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Master's Degree Thesis

A Study of Algorithms for Monitoring Heart Rate and Agility Index

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Graduate School of Chosun University

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심박수 및 운동량 모니터링 알고리즘 연구

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This is to certify that the Master's degree thesis of Luan Dinh

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Acronyms

ECG	Electrocardiogram
RA	Right Arm
LA	Left Arm
LF	Left Foot
APC	Atria Premature Contraction
VPC	Ventricular Premature Contraction
ADC	Analog-to-Digital Converter
ASP	Acceleration Start Point
APP	Acceleration Peak Point
AEP	Acceleration End Point
-thr	Negative Threshold
HR	Heart Rate
+thr	Positive Threshold
SA	Sinoatrial
AV	Atrioventricular

초록

심박수 및 운동량 모니터링 알고리즘 연구

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유비쿼터스 헬스케어 시스템에서 건강상태 관찰과 측정의 융통성 있는 방법은 필수 기능이다. 신체와 심장의 활동을 모니터링 할 수 있다면 심장 순환계 손상과 신체 활동정도, 건강상태의 관찰신체 활동을 관찰하는 의학 진단가에게 도움을 줄 수 있다.

이 논문에서는 패치형태의 센서모듈에 내장된 심박수와 운동량의 실시간 무선 모니터링을 위한 이론적인 알고리즘을 기술하였다. 심박수 측정을 위해 제안하는 방법은 디지털필터를 통한 잡음제거 효과와 QRS 신호 측정을 위한 임계값, T-파와 QRS 구별하는 기술과 VPC와 QRS 신호를 구별하는 표준정합 방법들의 복합적인 방법으로 개발되었다. 운동의 수행을 평가하기위한 유용한 지표로써 운동량을 제시한다. 운동량 계산을 위한 알고리즘은 다축가속신호(Multi-axis accelerometer signals)의 다양한 디지털처리방법들을 기반으로 한다. 건강측정과 평가를 위한 실시간 무선 시스템(AirBeat^{TM})은 센서모듈을 위한 효과적인 알고리즘과 컴퓨터에서의 분석을 위한 분석 프로그램을 기반으로 개발되었다. 평가를 위해 CASE 시스템은 기본시스템하고 Bruce 프로토콜을 적용하였다. 심박수 측정 오차는 6.2% 이내였다. 평균 운동량과 종래 운동점수의 상관계수는 0.8를 넘었다. 심박수와 운동량 변화는 매우 잘 관찰되었고, 동시에 이 시스템에서 공급하는 건강상태 측정 능력도 측정되었다.

ABSTRACT

A Study of Algorithms for Monitoring Heart Rate and Agility Index

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For ubiquitous healthcare systems, health monitoring and evaluation in a flexible way are essential functions. The ability to monitor physical activities and cardiac activities can aid in determining clinical diagnoses, observing the physical demand of human circulatory system, assessing the intensity of physical activity, and evaluating general health conditions.

In this thesis, algorithms for real-time wireless monitoring of heart rate and agility index, which were implemented in the patched-type sensor module are presented. The proposed method for detecting heart rate was developed by the combination of the following techniques: digital filtering to reduce the effect of noises, threshold QRS detection, T-wave discrimination technique, which provides high ability to distinguish QRS complex from T-wave and template matching method to discriminate QRS complex from VPC. We suggested agility index as a helpful indicator for the evaluation of exercise performance. The algorithm used to calculate agility index was based on several digital processing techniques of multi-axis accelerometer signals. We developed a real-time wireless system (AirBeat™) for health monitoring and evaluation based on the effective algorithms executed in sensor module and the analysis software. For testing, the CASE system (from General Electric Medical Co., USA) was used as a reference system, and the Bruce protocol was conducted. For heart beat, the error rate was within 6.2%. The correlation coefficient between average agility index and a conventional agility point was over 0.8. The change of heart rate and agility index can be monitored very effectively and measured at the same time during exercise. Such monitoring and measurement capabilities can provide our AirBeat™ system with the ability to evaluate health condition.

I. Introduction

A. General Description of ECG and Agility Index

1. Electrocardiogram (ECG)

1.1 Introduction

The electrocardiogram (ECG) describes the electrical activity of the heart. It is obtained by placing electrodes on the chest, arms, and legs. With every heartbeat, an impulse through the heart, which determines its rhythm and rate, causes the heart muscle contract to pump blood. The voltage variations measured by the electrodes are caused by the action potentials of the excitable cardiac cells, as they make the cells contract. An ECG is characterized by a series of waves, the morphology and timing provide information used for diagnosing diseases that can be identified by disturbances of the electrical activity of the heart. The pattern that characterizes the occurrence of successive heartbeats is also very important.

The Dutch physiologist, Willem Einthoven, developed using a string galvanometer that was sensitive enough to record electrical potentials on the body surface. He also defined sites for electrode placement on the arms and legs which remain in use today. ECG recording has developed incredibly and become an indispensable tool in many different contexts. The ECG record is used today in a wide variety of clinical applications.

1.2 The Integrated ECG

The heart comprises several different types of tissues such as: sinoatrial (SA) and atrioventricular (AV) nodal tissue, atrial, purkinje, and ventricular tissue. Each type of cells exhibits its own characteristic of action potential. During pumping action, the ECG corresponds to the sum of the electrical activities come from different tissues, as shown in Fig. 1.

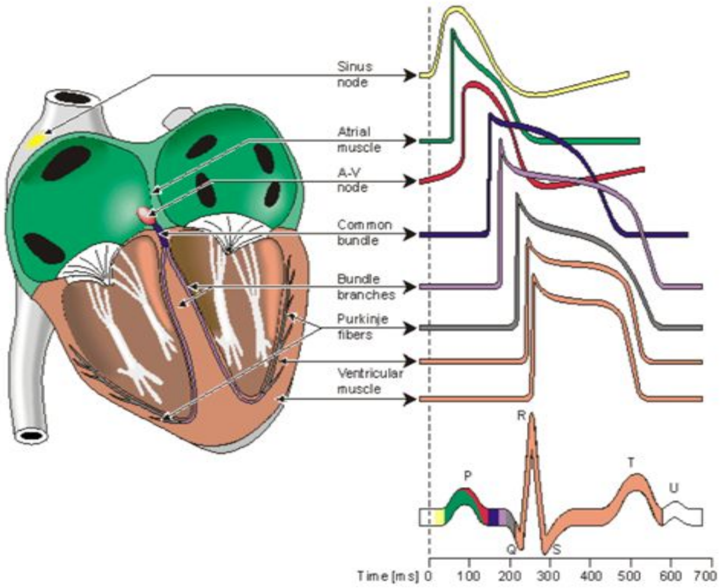


Fig. 1. The integrated ECG.

For monitoring of health condition, heartbeat is a very useful parameter, because it provides the vital signs of heart functions. The morphologies and inter-beat intervals of heartbeats can reveal the condition of heart contraction.

The ECG is used to analyze heart condition for many years. The use of ECG signal is the most accurate method for detecting heart rate. The QRS complex is the most outstanding waveform in the ECG, because it is related to the electrical activities in the heart during the ventricular contraction. Much useful information about current state of the heart is provided by the shape of the QRS complex and the time at which it occurs.

The electrodes used for ECG recording are positioned so that the spatiotemporal variations of the cardiac electrical field are sufficiently well-reflected. The difference in voltage between a pair of electrodes is referred as a lead. The ECG is typically recorded with a multiple-lead configuration.

1.3 The Standard 12-Lead ECG

The heart's electrical activity can be recorded from electrodes on the surface of the body. The lead system, which is used to record the ECG, is formed by 12 positions of a pair-electrode. The 12-lead ECG provides spatial information about the heart's electrical activity in three, approximately-orthogonal directions ie., right and left; superior and inferior; anterior and posterior. Each of the 12 leads represents a particular orientation in space, as shown in Fig. 2.

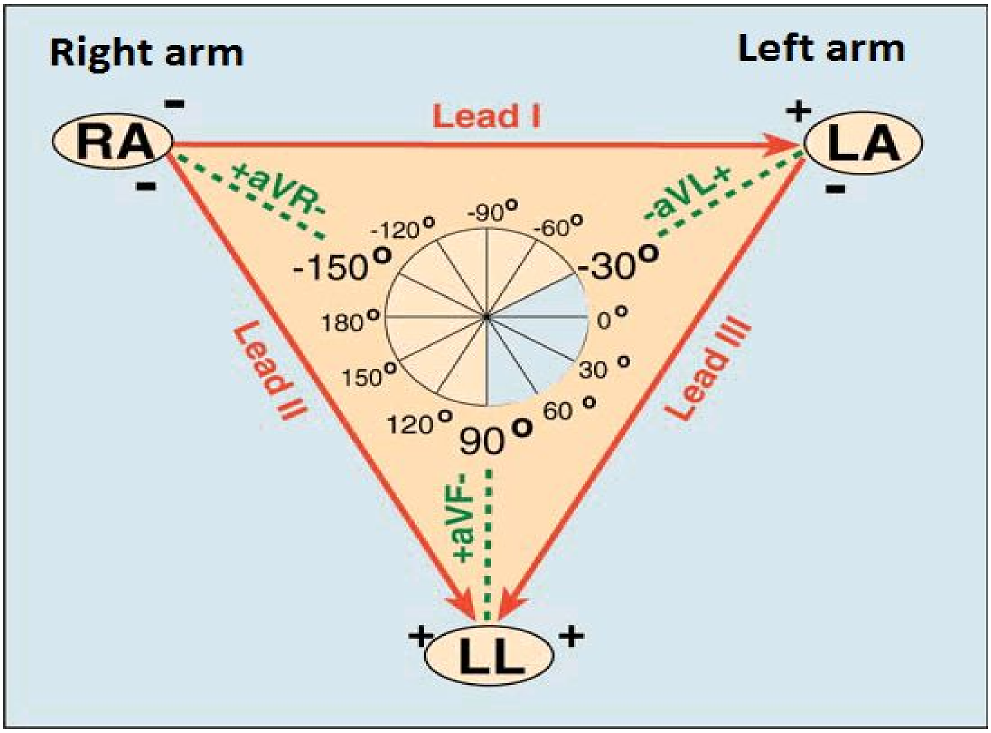


Fig. 2. Lead placement diagram.

Right Arm : RA, Left Arm: LA, Left Foot: LF.

Bipolar limb leads (frontal plane):

+ Lead I: RA (-) to LA (+)
+ Lead II: RA (-) to LF (+)
+ Lead III: LA (-) to LF (+)

Augmented unipolar limb leads (frontal plane):

+ Lead aVR: RA (+) to [LA&LF] (-)
+ Lead aVL: LA (+) to [RA&LF] (-)
+ Lead aVF: LF (+) to [RA&LA] (-)

And others unipolar (+) chest leads in horizontal plane include leads V1, V2, and V3 (posterior anterior), and leads V4, V5, and V6 (right left).

2. Agility Index

The Agility index is the ability to change the position of body in an efficient and effective way, which requires the combination of balance, coordination, speed, reflexes and strength. Balance is the ability to maintain the equilibrium during physical activity, which includes several coordinated actions controlled by body's sensory functions. For an athlete, the ability to maintain balance under changing condition of body movement (dynamic balance) is more important than ability to keep the center of mass above the base of support in stable conditions. Coordination is the ability to control the movement of body in cooperation with the body's sensory functions. Speed is the ability to move all or part of the body quickly. Strength is the ability of muscles to overcome a resistance.

In sports, agility can indicate the potential of athletes, in order to improve agility many training exercises have been proposed. Agility index is manually calculated by a supervisor. The measurement of agility is based on the time it takes an athlete to complete the prescribed exercise or how many steps he or she can complete during a given period of time.

B. Research Necessity

The increasing of social interest in healthcare has resulted in enhanced public demand for programs and activities that promote health and physical development. Currently, health-related devices are becoming the commercial products. Various types of devices have been developed for use in physical fitness training for assessing the physical state of the body. However, most of them are only used in the limited space (indoors) or cause some disadvantages in the exercise. In our modern society, people are confined in a stuffy, high press work environment and they have to deal with the lifestyle imposed by crowded cities. So, outdoor spaces, such as parks or nature-friendly areas, are preferred. The demand for the development of devices that can be used outdoors to measure and manage physical fitness and exercise training is increasing rapidly. For a healthcare system, especially in sports activities, a wireless patched-type sensor module that can provide the desired information and analyses is essential, because it provides subjects a flexible and freely-moving condition. The information provided by the combination of simultaneous monitoring of heart rate and body movement intensity comprises a valuable set of physiological and behavioral data related to the physical activity and cardiac activity. It is widely known that the intensity of body movement has a close relationship with the physical demand of the human circulatory system. The added knowledge about the subject's activity intensity provides valuable information for monitoring, diagnostics, or health alerts.

The manual measurement, calculation, and analysis of the agility index is inconvenient. The accuracy of heart rate monitoring during intensive physical activity is not high, which means that it is difficult to determine with appropriate accuracy when an emergency situation is occurring by just analyzing heat stress. Every year, many athletes and students have strokes and die after intensive exercises or athletic competition due to our inability to forecast such problems or manage them properly when they occur.

In this thesis, algorithms for flexible, high-accuracy monitoring of heart rate and agility index are proposed. A wireless system for evaluating, training and monitoring of athletes, as well as providing emergency forecast of potential problems by assessing the combination of heart rate and agility index information, was developed.

C. Research Goals

As mention above, the purposes of our study were to provide a suitable and high accuracy method for heart rate monitoring in harsh conditions of athletes encounter; develop a new indicator that correlates well with conventional agility index; focus on the development of a small, light-weight, patched-type sensor module to collect vital information about health conditions of subject. The aims of this study are:

(1) To increase the accuracy of Heart Rate detection of athletes by using multiple techniques.

(2) To provide a new method to calculate agility index in flexible, highly-sensitive way.

(3) To develop a real-time, wireless system for health monitoring and evaluation base on effective algorithms executed by a sensor module and by the analysis software in a computer.

D. Thesis Organization

In Chapter I, background knowledge and the principle of ECG signal and agility index are introduced. Also, the reasons for conducting the research and its final target are presented. In Chapter Ⅱ, we present the common methods for detecting heart rate, and calculating agility index. The problems and limitation of each methods are discussed, and our proposed methods are described. The system we developed and the results of its performance evaluation are described in Chapter III. Our conclusion are provided in Chapter IV.

II. Algorithms for Monitoring Heart Rate and Agility Index

A. Heart Rate Detection Algorithm

Normally, an ECG signal contains several types of waves with differing periods, as shown in Fig. 3. The P wave represents the initiation of the heartbeat in the upper chambers of the heart (atria); the duration of the P wave is usually less than 0.12 second. The QRS complex corresponds to the lower chambers (ventricular) depolarization. Its duration is normally 0.04 to 0.12 second. The T-wave represents the recovery phase.

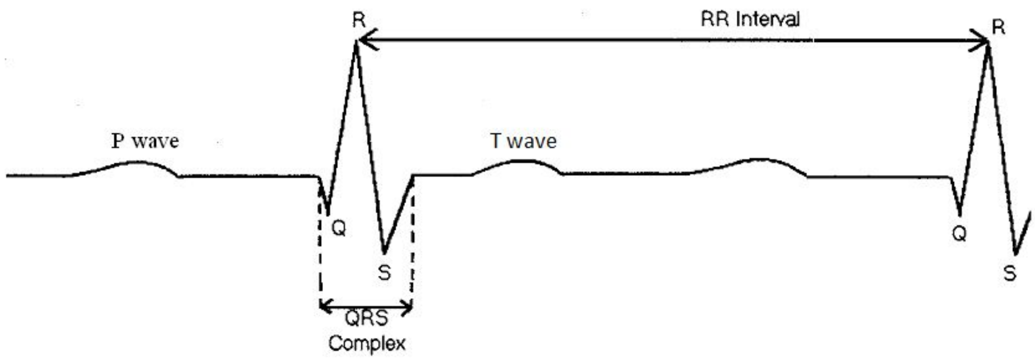


Fig. 3. The components of ECG signal.

In order to calculate heart rate, we must specify the position of the QRS complex and the RR interval precisely. (RR interval is the time that elapses between two consecutive R waves).

1. Problems in QRS Detection

Highly-accuracy QRS detection is difficult because various types of noises occur in the ECG signal. Muscle action, electrode motion, baseline instability can be the sources of noises. The occurrence of T waves with high frequency characteristics similar to those QRS complex can be obstacles for QRS detection. This is especially an issue for athletes engaged in high intensity activities, because the ECG may have a lot of noise. Unexpected noise with random amplitude and frequency easily can cause false detection. In addition, the physiological variability of the QRS complex requires more effort to detect heart rate. A detailed description of each noise signal and its characteristic is given bellow:

Motion artifacts: During the movement of subject, the motion of electrodes changes the electrode-skin impedance lead to the transient (not step) baseline changes. As electrode-skin impedance changes, the ECG amplifier recognizes a different source impedance, which form a voltage divider with the amplifier input impedance. Therefore, the amplifier input voltage depends on the source impedance. Normally, we consider motion artifacts as vibrations or movement of the subject. The shape of the baseline disturbance caused by motion artifacts can be assumed as a biphasic signal resembling on cycle of a sine wave. The peak amplitude varies up to 500 percent of peak-to-peak ECG amplitude, and the duration of the artifact ranges from 100 to 500 ms.

Electrode contact noise: Electrode contact noise is transient interference caused by loss of contact between the electrode and skin, which effectively disconnects the measurement system from the subject. Movements and vibration of subject bring the loose electrode in and out of contact with the skin, this loss of contact can be permanent or intermittent. The switching action at the input of measurement system can result in large artifacts since the ECG signal is usually capacitively coupled to the system. The 60-Hz interference may be significant as the amplifier input is disconnected. Electrode contact noise can be modeled as a randomly-occurring, rapid baseline transition (step), which decays exponentially to the baseline value and has a superimposed 60-Hz component. The transition may occur only one, or rapidly occur several times. The characteristics of this noise signal include the amplitude of the initial transition, the amplitude of the 60-Hz component, and the time constant of the decay. The duration can be 1 s and the amplitude is up to the maximum output of the recorder.

Electrical activity of muscles: Muscle contractions cause artifactual milivolt-level potentials to be generated. The baseline of electromyogram is in the microvolt range, so it is usually insignificant. The signals that result from muscle contraction can be considered as transient bursts of zero-mean, band-limited Gaussian noise.

Baseline drift and ECG amplitude modulation with respiration: The drift of the baseline with respiration can be represented as a sinusoidal component at the frequency of respiration added to the ECG signal. The frequency and amplitude of this component should be variable. The amplitude of the ECG signal also varies about 15 percent with respiration. The variation could be reproduced by amplitude modulation of the ECG and the sinusoidal component that was added to the baseline.

Sometimes atria premature contraction (APC) and ventricular premature contraction (VPC) occur in detected signal. The APC and QRS complex have similar wave form to a normal contraction while the VPC wave is difference from the shape of QRS. Using threshold method, one can recognize QRS and VPC waves, but cannot distinguish them because of the lack of information about wave form.

2. Related Works

Software QRS detection has been a research topic for long time, and, with the great advances in computer technology, the computational load is no longer a concern. Many new approaches of QRS detection have been proposed and implemented using computer such as algorithms from the field of artificial neutral networks, genetic algorithms and wavelet transforms. However, in this study, the algorithm for the detection of QRS was implemented in a battery-driven device. The computational load and power consumption need to be considered, and, for this reason we conducted studies to determine the strong points of the following approaches, and we incorporated those points in our algorithm, called the **First Derivative based Algorithm**: Holsinger *et al.* [5] proposed a QRS detection scheme base on first derivative, the equation they used is shown below :

$$Y_{(n)} = X_{(n+1)} - X_{(n-1)} \tag{1}$$

This array is searched until a point is found that exceeds the slope threshold $Y_{(i)} > 0.45$. QRS candidate occurs if another point in the next three sample points also exceeds the threshold:

$$Y_{(i+1)} \text{and } Y_{(i+2)} \text{and } Y_{(i+3)} > 0.45. \tag{2}$$

Amplitude and First Derivative based Algorithm: This algorithm was proposed by Gustafson [6]. The first derivative is calculated at each point of the ECG:

$$Y_{(n)} = X_{(n+1)} - X_{(n-1)} \tag{3}$$

The first derivative array is then searched for points which exceed a constant threshold: $Y_{(i)} > 0.15$, also the next three derivative value

$$Y_{(i+1)} \text{and } Y_{(i+2)} \text{and } Y_{(i+3)} > 0.15. \tag{4}$$

If all above conditions are met, and if the next two sample points have positive slope amplitude product

$$Y_{(i+1)}X_{(i+1)}\,\text{and}\,Y_{(i+2)}X_{(i+2)} > 0 \tag{5}$$

point i is considered as a QRS complex.

Digital Filters based Algorithm: Okada *et al.* [7] proposed a QRS detection algorithm, in which the first stage smooths the ECG using three-point moving average filter:

$$Y0_{(n)} = [X_{(n-1)} + 2X_{(n)} + X_{(n+1)}]/4 \tag{6}$$

then the output is passed through a low-pass filter:

$$Y1_{(n)} = [1/(2m+1)]\sum_{k=n-m}^{n+m}(Y0_{(k)}) \tag{7}$$

the difference between input and output of the low-pass filter is squared:

$$Y2_{(n)} = (Y0_{(n)} - Y1_{(n)})^2, \tag{8}$$

then the squared difference is filtered:

$$Y3_{(n)} = Y_{(2)}[\sum_{k=n-m}^{n+m} Y2_{(k)}]^2, \tag{9}$$

finally, the fourth array is formed by:

$$Y4_{(n)} = Y3_{(n)}\ \text{if}\,[Y0_{(n)} - Y0_{(n-m)}][Y0_{(n)} - Y0_{(n+m)}] > 0 \tag{10}$$

$$otherwise\ Y4_{(n)} = 0$$

the threshold is determined by:

$$Threshold = 0.125\max[Y4_{(n)}]. \tag{11}$$

The QRS complex occur when a point in $Y4_{(n)}$ exceeds the threshold.

3. Proposed Algorithm

As mention above, several methods have been suggested for eliminating noise in the ECG signal, with positive results. However, in our study we aim to find an effective method, that takes advantage of the strong points of these methods and that is suitable for low processing capacity of a patched-type sensor. The algorithm for detecting heart rate was focused on analyzing the athlete's heart rhythm during exercise.

We have redesigned a well-known, band pass filter-based R-wave detection algorithm to make it more robust during motion. This algorithm processes acquired Lead II signal according to the flowchart shown in Fig. 4.

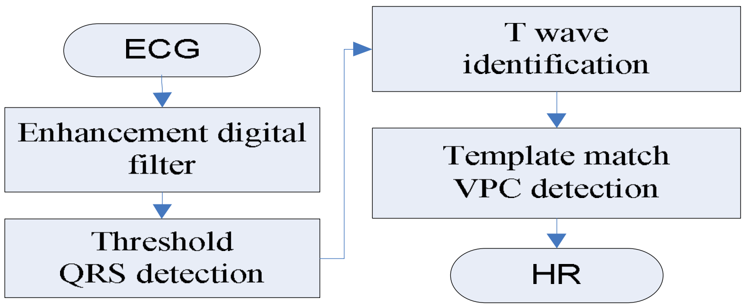


Fig. 4. The flowchart of heart rate detection.

The ECG signal is converted into digital signal by an analog-to-digital converter (ADC) with a sampling rate of 200 Hz, and this 12-bit A/D stores data for a period of 3 seconds before converting them to 8-bit data and sending them to processing components. The digitalized signal is passed through the enhancement digital filter stage to reduce the effect of noise and obtain other major information about QRS complex. The filter stage includes the following processing steps (Fig. 5).

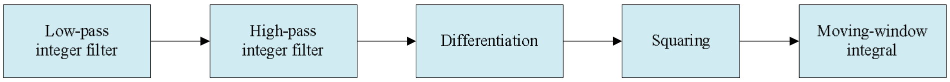


Fig. 5. Enhancement digital filter.

The combination of low and high pass creates an effective band-pass filter. The passband is up to the maximum energy of QRS complex, which is approximately 5 to 15 Hz. Because we only use the integer coefficient, which reduces the operation of the micro-processor by a considerable amount, the real-time filtering, and other calculations to identify the QRS can be implemented by micro-controller (MSP430F149). **Low-pass filter:** The transfer function of the low-pass filter is described by:

$$H_{(z)} = \frac{(1-z^{-6})^2}{(1-z^{-1})^2}. \tag{12}$$

The amplitude response is:

$$|H_{(wT)}| = \frac{\sin^2(3wT)}{\sin^2(3wT/2)}. \tag{13}$$

Where T is the sampling period (units). The difference equation of the filter is given by:

$$y_{(nT)} = 2y_{(nT-T)} - y_{(nT-2T)} + x_{(nT)} - 2x_{(nT-6T)} + x_{(nT-12T)}. \tag{14}$$

High-pass filter: The high-pass filter will subtract the low frequency components from the output signal of previous low-pass filter, the transfer function is:

$$H_{(z)} = \frac{(-1+32z^{-16}+z^{-32})}{1+z^{-1}}. \tag{15}$$

The amplitude response is:

$$|H_{(wT)}| = \frac{[256+\sin^2(16wT)]^{1/2}}{\cos(wT/2)}. \tag{16}$$

The difference equation is:

$$y_{(nT)} = 32x_{(nT-16T)} - [y_{(nT-T)} + x_{(nT)} - x_{(nT-32T)}] \tag{17}$$

The differentiation step will provide the QRS complex slope information, the transfer function is:

$$H_{(z)} = (1/8T)(-z^{-2} - 2z^{-1} + 2z + z^2.) \tag{18}$$

The amplitude response:

$$|H_{(wT)}| = (1/4T)[\sin(2wT) + 2\sin(wT)] \tag{19}$$

The difference equation is given by:

$$y_{(nT)} = (1/8T)[-x_{(nT-2T)} - 2x_{(nT-T)} + 2x_{(nT+T)} + x_{(nT+2T)}] \tag{20}$$

After differentiation, the signal is passed through squaring process in order to enhance the slope of the frequency-response curve of the derivative and reduce false positives caused by highly abnormal energy T wave. In this stage, the signal is squared point by point with the equation:

$$y_{(nT)} = [x_{(nT)}]^2. \tag{21}$$

Finally, the moving-window integral process was used to obtain information about slope and width of QRS complex. The equation of this process is

$$y_{(nT)} = (1/N)[x_{(nT-(N-1)T)} + x_{(nT-(N-2)T)} + \dots + x_{(nT)}] \tag{22}$$

The width (number of samples) of moving-window is very important; it should be the same as the widest possible QRS complex in ECG signal. If the window is too narrow, the integrated waveform will produce several peaks. On the other hand, if the window is too wide, the QRS and T wave will be merge to form the integrated signal. These problems can cause difficulty for detecting the QRS complex in the next step.

The filtered signal is passed through an adaptive-threshold, QRS detection procedure to detect the QRS candidate (QRS^*). Through the QRS^* detection stage, thresholds are chosen and adjusted to float over the noise. Taking the advantages of high signal-to-noise provided by digital filter in previous stage, both low and high threshold are used. First, the higher threshold is used to detect QRS*, and, if there is no found signal within pre-defined period, the back-searching process conducted using the lower threshold. The details of this process are shown in Fig. 6.

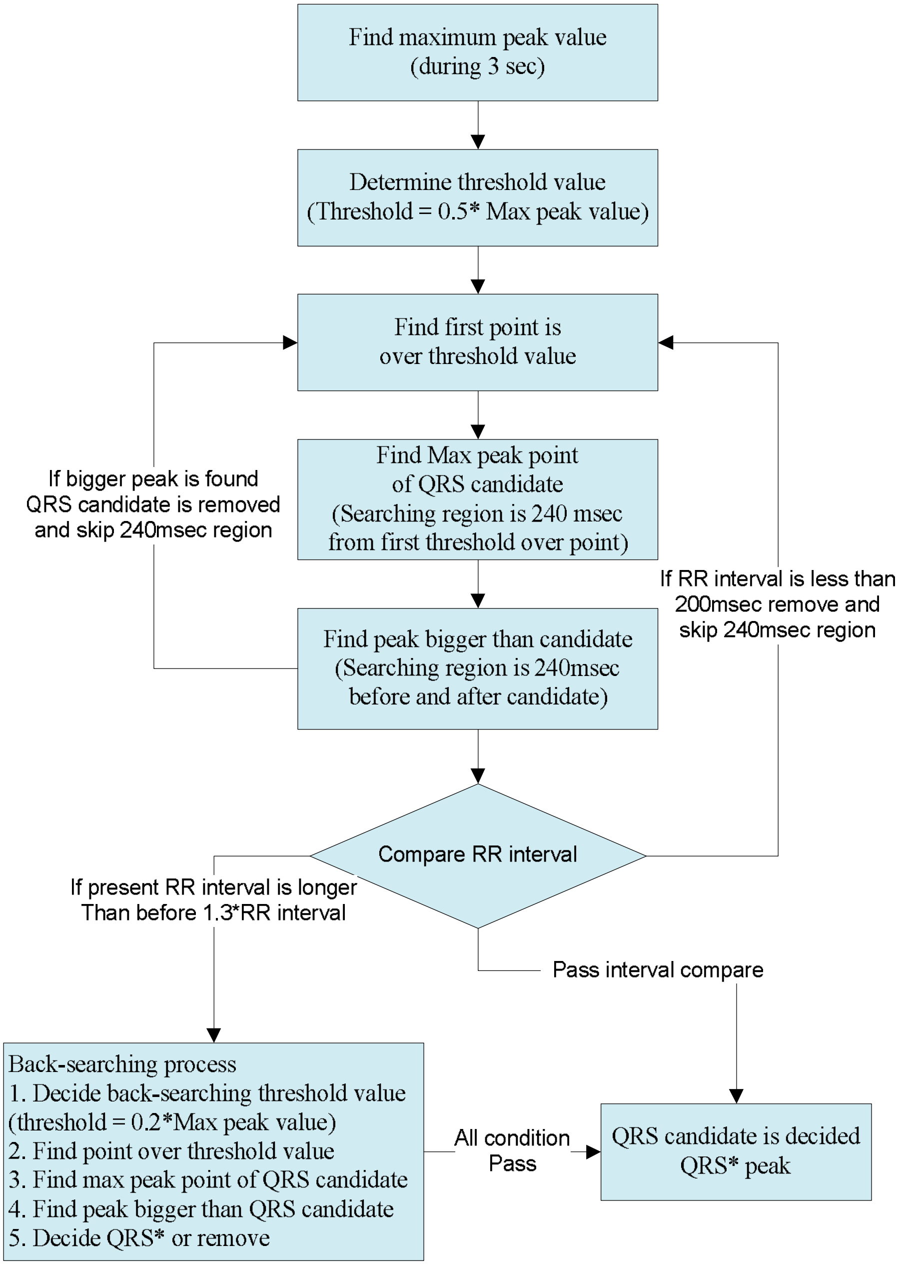


Fig. 6. Adaptive threshold QRS detection.

Find the maximum peak value: The input data are stored in three seconds, and, then max-value is selected by measuring the peak to peak. The high threshold is a half of max peak value. **Find the QRS candidate**: Search the max-value in 240-msec interval region from the first point over the threshold value. **Peak value comparison**: The comparison to other peak value is conducted, and the QRS candidate will be considered as a QRS complex if it is the only maximum value in the region of 240 msec before and after it. If there is a peak value greater than the QRS candidate, 240-msec interval region is skipped, and the candidate is removed. **QRS interval comparison**: The RR interval between the decided QRS candidate and previous QRS will be compared to the previous RR interval. If current RR interval is too short, it means that the T wave or other abnormal signal is detected. If current RR interval is longer than 1.3 times of the previous RR interval, there is a possibility of missing the QRS complex. So, the back-searching process is performed. **Back-searching process**: As back-searching process is conducted, the low threshold is decided by 0.2 times of the maximum peak value. After that, the decision of QRS complex is performed as above process. After going through the steps above, the QRS^* is decided and will be inspected again before being identified as a QRS complex by the template match stage. We calculate the cross correlation coefficients between QRS* and QRS template, defined as

$$Coe = \frac{\sum_{i=1}^{N}(x_i - X)(y_i - Y)}{\sqrt{\sum_{i=1}^{N}(x_i - X)^2}\sqrt{\sum_{i=1}^{N}(y_i - Y)^2}} \qquad (23)$$

Where x_i and y_i are QRS^* and QRS template, respectively. The coefficient has the values between −1 and +1. The values that are approximately equal to 1 show a high similarity to the QRS template. On the other hand, the lower numbers refer to VPC, which has a different wave shape. To minimize the calculation, the window size N of QRS template only spans the duration of detected QRS* and it is updated after each QRS is decided. In the above steps, the QRS peaks are dropped if they are lower than 50% of the previous value. The QRS complex which does not show heart rate within 30 to 250 bpm is rejected. Finally, the algorithm calculates the heart rate.

B. Agility Index Algorithm

1. Physical Activities Monitoring

Human motion analysis has been primarily dominated by video camera. C. R. Taylor *et al.* [8] digitized the captured video of motion states, and the movements, can be enhanced further for analysis through motion analysis software. In a study conducted by K. Aninian *et al.* [9], physical activities were monitored based on accelerometers and compared with video observation. T. Ryan Burchfield *et al.* [10] developed a wireless sensor application that detects abnormal human movements, such as seizure. In another study [11], a kinematic sensor that was composed of a multi-axial accelerometer and gyroscope was used to monitor the daily physical activities of elderly people. J. Ng *et al.* [12] developed a device that can record information about body position along with ECG signal in order to aid clinical diagnosis. However, motion detection with multiple cameras requires complicated setup in a limited space, so it is unsuitable for monitoring people in outdoor or mobile environments. The above studies, which were related to body posture, were limited by the accuracy of the system. In order to acquire more accurate depiction of body posture and position, it would be necessary to mount more sensors at various places on the body.

2. Proposed Algorithm

We developed an agility index for evaluating the exercise performance and potential of athletes. This new indicator has high correlation coefficient with conventional agility index. In this study, the change of acceleration in exercise was detected by using a 3-axis accelerometer (MMA7260Q). With the fine-grained sensitivity of this sensor, we were able to adjust the sensitivity range at low gravity levels or to acquire more coarse-grained data acquisition at high gravity levels. Because our study aim was to measure the motion signal of athletes, the accelerometer was configured at -6G to 6G range. The proposed algorithm that was used to calculate the agility index was based on several digital signal processing techniques, as shown in Fig. 7.

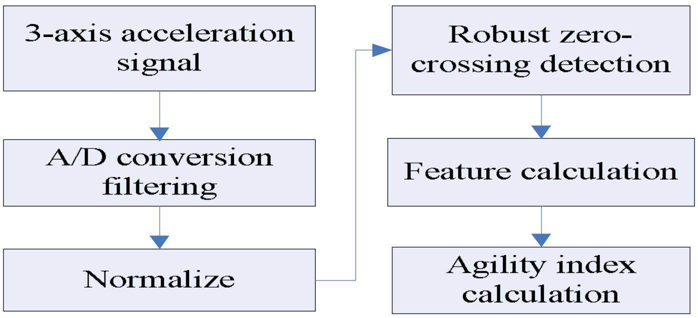


Fig. 7. The flowchart of the agility index calculation.

First, the acceleration signal is digitalized by using a 12-bit, analog-to-digital converter with a 100-Hz sampling rate. Because the signal is not noise free, a pre-processing stage was required to reduce the effect of noise. For digital filtering, a band-pass filter and the moving average were used.

For each axis, the accelerometer generates an analog voltage that is relative to the accelerometer force parallel to that axis. The g-value of each axis was computed independently and then combined into a single value that required less memory and computational resources of micro-controller. The root-mean squared formula is as follow:

$$g = \sqrt{g_x^2 + g_y^2 + g_z^2} \tag{24}$$

Base on the output characteristics of the MMA7260Q sensor, the detected signal was always positive. However, the real acceleration can be positive or negative, depending how the velocity changed. Therefore, the filtered signal was passed through a normalize stage, as shown in Fig. 8.

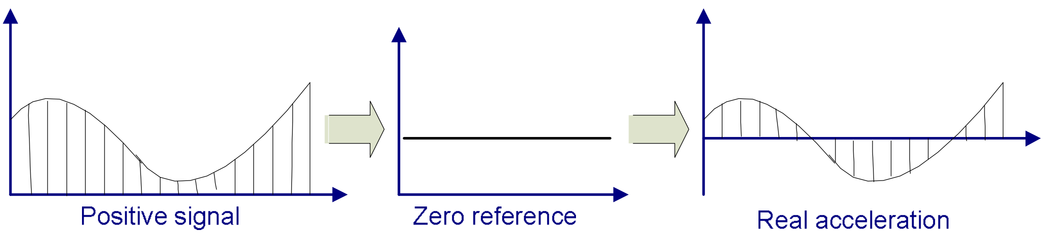


Fig. 8. Normalize stage.

In oder to reduce the effects of noises, the zero reference point is the output of accelerometer at non-movement condition. The accelerometer output varies from the minimum (V_{ddmin}) to the maximum (V_{ddmax}) value. The zero value is near to V_{ddmin} + (V_{ddmax} - V_{ddmin})/2. Values that are greater than the reference point represent positive values of acceleration, and the lower values represent deceleration.

In the above steps, zero-crossing detection is the most important step. Actually, "zero-crossing" is a common term in electronics, mathematics, and image processing. In math, this usually means the change of sign, e.g., from positive to negative, that occurs when the graph of a particular function crosses the axis (zero-value). In actuality, many noise factors affect the acceleration signal. So, we have to design the robust zero-crossing detector.

As shown in Fig. 9, our zero-crossing detection algorithm uses the following steps.

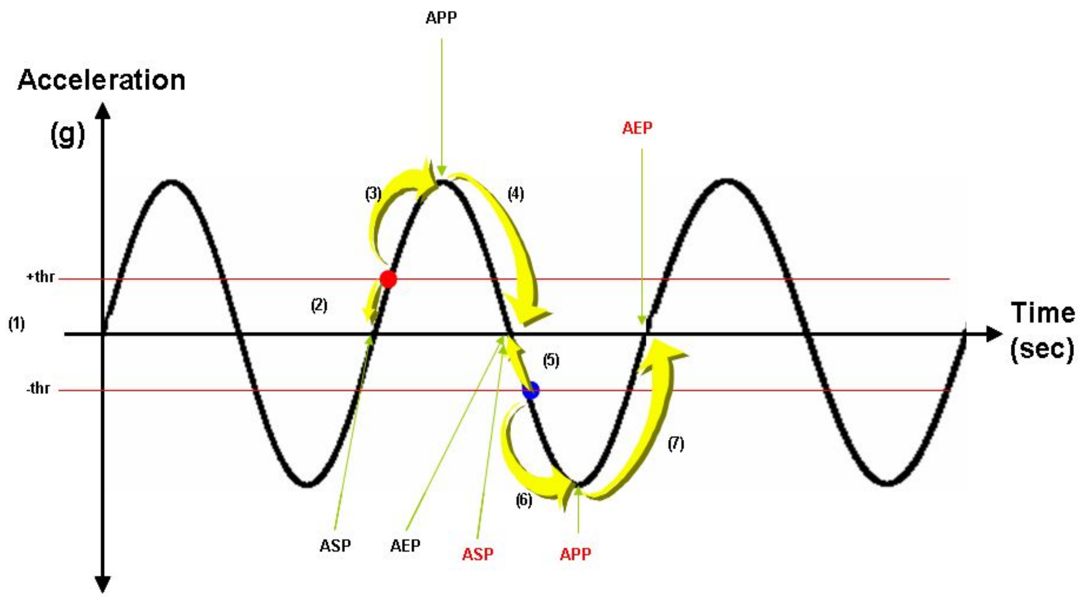


Fig. 9. The procedural drawing of the robust zero-crossing detection algorithm.

(1) Determine the positive and negative threshold (+thr and -thr) considering the noise margins.
(2) When signal strength goes above +thr, we can find zero-crossing point by decreasing sample index from the intersecting point. Then, the zero-crossing point is named as the Acceleration Start Point (ASP).
(3) After finding ASP, the Acceleration Peak Point (APP) can be detected as a peak value by increasing the sample index from +thr intersecting point.
(4) Then, we consequently find zero-crossing point as Acceleration End Point (AEP) by increasing the sample index.
(5), (6), (7) We reiterate these steps in the negative threshold, -thr.

With this procedure we can reduce the possibility of the extraction of the false value due to motion artifact noise. The results of algorithm's performance tests show that it achieved correct detections on the simulated acceleration signal 99% of the time. We can calculate feature values by using the extracted feature points that were provided by robust zero-crossing detection. The feature value is experimentally selected as tri-angular area of ASP, APP and AEP, since this area value shows the best correlation with agility performance test in zigzag run, side step test, burpee test and shuttle run test. Finally, agility index was defined as the average triangular areas of the graph of accelerations per second, as shown in Fig. 10.

We evaluated the new indicator by calculating the correlation coefficient between the agility index in this study and the conventional agility index used for exercise.

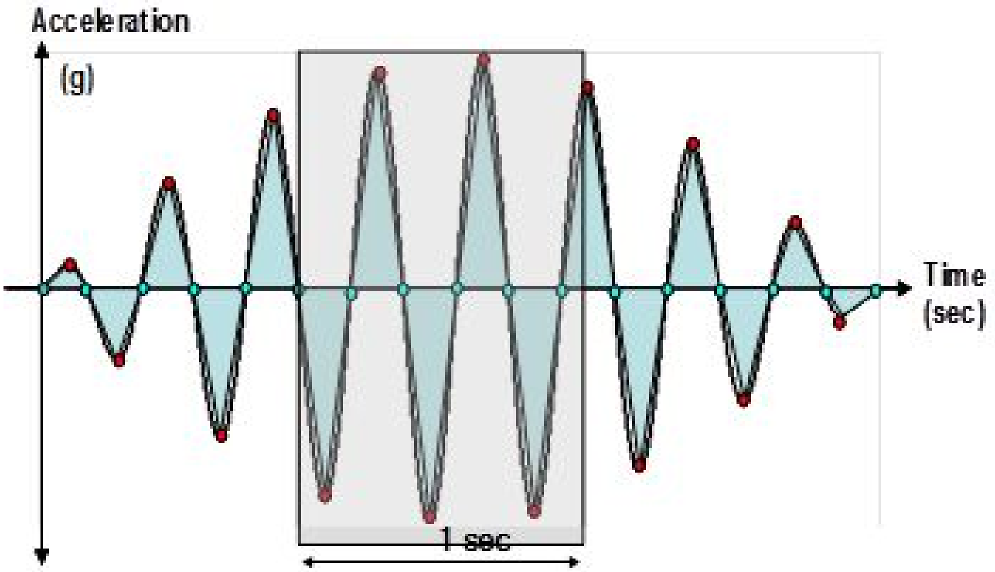


Fig. 10. The conceptual acceleration waveform with feature points, feature value (triangular area) and agility index (the sum of area per sec).

III. System and Performance Evaluation

A. AirBeat^{TM} System

Our health evaluating system includes a wireless sensor module with two proposed algorithms implemented and a computer with analysis software. The sensor is attached to the chest of the subject to measure heart rate and agility index. The measured information is sent to host computer where analysis software performs processing, analyzing, and displaying functions. The system is shown in Fig. 11. From left to right are the receiver, the sensor module, and the analysis software.

Fig. 11. AirBeat^{TM} system.

The patched-type sensor module for real-time monitoring of heart rate and agility index is shown in detail in Fig. 12.

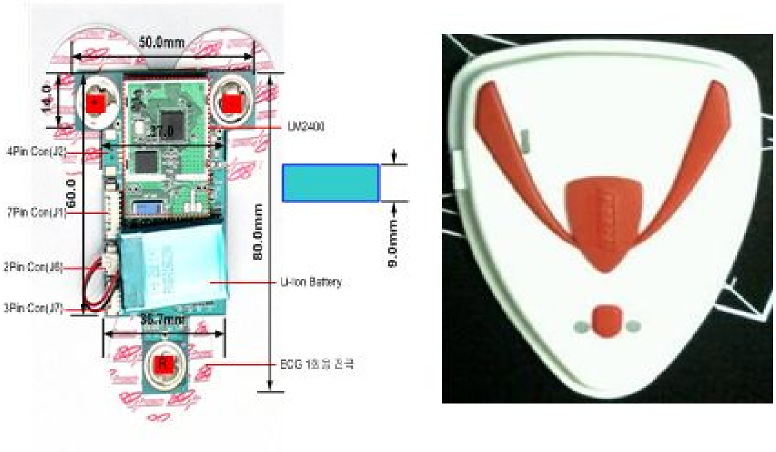


Fig. 12. The patched-type sensor module.

Table I shows the specification of sensor module

Table I. Specifications of the sensor module.	
Item	Description
System clock	4MHz
Program memory	64Kbyte flash memory
Data memory	2Kbyte RAM
AD converter	12-Bit internal reference
Sampling rate	200 sample/s
Program language	C
Compiler	IAR C/C++ compiler for MSP430
Power supply	DC 3.3V
Comm. module	Zigbee
Comm. distance	400m
Channel	8 ch

With the support of analysis software, a technician can observe both heart rate and agility index at the same time in real time or save subject's information for further offline analysis and evaluation. Detailed software specification are provided in table II.

Table II. Specifications of AirBeat™ software.	
Compiler	MS Visual studio .NET
Program language	C#
PC OS	Microsoft windows XP Professional V.2002 Service Pack 2
PC	Intel pentium® 4 CPU 2.60 GHz
RAM	1.0 GB
Port	USB 2.0

Fig. 13 is an example of heart rate (line graph) and agility index (bar graph) displayed by AirBeat™ system.

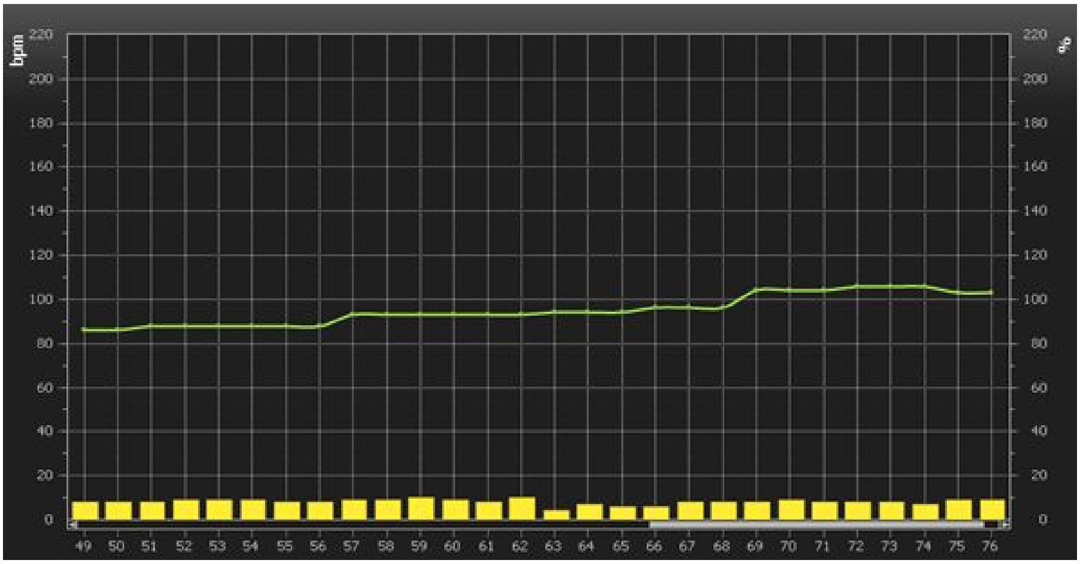


Fig. 13. Displayed information (heart rate and agility index).

B. Case System

CASE system, a commercial product of General Electric Medical Co., USA. is a well known system for heart rate monitoring and diagnosis.

The CASE system enables clinical excellence with outstanding data quality and accuracy in an easy-to-use system. Diagnostic support provided by the CASE system includes 1) full-disclosure data that enable the review and re-analysis of every beat and arrhythmia for enhanced clinical confidence and 2) risk-predicting algorithms that assist technician in predicting patients are at risk for sudden cardiac death.

The system is shown in Fig. 14.

Fig. 14. CASE system.

C. Evaluation of The Heart Rate Detection Algorithm

In order to evaluate the performance of proposed algorithm, we performed a test in which a runner's speed was change, and we monitored the test simultaneously with the reference system and with our system (AirBeat^{TM}), then compared the results.
We use the CASE system (GE medical, USA) as a reference system. Heart rate information was real time monitored and gathered simultaneously from both the reference system and our system. Fig. 15 shows the equipment setup.

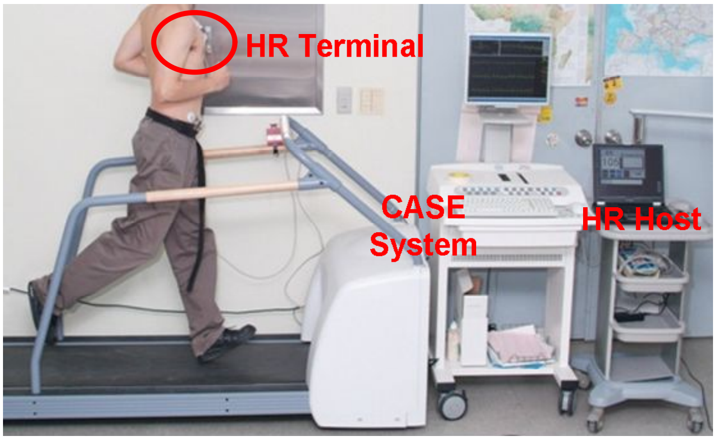
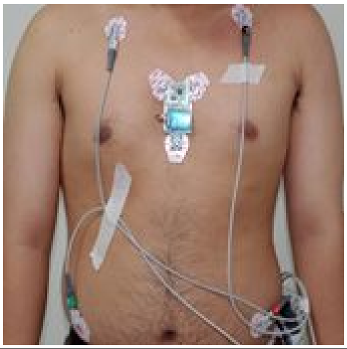


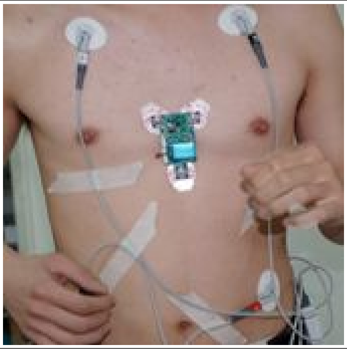
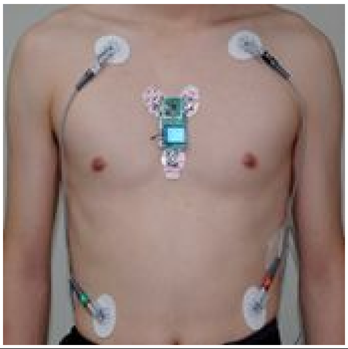
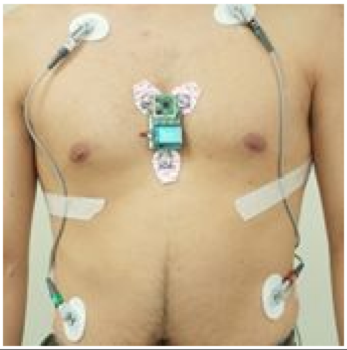
Fig. 15. Equipment setup for the comparative test.

During the test, five male subjects (Table III) at the ages 27 and 28, ran on the treadmill machine at speeds that ranged from 0.2km/h to 13km/h, with the speed increased incrementally as shown in Table IV.

Table III. Subjects information.					
Subject	Gender	Age	Height	Weight	Heart disease
S1	Male	28	168cm	76kg	no
S2	Male	28	176cm	71kg	no
S3	Male	27	177cm	71kg	no
S4	Male	28	168cm	64kg	no
S5	Male	27	170cm	68kg	no

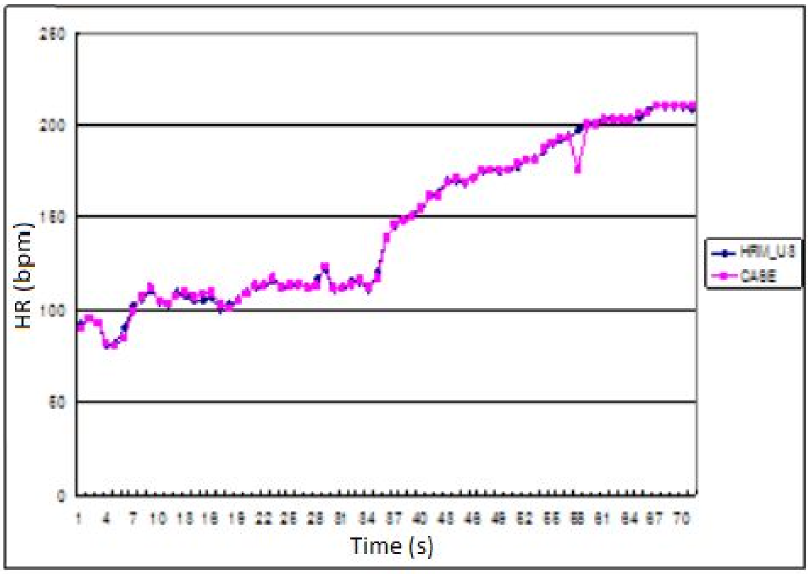
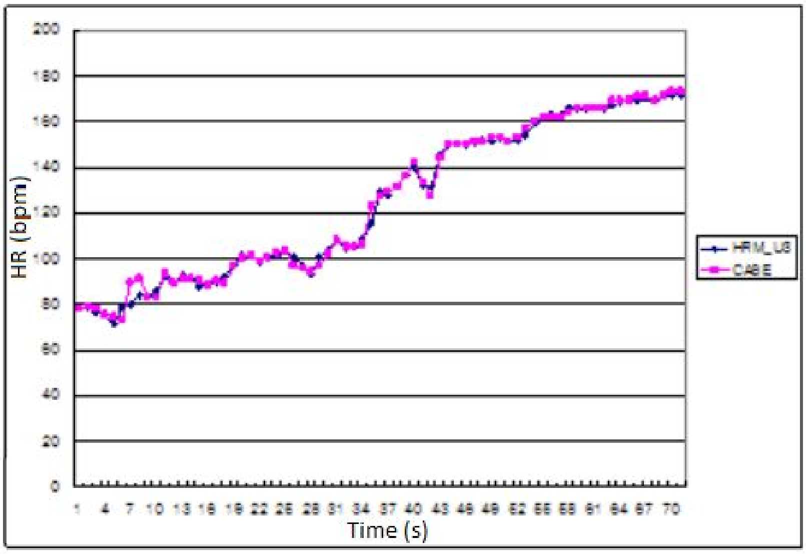
Table IV. Speed profile.		
Step	Duration (second)	Speed (km/h)
1	0 – 60	0.2
2	60 – 180	3
3	180 – 300	5
4	300 – 600	10
5	600 – 780	13

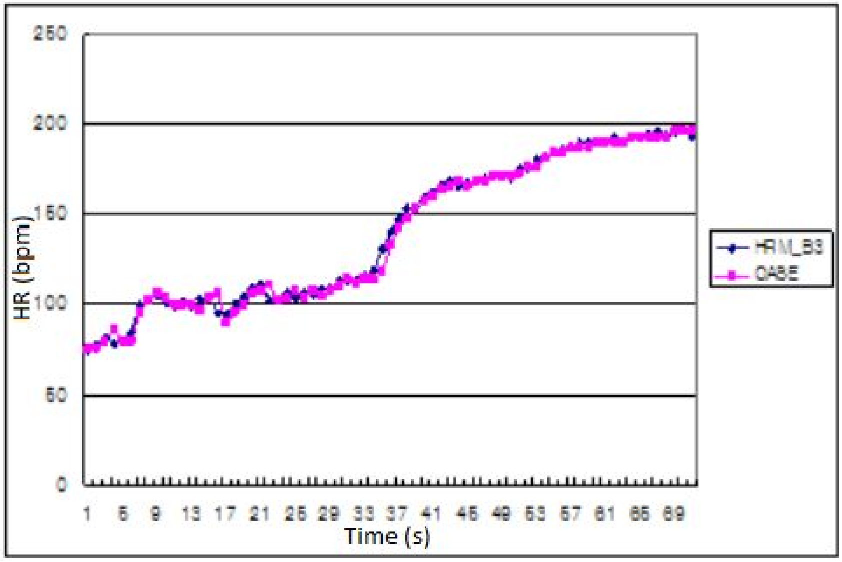
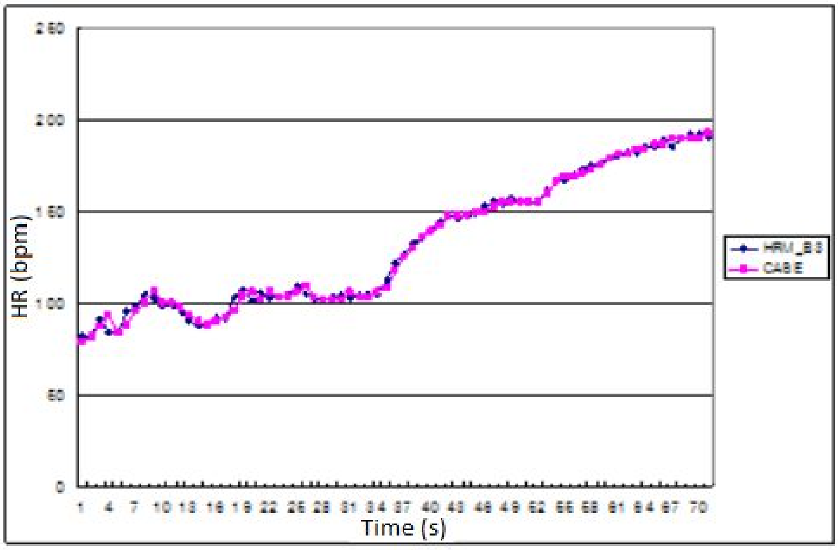
Table V. Electrode position on subjects.	
Subject	
S1	

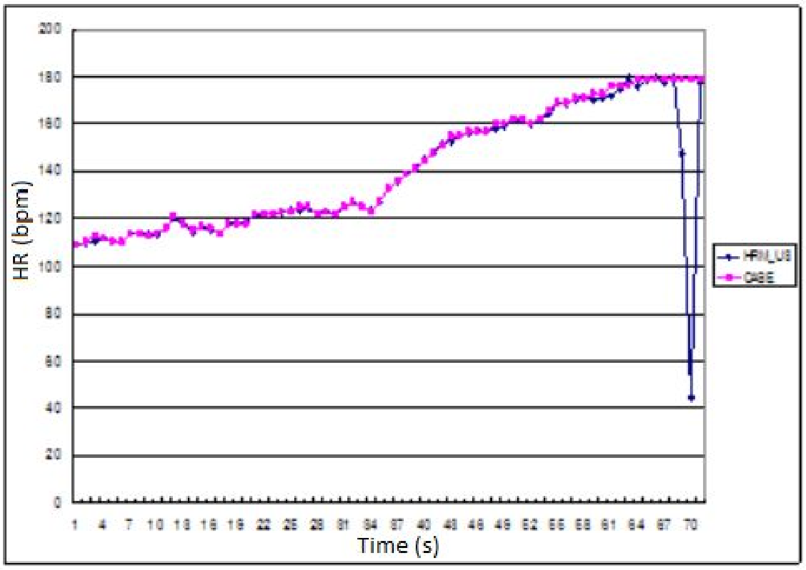
S2	
S3	
S4	
S5	

The results in comparison with CASE system are shown as follow:

Table VI. HR comparison results.

Subject	
S1	
S2	

S3	
S4	

S5	

These results show that during wide range of exercise speed, AirBeat™ system can provide highly accuracy of heart rate detection that was within 6.2% difference (compared to the CASE system). The average errors are shown in Table VII.

Table VII. Average errors.	
Subject	Error
S1	1.2%
S2	1.4%
S3	5.2%
S4	1.5%
S5	6.2%

As mentioned above, CASE system is well-known for heart rate monitoring and diagnosis which provides highly accurate information about heart rate. However, CASE system uses wired electrodes which attached to body surface of subject to measure the heart rate. The wired electrode system only works in limited space (indoor) and causes inconvenient for subject. According to the results of the comparison our wireless system and CASE system which shown in table VII, one can see the error range is from 1.2% to 6.2%. It means the difference between our AirBeat™ system and CASE system in measured heart rate is in acceptable range (less than 6.2%). In addition, our wireless system can provide a flexible way to measure heart rate. Without the constraint of wired electrode, our system can perform heart rate monitoring with high accuracy in outdoor condition.

D. Evaluation of Agility Index Algorithm

As mention above, in our approach to calculate agility index, detecting the zero-crossing is a very important process that extracts feature points of the acceleration signal. This function was evaluated by using simulated signal in an environment that included noise. We use a generator to simulate the signals with noises level control shown in Fig. 16. Our robust zero-crossing detector showed good extraction of feature points with 1% error.

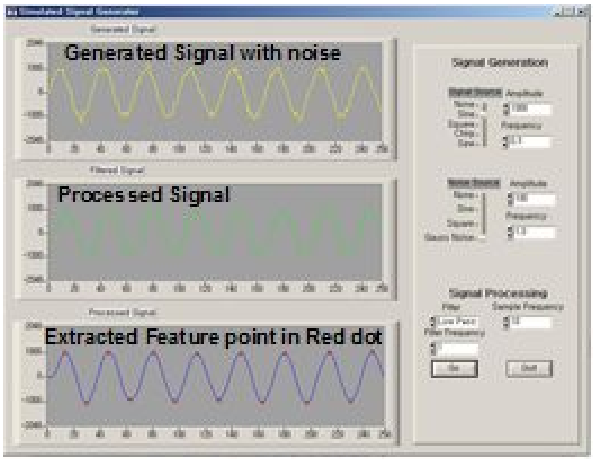


Fig. 16. Screen shot of the simulated signal generator program for evaluating the feature point extraction.

After zero-crossing detection, we conducted real-time monitoring of agility index. We evaluated the accuracy of our agility index that were determined based on the athlete's exercise states. In this experiment, 10 athletes performed several kinds of tasks, such as a zigzag run, the burpee test and side step, and a 20-m shuttle run. The zigzag run was a run in a zigzag pattern, using long strides with each step, swinging both elbows from side-to-side and leaning the body toward the direction of motion. The burpee test is a full body exercise that is performed in five steps, ie., (1) standing position, (2) drop into a squat position with hands on the ground, (3) kick foot back while lowering yourself without a pushup, (4) return foot to the squat position while straightening arms, (5) leap up as high as possible from the squat position with arms overhead. The Side-step test is performed by standing at a center of line, then jumping to the side and touching the line with the closest feet, jumping back to the center then jumping to the other side. The shuttle run is performed by sprinting as fast as possible from the starting line to the finishing line, picking up a block, and returning the block to the ground behind the starting line. In each task the conventional agility point and our agility index were determined by a supervisor (base on time or counts) and the AirBeat^{TM} system. We calculated the correlation coefficient between them, and the results are shown in table VIII.

Table VIII. Correlation coefficient between average agility index measured by AirBeat^{TM} and conventional agility point.

Test	Correlation coefficient
Zigzag run	0.90
Burpee test	0.89
Side step test	0.91
Shuttle run	0.80

Originally, the correlation coefficient was a statistical measure of the strength of the linear relationship between two variables. Positive values indicate a relationship between x and y variables, such that as values for x increase, values for y also increase. If x and y have a strong positive linear correlation, the correlation coefficient is close to +1.

With the correlation coefficients from 0.8 to 0.9, as shown in table VIII, it is apparent that the proposed agility index shows good correlation with conventional agility test. Therefore, it can be applied in sport and exercise programs for evaluating the athlete's exercise states.

E. Evaluation of Heart Rate and Agility Index Relationship Using the Bruce Protocol

In this step, we show the relation between heart rate and agility index. In keeping with the Bruce protocol, an exercise with multiple steps was performed. After each step (each of which had a duration of three minutes) the exercise intensity was increased.

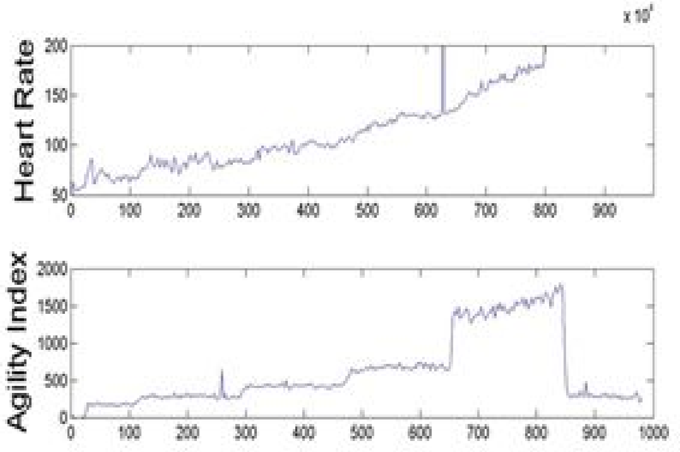


Fig. 17. The result field test using the bruce protocol.

Fig. 17 shows the result of the field test using the Bruce protocol. According to the test results, both the agility index and heart rate increase after each steps. The change of agility index can cause a corresponding change in heart rate. Heart rate and agility index can be monitored and measured accurately during the exercise.

IV. Conclusion

We confirmed that the minute measurement of heart rate and agility index was possible by using the patched-type sensor module that we designed. The proposed agility index showed good correlation with conventional agility test and it can be used to evaluate the athlete's exercise state. The change of the heart rate and the agility index according to the change of the exercise intensity was confirmed through the analysis of heart rate variability and 3-axis acceleration. The ability of the proposed module to detect heart rate and agility accurately using a wireless patched-type sensor provides a reliable and flexible way to monitor and evaluate the health status of athletes and others engaged in strenuous physical activity.

Our experiment showed that agility index is a vitally important parameters for determining the heart rate during exercises. Heart rate has been shown to be higher as agility index increases. Because of the ability to provide useful information about the status of the athletes during periods of exercise, we aim to apply our wireless system training, monitoring, and evaluating athletes in various sports, as well as an emergency forecast method for monitoring in-situ heart rate.

However, in the conditions when subjects were engaging in highly intense activities, the error rate of heart rate detection was still high, about 6.2% compared to the CASE system. Also, the current size of the sensor module (100*50*5 mm) is quite large, and it must be reduced in size for future applications. Therefore, in future work, we plan to increase the accuracy of heart rate detection and reduce the size of the sensor module.

References

[1] S. Bhardwaj, D. Lee, S.C. Mukhopadhyay, et.al., "Ubiquitous healthcare data analysis and monitoring using multiple wireless sensors for elderly person," Sensors & Transducers Journal, Vol. 90, pp. 87-99, 2008.

[2] L. Chuanjun, K. Latifur, and P. Balakrishnan, "Real-time classification of variable length multi-attribute motions," Knowledge and Information System: An International Journal (KAIS), Springer, Vol. 10, pp. 163-183, 2006.

[3] M.H. Crawford, "ACC/AHA guidelines for ambulatory electrocardiography," Journal of the American College of Cardiology, Vol. 34, pp. 912-948, 1999.

[4] H. Qu, D. Fang, H. Xie, "A single-crystal silicon 3-axis CMOS-MEMS accelerometer," IEEE Sensors, Vol. 2, pp. 661-664, 2004.

[5] W.P. Holsinger, K.M. Kempner, and M.H. Miller, "A QRS preprocessor based on digital differentiation," IEEE Trans. Biomed. Eng., Vol. 18, pp. 212-217, May. 1971.

[6] D. Gustafson, "Automated ECG interpretation studies using signal analysis techniques," R-1044 Charles Stark Draper Lab., Cambridge, MA, 1977.

[7] M. Okada, "A digital filter for the QRS complex detection," IEEE Trans. Biomed. Eng., Vol. 26 pp. 700-703, Dec. 1979.

[8] C.R. Taylor, B.R.V. Konsky, "Polynominal approximation of gait for human motion analysis and visualization," in Proceedings of the

20th annual international conference of the IEEE engineering in medicine and biology society, Vol. 20, No. 5, 1998.

[9] K. Aminian, et al., “Physical activity monitoring based on accelerometry: validation and comparison with video observation,” Med. & Biol. Eng. & Comp., Vol. 37, No. 3, pp. 304-308, 1999.

[10] T.R. Burchfield and S. Venkatesan, "Accelerometer-based human abnormal movement detection in wireless sensor networks," In HealthNet 07 Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for healthcare and assisted living environments, pp. 67–69, New York, USA, ACM, 2007.

[11] B. Najafi, K. Aminian, "Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly," IEEE Transactions on Biomedical Engineering, Vol. 50, No. 6, June. 2003.

[12] J. Ng, A.V. Sahakian, S. Swiryn, "Sensing and documentation of body position during ambulatory ECG monitoring," Computers in cardiology, Vol. 27, pp. 77-80, 2000.

[13] M. Mao, B. Kaminska, Y. Chuo, "Multi-functional sensor system for heart rate, body position and movement intensity analysis," Sensors & Transducers Journal, Vol. 3, pp. 59-70, 2008.

[14] M.L. Ahlstrom and W.J. Tompkins, "Automated high-speed analysis of holder tapes with filter banks," IEEE Trans. Biomed. Eng., Vol. 46, pp. 192-202, 1999.

[15] P.M. Mahoudeaux, C. Moreau, D. Moreau, and J.J. Quarante, "Simple microprocessor-based system for online ECG arrhythmia analysis," Med. Biol. Eng. Comput., Vol. 19, pp. 497-501, July.

1981.

[16] F. Yin, J. Wang, and C. Guo, "Optimizing sensor node distribution with genetic algorithm in wireless sensor network," ISNN 2004, LNCS 3174, pp. 242-247, 2004.

[17] J. Pan and W.J. Tompkins, "A real-time QRS detection algorithm," IEEE Trans. Biomed. Eng., Vol. 32, pp. 230-236, 1985.

[18] P.O. Borjesson, O. Pahlm, L. Sornmo, and M.E. Nygards, "Adaptive QRS detection based on maximum a posteriori estimation," IEEE Trans. Biomed. Eng., Vol. 29, pp. 341-351, May. 1982.

[19] O. Hernandez, E. Olvera, “Noise cancellation on ECG and heart rate signal using the undecimated wavelet transform," in International Conference on e-Health, pp. 145-150, 2009.

[20] W.A.H. Engelse and C. Zeelendberg, "A single scan algorithm for QRS-detection and feature extraction," in IEEE Computer in Cardiology. Long Beach, CA: IEEE Computer Society, pp. 37-42, 1979.

[21] P.S Hamilton and W.J. Tompkins, "Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmiac database," IEEE Trans. Biomed. Eng., Vol. 33, pp. 1157-1165, 1986.

[22] D. Ebenezer and V. Krishnamurthy, "Wave digital matched filter for electrocardiogram pre-processing," J.Biomed. Eng., Vol. 15, No. 2, pp. 132-134, 1993.

[23] K.G. Lindecrantz and H. Lilja, "New software QRS detector algorithm suitable for real-time application with low signal-to-noise ratios," J.Biomed. Eng., Vol. 10, pp. 280-284,

1988.

[24] A. Ruha, S. Sallinen, and S. Nissila, "A real-time microprocessor QRS detector system with a 1-ms timming accuracy for the measurement of ambulatory HVR," IEEE Trans. Biomed. Eng., Vol. 44, pp. 159-167, 1997.

[25] S.E. Dobbs, N.M. Schmitt, and H.S. Ozemek, "QRS detection by template matching using real-time correlation on a microcomputer," J.Clinic. Eng., Vol 9, pp. 197-212, 1984.

[26] B.C. Yu, S. Liu, M. Lee, C.Y. Chen, and B.N. Chiang, "A nonlinear digital filter for cardiac QRS complex detection," J. Clin Eng., Vol. 10, pp. 193-201, 1985.

[27] S. Suppappola and Y. Sun, "Nonlinear transforms of ECG signals for digital QRS detection : a quantitative analysis," IEEE Trans. Biomed. Eng., Vol. 41, pp. 397-400, 1994.

[28] Y. Sun, S. Suppappola, and T.A Wrublewski, "Microcontroller-based real-time QRS detection," Biomed. Instrum. Technol., Vol. 26, No. 6, pp. 477-484, 1992.

[29] G.M. Friesen, T.C. Jannett, M.A. Jadallah, S.L. Yates, S.R. Quint, and H.T. Nagle, “A comparison of the noise sensitivity of nine QRS detection algorithms,” IEEE Transactions of Biomedical Engineering, Vol. 37, No. 1, pp. 85–98, Jan. 1990.

[30] R.A. Balda et al., “The HP ECG analysis program,” Trends in Computer- Processed Electrocardiograms, North Holland, pp. 37-42, 1977.

[31] J. Fraden and M.R. Neumann, "QRS wave detection," Med. Biol. Eng. Comput., Vol. 18, pp. 125-132, 1980.

[32] R.A. Balda, "Trends in computer-Processed electrodiograms," Amsterdam: North Holand, pp. 197-205, 1997.

[33] GE Medical System, http://www.egeneralmedical.com , 2011.

List of Publications

Luan Dinh, Li Meina, Ji Hwan Lee, and Youn Tae Kim, "Algorithm for real-Time wireless monitoring of heart rate and agility index," Proceedings of AMA-IEEE Medical Technology International Conference on Individualized Healthcare, Washington, DC. USA, Mar. 2010.

Li Meina, **Luan Dinh**, Ji Hwan Lee, and Youn Tae Kim, "In-situ monitoring of energy expenditure by the application of wireless patch type sensor module," Proceedings of AMA-IEEE Medical Technology International Conference on Individualized Healthcare, Washington, DC. USA, Mar. 2010.

Luan Dinh, Youn Tae Kim, "Algorithm for monitoring of heart rate and agility index apply in real-time wireless health evaluating system," Submitted to Computer Methods and Programs in Biomedicine.

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Although I tried my best to make this thesis as good and as meaningful as possible, I know there will inevitably be some mistakes and omissions. In that case, as always, it will be my pleasure to receive informative advise and thoughtful guidance from my professors, teachers, and friends.

Gwangju, May 2011

Luan Dinh

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논문제목	한글 : 심박수 및 운동량 모니터링 알고리즘 연구 영어 : A Study of Algorithms for Monitoring Heart Rate and Agility Index				

본인이 저작한 위의 저작물에 대하여 다음과 같은 조건아래 조선대학교가 저작물을 이용할 수 있도록 허락하고 동의합니다.

- 다 음 -

1. 저작물의 DB구축 및 인터넷을 포함한 정보통신망에의 공개를 위한 저작물의 복제, 기억장치에의 저장, 전송 등을 허락함
2. 위의 목적을 위하여 필요한 범위 내에서의 편집・형식상의 변경을 허락함. 다만, 저작물의 내용변경은 금지함.
3. 배포・전송된 저작물의 영리적 목적을 위한 복제, 저장, 전송 등은 금지함.
4. 저작물에 대한 이용기간은 5년으로 하고, 기간종료 3개월 이내에 별도의 의사 표시가 없을 경우에는 저작물의 이용기간을 계속 연장함.
5. 해당 저작물의 저작권을 타인에게 양도하거나 또는 출판을 허락을 하였을 경우에는 1개월 이내에 대학에 이를 통보함.
6. 조선대학교는 저작물의 이용허락 이후 해당 저작물로 인하여 발생하는 타인에 의한 권리 침해에 대하여 일체의 법적 책임을 지지 않음
7. 소속대학의 협정기관에 저작물의 제공 및 인터넷 등 정보통신망을 이용한 저작물의 전송・출력을 허락함.

동의여부 : 동의(○) 반대( )

2011년 8월

저작자: 딘 루안 (서명 또는 인)

조선대학교 총장 귀하