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Emotional empathy transition patterns from human brain responses in interactive communication situations

Brain–computer and machine interactive interfacing approach

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Abstract The paper reports our research aiming at utilization of human interactive communication modeling principles in application to a novel interaction paradigm designed for brain–computer/machine-interfacing (BCI/BMI) technologies as well as for socially aware intelligent environments or communication support systems. Automatic procedures for human affective responses or emotional states estimation are still a hot topic of contemporary research. We propose to utilize human brain and bodily physiological responses for affective/emotional as well as communicative interactivity estimation, which potentially could be used in the future for human–machine/environment interaction design. As a test platform for such an intelligent human–machine communication application, an emotional stimuli paradigm was chosen to evaluate brain responses to various affective stimuli in an emotional empathy mode. Videos with moving faces expressing various emotional displays as well as speech stimuli with similarly emotionally articulated sentences are presented to the subjects in order to further analyze different affective responses. From information processing point of view, several challenges with multimodal signal conditioning and stimuli dynamic response extraction in time frequency domain are addressed. Emotions play an important role in human daily life and human-to-human communication. This is why involvement of affective stimuli principles to human–machine communication or machine-mediated communication with utilization of multichannel neurophysiological and periphery physiological signals monitoring techniques, allowing real-time subjective brain responses evaluation, is discussed. We present our preliminary results and discuss potential applications of brain/body affective responses estimation for future interactive/smart environments.

Keywords Emotional stages from brain responses estimation · Communication with emotional stages evaluation · Socially aware intelligent environments design · Brain–computer or machine interfacing paradigms

1 Introduction

Human factor in design of contemporary interactive communication systems as well as socially aware environments plays an important role in a design process as discussed by Rutkowski et al. (2007), Rutkowski and Mandic (2008). A concept of communication supportive environments receives broad support from the users who usually require

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them to follow human communication principles resulting from a long evolution (Adler and Rodman 2003). Human brains are somehow pre-wired genetically so children are able to learn how to communicate easily. Those who lose their communication skills due to brain stokes, tragic accidents, or neurological diseases hope for smart supporting technologies/prostheses that would bypass such disabilities enabling natural and interactive communication with their environments (Cichocki et al. 2008; Pfurtscheller et al. 2008; McFarland and Wolpaw 2008). Already established neuroscience tools such as electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) correlate conscious and affective experiences with electromagnetic field activity and oxygenation changes localized in cortical areas of the human brain. Additional peripheral body measurements such as skin conductance, heart rate, breath and pulse variability, as well facial muscle and eye-movement characteristics also correlate to emotional arousal (Rutkowski et al. 2007, 2008). These physically based measures provide an objective way to explore the realm of perception, experience, mind and emotional processes estimate in real-time from human subjects exposed to emotional stimuli, which could be results of social interaction with other humans or socially aware environments. Various multimodal stimuli presented in a form of mythology, stories, and media through the use of imagination, movies, music, and sounds influence usually the mind to evoke a wide range of emotions of which response could be further utilized in social communicative situation, or captured, analyzed, and further classified in neuroscientific studies (Rutkowski et al. 2007, 2008, 2010). Contemporary media such as video games provide a highly interactive platform to test how users interact with the environment based upon their unique experiences and anatomical structure of prefrontal cortices. With hooks into the realm of the mind as well as the realm of the body, interactive multimedia combined with neuro- or biofeedback provide a unique platform for conducting objective investigations into the mind–body and mind–environment relationships, which in connection with interactive communication (Rutkowski et al. 2007; Rutkowski and Mandic 2008) paradigms can be further utilized in design of brain–machine-interfacing technologies as well socially aware interactive environments. 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 (Cichocki et al. 2008; Rutkowski et al. 2008). There are recognized two general classes of BMI paradigms, those that are related to external environment stimuli and utilizing stimuli-driven brain responses and others that are completely independent from environmental stimulation and relay only on an internal (imagery) brain activity managed by the users' will. The second class of imagery paradigms is usually more difficult for non-trained subjects (Guger et al. 2009), since they require learned brain activity patterns to be captured by non-invasive brain activity methods such us EEG and fNIRS. In this paper, we focus on the first class of dependent and stimuli-driven paradigms with an interactivity concept involved, so they could be considered as test platforms for affective or emotional influence on human subjects.

2 Communicative interactivity background

Rutkowski et al. (2007) proposed a novel concept of communicative interactivity evaluation from natural conversations in audiovisual streams. The concept was based on previously proposed analysis of communication atmosphere as discussed by Rutkowski and Mandic (2007) and further summarized by Rutkowski and Mandic (2008) where a presence of interactive communication was judged based on mutual information(s) between visual and audio features (MFCC in audio and DCT in visual modalities, respectively) for selected regions of interest (ROI) (Hyvarinen et al. 2001), as

$$\begin{aligned} I_{A_iV_i} &= H(A_i) + H(V_i) - H(A_i, V_i) \\ &= \frac{1}{2}\log(2\pi e)^n |R_{A_i}| + \frac{1}{2}\log(2\pi e)^m |R_{V_i}| \\ &\quad - \frac{1}{2}\log(2\pi e)^{n+m} |R_{A_iV_i}| \\ &= \frac{1}{2}\log\frac{|R_{A_i}||R_{V_i}|}{|R_{A_iV_i}|}, \end{aligned} \tag{1}$$

where $i = 1, 2$ and $R_{A_i}, R_{V_i}, R_{A_iV_i}$ stand for empirical estimates of the corresponding covariance matrices of the feature vectors (Rutkowski et al. 2003) (computed recursively).

Simultaneous activity estimates in the same modes (audio and video, respectively) were estimated for video audio streams as:

$$I_{V_1V_2} = \frac{1}{2}\log\frac{|R_{V_1}||R_{V_2}|}{|R_{V_1V_2}|} \tag{2}$$

and, analogously, for audio streams:

$$I_{A_1A_2} = \frac{1}{2}\log\frac{|R_{A_1}||R_{A_2}|}{|R_{A_1A_2}|}, \tag{3}$$

where $R_{A_1A_2}$ and $R_{V_1V_2}$ are the empirical estimates of the corresponding covariance matrices for unimodal feature representing different communicators activities. Quantities $I_{A_1V_1}$ and $I_{A_2V_2}$ evaluate the local synchronicity between the audio (speech) and visual (mostly facial movements) flows, and it is expected that the sender should exhibit the higher synchronicity, as presented in Figs. 2 and 3 where only

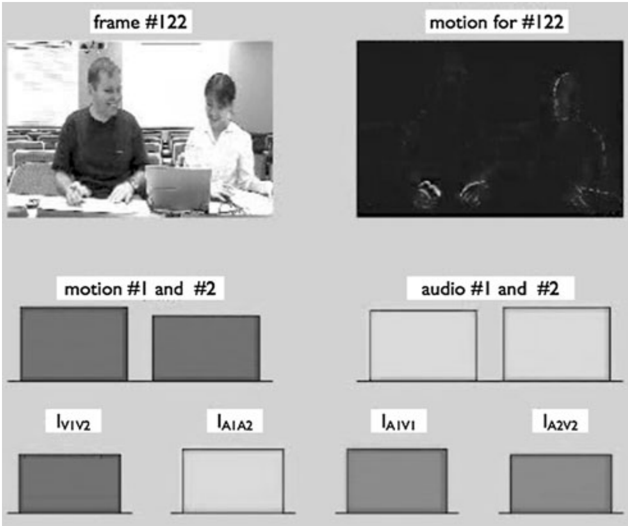


Fig. 1 Example of communicative interactivity analysis with both communicators being active at the same time causing similar amount of visual and auditory features levels, which result in similar levels of mutual information estimates $I_{A_1V_1}, I_{A_2V_2}, I_{V_1V_2}$ and $I_{A_1A_2}$

single from interacting communicators exposed higher audiovisual synchrony $I_{A_1V_1}$ or $I_{A_2V_2}$, respectively. Quantities $I_{V_1V_2}$ and $I_{A_1A_2}$ were related to the possible cross talks in same modalities (audio–audio, video–video), reflecting the higher activity as presented in the form of bar-plots under captured videos in Figs. 1 and 4 where both interacting communicators exposed (overlapped) similar audiovisual activities resulting in lower communicative efficiency evaluation as it was introduced by Rutkowski and Mandic (2008). Communicative interactivity evaluation allowed the author to assess the behavior of the participants in the communication from the audio–visual channel and reflected their ability to "properly" interact in the course of conversation. This allowed us to quantify a synchronization and interaction of face-to-face communicative events.

3 Extension of communicative interactivity model to brain–machine-interaction design

We propose to extend communicative interactivity approach presented in Sect. 2 to brain (human) computer (machine) interfacing paradigms of which contemporary applications are presented by Cichocki et al. (2008), Schlögl and Brunner (2008), Pfurtscheller et al. (2008), McFarland and Wolpaw (2008), Lécuyer et al. (2008). We postulate to apply face-to-face communicative interactivity principles to study human brain responses during an interaction with affective stimuli presented in visual and auditory domains. The aim of the research is to detect possible changes in brain response patterns in a course of

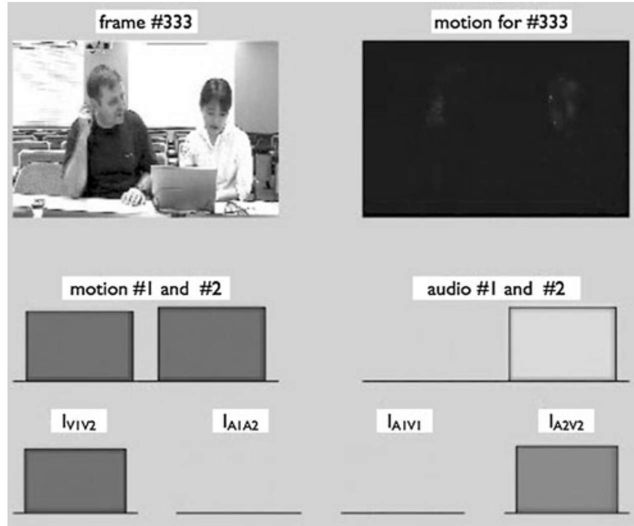


Fig. 2 Example of communicative interactivity analysis with both communicators being active in visual domain (similar levels of extracted motions) but only communicator #2 being more active in auditory domain (talking), resulting in higher level of $I_{V_2A_2}$ mutual estimate (thus classified as "a sender")

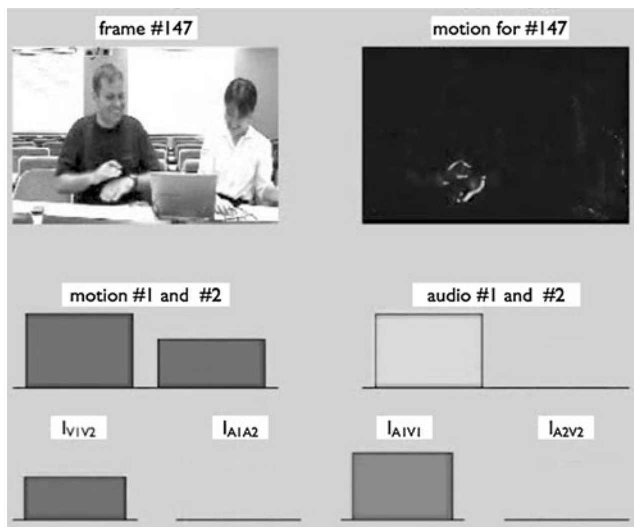


Fig. 3 Example of communicative interactivity analysis with both communicators being active in visual domain (similar levels of extracted motions) but only communicator #1 being more active in auditory domain (talking) resulting in higher level of $I_{V_1A_1}$ mutual estimate (thus classified as "a sender")

stimuli presentation to the subjects. For this purpose, multimodal brain and body peripheral measurements are taken as described in the following sections.

3.1 Methods of brain and body electrophysiological as well as oxygenation activity monitoring

Combined EEG, fNIRS, and peripheral electrophysiological signals recording experiments were conducted at the

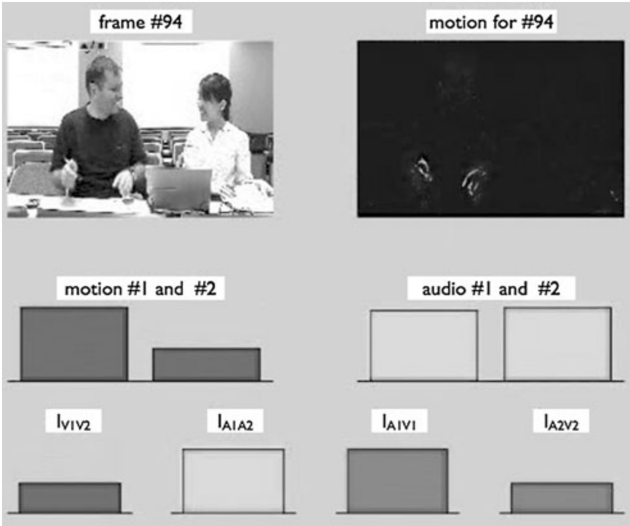


Fig. 4 Example of communicative interactivity analysis with similar outcome as the one presented in Fig. 1 with only different distribution of mutual information estimates $I_{A_1V_1}, I_{A_2V_2}, I_{V_1V_2}$ and $I_{A_1A_2}$, due to different communication event dynamics

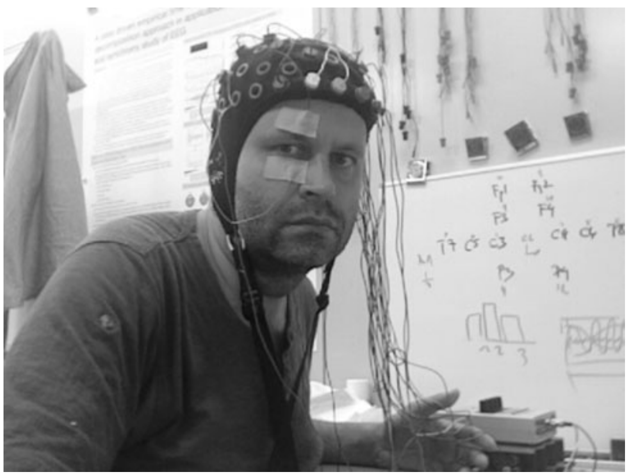


Fig. 5 A subject with EEG and peripheral electrophysiology electrodes setup. In this figure, EEG cap with passive electrodes is presented together with vertical EOG (vEOG) electrodes attached around subject's right eye

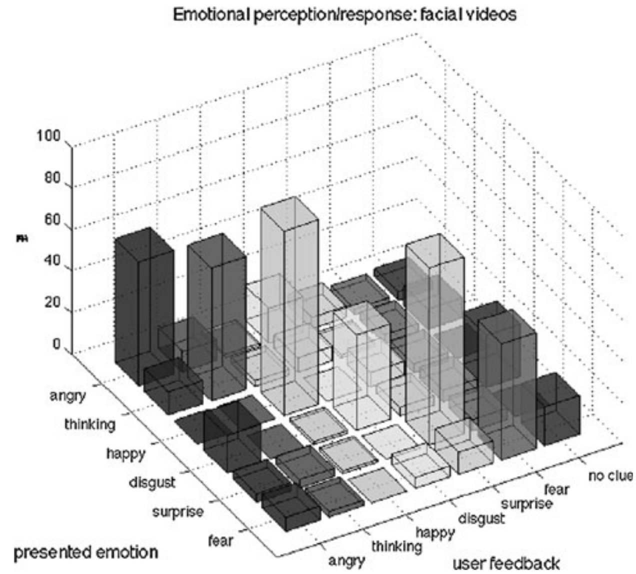


Fig. 6 Mean subject's responses of subjects to presented affective video faces stimuli, confirming subjects' recognition

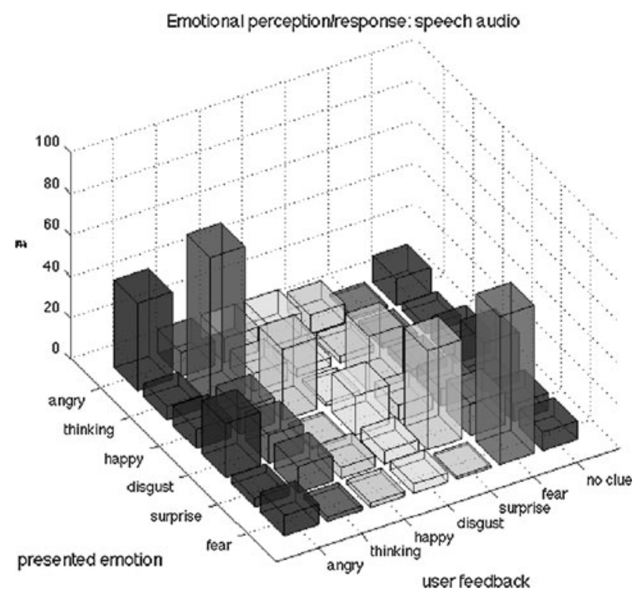


Fig. 7 Mean subject's responses of subjects to presented affective speech stimuli, confirming subjects' recognition

Advanced Signal Processing Laboratory of the RIKEN Brain Science Institute, Wakoshi, Japan, using two synchronized g.USBamp biosignal data acquisition systems with 16 EEG electrodes placed over frontal, temporal, and parietal lobes; two channels of vertical and horizontal eye movements tracing electrooculography (EOG); a single electrocardiography (ECG) channel to monitor heart rate variability; and pulse. Additionally, two frontal functional near-infrared spectroscopy (fNIRS) channels were recorded synchronously with NIRO-200 cerebral oxygenation recorder. An example of such multimodal recording is shown in Fig. 8, where a subject with electrodes placed on his head is depicted, as well as in Fig. 5, where captured neuro- and electrophysiological signals are visualized. Details of brain and body monitoring methods are explained below.

Electroencephalography (EEG) is a recording of bioelectrical activity along the scalp produced by the firing of neurons within the brain. In practical applications, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time from multiple electrodes placed on the scalp and attached to a cap with fixed positions (see Fig. 5). EEG reflects

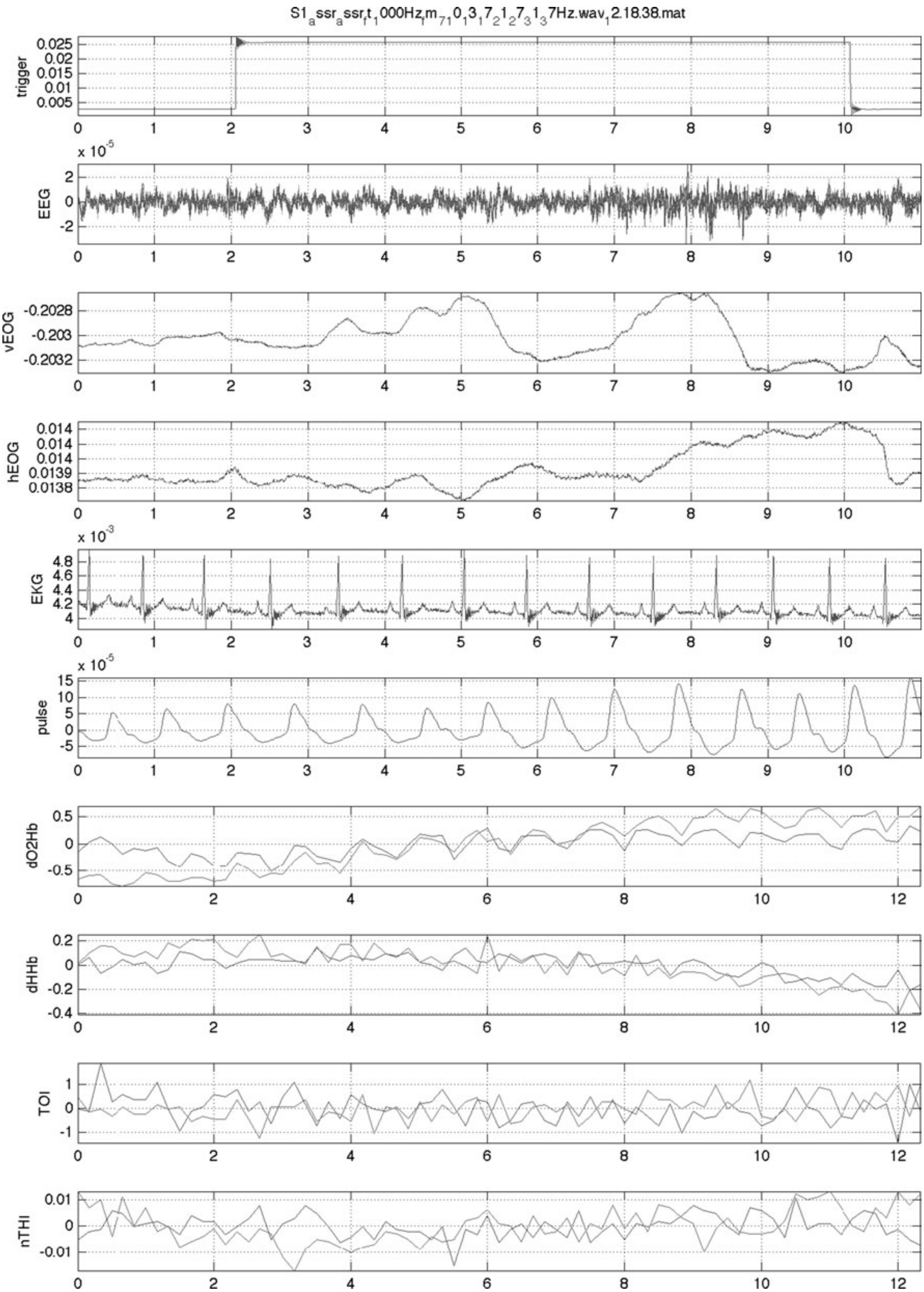


Fig. 8 Example of multimodal bio-signals recorded from a single subject's body surface. The *top panel* presents stimulus onset and offset times. The *second* from the *top panel* presents 16 EEG channels plotted together, while *next two panels* depict ECG and pulse-oximetry time series. *Two following 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

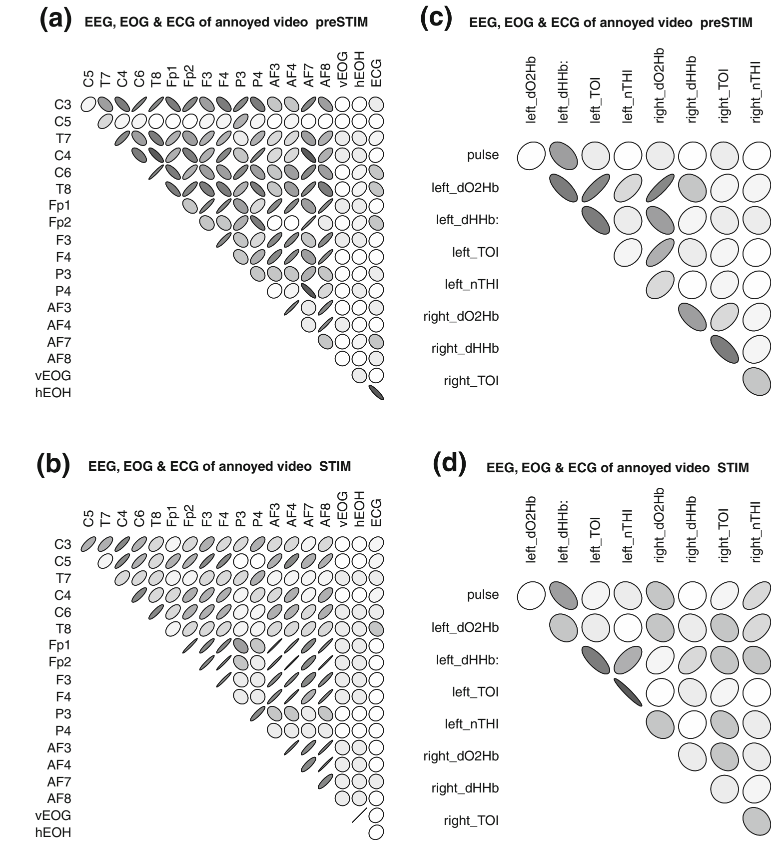


Fig. 9 Annoyed (angry) affective video stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

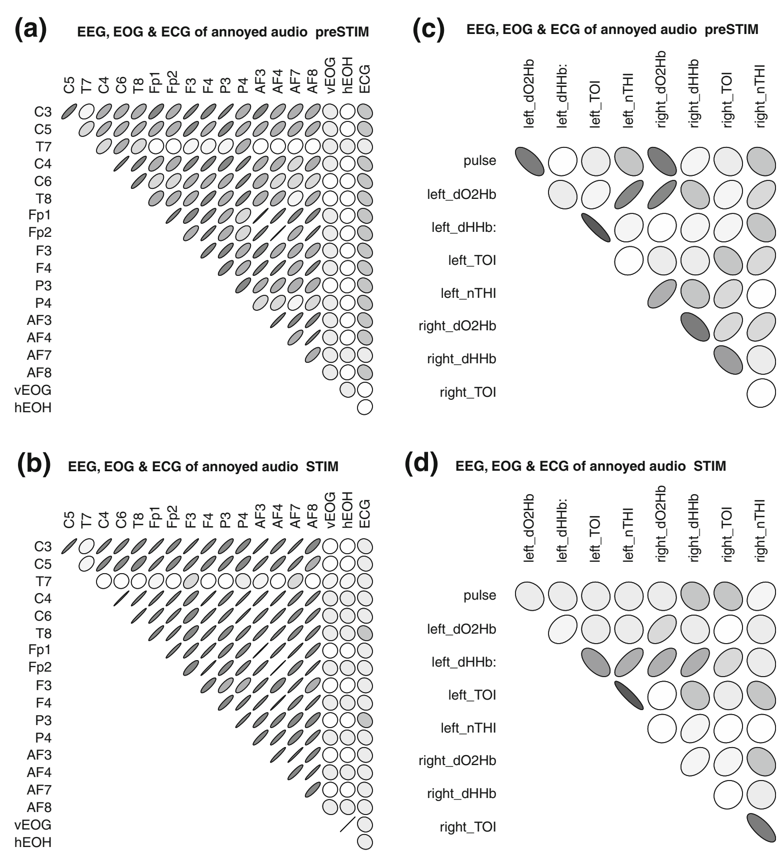


Fig. 10 Annoyed (angry) affective audio stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

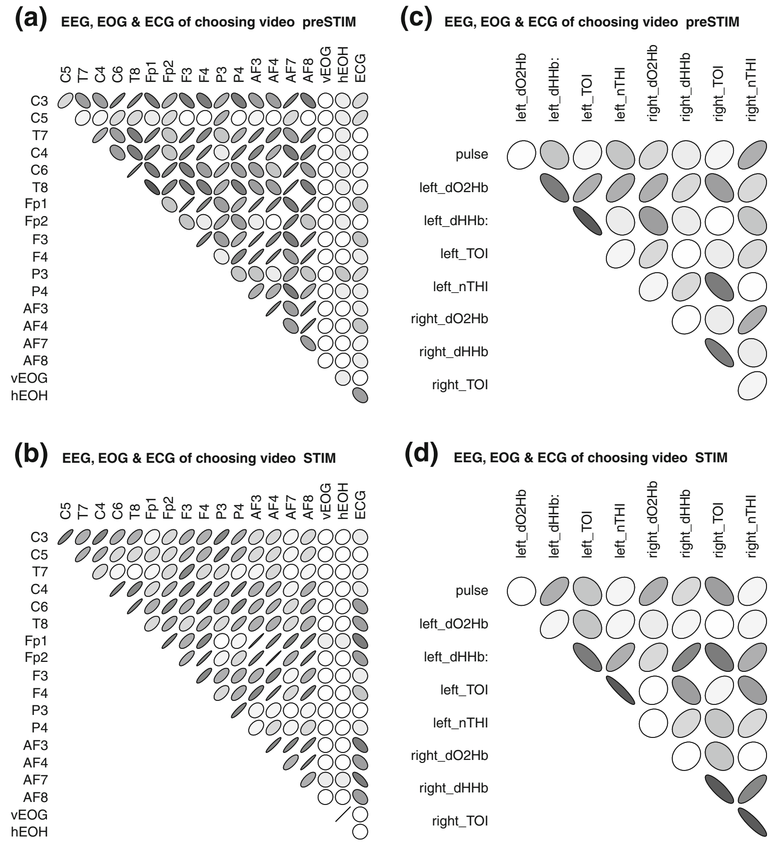


Fig. 11 Choosing (thinking) affective video stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

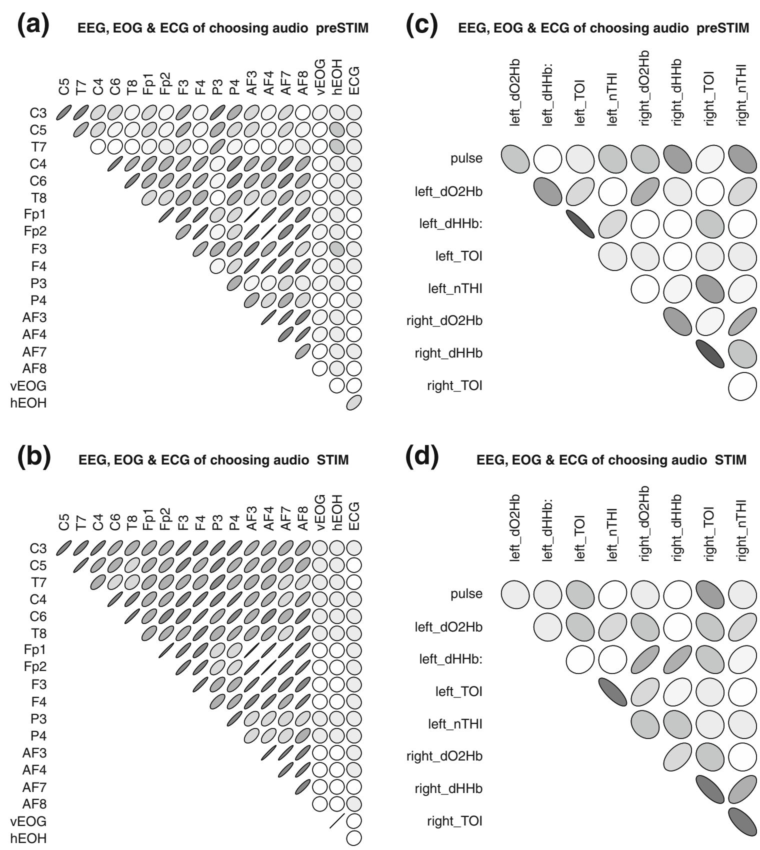


Fig. 12 Choosing (thinking) affective audio stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

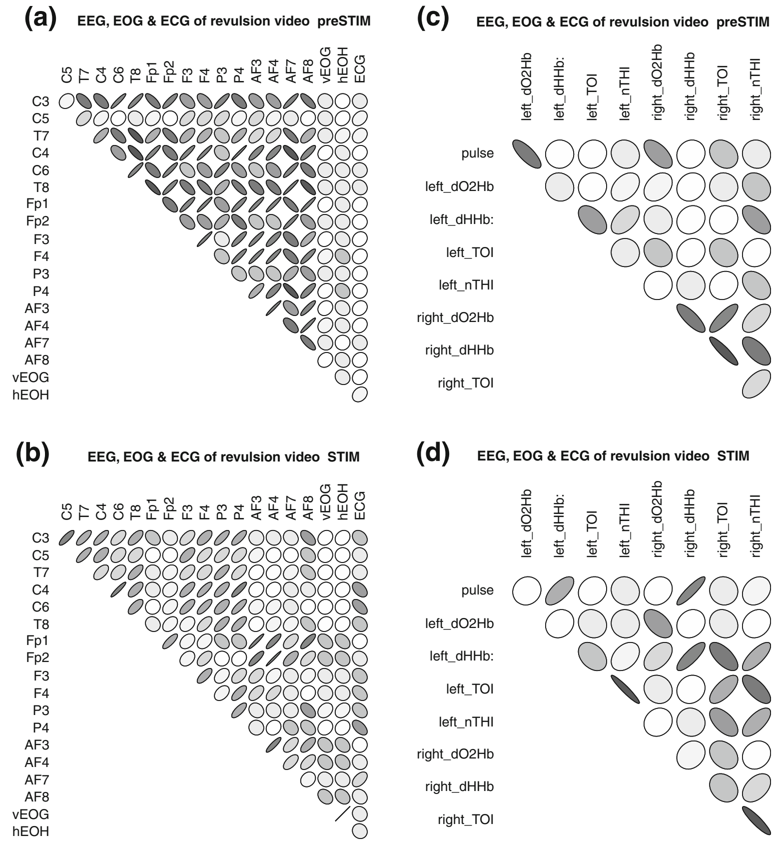


Fig. 13 Revulsion (disgust) affective video stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

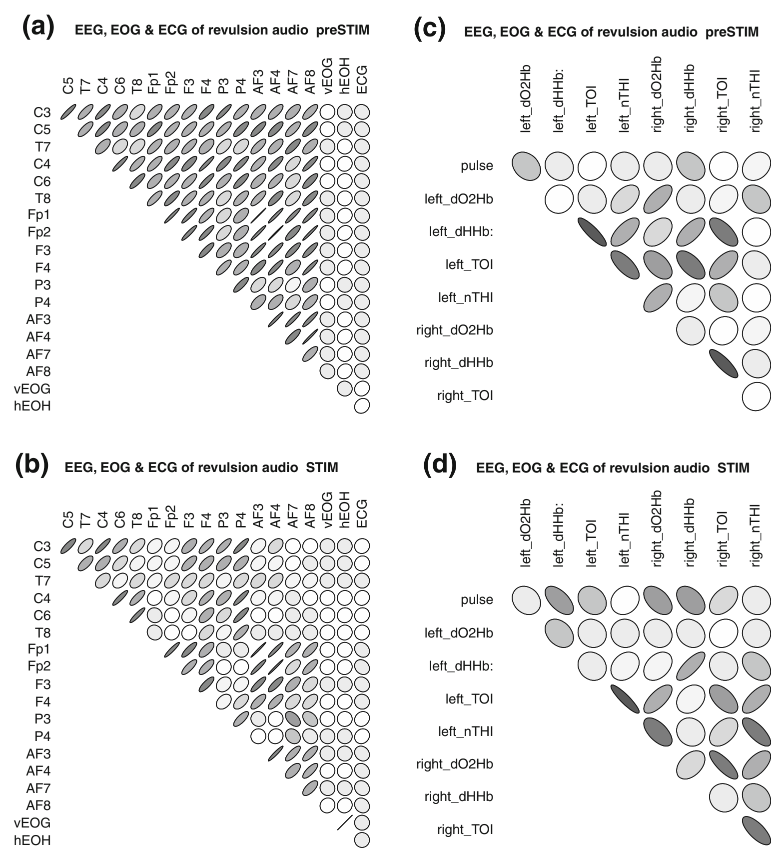


Fig. 14 Revulsion (disgust) affective audio stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

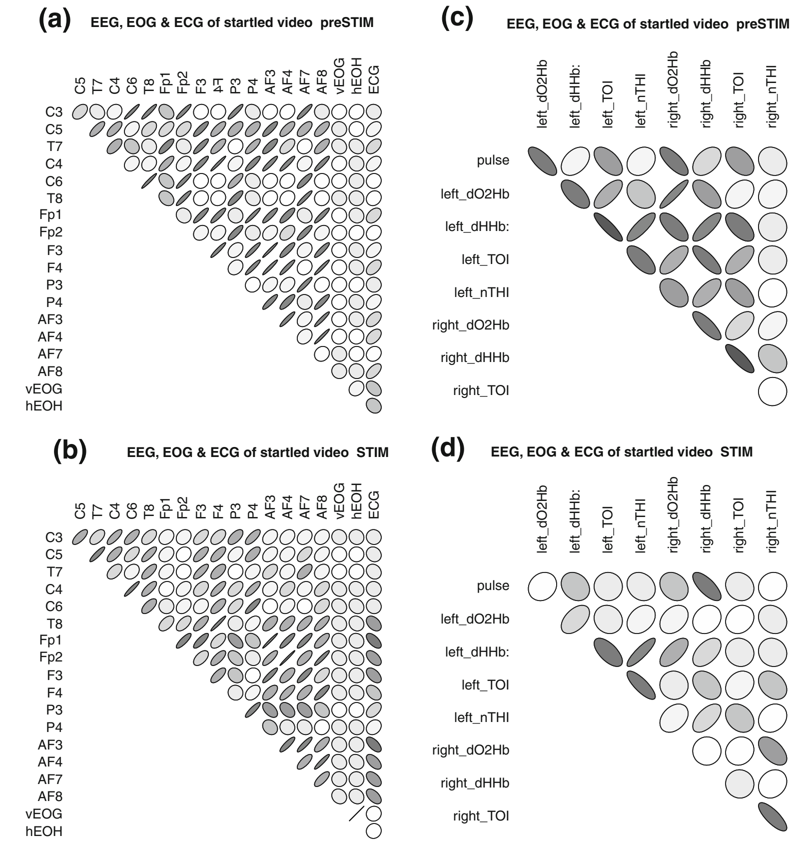


Fig. 15 Startled (surprise) affective video stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

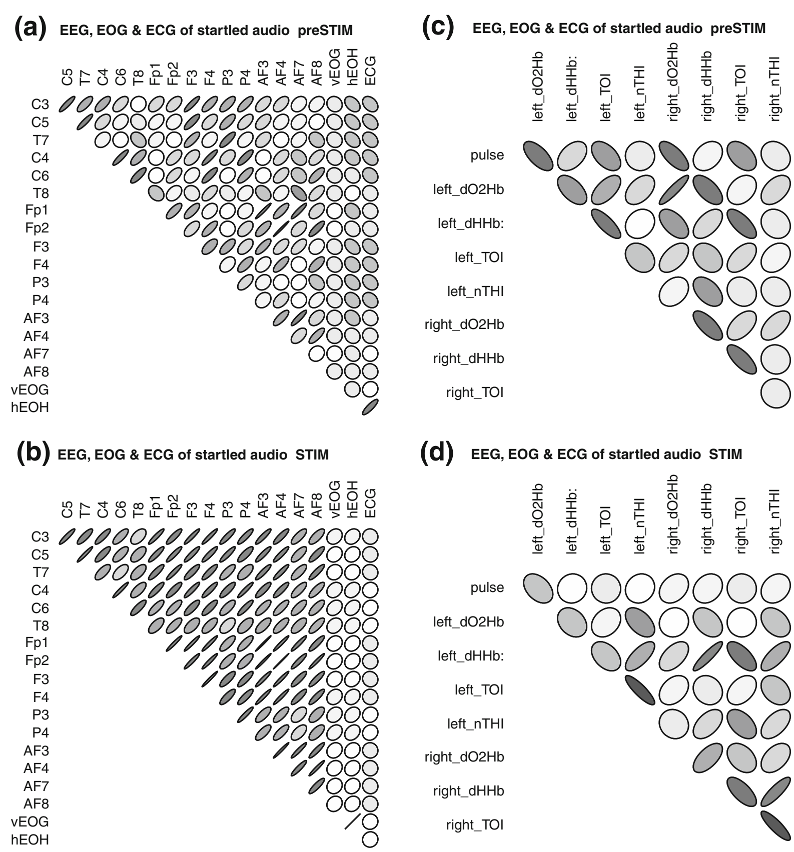


Fig. 16 Startled (surprise) affective audio stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

correlated synaptic activity resulting from post-synaptic potentials of cortical neurons. However, the electric potentials generated by single neurons are far too small to be represented within the EEG; therefore, the recorded activity always reflects a summation of the synchronized thousands or millions of neurons that have similar spatial orientation which is radial to the scalp. The EEG technique therefore benefits from the parallel, radial arrangement of apical dendrites in the cortex. Additionally, problem of the method is a voltage field falling off with the fourth power of a radius, causing an activity from deep sources to be more difficult to detect than currents near the skull of cortical areas (Niedermeyer and Da Silva 2004). To the main advantages of the technique belongs low cost and very good temporal resolution of which the latter is perfectly suited for analysis of very fast affective/emotional responses. Functional EEG technique refers to utilization of electric brain potentials topographic features differences localizations in brain regions covered by scalp electrodes resulting in temporal EEG activation maps.

Functional near-infrared spectroscopy (fNIRS) is a spectroscopic method that uses the near-infrared region of the electromagnetic spectrum for a non-invasive measurement of the amount and oxygen content of hemoglobin. Functional NIRS is recently used for non-invasive assessment of brain function through the intact skull by detecting changes in blood hemoglobin concentrations associated with neural activity. fNIRS is a very compact and cost-effective technique, compared to fMRI, but similar to EEG, it can only be used to scan cortical tissue due to limited depth of infrared penetration. To the main advantages of the technique belong low cost and no need for any subject preparation.

Electrooculography (EOG) is a technique for measuring the resting potential of a retina for recording of eye movements; thus, EOG does not represent a response to individual visual stimuli. Usually, pairs of electrodes are placed either above and below the eye (vertical EOG) or to the left and right of the eye (horizontal EOG). When the eye is moved from the center position toward one electrode, a positive or negative potential difference occurs between the two electrodes. Assuming that a resting potential is constant, the recorded potential is a measure for the eye position, allowing monitoring of subjects visual focus of attention.

Electrocardiography (ECG) is a measurement of electrical activity in the heart using electrodes placed on the skin of the limbs and chest (limbs only in case of this paper). It allows to analyze the overall rhythm of the heart variability analysis caused by various affective/emotional stimuli.

Pulse-oximetry is a non-invasive method allowing monitoring of oxygenation of a patient's hemoglobin in peripheral blood vessels (finger tip in presented case), resulting in a good peripheral pulse rhythm modulations estimate caused by affective/emotional stimuli.

4 Affective stimuli interaction experiments

The five subjects in our experiment were given audio-only and video-only presentations of affective displays from the emotional utterances corpus, designed by Baron-Cohen (2004), as portrayed by five British English professional actors. Both the video and the audio presentations portrayed affective expressions of six basic emotions. The video-only presentations involved short (3–7 s long) movies; the audio-only involved short (3–7 s long) sentences. Those stimuli were chosen to emulate natural "emotionally charged" communicative situations, which are very common in daily life situations (Adler and Rodman 2003). Subjects were seated in front of a table with a computer display and speakers from which video and audio stimuli were presented, respectively. After attaching the monitoring electrodes (see Fig. 5), 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 in electrophysiological signals. Such little not natural situation and lack of possibility to "bodily interact" with emotional stimuli was created in order to search for "pre-movement" or "movement-planning" related responses that in central- or peripheral nervous system system are generated in human body. We should keep in mind that target and potential artificial intelligence application for smart interactive/communicative environments would be designed primarily for locked-in patients who are not able to interact with usage of their peripheral nervous and muscular systems. The subjects were also instructed to answer a question on the screen after the audio or visual presentation which emotion did they perceive. The purpose of these questions was to focus subject's attention on the task and to give them a period of relaxation time, as well to check validation of chosen emotional responses. Results of subject's responses are presented in Figs. 6 and 7. 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 that characterize subjects emotional involvement in a simulated communication process. A concept of empathy is characterized as a capability to share one's feelings and understand another's emotion or feelings. It was shown

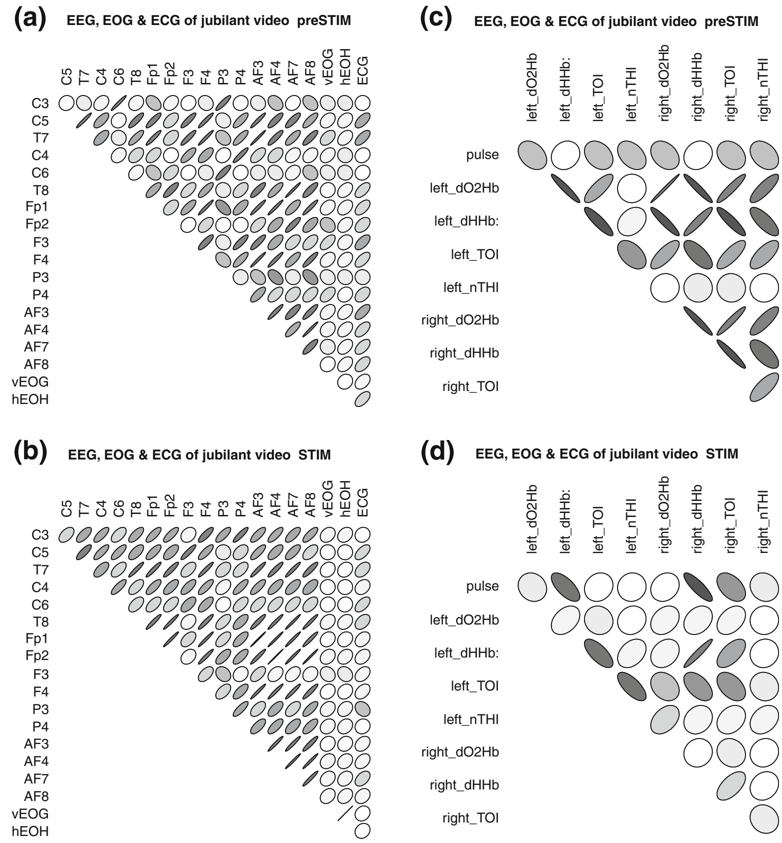


Fig. 17 Jubilant (happy) affective video stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

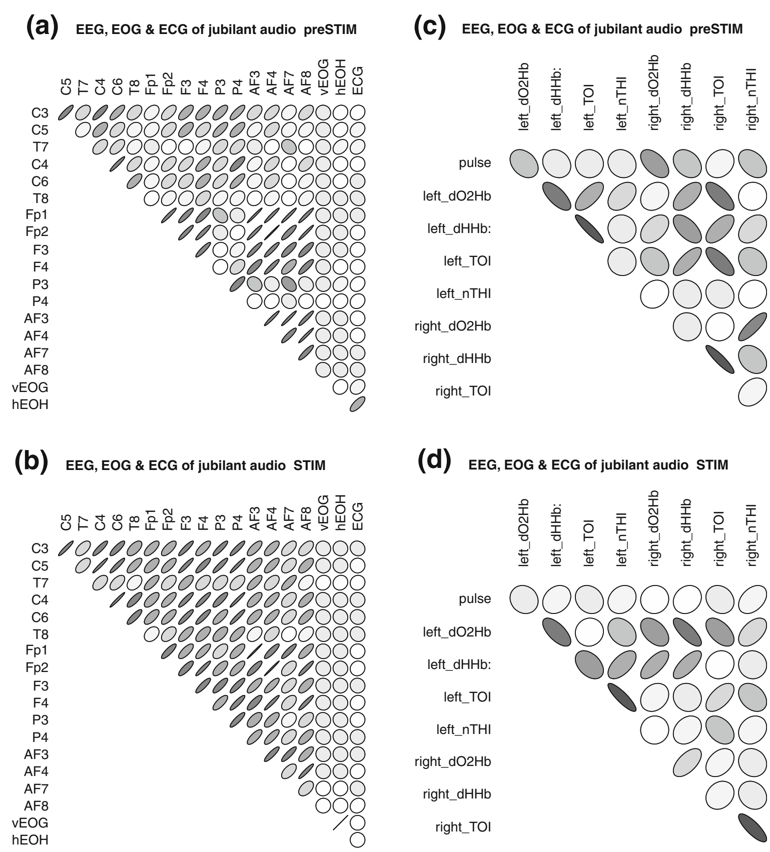


Fig. 18 Jubilant (happy) affective audio stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

previously by Rutkowski et al. (2008) that empathy response could be recognized and classified from the EEG responses only. The multimodal EEG, fNIRS, EOG, ECG, and pulse signals (see Fig. 8) 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 described by Rutkowski et al. (2009) 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 us to identify those components within each channel which expose spectral patterns similar across all data channels as well as synchronized with onsets and offsets of the stimuli as shown in the top panel of Fig. 8. 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 their multimodal cross-correlations, which we visualize in the form of ellipsoids of pairwise correlation coefficient matrices as in Figs. 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, and 20. The correlation coefficient values are visualized in the form of ellipsoids that are tangent to a unit character square, with the shape chosen to match the required correlation (R Development Core Team 2009; Murdoch and Chow 2007).

5 Results and discussion

Brain responses correlation patterns for electrophysiological signals (EEG, EOG, and ECG) as well as for blood oxygenation ones (fNIRS and pulse-oximetry) are presented for the following affective auditory and visual stimuli in Figs. 9 and 10 for annoyed (angry); Figs. 11 and 12 for choosing (thinking); Figs. 13 and 14 for revulsion (disgust); Figs. 17 and 18 for jubilant (happy); Figs. 15 and 16 for startled (surprise); Figs. 19 and 20 for terrified (fear); emotional displays, respectively. In all the above figures, correlation pattern transitions are presented in panels a and b for electrophysiological EEG (brain activity), EOG (eye movement), and ECG (heart rhythmic activity) signals (electrodes: C3, C5, T7, C4, C6, T8, Fp1, Fp2, F3, F4, P3, P4, AF3, AF4, AF7, AF8, vEOG, hEOH, ECG) and blood oxygenation levels in panels c and d from fNIRS, capturing also brain activity in the form of oxygen consumption in forehead left (dO2Hb, dHHb, TOI, nTHI) and right (dO2Hb, dHHb, TOI, nTHI) areas together with finger-pulse-oximetry, for stimulus and post-affective stimuli presentation. For all the cases, changes in correlation matrices patterns for stimuli and pre-stimuli (equal data lengths) are different generally causing transitions from less correlated (chaotic) into highly correlated responses (very synchronized) during the stimuli presentations. Such correlation changes reflect subjects' attentional synchronization of brain rhythms during affective stimuli presentation. The difference of average response reflect changes in stimuli processing. Such different patterns form perfect candidates for further automatic response classification from user's "body-surface-captured" physiological signals, which will be a subject of our further research.

All of the Figs. 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, and 20 results in panels a and b, for both auditory and visual responses, depict transitions from lower correlation patterns into higher ones, depicted in the form of more "organized" and "diagonal in shape" (similarly to an unitary diagonal matrix) ellipsoidal shapes. Higher correlation among electrophysiological channels means higher synchrony or similarity of the recored signals, which usually relates to coherent stimuli processing of various brain regions in response to presented stimuli.

Additionally almost perfectly correlated patterns ("diagonal matrix" alike ellipsoidal shapes) caused by interactions among EEG electrodes Fp1, Fp2, F3, F4 versus AF3, AF4, AF7, AF8 emerged (see middle areas of panels a and b in all of results Figs. 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, and 20), suggesting even higher synchrony in prefrontal cortices caused by affective/emotional stimuli interaction of the subjects' brains. Those two basic features of subjects' emotional responses and interaction with stimuli create a possibility to design brain machine interfacing paradigms based on inter-EEG-electrodes correlation patterns, similarly as mutual information features for natural communicative interaction evaluation utilized in our previous research and briefly summarized in Sect. 2 In case of blood oxygenation responses (presented in panels c and d of all results Figs. 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, and 20), a very interesting drop of correlation in left and right monitored hemisphere occurred for fNIRS quantities TOI, nTHI, dHHB. Interactions among fNIRS and pulse-oxymetry features were less significant, since the formed patterns did not allow for the classification of various responses. fNIRS technology responses are slower and with lower spatial accuracy, thus as also confirmed with our result, this technology is also well fitted for interactive affective responses estimation but with less pronounced features discriminability compared to electrophysiological signals discussed above in this section.

6 Conclusions

As a result of the presented research, we have shown a possibility to analyze multimodal brain and peripheral

Fig. 19 Terrified (fear) affective video stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in *panels* (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post-affective stimuli presentation

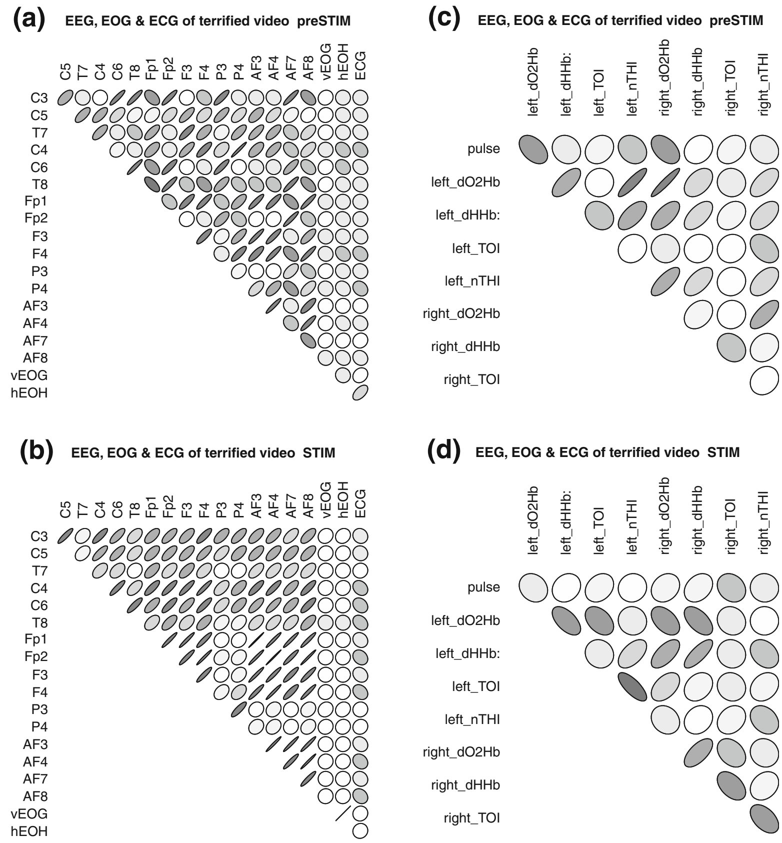
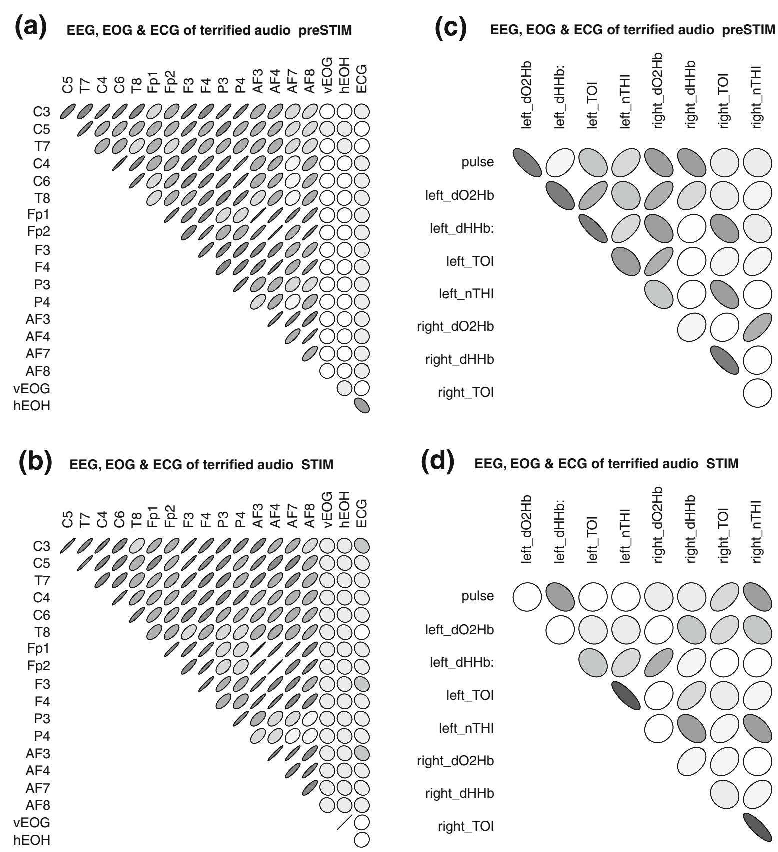


Fig. 20 Terrified (fear) affective audio stimuli correlation patterns (averaged over five subjects in the experiment) change in *panels* (**a**) and (**b**) for electrophysiological EEG, EOG, and ECG signals. The blood oxygenation levels are in panels (**c**) and (**d**) from fNIRS together with finger-pulse-oximetry for stimulus and post affective stimuli presentation



bodily responses to affective stimuli, which could be further utilized to design more socially aware communicative environments or avatars, which would employ enhanced (objective) emotional and affective features of which impact could be analyzed in the form of a feedback from human brain. All communicative and interactive actions are being recognized, processed, addressed, and planned to respond by our brains. Activity in human nervous system precedes any behavioral (bodily) actions, so once we will be able to efficiently classify those brain activity signatures, we will create new communication prostheses for patients in need or create new communicative and fully interactive experiences. In the presented study, we observed changes in multimodal electrophysiological (EEG, EOG, and ECG) as well as within blood oxygenation signals' correlations patterns as depicted in Figs. 9, 10, 11, 12, 13, 14, 15, 16, 17, and 18. The EEG and fNIRS channels present much stronger correlation patterns transitions before and during the emotional stimuli presentation (STIM, b and d panels in the figures) compared to the pre-stimuli (preSTIM, panels a and c). The remaining electrophysiological response patterns of ECG, EOG, and pulse-oximetry also showed changes in their patterns for pre- and stimuli periods, but their statistical significance was lower. Those remaining electrophysiological responses, however, show a very interesting perspective for an utilization of only such very simple monitoring techniques in future socially aware environments without necessity of direct brain response monitoring that are prone to very high noise and significant user-to-user variability. To the main advantages of a proposed approach to monitor human brain and bodily responses belong possibility to obtain objective very fast (before even subject could communicate verbally and bodily emotional states). The major drawback of such technology is a necessity to implement body electrical (EEG, EMG, EOG requiring conductive gel application, etc.) or optical (fNIRS or pulse-oximetry with additional infrared illumination sources) sensors. This is why further research with more user-friendly physiological sensors is necessary. We have shown that interactive empathy responses to emotional stimuli in auditory and visual domains are good candidates for their application to intelligent computing applications and socially aware environments since it has been possible to discriminate the response patterns for neurophysiological signals (EEG and fNIRS) together with periphery electrophysiological ones (ECG, EOG, pulse). The future research conducted by our group will focus on possible limitation of sensory modalities attached to human body (less EEG electrodes; possible estimation of emotional states from peripheral, non-brain, bodily sources; etc.) necessary for stable response patterns estimation. We will focus also on multimedia features (video and audio) that possibly could support body physiological features' estimation of interactive and affective user responses.

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