Information Fusion Analysis in Time-Frequency Domain of Brain Responses Dynamics to Affective Stimuli

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***Abstract*—An approach to estimate brain responses to emotional or generally affective stimuli is presented. Functional electroencephalography (fEEG) and functional near-infrared spectroscopy (fNIRS) signals are first preprocessed to remove muscle and peripheral body activity physiological noise with utilization of an extension of empirical mode decomposition (EMD) spectral clustering approach, which utilizes simultaneously recorded biosignals as references. The so preprocessed signals are further analyzed with quick signal change detection based on dynamical systems recurrence analysis technique. As a result we obtain clear signature estimates of subjects cognition state changes from fEEG and fNIRS in response to the presented emotional/affective stimuli.**

I. Introduction

The notion of brain affective or emotional empathy responses utilization in brain-computer interfaces creates a very interesting alternative to contemporary human-computer interfacing technologies. A new and growing in interest paradigm of emotional stimuli utilizing affective human brain regions responses is presented together with a new signal processing approach in time-frequency domain. Estimation of emotional responses from electrophysiological and cortical blood oxygenation signals has recently gained attention among the designers of brain computer/machine interfaces (BCI/BMI). Several results on the estimation of basic emotional responses generated while watching short videos with dynamic emotional contents; listening to emotionally charged speech or music will is discussed together with novel multichannel fEEG and fNIRS analysis approaches to discover representative components of the emotional responses. Already established neuroscience tools such as functional electroencephalography (fEEG) and functional near infrared spectroscopy (fNIRS) correlate conscious and affective experiences with electromagnetic field activity and oxygenation changes mostly in frontal cortical areas of the brain. Also peripheral body measurements such as skin conductance, heart-rate, breath rythm and pulse variability, as well facial muscle and eye-movement signals also correlate to emotional arousal [1], [2]. These physiological measures provide an objective way to explore the realm of perception, experience, mind and emotional processes visualize in real-time from human subjects exposed to emotional stimuli. Recent advances in brain-computer/machine-interfacing (BCI/BMI) reveal also a need to search for new and more challenging paradigms which would allow more natural interaction of humans and machines with utilization of so revealed new communication channels [3].

There are recognized two general classes of BMI paradigms, those which are related to external environment stimuli and utilizing stimuli-driven/interactive brain responses and the other which are completely independent from environmental stimulation and relay only on internal (passive or imaginary) brain activity managed by the users will. The second class of imaginary paradigms is usually more difficult for the non-trained subjects since they require learned brain activity patterns to be captured by non-invasive brain activity methods such us fEEG and fNIRS. In this paper we focus on the first class of dependent and stimuli driven affective (emotional) paradigms. The aim of the presented research is to seek for new paradigms and mostly neurophysiological responses from human brain which could be utilized for BCI/BMI. Presented results show that peripheral electrophysiological and physiological in general signals can be utilized as references to remove noise, while proposed quick signal detection approach can identify human cognitive pattern changes in fEEG and fNIRS.

II. Methods

For experiments presented in the paper a combined fEEG, fNIRS and peripheral electrophysiological signals recording was conducted at the Advanced Signal Processing Laboratory of the RIKEN Brain Science Institute, Wakoshi, Japan using two synchronized g.USBamp biosignal data acquisition systems with 16 fEEG electrodes placed over frontal, temporal and parietal lobes; two channels of vertical and horizontal EOG; a single EKG channel; and pulse. Additionally two frontal fNIRS channels were recorded synchronously with NIRO-200 cerebral oxygenation recorder. An example of such multimodal recording is shown in Figure 1. The subjects were given audio-only and video-only presentations of affective displays from the emotional utterances corpus [4] as portrayed by five British English professional actors. Both the video

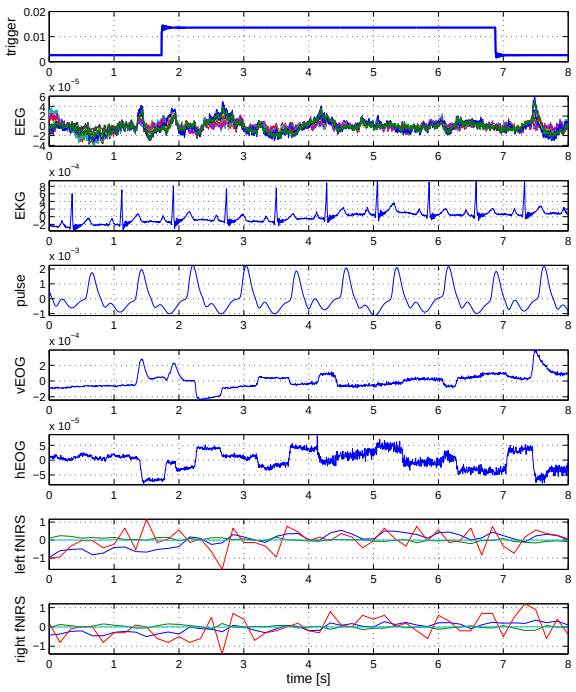

Fig. 1. Multimodal bio-signals recorded from subject's body surface. The top panel presents stimulus onset and offset times. The second from the top panel presents 16 fEEG channels plotted together, while next two panels depict EKG and pulse oximetry time series. Two following panels labeled vEOG and hEOG visualize vertical and horizontal eye movements respectively. The two bottom panels depict left and right frontal cortices fNIRS recordings. All measures presented in this figure were recorded synchronously with g.USBamp and NIRO-200 devices connected to a single workstation running Matlab.

and audio presentations portrayed affective expressions of six basic emotions. The video-only presentations involved short (2-5 seconds long) movies; the audio-only involved short (2-5 seconds long) sentences. After attaching the monitoring electrodes, the subjects were instructed to look at a white cross mark on the computer screen and to try not to blink or move in order to minimize muscular noise. The main goal of the experiment was a search for interactive responses captured within neurophysiological and peripheral electrophysiological signals carrying very short emotional empathy signatures. A concept of empathy is characterized as a capability to share ones feelings and understand another's emotion and feelings and it was shown previously by the authors that empathy response could be recognized and classified from the fEEG responses only [2].

The multimodal fEEG, fNIRS, EOG, EKG and pulse signals (see Figure 1) have to be first preconditioned due to their different sampling frequencies and dynamics. In order to obtain common coherent interactive responses carrying empathy responses an approach as in [5] is utilized, which first decomposes all signals with utilization of empirical mode decomposition (EMD) and later it clusters the similar components in Huang-Hilbert spectral domain. This method allows to identify those components within each channel which expose spectral patterns similar across all data channels as well synchronized with onsets and offsets of the stimuli as shown in the top panel of Figure 1.

The preprocessed multimodal neurophysiological and peripheral electrophysiological signals carrying only components exposing synchrony with the emotional stimuli presented to the subjects can be now analyzed for signatures allowing detection of modality changes as further discussed in quick signal change detection section.

A. Multimodal signals preprocessing with EMD

EMD utilizes empirical knowledge of oscillations intrinsic to a signal in order to represent them as a superposition of components, called *intrinsic mode functions* (IMF), with well defined instantaneous frequencies. To obtain an IMF from a single channel EEG, it is necessary to remove firs local riding waves (abrupt changes in time frequency representation) and asymmetries, which are estimated from local envelopes of minima and maxima of the waveform. The technique of finding IMFs corresponds thus to the separation of band limited semi-orthogonal components from recorded EEG. It also corresponds to eliminating riding-waves from the signal, which ensures that the instantaneous frequency will have no fluctuations caused by an asymmetric wave form. In each cycle, the IMF is defined by zero crossings and involves only one mode of oscillation, thus not allowing complex riding waves. Notice that an IMF is not limited to be a narrow-band signal, as it would be in the classic Fourier or wavelets decompositions. In fact, an IMF can be both amplitude and frequency modulated simultaneously, as well as non-stationary or non-linear.

The EMD decomposes a signal in hand into a number of IMFs [6] (oscillatory modes); which satisfy the following two conditions:

(i) the number of extrema and the number of zero crossings are either equal or differ at most by one;
(ii) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Since IMF represents an oscillatory mode within a signal; its periods, which are defined by zero crossings, correspond to the only *one* mode of oscillation. Both the amplitude and frequency of this oscillation may vary over time, in other words, the oscillation is not necessarily stationary nor narrow-band.

The process of extracting an IMF from a signal $x(t)$ is called "the sifting process" [6] and consists of the following steps:

(i) determine the local maxima and minima of $x(t)$;
(ii) generate the upper and lower signal envelope by connecting those local maxima and minima respectively by an interpolation method (e.g., linear, spline, piece-wise spline [6], [7]) (in this paper the linear method was chosen);
(iii) determine the local mean $m_1(t)$, by averaging the upper and lower signal envelope;

(iv) subtract the local mean from the data: $h_1(t) = x(t) - m_1(t)$.

Ideally, $h_1(t)$ satisfies the criterion of an IMF, however, typically this procedure needs to be repeated until the first IMF is extracted. In order to obtain the second IMF we applied the sifting process to the residual $\varepsilon_1(t) = x(t) - \text{IMF}_1(t)$, obtained by subtracting the first IMF from $x(t)$; the third IMF is in turn extracted from the residue $\varepsilon_2(t)$ and so on. The decomposition is complete when two consecutive sifting results are similar; the empirical mode decomposition of the signal $x(t)$ may be written as:

$$x(t) = \sum_{k=1}^{n} \text{IMF}_k(t) + \varepsilon_n(t), \tag{1}$$

where n is the number of extracted IMFs, and the final residue $\varepsilon_n(t)$ is either the mean trend or a constant. Note that the IMFs are not guaranteed to be mutually orthogonal, but often are close to orthogonal; it is also noteworthy that IMFs are adaptive, that is, two independent realizations of a signal with the same statistics may have a different number of IMFs.

B. Spectral clustering of time-frequency components

In order to compare all IMFs extracted from the analyzed multimodal channels we propose to cast them separately to Hilbert spectra domain in order to capture the detailed content (intrinsic frequency tracks) carried by all of them. The amplitude and phase ridge traces of all IMFs (note that adaptive nature of EMD may result in different numbers of IMFs in each channel) are combined together and correlated.

From the IMFs the corresponding time–frequency representations can be produced by applying the Hilbert transform to each component [6], time-frequency representation:

$$R(t) = \sum_{k=1}^{n} \text{IMF}_k(t) \exp\left(\text{i} \int \omega_k(t) dt\right), \tag{2}$$

ω_j denotes an instantaneous frequency. The Hilbert transform allows us to observe the variable amplitude and the instantaneous frequency in a form of very sharp and localized functions of frequency and time (in contrast to Fourier expansion, for example, where frequencies and amplitudes are fixed for their bases). Such an approach is very suitable for the analysis of non-stationary signals and modeling of common/sychronized activities within certain channels. In the presented approach fEEG and fNIRS signals were cleaned/denoised with utilization references from vEOG, hEOG, EKG and pulseoximetry signals (see Figure 1 for reference).

Using the above procedure in a single channel mode, the physiological signals from chosen modalities could be decomposed separately, thus forming subsets of IMFs, from which low frequency drifts and high frequency spikes can be removed. To analyze multimodal signal sets recorded synchronously in a single experiment we propose to decompose all channels separately preventing possible information leakage among the channels.

For this end, Hilbert domain amplitude and frequency traces as "a distance measure" in order to capture spectral similarity across the IMFs. Once the cross–correlation analysis is performed for all Hilbert transformed IMFs from all analyzed channels, a hierarchical cluster analysis using a set of dissimilarities for the n objects to be clustered is performed [8] (using "R" package [9]) for amplitude and frequency ridges separately. Initially, each vector representing amplitude or frequency ridges values is assigned to its own cluster and then the algorithm proceeds iteratively, at each stage joining the two most similar clusters. Such procedure continues until there is just a single cluster. At each stage distances between clusters are recomputed by the Lance–Williams dissimilarity update formula with a single linkage clustering method. This method is closely related to the minimal spanning tree concept and it adopts a "friends of friends" strategy for clustering [8].

A result of such procedure in the frequency domain is the sets of clusters are obtained. The first set is for distances defines a relatively compact cluster of similar components across the EEG channels. Those components are classified as similar and originating from very strong EOG interference. The respective IMF amplitude traces in phase and amplitude domain are being discarded. Those remaining are further analyzed for signal change onsets and offsets with statistical tests described as follows. The details of the application can be found in [10], [5].

C. Quick signal change detection with support of recurrence approach applied to multimodal recordings

Quick detection methods allow for detecting of abrupt changes in the behavior of observed time series [11], [12]. Quick detection refers to real-time detection of such changes using a framework of optimal stopping theory. In case of multimodal physiological signals it is very difficult to define priors or search for quantities that would have to involve averaging over the change-point distributions. To avoid such problems the non-Bayesian quick detection methods are being incorporated. To this end the analysis of EMD-preprocessed multimodal physiological signals is presented in form of recurrence plots [13], [9] as in Figures 2, 3, and 5.

The change in recording statistics between calibration signals (non-stimuli, background brain activity) and new data presenting stimuli EEG is obvious to observe after the time point 60 in the figures (the original sampling of time series from Figure 1 were unified to make different sampling frequencies of fEEG and fNIRS compatible). The recurrence quantification analysis is a part of fractal correlation dimension approaches since the sets of parameters used are practically the same [11].

Figures 2, 3, and 5 confirm the hypothesis of possibility to detect signal modality changes during affective stimuli responses captured in multimodal recordings.

III. CONCLUSIONS

The presented multimodal response patterns analysis approach (during the affective stimuli presentation compared to the pre-stimulus) has shown a possibility to utilize data-driven

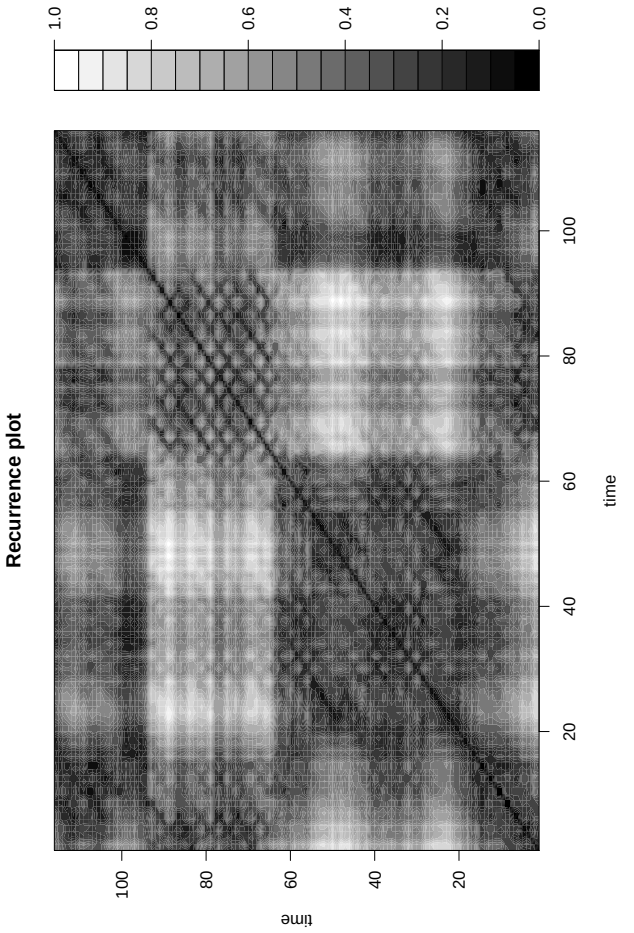

Fig. 2. Recurrence plot of $C3$ EEG electrode dynamics (*pre-stimulus fEEG* $<$ 60 samples and *stimulus fEEG* $>$ 60 samples). Graph created with [14].

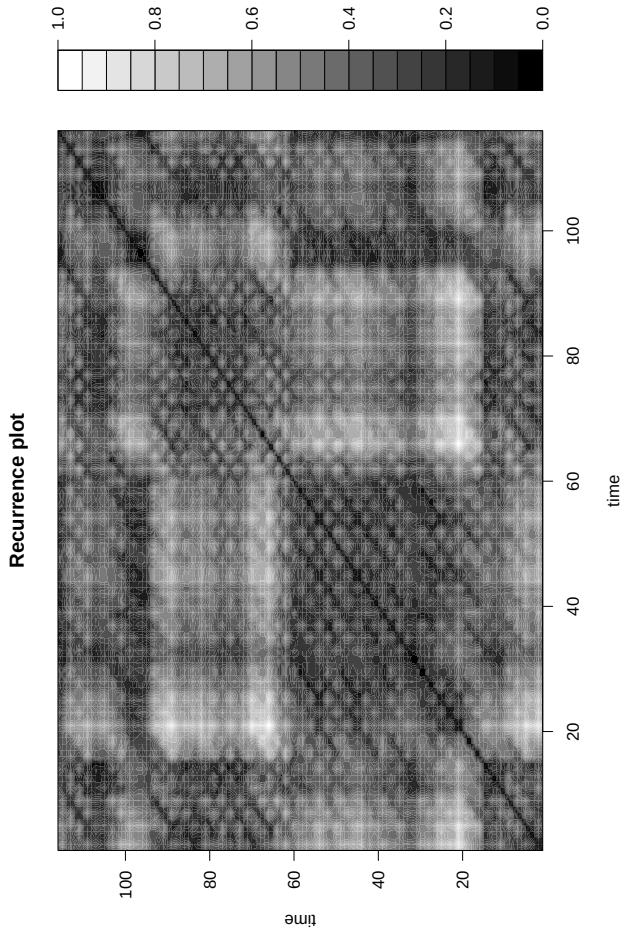

Fig. 3. Recurrence plot of $C4$ EEG electrode dynamics (*pre-stimulus fEEG* $<$ 60 samples and *stimulus fEEG* $>$ 60 samples). Graph created with [14].

preprocessing approach (EMD and Hunang-Hilbert spectral analysis) in combination with statistical dynamics analysis of fEEG and fNIRS signals. The remaining bio-signals (EKG, EOG, pulse oximetry) were utilized as references to remove noise in preprocessing step thus not interfering with a BCI/BMI approach based on brain-responses-only analysis.

We have shown that interactive empathy responses to affective/emotional stimuli in auditory and visual domains are good candidates for the utilization in applications such as BCI/BMI since it was possible to discriminate the response patterns from neurophysiological signals (fEEG and fNIRS) together with periphery electrophysiological ones (EKG, EOG, pulse) used as noise removal references.

A framework to separate interfering muscle activity (EOG in this paper) from multimodal physiological signals has been also presented. This has been achieved by proposing a novel decomposition technique, which allows a flexible sub-band signal decomposition while preserving the nonlinear and non-stationary features of the signals which is very crucial for brain activity analysis. The so obtained components from each multimodal channel processed separately have been further transformed to the Hilbert domain and compared within amplitude and phase domains using the clustering technique in order to identify those similar (spectrally correlated) across channels.

The resulting reconstruction has allowed us to separate common non-brain related interferences from underlying brain activity in the data-driven signal processing approach without information leakage between channels. The proposed approach was tested in several experimental sessions in a multiple subjects confirming the presented here results.

This is a step forward in EEG signal processing applications which could be useful primarily for creating user friendly brain-computer/machine-interfaces that would be less susceptible to common interferences resulting from human body activity.

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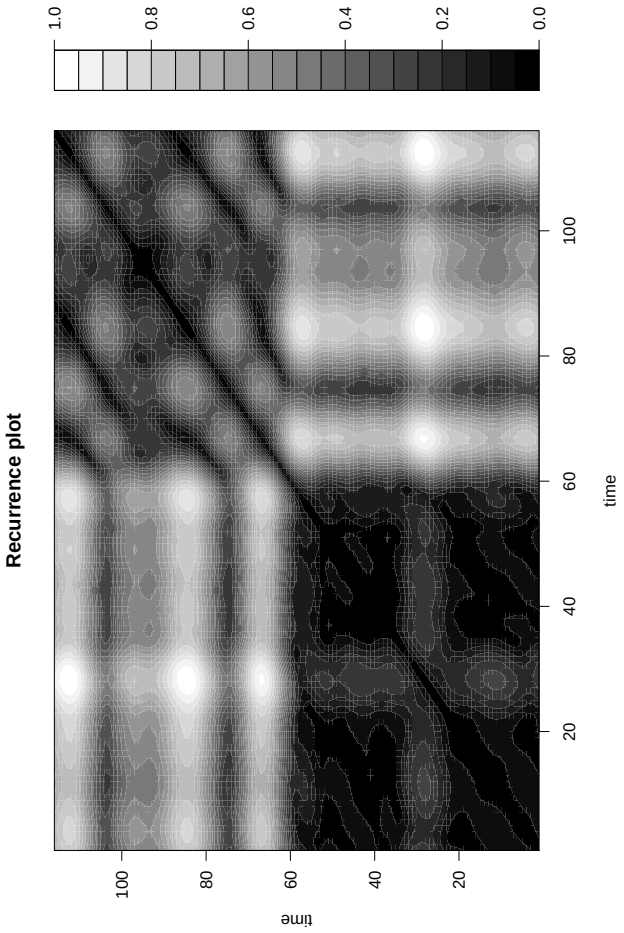

Fig. 4. Recurrence plot of fNIRS blood oxygenated hemoglobin dynamics for frontal right forehead (*pre-stimulus fNIRS* $<$ 60 samples and *stimulus fNIRS* $>$ 60 samples). Graph created with [14].

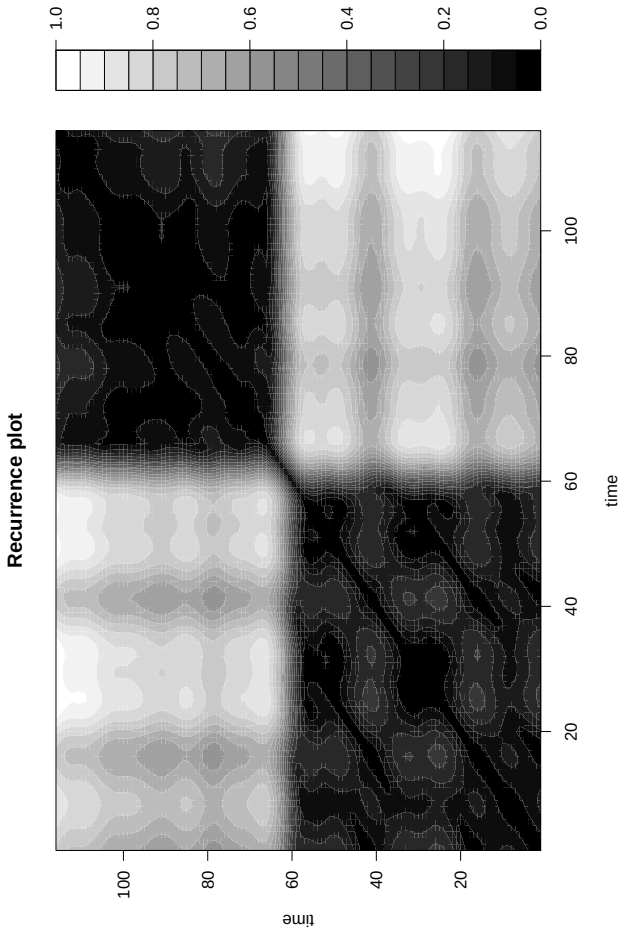

Fig. 5. Recurrence plot of fNIRS blood oxygenated hemoglobin dynamics for frontal left forehead (*pre-stimulus fNIRS* $<$ 60 samples and *stimulus fNIRS* $>$ 60 samples). Graph created with [14].

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