5

Automated Selection of Optimal ECG Lead Using Heart Instantaneous Frequency During Sleep

Yeon-Sik Noh, Ja-Woong Yoon and Hyung-Ro Yoon
Dept. of Biomedical Engineering, Yonsei University
Republic of Korea

1. Introduction

The analysis of the breath signal during sleep provides key information for the revelatory analysis of the clinical symptoms of sleep diseases such as sleep apnea, etc which disturbs normal sleep and further on can become the potential cause of heart diseases. This information can be used importantly for such purposes as to remove change quantity by breathing not only for the system modeling of the cardiovascular system for the function analysis of the autonomic nervous system (ANS), which is generated in the human body during sleep, but also for the accurate analysis during the analysis of the frequency of the changing rate of heartbeats, and the classification of significant electrocardiogram (ECG), which includes an accurate breath signal during sleep which has immense meaning (Park et al., 2004).

In general, the methods measuring breath signals can be largely divided into a direct method and an indirect method. A direct method which measures changes of air temperature around the nose by breathing and using a spirometer suggests a standard in research and can have accurate breath signals (Cysarz et al., 2008). However, because of the disadvantage of cumbersome and inconvenient measurements, an indirect method, which can measure the breath of the examinee without binding and consciousness in a relatively simple measurement method, is more preferred. As these indirect methods, a method, which extracts breath by measuring the inductance and impedance changes of the thorax by breath or by measuring column changes of the thorax, and ECG-derived respiratory (EDR) method, which induces breath signals from ECG by using impacts of changes of impedance within the thorax on ECG according to the filling and exhausting of air within the lungs which accompanies it during breathing, have been suggested (Yi et al., 2006; Moody et al., 1985).

However, in the case of using a method measuring inductance or impedance changes of the thorax or column changes of the thorax for monitoring the breath during sleeping, it can disturb the normal sleeping of the examinee because the examinee has to be put on a belt or attach an electrode on the thorax. In addition, it may be difficult to detect accurate breath because lots of noise components accompany it according to the surrounding environment. Therefore, recently, the EDR method, which extracts breath signals from the ECG measured during sleep by using the conductive textile electrode, is utilized more for detecting breath with the minimum binding of the examinee (Park et al., 2008; Yi et al., 2006). The EDR method does not need additional hardware except the ECG measurement and in cases when there is no distortion in the QRS complex of the ECG even if noise by a power source or noise by external interference and motion (tossing) during sleep is generated, better breath signals than the existing indirect method can be extracted.

In existing early research using the EDR method, research extracting breathing forms were carried out based on amplitude changes (amplitude modulation, AM) of the R wave of the ECG, which are modulated by breathing, were implemented. As the most representative methods, there is method extracting breathing information listed on ECG with amplitude changes of the R wave of ECG and a method extracting breath through changes of the axle of heart activity by using arctangent ratio of amplitude of QRS complex between the two leads which cross at right angles using multi-leads (Mazzant et al., 2003; Behbehani et al., 2002; Travaglini et al., 1998; Correa et al., 2008). However, in cases when applying these methods actually during sleep, there are disadvantages that its characteristic can deteriorate compared to the EDR through a single lead because aspects for breathing to modulate this ECG are different according to the breathing method, the location of hearts and the level of the spinning of an axle of each individual examinee and lead I and lead III do not orthogonal actually (Park et al., 2008).

However, breathing affects other cardiovascular functions as well as on the amplitude of the ECG with impedance changes within the thorax (Noh et al., 2007). The frequency modulation method of the ECG, which changed besides the amplitude of the ECG, also began to be studied because the EDR which extracted by the amplitude modulation due to breathing can include the wrong information under sensitive situations to motion like during sleep. The frequency modulation (FM) method was developed by using respiratory sinus arrhythmia (RSA) which causes the changes of heart activity due to breathing. RSA was first discovered in 1847 as Ludwig had observed breathing, the synchronized number of the heartbeat and the vibration of the artery blood pressure in dogs. The RSA, which is the physiological mutual interaction of respiratory quotient and circulatory system, is the change of breath and synchronized heart beat rate and interval of R peaks of the ECG becomes shortened during inhalation of the ECG and also becomes longer during exhalation (Eckberg, 1983; Hayano et al., 1996). The differences of the R-R intervals (RRIs) of these ECG can be considered to show respiratory sinus arrhythmia. RSA is generated by all of the reflective primary factors and centric primary factors and as reflective primary factors there are artery pressure reflection and lung and kidney reflection (Yi et al., 2006).

The EDR methods by the ECG amplitude modulation method and frequency modulation method were used broadly in lots of research for confirming breathing status during sleeping or walking. However, there exists a limit in extracting breathing only with simple EDR. The accurate measurement of the ECG is prioritized because these methods induce basically breathing signals through amplitude and R peak detection of the ECG. The reliability of the breathing information by these methods can be degraded if the ECG is distorted because the R peak detection of ECG is difficult due to the motions of the examinee. In particular, the algorithm for the deployment of electrodes and the lead selection of the significant optimum ECG became necessary because the changes of postures such as tossing during sleep can become very big obstacles in the acquisition of a significant ECG. Therefore, research to classify a significant ECG by judging whether the measured ECG reflects breathing signals well or not was implemented and Park et al estimated instantaneous frequency based on the Hilbert Transform and had suggested a new algorithm which selects optimum lead in which it possible to extract significant breathing signals by perceiving the point that the instantaneous frequency of the breathing signals with inappropriate lead show big frequency changes (Park et al., 2008). However, this method has a limit like selecting the wrong lead in cases when instantaneous frequency is changed by instantaneous motions or external noises, which can be generated during sleep because it selects optimum lead by judging with only the changed width of the instantaneous frequency.

So, Noh et al attempted to verify that the correlation of the power spectrum in HF (high frequency) range, which is a breathing related frequency range in the frequency analysis of the breathing signals and heart rate variability (HRV) induced from the ECG and also tried to classify significant data by using this fact (Noh et al., 2006). However, these elements require high electricity consumption in the system because it must be measured in the high sampling rate of the ECG over 500Hz for obtaining HRV signals and also a re-sampling course is required for the analysis between interpolation and the frequency following the R peak detection. Therefore, Noh et al had attempted the classification of the ECG signals including significant breathing signals during sleep by introducing the heart instantaneous frequency (HIF) concept which can efficiently replace HRV in a ubiquitous healthcare environment (Noh et al., 2007). But, this study has disadvantages as it is impossible to acquire a significant ECG in cases when the ECG signals become distorted by the motions of the human body or external interference noises generated during sleep because only the measured ECG under one lead during sleep was evaluated.

Therefore, in this study, we tried to automatically classify signals by evaluating respectively based on HIF signals whether the ECG measured in two ECG leads (I and III) possible to measure during sleep is a significant ECG which reflects sound breathing signals and consequently, we have selected a significant ECG lead.

We first explain correlation between the autonomic nervous system and breathing and intend to introduce HIF which can effectively replace correlation between the HRV representing the autonomic nervous system and breathing and HRV. And we explain the signal processing method used in this study and finally, we introduce the ECG classification algorithm based on HIF.

2. Autonomic nervous system and respiration

2.1 Autonomic nervous system

The human body is adjusted by the autonomic nervous system which maintains the balance of the internal environment with regards to changes of the internal and external environment. This is directly operated for enjoying healthy life by maintaining life preservation activity and homeostasis within the human body. The autonomic nervous system involves in functions which cannot be controlled consciously just like metabolism such as digestion, breathing and sweat. The autonomic nervous system is anatomically divided again into the two nervous systems of sympathetic nervous system and parasympathetic nervous system and these two are controlled through antagonism, which is a method that another one is suppressed if one becomes active. The sympathetic nervous system becomes active when physical or mental stress becomes immense while generating various reactions of physical constitutions for the homeostasis maintenance of the human body and in preparation for emergency situations. Reactions required for responding to these stresses due to the activation of the sympathetic nervous system and the supply of energy appears and consequently, blood pressure and the number of heartbeats increases, the pupils expand and gooseflesh is generated. On the contrary to operations of this sympathetic nervous system, the parasympathetic nervous system becomes activated if one’s status is comfortable. The parasympathetic nerve is distributed within the internal organs of the human body and maintains a smooth function by adjusting the internal organ functions. If the parasympathetic nervous system is activated, the number of heartbeats and blood pressure decreases and the whole body is operated directionally to secure energy as the digestive enzyme secretion becomes active with lots of blood circulation in digestive organs. The parasympathetic nerve is very local and impacts rippling into the whole body are little compared to the influence of the sympathetic nerve but it plays a very important role in the homeostasis adjustment mechanism. However, these two do not always operate in the opposite direction and operate in cooperation according to some organs.

A method, which judges the most accurate autonomic nervous system of the human body, is the way to evaluating by analyzing the nerve transmission material of the autonomic nervous system in blood, but it is difficult to evaluate realistically because the metabolism hours of the transmission materials of the autonomic nerve are very short and it must be measured in invasion. In addition, the electric physiological inspection regarding the autonomic nerve has a limit which is difficult to directly apply to the human body because it must be carried out by surgical operation such as severance of nerve, etc (Park et al., 2004). Therefore, recently, an indirect method, which observes the activity of the autonomic nervous system through the activity of the cardiopulmonary vascular system reflecting the best autonomic nervous system, is used broadly. Evaluating the autonomic nervous system by extracting activity information of the autonomic nerve from signals of the cardiopulmonary vascular system can be regarded as very significant because a method measuring activity of the cardiopulmonary vascular system is very convenient and used broadly compared to other methods.

2.2 Relationship between breathing and the autonomic nervous system

The operation of breathing is basically the operation of the somatic nervous system of the musculoskeletal system. Breathing can adjust coughing quickly and slowly if we want by using the somatic nervous system. We implement these adjustments by commanding orders to lower the motor neuron at the back of the cerebrum cortex. If we want to use the diaphragm quietly and deliberately when we breathe the axon signals are delivered to the diaphragm through the diaphragm nerve by commanding orders to lower the motor neuron.

The autonomic nervous system has a mutual interaction relation with the somatic nervous system. Let's review from the viewpoint of breathing. When the human body is active in physical sports and exercises, the number of heartbeats increase due to the autonomic nervous system and the output quantity of the heartbeats also increases, and at this time, breathing is adjusted as the autonomic nervous system sends signals to the somatic nervous system for fulfilling the oxygen quantity required for the human body. The adjustment of breathing immediately provides impacts on the autonomic nervous system after the completion of sports and exercises and the parasympathetic nerve is activated to operate the human body to reach a stable status. This operates in the same method when people take sleep. The somatic nervous system induces the most stable breathing when taking sleep. At this time, induced breathing is deeply involved in the activity of the parasympathetic nervous system of the autonomic nervous system (Song and Lehrer, 2003).

2.3 Autonomic nervous system and heart rate variability

The heartbeat change rate does not mean changes of the maximum or minimum number of heartbeat per minute appearing on the ECG recorder, but is to measure the variation from one heart cycle to the next heart cycle. That is, the HRV signals mean the level of the variation of the heartbeats and we can obtain information from a finer variation from one heart cycle to the next heart cycle. The heartbeat change rate represents the cardiovascular control mechanism, which changes endlessly, and quantifies the changing trend of heartbeats (Noh et al, 2008).

The heartbeat change rate changes every moment by the homeostasis mechanism which is adjusted by the autonomic nervous system. We judge the status of the human body only with these changes and we judge that there is a problem in the adjustment mechanism of the autonomic nervous system if there is almost no change during the stable period and on the contrary, we can judge that it is in a healthy status if changes are active.

The autonomic nervous system evaluation by the heartbeat change rate can be divided into a method using parameters in the time domain, a method using the parameters in the frequency domain and a method, which uses these in both domains. A method using parameters in the time domain evaluates the autonomic nervous system based on the hourly statistical data of the degree of the changes of heartbeats and also evaluates with the component size of the section by obtaining a power spectrum density (PSD) at signals of intervals between R

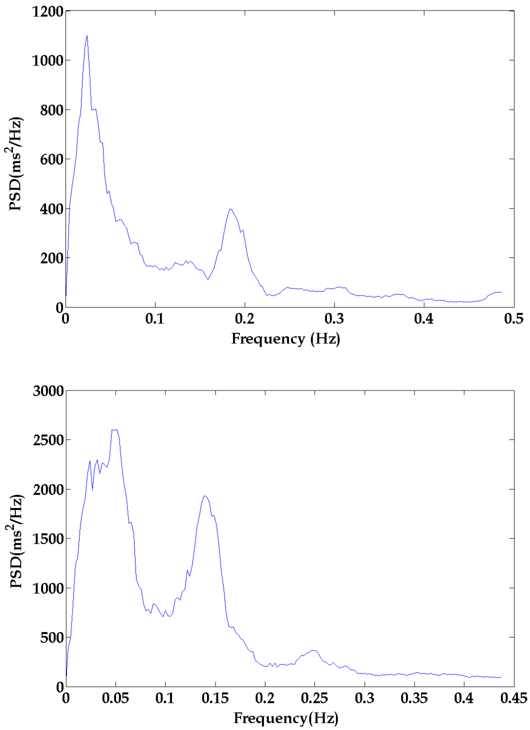

Fig. 1. HRV PSD (upper) in normal daily life and HRV PSD during deep sleep (lower)

peaks within a fixed times (typically 5 min) in the the frequency domain. In particular, in the the frequency domain, activities of the sympathetic nervous system and parasympathetic nervous system can be directly evaluated by using PSD (Task Force of the ESC & NASPE, 1996).

If we observe the the frequency domain of the HRV signals, we can observe through the activity of the parasympathetic nervous system range by breathing because breathing signals receive the impacts of the parasympathetic nervous system of the autonomic nervous system. Breathing provides impacts on the high frequency (HF) range in the the frequency domain of HRV signals and it appears, in general, in 0.15 ~ 0.4 Hz. However, in recent research, the necessity to observe in a lower frequency range was emphasized because there is almost no new volume activity and it is in a very stable status during sleep. As seen in Fig. 1, actual sleep breathing signals are much lower and stable than breathing frequency in normal daily life. So, in this study, the level of activation is evaluated through the PSD of 0.1 ~ 0.4 Hz section. If we compare the HF range section among the HF range of the HRV and the frequency range of the EDR extracted from the ECG, we can evaluate how a well measured ECG reflects breathing signals (Aysin and Aysin, 2006; Choi et al., 1999; Cammann and Michel, 2002).

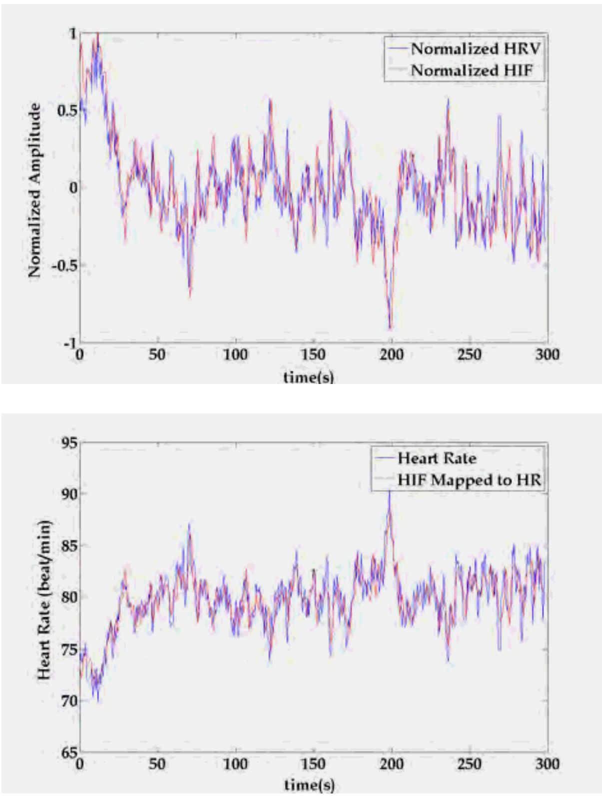

Fig. 2. HRV PSD(upper) in normal daily life and HRV PSD during deep sleep (lower)

2.4 Relationship between heart rate variability and heart instantaneous frequency

HRV and HIF extracted from the ECG are the same signals basically. It is because the modulation frequency, which is generated while intervals between each R peak is changed due to heartbeats, forms a fundamental frequency owned by the ECG and the HIF is the expression by finding out at every moment the maximum value of the fundamental frequency band changing every moment. In particular, HIF extracts the instantaneous frequency response of heart activity and was reported to have close correlation with HRV signals (Barros and Ohnishi, 2001). The HIF signals acquired from the ECG have the same form of time series of HRV and HIF can also provide the autonomic nervous system information which HRV provides. In addition, it can become the efficient alternative plan of the HRV in a ubiquitous healthcare environment because it can be extracted in time-frequency analysis base without a stage to detect R peak in ECG signals and has a much lower sampling rate and little signal processing courses than the HRV (Noh et al., 2008). Figure 2 and 3 are in comparison by obtaining each HRV and HIF regarding the ECG during the stable period. If we compare after normalizing the two signals, it is possible to confirm that they are almost the same signals and it can be noticed that there is almost no difference even in the PSD analysis.

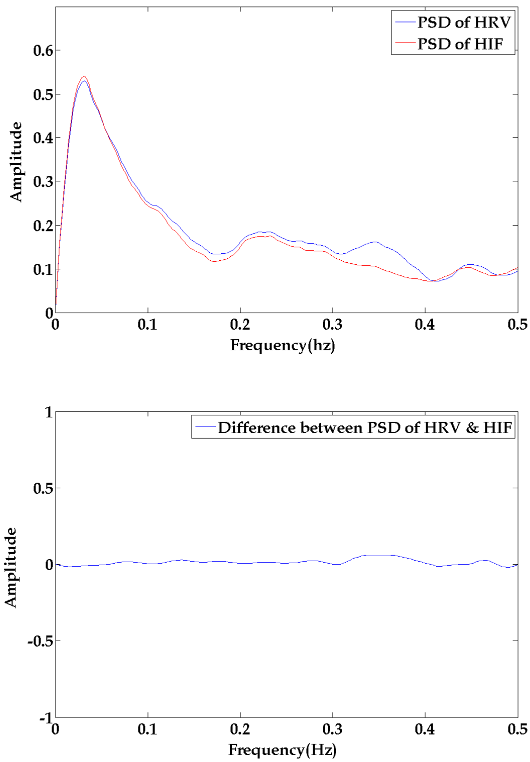

Fig. 3. PSD comparison (amplitude (upper), error (lower)) of HRV and HIF

3. Methodology

3.1 ECG measurement system using textile electrode

ECG lead I and lead III were measured by using the conductive textile electrode for measuring the ECG during sleep without consciousness and binding. The motions of the human body during sleep can be largely divided into lying left/right, lying supine and lying on one's front and the ECG lead, which can efficiently respond to these, was judged as I and III. Each ECG is measured continuously during sleep and the quality of breathing information is judged by calculating EDR and HIF with 5 minutes of data measured every 5 minutes. As seen in Fig. 4, electrodes (75cm × 41cm) of lead I are positioned on both shoulders for measurement and electrodes of lead III are measured through the neck electrode(103 cm × 50 cm) in the form of a pillow and the electrode (149 cm × 41 cm) of both legs. The conductive textile electrodes used in the test were coated with silver (Ag) and was selected in material property which does not aggravate users during sleep. And, the data was collected by additionally installing a thorax belt breath measurement device (AD instruments Powerlab, AUS) for comparison with actual breathing. The ECG signals are measured for 6 hours during a night and actually use 4 hours of data after subtracting one hour at the start and one at the end. This was carried out for using data during sufficiently deep sleep. ECG and breathing signals were acquired with the sampling rate of 500Hz and the ECG was acquired through self-developed module. The ECG module transmits data real-time to an automated ECG classification system to be suggested in this study by connecting with PC and wireless (bluetooth) or cable (RS232) communication. The examinees who have been selected and implemented are healthy and without sleep apnea or respiratory quotient pain disease. The average age of them was 23.5 years old ± 2.59 (mean ± SD), height was 176.3 cm ± 5.75, body weight was 77.7 kg ± 10.55 and Body Mass Index (BMI) was 24.94 ± 2.81. It was arranged that all examinees slept wearing running shirts and shorts.

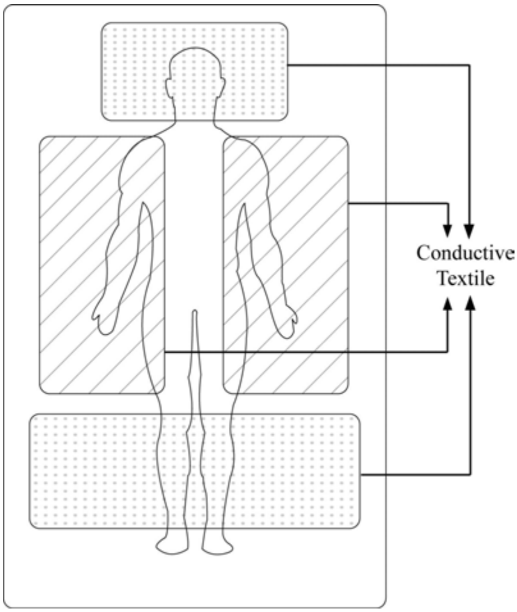

Fig. 4. Deployment map of conductive textile electrode

3.2 Extraction algorithm of ECG-derived respiration (EDR)

We use the EDR as it provides impacts on ECG, and which changes of impedance within the thorax according to the inflow and outflow of air in the breathing cycle are measured in electrodes contacted with the skin. Short period changes of thorax impedance indicate the filling and the exhausting of lungs and this phenomenon becomes the base of change records of impedance volume. Physical impacts of these breaths are appearing in changes of the amplitude of vibration in the ECG. In inhaling breath, the thorax impedance is increased as the volume is increased due to the inflow of air. The amplitude of the ECG to be measured by an electrode becomes smaller due to the impacts of the increased thorax impedance. On the contrary to this, in exhaling breath, thorax impedance is reduced as the volume is reduced due to the outflow of air. The amplitude of the ECG to be measured by an electrode becomes bigger due to the reduced thorax impedance.
However, as mentioned in the introduction, the breath generates RSA regarding heart activity in addition to size of the ECG. The number of heartbeats of a person is decided by the activity frequency of SA node with a cardiac pacemaker. This frequency is decided in balance of activities between the sympathetic nerve and the vagus nerve of the heart in SA node. In here, changes of breath are reflected in heart activity because the vagus nerve receives impacts with each breath. That is, during inhalation, R peak intervals of the ECG becomes short due to the reduction of activity of the vagus nerve and during exhalation, R peak intervals become longer due to the activity of vagus nerve. And it can be considered that the interval differences between the R peaks of the ECG due to inhalation and exhalation indicates RSA.
The most general method for inducing ECG-derived respiratory (EDR) is by using the size of the amplitude of vibration of the ECG is a method which goes through a ECG

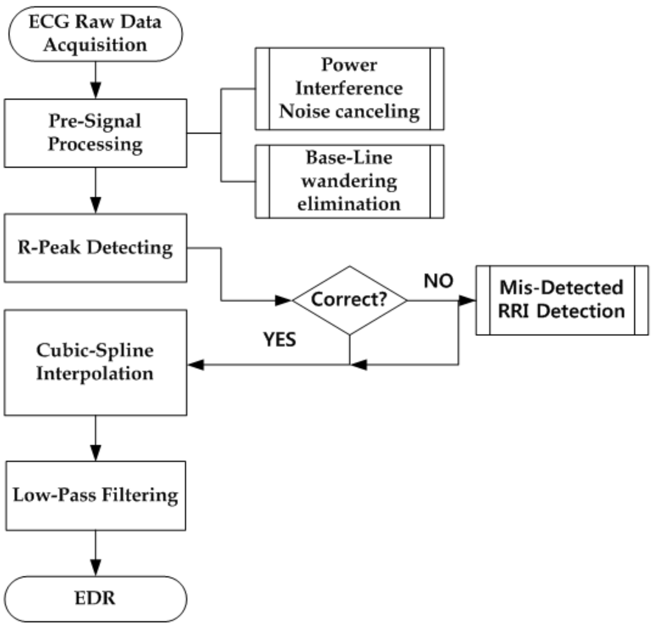

Fig. 5. Flow chart for EDR extraction.

measurement, a whole processing course removing baseline changes using median filtering, the ECG R peak detection and the QRS section area calculation, the movement average calculation of the obtained section area and cubic-spline interpolation, and the multi regression processing course to remove DC and low frequency components of finally induced signals. However, a method using the size of the amplitude of the vibration of the ECG can show a big error in the section area in cases when the ECG is distorted by motions, etc which can be generated during sleep. Therefore, in this study, a method obtaining amplitude or the QRS section area of the accurate R wave of the ECG was not used, but the frequency modulation based breath extraction method, which extracts EDR by using intervals between R peaks of the ECG receiving impacts by breathing, was used. If we can obtain only the R peak intervals in ECG to be measured in case of using this method, it has the possible advantage to extract breathing signals. Breathing signals were extracted through a baseline wandering removing course using the high pass filter, interval

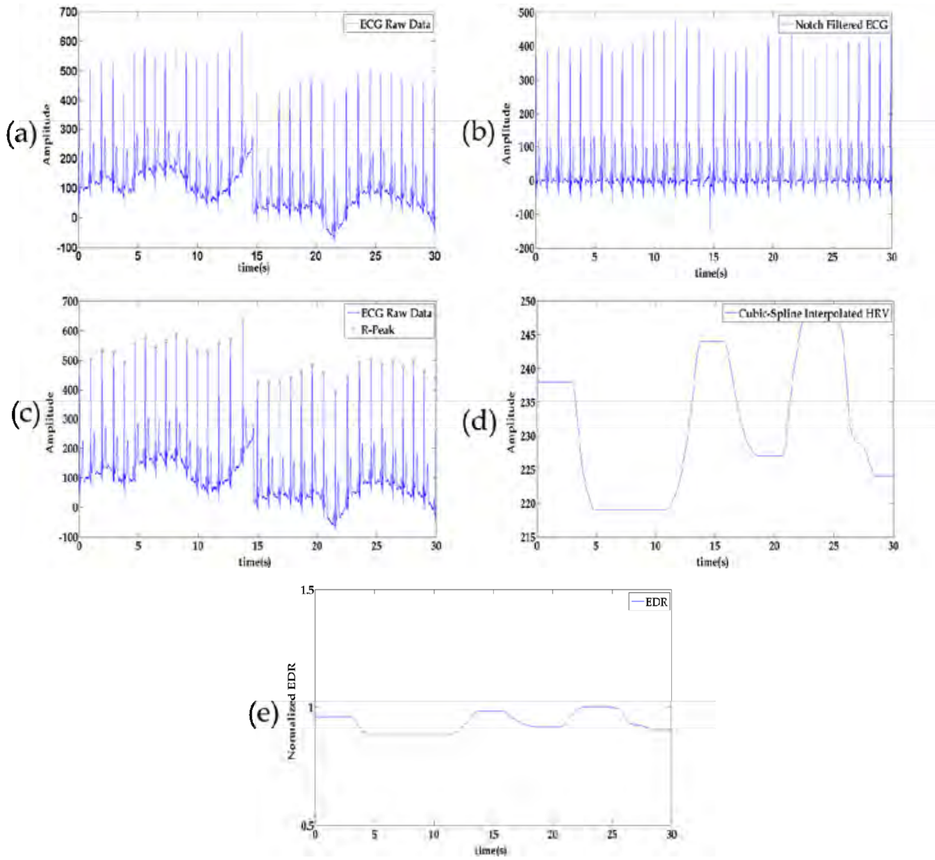

Fig. 6. Signal processing course extracting EDR. (a) ECG raw data, (b) The course of pre-signal processing (power interference noise cancelling & baseline wandering elimination), (c) The course of R-peak detection (Marked as red circle at ECG raw data), (d) The course of cubic-spline interpolation, and (e) The extracted EDR signal.

calculation between R waves through R wave detection and of course the band pass filter (0.2 ~ 0.8 Hz). Figure 5 shows the signal processing course and Figure 6 shows the signal processing result of each course.

3.3 Extraction algorithm of instantaneous heart frequency

A model having the basic frequency, which changes according to times, is necessary because the heart does not beat in a fixed ratio. For example, it is to make the heartbeat or heart frequency by changes of breathing through classifying the RSA, which modulates the ECG frequency according to changes of the breath. Under the given signal, each instantaneous angle frequency *w(t)* is calculated by using the equation (1) and the equation (2). In here, *H*[*s(t)*] is the Hilbert Transform value of the signal.

$$w(t) = \frac{d\Phi(t)}{dt} \tag{1}$$

$$\Phi(t) = \arctan\left(\frac{-H[s(t)]}{s(t)}\right) \tag{2}$$

The HIF signal is extracted from the spectrum response of the ECG. The ECG signal *z(t)* must be effectively filtered from instantaneous frequency, which a new signal *s(t)* with a basic frequency that is extracted, because it has multiple harmonics. Therefore, the filter characteristic for the fundamental frequency, which changes according to the times, must be changed properly in compliance to situations.

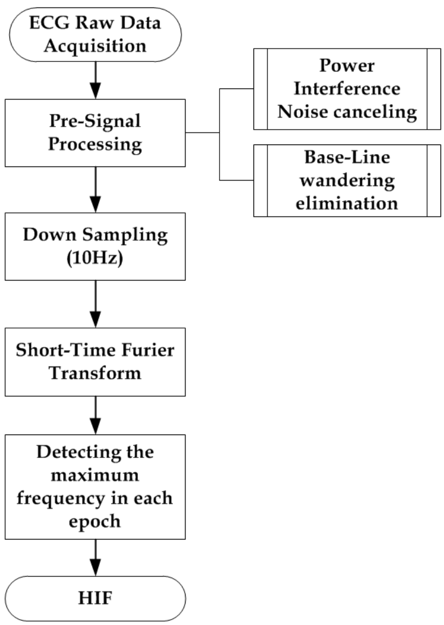

Fig. 7. Flow chart for HIF extraction

First, the extract course is an estimation of the spectrum graph. The spectrum graph of the ECG signal *z(t)* is defined in window function suggested in equation (3) according to the ECG signal *z(t)*.

$$P(t,f)=\frac{1}{2\pi}\left|\int e^{-2\pi f\tau}z(\tau)h(\tau-h)d\tau\right|^{2} \tag{3}$$

In second, we can be found the frequency values corresponding to the maximum values of *P(t,f)* of each point of time of frequency scope. When the founded value is considered *δ(t)*, it can be expressed in equation (4).

$$\delta(t)=\underset{f}{\arg\max}\left[P(t,f)\right]_{\delta(t^{-})-\alpha}^{\delta(t^{-})+\alpha} \tag{4}$$

As a frequency value limiting scope in equation (4) it can be defined as α and $\delta(t^{-})$ is defined as *δ(t)* at t^{-}. In addition, equation (4) represents an algorithm finding the maximum value of *P(t,f)* along the frequency axle with intervals of [$\delta(t^{-})+a$, $\delta(t^{-})-a$].
In third, instantaneous frequency can be calculated by using a band pass filter in the vicinity of the central frequency given at each point. In particular, the wavelet is used for the composition of filters. The basic wavelet is a little modification of the Gabor function, which is limited to all time and frequency domains. The equations are implemented according to the spectrum response movement of the filter at the central frequency. Therefore, the basic wavelet during short hour interval (Ω) is given like equation (5) and (6). The filtered signal in intervals Ω is given by equation (7).
Finally, the HIF signal can be obtained if it is calculated by substituting equation (7) in equation (1) and equation (2) (Barros and Ohnishi, 2001). Figure 7 shows the signal processing course for extracting HIF signals and Figure 8 shows the signal processing result for each course.

$$\psi(t)=\frac{1}{2\pi}\left[\exp\left(-\pi\left\{\frac{\overline{\delta(t)}t}{2}\right\}^{2}\right)\cos\left(2\pi\int_{\Omega}\delta(\tau)d\tau\right)\right] \tag{5}$$

$$\overline{\delta(t)}=\frac{1}{\Omega}\sum_{\Omega}\delta(t) \tag{6}$$

$$s_{\Omega}(t)=\int_{\Omega}z_{\Omega}(\tau)\psi(t-\tau)d\tau \tag{7}$$

4. Results and discussion

4.1 EDR evaluation

We have compared the EDR extracted from each lead with actual breathing. The purpose of this evaluation was to show that EDR extracted during sleeping is not always the same as actual breathing. EDR can show significant differences with actual breathing in case when the original ECG signals are not good as explained in the extraction course because it goes through the signal processing course between the R peak detection of the ECG and interpolation. In addition, as seen in Table 1, the actual respiratory quotient and the breathing of the EDR extracted from each lead appear in distribution of lead I and lead III without being concentrated on one lead. This means that the ECG of other lead has been distorted due to the motions of examinee and the external interference noises during sleep and it provides meaning to the necessity of the classification of a significant ECG suggested in this study.

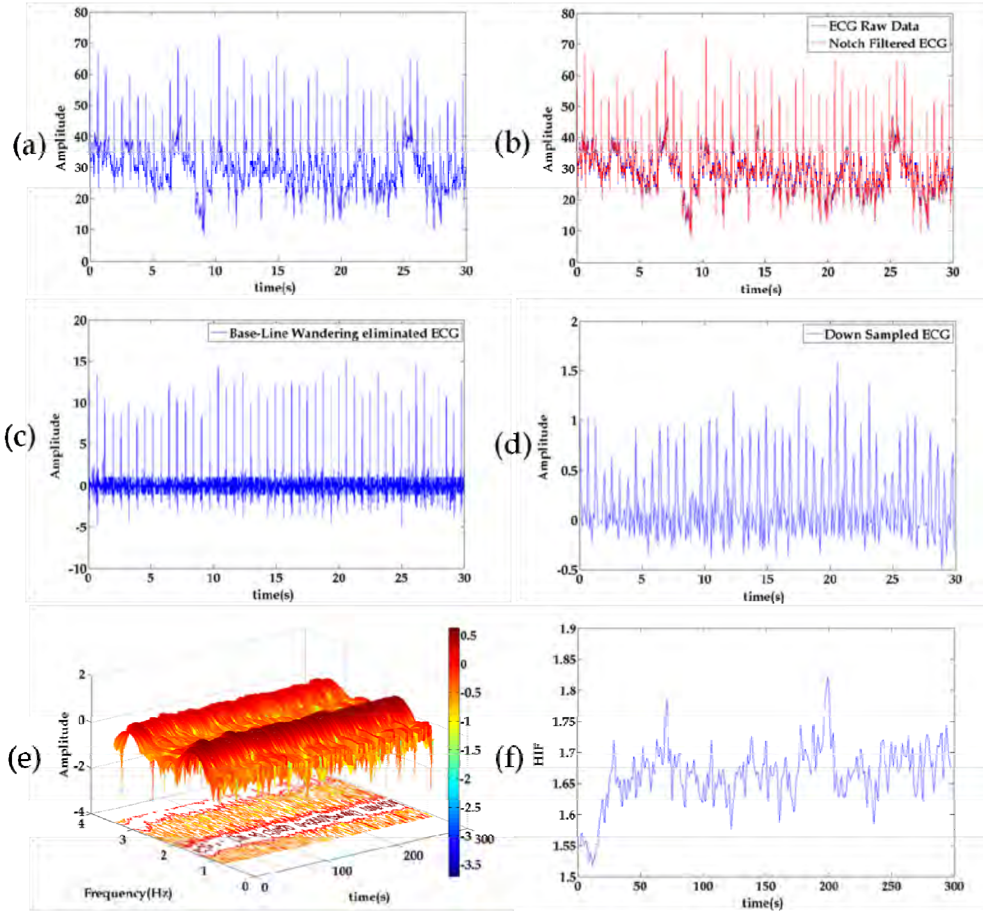

Fig. 8. Signal processing course for extracting HIF. (a) ECG raw data, (b) The course of pre-signal processing (power interference noise canceling), (c) The course of pre-signal processing (baseline wandering elimination), (d) The course of down sampling, (e) The course of Short time Fourier Transform (STFT) and (f) The extracted HIF signal.

We have analyzed a section of 4 hours when the examinee took a deep sleep and did not limit the sleeping habits of the examinee during sleep. We have evaluated the relativity with actual breathing based on the respiratory quotient and have confirmed the correlation between actual breathing in lead I and lead III under the unit of 1 hour and extracted the EDR regarding data during the sleep of each examinee.

Big differences of correlation coefficient between the leads per hour in the sleep information of several examinees (A, F, H, I and J) can be considered as they were basically the motions of the examinee during sleep. It mainly occurs when the conductive textile electrode forming each lead does not contact well with the skin according to changes of sleeping postures. In particular, in the case of examinee C, from the second hour, it noticed that the signal processing for extracting the EDR was not operated properly because the quality of the ECG signal from the electrode deteriorated.

Subjects	1st hour		2nd hour		3rd hour		4th hour	
	lead I	lead III	lead I	lead III	lead I	lead III	lead I	lead III
A	0.78	0.82	0.35	0.82	0.21	0.77	0.83	0.76
B	0.71	0.72	0.73	0.70	0.66	0.69	0.58	0.71
C	0.75	0.69	0.34	0.26	0.39	0.11	0.20	0.18
D	0.52	0.71	0.72	0.66	0.72	0.77	0.74	0.68
E	0.69	0.61	0.65	0.74	0.57	0.62	0.61	0.73
F	0.73	0.77	0.55	0.53	0.10	0.79	0.56	0.74
G	0.62	0.62	0.58	0.55	0.59	0.63	0.49	0.51
H	0.66	0.70	0.14	0.64	0.55	0.69	0.64	0.71
I	0.49	0.42	0.57	0.59	0.47	0.41	0.27	0.76
J	0.71	0.68	0.46	0.50	0.14	0.56	0.19	0.47

Table 1. Correlation coefficient comparison between actual breathing and the EDR of each extracted lead

4.2 Optimum ECG lead selection algorithm during sleep by using HIF

ECG data during actual sleep receive lots of impacts from the motions of the examinee and external interference noises. In particular, because the conductive textile electrode used as an electrode is not attached to the body of an examinee so it is possible to measure the ECG without binding and the consciousness of the examinee, but it is easily exposed to impacts from surrounding noise. So, we have developed an algorithm which can automatically classify the ECG including significant breath signals by evaluating each of the two leads measured during sleep.

The ECGs (lead I and lead III) measured during sleep apply the algorithm after an elapse of one hour from the start of sleeping. Each ECG data is divided into the unit of 5 minutes and classification work is implemented in real-time. 5 minutes unit ECG is measured in each ECG lead extracts EDR and HIF signals and transforms them again into a frequency range respectively. We select the optimum lead, which reflects breathing information well, by comparing the PSD of the two transformed signals and we classify and store them automatically. Figure 9 is the system screen which has realized the automatic selection algorithm of the ECG lead. The program was realized with LabVIEW 8.6 (National Instruments, USA).

Judgment standard analyzes how much high relativity does the PSD of EDR extracted in each lead have by comparing it to the PSD of HIF signals. HIF signals are not largely distorted by the motions of the examinee or external interference noises because it is based on instantaneous frequency component according to each time of information of measured ECG signals and also because it can be obtained without various courses required for HRV analysis or extracting EDR. Therefore, more stable and high reliability information can be obtained. So, in this study, we judge whether EDR extracted based on the standard of frequency analysis obtained from HIF signals has meaning or not and can classify the corresponding ECG as significant information. Figure 10 is a flow map of the algorithm for the automatic classification of the ECG leads suggested in this study.

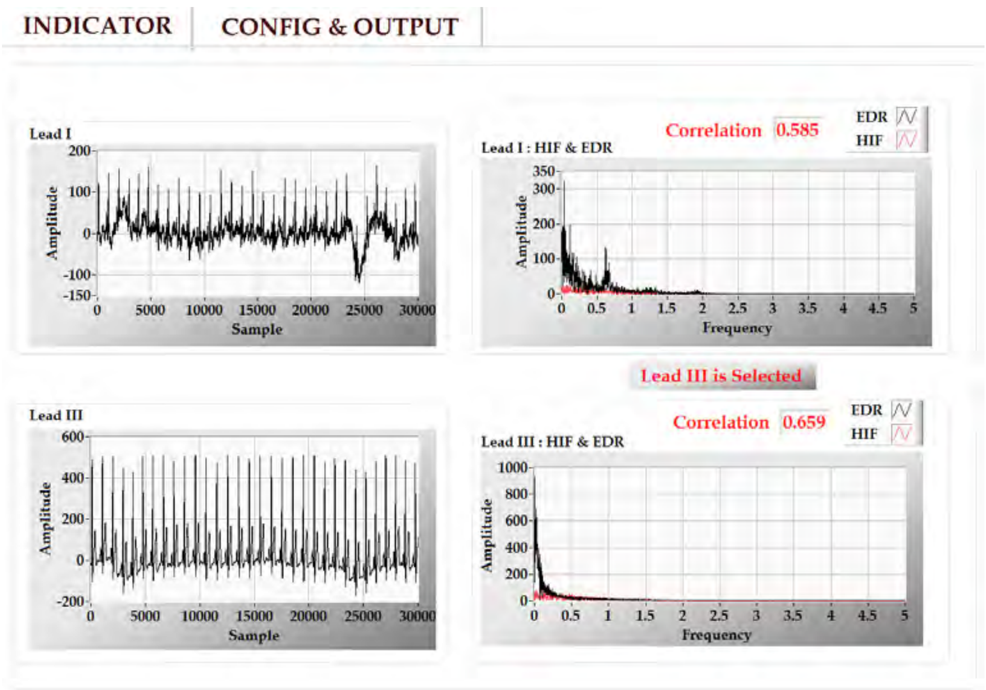

Fig. 9. Automatic classification system screen (LabVIEW)

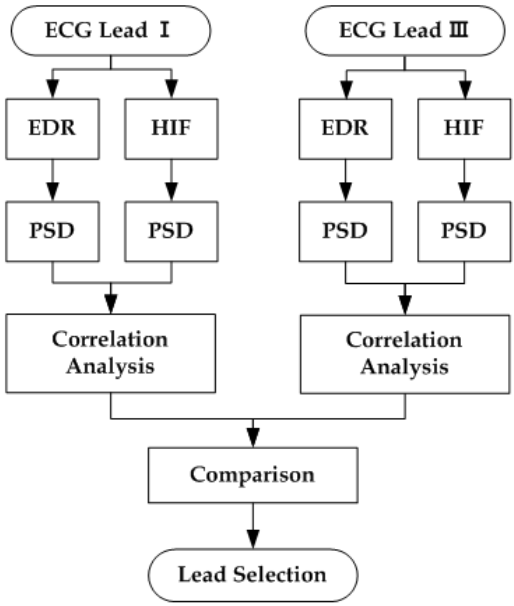

Fig. 10. Selection algorithm block diagram

In general HRV frequency analysis, shows the impacts of the parasympathetic nerve of the autonomic nervous system which includes breathing information appear mainly in the HF range of 0.15 ~ 0.4 Hz. However, as seen in Fig. 1, the intervals of breathing become larger and the quantity of one breath increases as a person becomes stabilized physically and mentally when the human body enters deep sleep. In reality, it can be activated in a much lower range than this one (Aysin and Aysin, 2006; Choi et al., 1999; Cammann and Michel, 2002). Therefore, in this study, it was evaluated by expanding the HF range into 0.1 ~ 0.4 Hz. Figure 11 shows the evaluation with regard to 1 hour(3rd) of examinee D in the unit of 5 minutes through the comparison of correlation between the PSD of HIF and the one of EDR.

We have basically judged and selected that the ECG lead, which has a high correlation coefficient among the two leads, and includes actual breathing properly during sleep. However, even if it is a lead with relatively high correlation, if the correlation coefficient is below an absolute number (<0.5), the two leads are all judged as meaningless signals. Even though we store the ECG with relatively high correlation coefficient, we did not classify them as significant ECG signals. Figure 12 shows the signal processing status when the ECG was distorted due to the motions of the examinee during sleep and also when the ECG was measured stably. In this case, lead I was discarded and the ECG of lead III was classified and stored.

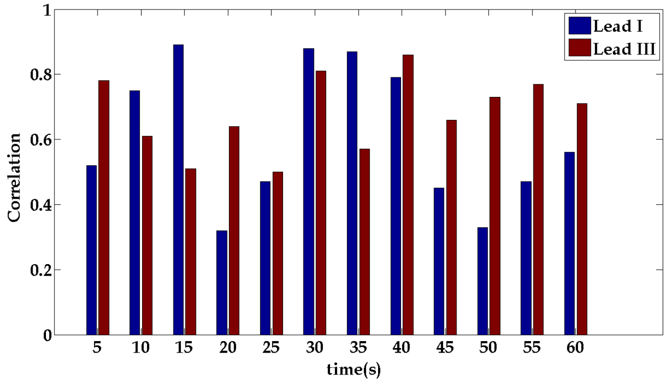

Fig. 11. Evaluation with regard to 1 hour(3rd) of examinee D in the unit of 5 minutes

5. Conclusion

HIF can provide frequency information like HRV, which is a biometric signal representing the best autonomic nervous system. Based on this fact, we can classify significant ECG signals which include accurate actual breathing information during sleep. We have developed algorithm which can automatically select and classify the significant ECG signals successively through PSD correlation analysis between the HIF signal and EDR which are acquired in the leads by acquiring the ECG with two leads (Lead I and III) in preparation for cases when the signal processing of the ECG is difficult due to motions or external interference noise, which can be generated during sleep. The continuous classification of the significant ECG acquired during sleep has a very important meaning and through the result of this study, it is believed that the very accurate and useful information can be provided to the sleep apnea symptom patients who need the accurate diagnosis or people who need breathing monitoring.

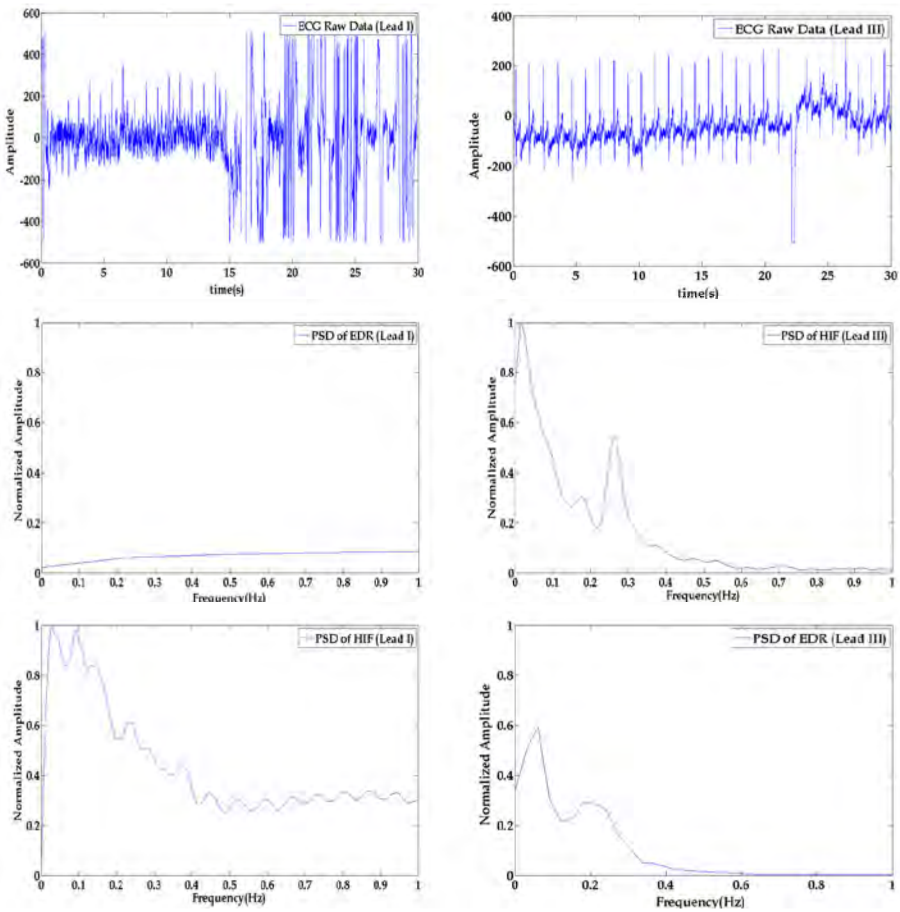

Fig. 12. Significant ECG lead (Right), and a lead which is not significant (Left)

6. Acknowledgment

We would like to thank Sung-Bin Park, Sung-Jun Park, Young-Myoun Han, and Jae-Hoon Jung. They provided a lot of support in the system configuration and signal processing for developing our algorithm. This study was supported by a grant of the Korea Health 21 R&D project, Ministry of Health & Welfare, Republic of Korea. (Grant No. A020602).

7. References

Park, SB.; Yi, KH.; Kim, KH. & Yoon, HR. (2004). An Improved Algorithm for Respriation Signal Extraction from Electrocardiogram Using Instantaneous Frequency Estimation based on Hilbert Transform, Trans. KIEE, Vol.53D, No.10, pp.733-740

Cysarz, D.; Zerm, R.; Bettermann, H.; Fruhwirth, M.; Moser, M. & Kroz, M. (2008). Comparison of Respiratory Rates Derived from Heart Rate Variability, ECG Amplitude, and Nasal/Oral Airflow. Annals of Biomedical Engineering, Vol.36, No.12, pp.2085-2094

Yi, KH.; Park, SB. & Yoon, HR. (2006). Real Time ECG Derived Respiratory Extraction from Heart Rate for Single Lead ECG Measurement using Conductive Textile Electrode, Trans. KIEE, Vol.55D, No.7, pp.335-343

Moody, GB.; Mark, RG.; Zoccola, A. & Mantero, S. (1985). Derivation of Respiratory Signals from Multi-lead ECGs, Computers in Cardiology, Vol.12, pp-113-116

Park, SB.; Noh, YS.; Park, SJ. & Yoon, HR. (2008). An improved algorithm for respiration signal extraction form electrocardiogram measured by conductive textile electrodes using instantaneous frequency estimation, Med Bio Eng Comput, Vol.46, pp.147-158

Mazzanti, B.; Lamberti, C. & Bie, J. (2003). Validation of an ECG-Derived Respiration Monitoring method, Computers in Cardiology, Vol.20, pp-613-616

Behbehani, K.; Vijendra, S.; Burk, JR. & Lucas, EA. (2002). An Investigation of The Mean Electrical Axis Angle and Respiration During Sleep, Proceedings of the Second Joint EMBS/BMES conference, pp.1550-1551, Houston, USA, Oct 23-26, 2002

Travaglini, A.; Lamberti, C.; DeBie, J. & Ferri, M. (1998). Respiratory Signal Derived from Eight-lead ECG, Computers in Cardiology, Vol.25, pp.65- 68

Correa, LS.; Laciar, E.; Torres, A. & Jane, R. (2008). Performance evaluation of three methods for respiratory signal estimation from the electrocardiogram, 30th Annual International IEEE EMBS conference, pp.4760-4763, Vancouver, British Columbia, Canada, Aug 20-24, 2008

Noh, YS.; Park, SJ.; Park, SB. & Yoon, HR. (2007). A Novel Approach to Classify Significant ECG Data Based on Heart Instantaneous Frequency and ECG-Derived Respiration using Conductive Textiles, Proceedings of the 29th Annual International Conference of the IEEE EMBS, pp.1503-1506, Cite Internationale, Lyon, France, Aug 23-26, 2007

Noh, YS.; Park, SB.; Hong, KS.; Yoon, YR & Yoon, HR. (2006). A Study of Significant data Classification between EDR extracted and frequency analysis of Heart Rate Variability from ECG using Conductive textile, World Congress 2006, pp.3958-3961, Seoul, Republic of Korea, Sep 28-30, 2006

Eckberg, DL. (1983). Human sinus arrhythmia as an index of vagal cardiac outflow, J Appl Physiol, Vol.54, No.4, pp.961-966

Hayano, J.; Yasuma, F.; Okada, A,; Mukai, S. & Fujinami, T. (1996). Respiratory Sinus Arrhythmia : A Phenomenon Improving Pulmonary Gas Exchange and Circulatory Efficiency, Circulation, Vol.94, pp.842-847

Noh, YS.; Park, SJ.; Park, SB. & Yoon, HR. (2008). Design of Real-Time Autonomic Nervous System Using Heart Instantaneous Frequency, Journal of Electrical Engineering & Technology, Vol.3, No.4, pp.576-583

Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology. (1996). Heart rate variability (Standards of measurement, physiological interpretation, and clinical use), European Heart Journal, Vol.17, pp.354-381

Aysin, B. & Aysin, E. (2006). Effect of Respiration in Heart Rate Variability (HRV) Analysis, Proceedings of the 28th Annual International Conference of the IEEE EMBS, pp.1776-1779, New York City, USA, Aug 30 - Sep 3, 2006

Choi, HJ.; Jeong, KS.; Lee, BC.; Kim, YK.; Ahn, IS. & Joo, KS. (1999). Study on HRV Analysis in Sleep Stage Using Wavelet Transform, Korean J Med Phys, Vol.10, No.3, pp.141-149

Cammann, H. & Michel, J. (2002). How to avoid misinterpretation of heart rate variability power spectra?, Computer Methods and Programs in Biomedicine, Vol.68, pp.15-23

Song, HS. & Lehrer, PM. (2003). The Effects of Specific Respiratory Rates on Heart Rate and Heart Rate Variability, Applied Psychophysiology and Biofeedback, Vol.28, No.1, pp.13-23