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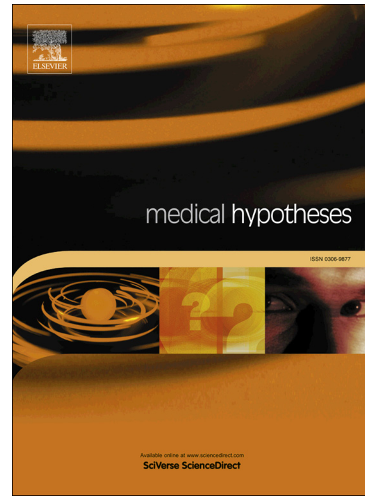

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Interview Based Connectivity Analysis of EEG in order to Detect Deception

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ABSTRACT– Deception is mentioned as an expression or action which hides the truth and deception detection as a concept to uncover the truth. In this research, a connectivity analysis of Electro Encephalography study is presented regarding cognitive processes of an instructed liar/truth-teller about identity during an interview. In this survey, connectivity analysis is applied because it can provide unique information about brain activity patterns of lying and interaction among brain regions. The novelty of this paper lies in applying an open-ended questions interview protocol during EEG recording. We recruited 40 healthy participants to record EEG signal during the interview. For each subject, whole-brain functional and effective connectivity networks such as coherence, generalized partial direct coherence and directed directed transfer function, are constructed for the lie-telling and truth-telling conditions. The classification results demonstrate that lying could be differentiated from truth-telling with an accuracy of 86.25% with the leave-one-person-out method. Results show functional and effective connectivity patterns of lying for the average of all frequency bands are different in regions from that of truth-telling. The current study may shed new light on neural patterns of deception from connectivity analysis view point.

Index Terms: deception detection, Electro Encephalography, functional/effective connectivity, classification

1 INTRODUCTION

Preliminary findings suggest that physiological deception detection uses many complicated equipment which monitors the body's activity for cues of deception. Polygraphs take several measures including heart rate, breathing rate and sweating [1]. Thermal imaging technology can be used to detect stress levels based on the radiated heat from their face [2]. In contrast to these methods that measure deception's physiological signs, EEG and functional magnetic resonance imaging (fMRI) directly measure deceptive activities from its source and less vulnerable to countermeasure; therefore, over the past two decades, deception detection methods based on central nervous system activity, such as fMRI [3,4,5], Event-Related Potential (ERP)[6,7,8,9], Magneto Encephalogram (MEG)[10] have been vigorously developed being used to measure the activity of the brain.

In all of these methods we must use a protocol to ask questions that can be used as open/close-ended interview; open ended questions are the ones require answers with more than one word i.e. having no-fixed answer. Those answers can come in the form of a list, a few sentences, or something longer such as a speech, paragraph or essay. In the close-ended form we can answer questions with only a "yes" or "no" response.

Polygraph always uses close-ended interview, therefore questions will be limited and interviewers cannot ask any questions. Deception detection based on cognitive approaches such as EEG or fMRI use ERP-based paradigm, i.e. to detect concealed information in the guilty knowledge test (GKT) depending on the detection of a well-known P300 'oddball' response, so it would be like a close-ended type. Questions should only be in an image or voice form and the answers are "yes" or "no" without talking with the click of a push button. On the other hand, many studies in the field of thermal imaging use open-ended interview to fix this limitation. Therefore, in order to remove the above restrictions in

the existing EEG protocols, we go to the open-ended interview procedure, so our challenge is to eliminate the effect of speech on brain signals.
Since deception is a rather complex mental activity, during lying, many functions of higher cognition are involved. Over the past few years, in the field of EEG, functional connectivity has been widely used in the detection of brain dysfunction in neuropsychiatric diseases [11]. Several studies have linked functional connectivity to deception detection. Davatzikos et al. used a high-dimensional, non-linear pattern classification method to discriminate lie-telling from truth-telling based on brain activity, ignoring the interactions among brain regions [12]. Weixiong Jiang et al. used a multivariate pattern analysis of functional connectivity MRI to decode the processing of lying [11]. They announced "deception has been demonstrated to be associated with greater activation within the prefrontal cortex compared to truthfulness". Gao et al. employed wavelet coherence to a better characterizing cognitive processes and mechanisms associated with deception, to evaluate functional connectivity between different brain regions; they also worked on single-trial event related potentials [13]. In 2016, Wang developed a functional brain network and multichannel analysis for the P300-based Brain Computer Interface system of lying detection [14]. In the field of lie detection with effective connectivity, a few studies have reported, Yue Wang et al. presented an Electroencephalography network and connectivity analysis for deception in instructed lying tasks [15]. Moreover, most previous connectivity analysis in deception detection studies mentioned before, focused on a frequently used ERP-based paradigm [8, 16, 17] with the accuracy of above 90% but in oddball paradigm, we must present sequences of repetitive stimuli to study effects of stimulus novelty and significance on information processing. Therefore, it cannot be generalized in any subject, particularly in the field of deception detection with interview. Also it can give a limited assessment of whether who knows the stimulus or not, but connectivity analysis can provide unique information about brain activity patterns of lying and interaction among brain regions and therefore, it is applicable to the interview.
Although, former studies have addressed many aspects of the current issue, discussed in this paper, none has so far worked on utilizing interview in the field of EEG analysis of deception detecting in real-life, so the novel aspect of this paper lie in using interview during EEG recording compared to existing work. We present our deception detection experiment where deception is designed around a learnt-story (i.e. based on character profiles). This design considers various aspects from the theories on deception, in particular, we exploit cognitive load [18,19] by requiring the participants to plan their lies before the test and by asking questions not being covered by the profile [20,21,22]. This requires the subject to extend their lies beyond the learnt story, and as such, increasing cognitive load [2, 23, 24]. In this paper, we investigate the potential use of connectivity analysis of EEG to detect deception based on information gathering interviews. We begin by presenting our experiment, data recording and pre-processing, in section 3 we present details of processing of recorded signals. Finally we present results in section 4.
The aim of this study is to use a new applicable protocol i.e. open-ended interviewing in the field of connectivity analysis of EEG to explore the potential neural mechanism of lying that can potentially provide a basis for future applications. One of advantages of this protocol is general and practical usage, i.e. we can design a protocol based on the interviewer's viewpoints by setting any types of questions to ask interviewees during signal recording process. Classifying subjects as liar or honest, will be achieved by finding different patterns in the input features using statistical and machine learning techniques (see section 3 for details).

2 METHOD

2.1 PARTICIPANTS

We recruited 40 healthy participants (males) from university ranging between the age of 20 to 34 years [mean age ± standard deviation (SD): 23.7 ± 1.72 years) with no history of neurological or psychiatric disease. All of volunteers were students or graduated of at minimum bachelor degree. After a complete description of the study provided to the participants, written informed consent was obtained. Data were collected in National Brain Mapping Laboratory (NBML) of Tehran University. This study is approved by the Ethical Committee of the Iran University of Medical Science (Number: IR.IUMS.REC.1396.930140180).

2.2 EXPERIMENTAL DESIGN AND PROCEDURES

In the first stage, participants were examined medically; second, they filled in a profile form and next, they were told the instruction formerly. In this study, we have used a modified interview scenario [21] to examine the brain network of deception.

For each subject the test was conducted by two conditions; a “true”, and a “lie session. During the true sessions, participants were required to give accurate, honest responses to all questions about autobiography. During the lie condition, the participants were required to give predetermined responses to all questions; in fact, the facilitator designed a fake profile with participants and allowed them 10 minutes to practice it before the interview. The participants were told that they are being to be tested on interviewing skills, and that the skill under examination is deception as part of human communications. The facilitator explained to the participants how the examination will be conducted, and they will be rewarded (1 million Rials) if they are able to convince the examiner of being honest. The participants were also paid 500000 Rials for the participation.

In both sessions, the questions were asked from the candidate’s own profile. Sequence of sessions (i.e. which session was played first) had been arranged randomly for each subject. Two sessions were separated by a 5-min break. After attaching electrodes and once the subject was ready to examine, the interviewer asked the participant four baseline questions which were answered truthfully to remove the test entrance stress. The interviewer was a psychologist and was ignorant of subjects label in any session (i.e. we had a blind study) and we emphasized that point to participants. Each session consisted of fifteen main questions including three types of neutral, lie/truth and descriptive lie/truth questions. To describe more and offhand, the interviewer asked some non-anticipated questions which did not exist in the character profile; e.g. “describe the place your parents were born”. At the end of the interview, the facilitator verified with that the participant completed the task successfully. Examples of the main questions used in our experiment are as the followings:

1. How old are you?
2. What is your occupation?
3. Where were you born?
4. What are your hobbies?

Names and surnames of the participants were actual in both sessions and did not change. The interviewer asked this item as a neutral question for both sessions.

2.3 DATA ACQUISITION

EEG signals were recorded using a 32-channel Electrocap according to the 10–20 international system. All active electrodes were referred to linked ear lobes, with a ground electrode placed on AFZ. Electrode impedance was maintained at below 5 kΩ. Data recording was performed using a g.tec amplifier with 32 channels and g.Recorder software (g.tec, version 2016, Austria). The EEG data were digitized at 512 Hz. To monitor autonomic nervous system (ANS) activity simultaneously by the EEG data, a photoplethysmographic (PPG) sensor was attached over the index finger of the right hand by means of a flexible Velcro strap for further data analysis. A piezo-electric snoring sensor was also placed on the neck in order to record voice synchronously, also to check the process and monitor movements of the subjects, they were recorded by a webcam during the interview. The scenario been mentioned before, consists of the two sessions and sequence of sessions had set randomly for each subject (21 subjects picked for lie sessions first and 19 subjects picked for truth sessions first). The participants were asked to sit on a chair ahead of an interviewer and answer to questions according to the sessions.

2.4 DATA PREPROCESSING

The EEG data were processed using EEGLAB functions (Version 14.1.1; Delorme & Makeig, 2004) running on MATLAB 2013a. The raw EEG signals were first high-pass filtered above 1 Hz and then, were filtered with 45-55 Hz using a windowed FIR sync filter with cleanline plugin to remove line noise or other artifacts. After removing severe peaks and some specified noises, we used ASR plugin to remove noisy signals automatically, and next, we interpolated to remove channels by signals of other subjects. After re-referencing to a common average reference, the EEG time series were removed from baseline and visually inspected to reject trials with abnormally high artifact levels. At this stage, using manual and automatic preprocessing method, to an acceptable extent, the effect of speech on the EEG signal was removed.

2.5 INDEPENDENT COMPONENT ANALYSIS (ICA) DECOMPOSITION

The preprocessed EEG data were decomposed using the Independent Component Analysis (ICA). After using this algorithm, eye blinks and muscles were identified by brain-related Independent Components (ICs) and manually removed based on their spectra, scalp maps, and time courses.

2.6 EQUIVALENT DIPOLE ESTIMATION

Next, the equivalent dipole source localization of these ICs was computed using DIPFIT plugin in EEGLAB. Template 10-20 scalp electrode positions were co-registered in a standard_BESA template brain, using nonlinear warping. A four-shell boundary element method head model based on BESA brain template was used to find the best fitting equivalent current dipole for each IC then fit dipoles automatically. After that by plotting dipoles, bad components were removed manually again if necessary.

2.7 EPOCH THE DATA

After preprocessing analysis, the data was arranged based on three types of questions in each session titled as epoch; for lie session there are neutral, lie and descriptive lie and for true session, neutral, true and descriptive true questions. On average, three artifact-free epochs in each session were extracted from each subject. To decrease conduct volume, we divide the head to nine regions and the average of some channels were assigned to one region. Figure 1 is shown regions selected for analysis.

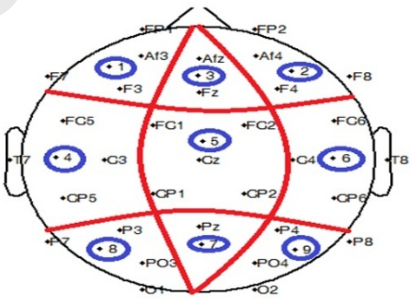

Fig. 1. Regions were selected for analysis: The average of some channels was assigned to one region.

3 PROCESSING

The block diagram of analysis is shown in figure 2. After preprocessing input signals, connectivity analysis was done; the results were compared against shuffled surrogate data using a permutation test (100 iterations) and corrected for multiple comparisons using a false discovery rate (FDR) correction. Then, features were extracted from connectivity analysis and finally a Linear Discriminant Analysis (LDA) was employed to solve the classification problem.

3.1 CONNECTIVITY ANALYSIS

In the processing part, SIFT data-processing Pipeline was used [25], analysis of channels was chosen, and then windows of signals across time and ensemble were normalized. In this step, a multivariate

autoregressive (MVAR) model should be fit to the data. A number of algorithms have been proposed to fit VAR models to non-stationary series.
For our data, ARfit was chosen and parameters were set to get a proper, valid model. After fitting the model, three types of connectivity such as dDTF (directed directed transfer function), GPDC (generalized partial directed coherence) and coherence computed for each epoch of all subjects, were obtained.

3.2 Statistical significance

The statistical significance was determined by phase-shuffling the connectivity values for each dataset. To remove fake connectivity, a separate set of surrogate data was computed by phase-shuffling the EEG data as described by Theiler et al. (1992). The phase was shuffled across frequencies within each trial for each channel, which ensures that the power of the original EEG signal was left intact while the phase was shuffled. The results were compared against shuffled surrogate data using a permutation test (100 iterations) and corrected for multiple comparisons using an FDR correction. FDR method used to correct for multiple comparisons as the critical p-value, jumps once the distribution of p-values significantly changes, which is an indication that there sampling procedure has not yet converged to a stable estimator.

3.3 Feature extraction

The features are extracted based on values of connectivity from one channel to the others, and also from outflow and inflow of channels in each method (Coherence, dDTF, GPDC), each epoch in all frequency bands (Alpha, Beta, Gamma, Theta, Delta). For five frequency bands and nine regions we have 9*9*5 connectivity values and for outflow or inflow we have 9*5 values. Numbers of features are listed as table 1.
After normalizing the features and reducing dimension by Principal Component Analysis (PCA), features are obtained and a Linear Discriminant Analysis is employed to solve the classification problem.

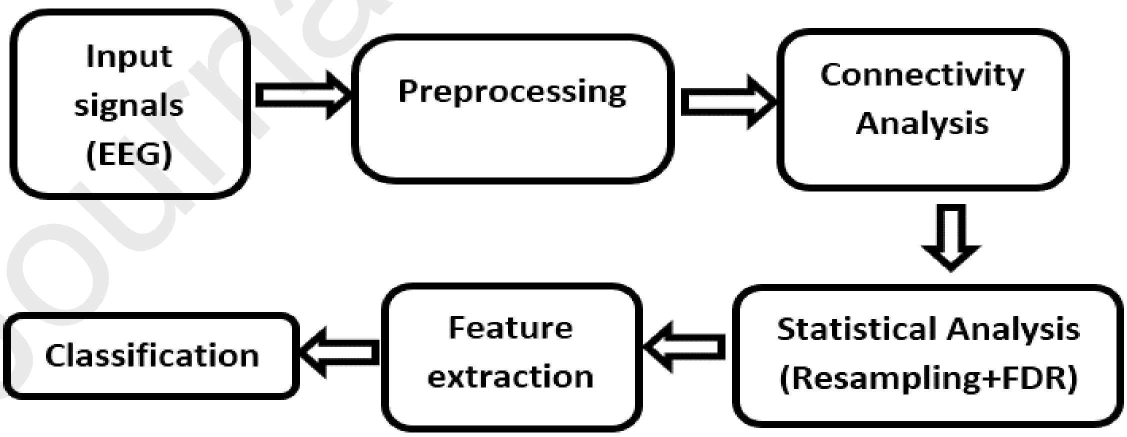

Fig. 2. Block diagram of analysis

Table 1
Number and type of used features for each method and each paired questions, a total of 3780 features were obtained.

Method	*Coherence*	*dDTF*	*GPDC*

Feature's /question's type	Connectivity values/outflow		Connectivity values /outflow-inflow		Connectivity values /outflow-inflow	
Neutral questions	225	45	405	45	405	45
				45		45
descriptive lie/ truth questions	225	45	405	45	405	45
				45		45
lie/ truth questions	225	45	405	45	405	45
				45		45
Sum	810		1485		1485	

4 Results

4.1 Pattern analysis of connectivity to distinguish lie-telling from truth-telling

After classifying each paired questions, accuracy for lie/ truth questions is 65%; for descriptive lie/truth questions is 61% and for neutral lie/truth questions is 67%. And accuracy for average of leave-one-person-out (LOO) for features of all questions and methods of connectivity is 69%. After that, to improve the results, t-test (at the $p<0.05$ level) was used to extract significant features. Table 2 shows number of remained features.

Table 2

Number of significant features after t-test was applied, a total of 164 features were obtained

METHOD	**COHERENCE**		**DDTF**	**GPDC**	
FEATURE'S/ QUESTION'S TYPE	Connectivity values /outflow		Connectivity values /outflow-inflow	Connectivity values /outflow-inflow	
Neutral questions	3	3	18	17	2
					2
lie/ truth questions	8	8	10	10	2
descriptive lie/ truth questions	12	12	14	33	6
					4
SUM	46		42	76	

Following the dimension reduction, the best optimal features were selected from the top N/4 of ranked PCA feature set (N=164 was the size of feature set and 41 features was the best size for achieving the best accuracy) and were used for the data classification. As we know, reducing the size of feature set can reduce the computation time and prevents overfitting of the classifier and enhances the generalization of the trained classifier. Some of other classifiers also have been tested and LDA had the best operation (see table 3).

For each paired questions (Guilty/Truth) accuracy is 70% and for (Guilty/Truth descriptive) questions is 68% and for neutral (Guilty/Truth) questions is 73%. Therefore, compound of features of all questions can give better results (see table 4).

Table 3
Accuracy for each method of connectivity and each classification method, average classification accuracy 86.25%

METHOD OF CONNECTIVITY	NAÏVE BAYESIAN(K=10)	DECISION TREE	LDA
dDTF	57٪	54٪	**62%**
Coh	56٪	54٪	**71%**
GPDC	70٪	71٪	**84%**
Features of all methods	69.5٪	59٪	**86.25%**

Confusion matrix for features of all questions after choosing significant features is shown in table 4 and table 5 shows accuracy of test data for each subject and average of LOO.

Table 4
Confusion matrix for average of LOO for significant features of all questions

		True condition Condition positive	Condition negative		
Predicted condition	Condition Positive	TP=34	FP=6	Precision = 85%	FDR=15%
	Condition Negative	FN=5	TN=35	FOR= 12.5%	NPV= 87.5%
		sensitivity =87.17%	FPR= 14.63%	F1-score=86.07%	
		FNR= 12.82%	Specificity= 85.36%	**Accuracy= 86.25%**	

4.2 CONNECTIVITY ANALYSIS

Analysis of functional connectivity by coherence shows that regions 7 & 5 were more active than others in lie, truth sessions, respectively. According to figure 3, outflow of connectivity across the time for all frequency bands in guilty and innocent subjects, shows less amplitude of guilty subjects; it means the amount of connectivity with other regions is reduced while lying. For guilty subjects, region 6 and 7 is more active than the other regions; also region 4 and 5 is more active in innocent subjects. As seen in most regions, average of outflow can give a good distinction between guilty and innocent subjects.

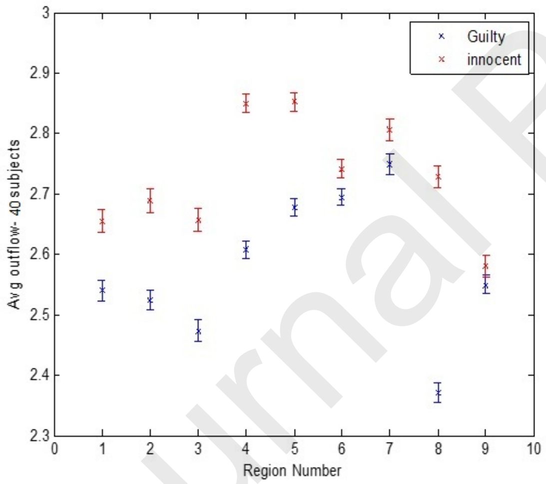

Fig. 3. Error bar (mean and variance) for average outflow of guilty/innocent subjects in each region

Table 5
Accuracy for each subject and average, for example accuracy of zero, means none of sessions were properly detected and so on.

Analysis of effective connectivity by GPDC method for the average of all frequency bands and the average of guilty subjects (A) and innocent subjects (B) are shown as figure 4.

As seen, effective connectivity pattern of lying different in regions from that of truth-telling. Also for guilty subjects, regions 6 & 7 are the receptor and regions 1 & 2 are the transmitter; and for innocent subjects regions 4 & 5 are receptor and regions 2 & 7 are transmitter. Moreover, in lie model, the direction is from front to back of the head that confirms the top-down theory which related to the processing of high-level brain information. Also in truth model, it is from back and front to middle of the head. Therefore, analysis of functional and effective connectivity support each other; i.e. both showed activity of regions 7 & 5 in lie and truth sessions respectively, either effective connectivity showed more complete information about directions. So for both regions, activity starts from frontal lobe and it flows to temporal lobe, but for innocents it flows to region 4 and 5 and for guilty it flows to region 6. Previous fMRI studies [19, 20] showed the increased activity in frontal, temporal, limbic lobes and prefrontal cortex, could be differentiated lying from truth sessions and our results confirm this.

5 Summary of results

This present study demonstrates and employs an interview protocol in EEG-based analysis for lie detection. It is stressed that one of the most important purposes of lie detection is to distinguish guilty from innocent subjects. However, only a few studies using connectivity have proposed a classification method while simultaneously providing its sensitivity and specificity.

So, in this study we present a classification method based on machine learning to separate lies from truthful responses using connectivity features and an LDA. High classification accuracies, including high sensitivity and specificity, were obtained to the test's data, strongly supporting the view that is reasonable and feasible to utilize this method in EEG to detect deceptive responses and hence to distinguish guilty from innocent subjects. Our findings showed a significant improvement in classification after selecting significant features.

As seen in connectivity analysis's section, different models could be achieved for guilty and innocent subjects. Our best results equate to review articles in the field of connectivity analysis or even thermal imaging to deception detection.

SUBJECT ID	ACCURACY	SUBJECT ID	ACCURACY
1	100	**21**	100
2	50	**22**	50
3	100	**23**	100
4	100	**24**	100
5	50	**25**	50
6	100	**26**	100
7	100	**27**	50
8	100	**28**	100
9	50	**29**	100
10	100	**30**	100
11	100	**31**	100
12	100	**32**	50
13	100	**33**	0
14	100	**34**	100
15	100	**35**	100
16	100	**36**	100
17	50	**37**	100
18	100	**38**	100
19	100	**39**	50
20	100	**40**	100
AVERAGE		**86.25%**	

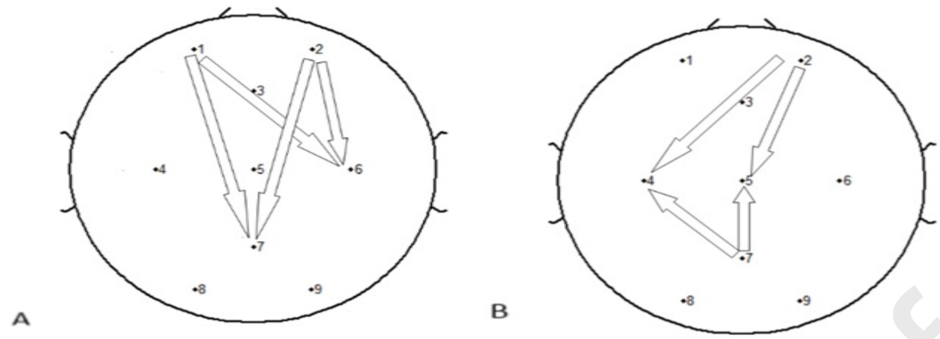

Fig. 4. Models of effective connectivity (GPDC method) for the average of all frequency bands
A. the average of guilty subjects B. the average of innocent subjects

6 DISCUSSION AND CONCLUSIONS

In this method of deception detecting, the EEG signal processing is used. This study has several advantages over most existing EEG-based lie detection studies as well. First, in this method there is no limit of those in other; for example ERP-based methods must be designed on image or voice basis only, but in this proposed protocol, interviewers can be asked questions during signal recording. At second, one of the advantages of interview as compared to polygraph's techniques like GKT and CQT is that the questions are open-ended, so it is hoped to increase the feasibility of implementing a real-time system for lie detection in an interview platform. This is concluded with outlining the practical application of connectivity-based research. Moreover, this recommends that it can be more practical to invest resources in improving the interview approach in EEG-lie detection field. In future work, analysis of connectivity along time can achieve more information about process of lying.

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