SAPIENZA
UNIVERSITÀ DI ROMA

Lie Detection Thesis

Facoltà di Ingegneria dell'informazione, Informatica e Statistica

Corso di Laurea Magistrale in Informatica

Candidate

Emanuele Orfanelli

ID number 1383726

Thesis Advisor

Prof. Luigi Cinque

Co-Advisors

Dr. Danilo Avola

Dr. Daniele Pannone

Academic Year 2018/2019

Lie Detection Thesis
Master thesis. Sapienza – University of Rome

This thesis has been typeset by LaTeX and the Sapthesis class.

Author's email: emanueleorfanelli@gmail.com

Dedicated to
my Family and Friends

Acknowledgments

fill

Contents

Chapter 1

Introduction

In this chapter we give an overview of the work (Par. 1.1). We then present a taxonomy of the current state of the art (Par 1.2) concerning computer vision lie detection. The last section is about the structure of this work and our contribution (Par 1.3).

1.1 Overview of the work

fill

1.2 State of the Art

In computer vision, lie detection is done using an array of different techniques, employing not only RGB cameras but also physical sensors and thermal cameras, with machine learning techniques, and often combining many of them to achieve better results. We now proceed to describe the state of the art, based on the latest researches done in the field:

Speech

Speech is one of the many methods used to recognize a lie, in fact the speech signal contains linguistic, expressive, organic and biological data. Speech analysis can reveal changes that affect behavior, such as stress, emotion, deception etc. by analyzing the pitch and the stress level. When a stressful situation arise, the hormonal levels of the body change, and this causes an increase in blood pressure and heart rate. This in turn affects the muscle in the respiratory system, and so speech is affected [16].

In sound processing, the mel-frequency cepstrum (MFC) is a representation of the short-term power spectrum of a sound. Mel-frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC [26].

In [14] the authors extract MFCC and pitch and process them through Matlab. An SVM classifier is then trained to classify new data, obtaining an accuracy of Lie and Truth detection of speech audio respectively 88.23% and 84.52%.

In [19] [13] Perez et al. utilize real life trial data to identify deception, achieving 60-75% accuracy employing a model that extracts features from both linguistic and gesture modalities.

Eyes

Using the eyes to detect lies is one of the most studied approaches as the eyes hold a lot of information [8]. Moreover is possible to generate a non invasive approach while analyzing the eyes. Cognitive load, which is set to increase while lying, is one of the factor. Significant are also the blink rate and pupil dilation.

In [9] the authors analyze blink count and blink duration of 50 subjects, while asking different questions, to see if there is a variation in them while the subject is being asked questions. The results show that both blink duration and count are increased while lying.

Singh et al. in [23] show that while lying there is an increase in cognitive load and a significant decrease in eye blinks, directly followed by an increase as soon as the cognitive demand ceases, after telling the lie. Blink detection is done with MATLAB using HAAR Cascade algorithm.

Lim et al. study eye gaze [12] to investigate the relation with lie detection. The result supports the theory that cognitive load decreases the number of eye movements.

Bhaskaran et al. measure deception by the deviation from normal behavior [6] at critical points during an investigative interrogation. For starters a dynamic Bayesian model of eye movement is trained during a normal conversation, then the remainder of the conversation is broken into pieces and each piece is tested against the normal

behavior. The deviation from normality are observed during critical points in the interrogation and used to deduce the presence of deceit, obtaining an accuracy of 82.5%.
In [20] Proudfoot et al. using latent growth curve modeling, research how the pupil diameter changes over the course of an interaction with a deception detection system. The results indicate that the trends in the changes are indicative of deception during the interaction, regardless if incriminating items are shown.
Nurcin et al. [17] analyze the segmentation of pupil and iris radius in images taken from the MMU iris database. The assumptio n is that bigger pupils are lying ones and small pupils are neutral. The algorithm does the segmentation of iris and pupil radius, and then trains a neural network to classify high and low pupil to iris radius. All images from the MMU database were correctly classified.

EEG

EEG (Electroencephalogram) is a monitoring method that records brain activities based on its potential. In [22] Simbolon et al, use ERP (Event Related Potentials) to measure brain response directly from thought or perception. Among the numerous types of signals that constitute the ERP signal, P300 is the most critical for lie detection. Eleven males of age between 20 and 27 took part in the study. The gathered data were then divided into training and test sets to produce different models. The highest accuracy of 70.83% was reached by a SVM classifier in detecting lying subjects.
In [11] twenty people were subject to a card test using an EEG. The authors used the EEG to identify frequency bands and measure lying state based on spectral analysis, with the use of fuzzy reasoning, obtaining 89.5% detection accuracy.
Arasteh et al. [5] use empirical mode decomposition (EMD) to extract features from the EEG signal. A genetic algorithm was then utilized for the feature selection. The classification accuracy of guilty and innocent subjects was 92.73%.

Head

Noje et al. [15] set up a study with ten subjects to observe the potential of head movements in lie detection. They built an application to detect head movement and position by performing a frame to frame analysis on a video stream. A correlation was made between head movement/position and the identification of lies. The results of the study are not concluding as this data can't be utilized without being incorporated with other modalities such as voice, gaze, words, expressions et cetera.

Facial Expression

Facial micro-expressions have been used and classified since 1977 [7] to classify and distinguish real or fake emotions.
Owayjan et al. [18] designed a lie detection system using micro-expressions. A video stream is converted into frames, and each frame is processed in four stages, converting the images, filtering out useless features, applying geometric templates and finally extracting the measurements to detect the micro-expressions. Eight facial expressions can be recognized and lies can be discerned with high precision.

In [10] Kawulok et al. explore how to exploit fast smile intensity detectors to extract temporal features using a SVM classifier. This allows to detect in real time between spontaneous or posed expressions.
Su et al. [24] aim to test the validity of facial clues to deception detection in high-stakes situations using computer vision approaches. By using invariant 2D features from nine separate facial regions they perform facial analysis on eye blink, eyebrow motion, wrinkle occurrence and mouth motion, integrated with a facial behavior pattern vector. Training a Random Forest to classify the patterns into deceptive or truthful, they achieved a 76.92% accuracy.

Thermal

In thermal imaging, thermal features are extracted from the face using a high definition thermal camera to analyze whether differences occur when a subject responded truthfully or deceptively. The most relevant zones are forehead and periorbital regions [21] [3].
In [25] data are gathered non-intrusively from the nostril and periorbital regions using two dimensional far infrared cameras. The temperature is converted in change in blood flow velocity and a signature of the respiration pattern is determined in terms of the ratio of the measured maximum and minimum temperatures in the nostril area. The classification rate for this study is 88.5%.

Multimodal

There are ways to detect lies that are a combination of different modalities. This improves the detection of deceptive behavior [4].
In [2] Abouelenien et al. examine thermal and visual clues of deception. Using the CERT (Computer Expression Recognition Toolbox) to detect facial expression and encoding them with AU (Action Units). They also calculated normalized blinking rates and the mean head orientation angle along the entire length of the response. In addiction over 60 physiological features were also extracted and stored. The experimental results show that the non-contact feature fusion model outperforms traditional physiological measurements.
In a following paper [1] Abouelenien et al. explore a multimodal deception detection approach comprised of physiological, linguistic, and thermal features. They determine the most discriminative region of the face based on thermal imaging, and perform feature analysis using a decision tree model. The result says that the forehead could be a better indicator of deceit than the periorbital area. The physiological features did not contribute very much, while the linguistic feature played a critical role, where self-referencing and exaggeration words where indicators of deceit. The overall accuracy of the system is 70%
Another example of multimodal detection is found in [27] where Wu et al. develop a system for covert automated deception detection. They utilize three modalities: vision, audio and text. For vision they employ a classifier trained on low level video features to predict on human micro-expressions. About text the transcript of the considered videos are analyzed, but the performance increase is marginal. For speech they integrate the vision side with MFCC features analysis from the audio, boosting

the performances significantly, reaching an AUC of 0.877.

1.3 My Contributions

fill

Chapter 2

Thesis Chap 1

th ch 1

Chapter 3

Th Ch 2

th ch 2

Bibliography

[1] M. Abouelenien et al. “Detecting Deceptive Behavior via Integration of Discriminative Features From Multiple Modalities”. In: *IEEE Transactions on Information Forensics and Security* 12.5 (May 2017).

[2] Mohamed Abouelenien, Rada Mihalcea, and Mihai Burzo. “Analyzing Thermal and Visual Clues of Deception for a Non-Contact Deception Detection Approach”. In: *Proceedings of the 9th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. 2016. URL: `http://doi.acm.org/10.1145/2910674.2910682`.

[3] Mohamed Abouelenien, Rada Mihalcea, and Mihai Burzo. “Trimodal Analysis of Deceptive Behavior”. In: *Proceedings of the 2015 ACM on Workshop on Multimodal Deception Detection*. 2015. URL: `http://doi.acm.org/10.1145/2823465.2823470`.

[4] Mohamed Abouelenien et al. “Deception Detection Using a Multimodal Approach”. In: *Proceedings of the 16th International Conference on Multimodal Interaction*. 2014. URL: `http://doi.acm.org/10.1145/2663204.2663229`.

[5] A. Arasteh, M. H. Moradi, and A. Janghorbani. “A Novel Method Based on Empirical Mode Decomposition for P300-Based Detection of Deception”. In: *IEEE Transactions on Information Forensics and Security* 11.11 (Nov. 2016).

[6] N. Bhaskaran et al. “Lie to Me: Deceit detection via online behavioral learning”. In: *Face and Gesture 2011*. Mar. 2011.

[7] P. Ekman and W. V. Friesen. *Manual for the Facial Action Coding System*. 1977.

[8] Kyosuke Fukuda. “Eye blinks: new indices for the detection of deception”. In: *International Journal of Psychophysiology* 40.3 (2001), pp. 239–245.

[9] S. George et al. “Eye blink count and eye blink duration analysis for deception detection”. In: *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*. Sept. 2017.

[10] Michal Kawulok et al. “In Search of Truth: Analysis of Smile Intensity Dynamics to Detect Deception”. In: *Advances in Artificial Intelligence - IBERAMIA 2016*. 2016.

[11] Ying-Fang Lai, Mu-Yen Chen, and Hsiu-Sen Chiang. “Constructing the lie detection system with fuzzy reasoning approach”. In: *Granular Computing* (Nov. 2017). URL: `https://doi.org/10.1007/s41066-017-0064-3`.

[12] Kai Keat Lim et al. “Lying Through the Eyes: Detecting Lies Through Eye Movements”. In: *Proceedings of the 6th Workshop on Eye Gaze in Intelligent Human Machine Interaction: Gaze in Multimodal Interaction.* 2013. URL: http://doi.acm.org/10.1145/2535948.2535954.

[13] Rada Mihalcea, Verónica Pérez-Rosas, and Mihai Burzo. “Automatic Detection of Deceit in Verbal Communication”. In: *Proceedings of the 15th ACM on International Conference on Multimodal Interaction.* 2013. URL: http://doi.acm.org/10.1145/2522848.2522888.

[14] H. Nasri, W. Ouarda, and A. M. Alimi. “ReLiDSS: Novel lie detection system from speech signal”. In: *2016 IEEE/ACS 13th International Conference of Computer Systems and Applications (AICCSA).* Nov. 2016.

[15] D. I. Noje and R. Malutan. “Head movement analysis in lie detection”. In: *2015 Conference Grid, Cloud High Performance Computing in Science (ROLCG).* Oct. 2015.

[16] Paola Noreña Cardona. “A COMPENDIUM OF PATTERN RECOGNITION TECHNIQUES IN FACE, SPEECH AND LIE DETECTION”. In: 24 (Nov. 2015).

[17] Fatih Veysel Nurçina et al. “Lie detection on pupil size by back propagation neural network”. In: *Procedia Computer Science* 120 (2017). URL: http://www.sciencedirect.com/science/article/pii/S1877050917324705.

[18] M. Owayjan et al. “The design and development of a Lie Detection System using facial micro-expressions”. In: *2012 2nd International Conference on Advances in Computational Tools for Engineering Applications (ACTEA).* Dec. 2012.

[19] Verónica Pérez-Rosas et al. “Deception Detection Using Real-life Trial Data”. In: *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction.* 2015.

[20] J. G. Proudfoot et al. “Deception is in the eye of the communicator: Investigating pupil diameter variations in automated deception detection interviews”. In: *2015 IEEE International Conference on Intelligence and Security Informatics (ISI).* May 2015.

[21] B. Rajoub and R. Zwiggelaar. “Thermal facial analysis for deception detection”. In: *IEEE Transactions on Information Forensics and Security.* 2014.

[22] A. I. Simbolon et al. “An experiment of lie detection based EEG-P300 classified by SVM algorithm”. In: *2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT).* Oct. 2015.

[23] B. Singh, P. Rajiv, and M. Chandra. “Lie detection using image processing”. In: *2015 International Conference on Advanced Computing and Communication Systems.* Jan. 2015.

[24] Lin Su and Martin Levine. "Does "lie to me" lie to you? An evaluation of facial clues to high-stakes deception". In: *Computer Vision and Image Understanding* 147 (2016). URL: `http://www.sciencedirect.com/science/article/pii/S1077314216000345`.

[25] S. Sumriddetchkajorn et al. "Simultaneous Analysis of Far Infrared Signals From Periorbital and Nostril Areas for Nonintrusive Lie Detection: Performance From Real Case Study". In: *Journal of Lightwave Technology* 33.16 (Aug. 2015).

[26] Wikipedia contributors. *Mel-frequency cepstrum — Wikipedia, The Free Encyclopedia.* 2018. URL: `https://en.wikipedia.org/w/index.php?title=Mel-frequency_cepstrum&oldid=835415759`.

[27] Zhe Wu et al. "Deception Detection in Videos". In: *CoRR* abs/1712.04415 (2017). URL: `http://arxiv.org/abs/1712.04415`.