to unit height. However, this linear scaling is not appropriate for the horizontal normalization because all the phases of a BCG cycle do not equally contribute to controlling the heart rate. It has been reported that the duration of ventricular systole (the H-L period) is fairly independent of changes in the heart rate [6]. Therefore, during the horizontal normalization, the H-L duration was not scaled, but the rest of the cardiac phases were temporally scaled so that each cycle of the BCG would have unit duration.

Each fiducial point in the BCG is associated with a specific cardiovascular event synchronized with the heartbeat. With the assumption that the time interval between each cardiovascular event and its relative amplitude has individually unique characteristics, two different categories of features were computed using fiducial points. One is the temporal feature, which includes the time interval between fiducial points referenced to the preceding ones. Another is the amplitude feature, which includes the heights of each fiducial point referenced to the preceding peaks. Figure 3-10 shows all the extracted features.

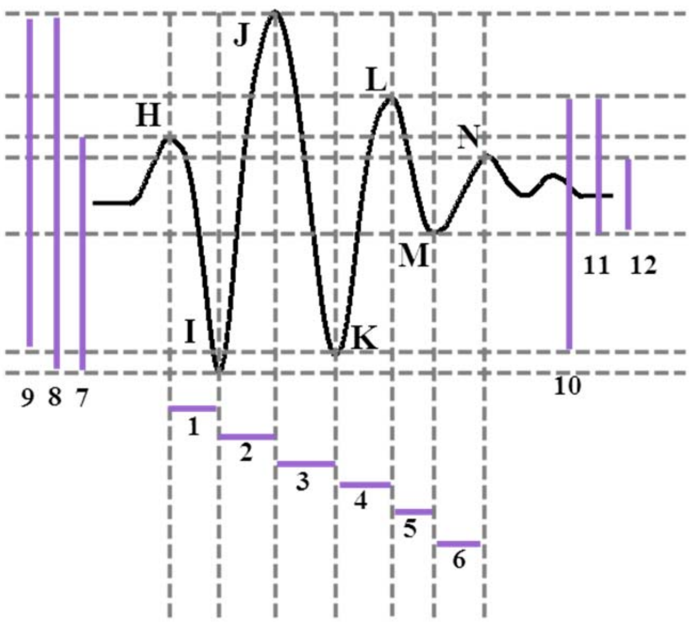


Figure 3- 10 Proposed feature set based on the fiducial points

The importance of the features was scored using feature selection algorithms. Two popular feature selection methods, namely Wilks' Lambda and Relief-F, were used to rank the features. Whereas Relief-F is a heuristic method that randomly picks a sample and updates the weight of each feature by observing its k-nearest samples of the same class and other classes, Wilks' Lambda is an analytic method based on the statistical measure of the divergence. A more significant feature has a higher value in Relief-F and a lower value in Wilks' Lambda. In executing Relief-F, the number of iterations was set to 300.

A standard linear discriminant classifier was used for the single beat identification. The first half of the BCG beats of each subject were used to train the classifier and its identification accuracy was tested using a randomly selected beat from the rest half.

It was expected that the accuracy would increase with the number of beats used for the identification. Considering the real biometric situation, the given numbers of beats were consecutively selected. When the identification results of the single beat did not correspond, the final decision was made by vote. The number of BCG beats used for the identification was increased from 1 to 11.

3.3. Results and Discussions

During the preprocessing, 5.79% of the collected BCG beats were exempted from the analysis owing to abnormalities in their morphology. Figure 3- 11 shows the overlay plot of the BCG beats of 12 selected subjects before normalization and their averaged waveform. In addition to the intra-individual variations, inter-individual variations were also observed in the averaged waveforms by visual inspection.

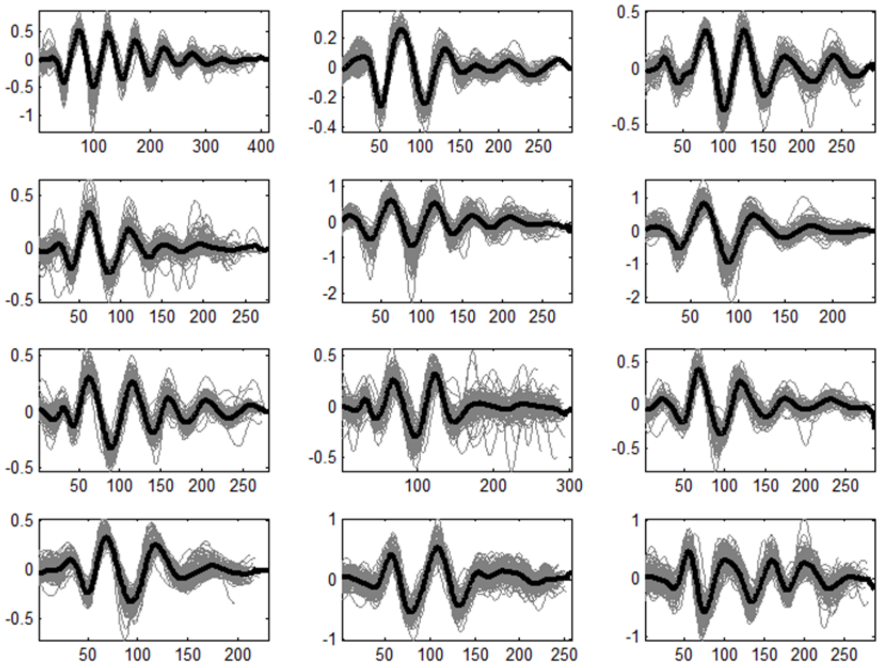


Figure 3- 11 Overlay plot of unscaled BCG beats of the selected 12 subjects

The results of ranking the features using two different feature selection algorithms are shown in Figure 3-12 Both algorithms indicated similar weights in each feature (Note that the heights of the bars in the Wilks' Lambda mean less importance of the feature, whereas it means more importance in the Relief-F). It is interesting to note that the IJ interval (F2) is the most individually unique characteristic, whereas the adjacent JK interval (F3) was least significant though both features are derived from J wave. Since the IJ interval has been known to reflect the cardiac contractility [29], which indicates an intrinsic ability of the myocardium to contract, the significance of the F2 is in agreement with commonsense expectations. However, the reason for the low significance of the F3 is uncertain. It is presumably related to the fact that the JK interval, which reflects the deceleration and cessation of blood flow after rapid ejection, is not actively driven by the heart [29]. The process is therefore might possess less unique indication of cardiovascular activity.

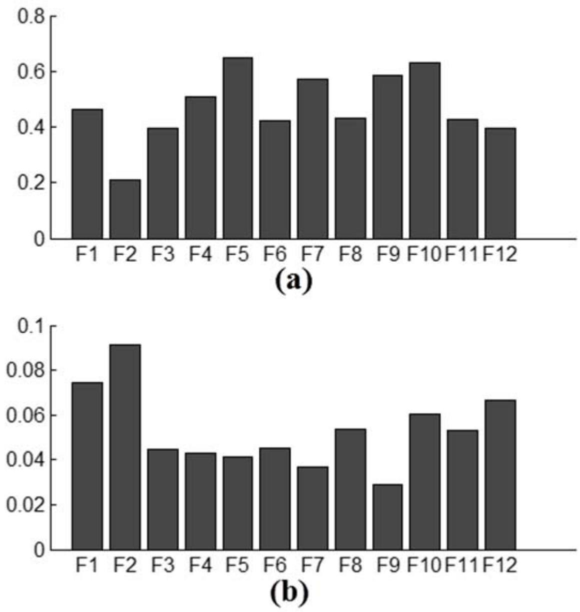


Figure 3- 12 Results of the feature selection

(a) Using Wilks' Lambda algorithm

(b) Using Relief-F algorithm

The features could identify uniqueness of BCG on each subject. The results of the single beat personal identification are shown in Table 3-2 in a contingency matrix form. Using both temporal and amplitude features, the proposed classifier was able to match 90.20% of the 4502 tested BCG beats with the correct subjects. An examination of the diagonal numbers in the table reveals that Subject 2, 15 and 28 had the highest probability (99%), and Subject 4 the lowest probability (68%), of being correctly identified by a single BCG beat. The off-diagonal numbers indicate that percent probability of one subject to be misclassified to another subject.

Table 3-2 Result of single beat personal identification

Original Subject

Recognized Subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30	S31	S32	S33
S1	98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
S2	0	99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
S3	0	1	98	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
S4	0	0	0	85	3	1	0	0	0	0	0	1	1	8	1	0	2	0	0	2	1	0	0	0	2	1	0	0	0	0	0	0	1
S5	1	0	0	5	91	0	4	0	0	0	0	0	0	0	0	0	0	1	1	2	0	0	1	0	6	0	0	0	0	0	0	0	0
S6	0	0	0	0	0	97	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	2
S7	1	0	0	0	1	0	96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
S8	0	0	0	0	0	0	0	98	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
S9	0	0	0	0	0	0	0	0	96	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
S10	0	0	0	0	0	0	0	0	0	96	3	0	1	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1
S11	0	0	0	0	0	0	0	0	0	1	85	0	5	0	0	0	0	0	1	0	0	0	0	11	1	0	0	0	0	0	0	0	1
S12	0	0	0	0	0	0	0	1	0	0	0	97	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S13	0	0	0	0	0	0	0	0	0	0	2	0	91	0	0	0	1	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
S14	0	0	0	1	0	0	0	0	0	0	0	2	0	89	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0
S15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
S16	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	85	1	0	7	1	0	0	0	0	0	0	0	0	0	0	1	15
S18	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2	79	1	9	1	1	0	0	0	3	1	0	0	0	1	0	2
S19	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	87	0	1	0	0	0	0	0	0	0	3	0	0	5	0
S20	0	0	0	2	0	1	0	0	3	0	0	0	0	0	0	0	3	7	1	76	1	5	0	0	0	0	0	0	0	1	1	1	0
S21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	7	0	0	88	0	0	0	0	0	0	0	0	0	1	0	1
S22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91	0	0	0	0	0	0	0	4	1	0	0
S23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97	0	0	0	0	1	0	0	0	0	0
S24	0	0	0	0	0	0	0	0	0	0	5	0	2	0	0	0	0	1	0	2	0	0	0	84	0	0	0	0	0	0	0	0	0
S25	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80	0	0	0	0	1	0	0	0
S26	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	4	1	1	0	0	1	0	0	0	0	96	0	0	0	0	0	0	6
S27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	97	0	0	0	0	2	0
S28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99	0	0	0	0	0
S29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97	0	0	0	0
S30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	1	0	0	0	2	0	0	0	0	85	3	1	0
S31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	6	93	0	0
S32	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	7	1	0	0	0	1	1	0	1	0	0	2	1	89	2
S33	0	0	0	2	1	0	0	0	1	2	4	0	0	0	0	0	2	1	0	0	0	3	0	3	0	0	1	0	0	0	0	1	68

Single beat identification rate = 90.20%

This identification accuracy can be improved when we use multiple beats to in recognition. For this, we simulated personal identification process, by using some succeeding beats as an input to the classification model. Identification was carried out by voting, and we assumed that 10 seconds might set the maximum duration that user can wait until a recognition process to occur. Therefore, the number of the input beats varied from 1 to 11.

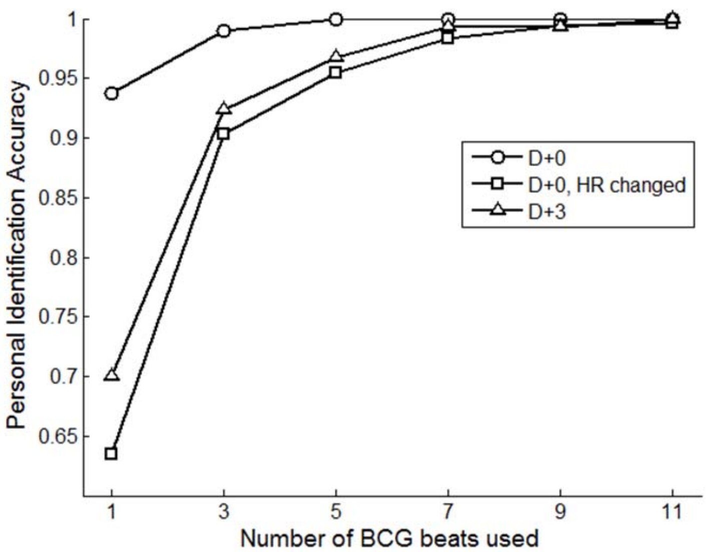


Figure 3- 13 Result of personal identification using multiple beats

Figure 3- shows the result of personal identification. As the number of the beats used increased, the recognition accuracy increased accordingly. The reproducibility of the identification was also tested. When the model was tested with the beats collected on the same day (D+0), two succeeding beats were enough to achieve the personal accuracy over than 98%. However, seven beats were required to achieve same level of accuracy, when the input beats were collected from the other day. Changes in heart-rate also decreased the performance. These results indicate that the morphology of BCG changed according to the heart-rate and by time, to the degree that can be overcome with a reasonable trade-offs in recognition time.

Compared to the ECG-based biometric method, which similarly used an LDA classifier and fiducial point-based features, BCG appears to be comparable to, or richer in biosignal information than the ECG. With our BCG-based biometric method, more subjects could be classified at a higher rate identification accuracy using fewer features without strict requirement on deciding the normality of the beat.

The individual uniqueness of BCG might come from the facts following. Whereas ECG is a transthoracic interpretation of the electrical activity of the heart, BCG reflects not only the 1. anatomy of the heart, but also information about the subject, such as 2. size of body [50] and 3. complexity of the vascular system [4], that might affect the pathway between the source (blood flow) and the measured signal (BCG). The personal information mentioned above might have contributed to the improvement in its identification accuracy compared to ECG.

3.4. Conclusion

In pursuit of new practical applications of BCG, its variability, which has hitherto been a limitation, was successfully engineered for use in identifying human subjects. The timings of cardiovascular events, especially the I-J interval that reflects cardiac contractility, were found to be rich in individually unique information. Three or five successive BCG beats were sufficient for achieving an accuracy of over 98% in human identification using 12 features.

However, some features used in this study could change over life; a longitudinal assessment of the intra-individual variability should be considered in future study. Moreover, practical application of the BCG-based biometric might require a more elaborate feature design and an intelligent classification algorithm.

Since BCG can be measured non-intrusively and is difficult to make a forgery, BCG-based biometric is expected to find specialized applications, either standalone or incorporated with existing ID-management methods. Further studies to uncover the innate variability of BCG among humans would advance the performance of the proposed BCG-based biometric method and also our knowledge of BCG.

Chapter 4

4. Conclusions and Discussions

Ballistocardiogram (BCG) is an information-rich biosignal since it reflects not only the cardiac activity but also the conditions of the vascular system of body. Though many researches have revealed that the morphology of BCG carries a great diagnostic value especially in early diagnosis and prognosis monitoring of cardiovascular diseases, and even non-clinical applications have emerged with help of recent technological advancements, the usage of BCG is yet to become reality due to its limitations in instrumentation and signal processing aspects.

This thesis was focused on the methods to further exploit the usefulness of BCG by developing a new sensor and applications. In the first application, we introduced a new sensor, namely BE-patch, which is capable of simultaneous pickup of electrical and mechanical signal with a single film. The essence of this sensor was on the patterning multiple electrodes onto the piezo-electric film. By imposing different role to each electrode in the signal recording we could make it as a unified sensor for the BCG and ECG. The application of this sensor on the blood pressure estimation showed medical grade performance of BP monitor under limited experimental conditions. The sensor, however, needs more extensive validation on a large clinical population and its reproducibility should be checked.

As the sensor is small in size, light-weight and advantageous in terms of power consumption (The BE-patch reads BCG in a passive way while the accelerometer-based ones require power supplies to work), we expect that the developed sensor would be used in other areas of wearable applications. For example, the sensor can be used as simple patch-type monitor the ECG and BCG. Respiration can also be recorded with a little modification of cut-off frequencies of BCG circuitry. Taking advantage of mutual information obtained from heart and respiration signals, infotainment services like stress management and circadian rhythm might also be feasible. We also expect that the motion artifacts in BCG reflect the movements of center of body. If that is the case, the BE-patch might be applicable as an activity tracker or fitness monitor. Incorporating biometric functionality in BE-patch, which we introduced in chapter 3, would be beneficial to resolve security concerns on medical record, when we think home-based healthcare services is coming near future.

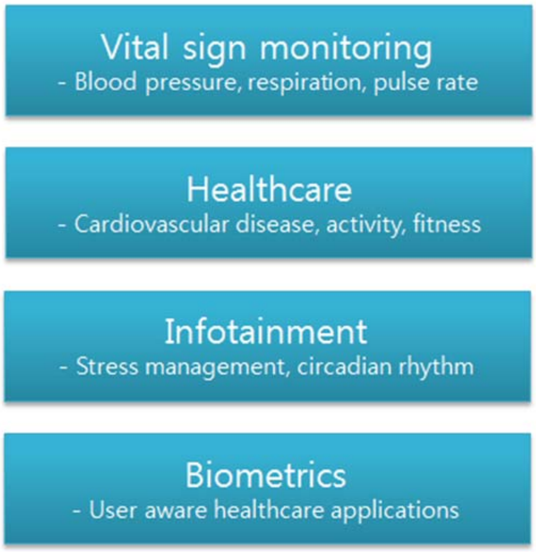


Figure 4- 1 Potential applications of BE-patch in wearable services

In chapter 3, biometric application of BCG was introduced. In this chapter, the inter-individual variability of BCG that previously limited its analysis was revealed to be unique on individuals. Total number of 33 subjects could be classified with over 95% of accuracy with 12 features. The method was reproducible at least 1-week of duration and even when the heart rate was changed. Further studies to improve performance might be necessary with application of more advanced algorithms on the preprocessing, feature design and classifier design steps.

Longer stability should also be checked since the morphology of BCG might be changed when the vascular system is affected by internal or external stimuli. Based on the Caccese's report [51], the morphology of BCG is affected by smoking. In this study, 31 smokers were recruited and asked to refrain from smoking at least 2 hour before the experiment. Subjects underwent two times of BCG recordings first on their arrival to the lab and the second on after smoking cigarettes. Eighteen subjects showed changes in BCG morphology after smoking and 11 of them presented merely the baseline fluctuations due to increased respirations. However, for the rest seven, changes in BCG morphology were significant. How signals changed were not consistent among subjects but the changes disappeared and restored to normal after 1 to 20 minutes of smoking.

However, Caccese's findings do not necessarily imply that BCG based biometric method will not work when the measurements are made at long time interval. Apparently, there are lots of physiological and geometrical factors that result in a certain morphology of BCG. Some of these factors will play differently by time and some would not. The answer to the question depends on whether we can design a set of features that can represent intrinsic uniqueness of one’s cardiovascular systems or not. A series of supervised learning process, similarly presented in this thesis, would reveal the answer when we have data to prove this issue.

Rather, the concern is the amount of information. Though more advanced design of feature sets and classification models might increase the accuracy of the proposed BCG-based biometric method, chances BCG is not as unique to the as fingerprints or iris exist. In this case, BCG might be used as a soft biometric modality; a set of traits providing information about an individual though these are not able to individually authenticate the subject because they lack distinctiveness and permanence. Or, combination with other modalities of identification method to add increase security level would be feasible.

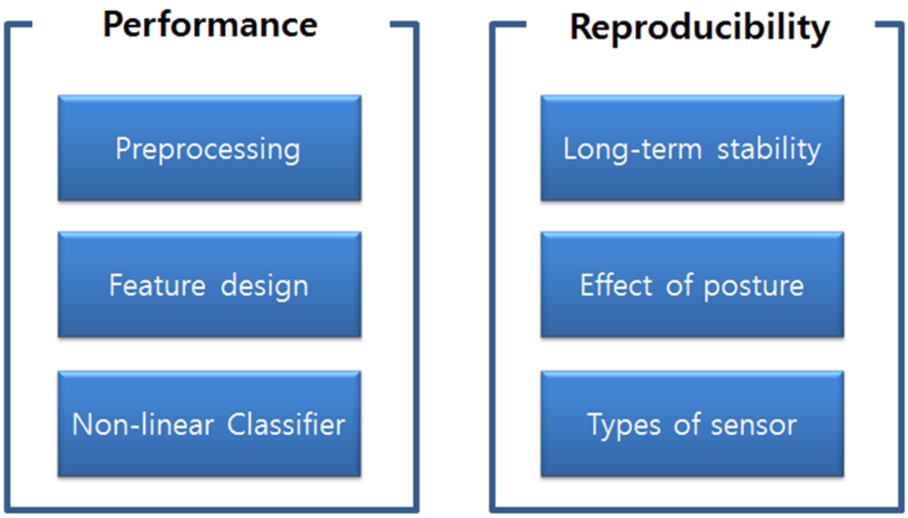


Figure 4-2 Further studies needed for the fulfillment of BCG-based biometrics

Though a number of biometric traits of human, for example finger prints, palm vein and gait are already known, researches to discover new biometric modalities continued since each biometric method has differentiated characteristics to suit for specific applications. The BCG based biometric method would be more robust to the forgery, since the signal is concealed and dynamic (Figure 4-3).

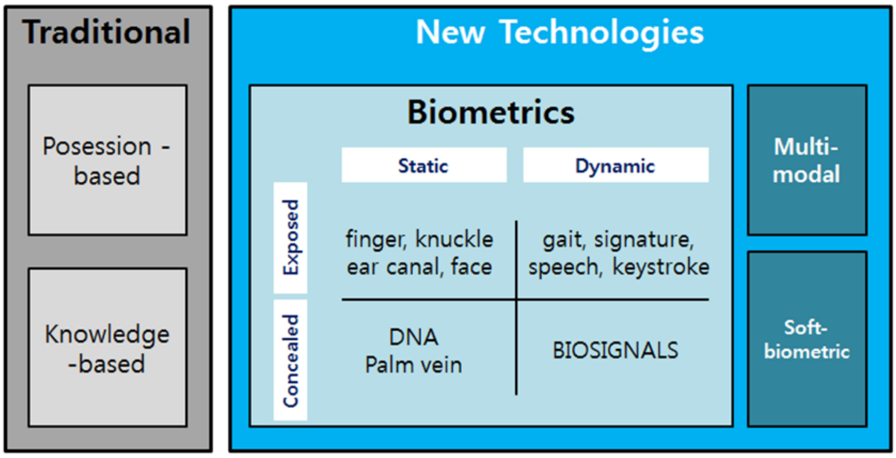


Figure 4- 3 Types of biometric methods

Potential usage of BCG biometric method might include an automotive application, in this a car automatically adjusts the car seat, mirror and air conditioner when a passenger or a driver sits on and biometric recognition occur non-intrusively. Or, the technology could be of use for groups trying to use one BCG system for an entire family - this may provide a means of determining which member of the family is using the device, which would be valuable. As the u-healthcare system might prevalent in near future, home-used healthcare devices would require frequent identification of users to classify the acquired data according to the name of specific family members. In this case, rather than a high level of security, identification system with high affordability and user compliances would be of value.

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국문초록

심탄도 (Ballistocardiogram)는 심박에 동기되어 발생하는 우리 몸의 미세한 진동을 측정한 신호이다. 비침습적으로 심혈관계의 활동을 관찰할 수 있다는 장점 때문에, 20 세기 초반에 심탄도의 해석에 대한 많은 연구가 이루어졌다. 그러나 초음파 기기 등 심혈관계 관련 질병들을 진단할 수 있는 새로운 기술들이 개발되면서 상대적으로 실용적이지 못한 특성을 가진 심탄도에 대한 관심은 1970 년대 이후에 급격히 줄어들었다.

새로운 센서들의 등장과 마이크로프로세서, 신호처리 기술들의 발전에 힘입어 심탄도 연구는 다시 활기를 띠고 있다. 그러나 이러한 발전들에도 불구하고 심탄도는 의자나 침대 등 상당한 부피를 차지하는 사물을 이용하여 계측되고, 분석을 위해서는 동기화 된 심전도가 동시에 측정되어야 하는 등 측정상의 번거로움이 있다. 또한, 심탄도는 개인 간에는 물론 한 개인에게서도 파형에 많은 변이를 보여 신호의 일관된 해석에 어려움이 있다.

본 학위논문에서는, 이러한 측정 측면과 신호처리 측면에서 현 심탄도 응용의 한계점을 극복할 수 있는 방안을

마련하여, 심탄도의 실질적인 활용 범위를 더욱 확장할 수 있는 방안에 대해 연구하였다.

우선, 심탄도를 심전도와 동시에 무구속적으로 잴 수 있는 필름기반의 패치타입 센서를 개발하였다. 압전소자의 양면에 복수개의 전극을 패터닝하고 각각의 전극에 독립된 기능을 부여해 회로에 연결함으로써 필름 한 장으로 물리적인 신호 (심탄도)와 전기적인 신호(심전도)의 동시 측정이 가능하게 하였다. 센서를 가슴에 부착하였을 때 심전도의 특징적인 R 피크과 심탄도의 특징적인 J 피크를 확인하여 기능을 확인할 수 있었으며, 추가적으로 R-J 간격이 수축기 혈압과 음의 상관관계를 가짐을 이용하여 개발된 센서로 혈압을 추정할 수 있었다. 센서를 통해 예측한 수축기 혈압 오차의 평균값과 표준편차는 각각 -0.16 mmHg 와 4.12mmHg 으로, 미국과 영국의 혈압계 가이드라인을 모두 만족시킬 수 있었다.

다음으로, 심탄도의 변이적 특성을 새로운 생체인식 기법으로 발전시키는 방안에 대한 연구를 진행하였다. 이를 위하여 심탄도 한 파형 내의 특이점들을 기반으로 특징 벡터를 추출하고 기계학습을 통해 특징들의 변이를 개인들 간의 변이와 한 개인 내에서의 변이로 구분 하였다. 추출된

특징들을 이용하여 35 명의 피험자들에게 실험해 본 결과, 단일 심박신호로는 90.20%의 확률로 개개인을 구분할 수 있었으며 7 개의 연속된 심박신호로는 98%이상의 성능을 낼 수 있었다. 또한 약 일주일 간격을 두고 반복하여 측정한 데이터와 운동을 통해 심박수가 변화된 데이터의 적용을 통해서 심탄도를 이용한 생체인식 방법의 재현성을 확인할 수 있었다.

키워드 심탄도, 생체인식, 혈압, 비패치

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