Suitability of Huang Hilbert Transformation for ERP detection

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***Abstract*— Event Related Potentials (ERPs) are gained from continuous EEG usually by averaging large amount of epochs or by Wavelet Transformation usually used for single trial ERPs detection. ERPs are very difficult to detect because of the very bad signal to noise ratio (SNR) which is 1:10 at best. Continuous EEG signal is considered as random noise in ERPs processing techniques. Also the signal is quasi-stationary. This fact is cause of more difficulties discussed in this paper. They include artefacts in EEG signal such as eye movement, blinks or heart beat.**

Basic idea of using Huang-Hilbert Transformation for ERPs detection is to decompose the EEG signal by Empirical Mode Decomposition (first phase of HHT) into Intrinsic Mode Functions (IMFs). They should correlate with artifacts, alpha waves, EKG or ERPS. Another challenge is to force HHT to handle the decomposition in the way we intend to. After successful decomposition it is simpler to remove noise and detect ERPs with their latencies and precise amplitudes.

I. INTRODUCTION

Event Related Potentials (ERPs) play the main role in Brain-Computer Interface (BCI) and in the medicine. In the medicine ERPs are usually used at ear examination. Also it is intended to utilize them for comatose conditions clasification or another cases.

A. Acquiring ERPs

II. EEG AND ERPS SIGNALS

EEG is abbreviation of electroencephalogram and it is a result of the neurophysiologic measurement of electrical activity emitted by the brain. The method is called electroencephalography.

A. Continuous EEG signals

EEG signal (Figure 1) is a time variation of potential difference between two electrodes placed on patients scalp surface. EEG signal is a weighted summation composed of signals produced by huge amount of neurons placed in parts of brain called cortex and thalamus. Intensity of the neuron groups electric activity depends on distance from the electrode. It means that further neurons contribute less to the EEG than neurons closer to the electrode. There is no way to separate single contribution of one neuron from another.

B. Interferece of the EEG signals

We can clasify inteference into two basic classes:

- artifacts
- surrounding electromagnetic field.

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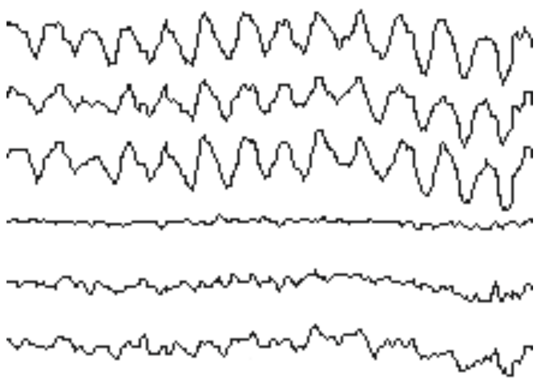

Fig. 1. Example of typical EEG signal filtered by low-pass filter 0-45Hz.

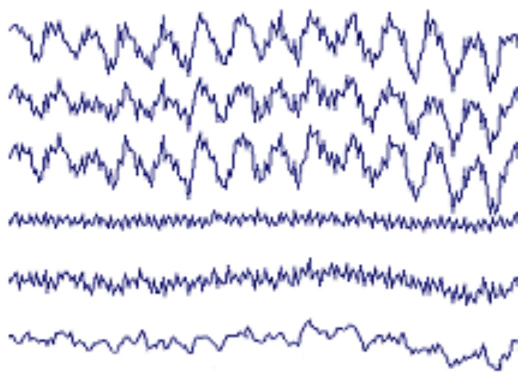

Fig. 2. Example of typical EEG signal interferenced by 50Hz from electrical grid.

1) Artifacts: Signals in the EEG of non-cerebral origin are called artifacts. The EEG is almost always contaminated with such signals. This is one of the reasons why it takes considerable experience to interpret EEGs clinically. The most common types of artifacts are:

- Eye artifacts (including eyeball, ocular muscles and eyelid)
- EKG artifacts (from heart)
- EMG artifacts (from muscles)
- Gloss kinetic artifacts

2) Surrounding Electromagnetic Field: In addition to internal artifacts there are many artifacts which originate outside the patient. Movement by the patient or even just settling the electrodes may cause electrode pops, spikes originating from a momentary change of an electrode impedance. Poor grounding of the EEG electrodes causes significant 50 or 60Hz artifact (as you can see in Figure 1 and Figure 2), depending on the local power system frequency. The third source of possible interference can be presence of an IV drip; such devices can cause rhythmic, fast, low-voltage bursts which may be confused for spikes.

C. Interference and Artifacts in ERPs

In ERPs detection the continuos EEG signal is considered to be random noise which should be removed. Averaging technique is usual for ERPs detection (see II-D). During the averaging process the EEG signal eliminates itself and the ERP signal remains. The technique brings several dificulties which have to dealt with.

First we have realized that strongest ERP called p3 or p300 (p means positive peak and the the figure 300 means that its latency is 300 ms from the stimulus, see more in [1]). It has amplitude up to $30\mu V$, but the amplitude of EEG signal is usually ten times greater. It means that the signal to noise ratio (SNR) is very low.

Because of low SNR we need to ensure that we have sufficient number of epochs acquired during exmination process. We have to keep in mind, that epochs affected by some artifacts can not to be included in the average. Amplitude of artifacts can reach $200\mu V$ or even more, their inclusion into the average hinders the ERP detection.

Finally that distortion of resulting ERP signal is caused by changing latency time of ERP during epochs. The averaging technique cannot localized the ERP in the original signal precisly and it cannot provide the information about exact amplitude value (see more in [4]).

D. ERPs detection techniques

There is several techniques of ERPs detection. Basic technique is averaging. We assume that each epoch (after stimuli) consists of ERP and random noise (EEG). Also we assume that the ERP is almost indentical in each epoch. On the other hand the noise is completely independent to time of the event. Averaging large amount of epochs without ERP should result in the flat line with zero microvolts. Thus when many epochs containing ERP and random noise are averaged, the noise is reduced but the ERP remains ([4]).

Other method of ERPs detection is the Discrete Wavelet Transform (DWT). This method could reveal ERP latency and it is usually used for single trial analysis. Other possible methods are the PCA or ICA, discused in [1].

All of these methosd have to be combined together with signal filtering and artifact rejection or removal[2]. Other difficulties originates from nonstationarity[1] of EEG signal. Thus we need segmentation methods and also we could detect false ERP signal for example from alfa waves[2].

After evaluation of all problems with EEG and ERP signals processing we intend to use Hilbert-Huang transform. It is designed to analyze the non-stationary data.

III. HUANG-HILBERT TRANSFORMATION

Hilbert-Huang transform (HHT) is the designated name for the result of empirical mode decomposition (EMD) and the Hilbert spectral analysis (HSA) methods. Both of them were introduced recently by Huang. They are useful specifically for analyzing the data from nonlinear and nonstationary processes. Data analysis is an indispensable step in the understanding of the physical processes. Traditionally, the dominating data analysis method is Fourier-based analysis[5].

A. Intrinsinc Mode Functions

An intrinsic function (IMF) is a function fulfilling following conditions:

1) in the whole data se, the number of extrema and the number of zero crossing must be either equal or differ by one at most,
2) at any point the mean value of the envelope defined by the local maxima and the the local minima is zero[6].

B. Empirical Mode Decomposition

The purpose of Empirical Mode Decomposition(EMD) is to find IMFs in the data. 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 data has to be decomposed into IMF.

The procedure of EMD is very simple and has few steps[6] It is called "sifting":

1) Identify the extrema (both minima and maxima) of the data X(t).
2) Generate the envelope by connecting maxima and minima points with a cubic spline
3) Determine the local mean, m_1 by averaging the envelopes
4) Since IMF should have zero local mean, substract the mean from the data like in equation 1.

$$X(t) - m_1 = h_1 \tag{1}$$

5) h_1 is probably not an IMF; repeat until it is
6) End up with the IMF, a standard deviation[6] computed from the two consecutive sifting results could be the stopping criteria:

$$SD = \sum_{t=0}^{T} \left[\frac{\left| \left(h_{l(k-1)}(t) - h_{lk}(t) \right) \right|^2}{h_{l(k-1)}^2(t)} \right] \leq 0.3 \tag{2}$$

Now we have found one IMF $c_1 = h_{1k}$. Now we have to find the rest of them:

1) Generate the residue, r_1, of the data by subtracting out c_1 like in equation 3

$$X(t) - c_1 = r_1. \tag{3}$$

2) The residue now contains information about longer period.
3) Start the sifting process with residue.
4) Repeat step one and two until all necessary IMF are acquired (residue is close to zero)

C. Hilbert transform

Hilbert transform[7] returns the analytic signal from real data sequence. The analytic signal $x = x_r + i * x_i$ has a real part, x_r, which is the original data, and an imaginary part, x_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 is the time rate of change of the instantaneous phase angle. For a pure sinusoid, the instantaneous amplitude and frequency are constant.

1) Hilbert transform algorithm: The analytic signal for a sequence x has a one-sided Fourier transform, that is, negative frequencies are 0. To approximate the analytic signal, the hilbert method calculates the FFT of the input sequence, replaces those FFT coefficients corresponding to negative frequencies with zeros, and calculates the inverse FFT of the result.

In detail, hilbert uses a four-step algorithm:

1) It calculates the FFT of the input sequence, storing the result in a vector x.
2) It creates a vector h with following values:
   - 1 for i = 1, (n/2)+1
   - 2 for i = 2, 3, ... , (n/2)
   - 0 for i = (n/2)+2, ... , n
3) It calculates the element-wise product of x and h.
4) It calculates the inverse FFT of the sequence obtained in step 3 and returns the first n elements of the result.

IV. Huang-Hilbert transformation and ERPs

There are items about HHT that has to be tested before we can decide whether it is suitable for ERPs detection. These items esentials for ERPs detection are:

- IMFs correlation with signal components,
- sensitivity to SNR,
- sensitivity to artifacts in the signal.

With real data recorded in some experiment it isn't possible to test at any point, because in real data we can't recognize signal components correctly. The HHT will be tested with artificial generated signal. This signal will be the worst case we can imagine for ERPs detection techniques.

A. EEG signal modeling

We use simple modeling technique for the testing of HHT. The generated signal compoments will be sine waves mostly. To generate valid signal we use more than three components:

1) alpha wave,
2) noise from power grid,
3) some artifacts (random high peaks),
4) and of course ERP (small peak).

During generating signal we have to keep in mind the SNR, which should change it during experiments.

1) Modeling Alpha Waves Rythm: When we are modeling Alpha Waves we will need two sine waves. The frequency of Alpha Waves is 8-13Hz. They make spindles and they can be clearly spotted in the recording, when the patient has his eyes closed. The wave is generated according to the formula 4:

$$\alpha(t) = A_{\alpha 1} sin(10 \cdot t) + A_{\alpha 2} sin(12 \cdot t) \quad (4)$$

The examples of the artificialy generated Alpha waves are in figure 3.

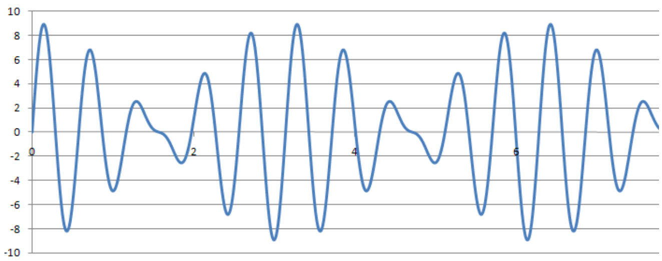

Fig. 3. Artificialy generated Alpha Waves according to formula 4, where amplitudes are $A_{\alpha 1} = 5\mu V$ and $A_{\alpha 2} = 4\mu V$.

2) Modeling Artifacts and Noise: Artifacts can be modeled as peaks with high amplitude randomly superimposed to the signal. Its amplotude is ten times higher than normal EEG signal. Shape of the artifact is not relevant, because it could have any possible shape.

The basic noise from the power grid is easy to generate. All over the Europe it is 50Hz almost sine wave. We assume that its amplitude is about $1\mu V$. The exact amplitude depends on conditions of the laboratory and on the recording device as well.

When we put all this together, the resulting EEG signal looks like the one in figure 4.

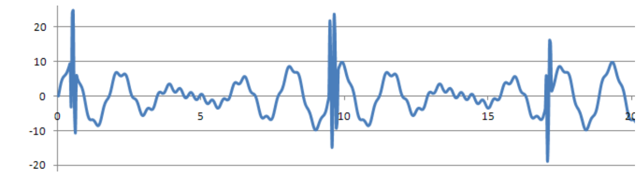

Fig. 4. Artificialy generated EEG signal containing Alpha wave spindles, 50Hz noise, Artifacts and ERP peak(invisible in the time domain).

B. Empirical Mode Decomposition of EEG

Few weak points of this approach appeared during the testing process of EMD. First there are disortions near the begin and end points of the signal. They are also described in [6]. The disortion is not big deal for us, because we almost always know the aproximal position of the ERP peak. We can avoid these disortions by including large segment of the processed signal around ERP peak.

The second weak point is another story. The cubic spline fitting is very intensive and it is only one part of HHT. There are also some time consuming operations like FFT in the next phase of Hilbert transform. Thus it is dificult to use it for online ERPs detection.

Because of distortion caused by artifacts and other noise, the IMFs doesn't corelate with original signal components. On the other hand this approach can be also used for artifact detection and removal. The sifting process stopping criterion in formula 2 isn't suitable for ERPs detection. Usualy ERPs, which have very low SNR(usualy lower than 0.1) are lost in the residuum after EMD and can't be recognized and transformed in the next phase of HHT. And its time consumption is very high, because we do not acquire the signal sooner than after the sifting process is complete.

Hilbert transformation isn't discused in this paper, beacuse of weak points of the method described above. These weak points make the Hilbert transformation meaningless for now.

V. CONCLUSION

Hilbert-Huang transform brings new approach to signal processing, its capability doesn't lie in exact way how to use it, but in the way how to think about processing nonstationary signals, such as EEG. In this paper we demonstrate that processing of EEG and ERPs. HHT is efficient in EEG processing, but for detection ERPs it isn't suitable in the way how it was used in my work.

A. FUTURE WORK

There is a great amount of posibilities how to deal with weak points of EMD use it finaly for ERP detection. It works pretty well in artifacts detection, beacause of their high amplitude. So one way how to use HHT could be in artifacts and artifacts removal, which could be also essential and very helpfull in ERPs detection.

The Second way is to fix these weak points, use alternate stopping criterion and extend conditions for IMFs detection. Extended criterions for IMFs could be for example corellation with signal and others. Stopping criterion should be also changed according to the chosed criterions for IMFs.

Third way means to use some preprocessing methods, such as signal filtering and artifacts removal techniques. When we succeed in upgrading EMD, we will try some other methods than Hilbert transform. Matching-pursuit or wavelet transform seems to be useful in this way.

There is a lot of work to be done and finally we will be able to use this method for ERPs detection.

VI. ACKNOWLEDGMENTS

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