Micro Expression classification using facial color and deep learning methods

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Abstract

Micro emotions are a unique type of facial expression as they are involuntary and very brief. They usually occur when a person attempts to suppress or hide their emotions. Lasting less than 500 ms, they can be very hard to detect even for the human eye, however, since they reveal a person's true feelings, they are of extreme interest in many fields of study. Most approaches to automatic detection and classification of micro emotions rely on detecting the small residual facial movements. In this paper, we propose to exploit an aspect of the human face which is much harder to subdue, namely, facial color change due to blood flow during expression of emotion. We propose a system that evaluates color change during micro emotion expression and successfully classifies the emotion type. This approach is unique in that it disregards the motion related aspects of the expression, and relies entirely on the facial color. We show that our system improves over movement based approaches.

1. Introduction

Emotion identification is a field that has been researched extensively. To differentiate between an extreme 'Happy' and 'Sad' facial expression is a somewhat easy task with today's technology, as there is a noticeable difference in the facial muscles position and tension. The study of facial movement as indicators of emotion has been standardized in the form of Action Units (AU) [16] each of which describes a facial deformation which occurs due to a facial muscle movement. A complete coding system, the 'Facial Action Coding System' (FACS) has been defined, which is a detailed list containing the deconstruction of each facial emotion into a set of AUs which are activated during the emotion [13].

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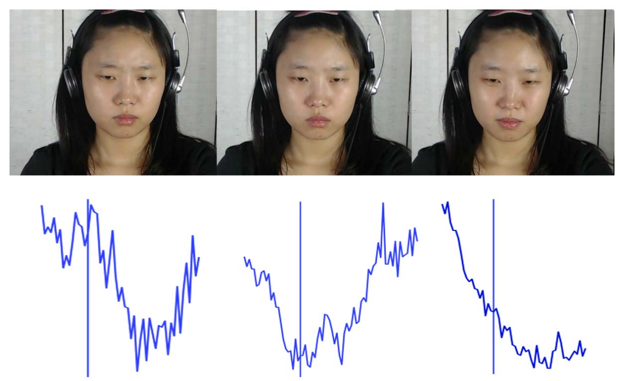

Figure 1. Images from the CAS(ME)^2 dataset. The images are the apex frame of the portrayed emotion - left to right anger, disgust and happiness. The corresponding graphs show the average value of the red-green color channel over the video, in relation to the neutral frame. The vertical line marks the apex frame.

However, quite often, facial emotions are not as expressive. These expressions are termed *micro expression*. Micro expressions are very brief and involuntary facial expressions. They usually occur when a person attempts to suppress or hide their emotion. Lasting less than 500 ms [48], they can be very difficult to detect even for the human eye, however, since they reveal a person's true feelings, they are of extreme interest in many fields of study [11]. This is also true for subdued emotions such as stress and anxiety, where it is much more difficult to determine whether an individual is stressed as the emotion is often not accompanied by any distinct combination of AUs [3, 36]. For a brief review on studies of facial expressions see [12].

Most approaches to automatic detection and classification of micro emotions, attempt to detect the minute facial movements that sneak through. In this paper, we propose to exploit an aspect of the human face which is much more difficult to subdue, namely, facial color change due to blood flow during expression of emotion. We propose a system that evaluates color change during emotion expression and

Figure 2. Video frames of a subject expressing a micro-emotion. From the CASME II dataset

successfully classifies the emotion type. We show that our system performs on par and often improves on movement based approaches. Furthermore, we show this across all benchmark micro-emotion datasets (see Section 3.2).

2. Related Work

To date, studies on detection and classification of micro expressions rely on detecting the small facial movements involved in micro-expressions. The most common methods for detecting the movement features include 3D Histograms of Oriented Gradients (3DHOG) [39, 6], Local Binary Pattern-Three Orthogonal Planes (LBP-TOP) [50, 37] and Histogram of Oriented Optical Flow (HOOF) [29]. These methods generally divide the face into segments, and calculate a metric to determine whether there was significant movement in the area. This data is later fed into a classifier (SVM, KNN, RF, etc) in order to predict which type of micro-expression occurred. Recently, deep learning approaches were also applied to detect micro emotions [24, 27, 9]. Unfortunately these studies test on only one of the benchmark micro-expression datasets (see Section 3.2).

In this paper, we propose to exploit change in facial color, rather than facial movement, to classify micro-emotions. In a recent study [2], it was shown that facial color alone, without the shading information, could be used by human observers to determine emotion. They have proved this method performs well regardless of the subject's ethnicity, gender or skin color. Additionally, the authors created a Linear Discriminant Analysis (LDA) classifier which uses only the color information of still images to classify 18 human emotions with an accuracy of 50.5% (where chance was 5.5%). This system however, was only tested on the more expressive emotions, where significant facial movement is involved, and on still images rather than videos.

In [45, 46], different color spaces were tested and a novel color space was introduced to improve micro-emotion classification. However, these studies evaluated the effect of different color spaces on detection based on facial motion and not facial color change.

3. Micro Emotion Detection

3.1. Facial Color - Background

As we aim to exploit the color changes in the skin, we first briefly review the skin basic structure and color changes model.

A common simplification of the skin structure consists of a 2-layer model [1] (see Figure 3):

- Layer1 - the Epidermis
- Layer2 - the Dermis

The Epidermis contains Melanin, a chemical pigment within the skin, that changes the facial color very slowly when exposed to UV light. The Dermis contains Hemoglobin, which is oxidized blood. Hemoglobin changes facial color very fast due to blood flow under the

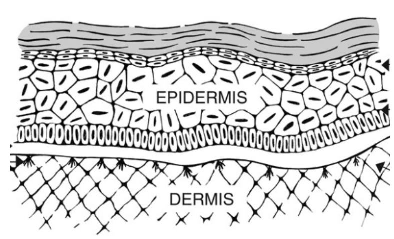

Figure 3. The 2-layer model of the skin

skin. The color of our skin is determined by a combination of these 2 chemicals - melanin and hemoglobin. The greater the concentration of hemoglobin, the more flushed we look- i.e. the skin takes on a more reddish hue. Increase in melanin on the other hand, causes the skin tone to darken, as occurs in suntanned skin. Melanin also determines the characteristic skin tones of different human races.

Emotional states are typically accompanied by changes in blood flow, especially in facial skin areas, which imply changes in hemoglobin concentration [10].

In [18] it was shown that there is a direct correlation between the emotional state of an individual, and his level of oxygenated Hemoglobin, while in [7] and [21] it was shown that changes in emotion also affect the facial areas temperature due to blood-flow changes. This correlation can be exploited to detect and classify expressions which are difficult to detect using motion-based algorithms, namely, micro expressions. Since the human face contains an abundance of blood vessels very close to the skin surface [32], this makes it an excellent location in which to monitor changes in blood-flow in a non-invasive manner. Specifically, we chose to focus on the cheek areas as these contain numerous blood vessels and is relatively unaffected by shading, which adds noise to the color information.

Several studies have attempted to model and calculate the concentration of melanin and hemoglobin in facial and hand skin from visual images of the skin using multispectral input [22, 23] or RGB input [38, 43, 41]. For micro emotion detection we focus on detecting changes in facial color using RGB images.

3.2. Datasets

There are very few spontaneous micro-expression datasets, since natural micro-expressions are challenging to produce under a controlled environment. Early studies on micro-emotion analysis collected their own data, typically consisting of 10-20 individuals (see review in [33]). Recently, several datasets have become benchmarks for micoemotion studies. These include SMIC [28], CASME [49], CASME II [47], SAMM [8] and CAS(ME)^2 [40]. These datasets are used extensively in the field of Micro expression detection and classification and are considered a good basis for evaluation of performance. All dataset samples are videos of individuals performing a single expression. An example sequence is shown in Figure 2 where a subject is expressing a micro-emotion. The videos are labeled with the expression and the apex frame of the expression is often given as well. Table 1 compares the 5 datasets. Since we rely on facial color, we do not consider the grayscale SAMM dataset in this study. To the best of our knowledge this work is the first to show successful performance across all 4 databases.

Dataset	Color	Emotion classes	FPS	Number Samples
SMIC	YES	3	100	164
CASME	YES	8	60	190
CASME II	YES	7	200	255
SAMM	NO	8	200	159
CAS(ME)^2	YES	3	30	357

Table 1. Comparison between 5 major micro-expression datasets.

Original tag	**New tag**
Contempt	Others
Disgust	Negative
Fear	Negative
Happiness	Positive
Repression	Others
Sadness	Negative
Surprise	Surprise
Tense	Others

Table 2. The mapping performed to equate the number of samples in each class in CASME and CASME II

In CASME and CASME II databases, some of the classes contain very few samples, so we follow the methodology of [35, 15, 29] and group these into new classes, better aligned with the classes in SMIC and CAS(ME)^2. Thus, Disgust, Fear and Sadness were grouped into a 'Negative' class. Contempt, Repression and Tense were grouped into 'Others' class. Surprise and Happiness remained as individual classes. This results in 4 classes for CASME and CASME II instead of the original 8 and 7, respectively, as shown in Table 2. SMIC and CAS(ME)^2 both contain 3 classes each - positive, negative and surprise for SMIC, and happiness, anger and disgust for CAS(ME)^2.

3.3. Facial Color Detector

We have implemented a facial color change detector that is invariant to facial motion and is used for micro emotion

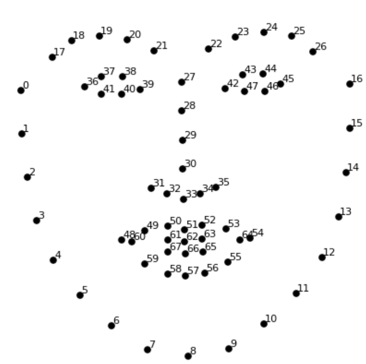

Figure 4. Extracted facial landmarks (68 points).

classification. Facial emotion databases are tested using our method and compared to AU based methods. Our feature extraction method is based on that of [2], however, we use a deep neural network to complete the model and perform emotion classification. We assume a sequence of RGB images of a face performing a micro-emotion (see example in Figure 2). We additionally assume that we are given a face of the same individual under a neutral expression. Since in all datasets, the provided sequences always begin in a neutral expression, the first frame is used as the neutral state.

The facial color detector creates a feature vector per video sequence that represents the normalized color information in regions of the face, over time. In each frame, facial feature points are detected (Figure 4) and patches of the cheeks are computed as shown in Figure 5. Color information from selected patches in each frame are collated into a feature vector. Creating the feature vector involves the following steps (Figure 6):

1. Sequence Length Normalization

   The micro-emotion video sequences vary in length (number of frames) across datasets as well as within each dataset. Thus, to standardize the inputs, we follow the common procedure when using these datasets, and map each sequence into 50 frames using sampling and cubic interpolation [15, 20]. Frame sizes are allowed to vary across different sequences since our representation is invariant to face scaling. The tested sequences start and end in a neutral expression, thus, we use the first frame as the neutral image.

2. Segmentation

   Since our aim is to use facial blood flow to classify emotions, we focus on an area of the face with a concentration of blood vessels, but little movement, so as to avoid noise from shading. Thus, we chose to consider only the cheeks of the face.

   Facial landmarks are determined using a machine learning based landmark detector [25] resulting in 68

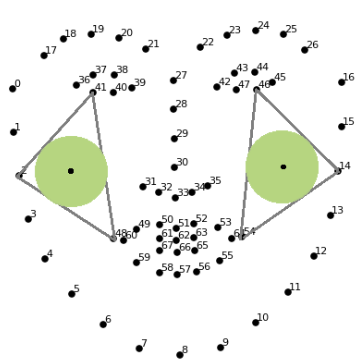

Figure 5. Calculated cheeks' center point and selected patch.

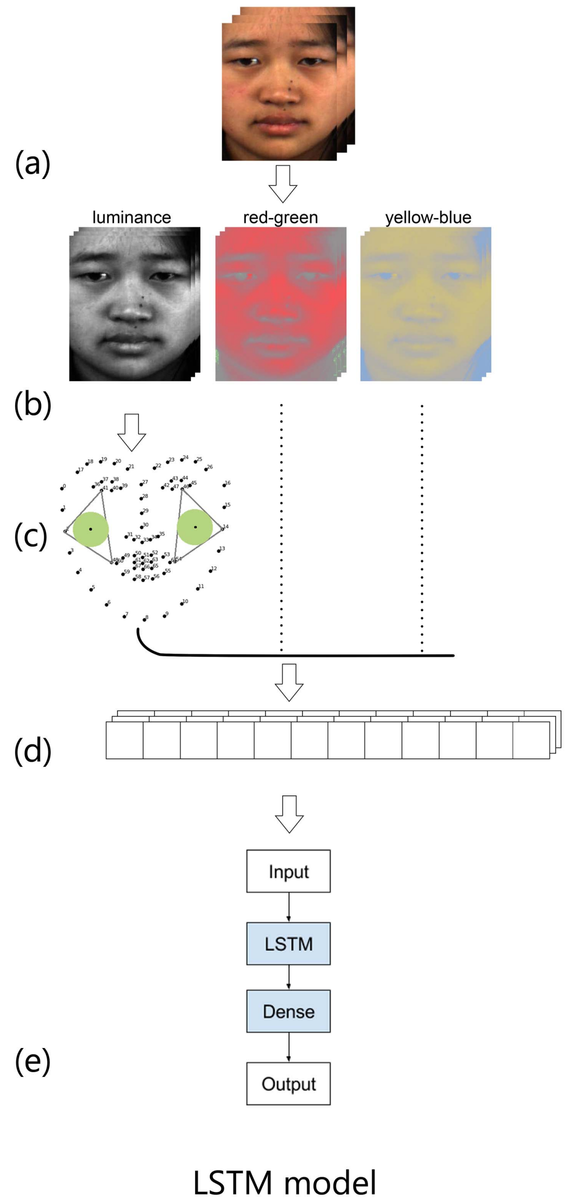

Figure 6. Feature vector generation from Micro-emotion video sequence. (a) The micro-emotion image sequence, with normalized number of frames. (b) Conversion to the oRGB color space, resulting in the luminance, red-green and yellow-blue channels (c) Performing facial landmark detection and calculating cheeks location on the luminance channel. d) Color information from each patch from both color channels are concatenated across all frames into a single feature vector, which serves as input to (e) the LSTM classifier.

points (Figure 4). Based on these points, the cheek triangles are computed as shown in Figure 5. The center point of each triangle is calculated, and a circular patch contained in the triangle is taken. Only the pixels in these circular patches are considered in later steps. We have found this method to be the most robust when accounting for errors in face point detection and providing consistent skin area.

3. Colorspace processing

   It has been shown that various color spaces outperform the standard RGB color space when dealing with faces, in terms of face detection [30, 42] as well as facial emotion analysis [45, 46, 26].

   Our approach is based on changes in blood flow, which in turn is expressed as changes in pixel color, thus we require a colorspace that provides good separation of the flushed red channel, as well as the luminance channel. The latter is important in order to eliminate the effect of scene illumination as well as object shading. Testing over several color spaces, we found that the oRGB colorspace [5, 44] provides a better decomposition into the red-green and yellow-blue channels and has been shown to improve facial emotion analysis.

   Thus, the RGB data of the given face image is transformed into this isoluminant colorspace that produces two chroma channels and a luminance channel. We ignore the luminance channel, resulting in two color values per pixel. This conversion also allows us to disregard the color changes that are due to lighting, shading and facial geometry.

4. Feature Extraction

   For each cheek patch, the average value per color channel within the patch is computed and the corresponding average color value of the same patch in the neutral image is subtracted to obtain color values normalized for each individual, thus compensating for base skin tone as well as scene illumination. Additionally, the standard deviation of the two color channels within the patch are computed.

   Thus, for each frame the color information over the 2 selected patches (Figure 5) are collected, resulting in 8 features per frame. These are collected across all 50 frames of the standardized sequence, and concatenated into a single feature vector of size 400, which is then used as input for classification.

4. Micro Emotion Classification

For every dataset, feature vectors were created for each video sequence. The feature vector together with the associated emotion label were used as input to a classification process. We use a Long Short Term Memory model (LSTM), a recurrent neural network which is especially effective for classifying time series, due to its memory retention feature [17, 14].

Database	Training	Validation
SMIC	148	16
CASME	171	19
CASME II	230	25
CAS(ME)^2	322	35

Table 3. The split between training and validation data per database

Our LSTM model consists of 2 layers - a single LSTM layer followed by a dense layer (Figure 6e). Training and validation was performed for each dataset separately, and the accuracy was evaluated using 10-fold cross validation, i.e 90% of the data was used for training and 10% of the data was used for validation. The division of samples between the training and validation data was performed randomly. The actual numbers are detailed in Table 3. Training was performed for 750 epochs with batch size of 100 A Stochastic Gradient Descent was used as optimizer [4].

5. Results

We ran our system on the CASME, CASME II, CAS(ME)^2 and SMIC databases. To the best of our knowledge, this is the first study to report across all 4 datasets. Previous studies in micro-emotion classification, reported results on only one or two of these datasets. Some of these reported very good success rates but did not show validation across-the-board [31]. We present results on all four datasets and compare with the few studies that report results on 3 of the 4 datasets.

In our method as well as in all comparison methods, the videos were normalized to a constant number of frames, and as described in Section 3.2 the number of classes in the CASME and CASME II datasets was reduced to avoid classes with too few examples or ambiguous emotions.

Table 5 displays the collected results. Accuracy is shown in percentages. Chance levels are 25%, 25%, 33% and 33% for the datasets CASME, CASME II, CAS(ME)^2 and SMIC respectively. We compare our method with other methods that were tested on at least 3 of the four datasets. In [19], Huang et. al.used SpatioTemporal Local Binary Pattern with Integral Projection (STLBP-IP) to improve upon the traditional LBP from three orthogonal planes (LBP-TOP) [50] achieving an accuracy of 64.33% on CASME, 64.78% on CASME II and 63.41% on SMIC. In [20], Huang et. al. introduced the Spatio-Temporal Completed Local Quantization Patterns (STCLQP) which also provided sign, magnitude and orientation as features, in addition to the LBP output. They created their own encoding of each class and used it as a classifier. Results improved over the SMIC database but at the expense of the CASME and CASME-II dataset results. Happy and Rotary [15] introduced the Fuzzy

Dataset	CASME	CASME II	CAS(ME)^2	SMIC
Our results	**80.00%**	**66.66%**	**91.89%**	**70.50%**
STLBP-IP with SVM [19]	64.33%	64.78%	NA	63.41%
STCLQP with codebook [20]	57.31	58.39%	NA	64.02
FHOFO with SVM [15]	65.99%	55.86%	NA	51.22%
Deep learning [35, 34]	66.67%	66.67%	NA	53.6%

Table 4. Comparison between our system and the top motion-based methods.

Histogram of Optical Flow (FHOFO) as an extension to the traditional Histogram of Oriented Optical Flow (HOOF). They showed good results on the CASME dataset but with lower accuracy on the CASME-II and SMIC datasets.

In [34], Patel et.al. used a deep learning approach for determining micro expressions, using transfer learning on macro expressions, in a CNN model. This approach proved to be ineffective in classifying micro expressions as they have achieved an accuracy of only 53.6% on SMIC and 47.3% on CASME II.

In [35] Peng et.al. proposed the use of a Dual Temporal Scale Convolutional Neural Network (DTSCNN) that used optical flow information extracted from the micro expression sequences. The system the authors presented uses a two-stream network to adapt to different frame rates. They achieved better results on the CASME I/II database than previous deep learning techniques and reached an accuracy of 66.67%.

We note that all these methods relied strictly on the geometric and motion information of the sequence, ignoring the color entirely and working on grayscale data. As can be seen, our method improves over the compared methods for the CASME and SMIC datasets, is on par for CASME II, and we show additional accuracy results on CAS(ME)^2 with accuracy over 90%.

We believe our proposed method outperforms the motion based approach since facial color is much more difficult to subdue than facial motion. Additionally, while the same emotion can be expressed in multiple different ways using movement, the blood flow changes are usually the same, therefore creating a more well-defined distinction between micro-emotion classes.

6. Conclusion

In this paper, we performed automatic classification of micro expressions. We exploited an aspect of the human face which is very difficult to subdue, namely, facial color change due to blood flow during expression of emotion. We proposed a method to evaluate color change during emotion expression and used an LSTM neural network to successfully classify the emotion type. We showed that our approach is successful across four benchmark datasets and improves accuracy over methods that test on these databases. These methods are based on geometry and movement analysis in the input sequence. Given that motion is very subdued in micro expressions, it is reasonable that analysis of facial color change is advantageous in these cases.

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