Customer satisfaction measuring based on the most significant facial emotion
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Abstract—Customer satisfaction (CS) measuring has become one of the strategic tools for companies. Many methods exist to measure customer’s satisfaction. However, generally results could be wrong. Otherwise, CS can be deduced from customers emotion state. In this paper, we propose a new end-to-end method for facial emotion detection. For that, six new characteristic features are proposed. We characterize especially the most significant emotions namely “Happy”, “Surprised” and “Neutral”. The proposed method is invariant to camera position. A very challenging datasets as Radboud Faces and Cohn-Kanade (CK+) are used for study and evaluation. Obtained results show that our method reaches a high recognition accuracy and outperforms Action Unit (AU) features based Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).

Index Terms—Facial expression, emotion recognition, most significant emotions, feature extraction, action unit, SVM, KNN.

I. INTRODUCTION

In an increasingly competitive world, negative reviews of customers can have an important impact on a business. Indeed, customer satisfaction is actually measured in many applications such as shops, banks, mobile apps and others. Many methods and metrics are designed. In instance, Customer Satisfaction (CSAT) is asked using emails, phones, face-to-face interview, tablets and touchpads. As well, Net Promoter Score (NPS) is asking about the intention of product or service recommendation and consumer respond by assigning a rating or a number of stars. However, collected information with these methods could be wrong.

In another way, human interaction is recognized essentially through facial expressions which provide a natural and compact way for humans to convey their emotional state to another party. In addition, nowadays, supervision cameras are everywhere. Thus, we can consider that facial expressions are accessible and we can deduce whether the customer is satisfied or not based on his emotional state.

Across different cultures, we found seven universally recognizable emotions [1]: anger, disgust, fear, happy, sad, surprised and neutral. However, in this work, we note that no need to recognize all emotions. In fact, for customer satisfaction, only “Happy”, “Surprised” and “Neutral” are significant. In this paper, we propose an original and performing method for customer satisfaction measuring based on the most significant facial emotion.

The organization of the paper is as follows: In section II, related works are presented. Then, we propose a novel facial emotion recognition in Section III. Experimental results are discussed in Section IV and finally conclusions are drawn in Section V.

II. RELATED WORKS

For the first time, Charles Darwin demonstrated that despite their differences and countries, human beings have innate and common emotion [2]. Historically, there are seven types of human emotions: anger, disgust, fear, happy, sad, surprised and neutral (Fig. 1). Paul Ekman later conducted several experiments and observations on a large number of individuals and confirmed that emotions are universal recognizable expression [2].

![Fig. 1: The basic emotions.](image)

Many approaches are proposed to recognize facial expressions. They can be split into two broad categories: appearance-based approaches and features-based approaches. Appearance-based approaches detect emotion via a model which illustrate the general facial shape and texture ( [3], [4] ). On the other hand, features-based approaches extract person’s characteristics. Then, extracted features can be combined and classified
Facial emotion recognition systems comprised essentially three steps [6] (Fig. 2). The first step is face and landmarks detection. For that, several open source facial behavior analysis systems exist. In instance, CHEHRA1 [7], TCDCN2 face alignment tool [8], CLandmark3 [9], OpenFace4 [10]... etc. We note that OpenFace is the most recent fully real time and open source system [10].

Feature extraction is the second step of facial emotion recognition system. P. Ekman and W. Friesen developed the Facial Action Coding System (FACS) to describe movements (action units) caused by expansion and contraction of facial muscles [11]. Using FACS, human coders can manually code almost any anatomically possible facial expression [12]. More recently, Hammal et al propose the use of just 5 characteristic distances as features [5]. They supposed that all the necessary information is contained in the castration of the eyes, mouth and eyebrows.

The final step is emotion recognition. Many features based emotion classification methods exist. Two main categories can be identified: supervised and unsupervised classification techniques [13]. Unsupervised learning or clustring don’t require human intervention and don’t need a prior knowledge or predefined categories [14]. In the other side, supervised learning requires an expert labeled database. The process is performed in two phases. During the learning phase, a model is determined from the labeled data. Using the learned model, the test phase called consist on predicting the label of a new non labeled data [15]. We note that, supervised learning is more efficient and used to resolve linear and non-linear classification problems [16]. The most popular supervised machine learning algorithms [17] are: Support vector machine (SVM) [18], k-nearest neighbors (KNN) [19], Convolutional Neural Networks (CNN) [20]. However, generally these methods could require a large number of attempts to move towards the best possible recognition performance [21].

Up to our knowledge, no facial emotion recognition model has yet proposed an affordable and performing system for customer satisfaction. Otherwise, our method deals with emotion recognition from images, and focus on feature extraction and analyze. To measure customer satisfaction, we note that in the rest of this paper, we consider only three significant emotions: “Happy”, “Surprised” and “Neutral”.

1https://sites.google.com/site/chehrahome/
2https://github.com/zhzhamp/TCDCN-face-alignment
3https://github.com/aricamic/clandmark
4https://github.com/TadasBaltrusaitis/OpenFace
Fig. 4: The frame’s diagonal (D).

![Image of facial landmarks]

Fig. 5: Our feature extraction (F₁ to F₆).

C. Emotion recognition

Our aim is to characterize each “Happy”, “Surprised” and “Neutral” emotion by a specific hyper-planes which allow to recognize the corresponding emotion depending on the associated characteristic features. The conducted hyper-planes have to be invariant to the frame’s diagonal (D) of each face. Radboud facial database⁵ [22] is used. First, we evaluate each extracted features according to the number of images (see Fig. 8(a)-(f)). According to this feature study and based on predicted behavior of each extracted feature for the most significant emotions, we present in the following our proposed hyper-planes for each emotion.

1) Happy emotion: We note that in this case, F₁ have to be small because eyes are little closed. In addition, generally, smiling increases the values of F₃ and F₆ and decreases F₅’s value. Equation 1 presents our proposed feature combination F₇ to well distinguish the “Happy” emotion:

\[ F₇ = F₃ + F₆ - F₅ - F₁ \]  

(1)

Eq. 1 illustrates the evaluation of the new F₇ representation of the most significant emotions versus the frame’s diagonal D. We can see that the “Happy” emotion curve can be entirely separated from the two other emotions according to the affine hyper-plane Y₇ (equation 2):

\[ Y₇ = A₇ * D + B₇ \]  

(2)

Where A₇ = 0.21 is the slope and B₇ = -1 is the Y₇-intercept.

Fig. 6: F₇ representation of the most significant emotions versus the frame’s diagonal D within Radboud Face database.

Finally, the recognition of the “Happy” emotion is ensured through the equation 3:

\[ F₇ > Y₇ \implies “Happy” \text{ emotion} \]  

(3)

2) Surprised emotion: In this case, we note that F₂ value have to be high because eyebrows are raised. In addition, the mouth is like the letter “O” so it increases the value of F₄ and decreases F₃ value. Thus, the “Surprised” emotion is distinguished by the feature combination F₈ (equation 4):

\[ F₈ = 2 * F₂ + 3 * (F₄ - F₃) \]  

(4)

The evaluation of the new F₈ representation of the most significant emotions versus the frame’s diagonal D is illustrated in Fig. 7.

Fig. 7: F₈ representation of the most significant emotions versus the frame’s diagonal D within Radboud Face database.

The “Surprised” emotion curve can be entirely separated from the two other emotions (Fig. 7) according to the affine hyper-plane Y₈ (equation 5):

\[ Y₈ = A₈ * D + B₈ \]  

(5)

\[ http://www.socsci.ru.nl:8180/RaFD2/RaFD?p=main \]
Fig. 8: Behaviour feature study: (a) $F_1$, (b) $F_2$, (c) $F_3$, (d) $F_4$, (e) $F_5$, (f) $F_6$, curves of the most significant emotions according to 3*67 images from Radboud Face database.

Fig. 9: The three proposed feature representation of the most significant emotions versus the frame’s diagonal D within CK+ database: (a) $F_h$ for “Happy” emotion (b) $F_s$ for “Surprised” emotion and (c) $F_n$ for “Neutral” emotion.
Where $A_s = -0.03$ is the slope and $B_s = -62.2$ is the $Y_s$-intercept.

The recognition of the “Surprised” emotion is ensured through the equation 6:

$$F_s > Y_s \implies \text{“Surprised” emotion} \quad (6)$$

3) **Neutral emotion:** To differentiate “Neutral” emotion, $F_2$ and $F_6$ have to be smaller compared to their respectively “Surprised” and “Happy” values. In addition, we note that the closed mouth in this case decreases $F_4$ value. Then, we consider that feature combination $F_n$ (equation 7) allows to well distinguish the “Neutral” emotion:

$$F_n = F_4 + F_2 - 1.5 \times F_6 \quad (7)$$

Fig. 10 illustrates the evaluation of the new $F_n$ representation of the most significant emotions versus the frame’s diagonal D. We can see that the “Neutral” emotion curve can be entirely separated from the two other emotions according to the two affine hyper-planes $Y_{n1}$ and $Y_{n2}$ (equations 8 and 9).

$$Y_{n1} = A_{n1} \times D + B_{n1} \quad (8)$$

$$Y_{n2} = A_{n2} \times D + B_{n2} \quad (9)$$

Where $A_{n1} = -0.02$, $B_{n1} = -20$, $A_{n2} = -0.18$ and $B_{n2} = 0.5$.

The recognition of the “Neutral” emotion is finally ensured through the equation 10.

$$Y_{n1} > F_n > Y_{n2} \implies \text{“Neutral” emotion} \quad (10)$$

IV. EXPERIMENTAL RESULTS

Many facial expression databases (e.g. The Cohn-Kanade database [23], Radboud Faces Database [22], the MMI-Facial Expression Database [24], and the JAFFE database [25]) exist. In our experiments, we use a well known and popular facial expression dataset. Indeed, the extended Cohn-Kanade database (CK+)\(^6\) [23] is used in this work to evaluate the performance of our method. This database have a large number of images with expressions’ labels. The CK+ database contains 327 image sequences for “Happy”, “Surprised” and “Neutral” emotions. To develop our method, we use Microsoft Visual Studio 2015 to employ OpenFace and MATLAB R2017a for drawing curves and illustrate results.

Fig. 11 and 12 shows the performance of our method on both Radboud Faces and CK+ databases. We note that our reached accuracy is higher then 94% for all the three used most significant emotions.

Fig. 9(a)-(c) confirm on CK+ database the previously conducted study using Radboud Faces Database. That validates our original feature presentation $F_h$, $F_s$ and $F_n$ and proposed affine hyper-planes $Y_h$, $Y_s$, $Y_{n1}$ and $Y_{n2}$.

For comparison reasons, we employ two machine learning methods SVM [18] and KNN [19]. Facial Action Coding System (FACS) [11] are used as features with these two classifiers. For fair comparison, we use Radboud dataset for training and CK+ dataset for prediction. Obtained results illustrated in Fig. 13(a)-(b) and presented in table I prove that our proposed method outperform SVM and KNN classifiers.

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\(^6\)http://www.consortium.ri.cmu.edu/ckagree/
Table I shows the obtained average accuracy (Av Acc) of the three compared methods. We can see that our method reach 97.02% and outperforms SVM (84.04%) and KNN (95.32%) classifiers.

TABLE I: Our proposed method, SVM, KNN recognition rate comparison within CK+ database

<table>
<thead>
<tr>
<th>Method</th>
<th>Emotion</th>
<th>Av Acc</th>
<th>Happy</th>
<th>Surprised</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our method</td>
<td>97.02%</td>
<td>98.59%</td>
<td>94.83%</td>
<td>98.12%</td>
<td></td>
</tr>
<tr>
<td>KNN + AU</td>
<td>95.12%</td>
<td>97.05%</td>
<td>92.49%</td>
<td>94.84%</td>
<td></td>
</tr>
<tr>
<td>SVM + AU</td>
<td>84.04%</td>
<td>88.73%</td>
<td>76.53%</td>
<td>86.85%</td>
<td></td>
</tr>
</tbody>
</table>

V. CONCLUSION

We propose in this paper a new and performing method for customer satisfaction measuring based on the most significant facial emotion. Six new characteristic features are used and original feature representation and hyper-planes emotion separation are proposed. The proposed method is invariant to camera position. A very challenging datasets as Radboud Faces and Cohn-Kanade (CK+) are used for study and evaluation. Obtained results show that our method reaches a high recognition accuracy and outperforms Action Unit (AU) features based Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).

REFERENCES