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힐버트-황 변환에 통한 Hand Accelerometer 데이터의 핵심 패턴 추출

Applying Hilbert-Huang Transform to Extract Essential Patterns from Hand Accelerometer Data

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요 약 Hand Accelerometer는 인간신체 운동 패턴을 실시간으로 파악하는데 널리 사용되고 있다. 그러므로 행동 유형을 정확하게 파악하는 것은 아주 중요하다. 이 과정에서 각 행동유형의 형태를 미리 정확하게 파악하는 것이 중요하다. 인간의 신체 행동은 센서를 통해 수집된 시계열 데이터로 표현된다. 이 데이터는 비안정적, 비선형적 성격을 가지고 있다. 그래서 이런 성격의 데이터의 유형을 효율적으로 추출하는 방법을 찾는 것은 매우 중요하다. 힐버트-황 변환은 비안정적 비선형적 요소를 시계열데이터에서 효율적으로 추출하는 방법이다. 이 방법을 위의 시계열 데이터에 적용한 결과 핵심패턴이 성공적으로 추출되었다.

Abstract Hand Accelerometers are widely used to detect human motion patterns in real-time. It is essential to reliably identify which type of activity is performed by human subjects. This rests on having accurate template of each activity. Many human activities are represented as a set of multiple time-series data from such sensors, which are mostly non-stationary and non-linear in nature. This requires a method which can effectively extract patterns from non-stationary and non-linear data. To achieve such a goal, we propose the method to apply Hilbert-Huang Transform which is known to be an effective way of extracting non-stationary and non-linear components from time-series data. It is applied on samples of accelerometer data to determine its effectiveness.

Key Words : Hilbert-Huang Transformation, Accelerometer, Hand Motion

Ⅰ. Introduction

Many new software of today require real-time monitoring of human activity to perform their task[16,17,19,20,21,22]. Sensors are attached to a human subject. They send streams of real-time time-series data for analysis in order for computer programs to formulate a proper response. Of great importance is to figure out what kind of activity a human subject is engaged in based on time-series data the computer is receiving [21,22,23]. Each activity shows distinctive pattern. It is necessary to find essential temporal pattern of each activity. Noisy extraneous parts of time-series needs to be removed. These are usually

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occur on short time scale. By removing it, we can arrive at a pattern on proper time scale which can show essential characteristic of a given activity. The trouble is that the time-series data are mostly non-stationary and non-linear, and decomposing time-series data into components of predetermined set of frequency(period) could lead to inaccurate result. A method which perform decomposition into non-stationary and non-linear components of various time-scale is needed. Hilbert-Huang Transform (HHT) is ideally suited to performing such a transform. Time-series data can be broken down into components of multiple time scale, and choose a component on a proper time scale [11,12].

Time-series usually contains some type of fluctuation over time, which appears to occur at certain frequencies. Unfortunately, it rarely has precise periods. In addition, its perceived frequency could change over time. Human physical activities are no exception. Human hand motion while performing certain activities such as walking, eating a particular type of food, or brushing teeth all show contains oscillatory pattern with dynamically changing frequency and amplitude.

Fast Fourier Transform (FFT) and Wavelet Transform have wide-spread application in many fields [8,9,15]. While they can be effective in solving certain problems, they do have some limitation. They are essentially static in that they start with predetermined basis of frequencies. In case of FFT, time-series is represented as a static periodic function over the entire range of interest. To remedy this limitation, Windowed FFT was introduced with varying level of success. Still it is not suitable for representing non-linear and non-stationary time-series.

Wavelet Transform is designed to tackle this problem. It can produce three dimensional charts which can show change of frequency amplitude distribution over time. However, it still requires the use of predetermined basis. Wavelet Transform can handle non-stationary time-series but not non-linear one. In contrast, HHT has adaptive basis. The basis is not predetermined. It is derived from the data while HHT is performed. It is especially effective in catching instantaneous frequencies and amplitudes [8,9].It is well-suited to identifying profiles of aforementioned human physical activities.

Previously, HHT has been applied to a wide range of problems with great success. It is used for analyzing heart beats or EEG signals while a subject is performing a particular cognitive task [23].It is applied to analyze wave signals propagating through structures such as vibration and detect anomalies such as cracks [18]. Image processing is another area of application in which it was used for filtering and feature detection [24].On a more macro scale, it has been applied to extracting periodic modes of epidemic outbreak time-series, and analyzing time-series data from weekly mortgage rates [25,26]. Another area where HHT has been extensively used is structural engineering [18]. While they all employed HHT, the manner of application may vary. In some cases, it is used to remove noisy components, usually signals in high frequency range [16]. In other cases, it is used to identify particular pattern which can characterize an onset of significant event such as heart attacks or structural failure [17,18].

A prior research on the application of HHT to analyzing human hand motion is the application of HHT to aiding minimally invasive surgery. The procedure requires surgeons to manipulate specialized tools in uncomfortable posture for extended duration. Over time, it will introduce hand muscle fatigue, generating hand-tremors which will affect accuracy of the procedure. Computer software is attached to analyze signals from hand motions. Then it identifies the high frequency components which are the result of hand tremor, which are filtered out and the resulting signal, now with hand-tremor removed, is sent to a slave manipulator inside a body of patient undergoing surgery. This is a way to self-correct signals so that the surgery maintains its accuracy.

In this paper, we used hand motion data from tri-axial

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accelerometer and apply Empirical Mode Decomposition to them. It will produce components on different time scale.

We will analyze which ones can be suitable for identifying a particular type of activity.

II. Hilbert-Huang Transform

The Hilbert-Huang transform (HHT) ([10], [11],[12], [13], [14]) is a method which is superior to any comparable techniques when it comes to non-stationary and non-linear time-series data. It first split the original time-series into multiple oscillatory components, which are called Intrinsic Mode Functions (IMF.) This process is called Empirical Mode Decomposition (EMD.) This is essentially a process of decomposing time-series data into components in separate frequency bands. The bands are not static but dynamic. Furthermore, it can show change of instantaneous frequencies. It can catch intra-wave frequency modulation, which other techniques like FFT or Wavelet Transform tend to destroy. Highly complex non-linear systems exhibit such a pattern. HHT is a proper tool to analyze data from such a system.

As has been mentioned in the previous section, the basis of HHT is not determined in advance. It will be derived through the process of Empirical Mode Decomposition(EMD.) EMD is essentially an iterative process which isolates components in different time-scales in stages. Each stage employs a sifting process which is to produce proper oscillatory component without containing components which is on larger time scale. Each component isolated via this process is an Intrinsic Mode Function. IMF is isolated starting with the highest frequency (smallest time-scale.) Isolated IMF is subtracted from the current time-series, producing new time-series with lower frequencies. This process continues, producing IMF's of lower and lower frequency (larger time-scale) until a terminating condition is met, at which point EMD ends.

표 1. Empirical Mode Decomposition 알고리즘
Table 1. Empirical Mode Decomposition Algorithm

Given a time-series X_t, perform the following:
$r_t^{(0)} = X_t$
$k = 0$
Repeat
  $h_t^{(0)} = r_t^{(k)}$
  $i = 0$
  Repeat
    Find all local maxima of $h_t^{(i)}$ in the entire data set
    compute their envelope curve $u_t^{(i)}$ using cubic-spline lines
    Do the same for local minima and compute their envelope curve $l_t^{(i)}$
    Compute the mean curve
    $m_t^{(i)} = \frac{1}{2}(u_t^{(i)} + l_t^{(i)})$
    Compute $h_t^{(i+1)} = h_t^{(i)} - m_t^{(i)}$.
    (For two successive zero crossings, do steps (2) and (3))
    $i = i + 1$
  Until $m_t^{(i)}$ becomes nearly a constant value.
  $c_k(t) = h_t^{(i+1)}$ is the k-th IMF.
  $r_t^{(k+1)} = r_t^{(k)} - c_t^{(k)}$
  $k = k + 1$
Until $r_t^{(k)}$ becomes a monotone function which cannot generate IMF any further.

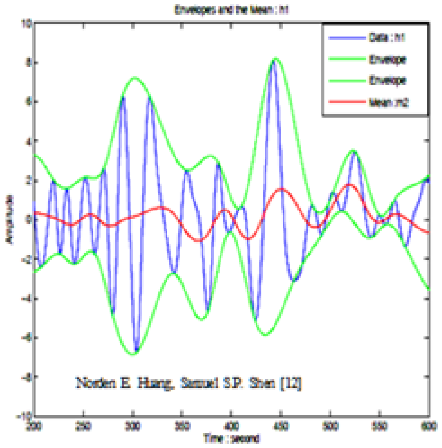

그림 1. 극대 극소 값의 포락선을 이용한 평균곡선의 도출
Fig. 1. Deriving a Mean Curve from Envelope Curves of Local Maxima and Minima

A rough description of Hilbert-Huang Transform is shown in Table 1 ([12].) As a result,

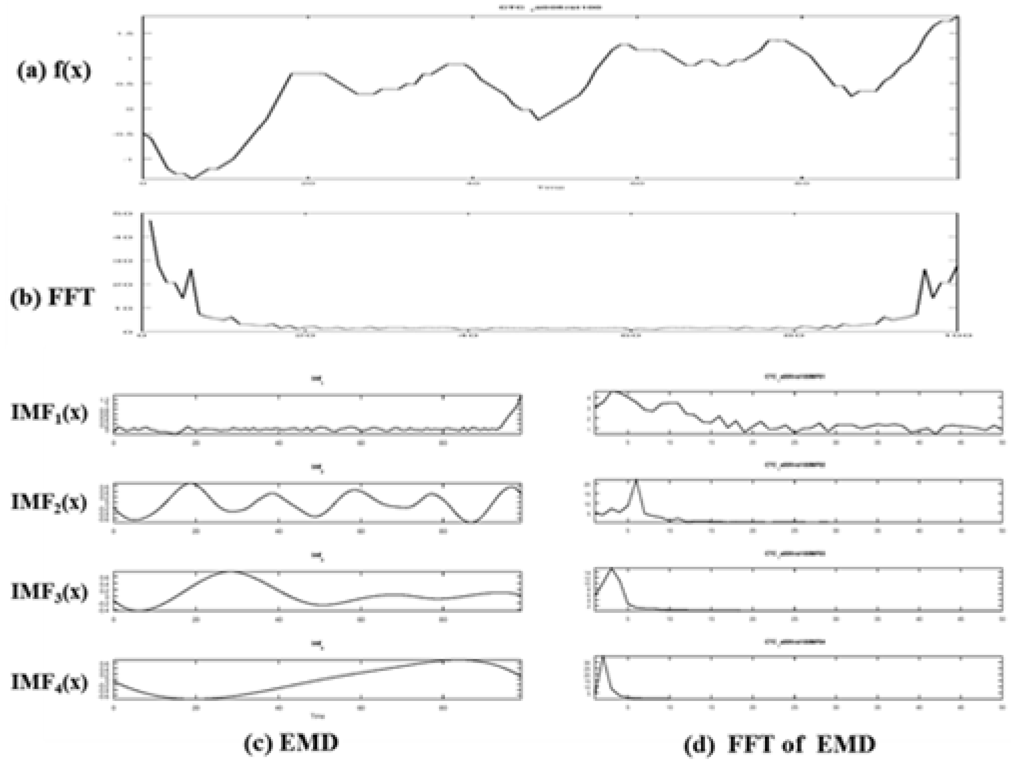

그림 2. (a) 샘플 곡선 f(x) (b) f(x)의 프리에 변환결과(파워 스펙트럼) (c) EMD를 통해 도출된 IMF곡선들 (d) 각 IMF곡선에 대한 푸리에변환 결과(파워 스펙트럼)

Fig. 2 (a) a Sample curve f(x) (b) Power Spectrum of f(x) (c) IMF curves derived from f(x) via EMD (d) Power Spectrum of each IMF curve.

$$X_t = \sum_{k=1}^{n} c_k(t) + r_n(t)$$

X_t is now decomposed into n IMF's. Figure 1 shows how two envelope curves, $u_t^{(i)}$, $l_t^{(i)}$and its mean curve $m_t^{(i)}$ are derived. The sample result of EMD is shown in Figure 2.

Figure 2(a),(b) shows a sample curve(top) and its power spectrum(bottom). EMD produces IMF's in Figure 2(c). Figure 2(d) shows power spectrum of each IMF. Each IMF has a power spectrum concentrated around a single major frequency unlike the original curve with more spread-out power spectrum. Original time-series is decomposed into IMF's in different frequency bands, which are not known in advance but rather found during EMD. Since each IMF is not a simple periodic curve, its power spectrum can be complicated. Some have sharp peaks clearly showing dominant frequencies, while others have more spread-out distribution. Since EMD relies on envelope curve of peaks, it does not perform well if there are no available peaks. IMF's on either end of time-series tend to be inaccurate, frequently showing significant deviation from original time-series data. So segments of IMF on both ends should be discarded.

III. Experiments

We used data from Activities of Daily Living (ADLs) Recognition at UCI Machine Learning Repository. Tri-axial accelerometers are attached to a wrist of human subjects [21,22]. Figure 3 shows one

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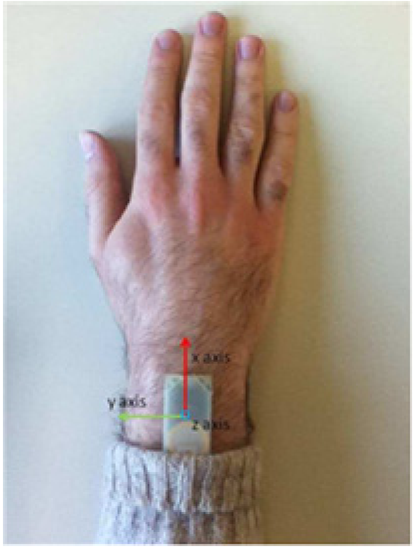

그림 3. 3축 가속도계 (손목에 장착)
Fig. 3. Tri-axial Accelerometer(attached to a wrist)

type of tri-axial accelerometer. The subjects are asked to do a variety of activities including eating, brushing teeth, or lying down on the bed. The accelerometer records movement in three different directions:

- x axis: pointing toward the hand
- y axis: pointing toward the left
- z axis: perpendicular to the plane of the hand

Three sets of time series data are generated for each trial. Some of collected time series data were chosen. For time-series corresponding to each axis, HHT was applied and IMF's were derived via EMD. Each IMF represent pattern on a particular time-scale. IMF's are subtracted from original time-series in succession, removing component of shorter time-scale(fast changing component) one at a time, until the resulting time-series data turns out to be the one which best represents essential pattern of original time-series data. It is a process of choosing a right time scale where essential pattern can be found. To put it formally, we are trying to find the best LIMF_i where $\mathrm{LIMF}_i = X_t - (\mathrm{IMF}_1 + \cdots + \mathrm{IMF}_i)$ where X_t represents original time-series.

(a)

(b)

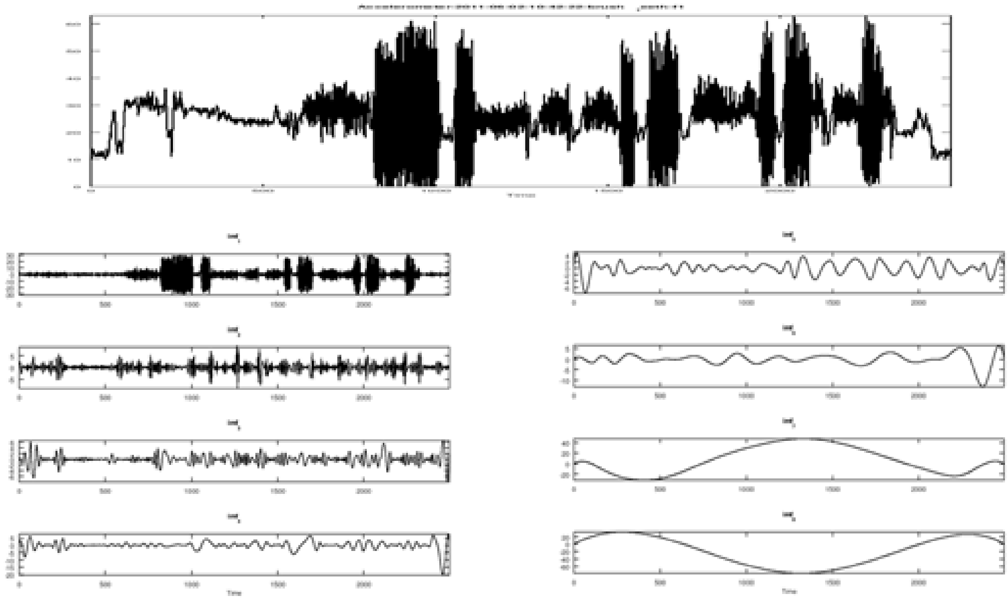

그림 4. (a) 칫솔질을 할 때 움직임을 기록한 3축 가속도계의 x-축 측정치 (b) 측정치에 EMD를 적용해서 얻은 8개의 IMF곡선(왼쪽위에서 아래로 다음에 오른 쪽 위에서 아랫방향으로 보다 완만한 IMF가 배열되어 있다.)
Fig. 4. (a) X-axis values from an tri-axial accelerometer during "Brushing Teeth" activity (b) 8 IMF curves derived via EMD. IMF's are arranged according to their time-scale (top-left is the shortest, and the bottom-right is the longest.)

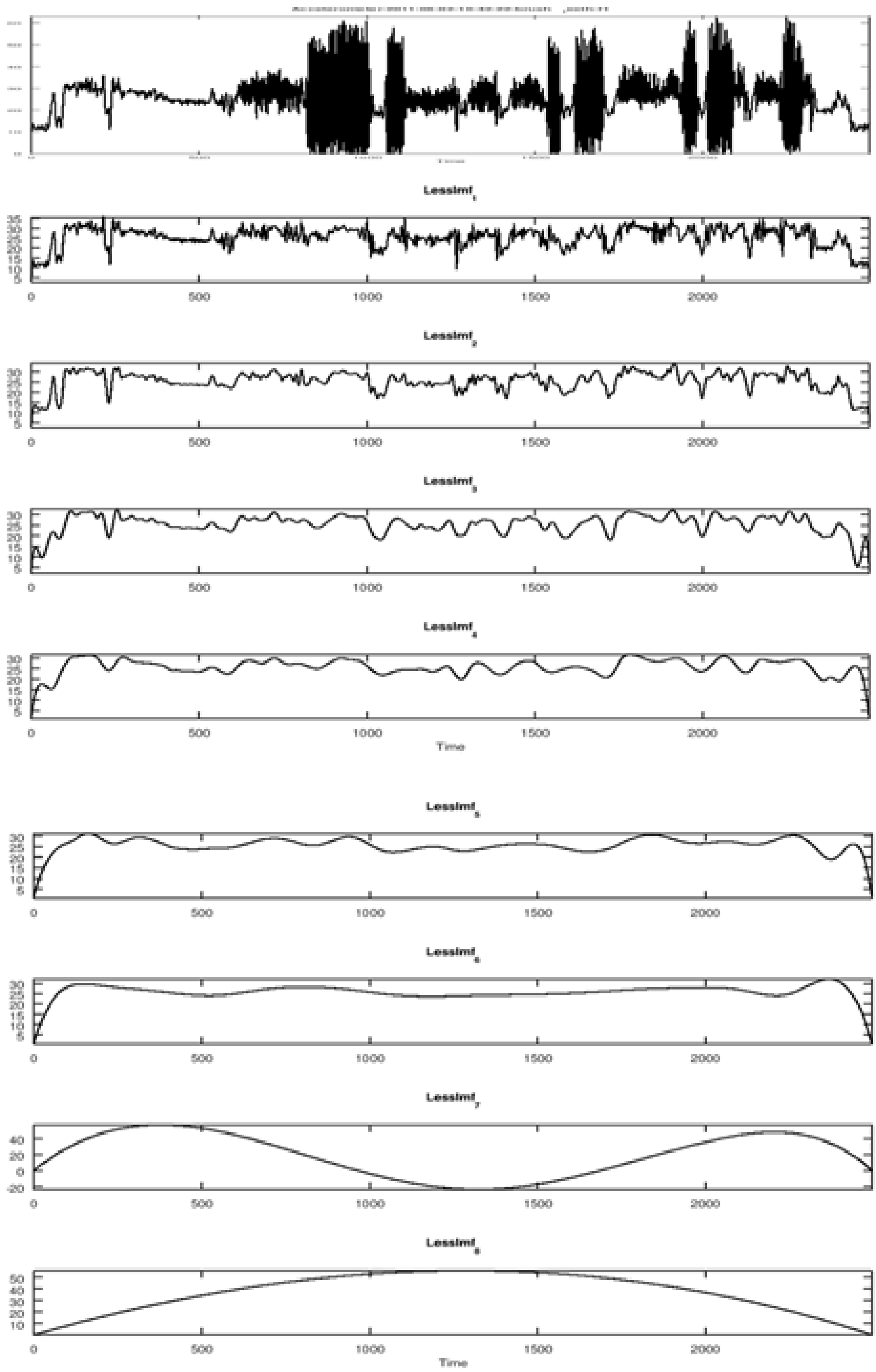

그림 5. 칫솔질운동의 x-축 측정치의 LIMF 곡선
Fig. 5. LIMF Curves from x-axis Values of "Brushing Teeth" Activity

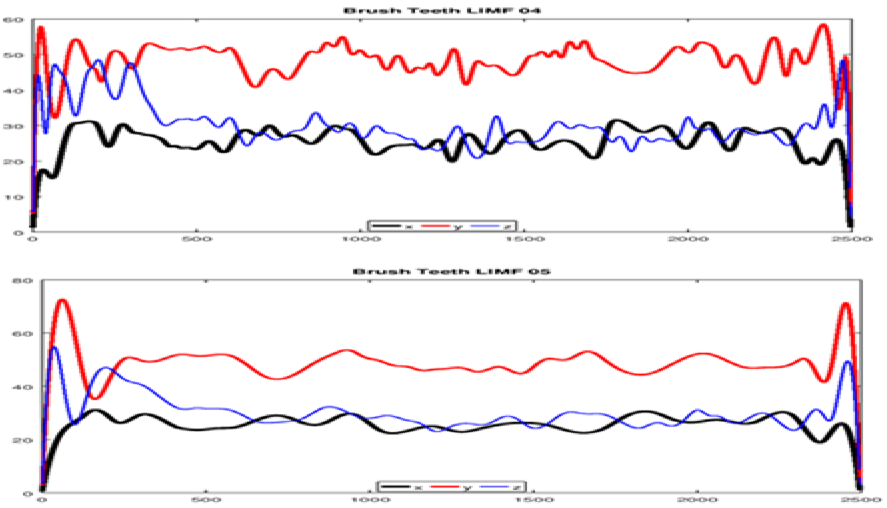

그림 6. 모든 축의 값의 4번째(위), 5번째(아래) LIMF 곡선($LIMF_4$, $LIMF_5$): 검은색(x-축), 빨간색(y-축), 파란색(z-축)
Fig. 6. 4th (top) and 5th (bottom) LIMF' s ($LIMF_4$, $LIMF_5$) for each axis: red(x-axis), black(y-axis), blue(z-axis)

IV. Result

Figure 4 shows the result of Empirical Mode Decomposition (EMD) performed on time-series data from x-axis measurement of “brushing teeth” activity. The top graph is the original time-series data and 8 IMF’s are shown. As can be seen here, time-series is broken into multiple components of varying time-scale. These are pieces of original time-series. Since we are trying to find overall pattern which can represent the time-series best, an individual piece may be not a suitable candidate. Instead we are peeling off each IMF one at a time starting with $\mathbf{IMF}_1$. This would remove noisy or non-essential components from the time-series. Conventional filtering can be used for the same purpose, but it may not be as effective because it lacks a kind of good adaptive feature HHT can provide. LIMF’s obtained by removing IMF one by one are shown in Figure 5. Starting from the top which is the original time-series, the figure shows the result Figure 5 of removing each IMF one at a time. After performing the removal process 4 or 5 times, we have the result which may best capture overall pattern of the original time-series. If we proceed further, the resulting time-series is on the time-scale too long to contain useful information. Performing the same operation for time-series data from y,z-axis, we have a result shown in Figure 6. It has $\mathbf{IMF}_4$ and $\mathbf{IMF}_5$ for all three axis. $\mathbf{IMF}_4$ may have more details but too many peaks and valleys.

To capture the overall pattern $\mathbf{LIMF}_5$ may be more suitable. The same operation can be done for other data. The rule of thumb to pick the right **LIMF** is to find a number by dividing the number of LIMF’s by 2 and pick LIMF corresponding to the number. That is, pick $\mathbf{LIMF}_{[\frac{n}{2}]}$ where $[n/2] = \lfloor n/2 \rfloor$ or $\lceil n/2 \rceil$. Figure 7,8,9,10 shows additional result for various activities. Most of LIMF’s shown here capture essential pattern of activities, except brushing teeth. Its high frequency IMF’s do reflect significant pattern of activities, and it may not have to be discarded. This requires further analysis on Instantaneous Frequency(IF) of the activity.

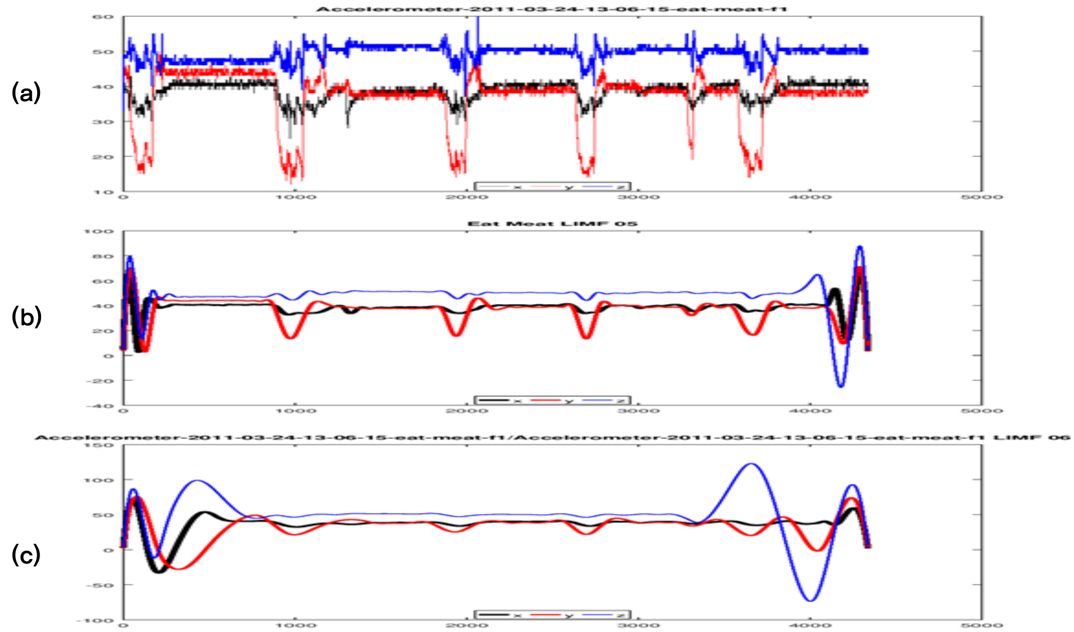

Fig. 7. Eating Meat-1 (a) time-series data from x,y,z direction (x: black, y: red, z:blue) (b) 5^{th} LIMF (c) 6^{th} LIMF

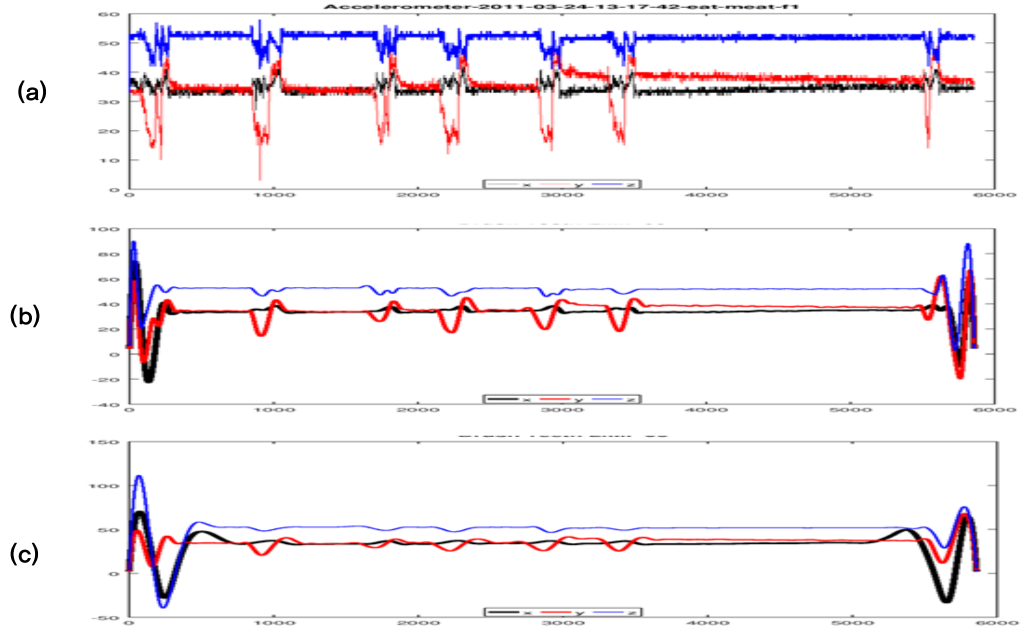

그림 8. 육류 섭취시 움직임-2 (a) x,y,z 축 방향 시계열 데이터 측정치(x:검은 색, y:빨간 색, z:파란 색) (b) 5번째 LIMF (c) 6번째 LIMF

Fig. 8. Eating Meat-2 (a) time-series data from x,y,z direction (x: black, y: red, z:blue) (b) 5^{th} LIMF (c) 6^{th} LIMF

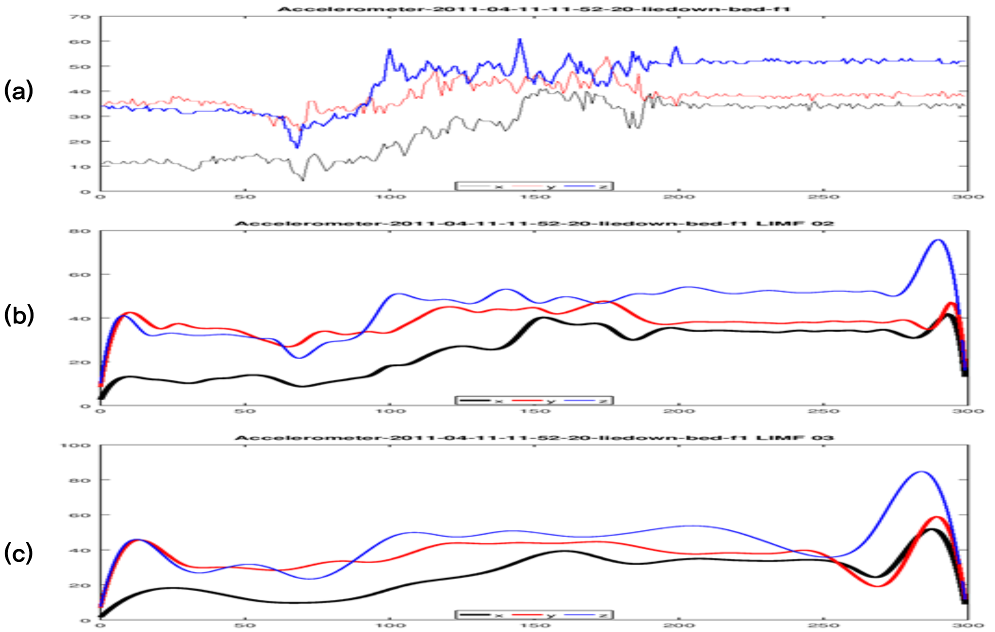

그림 9. 침대에 누을 때 움직임 (a) x,y,z 축 방향 시계열 데이터 측정치(x:검은 색, y:빨간 색, z:파란 색) (b) 2번째 LIMF (c) 3번째 LIMF

Fig. 9. Lying Down to Bed (a) time-series data from x,y,z direction (x: black, y: red, z:blue) (b) 2nd LIMF (c) 3rd LIMF

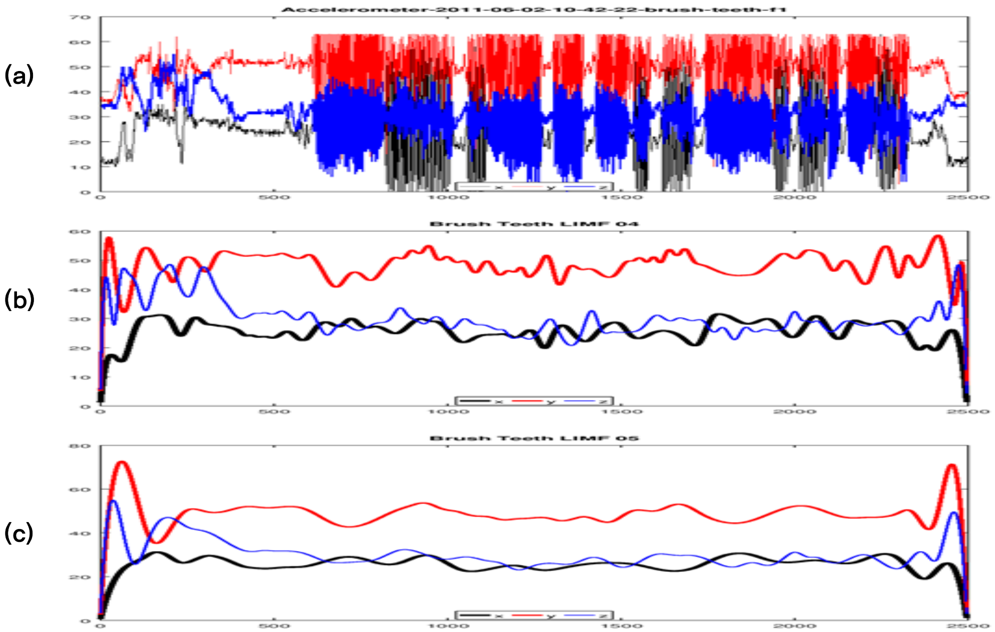

그림 10. 칫솔질할 때 움직임 (a) x,y,z 축 방향 시계열 데이터 측정치(x:검은 색, y:빨간 색, z:파란 색) (b) 4번째 LIMF (c) 5번째 LIMF

Fig. 10. Brushing Teeth (a) time-series data from x,y,z direction (x: black, y: red, z:blue) (b) 4th LIMF (c) 5th LIMF

V. Conclusion

The application of HHT to derive a series of LIMF's to find the essential pattern which best captures the essential feature of time-series has been investigated. It turns out that this method is good at capturing non-stationary and non-linear feature of time-series. The resulting time-series can be used as a good template for identifying the type of activities a human subject is engaged in. However, depending on the activities, we cannot pinpoint the right IMF to characterize the type of activity. For example, brushing teeth contains significant component of high frequency activity and it is not noise. It constitutes one of important features. For this paper, we only used IMF's derived via EMD. We left out Instantaneous Frequency (IF) and Instantaneous Amplitude (IA,) which make the other half of HHT.

To address the problem with activity like brushing teeth, we need to use IF and IA plot. HHT can be used in a nested fashion. EMD can be applied to IF and IA plot, generating new IMF's for each, which can be used to address the problem, a topic our future research could explore.

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