Subtle Expression Recognition using Motion Magnification

Nitish Gupta[1], Rahul Maji[2]
Advisor: Dr. Amitabh Mukerjee[2]
{gnitish,rmaji,amit}@iitk.ac.in
[1] *Dept. Of Electrical Engineering*
[2] *Dept. Of Computer Science and Engineering*

April 17, 2013

Abstract

Automatic facial expression recognition is an interesting and challenging problem, and impacts important applications in many areas such as humancomputer interaction and data-driven animation. Subtle Facial Expression Recognition is a challenging task because of the difficulty in classifying various expressions due to small spatial movements in subtle expressions. We use AAM Fitting algorithm to extract feature points in the test data, and use Motion Magnification to amplify the subtle facial expressions to exaggerate them which helps in better classification.

1 Introduction

Facial Expression recognition has been an active research topic for quite a few years and has wide applications in various domains. Facial expressions can convey the emotional state, intention, psychology or psychopathology of a person. During interactions, they can convey certain non-behavioural cues and hence proper recognition of facial expressions can improve the quality of interaction. Human beings can very well identify facial expressions but it is still quite a challenge for a machine to do so. Moreover, they form an important component of human-machine interaction and hence correct recognition of subtle expressions would be indispensable.

Principal Component Analysis (PCA), Independent Component Analysis (ICA), Active Appearance Model (AAM) based emotion recognition has been done in the last decade. The AAM fitting algorithm was first developed by T.F. Cootes, G.J. Edwards and C.J. Taylor[1]. We refer to the work done by Park and Kim[2]. We are using Inverse Compositional Active Appearance Model algorithm improved by Iain Matthews and Simon Baker[3] to extract the feature points of the faces in the test set.

The AAM fitting is an algorithm for matching a statistical model of object shape and appearance to a new image. The algorithm uses the difference between the shape vector and the appearance of the current estimate and the target image to run an optimization process. By taking advantage of the least squares techniques, it can match to new images very efficiently.

The human visual system can recognize spacial variations upto a certain extent. Motion Magnification amplifies these subtle spatial variations to reveal certain hidden information. We have implemented Motion Magnification which converts subtle facial epressions into exaggerated ones and hence classify them accurately.

We are using the **Facial Expressions and Emotion Database, FEED**, by the **Interactive Systems Group**. Our training dataset consists of 150 exaggerated expressions, which has 5 sets of 30 images each belonging Neutral, Happy, Sad, Surprise or Angry expression. The test dataset consists of 50 sets of sequences, each set consisting of a sequence of 5 frames starting from a neutral expression which gradually turns to a subtle expression. These subtle expressions are magnified and then classified from a class of 5 expressions namely Neutral, Happy, Sad, Surprise and Angry.

2 Our Approach

2.1 Training

Our training data consists of 150 labelled images containing 30 images for each exaggerated expression, namely Neutral, Happy, Surprise, Sad and Angry. The faces in these images are manually marked with 58 feature points or landmarks. The set of these 58 feature points is called the shape vector of the face. Shape vector contains the (x, y) coordinates of the feature points of the face. These shape vectors form the feature space for training different expressions to the AAM Fitting algorithm.

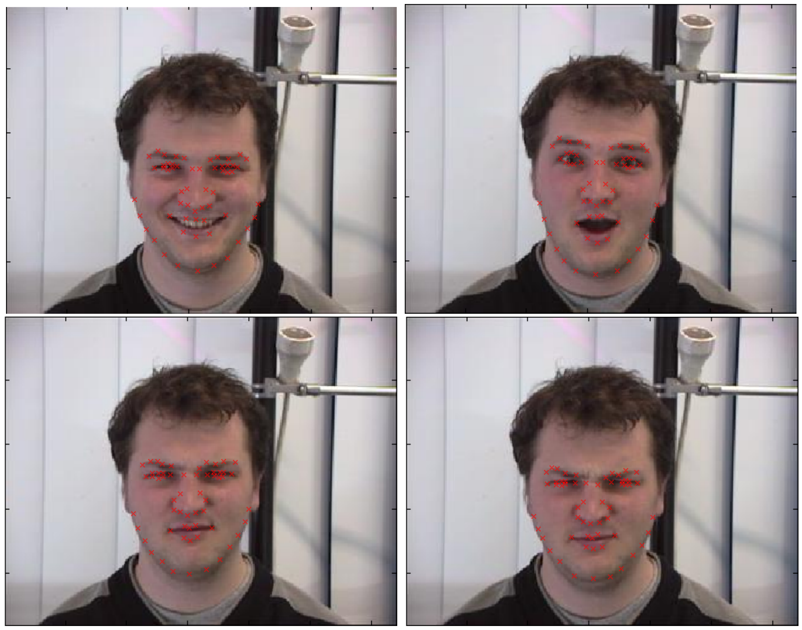

Figure 1: Exaggerated Emotions with 58 Feature Points

2.2 Testing

Our testing data consists of sequences of 5 images in which the facial expression of the person changes from neutral to a subtle expression. We take the following approach to apply motion magnification and then classify the magnified expression.

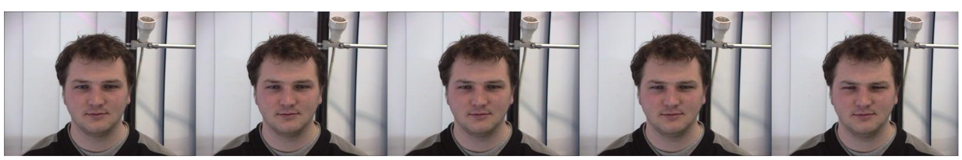

Figure 2: Test Sequence for Subtle Angry

Figure 3: Test Sequence for Subtle Surprise

2.2.1 AAM Fitting

We use the AAM Fitting algorithm[1] to extract the shape vector of the images in the test sequences. The shape vectors extracted for all 5 images in the test sequence is used to magnify the expression. Figure 4 shows the Delaunay Triangle representation of the output of the AAM fitting done on the testing images.

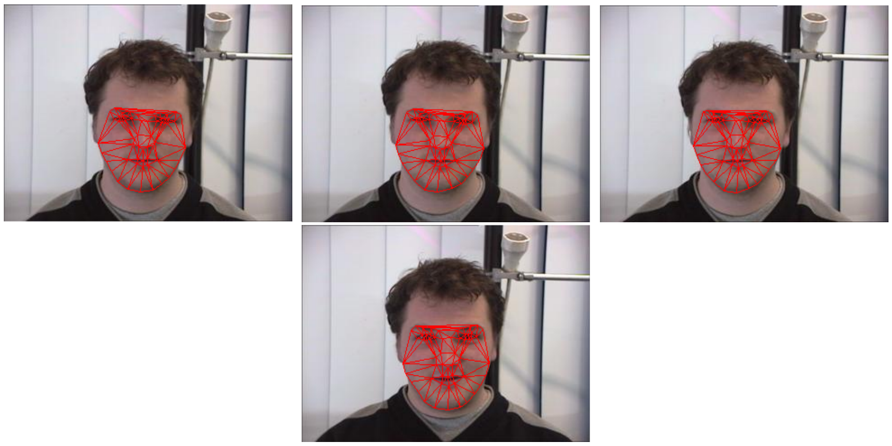

Figure 4: Delaunay Triangle Representation of the extracted shape vector

2.2.2 Magnification of Subtle Expression

After getting the shape vector **'s'** of all the 5 frames of the test sequence we apply motion magnification given by the following approach to magnify the subtle eprression. We use the **Magnification Factor of 1.8**. Let the shape vector in the first frame to be **'s(t)'**. The algorithm to magnify the expression proceeds as follows:

function MAGNIFY($init\_shape$)
  $mag\_shape \leftarrow s(t)$
  for k=1:4
    $flow\_vector \leftarrow 0$
    $flow\_vector \leftarrow [s(t+k) - s(t+k-1)] * mag\_factor$
  end
  $mag\_shape \leftarrow mag\_shape + flow\_vector$
end function

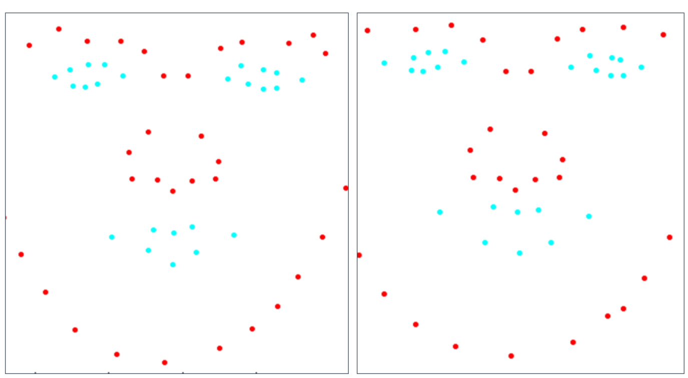

Figure 5: 1. Shows 5th Frame of Subtle Happy 2. Shows Magnified Shape vector of Subtle Happy

2.3 Results and Conclusions

For testing purposes, we used 50 sets of images, each set consisting of a sequence of 5 images starting from a neutral expression to a subtle expression. After magnification of the shape vector of the subtle expressions, we used 3 Classifiers to classify them into Neutral, Sad, Surprise, Anger and Happy expression.

We used the **k-NN based classifier** and **Neutral Network Training** provided by MATLAB and built our own **Multi-SVM Classifier**. The k-NN based classifier did not give satisfactory results whereas the results from the Neural Network Training and Multi-SVM classifier were quite similiar and satisfactory.

Out of the 50 tests conducted, 34 expressions were classified correctly, which means an accuracy of 68%.

Neutral expression was classified 100% times, Happy 80% times, Surprise 70% times, Sad 50% times and Angry 40% times. The main reason for the poor classification of the sad and angry expressions is that in both the expressions the eye and the eyebrows are very close to each other which makes the shape vector distorted and hence difficult to classify.

			Classified Emotion			
		Neutral	Happy	Surprise	Sad	Angry
	Neutral	10	0	0	0	0
Known Emotion	Happy	1	8	1	0	0
	Surprise	0	2	7	1	0
	Sad	1	1	1	5	2
	Angry	1	1	1	3	4

Figure 6: Confusion Matrix of Classification Results

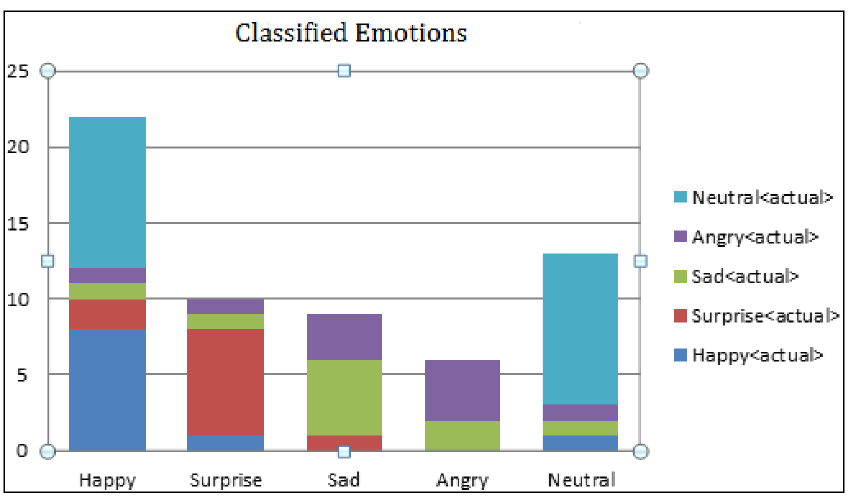

Figure 7: Histogram depicting Classified Emotions

3 Future Work and Improvements

In future, we would like to propose and make the following additions to make the classification more accurate:

- To design a better algorithm for motion magnification.
- To take into account the subtle movements in the camera.
- The classification can also be improved by using high quality images/videos. This increases the efficiency of the AAM fitting algorithm.

4 Acknowledgment

We thank Prof. Amitabha Mukerjee for his valuable support throughout the project, guiding us from time to time and looking into the project when it was needed. We would also like to thank 'Luca Vezzaro' from Universit degli Studi di Verona to provide us with the code for the Inverse Compositional Active Appearance Model (ICAAM) algorithm, which he wrote as a part of his Master's Thesis. We acknowledge you for your support.

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