Multimodal Deception Detection in Videos via Analyzing Emotional State-based Feature

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Abstract—Deception detection is an important task that has been a hot research topic due to its potential applications. It can be applied to many areas from national security (e.g., airport security, jurisprudence, and law enforcement) to real-life applications (e.g., business and computer vision). However, some critical problems still exist and worth more investigation. One of the major challenges is the data scarcity problem. Until now, only one multimodal benchmark dataset on deception detection has been published, which contains 121 video clips for deception detection (61 for deceptive class and 60 for truthful class). This amount of data is hard to drive deep neural network-based methods. Hence, they often suffered from the overfitting problem and the bad generalization ability. Also, the ground truth data contains some unusable frames for many factors including the face is too small to be recognized the facial expression, face is covered by text, file corruption, etc. However, most of the literature did not consider these problems. In this paper, we design a series of data preprocessing methods to deal with the problem first. Then, we propose a multimodal deception detection framework to construct our novel emotional state-based feature and used open toolkit openSMILE to extract the features from audio modality. A voting scheme is also designed to combine the emotional state-based features from both visual and audio modalities. Finally, the novel emotion state transformation (EST) feature is determined by our algorithm. The critical analysis and comparison of the proposed methods with the state-of-the-art multimodal method are showed that the overall performance has a great improvement of accuracy from 84.16% to 91.67%

Index Terms—Multimodal, Deception Detection, Machine Learning, Video Analysis, Emotion Recognition.

I. INTRODUCTION

Human deception frequently occurs in our daily life. Although some deceits are innocuous, others may cause serious consequences and may become a fatal threat to enterprises, social security, and even countries. For example, deceiving in a court may influence the judgment of judiciary and cause a guilty accuse to be acquitted. Therefore, accurate methods for detecting deceits are very important to personal and public safety in nowadays society.

Over the past few decades, deception detection theory has attracted many researchers from many different fields such as jurisprudence, law enforcement, business, not to mention national security, to build up applications. Some physiological-based methods such as Polygraph and functional Magnetic Resonance Imaging (fMRI) have been designed for deception detection, but the results are not always correlated with deceits. Moreover, since the results need to be determined by trained experts, they are often biased. Hence, some court trials based on these results will be misjudged. People who are not guilty will be put in prison, but the guilty one will be released.

Recently, identifying behavioral clues for deception detection has become a hot issue for researchers in psychology, security, criminology, and computer vision fields. Those behavioral clues can be classified into verbal features (phonetic tones, self-reference, and cognitive words) and non-verbal features (facial expressions and body movements). However, video data is very suitable for deception detection due to its naturally multimodal property (e.g., visual, audio and textual). In addition, features extracted from both visual modality and audio modality have been shown that they are rich in information related to human deception. There are some challenges in both the feature extraction stage and the computational efficiency stage for deception detection in videos since video data contains complicated information for both spatial domain and temporal domain. Hence, how efficiently extract the features that are highly correlated to deceptive behavior from both visual modality and audio modality in videos and effectively fusion the information of both spatial domain and temporal domain is a big issue.

On the other hand, data scarcity is also a serious problem for deception detection task. The main reason is that the objective of deception is to conceal the truth. Therefore, without some reference information from subject, it is very difficult for data collector to subjectively determine the label information for the collected data. Until now, only one new and unique public multimodal benchmark dataset (contains only 121 video clips) for deception detection is introduced in [2]. But, this quantity of data may still not be enough to train a deep neural network (DNN) model. Some DNN models that have been developed with this dataset for deception detection often suffered the overfitting problem and lacked generalization ability. Hence, how to design the feature extraction methods with limited data becomes a critical issue.

In this paper, we propose a framework that extracts the emotional state-based features from both visual modality and audio modality to study multimodal deception detection in videos. The features from the two modalities are combined into final training data. Then, a
series of classifiers are trained to evaluate performance of the features. Our contributions can be concluded as follows:

1) A framework of multimodal deception detection model is proposed to consider the deception detection task.
2) A series of preprocessing procedures are designed to deal with the problem in the considered dataset.
3) A voting scheme is designed to combine the emotional state information from both visual modality and audio modality for intensifying the correctness of the emotional state information.
4) The novel emotional state-based features are proposed to train our multimodal deception detection model.
5) Our methods can improve the overall performance of accuracy and ROC-AUC for deception detection task and outperform the state-of-the-art method.

The new proposed features contain the information from both spatial and temporal dimensions at the same time. Experimental results demonstrate the effectiveness of the proposed features for multimodal deception detection in videos. These results also show that our methods perform well even if the amount of the dataset (121 video clips) is limited.

The rest of this paper is organized as follows. Section 2 gives introduction of related work. Section 3 introduces our proposed method. Experimental results are provided in Section 4 and Section 5 concludes this paper.

II. RELATED WORK

A. Physiological characteristics based methods

Polygraph is the most representative example for physiological characteristics based method. The purpose of Polygraph tests is to measure the physiological characteristics such as heart rate, respiration rate, blood pressure and skin conductivity when the subject is asked a series of well-designed questions. Then, the measured characteristics are used as evidence to determine whether the subject is deceit or not. But the results are usually not credible because people’s judgments are often biased due to individual differences [12][13]. Thermal imaging is also used to record the thermal patterns [14]. Then, the patterns show the distribution of blood flow of the subject body [15]. Although this method can output an acceptable result, the technique can not be applicable in worldwide because the cost of thermal camera is very expensive. Recently, the fMRI method has been applied to scan the structure of brain of the subject. Then, the brain images are used to find the regions that are related to human deception. Although high accuracy can be achieved, some challenges (such as mechanism design, experimental setting and reliability) still need to be considered [4][16]. To sum up, due to the testing procedures of these three physiological characteristics based method are public, people can easily trick the detection procedures through expert training [17].

B. Computer vision based methods

Previous research based on computer vision in deception detection has developed many methods by considering verbal clues and non-verbal clues. Examples for non-verbal case, Blob analysis was used to track head, hand movements and body gestures [18]. Then, those information were used to classify human behavior into three distinct states. But the small size dataset made the blob classifiers prone to overfitting and not applicable to new data. Recently, Ekman’s research showed that people reveal some unavoidable facial clues when they are preparing deceit [19]. These facial clues have been served as evidence for deception detection, and many computer vision based methods were designed [20][21]. Examples for verbal case, some researches showed that acoustics-related features such as speaking rate, energy, pitch, range as well as the...
A. Feature extraction for visual modality

Due to the results [25] showed that facial expression is one of the most important clues to deception detection, we get inspiration from emotional state-based features by combining the information from both modalities. Our framework can be separated into three parts: feature extraction from visual modality, feature extraction from audio modality and EST feature construction. The framework is showed in Fig. 1.

B. Feature extraction for audio modality

Information from audio modality is also important for deception detection task. We use similar concepts and procedures for visual modality to deal with audio data. First of all, we limit the audio segments into a fixed length (e.g., 0.5-second) to satisfy the form of input of algorithms. We also redefine the label information of each audio segment with the seven emotional states. Then, we refer to the audio emotion recognition method mentioned in [31] to determine the emotional state of each audio segment. Here, we extract the Mel-frequency cepstrum coefficients (MFCC) and modulation spectral (MS) features from the redefined data. Then, we use these features to train the support vector machine (SVM) classifier to obtain the audio emotional state information. Finally, it is considered as the reference to determine the final EST feature with the visual emotional state. The details will also be introduced in the next section.

B. Feature extraction for audio modality

In this part, we also use an open source software called openSMILE [32] to extract some meaningful features for audio modality. Since the audio segments contain background noise, we use the audio processing tool [33] to remove it. Then, we use the IS13-ComParE configuration to extract the well-performed audio features (e.g., MFCC, low-level descriptor (LLD), etc.) which are of dimension 6373 for each audio segment. In addition, we try a series of filter-based feature selection methods (e.g., Pearson’s correlation, LDA, ANOVA, Chi-Square, etc.) and finally use the Pearson’s correlation to reduce the dimension of audio features from 6373 to 43.

C. EST feature construction

After the emotional states from both modalities have been obtained, we can determine the revised emotional state now. The EST feature will be affected by the results of emotion recognition during the feature extraction process, more specifically, in emotion recognition, there are face expressions that are prone to be misclassified between two emotions, e.g., sadness or fear. This issue results in the staggered appearance of two emotions in the sequence of emotion recognition results. If one emotion in the sequence of emotions in which the same emotion appears consecutively is mistaken for other emotions, it will result in two additional incorrect records in the emotion transition. Since we limited audio segments to a fixed length, the emotional state for each audio segment represented the
information of 15 frames. Therefore, we expand the emotional state with 15 times for each audio segment to match the information of visual emotional state. Then, voting method is designed to take the emotional state information from both visual modality and audio modality into account to determine the final emotional state information. The idea of utilizing the majority vote is to realize the cross-comparison between the emotional state information of both modalities. By this way, we can further improve the correctness of the final emotional state information. Then, our self-defined algorithms are applied to construct the EST feature with it.

Finally, we conduct a series of experiments to show the effectiveness of our proposed methods and features in the next section. Experiments contain both unimodal and multimodal to show the importance of both features from visual modality and audio modality.

IV. EXPERIMENTAL RESULTS

In this section, we first describe the ground truth dataset used for our experiments and the implementation detail. Then, we perform an experimental analysis of our proposed method and compare it with relative works.

A. Dataset

Real-life deception detection dataset [1] contains 121 videos, including 61 deceptive and 60 truthful trial clips. The average length of the video clips in the dataset is 28.0 seconds. Most of them in this dataset are human edited, which means the video clips contain transition effects and scenes that are irrelevant to the person we want to observe. The unusable parts may appear at any point in the timeline of a video. We divide a video into multiple clips based on the unusable parts and label the separated clips as new clips. Therefore, after we remove the unusable parts, the total number of video clips becomes 90 deceptive and 90 truthful.

B. Details of our EST feature extraction

To extract EST feature, we first obtain a sequence of revised emotional states determined with the emotional states detected in the visual and audio information. Then, they are used to construct our EST feature. To detect visual emotional state, we extracted an image sequence from a video clip using a frame rate of 30 fps. For each frame, we detect and align the faces using the DSFD proposed in [26]. Since multiple people may appear in the video scene at the same time, we need to identify the target person from the crowds. We crop the image of the target person in advance as the reference, and we select the face most similar to the reference from the results detected with DSFD. After cropping the selected face region, we scale it to size of 48*48. Then, we obtain visual emotional states of each image with multiple facial emotion recognition model [28][29][30]. Similarly, to detect audio EST, we split the audio file separated from the video clip into multiple 0.5-second audio segments. We obtain the emotional state of each audio segment with an speech emotion recognition model [31]. Then, we determine the revised emotional state based on the number of occurrences of emotional states in $e_v[i]$, $e_v[i + 1]$, and $e_{ax}[i]$, where $e_v[i]$ is the visual emotional state of frame $i$ in the corresponding video clip, and $e_{ax}[i]$ is the speech emotional state corresponding to the frame. The emotional state with most occurrence is considered as the revised emotional state of frame $i$, denoted as $e_{re}[i]$. If the emotional states are all different, we regard the visual emotional state as the revised emotional state. The processing details to obtain the revised emotional state are organized in Algorithm 1. The construction of EST feature is based on the transition between two adjacent revised emotional states. Under the premise that the emotional state was classified into 7 types in the previous stage, we classify the possible changes between two adjacent emotions into 49 categories based on the

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TABLE I

| EST(Top 5) | Deceptive | EST(Top 5) | Truthful |
|------------|-----------|------------|---------|
| Sad → Fear | 0.43      | Fear → Angry | 0.36    |
| Neutral → Sad | 0.18      | Neutral → Neutral | 0.15    |
| Happy → Neutral | 0.10    | Neutral → Happy | 0.13    |
| Fear → Angry | 0.08      | Fear → Neutral | 0.09    |
| Neutral → Neutral | 0.05    | Sad → Angry | 0.08    |

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Fig. 2. The emotion distribution of deceptive and truthful case.
order of arrangement and the categories of the two emotional states. By counting the frequency of all emotion changes in the sequence of the revised emotional states, we obtain the EST feature. Note that if the same emotion occurs continuously, we consider it as one emotional state transition. The processing details are presented in Algorithm 2.

C. Analysis of emotion on deception detection

In order to discuss the impact of emotions on deception detection, for both deceptive and truthful case, we evaluated the emotion distribution and the five main EST with the largest occurrence probabilities of each clip, which are shown in Fig. 2 and Table I respectively. We discovered that emotions are mainly distributed in five emotions, and the difference between truthful and deceptive clips appears in sadness and neutral emotions. We also found that people tend to accompany a sad emotional state when they are lying. Moreover, in the process of human deception, the sad to fear EST feature occurs most frequently. We think that the reason for this phenomenon is that people may undergo a heavy emotional load while deceiving and result in a depressive expression, or they might just pretend to be sad as if they feel wronged.

D. Evaluation setting and metrics

The dataset contains only 58 identities, which is less than the number of video clips. Since the same identity appears in both deceptive and truthful clips, a deception detection method may suffer from overfitting to identities. To avoid the overfitting issue, we conduct experiments across different feature sets and classifiers using 10-fold cross-validation. To test the reliability and robustness of the proposed features, we built various deception classifiers using several widely used binary classifiers, which are linear kernel support vector machine (L-SVM), decision tree (DT), random forest (RF), k-nearest neighbor (kNN), and logistic regression (LR). After we try several cases of hyperparameter for each classifier, we obtain the following optimal setting. The regularization parameter of L-SVM is set as 10. The number of nearest neighbors used in kNN is 3. The maximum depth of the DT is 5 layers. The number of estimators used in RF is 50.

E. Evaluation of combined feature

In this section, we evaluate different combinations of multimodal features using ROC-AUC metric, as shown in Table II. The first 6 features are the combination of EST feature constructed of visual emotional states (ESTv), EST feature constructed of revised emotional states (ESTre), Interspeech 2013 ComParE Challenge features (IS13), and the ground truth micro-expression (MEg) feature collected in prior work [1], where ESTv can be obtained by performing algorithm 2 with the visual emotional states as input. The last two features are used in the state-of-the-art work, where Improved Dense Trajectory (IDT), high-level micro-expression (MRh), MEg, MFCC (Mel-frequency Cepstral Coefficients), and transcripts are scored and fused to obtained final features. From Table II, we observe that the performance of the revised feature at least improves by more than 17% compared to visual feature alone. Similar improvements can be achieved when visual features are combined with MEg. With the addition of MEg, the proposed feature ESTre can improve at least 1% and it can achieve 0.8822 on kNN. The combination of our proposed features with MEg and IS13 (the dimension is 180) achieves the best performance on L-SVM and RF, 0.9244 and

Fig. 3. The confusion matrices of classifiers including Logistic Regression (LR), Random Forest (RF), Linear Kernel Support Vector Machine (L-SVM), Decision Tree (DT), and k-Nearest Neighbor (kNN) with ESTre + ME + IS13 features.
0.8934 respectively, which are even better than state-of-the-art performance.

**F. Comparison of our model with baseline methods**

Pérez-Rosas *et al.* had discussed thoroughly on frequency counts for facial displays and hand gestures that constructed the MFg [9]. They also took the unigrams, psycholinguistic, and syntactic complexity into account and incorporated them in their proposed features. Here, we consider their result as a baseline, and we also compare our method with the performance of the end-to-end DEV framework proposed by Karimi *et al.* [14], as shown in Table 2. We can see that our approach outperforms the baseline by a huge margin and is slightly better than DEV framework. In Fig. 3 we provide confusion matrices corresponding to different classifiers to verify that our results do not have the problems with skewness in data.

**Algorithm 1** Framework of extracting revised emotional state feature.

**Input:** Video clip  
**Output:** Revised emotional state e_re  
1: Convert video clip to a sequence of n frames;  
2: Crop face region of each frame and resize it into an image of size 48*48;  
3: Detect emotional state e_v[i] of the i-th image, i = 1 ... n;  
4: Extract sound track from video clip;  
5: Split sound track into m 0.5-second audio segment;  
6: Detect emotional state e_a[j] of the j-th audio file;  
7: Expand e_a by 15 times to obtain e_a = e_a ⊗ I_{1×15};  
8: for i ← 1 to n - 1 do  
9: \[ e_{re}[i+1] = e_{re}[i] \]  
10: \[ e_{re}[i] = e_v[i+1] \]  
11: else  
12: \[ e_{re}[i] = e_a[i] \]  
13: end if  
14: end for  
15: \[ e_{re}[n] = e_v[n] \]  
16: return e_re;

**Algorithm 2** Construction of emotional state transformation feature.

**Input:** Revised emotional state e_re  
**Output:** Emotional state transformation feature f_est  
1: let \( t \leftarrow 0 \), emotional state transformation \( T \leftarrow 0_{T×T}; \)  
2: for \( k \leftarrow 1 \) to \( n - 1 \) do  
3: if \( e_{re}[k] \neq e_{re}[k+1] \) or \( k = 1 \) then  
4: \[ T \{e_{re}[k], e_{re}[k+1] \} \leftarrow T \{e_{re}[k], e_{re}[k+1] \} + 1 \]  
5: \( t \leftarrow t + 1 \)  
6: else  
7: if \( e_{re}[k] = e_{re}[k+1] \) and \( e_{re}[k] \neq e_{re}[k-1] \) then  
8: \[ T \{e_{re}[k], e_{re}[k+1] \} \leftarrow T \{e_{re}[k], e_{re}[k+1] \} + 1 \]  
9: \( t \leftarrow t + 1 \)  
10: end if  
11: end if  
12: end for  
13: \( f_{est} \leftarrow \text{vec}(T^T)/t; \)  
14: return \( f_{est}; \)

**V. Conclusion**

In this paper, we propose a series of data preprocessing procedures for dirty information and unusable frames in the ground truth data. Then, our propose multimodal deception detection framework can be used to extract features from both visual modality and audio modality. We also introduce in a novel emotional state-based feature called EST feature to analyze deception detection task. With our designed voting method, the emotional state information from both modalities are considered to construct EST feature. Surprisingly, our EST feature can perform very well on it even the quantity of the dataset is very limited. We think the reason is because our EST feature includes both temporal information and spatial information from the change of emotional state in frames and audio segments. Finally, critical experiments based on our proposed methods show that we outperform the state-of-the-art method. The accuracy and ROC-AUC of deception detection in video are improved up to 91.67% and 0.9244, respectively. In our future work, we will take the information from textual modality into account to analyze the relationship between textual features and human deception. Also, we will design a series of data collection mechanism for extending the diversity of data for deception detection task.

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### TABLE II

| Papers        | Features          | L-SVM | DT  | RF  | kNN | LR   |
|---------------|-------------------|-------|-----|-----|-----|------|
| EST           |                   | 0.650 | 0.6846 | 0.7115 | 0.6115 | 0.6245 |
| EST+MEG       |                   | 0.8759 | 0.7656 | 0.8166 | 0.8249 | 0.8777 |
| ESTe          |                   | 0.8611 | 0.8444 | 0.8389 | 0.8444 | 0.8833 |
| ESTe+MEG      |                   | 0.8767 | 0.7889 | 0.8544 | 0.8822 | 0.8944 |
| ESTe+IS13     |                   | 0.9178 | 0.7633 | 0.8789 | 0.8456 | 0.9122 |
| ESTe+MEG+IS13 |                   | 0.9244 | 0.7808 | 0.8934 | 0.8477 | 0.9175 |
| Wu et al.     | IDT+ME+Transcripts+MFCC | 0.8773 | 0.7777 | 0.8477 | -     | 0.7894 |
|               | IDT+ME+Transcripts+MFCC | 0.9065 | 0.8074 | 0.8731 | -     | 0.9221 |

### TABLE III

| Papers        | Features          | L-SVM | DT  | RF  | kNN | LR   |
|---------------|-------------------|-------|-----|-----|-----|------|
| Pérez-Rosas et al. | Unigrams           | 69.49% | 76.27% | 67.79% | -   | -    |
|               | Psycholinguistic   | 53.38% | 50.00% | 66.10% | -   | -    |
|               | Syntactic Complexity | 52.54% | 62.71% | 53.38% | -   | -    |
|               | Facial Displays    | 78.81% | 74.57% | 57.79% | -   | -    |
|               | Hand Gestures      | 59.32% | 57.62% | 57.62% | -   | -    |
|               | All Features Combined | 77.11% | 69.49% | 73.72% | -   | -    |
| Karimi et al.  | DEV-vocal          | -     | -   | -   | 74.16% | -    |
|               | DEV-visual         | -     | -   | -   | 75.00% | -    |
|               | DEV-Hybrid         | -     | -   | -   | 84.16% | -    |
| Our proposed method | ESTe + ME + IS13 | 91.67% | 76.67% | 87.78% | 84.44% | 91.67% |

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