Using an Open source face tracker for identity detection and facial expression Recognition

Eduardo Neiva, Jesus Nuevo, David Rozado

March 17, 2013

1 Abstract

Face and eye tracking technology are fairly well developed and robust technologies. Eye tracking in combination with gaze estimation permits the monitoring of the user's area of attention on a computer screen while also providing a hint about possible intention. Facial tracking can augment eye tracking by monitoring facial features that can convey the identity of the user or its internal cognitive state as expressed through its facial expression. In this work, we use an open source face tracker that can recognize and classify facial expressions from continuous video input. The system uses ———- for jesus to fill ————. We show that the face tracker is a powerful tool to recognize the identity of the user among a large pool of subjects. We also show that it can robustly recognize facial expressions of users on which the system has been trained while also performing well on users never exposed before to the system. This positive results and the open source nature of the system suggest the advantages of augmenting traditional eye trackers by combining them with face tracking algorithms as the one suggested to enrich the set of features available to monitor a human while interacting with a computer.

2 Introduction

Traditional Human Computer Interaction (HCI) could be augmented by providing computer systems with the ability to recognize the emotions of the humans interfacing them. Emotions are conveyed by humans using the visual, vocal and other physiological means such as body gestures. Facial expressions are an indirect proxy to measure the internal cognitive emotions of humans. Impaired facial expression recognition by humans can be a sign of serious cognitive dysfunction such as schizophrenia [10]. Facial attributes can be tracked computationally through a video stream of the subject's face. Making the computer aware of the emotions of the user could lead the way towards more natural in fluid forms of interaction.

In this work we describe the usage of an open-source face tracker to feed a set of machine learning classifiers striving to identify subjects identity and their facial expressions. The face tracker provides a set of invariant features extracted from the tracked faces (MAYBE JESUS COULD COMPLETE THIS). We used support vector machines to classify the invariant features provided by the face tracker.

The psychological literature has traditionally classified facial expressions in seven categories: neutral, anger, disgust, fear, joy, sadness and surprise. in these experiments, we use some additional facial gestures such as: raising eyebrows and open mouth. (EDUARDO PLEASE COMPLETE THIS LIST with the accurate info).

Researchers have employed a variety of methods to carry out facial expression recognition such as optical flow computation and symbolic representations [18], local binary patterns [16], Bayesian network classifiers [7], geometric deformation features and support vector machines [14], hidden Markov models [1, 8], Parametric flow models [4], AdaBoost and linear discriminant analysis [3]. The surveys from [3] and [11] are two good review sources about machine learning methods for fully automatic recognition of facial expressions.

Previous work has employed a variety of techniques to classify facial expressions. The work from [8] tested the classic neural network classifiers for classifying expression from video, focusing on changes in distribution assumptions and feature dependency structures. Authors also proposed an tested the architecture of Hidden Markov Models (HMM) for automatically segmenting and recognizing human facial expressions. Authors reported recognition rates up to 83% For frame-based recognition methods and 82% for the multilevel HMM.
The work from [6] investigated the emotional contents of speech and video based facial expression to proposes a bioinspired algorithm for human facial expression recognition, concluding that both modalities can be complimentary and able to achieve higher recognition rates than either modality alone. Authors in [5] also used a multimodal approach to combine acoustic information and facial expression analysis in order to detect human emotions. In their work, authors demonstrated that when both modalities are fused, the performance and the robustness of the emotion recognition system improves considerably.
Authors in [2] used perceptual primitives to code seven facial expressions in real-time. Their system first detects frontal faces using a cascade of feature detectors trained with boosting techniques. The expression recognizer receives image patches located by the phase detector. A Gabor representation of the parts is used by a bank of kernel based classifiers. Authors used a combination of Adaboost and support vector machines to enhance performance. One of the most interesting properties of this work was its ability to change the outputs of the classifiers smoothly as a function of time, hence, providing a dynamical representation of facial expression.
The work from [19] deviates from the typical 2D static image or 2D the video sequence recognition of facial expression arguing that that a 2D-based analyses is incapable of handling large pose variations and proposing instead the usage of classification techniques on 3-D facial expression models and making available to the community a database of prototypical 3D facial expression shapes.
The work from [13] made available over 2000 digitized image sequences from 182 adult subjects of varying ethnicity, performing multiple tokens of most primary facial expressions to create a comprehensive testbed for comparative studies of facial expression analysis.
Facial identity recognition is another subject that has drawn a lot of attention in the research literature. While being apparently trivial for humans to solve, automatic approaches have traditionally lagged behind the performance of humans by at least one order of magnitude in terms of recognition performance. These approaches have only recently started to catch up with the ability of the human brain to recognize faces [12, 15]. Face recognition is important for a wide range of commercial and law enforcement applications. Only recently has the technology required to carry out automatic classification of faces become available. But the recognition of faces in outdoor environments where variation in pose and illumination are continuous remains a largely unsolved problem.
The work from [21] provides a good literature survey on the subject of face recognition. In [9], authors undertake an in-depth discussion of face features automatic extraction for classification purposes of grayscale images.
The work from [20] undertakes a comprehensive review of the challenging topic of pose invariant face recognition, and while showing that the performance of different methods is still far from perfect, several promising directions for future research are suggested.
Authors in [17] review the also challenging topic of face recognition using just one image per class for training comparing several prominent algorithms for the tasks. the rationale for the study is the reported critique that several face recognition techniques rely heavily on the size of the training set.
(i NEED TO COMPLETE THE LITERATURE REVIEW FOR IDENTITY RECOGNITION)
In summary, in this paper we apply that open source face tracker XXXXX for identity recognition and for facial expression recognition. We suggest that facial tracking can be a powerful complement to traditional eye tracking by augmenting the set of features being tracked during human computer interaction. This can potentially allow computer systems to more precisely recognize the cognitive state of the human interfacing them through the proxy features of facial dynamics.

3 Methodology

(eDUARDO IT IS VERY IMPORTANT THAT THE THE SECTION YOU INCLUDE A BRIEF subsection OF JUST ONE PARAGRAPH IN WHICH YOU PROVIDE A BRIEF DESCRIPTION OF WHAT SUPPORT VECTOR MACHINES ARE)

3.1 Face Tracker

—- For Jesus to fill in——————

3.2 Experimental Setup

The dataset that was used to train and test the recognition algorithms was specifically generated for this work. It consists of 50 people (age distribution ranged from 19 to 40 years old). From the entire set, 80% were male, 16% were Latino and 10% were Asian. The data extraction was made using a standard notebook webcam, 1.3 MP, running at a resolution of 640x480. The distance between the camera and the subject's face was about 114cm. The data extracted from the face tracker was a vector with 24 dimensions that represents a particular face shape at any given time point. This vector has the property of being invariant within a particular face shape. (i DON'T LIKE THE LAST SENTENCE, MAYBE jESUS COULD IMPROVE OR ADD SOMETHING so it makes better SENSE)

3.2.1 Metodology of the data extraction

Every participant involved in the experiment was asked to perform eleven different facial shapes or expressions. Five of them were stereotypical emotion common to every person (i.e., neutral, anger, disgust, fear, happiness, surprise). The remaining facial expressions where: open mouth, raised eyebrows (FOR eDUARDO TO COMPLETE)
Even though the feature vector produced by the face tracker was invariant to changes in scale, the distance between the camera and the subject was kept constant to maintain uniformity during the data collection.
The data collection was divided in two phases, the training and the capturing. The training was the phase in which the subject was told to perform every face shape in order to practice how to perform each of the requested face representations.
The capturing phase consisted on the subject representing them again and the computer system recording these instances for subsequent training and validation.
For every face shape recorded, 20 samples were recorded with a small time interval between them (less than one second). Each sample consists on recording the invariant vector that transforms a neutral face shape into the deformed face shape that fits the subject facial expression. Since there was fluctuations on the borders of the face shape tracker and this generated some instability on the invariant vector, 20 samples to smooth out this error.
During the data extraction period, we observed that every person had a unique invariant vector signature which was specific for each facial expression on for different persons. We thought that this invariant feature vector could be used to recognize people as well as data facial expressions. The invariant feature vector specific for each person and facial expression can be seen in the Figure 2.
For the task of facial expression recognition, even though every person has its own unique feature vector signature for each face expression, there is a similarity between these vectors when comparing the same face shape of different people, thus the goal of the SVM was to generate an abstraction of each facial expression class in order to be able to carry out facial expression classification.

3.2.2 Data training

10-fold cross validation of the training set was used in all experiments. (eDUARDO YOU NEED TO EXPLAIN how you partition THE DATA SET INTO TRAINING AND TEST SET)

Figure 1: **Data extraction** Samples of the face shapes recorded.

4 Results

The first experiment tried to recognize people's identity using the entire data set of the study participants. Two experiments were carried out, (eDUARDO HERE YOU NEED TO EXPLAIN THE SPECIFICS OF THESE EXPERIMENTS, where you using ALL FACIAL EXPRESSIONS OR JUST NEUTRAL? what is THE FRIENDS BETWEEN the labels in the figure including and excluding?). The results of the identity recognition experiments are shown in Figure 3.

4.1 Recognizing Face Expressions

In this experiment, the goal was to recognize each of the 11 different classes of facial expressions in the training set. It was used all the 24 features of each face shape. It was given two different aproaches on the performance measurement. The first one was by separating the 20 samples of each person face expression into two segments, one containing 17 samples and other 3. The 17 samples were used to train while the remaining ones to test. This approach will be called Including. The second approach was by using all the 20 samples but using different people one the training set and the testing set. It was kept the same ratio for the second approach, 70%.
The results of the facial expression recognition are shown in Figure 3.

4.2 Recognizing Face Expressions increasing the number of classes

Using a 10-fold cross validation, in this approach the goal was to measure the change of effiency of the algorithm by increasing the number of classes from 2 to 11. The amount of people used was 50.
Figure 5 shows the results of increasing the number of people to be recognized by the classifier.

4.3 Recognizing People

In the third approach, there is a change on what are the classes of the algorithm. Instead of face shapes being the classes, in this method, the people to recognize were transformed into the classes. Therefore, the increase of people to recognize increase the number of the classes, thus decreasing the efectiviness of the algorithm. It was analysed from 2 to 50 people the algorithm accuracy. It was also analysed in three different scenarios, using only the normal face shape, using only 6 and using all 11 face shapes in each classe.

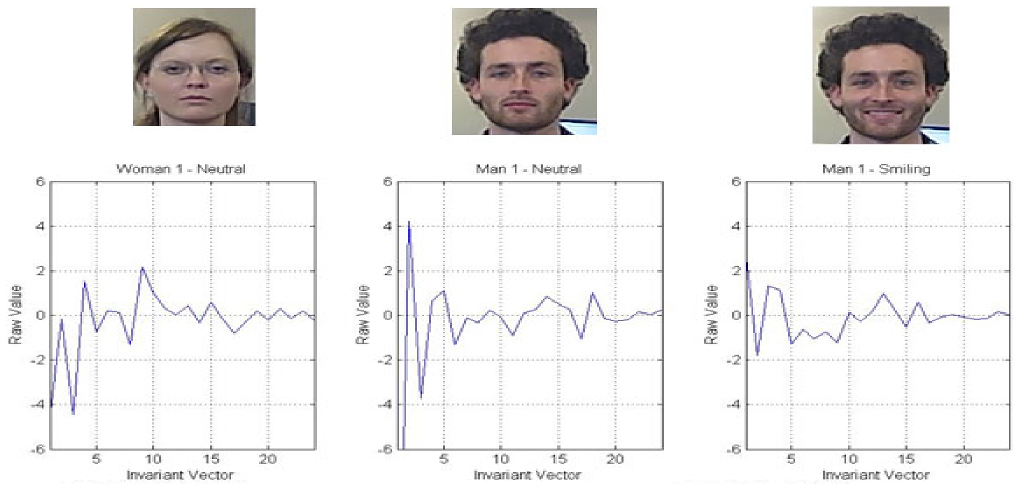

Figure 2: **Invariant and Unique Feature Vectors of Facial Expressions.** this figure displays a. Typical feature vector signature specific for a given person. These constraint can be used to recognize people. The feature vector provided by the face tracker changes for each facial expression perform but remains invariant we seen a given facial expression. Furthermore, features vectors of the same facial expression among different people share commonalities that can be exploited to carry out facial expression recognition among different people.

Figure 5 shows the results of increasing the number of people to recognize facial expressions

5 Discussion

In this work we have used an open-source face tracker to recognize facial identity and to classify facial expressions.

References

[1] P.S. Aleksic and A.K. Katsaggelos. Automatic facial expression recognition using facial animation parameters and multistream hmms. *Information Forensics and Security, IEEE Transactions on*, 1(1):3 – 11, march 2006.

[2] Marian Stewart Bartlett, Gwen Littlewort, Ian Fasel, and Javier R. Movellan. Real time face detection and facial expression recognition: Development and applications to human computer interaction. In *Computer Vision and Pattern Recognition Workshop, 2003. CVPRW '03. Conference on*, volume 5, page 53, june 2003.

[3] M.S. Bartlett, G. Littlewort, C. Lainscsek, I. Fasel, and J. Movellan. Machine learning methods for fully automatic recognition of facial expressions and facial actions. In *Systems, Man and Cybernetics, 2004 IEEE International Conference on*, volume 1, pages 592 – 597 vol.1, oct. 2004.

[4] MichaelJ. Black and Yaser Yacoob. Recognizing facial expressions in image sequences using local parameterized models of image motion. *International Journal of Computer Vision*, 25:23–48, 1997.

[5] Carlos Busso, Zhigang Deng, Serdar Yildirim, Murtaza Bulut, Chul Min Lee, Abe Kazemzadeh, Sungbok Lee, Ulrich Neumann, and Shrikanth Narayanan. Analysis of emo-

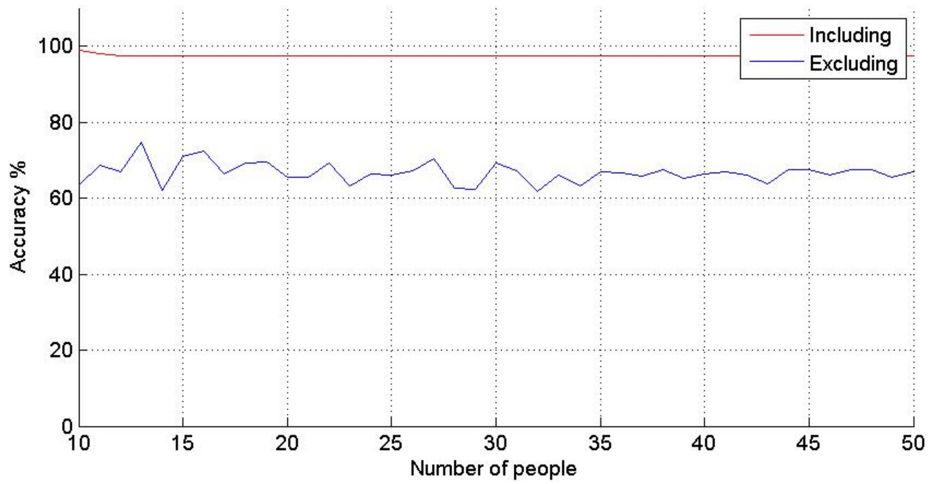

Figure 3: **Identity Recognition Results** Explanation of the figure.

tion recognition using facial expressions, speech and multimodal information. In *Proceedings of the 6th international conference on Multimodal interfaces*, ICMI '04, pages 205–211, New York, NY, USA, 2004. ACM.

[6] L.S. Chen, T.S. Huang, T. Miyasato, and R. Nakatsu. Multimodal human emotion/expression recognition. In *Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on*, pages 366 –371, apr 1998.

[7] I. Cohen, N. Sebe, F.G. Gozman, M.C. Cirelo, and T.S. Huang. Learning bayesian network classifiers for facial expression recognition both labeled and unlabeled data. In *Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on*, volume 1, pages I–595 – I–601 vol.1, june 2003.

[8] Ira Cohen, Nicu Sebe, Ashutosh Garg, Lawrence S. Chen, and Thomas S. Huang. Facial expression recognition from video sequences: temporal and static modeling. *Computer Vision and Image Understanding*, 91(1â2):160 – 187, 2003. ¡ce:title¿Special Issue on Face Recognition¡/ce:title¿.

[9] I. Craw, H. Ellis, and J.R. Lishman. Automatic extraction of face-features. *Pattern Recognition Letters*, 5(2):183 – 187, 1987.

[10] Jane Edwards, Henry J Jackson, and Philippa E Pattison. Emotion recognition via facial expression and affective prosody in schizophrenia: A methodological review. *Clinical Psychology Review*, 22(6):789 – 832, 2002.

[11] B. Fasel and Juergen Luettin. Automatic facial expression analysis: a survey. *Pattern Recognition*, 36(1):259 – 275, 2003.

[12] J Hawkins. *On Intelligence*. Cambridge University Press, 2004.

[13] T. Kanade, J.F. Cohn, and Yingli Tian. Comprehensive database for facial expression analysis. In *Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on*, pages 46 –53, 2000.

[14] I. Kotsia and I. Pitas. Facial expression recognition in image sequences using geometric deformation features and support vector machines. *Image Processing, IEEE Transactions on*, 16(1):172 –187, jan. 2007.

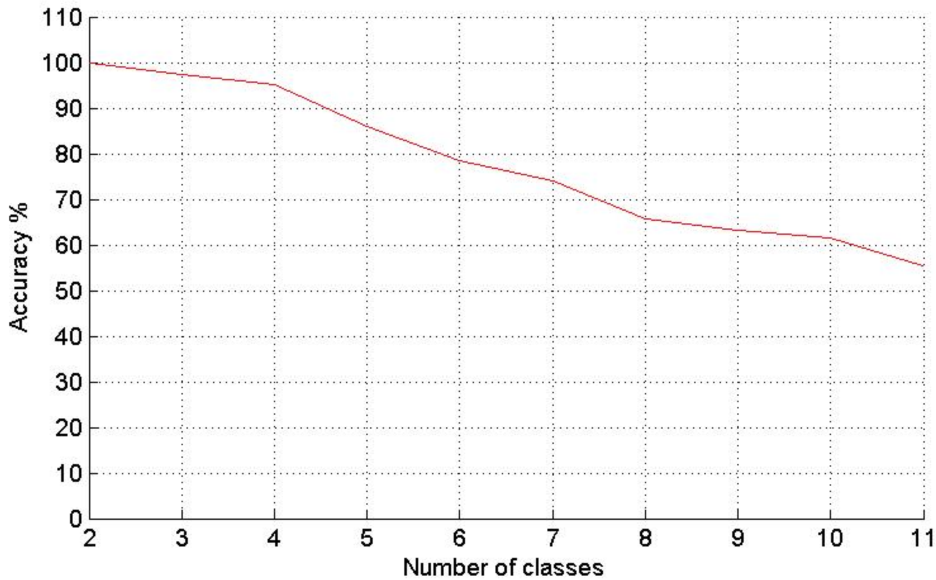

Figure 4: **Effect of Increasing the Number of Facial Expressions to Recognize** Explanation of the figure.

[15] David Rozado, Francisco B. Rodriguez, and Pablo Varona. Extending the bioinspired hierarchical temporal memory paradigm for sign language recognition. *Neurocomputing*, 79(null):75–86, March 2012.

[16] Caifeng Shan, Shaogang Gong, and Peter W. McOwan. Facial expression recognition based on local binary patterns: A comprehensive study. *Image and Vision Computing*, 27(6):803 – 816, 2009.

[17] Xiaoyang Tan, Songcan Chen, Zhi-Hua Zhou, and Fuyan Zhang. Face recognition from a single image per person: A survey. *Pattern Recognition*, 39(9):1725 – 1745, 2006.

[18] Y. Yacoob and L.S. Davis. Recognizing human facial expressions from long image sequences using optical flow. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 18(6):636 –642, jun 1996.

[19] Lijun Yin, Xiaozhou Wei, Yi Sun, Jun Wang, and M.J. Rosato. A 3d facial expression database for facial behavior research. In *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on*, pages 211 –216, april 2006.

[20] Xiaozheng Zhang and Yongsheng Gao. Face recognition across pose: A review. *Pattern Recognition*, 42(11):2876 – 2896, 2009.

[21] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld. Face recognition: A literature survey. *ACM Comput. Surv.*, 35(4):399–458, December 2003.

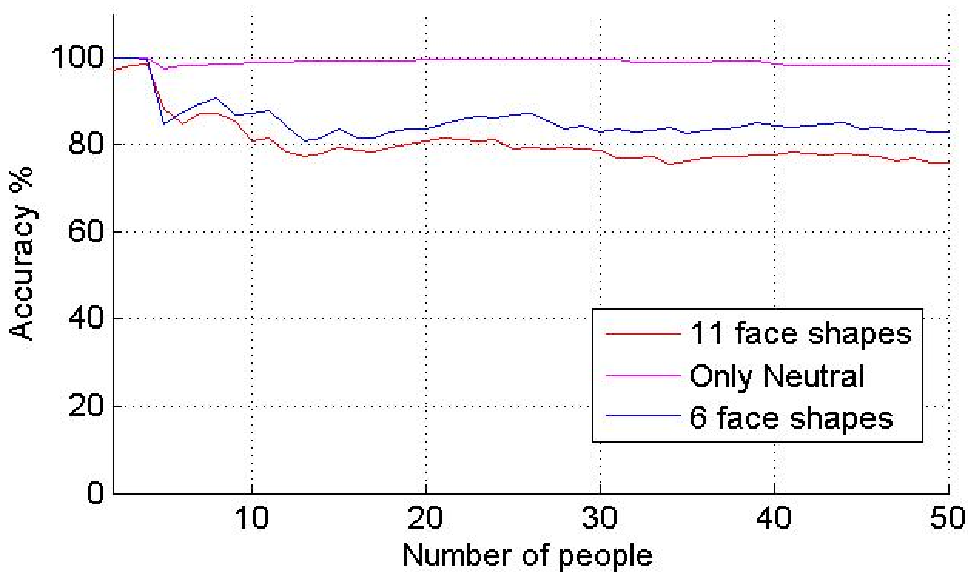

Figure 5: **Facial Expression Recognition Results** Explanation of the figure.