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# A STUDY ON FEATURE EXTRACTION FROM HUMAN BODY MOTION BY USING CEPSTRUM ANALYSIS

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Abstract. *In this paper, we propose a method that classifies human body motions into four states, running and walking on flat ground, going up and going down the stairs. In our approach, we first use the 3-axis accelerometer of a mobile device to collect time-series data. Then, we focus on the periodicity of body motion and apply cepstrum analysis for classification. In this research, cepstrum analysis is a typical analysis method used in audio signal processing, but also used for feature extraction from human body motion. And, we apply continuous Hidden Markov Model (HMM) to automatically cluster the four types of data from the mobile device. As a result, just only 45% data were classified into the four classes correctly by using the raw data, and 60% by using its power spectrum. But in the case of using cepstrum analysis, the accuracy reached 73%. This indicates that our approach is effective in feature extraction from human body motion.*

**Keywords:** Human Body Motion, Accelerometer, Time-series Data, Cepstrum Analysis, Hidden Markov Model

1. **Introduction.** In recent years, due to the spread and the advance, mobile devices have been developed to be used as powerful tool for supporting our daily life. By using various sensors in it, such as accelerometer, gyroscope, magnetic sensor and air-pressure sensor, one is able to measure large amount of spatio-temporal data of human movement behavior much more easily and richly than before. Since these data could be used practical as a kind of life log, it could be expected to adaptively provide different services or contents according to the attribute information of the user. Against this background, the final goal of our research is not to develop a new special device. It is to provide some new services by complexly analyzing the user's life logs, which are easily and comfortably collected by mobile device already used in daily life.

2. **Previous Researches.** Various works aim to recognize the user context from sensor information so far [1, 2]. Takenoshita et al. [3] developed a handy gait assessment system and applied it to quantitatively assess the gait of elderly people. Ryu et al. [4] proposed an energy expenditure estimation method for non-exercise activity thermogenesis by using 3-axis accelerometer in the mobile phone. Tamura et al. [5] constructed a discrimination system of the walking style with human emotion by using single accelerometer. Ohno et al. [6] approached an analysis method for customer patterns from the trajectory collected by Radio Frequency Identification (RFID) in a supermarket. Jiang et al. [7] proposed a model to extract the characteristic of human movement with singular value decomposition from the time-series data of various sensors. It is very important and difficult to decide what kind of feature values should be extracted. Hence, the most conclusive and optimal one does not exist at present.

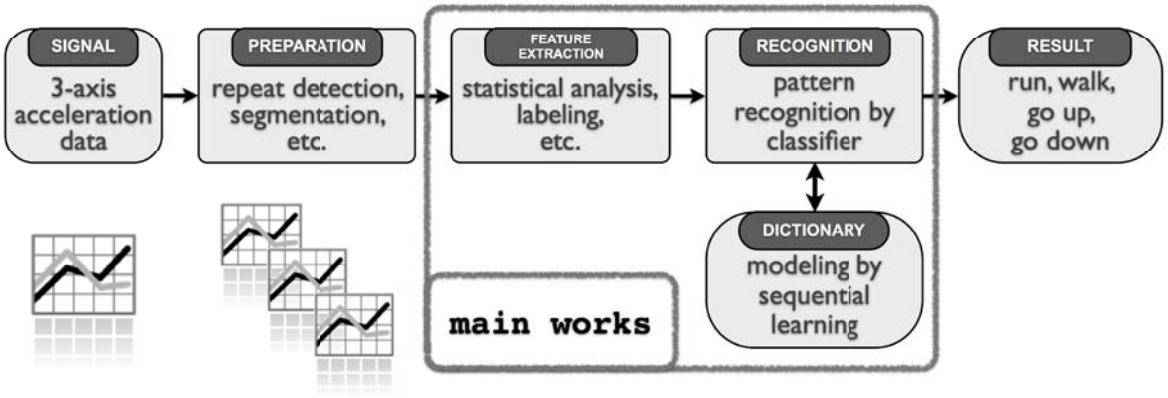



FIGURE 1. The generally used processing of pattern recognition with the main focus of this research highlighted

In this paper, we focus on the periodicity of body motion and propose a method for feature extraction by using cepstrum analysis, which is a typical analysis method in audio signal processing. Then, we apply continuous Hidden Markov Model (HMM) to body motion recognition. In addition, the objects of body motion in this study are running and walking on flat ground, going up and going down the stairs. And the sensor to measure the data is only a 3-axis accelerometer built into mobile devices.

## 3. Proposed Method.

3.1. **Summary.** In this study, we designed a classifier using pattern recognition to evaluate the accuracy of body motion recognition. Figure 1 shows the general processing of pattern recognition, especially for human body motion. First, the input signal, 3-axis acceleration data, is obtained from the mobile device. Then, as data preprocessing, the repeat points are detected, segmented, or otherwise prepared. In the next step, the feature extraction section analyses these data by statistical methods such as spectral analysis, and obtain several feature values as input symbol sequences of classifier. In the pattern recognition section, the model dictionary is applied into computing the probability of these symbol sequences drawn from each model. Depending on the result, one can decide, if the data should be used as a training data for the already existing model or the new additional one.

Due to the great effect to the performance of classifier, feature extraction is particularly important in the design of the classifier. Different feature extraction methods may result in different distributions of each object in the feature space. Therefore, we study mainly about the feature extraction and recognition of human body motions in this work.

3.2. **Cepstrum Analysis.** The word cepstrum is a word for the result of taking the Fourier transform of the logarithm of the estimated spectrum of a signal and finding applications in the analysis of human speech in particular [8]. It has a feature that enables us to separate and to approximate extract the spectral envelope and the fine structure of spectrum. The former represents the comprehensive feature and the latter represents the fundamental period in time waveform. When $g_i$ is defined as a periodic signal and $h_t$ is the impulse response, the waveform of body motion $x_t$ could be given as Equation 1 by the convolution of these two signals.

$$X_\xi = G_\xi \cdot H_\xi \tag{1}$$

Here $X_\xi$, $G_\xi$ and $H_\xi$ are the Fourier transforms of $x_t$, $g_t$ and $h_t$. With taking the logarithm for Equation 1, it becomes Equation 2 as follow.

$$\log|X_\xi| = \log|G_\xi| + \log|H_\xi| \tag{2}$$

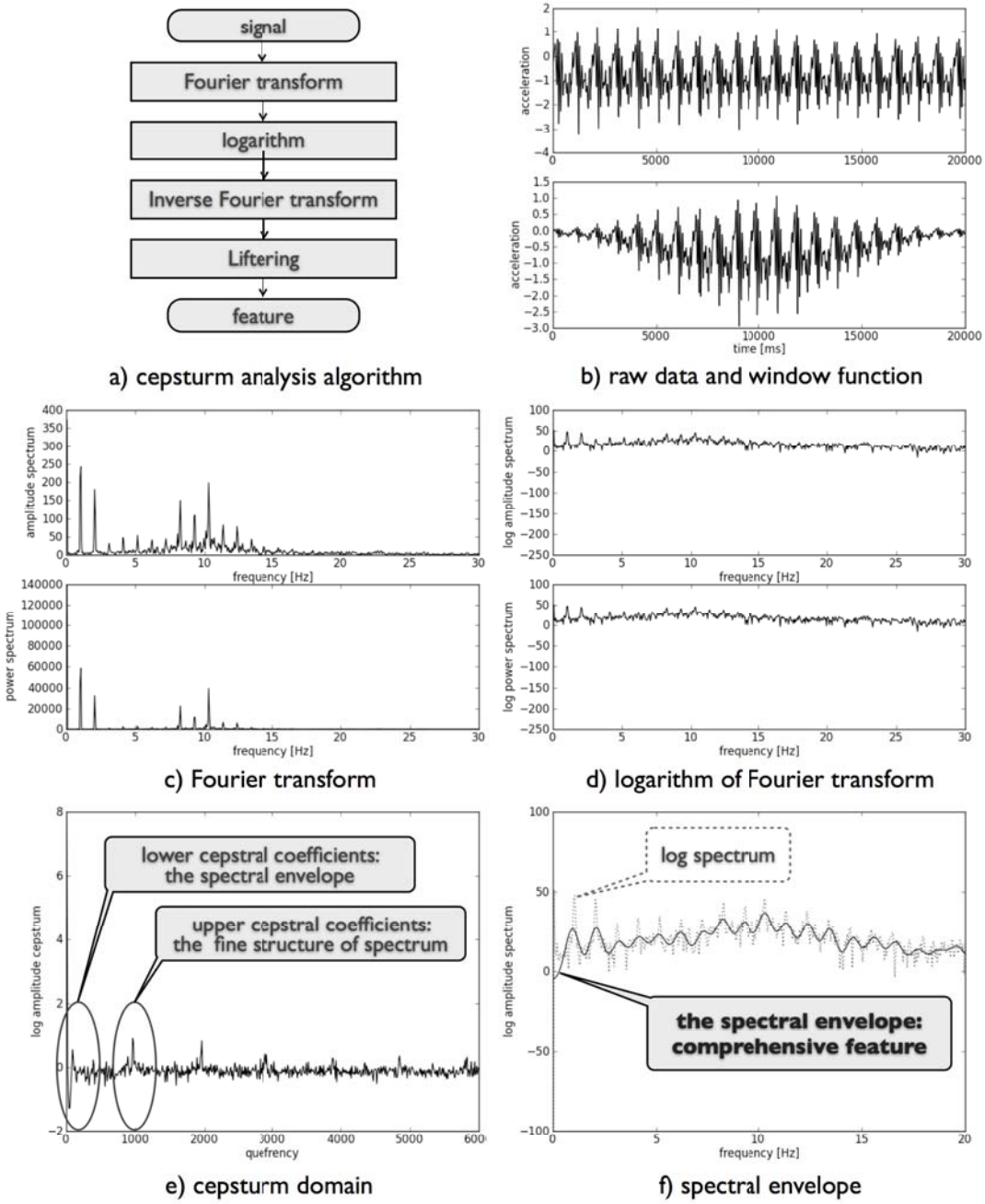



FIGURE 2. Cepsturm analysis algorithm in a) and a processing example for walking data in b)–f)

Here $\log|G_\xi|$ means the fine structure of spectrum, and $\log|H_\xi|$ means the spectral envelope. Hence, in the cepstral domain, which could be obtained by taking the inverse Fourier transform of them, one can observe that the signal is decomposed into lower cepstral coefficients (the spectral envelope) and upper cepstral coefficients (the fine structure of spectrum). Then, the separation of fundamental period and the comprehensive feature is available by using a lifter (a filter that operates on a cepstrum). Figure 2 shows the cepstrum analysis algorithm and an example of walking. The fine structure of spectrum represents the period information of the time waveform. Because it is a kind of element that has subtle changes, it may be susceptible to the environment. On the other hand, the spectral envelope represents the amplitude information of the time waveform, and has so slow changes in proportion to the frequency, that is not easily affected by the environment. Hence, in this study, we apply cepstrum analysis to extract it as a body motion feature.

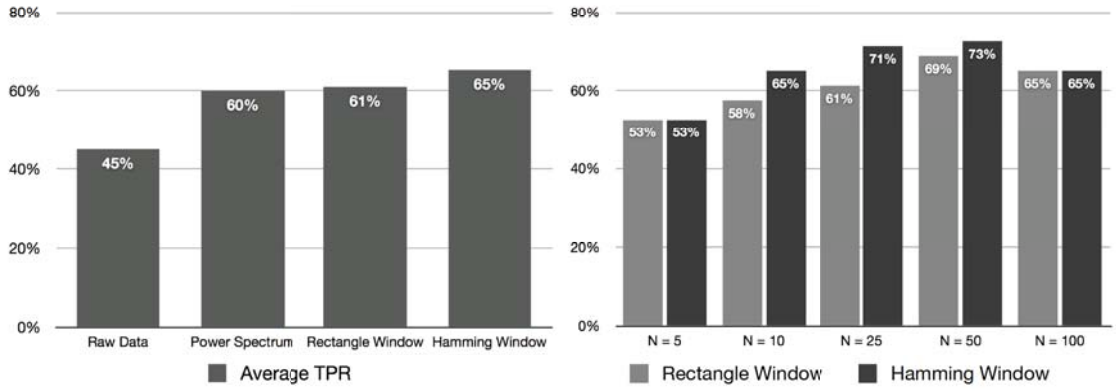



FIGURE 3. The result of the experiments

3.3. **Continuous HMM.** In our previous work have applied continuous HMM as a classifier for modeling and recognizing the body motions before [9]. The models are constructed by the sequential learning that repeats recognizing and training processes based on HMM. In this study, we also apply it to evaluate the usefulness of the features extracted by cepstrum analysis.

## 4. Experiments.

4.1. **Data Collection.** Running and walking on flat ground, going up and going down the stairs are the four objects of human body motion in this experiments. We used an iPhone 4 to collect 3-axis acceleration data. The iPhone 4 was placed in the trousers where the one experimental subject habitually put his mobile in. Data was collected five times with a 20-senconds period each, using a sampling rate of 100 Hz.

4.2. **Preparation.** Since the accelerometer is not fixed, but simply put in the subject's trousers pocket, it should be considered that the direction information of acceleration might get lose in some times. Therefore, we composited the values of $x$, $y$ and $z$ axis into $r$ by Equation 3.

$$r = \sqrt{x^2 + y^2 + z^2} \tag{3}$$

This translation only leaves the magnitude of acceleration. But our target is to get a comprehensive feature, which almost has no relation with the environment (the state of the sensor). Consequently we used the composite value. And we segmented the 100-seconds data of each body motion into twenty 5-seconds data.

4.3. **Evaluation.** By changing half of data in each body motion with the role of learning data and test data for cross validation, we calculated the average of True Positive Ratio (TPR) to valuate the usefulness of the feature extracted by the propose method. In addition, it is necessary to determine the features of lower cepstral coefficients for extraction in cepstrum analysis. Therefore, we compared the differences of the performance by the parameter settings.

4.4. **Results.** Figure 3 shows the result of the experiments. The left side indicates that no matter using the cepstrum analysis with rectangle window or Hamming window, its average TPR is better than using raw data or the power spectrum of data. It implies that cepstrum analysis extracted more useful features than power spectrum. The later one is a typically used in pattern recognition.

And the right side shows the difference of the performance by different parameter settings. Here, $N$ is the number of cepstral coefficients for extraction in cepstrum analysis. We found the performance of Hamming window seems better than rectangle window, or

TABLE 1. The result explanation of audio/motion signal processing

| | Fine structure of specturm | Sepctral envelope |
|---|---|---|
| Audio | Period information of the sound source | Feature of sound-producing mechanism |
| Motion | Impulse response for the environmental impact | Period information of the central pattern generator |

no window. It indicates that the best TPR almost in the lower cepstral coefficients, such as 25 and 50. But too few cepstral coefficients, in this case of 5 and 10, might let the spectral envelope lose some information, and too much might also produce the opposite effect. In any case, we can find that the quality of feature extraction by cepstrum analysis is better than raw data or its power spectrum. It confirmed the usefulness of feature extracted by this propose method.

5. **Conclusions.** In this paper, we proposed a method that classifies human body motion into four states, running and walking on flat ground, going up and going down the stairs. We focused on the periodicity of body movement and apply cepstrum analysis for this classification. Table 1 compares the result explanation with audio signal processing, we can consider that the sepctral envelope is a kind of useful feature. And, on the other hand, the fine structure of specturm also can be used as a feature the segmentaiton, when there are different body motions in a same time-series data.

We apply continuous HMM to automatically cluster the four types of data from the mobile device. The resule of accuracy in the case of using cepstrum analysis reached 73%. It was better than using the raw data (45%) or the other typical features, such as the power spectrum (60%). It indicated that our approach is effective in feature extraction from human body motion. For future work, we will investigate the effectiveness of the proposed method in the case of complex environment and multiple users.

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