

# Estimation of Human Movements from Body Acceleration Monitoring for Ubiquitous Health Care

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**Abstract**—We are developing a BAN (body area network) using a machine measuring human 3D acceleration and electrocardiogram communicating to a PC by wireless during 24-hours. The purpose of our study is human healthy watching to alert to himself (herself) or care staffs by network if his (her) condition is bad, and not to alert if good. Our system estimate a person's bodily movement (walking, running, standing in a house, sitting in a train or else) from his/her acceleration data, and triage the electrocardiogram according to the estimated bodily movement then classify a human health condition. We collect acceleration and bodily movement records of our staffs and voluntary people for correct estimations and correct triages.

**Keywords**— acceleration, accelerometer, electrocardiogram (ECG), Holter ECG monitoring, clinical test, home health care

## I. INTRODUCTION

To aim to provide more advanced medicine, information communication and technologies (ICT) have an important role in health care systems in ubiquitous sensor networks. The need for more medical workers has long been pointed out by those involved in health care, and there might be also a problem that lack of beds causes hospital crisis. Hence, ICT home care is one of the topics that medicine must deal with in the future.

The electrocardiogram (ECG) is still most important non-invasive testing used in medical institutions. In general, short-term 12-lead ECG is used, but it is difficult to make a correct diagnosis for transient arrhythmia.[1][2][3] The Holter ECG has been widely spread among hospitals to detect such unstable angina, and have been accepted as an accurate and reliable alternative to the 12-lead ECG.[4][5] The Holter recorder can provide long-term ECG monitoring and analysing, but the patient must go back to the hospital to receive a diagnosis after the simultaneous 24-hour examination.[6]

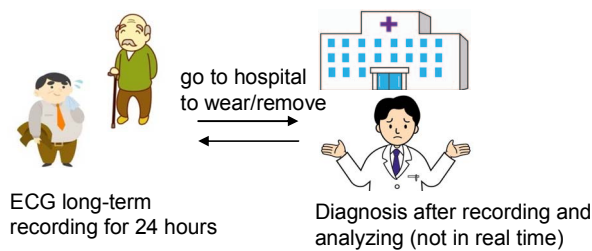
Recently, a tiny wireless ECG sensor was developed, that can transmit ECG signal to neighbouring computer terminals. While the Holter ECG offers 2-channel monitoring, the wireless ECG sensor has just one monitoring channel.

However, the wireless ECG sensor has much potential to real time ECG monitoring and analysing for home health care, in which a large quantity of data is automatically classified with sufficient accuracy. Moreover, the wireless ECG sensor has a built-in 3-dimensional (3D) acceleration sensor. If an accurate estimation of human movements is possible, a real time and correct diagnosis can be provided by ECG data combined with such estimation results.

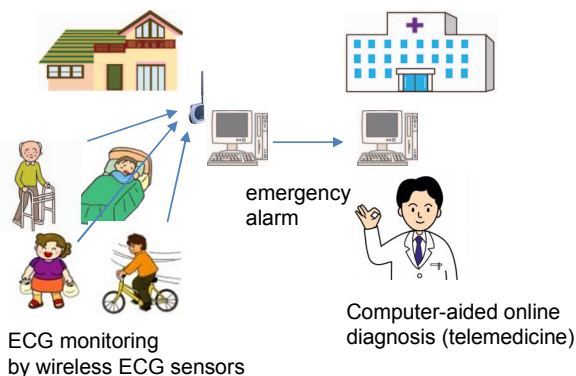
In this paper, we propose a concept of a home health care system using the wireless ECG sensors. A clinical test using the wireless ECG sensors was established in more than 60 patients from October to November in 2009. We focus on estimation of human movements. The results of experimental evaluations in the clinical test are also reported.

## II. CONCEPT OF ECG MONITORING FOR ARRHYTHMIA DETECTION

A conventional method to detect arrhythmia is the Holter ECG long-term recording. Figure 1(a) depicts the conventional diagnosis procedure using the Holter ECG monitoring. First, patients must go to a hospital to wear Holter ECG monitor. 24 hours later, they must go back to the hospital again to transfer their recorded ECG data to a Holter analyser. Only after that, a medical specialist can make a diagnosis. To solve this problem of time delay diagnosis, we propose computer-supported online diagnosis system. Figure 1(b) shows the concept of the proposed online diagnosis using the wireless ECG sensors. All patients with suspected unstable angina like arrhythmia wear the wireless ECG sensors attached to their chests. They don't need the admission to the hospital, but take usual normal life. ECG signals are continually transmitted to neighbouring PC terminals and automatically analysed by computer programs for diagnosis. When an emergency event is detected, an alarm signal is sent to a doctor at a hospital immediately, and the doctor can make a remote diagnosis or call an ambulance to rescue the corresponding patient. The computer programs always must provide exactly correct decisions that are well analysed and aided for the doctor. For this purpose, in our research, medical knowledge of us is indispensable to improve and realize the proposed diagnosis system.



(a) Conventional diagnosis using Holter ECG monitoring.



(b) Proposed online diagnosis using wireless ECG sensors.

Figure 1. Comparison of conventional and proposes diagnosis.

### III. WIRELESS ECG SENSOR

The wireless ECG sensor is employed in this paper. Figure 2(b) depicts the sensor's position with a disposable electrode, Vitorode-T, for two direct connections attached to patient's chest. The sensor sends ECG and 3D acceleration data to a neighbouring PC terminal with simple one way transmission and no handshake control to avoid delay of retransmissions. The PC terminal is connected to a server at a hospital via wireless/wired local area networks (LANs). A real time analysis can be processed at the PC and the server, if necessary. The ECG data also can be recorded in a hard drive in the PC, similarly to the Holter recorder.

The difference is no need for keeping a diary of patient's symptoms and activities in the proposed system. In the conventional Holter monitoring, the patients must write down when symptoms occur, what they are, and what the patient was doing at that time during test into the diary. It's important to write the time that symptoms occur, because the doctor matches the data with the information in the diary. This allows the doctor to see whether certain activities trigger changes in patient's heart rate and rhythm. In the proposed system, estimation of human movements will be helpful for analysis even if the patients don't keep the diary. In other words, because we aim to realize the online diagnosis system, we cannot use diaries written by patients. Therefore, the estimation of human movements and events of daily activities is quite important for the system, and we make an analysis of estimation using 3D acceleration data of a human body in this paper.

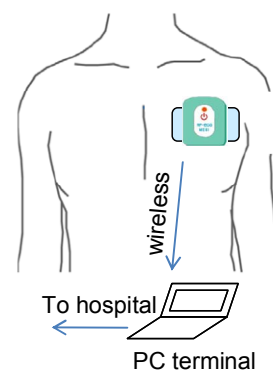


Figure 2. Electrode position of wireless ECG monitoring.

The wireless ECG sensor also has built-in detection circuit for 3-axis acceleration, so that more detailed analysis of ECG data combined with body's movements can be realized. The basic specifications of the sensor are listed in Fig. 3.

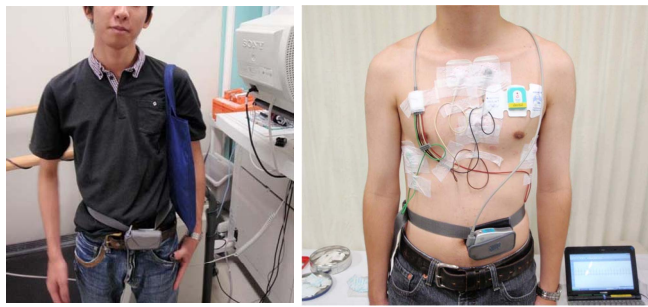
|            |                           |
|------------|---------------------------|
| Dimensions | 40 x 35 x 7.2mm           |
| Weight     | 11.8g (including battery) |
| TX Freq.   | 2.4 GHz Band              |
| TX Power   | 1mW                       |
| Coverage   | 15m (approx.)             |
| Battery    | CR2032 x 1                |
| Sensing:   |                           |
| Input Imp. | over 100 Mega Ohm         |
| Range      | 0.05Hz – 100Hz            |
| Gain       | 60dB                      |
| Sampling   | 102Hz or 204Hz, 10bit     |

Figure 3. Specifications of the wireless ECG sensor.

### IV. CLINICAL TESTS FOR EVALUATIONS

#### A. Outline of Tests

The goal of this paper is to confirm whether the wireless ECG sensor has sufficient performance to estimate human movements or not. For this purpose, the authors and additional several medical stuffs requested clinical tests to more than 70 subjects (persons as clinical volunteers) and made tests every weekend from October to November of 2009 at the attached hospital of our university. Currently, just 61 test data are available to be evaluated. The wireless ECG sensors were attached to the subject's chest and their ECG data are recorded into the hard drive of PCs. Figure 4 shows photos of subjects. Figure 4(a) shows an example of a style of subjects under the test. He brings a PC for receiving wireless signal from the sensor. He also has a Holter recorder authorized as a medical device for comparison. Figure 4(b) shows patched lead positions of two sensors. The wireless ECG sensor coloured with green is attached to the left side of his chest, and the Holter recorder is put in a small bag clipped to his belt. In this paper, we used just only 3D acceleration data of the wireless ECG sensor for estimating movements of the subjects during the test. For a simple analysis, we also referred described information described information in Holter's diary in Figure 5 to clip the data corresponding various movements like walking, riding on bikes and trains.



(a) Under testing with a PC and a Holter recorder.

(b) Lead positions of disposable electrodes for both Holter and wireless ECG.

Figure 4. Subjects for experimental evaluations.

| Time        | Behavior |      |    |    |      |    |    |      |    |      | Symptom | Note   |
|-------------|----------|------|----|----|------|----|----|------|----|------|---------|--------|
|             | 服薬       | 排尿排便 | 歩行 | 運動 | 階段昇降 | 食事 | 飲酒 | 起床就寝 | 胸痛 | 胸不快感 | 動悸      | ふらつき   |
| 3-5         |          |      |    |    |      |    |    |      |    |      |         |        |
| Walking     |          |      |    |    |      |    |    |      |    |      |         |        |
| 9:45~9:55   |          |      |    |    |      |    |    |      |    |      |         | 睡眠     |
| 10:00~10:30 |          |      |    |    |      |    |    |      |    |      |         | 駅まで移動  |
| 10:30~10:35 |          |      |    |    |      |    |    |      |    |      |         | 電車に移動  |
| 10:35~10:50 |          |      |    |    |      |    |    |      |    |      |         | 自転車    |
| 11:32~11:38 |          |      |    |    |      |    |    |      |    |      |         | せんたく物干 |
| 11:40~11:53 |          |      |    |    |      |    |    |      |    |      |         | 食事準備   |
| 11:55~12:05 |          |      |    |    |      |    |    |      |    |      |         |        |
| 12:50~13:00 |          |      |    |    |      |    |    |      |    |      |         | 片付け    |
| 13:02~      |          |      |    |    |      |    |    |      |    |      |         |        |
| 13:05~14:20 |          |      |    |    |      |    |    |      |    |      |         | 昼食     |

Figure 5. Holter's diary

## B. Time and Frequency Domain Analysis

Based on Holter's diary, we clipped acceleration data of some person's bodily movement of daily life. but this clipping is too coarse, so we use only typical part of clipping data. Acceleration Signal time sequence yielded by RF-ECG are transformed to frequency distributions using DFT (discrete Fourier transform) method. There are other selections. We can employ FFT (fast Fourier transform) or DCT (discrete cosine transform). But FFT is sparse at frequency sampling in low frequency area. DCT is not good to measure a phase value at a particular frequency. DFT is the best method to detect human bodily movement in the frequency analysis. There is other method One Nearest Neighbor [9] and PCA (principle component analysis) [10] for reduce vector dimension. PCA transforms space axes to reduce dimensions (e.g. a 180D space to a lower dimension space). PCA emphasizes important axes and ignores no-important axes.

Figure 6 shows One Nearest Neighbor PCA method. PCA collapses a cluster  $C_i$  to the light blue super-plane. A vector  $q_{j-col}$  is another fundamental vector belonging to another cluster  $C_k$ . A vector  $q_{j-non}$  is a test vector. If the distance  $D_{j-col}$  is large enough, we can set threshold  $T_i$  ( $D_{j-non} < T_i < D_{j-col}$ ). And we can conclude that  $q_{j-non}$  belongs to  $C_i$  if its distance to the light blue super-plane is smaller than  $T_i$ .

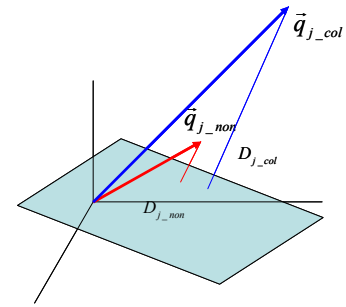


Figure 6. PCA and nearest neighbour.

## V. CLINICAL TEST RESULTS

### A. Walking

Figure 7 shows walking acceleration in 8 second. These values include gravity acceleration, so value is changed by posture if in rest state. The wireless ECG sensors were attached chest on left side, so the value of horizontal is not symmetry. These values of acceleration periodically change. Figure 8 shows frequency distribution of acceleration of human walking measured by the wireless ECG sensors. There are typical two peaks under a normal situation. The lower peak is a stride peak and the higher peak is a step peak[7][8]. A Stride peak appears around the 2Hz. Peak amplitude and frequency are sift by an individual walk. Stride and step peak's frequency ratio is about 1:2.

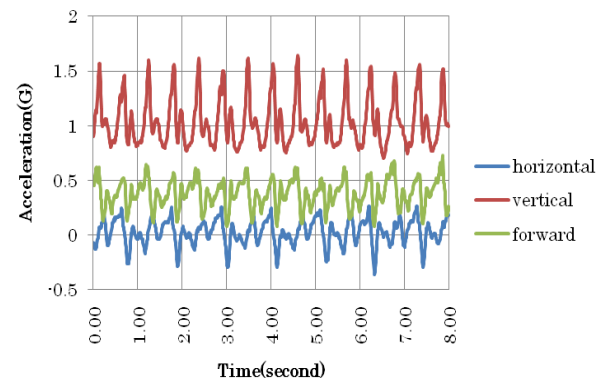


Figure7. acceleration of walking

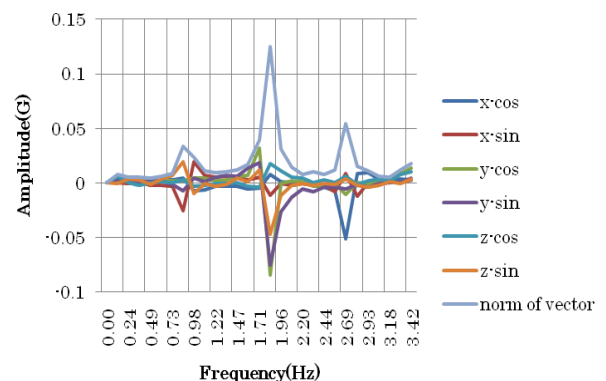


Figure 8. DFT of walking acceleration

### B. Riding on a bike

Figure 9 shows the data in the case of riding on a bike acceleration in 8 second. This part is clipping pedal a bicycle. Form of bike and road surface condition effect values. This is also periodical acceleration. Axis of forward shows human body's forward tilt. Figure 10 shows the result of frequency domain analysis on 3D acceleration in the case of riding on a bike measured by RF-ECG. Unlike the walking, there are no peaks which corresponding to step peak in walking.

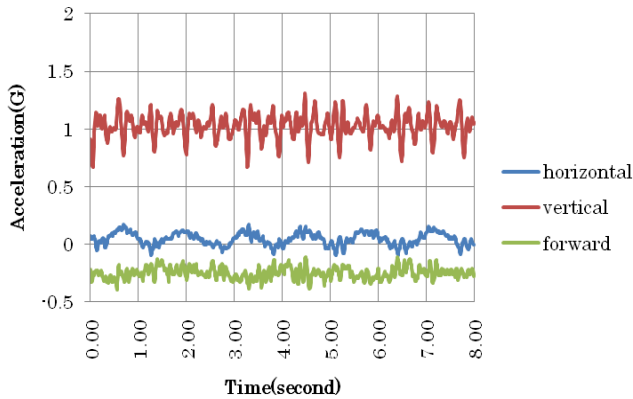


Figure 9. Time Sequence of Acceleration in Case of Riding on Bike

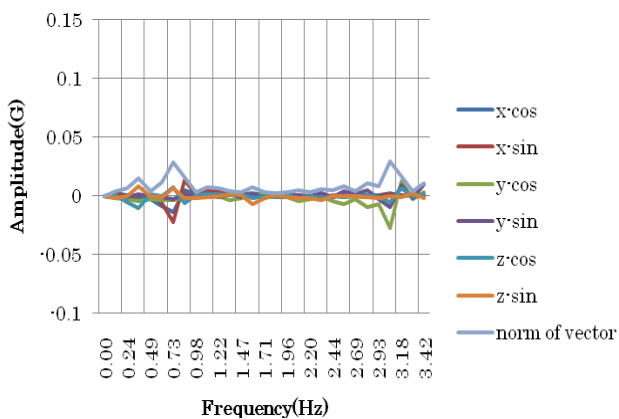


Figure10.DFT of Acceleration in Case of Riding on a Bike

### C. Getting on a train

Figure 11 shows a time sequence of accelerations of a subject on a train. It is difficult to distinguish this state from resting state. But unlike in resting state, vibrations of the train effect the value of acceleration.

Figure 12 shows a frequency distribution of accelerations of the subject on the train measured by RF-ECG. There are no step peaks nor stride peaks (cf. walking).

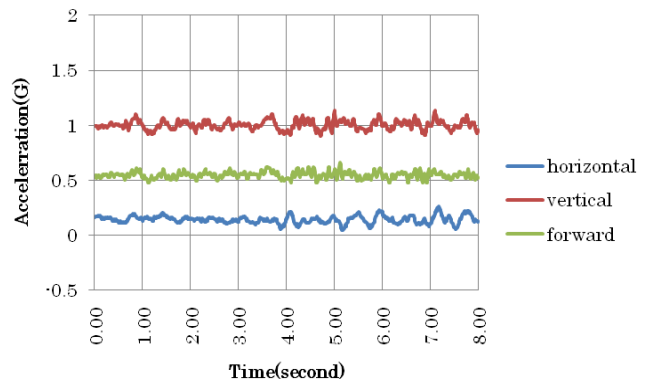


Figure11. Time Sequence of Acceleration of Subject on train

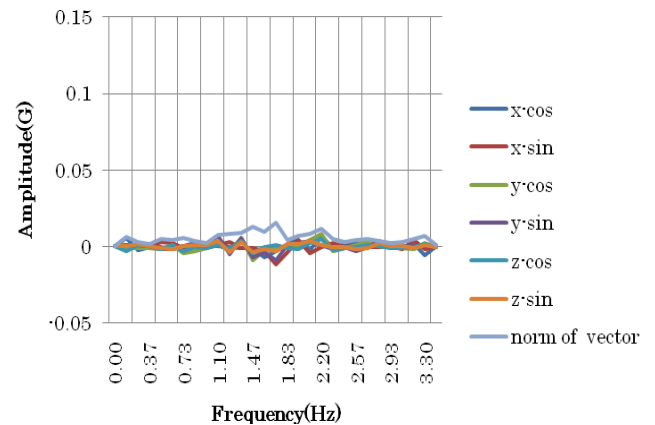


Figure12. DFT of Acceleration of Subject on Train

### D. Sleeping

When we attach the wireless ECG sensors to subjects, we told them to remain some postures for a short time. Firstly, flat on their back, secondly, lie down on right side, and left side. Figure 13 shows data of 10 minutes after record had started. Acceleration data of those posture is showed around 20000-30000 timestamps (the interval is 0.0098 sec at 102 Hz ). Those are obviously identified.

Figure 14 shows acceleration of sleep-onset time. Value of axis of vertical is changed around 15000-20000 timestamp. It means he is going to bed.

Figure 15 shows acceleration data in the middle of the night. Those values are very stable. Sleep of time is approximately find by acceleration data in time domain.

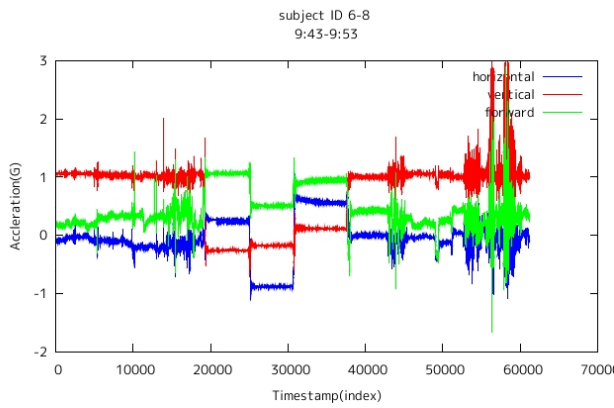


Figure 13. 10 Minutes after Record Started

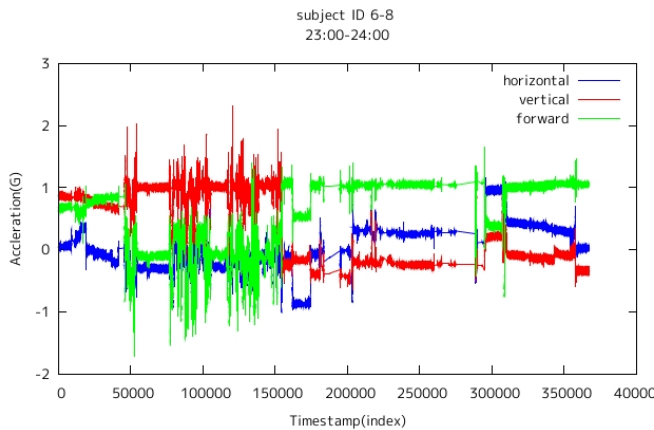


Figure 14. Time Sequence of Acceleration of Sleep-onset Time

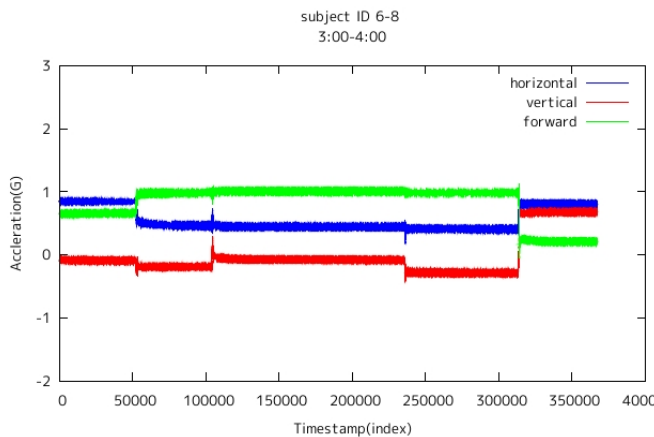


Figure 15. Acceleration of Sleeping

### E. One Nearest Neighbor

Then we show the result of One Nearest Neighbor method. We selected 30 DFT power distributions of walk data under 3 Hz (27-dimension vector) as standard data  $s_i$ . Then we selected other 10 walk data  $w_j$  for control and selected 10 bike data  $b_k$ . We search the nearest vector  $s'_k$  to a bike  $b_k$  among  $s_i$ . A value  $d'_{min}$  is the minimum of distance  $d'_k (= |s'_k - b_k|)$ . Also we search the nearest vector  $s''_j$  to a walk  $w_j$

among  $s_i$ . A value  $d''_{max}$  is the maximum of distance  $d''_j (= |s''_j - w_j|)$ . There is a threshold value  $T$  0.086 (g) ( $d''_{max} < T < d'_{min}$ ). We could recognise all  $w_j$  as walk data because they are all under  $T$ . And we could recognize all  $b_k$  as bike data because they are all over  $T$ .

### F. PCA

The number of the standard data  $s_i$  will increase if we hope high accuracy of the result of discrimination for more data. We have to save memory of the standard data. PCA method can collapse 27-dimension vector. Table 1 shows a relation between the dimensions of the collapsed vectors and the contribution ratio. PCA with contribution ratio 0.8 ordinarily works well. The memory saving ratio is 0.206(=8/27) with 8-dimension vectors with contribution ratio 0.808. And after the PCA of standard data, we also could distinguish 10 walk vectors and 10 bike vectors with accuracy 100%.

Table 1. Dimensions and Contributing Ratio of PCA

| Dim.  | 8     | 9     | 10    | 11    | 12    | 13    |
|-------|-------|-------|-------|-------|-------|-------|
| Cont. | 0.808 | 0.844 | 0.872 | 0.896 | 0.922 | 0.941 |

| Dim.  | 14    | 15    | 16    | 17    | 18    | 27  |
|-------|-------|-------|-------|-------|-------|-----|
| Cont. | 0.955 | 0.968 | 0.976 | 0.985 | 0.991 | 1.0 |

## VI. DISCUSSIONS

A classification between riding on a bike and a train is a simple job. We are needed to classify more other situations.

There are other many states in human bodily movements. E.g. "sleeping", "watching TV", "lunch" or so. There may be similar frequency distributions of such movements. We can employ Nearest Neighbour method to distinguish similar states.

The frequencies shown in Fig. 8 are between 0Hz and 3Hz. The number of sampled frequencies are about 30. There are 3D  $\sin()$  and  $\cosine()$  values at one frequency. So there are  $3 \times 2 \times 30 = 180$  data. Those data forms a 180D vector. We can collect many fundamental data from ourselves and voluntary people. Those fundamental data forms clusters for each movement. A test data  $V_i$  is investigated. Nearest Neighbour method finds out the nearest data  $V_n$  from the fundamental data included cluster  $C_i$ .  $C_i$  indicates a bodily movement such as "walking". There is a threshold  $T_i$ . If  $|V_i - V_n| < T_i$  we can clearly conclude that  $V_i$  is the result of movement  $i$ . But if  $|V_i - V_n| \geq T_i$  the result is not clear.

## VII. RELATED WORKS

There were some studies about acceleration data and human bodily movement. There was a study about 3D acceleration data and prognosis THR (total hip replacement). They have relatively to each other. Acceleration data are transformed into frequency domain. Walk acceleration data in frequency domain has a step peak and also a stride peak. The ratio of the heights of the two peaks is changed according to the patient's recovery

period. So the ratio is assumed to indicate objective numerical recovery value of the patient.

## VIII. CONCLUSIONS

We have proposed the concept of health care system using the wireless ECG sensor monitoring. We examined clinical tests by more than 60 subjects. Currently, 67 data were available to be evaluated. We also proposed a method employing DFT to distinguish human bodily movements using RF-CFG signals. Also we could use One Nearest Neighbor and PCA method. Those methods well worked with data of our staffs.

We will investigate the method with more data of voluntary people.

## ACKNOWLEDGMENT

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