EMD OVERSHOOT EFECT IN ERP DETECTION
ERP Detection related Specifics of the Empirical Mode Decomposition in EEG Analysis

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Abstract: Event related potentials (ERPs) are detected from continuous EEG. Most common method for ERPs detection is averaging. But this method is not suitable for single trial detection, because it requires lot of epochs. When we are performing attention experiments, it is required to detect ERPs ideally from single epoch. To detect ERP means determine its amplitude and latency. EEG signal is quasi-stationary therefore it is necessary to use signal processing methods designed for this task. We decided to use Hilbert-Huang transform. Its capabilities and problematic for ERP detection are discussed in the paper.

1 INTRODUCTION

Event Related Potentials (ERPs) play the main role in the Brain-Computer Interface, in the medicine and attention experiments. Our laboratory is focused on assessment of drivers attention. We cooperate with the University Hospital in Pilsen, Skoda Auto Inc., and Faculty of Transportation Science of Czech Technical University in Prague.

Our experiments are performed in the commercial simulation software Virtual Battlespace. Continuous EEG with stimuli marks is recorded during experiments. The marks provide information when each stimulus comes and where is ERP wave in the EEG signal. The short time period after stimulus is called epoch. The interval between stimulus and ERP wave is called latency, see (Luck, 2005; Sanei and Chambers, 2007).

For correct evaluation of our experiments results, it's fundamental to precisely determine amplitude and latency of ERP waves.

2 HILBERT-HUANG TRANSFORM

Hilbert-Huang transformation was designed to analyze data which are nonlinear and nonstationary. This method was proposed by Huang in (Huang and et al., 1998). It consists of empirical mode decomposition (EMD) and the Hilbert spectral analysis (HAS) methods, both of these methods were introduce by Huang et al.

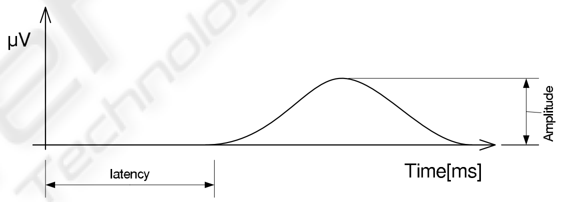

Figure 1: ERP wave is described by its latency and amplitude.

2.1 Intrinsic Mode Functions

An intrinsic function (IMF) is function which has to fulfill following two conditions:

1. In the whole data set, the number of extremes and the number of zero crossings must be either equal or differ by one at most.
2. The mean value of the envelope defined by the local maxima and the local minima is zero at any point (Liu, 2002; Huang and et al., 1998).

An IMF represents simple oscillatory mode as counterpart to a simple harmonic function, but it is much more general by its definition. The conditions which

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IMF fulfills are necessary for defining instantaneous frequency.

2.2 Empirical Mode Decomposition

The goal of the empirical mode decomposition is to decompose original data (signal) to the IMFs and the residue. The most of the data are not IMFs. At any time, the data may involve more than one oscillatory mode. That is why simple Hilbert transform cannot provide the full description of the frequency. The process of acquiring the IMFs is called sifting and it's described below (Qu and Wu, 2008; Huang and Attoh-Okine, 2005):

1. Initialize the residue to the original signal $r_0(t) = x(t)$ and IMF counter $i = 1$
2. Extract the i-th IMF:
3. Initialize $h_0(t) = r_{i-1}(t)$ and initialize step counter $k = 1$
4. Locate local maxima and minima in $h_{k-1}(t)$
5. Create upper envelope by connecting detected maxima with cubic spline
6. Create lower envelope by connecting detected minima with cubic spline
7. Calculate the mean $m_{k-1}(t)$ by averaging the upper and lower envelopes
8. Calculate $h_k(t) = h_{k-1}(t) - m_{k-1}(t)$
9. Check stopping criteria
10. If stopping criteria are satisfied then $IMF_i(t) = h_k(t)$
11. Else $k = k+1$ and continue with 4
12. New residue is $r_i(t) = r_{i-1}(t) - IMF_i(t)$
13. Check stopping criteria of EMD
14. If $r_i(t)$ has at least 2 extremes then $i = i+1$ and continue with 2
15. Else the decomposition is finished and $r_i(t)$ is the residue after decomposition

2.3 EMD Stopping Criteria

During EMD we want to retrieve IMFs described in chapter 2.1. These functions have to fulfill two conditions. The second condition (mean of the envelopes is meant to be zero) is very difficult to fulfill. As the points 4 to 9 of the EMD (from chapter 2.2) are repeated, the mean approaches to zero. But this makes amplitude variations of the individual waves more even. When we want to achieve strictly zero mean, we can assume that the amplitudes become constant and we lose very important information of the signal. So there were proposed two stoppage criterions. One original proposed in (Huang and et al., 1998) equation 1.

$$SD = \sum_{t=0}^{T} \frac{|h_{k-1}(t) - h_k(t)|^2}{h_{k-1}^2(t)} \tag{1}$$

Alternative for the first one is similar to Cauchy convergence test:

$$SD = \frac{\sum_{t=0}^{T} |h_{k-1}(t) - h_k(t)|^2}{\sum_{t=0}^{T} h_{k-1}^2(t)} \tag{2}$$

The sifting process will stop, when the SD is smaller than the selected threshold. The second stoppage criterion is based on the S-number which is defined as the number of consecutive sifting when the number of zero-crossings and extremes are equal or differs by one at most.

2.4 The Hilbert Spectrum

Hilbert transform (Mathworks, 2010; Marple, 1999) returns the analytic signal from real data sequence. The analytic signal $x = x_r + i \cdot x_i$ has its real part, x_r which represents the original data, and its imaginary partx_i, which contains the Hilbert transform. The imaginary part is a version of the original real sequence with a 90 phase shift. Sines are therefore transformed to cosines and vice versa. The Hilbert transformed series has the same amplitude and frequency content as the original real data and includes phase information that depends on the phase of the original data. The Hilbert transform is useful for calculating instantaneous attributes of time series, especially the amplitude and frequency. The instantaneous amplitude is the amplitude of the complex Hilbert transform; the instantaneous frequency expresses the rate of change of the instantaneous phase angle. In case of a pure sinusoid, the instantaneous amplitude and frequency are constant.

3 EMPIRICAL MODE DECOMPOSITION OF EEG

When the EMD is performed on the data series, we are trying to create upper and lower envelopes by connecting local extremes with cubic spline. Though, some difficulties surface in the process. When we want to create an envelope which covers whole signal, we have to realize that the first (last) extreme point is not present in the data at all. So, the closest extreme to the beginning or the end of the signal belongs to the upper or lower envelope. Then the second closest extreme is the point from where the both envelopes are defined.

So we have to add additional extreme points to extend the envelopes over the whole signal. But it is the tricky part. We have to position them very carefully, because their incorrect location leads to imprecise estimate of the cubic spline (2.). This overshoots or undershoots don't describe characteristics of the signal, but they could be propagated inward and corrupt the whole signal. The problem is described in detail in (Dătig and Schlurmann, 2004). To restrain this effect,

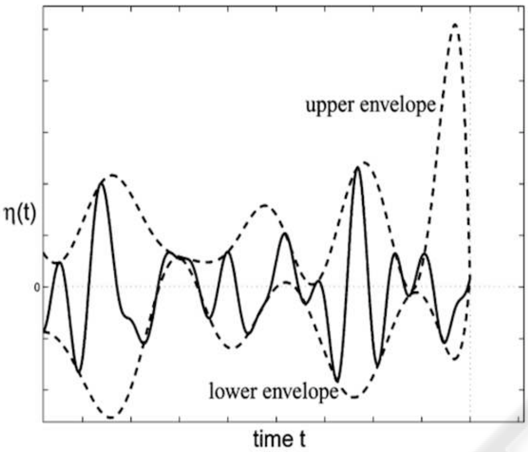

Figure 2: Example of overshoot from (Dătig and Schlurmann, 2004).

several methods of additional extreme selection were proposed. They are described in following chapters.

3.1 Mirror Method

Mirror method was proposed by Rilling and described in (Qu and Wu, 2008). The procedure is very simple. Additional extremes are mirror symmetric to the extremes that are closest to the beginning or end of the signal. The algorithm follows:

1. Locate the extreme closest to the begin of the signal (we found Max(1)). Then locate the extreme closest to Max(1), this is Min(1)
2. Create new extreme on the begin of the data by creating Min(0) respecting the mirror symmetry. $Min_x(0) = Max_x(1) - (Min_x(1) - Max_x(1))$, $Min_y(0) = Min_y(1)$

3.2 Slope based Method

Slope based method was proposed in (Dătig and Schlurmann, 2004) and described in (Qu and Wu, 2008). This method also extends extremes, but add one minimum and one maximum to the beginning or end of the signal. The new extremes are generated using two mathematically defined slopes created through the extremes. These slopes are derived from the distances between successive minima and maxima and from amplitude differences. In the first step we

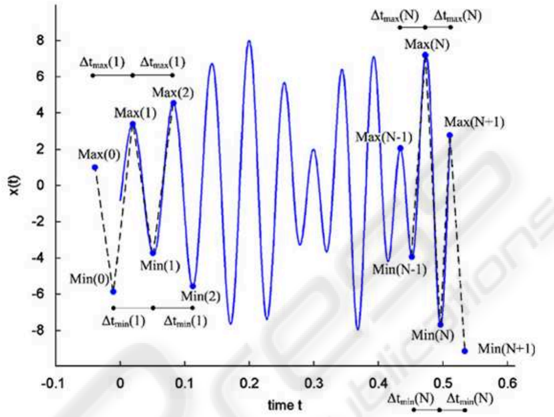

Figure 3: The illustration of the slope based method from (Qu and Wu, 2008).

have to calculate the slopes s1 and s2 for the signal x(t) shown on the figure 3. The slopes are defined as:

$$s_1 = \frac{Max_y(2) - Min_y(1)}{Max_x(2) - Min_x(1)} \tag{3}$$

$$s_2 = \frac{Min_y(1) - Max_y(1)}{Min_y(1) - Max_x(1)} \tag{4}$$

The x coordinates are defined as:

$$\Delta t_{\max}(1) = Max_x(2) - Max_x(1) \tag{5}$$

$$\Delta t_{\min}(1) = Min_x(2) - Min_x(1) \tag{6}$$

$$Max_x(0) = Max_x(1) - \Delta t_{\max}(1) \tag{7}$$

$$Min_x(0) = Min_x(1) - \Delta t_{\min}(1) \tag{8}$$

Then we have to calculate the Y values of new maxima and minimum:

$$Min_y(0) = Max_y(1) - s_2 \cdot (Max_x(1) - Min_x(0)) \tag{9}$$

$$Max_y(0) = Min_y(0) - s_2 \cdot (Min_x(0) - Max_x(0)) \tag{10}$$

This procedure has to be repeated in order to generate additional extremes at the end of the signal. See more in (Dătig and Schlurmann, 2004; Qu and Wu, 2008).

3.3 Problematic EEG Signal Processing by EMD

When we are performing EMD on the EEG signal, we want to create envelopes covering the signal completely. The mirror method and slope based method create additional extremes to ensure this condition. The weak point of these two methods is the estimate of additional extremes x-coordinates.

When edges of the processed signal contain time-short components of significantly higher frequency (in our case artifacts), the insufficiency of methods is apparent. So, the problem surfaces distinctively when we use artificial signals with randomly placed artifacts.

When we calculate a new extreme with mirror method we get a new minimum with x-coordinate:

$Min_x(0) = Max_x(1) - (Min_x(1) - Max_x(1)) = 13 - (15 - 13) = 11$

Index of a sample was used as the x-coordinate. The new minimum is at the position of the 11^{th} sample. Therefore we cannot create envelope covering all the data.

Similar problem appears when we use the slope based method to estimate x-coordinates of new extremes:

$Max_x(0) = Max_x(1) - \Delta t_{\max}(1) = Max_x(1) - (Max_x(2) - Max_x(1))$

$Max_x(0) = 13 - (16 - 13) = 10$

$Min_x(0) = Min_x(1) - \Delta t_{\min}(1) = Min_x(1) - (Min_x(2) - Min_x(1))$

$Min_x(0) = 15 - (19 - 15) = 11$

We also use the index of the sample as the x-coordinate. Newly estimated extremes have its x-coordinate before the beginning of the signal. So we cannot construct the proper envelope for the sifting process.

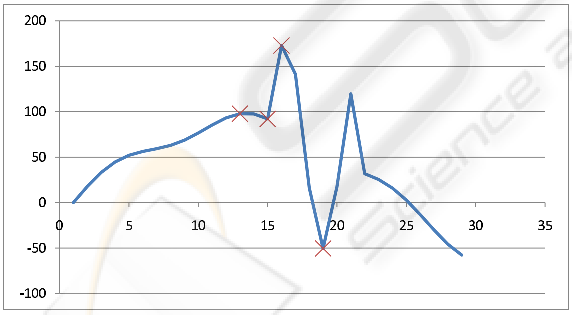

Figure 4: Detail of the EEsignal with artifact.

4 CONCLUSIONS

The Hilbert-Huang transform seems to be very promising method for analysis of quasi-stationary data series (signals). The HHT can offer very high time-frequency resolution which makes it perfectly suitable for our task (ERP detection when processing EEG). Also, we have to keep in mind that HHT is recently developed method and it has some issues which have to be solved before its application.

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