

An Approach for Automatically Measuring Facial Activity in Depressed Subjects

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Abstract

This paper is motivated by Ellgring's work in non-verbal communication in depression to measure and compare the levels of facial activity, before and after treatment, of endogenous and neurotic depressives. Similar to that work, we loosely associate the measurements with Action Units (AU) groups from the Facial Action Coding System (FACS). However, we use the neologism Region Units (RU) to describe regions of the face that encapsulate AUs. In contrast to Ellgring's approach, we automatically generate the measurements and provide both prototypical expression recognition and RU-specific activity measurements. Latency between expressions is also measured and the system is conducive to comparison across groups and individual subjects. By using Active Appearance Models (AAM) to locate the fiducial facial points, and MultiBoost to classify prototypical expressions and the RUs, we can provide a simple, objective, flexible and cost-effective means of automatically measuring facial activity.

1. Introduction

Facial expressions convey information about a person's internal state. The ability to correctly interpret others facial expressions is important to the quality of social interactions. In phatic speech, in particular, the affective facial process-

ing loop, i.e. interpreting others facial expressions then responding with one's own facial expression, plays a critical role in the ability to form and maintain relationships.

A predisposition to misinterpret expressions often underlies dysphoria, e.g. anxiety and depression. More specifically, the impaired inhibition of negative affective material could be an important cognitive factor in depressive disorders. Recent studies using functional magnetic resonance imaging (fMRI), have provided some evidence that the severity of depression in major depressive disorder (MDD) groups correlates with increased neural responses to pictures with negative content [16, 26]. In turn, this bias to favour negative material by depressed patients has been shown to be signaled in the resulting facial expressions.

The difficulty is that capturing and recording measurements of facial activity manually requires time, effort, training, and some way of maintaining objectivity. Such manual work quickly becomes tedious and is prone to errors. The most popular method in the research community of describing facial activity is the Facial Action Coding System (FACS) which is described in Section 2. However, even the abridged version of FACS, EMFACS [1], which deals only with emotionally relevant facial action units, requires a scoring time of approximately 10 minutes of measurement for one minute of facial behaviour. Further, only people who have passed the FACS final test are eligible to download EMFACS for use.

In Ellgring [12], the levels of facial activity, before and after treatment, of endogenous and neurotic depressives were measured through several key indicators. We are motivated by a desire to automate and extend on these types of measurements. Similarly to Ellgring’s work, we loosely associate the measurements with Action Units (AU) groups from FACS. However, we use the neologism Region Units (RU) to describe regions of the face that encapsulate AUs. In contrast to Ellgring’s work, we automatically generate the measurements and provide both prototypical expression recognition and RU-specific activity measurements. Latency between expressions is also measured and the system is conducive to comparison across groups and individual subjects.

First, frontal facial images are detected in images captured from videos, for example using the Viola and Jones [34] (or any derived) technique to determine the global location in the image and rough pose parameters. Next, Active Appearance Models (AAM) are used to track and measure the local shape and texture features, which are then used to classify the regions using an MultiBoost classifier [5]. Ultimately, the number and changes to classifications over specific time intervals are reported. The processing described is in some ways similar in concept to [36], which concentrates on prototypic facial expressions, i.e. fear, anger, happiness, sadness, surprise, disgust and neutral. However, we use a different classifier, i.e. MultiBoost, and derive both macro and micro-level facial observations, more in the way of [12].

This paper presents an approach for simple, objective, flexible and cost-effective measurements of facial activity along with an overview of the processing of capturing them. Section 2 explains the manual methods of measuring facial activity and the motivation for automating these. An exemplary case in point, and one that forms the research work of the authors, is presented in Section 3. Section 4 describes the automation of the capture of facial activity. Section 5 then presents the measurements we use to describe facial expression. Section 6 summarises the paper with a discussion of future enhancements. Section 7 describes the collaborative project currently in progress and section 8 reports the progress.

2. Describing Facial Activity

2.1. Facial Action Coding System

The most ubiquitous and versatile method of describing facial behaviours, pioneered by Ekman [7–11], is FACS. The goal of FACS is to provide an accurate description of facial activity based on musculature and to lead to a system of consistent and objective description of facial expression.

Despite being based on musculature, FACS measure-

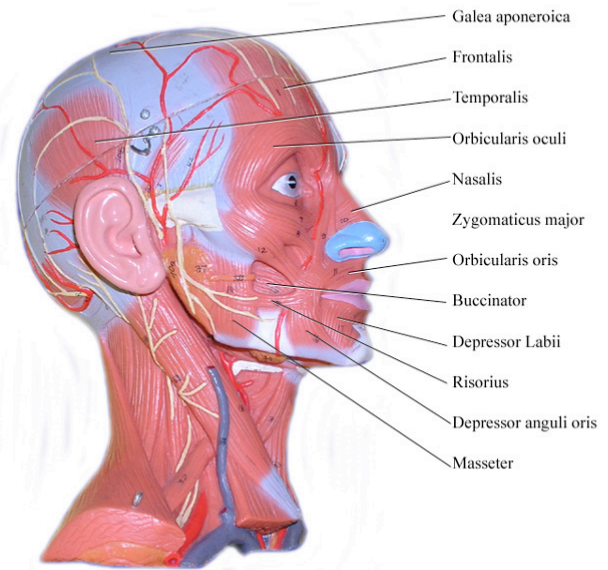


Figure 1. Facial Muscles [2]

ment units are AUs, not muscles. One muscle can be represented by a single AU. Conversely, the appearance changes produced by one muscle can sometimes appear as two or more relatively independent actions attributable to different parts of the muscle. A FACS coder decomposes an observed expression into the specific AUs that produced the movement, recording the list of AUs that produced it. For example, during a smile, the *zygomaticus major* muscle is activated, corresponding to AU12. During a spontaneous or Duchenne smile, the *orbicularis oculi* muscle is recruited, corresponding to AU6. The FACS coder would record the AUs, and if needed, the duration, intensity, and asymmetry. Figure 1 and Table 1, together, are included to give a description of the facial muscles and an example of some common AUs. FACS scores, in themselves, do not provide interpretations. EMFACS, as mentioned previously, deals only with emotionally relevant facial action units.

2.2. Motivation

Many studies have attempted to link facial expressions to disorders such as anxiety and depression. In [20], subjects were videotaped describing their feelings and reactions to the most anxious events they had experienced. The participants rated their anxiety ranging from 1 to 9 on an adjective scale (uncomfortable, nervous, apprehensive). The videos were segmented to get the participants’ high state anxiety periods. The facial movements were coded using FACS and

AU	Description
1	Inner Brow Raiser – Frontalis (pars medialis)
2	Outer Brow Raiser – Frontalis (pars lateralis)
4	Brow Lowerer – Corrugator and Depressor supercilii
5	Upper Lid Raiser – Levator palpebrae superioris
6	Cheek Raiser – Orbicularis oculi (pars orbitalis)
7	Lid Tightener – Orbicularis oculi (pars palpebralis)
9	Nose Wrinkler – Levator labii superioris alaeque nasi
10	Upper Lip Raiser – Levator labii superioris
11	Nasolabial Deepener – Zygomaticus minor
12	Lip Corner Puller – Zygomaticus major
13	Cheek Puffer – Levator anguli oris
14	Dimpler – Buccinator
15	Lip Corner Depressor – Depressor anguli oris
16	Lower Lip Depressor – Depressor labii inferioris
17	Chin Raiser – Mentalis

Table 1. Facial Action Coding System - sample AUs

EMFACS. The study reports that,

”As hypothesized, self-reported high state anxiety compared with low state anxiety resulted in a greater frequency of facial action unit indicative of fear.”

Similar studies have also claimed a correlation between facial activity and anxiety [21, 22].

Earlier attempts to link facial activity with depression used broad measurements such as cries, smiles, frowns [18]. Some studies have used electromyography (EMG) to measure muscle response, notwithstanding the somewhat intrusive and constraining nature of the equipment [15]. The more recent trend is to use FACS to add rigour and objectivity to the process [31, 32].

2.3. Ellgring’s study

In one such study, [12] hypothesises that facial activity and the repertoire of its elements will be reduced during depression and will expand with improvement of subjective wellbeing. Facial behaviour was analysed by applying EMFACS to the videotapes of 40 clinical interviews of 20 endogenous depressed patients. After analysing a frequency distribution of all of the AU observations across all of the interviews, 13 AUs or groups of AUs were then used to complete the study. AUs that nearly always occur together, e.g. AU1 and AU2 (inner and outer brow raiser), AU6 and AU12 (cheek raiser and lip corner puller) were considered as one AU group. Activity, repertoire and patterns were defined as parameters of facial activity and can be summarised as the following three measurements:

- **General facial activity:** The first measurement, total number of AUs in a specific interval, counts the num-

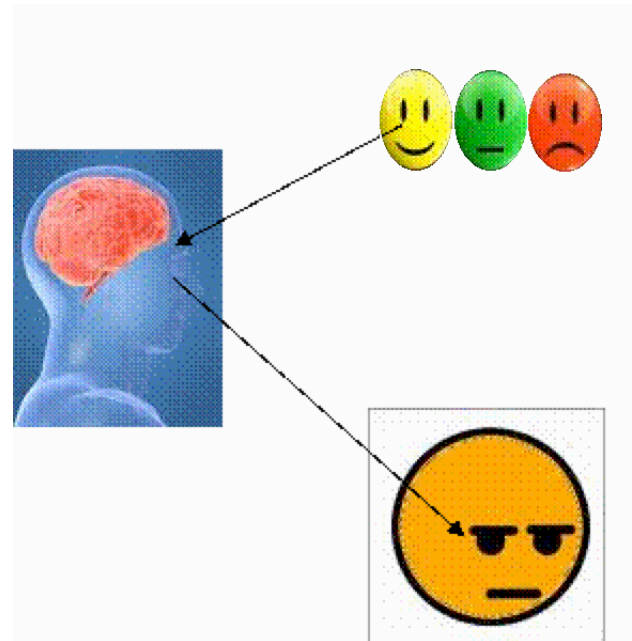


Figure 2. The affective facial processing loop

ber of single, significant AUs and groups of closely related AUs that occur within a 5 minute interval.

- **Specific facial activity:** The second, frequency of specific, major AUs, defines the number of major AU combinations, e.g. AU6+12 in the case of a spontaneous smile, occurring within a 5 minute interval.
- **Repertoire:** The third, repertoire of AUs, is the number of distinct AUs occurring more than twice within a 5 minute interval.

3. A Case in Point - Facial Activity in Depression

3.1. The Affective Facial Processing Loop

Depressed subjects have been shown to respond differently to images of negative and positive content, when compared with non-depressed subjects. The underlying cause could be the impaired inhibition of negative affect, which has been found in depressed patients across several studies [17, 26]. In turn, altered patterns of facial activity have been reported in those patients suffering major depressive disorders [31, 32]. If this “affective facial processing loop”, as shown in Figure 2, is reliable, then 1) objective observations could be of clinical importance in diagnosis; and 2) measurements of facial activity could possibly predict response to treatments such as pharmacotherapy and cognitive behaviour therapy (CBT).

3.2. Processing of Emotional Content

As stated previously, it is commonly hypothesised that depression is characterised by dysfunctional inhibition toward negative content. The reason for this has been postulated that depressed subjects show lowered activation in the regions responsible for gaining attentional control over emotional interference. In [17], inhibition to positive and negative stimuli was studied across subjects including hospitalised depressed patients, formerly depressed, and never-depressed control subjects. They report that depressed patients show a specific failure to inhibit negative information whereas positive information was unaffected. Surprisingly, they report that formerly depressed subjects display impairment to inhibiting negative content.

[24] similarly found attentional bias was evident even after individuals had recovered from a depressive episode. In that study, the attentional biases in the processing of emotional faces in currently and formerly depressed participants and healthy controls were examined. Faces expressing happy or sad emotions paired with neutral faces were presented (in a dot-probe task). Currently and formerly depressed participants selectively attended to the sad faces, the control participants selectively avoided the sad faces and oriented toward the happy faces. They also report that a positive bias that was not observed for either of the depressed groups.

In an evaluation of the evidence in studies which have used modified Stroop and visual probe test, [28] has found that the “inhibition theory” only holds true if the material is relevant to their “negative self-concept” and the stimulus is presented for longer durations. [23] found that depressed participants required significantly greater intensity of emotion to correctly identify happy expressions and less intensity to identify sad than angry expressions.

Medical imaging studies also find impairment of neural processing of depressed subjects. [16] conducted a comparison of 16 participants who had suffered from acute unipolar major depression and 16 healthy volunteers. The patients received 16 weeks of CBT. fMRI scans were undertaken at weeks 0 and 16 while the participants viewed facial stimuli displaying varying degrees of sadness. Although there are some limitations to the study due to sample size, there seems to be evidence that excessive *amygdala* activity correlated to the processing of sad faces during episodes of acute depression.

This impairment may extend to the offspring of parents with MDD. [29] found (small volume corrected) greater *amygdala* and *nucleus accumbens* activation to fearful faces and lower *nucleus accumbens* activation to happy faces in high-risk subjects when attention was unconstrained.

3.3. Facial Feedback in Depression

In a study of 116 participants (30 men, 86 women), some with a history of MDD and individuals with no psychopathological history, the smile response to a comedy clip was recorded. Participants were asked to rate a short film clip. FACS coding was applied to 11 seconds of the clips - long enough to allow for the 4-6 second spontaneous smile [13]. Those with a history of MDD and current depression symptoms were more likely to control smiles than were the asymptomatic group [32].

4. Automatic Measurement of Facial Activity

4.1. Measuring Facial Features

We subdivide the facial image into regions in order to track inter-region movement and a common scale is applied to the facial images. Similar to [33], we do this by first creating a horizontal or transverse delineation line, midway between the topmost and bottom most landmark points on the facial image being examined, as shown in Figure 3. A second, less dynamic, horizontal delineation, running through the tip of the nose, is used as a reference for the local, intra-RU measurements. Next, the vertical distance between the feature points and the reference lines are measured and normalised. Some are shown in Figure 3 for illustration. This process is applied to any facial image used to train or test the system. With the exception of RU3, only vertical displacements have been derived since most relevant facial expression involves some degree of vertical movement, e.g. the contraction of the *corrugator* muscles typically accompanied by a vertical shift in the *frontalis* muscles in the forehead. RU3 includes a horizontal displacement measurements in order to improve the tracking of lateral movements such as in AU20 - lip stretcher.

Whereas measurement of inter-region RUs, used to classify prototypical expressions, use displacements from a mid-horizontal line, local, intra-RU features are treated slightly differently, in that the measurements are based on displacement to the reference line running horizontal through the tip of the nose.

4.2. Classification

Two sets of classifiers are used in our work, one for prototypical expressions and the others specific to RUs. Those specific to RUs are trained to classify the major intra-RU patterns that would normally accompany prototypical expressions. For instance, the mouth and lip movements of fiduciary points in an image of the prototypical smile are re-used and represent one class in the RU3 classifier. The relevant normalised measurements are used as inputs to all of the classifiers. For example, in the case of RU1, only the landmark points within RU1 are input to the classifier. The

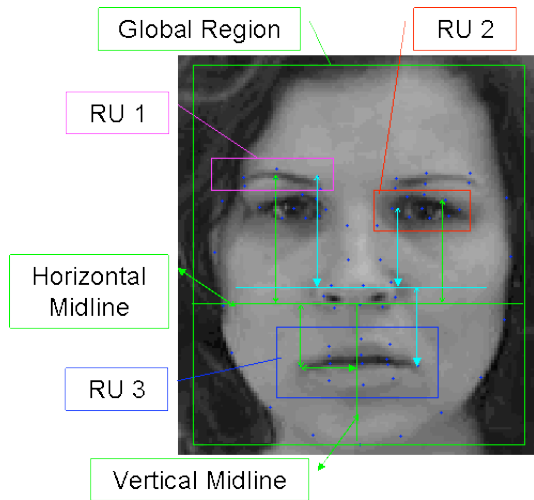


Figure 3. Measurements from horizontal delineations image from Feedtum database [35]

mappings are shown in Table 2. Note that eye movement

AU	Description	RU
1, 2, 3, 4	Brow movement	1
5, 6, 7	Eyelid activity and orbicularis oculi	2
9, 10, 12, 15, 17, 20, 25, 26, 27	Nose, mouth and lip regions	3

Table 2. Mapping AUs to RUs

AUs, such as those that effect blinks, are not incorporated at present, e.g. AU43, AU45-46 and AU61-68.

4.3. System processing

The processing sequence is depicted in Figure 4. First, images are captured at predefined intervals from video, 500ms in our case. Frontal face poses are then segmented from the images using the Viola and Jones [34] (or a derived) technique to determine the global pose parameters. See [34] for details. Next, AAMs, which have been prepared in advance, are fitted to new and previously unseen images to derive the local shape and texture features. The measurements obtained (see Section 4.1) are then used to classify the regions using MultiBoost classifiers [5, 14], which is discussed in Section 4.3.2. Ultimately, the number and mixture of classified regions are used to report facial activity.

4.3.1 Active Appearance Models

In recent years, a powerful deformable model technique, known as the Active Appearance Model [6], has become

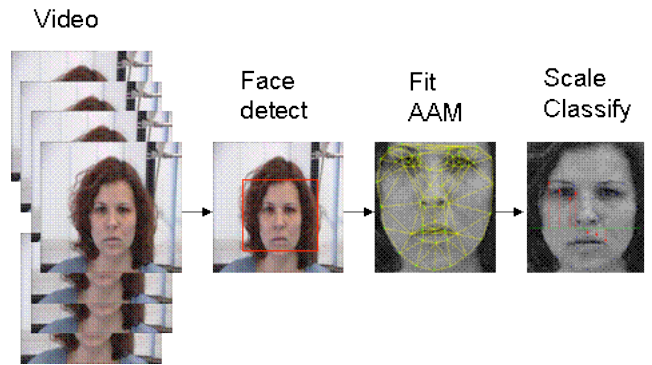


Figure 4. Processing of facial activity measurements

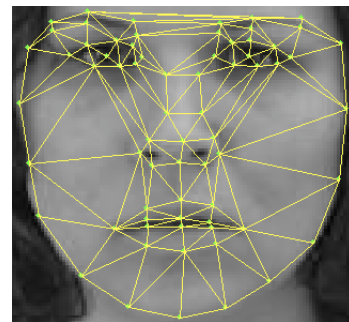


Figure 5. Face mesh used to group AUs

very popular for real-time face and facial expression recognition. In the AAM approach, the non-rigid shape and visual texture (intensity and colour) of an object are statistically modelled using a low dimensional representation obtained by applying PCA to a set of labelled training data. After these models have been created, they can be parameterised to fit a new image of the object, which might vary in shape or texture or both.

Figure 5 depicts the facial triangulation mesh, based on the feature points, used to divide the facial image into regions. In our case, AAMs are pre-trained on static images using the Simultaneous Inverse Compositional (SIC) fitting method [3]. SIC is an another adaptation of inverse compositional image alignment for AAM fitting that addresses the problem of the significant shape and texture variability by finding the optimal shape and texture parameters simultaneously. Rather than recomputing the linear update model at every iteration using the current estimate of appearance parameters, it can be approximated by evaluating it at the mean appearance parameters, allowing the update model to be pre-computed, which has significantly more computational efficiency. See [3] for details. The system described in section 7 involves the recording of frontal face images while the participant views stimuli on a computer display. Under this setup, there is a reasonable tolerance to head

movement and short-duration occlusion.

4.3.2 Classification using MultiBoost

AdaBoost [14] is a “meta-algorithm” that calls a “weak” classifier repeatedly, eventually yielding a strong classifier. The key concept of the algorithm is that a set of weights is maintained over an input training set. Initially the weights are set equally. After each round of classification using the “weak” learner, the weights of the misclassified examples are increased thus forcing the weak learner to focus on the hard examples in the training set. Although intended for binary classification, AdaBoost can be extended to the multiclass problem and we use the implementation from [5]. In our case, multiple classifiers are prepared in advance. As stated previously, these include one classifier for prototypical expressions and three RU-based as described in Table 2.

5. Measurements

Total number of each RU in a specific interval

The total number of each RU in a specific interval counts the number of each single RU that occurs within a specific period. In our research the period would typically be the trial duration within the experiment. However, this can be set to a nominal interval, e.g. 5min.

Total number of prototypical expressions in a specific interval

The prototypical expressions currently used are fear, anger, happiness, sadness, surprise, disgust and neutral. These are individually counted within a given period - in our case the trial duration, otherwise, a fixed duration.

Total number of non-prototypical expressions in a specific interval

This includes more subtle expressions and nuances of prototypical expressions, including anxious, bored, smiling, laughter. These are individually counted within a given period - in our case the trial duration, otherwise, a fixed duration is used.

Positive versus negative prototypes

This count is a derivative of the last two measurements. Expressions of sadness, fear, anger, boredom have been included as negative. Positive expressions include smiling, happiness, laughter. The total of positive and negative expressions are counted within a given period - in our case the trial duration, otherwise, a fixed duration is used.

Latency between valency of expressions

This is a two-way measurement aimed at discovering the

time taken to change between negative and positive expressions.

5.1. Cross population measurements

One benefit of automatically generating facial activity measurements is that facial expression responding to specific stimuli can be accumulated over time and the variance across groups gathered. The following measurements are reported against population groups:

- Repertoire of RUs,
- Repertoire of prototypical expressions,
- Repertoire of non-prototypical expressions,
- Positive versus negative prototypes, and
- Latency between valency of expressions.

6. Discussion and Conclusion

The usefulness of the system is not limited to assessment of depressed subjects, but also for comparing patterns of facial activity in subjects with other neuropsychiatric disorders. We have presented a simple, objective, flexible and cost-effective means of automatically measuring facial activity. As can be seen, a benefit of automatically measuring facial activity is that it is fairly easy to extend the system to new measurements. Two such measurements to be included later relate to the incidence of Veraguth folds and Duchenne smiles.

Veraguth folds, have for some time been, somewhat phenologically, associated with depression. They are the folds running obliquely from the upper inside to the lower outside of the upper eyelid. [12] conducted a post-hoc study into the incidence of Veraguth folds and [27] reports that in a US study,

“Veraguths eyelid folds occurred more often during depressive episodes in patients of European descent and were more strongly correlated with severity of depression compared with patients of African descent.”

“Duchenne” smiles are spontaneous, involuntary smiles where the *orbicularis oculi* muscle is recruited, corresponding to FACS AU6.

7. Experimental setup

The processing and system described above is currently in trial in a collaborative project at the Black Dog Institute,

Sydney, Australia¹. The experimental mood/affect induction paradigm is presented by way of an interactive computer package in a setup similar to that in figure 6.

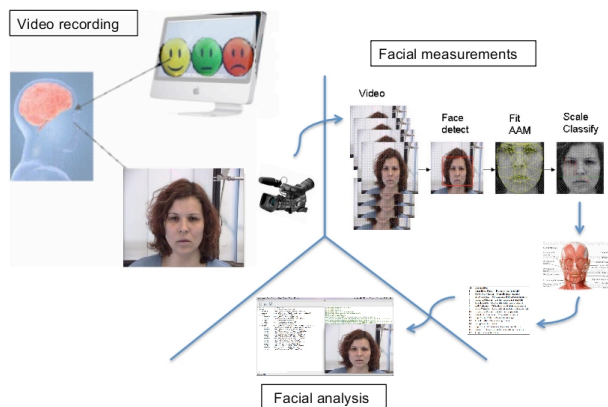


Figure 6. Experimental setup

The participant's face and voice expressions are recorded as they face the computer display. The interview includes:

Watching movie clips Six short movie segments of around two minutes each, some positive and some negative are presented. They have previously been rated for their affective content [19]. Synchronising the start of the stimuli with recording enables us to draw a correlation between facial activity and the stimuli.

Watching and rating IAPS pictures Pictures from the International Affective Picture System (IAPS) [25] compilation are presented and participants rate each image as either positive or negative. Reporting logs enable correlation of the image presentations, the participant's ratings, and their facial activity.

Reading sentence containing affective content Two sets of sentences used in the study by [4, 30] are read aloud. The first set contains emotionally arousing "target" words. The second set repeats the first, with the "target" words replaced by well-matched neutral words.

Answering specific questions Finally, participants are asked to describe events that had aroused significant emotions. For instance, ideographic questions such as, "Describe an incident that made you feel really sad."

8. Progress to date

As far as the authors are aware, there are no available, high-quality recordings of facial and vocal activity in de-

¹The Black Dog Institute is a not-for-profit, educational, research, clinical and community-oriented facility in Sydney, Australia, offering specialist expertise in depression and bipolar disorder.

pression and anxiety. To overcome this, images of prototypical expressions from [35] have been used to "bootstrap" the system. Currently, the project is in the process of recording interviews with depressed subjects and the control group, and analysing the results. By the end of 2009 we will have validated our analysis and be in a position to report on the findings.

References

- [1] EMFACS. <http://www.face-and-emotion.com/dataface/facs/emfacs.jsp>. Last accessed 2 April 2009.
- [2] Facial Muscles. <http://www.csupomona.edu/~jlbath/Lab> Last accessed 30 Jun 2009.
- [3] S. Baker, R. Gross, and I. Matthews. Lucas-kanade 20 years on: A unifying framework: Part 3. Technical Report CMU-RITR-03-35, Robotics Institute, Carnegie Mellon University, Pittsburgh (PA), USA, Nov. 2003.
- [4] B. Brierley, N. Medford, P. Shaw, and A. Davidson. Emotional memory for words: Separating content and context. *Cognition & Emotion*, 21 (3):495–521, 2007.
- [5] N. Casagrande. Multiboost: An open source multi-class adaboost learner. 2005-2006. <http://www.iro.umontreal.ca/casagran/multiboost.html>, Last accessed 20 August 2008.
- [6] G. Edwards, C. Taylor, and T. Cootes. Interpreting Face Images Using Active Appearance Models. In *Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition FG'98*, pages 300–305, Nara, Japan, Apr. 1998. IEEE.
- [7] P. Ekman. *The Handbook of Cognition and Emotion*, chapter Facial Expressions, pages 301–320. John Wiley and Sons, Ltd, Sussex, U.K, 1999.
- [8] P. Ekman. Darwin, deception, and facial expression. *Annals New York Academy of Sciences*, pages 205–221, 2003.
- [9] P. Ekman and W. Friesen. *Unmasking the Face*. Prentice Hall, Englewood Cliffs NJ, 1975.
- [10] P. Ekman and H. Oster. *Emotion in the human face*. New York: Cambridge University Press, 2nd edition, 1982.
- [11] P. Ekman and E. Rosenberg. *What the Face Reveals*. Series in Affective Science. Oxford University Press, Oxford, UK, 1997.
- [12] H. Ellgring. *Nonverbal communication in depression*. Cambridge University Press, Cambridge, UK, 2008.
- [13] M. Frank, P. Ekman, and W. Friesen. Behavioral markers and recognizability of the smile of enjoyment. *Journal of Personality and Social Psychology*, 64(1):83–93, 1993.
- [14] Y. Freund and R. Schapire. A short introduction to boosting. *J. Japan. Soc. for Artif. Intel.*, 14(5):771–780, 1999.
- [15] A. Fridlund and J. Izard. *Social Psychophysiology: A Sourcebook*, chapter Electromyographic studies of facial expressions of emotions and patterns of emotion, pages 163–218. Academic Press, New York, 1983.
- [16] C. Fu, S. Williams, A. Cleare, J. Scott, M. Mitterschiffthaler, N. Walsh, C. Donaldson, J. Suckling, C. Andrew, H. Steiner, and R. Murray. Neural responses to sad facial expressions in major depression following cognitive behavioral therapy. volume 64, pages 505 – 512. 2008. Neurostimulatory and Neuroablative Treatments for Depression.

- [17] E. Goeleven, R. De Raedt, S. Baert, and E. Koster. Deficient inhibition of emotional information in depression. *Journal of Affective Disorders*, 93(1-3):149 – 157, 2006.
- [18] R. Grinker, N. Miller, M. Sabshin, R. Nunn, and J. Nunnally. *The phenomena of depressions*. Harper and Row, New York, 1961.
- [19] J. Gross and R. Levenson. Emotion elicitation using films. *Cognition & Emotion*, 9:87–108, 1995.
- [20] J. Harrigan and D. O’Connell. How do you look when feeling anxious? facial displays of anxiety. *Personality and Individual Differences*, 21:205–212(8), August 1996.
- [21] J. Harrigan and K. Taing. Fooled by a smile: Detecting anxiety in others. *Journal of Nonverbal Behaviour*, 21:203, 1997.
- [22] J. Harrigan, K. Wilson, and R. Rosenthal. Detecting state and trait anxiety from auditory and visual cues: a meta-analysis. *Personality and Social Psychology Bulletin*, 30(1):56–66, 2004.
- [23] J. Joormann and I. Gotlib. Is This Happiness I See? Biases in the Identification of Emotional Facial Expressions in Depression and Social Phobia. *Journal of Affective Disorders*, 93(1-3):149 – 157, 2006.
- [24] J. Joormann and I. Gotlib. Selective attention to emotional faces following recovery from depression. *Journal of Abnormal Psychology*, 116(1):80 – 85, 2007.
- [25] P. Lang, M. Bradley, and B. Cuthbert. International affective picture system (iaps): Affective ratings of pictures and instruction manual. Technical Report A-6, University of Florida, Gainesville, FL, 2005.
- [26] B. Lee, S. Cho, and H. Khang. The neural substrates of affective processing toward positive and negative affective pictures in patients with major depressive disorder. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, 31(7):1487 – 1492, 2007.
- [27] W. McDaniel, B. Brar, M. Srirama, S. Shaikh, and A. Kaur. Prevalence of veraguths eyelid folds during depression in different ethnic groups. *The Journal of Nervous and Mental Disease*, 192(10):705–7, 2004.
- [28] K. Mogg and B. Bradley. Attentional bias in generalized anxiety disorder versus depressive disorder. *Cognitive Therapy and Research*, 29:2945, 2005.
- [29] C. Monk, R. Klein, and E. Telzer et al. Amygdala and nucleus accumbens activation to emotional facial expressions in children and adolescents at risk for major depression. *American Journal of Psychiatry*, 165(3):90–98, Jan 2008.
- [30] N. Medford et al. Emotional memory: Separating content and context. *Psychiatry Research: Neuroimaging*, 138:247–258, 2005.
- [31] B. Renneberg, K. Heyn, R. Gebhard, and S. Bachmann. Facial expression of emotions in borderline personality disorder and depression. *Journal of Behavior Therapy and Experimental Psychiatry*, 36(3):183 – 196, 2005.
- [32] L. R. M. Sayette and J. Cohn. Impact of depression on response to comedy: A dynamic facial coding analysis. *Journal of Abnormal Psychology*, 117(4):804–809, May 2007.
- [33] S. Strupp, N. Schmitz, and K. Berns. Visual-based emotion detection for natural man-machine interaction. In *KI ’08: Proceedings of the 31st annual German conference on Advances in Artificial Intelligence*, pages 356–363, Berlin, Heidelberg, 2008. Springer-Verlag.
- [34] P. Viola and M. Jones. Robust real-time face detection. *Proceedings Eighth IEEE International Conference on Computer Vision ICCV 2001*, 2:747, 2001.
- [35] F. Wallhoff. Database with Facial Expressions and Emotions from Technical University of Munich (FEEDTUM). <http://www.mmk.ei.tum.de/~waf/fgnet/feedtum.html>.
- [36] P. Wang, F. Barrett, E. Martin, M. Milonova, R. Gur, R. Gur, C. Kohler, and R. Verma. Automated video-based facial expression analysis of neuropsychiatric disorders. *Journal of Neuroscience Methods*, 168(1):224 – 238, 2008.