Detecting the neural processes of lie generation with low-cost EEG: a preliminary study

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***Abstract*—Lying and being deceptive is a common and costly behaviour among human beings which has been studied from different perspectives and with a range of different protocols, with the aim of bringing to light the physiological mechanisms accompanying lie generation. The goal of this preliminary study was to investigate the feasibility of lie detection using a portable low cost device (Muse 2016, InteraXon Inc.) . EEG was recorded from 4 electrode sites (AF7, AF8, TP9, TP10) during a modified version of the Guilty Knowledge Test in 39 subjects. Joint time-frequency analysis revealed significant differences between deceptive and truthful responses. These differences were detected in three distinct time windows and covered the whole alpha band. The first time window well corresponds to the P300 component and highlights a neural desynchronization during the process of lie generation; the second window highlights an alpha synchronization; the third window highlights a neural synchronization covering also part of the low beta and high theta bands and reflects the variability in response times. These preliminary results indicate that the Muse device is potentially capable of detecting neural processes involved in human lie generation and could be possibly used for fast and low cost experimenting of lie detection systems outside laboratory environments. Moreover, the data coming from this exploratory analysis could be exploited in future studies by artificial intelligence techniques with the purpose of automatically detect guilty individuals.**

***Keywords*—EEG, lie-detection, low-cost, GKT.**

I. INTRODUCTION

Lie detection is a research area that, in the past few decades, has found many important applications in the legal, social and clinical fields [1]–[3]. The advantage of using EEG to measure the physiological responses associated with lie generation cognitive processes resides in the fact that it is way more difficult, sometimes impossible, to fake a cognitive process than a more peripheral physiological response. The most common protocol in lie detection is the Concealed Information Test (CIT) [4], usually referred to as the Guilty Knowledge Test (GKT) [5]–[7]. In the last decade this protocol has been used largely in Japan, while in other countries such as Lithuania, the possibility of adoption is under discussion; however, it is not considered legally valid in most countries. The GKT assumes that a guilty person possesses critical information known only to the people involved in the crime; this critical information is exploited in the method by presenting it to the subject as a series of rare stimuli (probes) embedded into a longer series of irrelevant stimuli. Among these, some specific stimuli (targets) are similar to the probes in that they elicit a unique response of the subjects, albeit these are only needed as an attention holder. This experimental design is a variant of the odd-ball paradigm which is commonly used in the EEG research. Particularly, it has been shown that a P300 event-related potential (ERP) response is elicited to infrequently presented probe or target stimuli embedded within frequently occurring task-irrelevant items [8], [9]. Until recently, these kinds of experiments have always been conducted in laboratory due to machinery not suited for outdoor experiments. Thanks to the development of dry electrodes [10], EEG technology has become portable and many new low-cost devices are being built every year and brought out of laboratory environment [11]–[13], with some of them showing good results in detecting P300 components [14]. The aim of this paper is to show how a modern portable low-cost EEG device could be used to measure some neural processes involved in human lie generation and therefore potentially suitable for a lie-detection system. ERP and event-related spectral perturbation (ERSP) analyses have been conducted to evaluate the statistical significance of the differences between responses measured in truth and lie trials. The proposed protocol for this investigation is the modified GKT, which is based on a card game similar to others adopted in literature [15]–[17]. The goal of the modified GKT is to minimize the emotional involvement of a subject [18]. In this work, experiments have been conducted in realistic environments to enable a fast and easy collection of EEG data. The low cost EEG device used is the Muse device that costs more than 100 times less than a medical device; one study compared it with an ActiChamp system and showed that Muse was sensible enough to conduct ERP analysis. [19].

II. MATERIALS AND METHODS

A. Participants and settings

The experiment involved 39 healthy subjects (7 females, 37 right-handed) with no history of mental disorder, with ages ranging from 17 to 62 and a mean age of 31.3 . Environment settings included parks, university classrooms and private houses. Before every experiment, sufficiently isolated places were identified to minimize distractions for the subjects.

B. Experimental protocol

Before the experiment, participants were instructed to lie during the card game in such a way that it would not have been possible to discover a secret card by simply analyzing the behavioral responses. The card game was implemented on an Android smartphone. A random card (probe) was initially shown to the subject who was asked to keep this card secret in memory. A series of 39 random cards appeared on the screen of a smartphone with an inter stimulus of 2 s; the subject was instructed to answer “Yes” or “No” to the (implicit) question about the possible matching between the displayed card and the probe card by pressing the left or right button on a smartphone screen. As participants were asked to lie during the game, the suggested strategy was that they had to press “No” when the secret card occurred (probe trial) and “Yes” when a different card, freely chosen by them during the game, occurred (target trial). Otherwise, they had to press ”No” to the occurrence of all other irrelevant cards (excluding the chosen target). As an additional attention control, at the end of each round, the probe, the target and one irrelevant card were shown to the participants who were asked to indicate the probe. Every subject did a first partial test without EEG recording, in order to understand the game mechanics. Probe and target cards randomly appeared more than once (min 1 max 4) during the experiment, with an average of 3.5 probes, 3.5 targets and 32 irrelevant stimuli. Participants did a minimum of 3 recorded experiment repetitions and a maximum of 5.

C. EEG Data Acquisition and pre-processing

The InteraXon’s Muse 2016 headset system has a sampling rate of 256 Hz and five electrodes: three Ag electrodes are located analogous to Fpz, used as reference electrode, AF7 and AF8 and two additional electrodes made of conductive rubber, are located at TP9 and TP10. To stream the data from the headband, the Muse Direct application was running in background on an Android smartphone, while, on the same device, the card game application was executed in foreground. MATLAB’s toolbox EEGLAB [20] has been used for the pre-processing and the statistical analysis of the EEG traces. Data were high pass filtered at 0.1 Hz and baseline corrected. Noise was removed at 50Hz with CleanLine, an EEGLAB plugin which adaptively estimates and removes sinusoidal artefacts. Excessively noisy trials were then removed by visual inspection. Lastly, 4 seconds epochs time locked to the stimulus presentation were extracted from single trials with 1 s of pre-stimulus baseline.

D. Exploratory analysis

The analysis has been made using EEGLAB and MATLAB. After the pre-processing steps, the trials have been divided into two categories: Truth and Lie. “Truth” groups all the irrelevant responses, while “Lie” groups probes and targets. The statistical analysis has been conducted using permutation statistics with 2000 permutations. All the trials in each of the two groups have been averaged and baseline corrected [-200 ms 0 ms] and then compared by using a paired t-test. To visually inspect the ERPs, ERP images were generated (Figure 2). ERP-image plots are 2-D transforms of epoched data expressed as 2-D images in which data epochs are first sorted along some relevant dimension (e.g. subject reaction time) and then smoothed (across adjacent trials and time points) and color-coded. The ERSP analysis has also been performed to analyse the EEG responses in the time-frequency domain (Figure 3). In EEGLAB, Morlet wavelets were used with the default parameters (3 cycles, 0.5). Namely, the number of cycles in the wavelets was increased from lower to higher frequencies reaching half the number of cycles in the equivalent fast Fourier transform (FFT) window at its highest frequency.

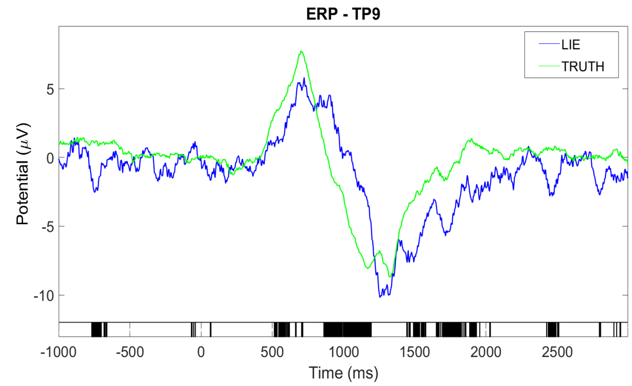

Fig. 1: Superimposed inter-subject grand average of lie (blue) and truth (green) trials. Black stripes indicate intervals of statistically significant ($p<0.05$) differences between the two conditions.

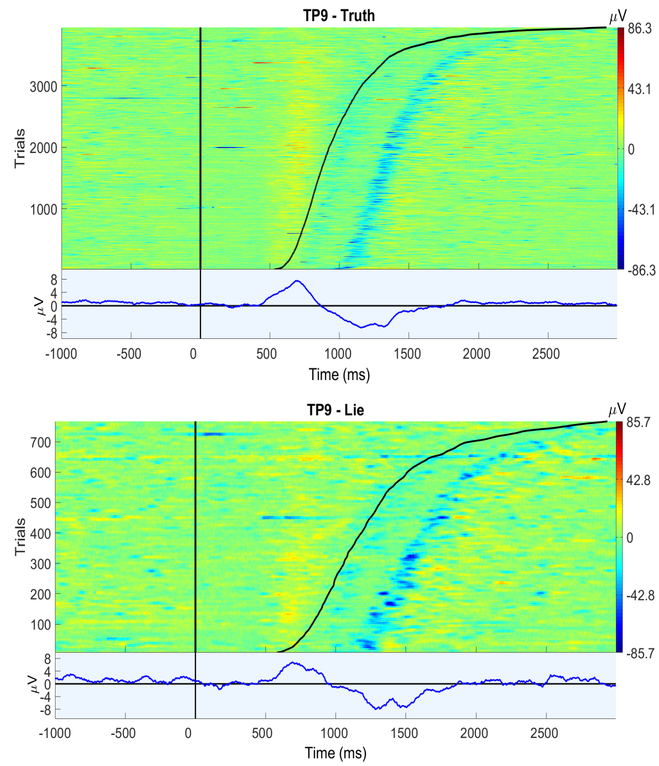

Fig. 2: ERP-image plots for Truth (upper) and Lie (bottom) trials. Trials are vertically stacked after being sorted by reaction times. The black curve denotes the moment in which subjects pressed the response button: this is visibly slower in Lie trials.

III. RESULTS AND DISCUSSION

The most statistically significant results were obtained from the analysis of the electrode TP9. Although the electrode is on the left, which is close to the region controlling language, this might be also related to the fact that most subjects were

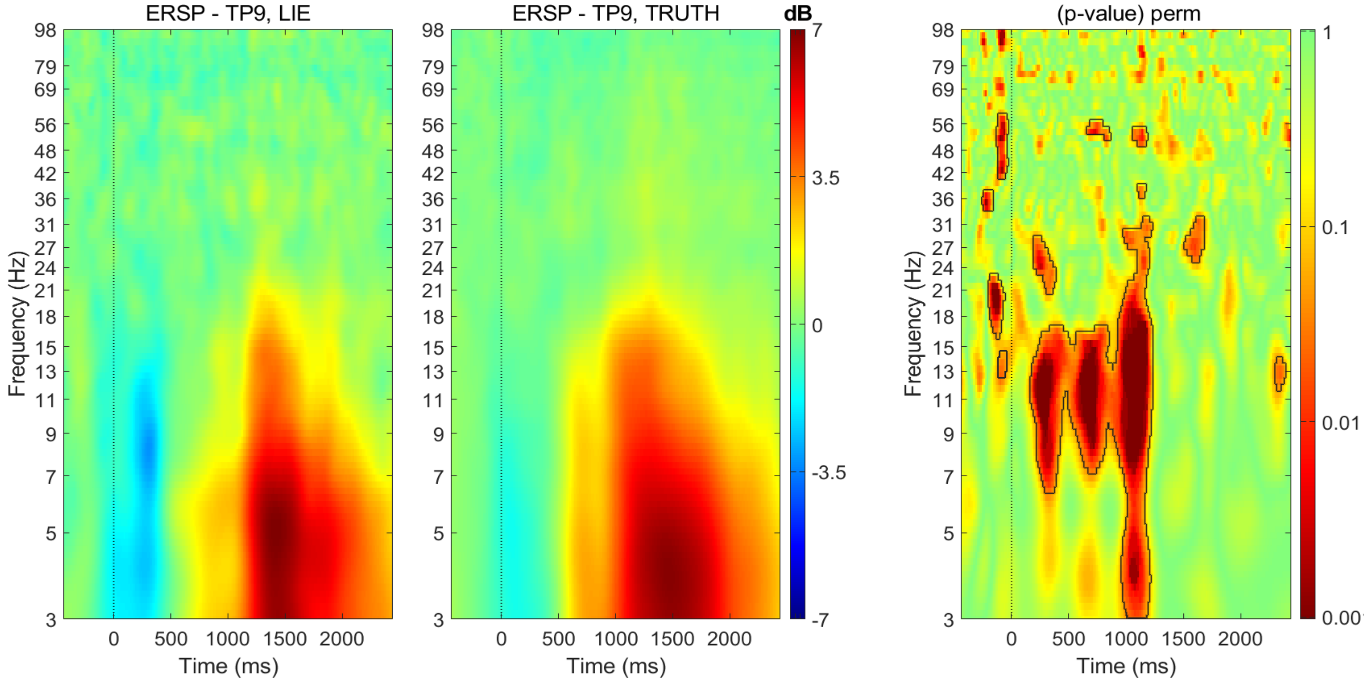

Fig. 3: ERSP analysis. Time-frequency plots of averaged ERSP responses from lie (left) and truth (center) trials. Time-frequency plot of the p-value for the differences between lie and truth trials (right) obtained with permutation testing. Statistically significant regions($p<0.05$) are marked with a black line.

right-handed. In Figure 1, a positive peak is visible in the ERP response, starting at 500 ms and a subsequent negative peak at 1000 ms. The black bars under the time axis denote statistically significant differences, with a p-value less than 0.05, in the windows 500-600 ms and ~900-1200 ms. In Figure 2 the impact of the response times is even more evident. As shown in [21], [22], response times for telling a lie are slower. This clarifies the presence of the significant statistical difference seen before between 900-1200 ms as being the difference in response times.

The results of the ERSP analysis are shown in Figure 3. Three main time windows exhibited statistically significant differences between lie and truth responses ($p<0.05$); these differences are located respectively around 300 ms, 500 ms, 1000 ms and cover the whole alpha band (~7.5-15 Hz) and part of the low beta band. As lies almost certainly involve inhibitory neural processes, the observed changes in the alpha synchronization, especially in the two later time windows, could be related to the fact that alpha is often associated with inhibitory neural processes [23]. On the other hand, the earlier time window, around 300 ms, denotes a desynchronization response during the process of lying, thereby, given also a slight trend towards lower frequencies (theta rhythm), this is probably associated with the additional neural cost of telling a lie [24], [25]. This earlier response was not visible in the time domain. The second time-frequency window, around 500 ms, comes in conjunction with the positive peak in the time domain. As already observed by [17], the absence of a prominent P300 response could be due to the modified GKT protocol. This 500 ms peak is possibly a late positive component associated with working memory and recognition of old/new stimuli [26]. The last time-frequency window, around 1000 ms, reflects the response times of the subjects and has a wider spectrum range respect to the first two. A preliminary attempt to distinguish between Lie and Truth classes with machine learning techniques has been performed using a Random Forest model. The input for training the model was the concatenation of the epoched time series (3 s epoch starting from stimulus onset) and their spectra (0-128 Hz) for each electrode. The best preliminary result obtained was a mean prediction accuracy of 66 percent on the test set. The mean accuracy has been obtained by applying k-fold cross validation (k=5).

IV. LIMITATIONS

Although this study is one of the few in Lie Detection that uses measurements within the wavelet domain, it does have some limitations. The first is the lack of midline electodes, as it is well known that the P300 has a centro-parietal scalp distribution with its maximum over midline scalp sites [27]. The second important limitation is the intra and inter subject variability of the late positive response: all subjects showed this response but with slightly different latencies. This could probably be the reason why the first attempts with machine learning approaches on the dataset of this study did not bring good results, as also happened with the use of wavelet entropy [28]. The use of other wavelet features, such as wavelet entropy and coherence [28]–[30], has shown promising results in the detection of lies in recent years, therefore it could be further investigated as a support for the classification process.

V. CONCLUSION

The results of this study suggest that the Muse device could be sensitive to the effects of neural processes associated with lie generation in non standard laboratory conditions. This promotes the usage of the Muse device in portable (out of lab) applications where both ERP and ERSP measures represent an useful readout of complex cognitive processes such as lie generation. Future works could analyse the impact that different environment settings have on the experiment; moreover, a deeper systematic study should be conducted to understand the feasibility of an automatic lie detection process. With this aim artificial intelligence techniques, relying on the ERP/ERSP features illustrated in the present work, will be explored.

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