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Development of Facial Expression Recognition for Training Video Customer Service Representatives

Linh Tuan Dang
Graduate School of Information Science and Engineering
Ritsumeikan University
Kusatsu, Japan
Email: linhdt@spice.ci.ritsumei.ac.jp

Eric W. Cooper and Katsuari Kamei
College of Information Science and Engineering
Ritsumeikan University
Kusatsu, Japan
Email: cooper@is.ritsumei.ac.jp, kamei@ci.ritsumei.ac.jp

***Abstract*—This paper describes a study of the relation between facial expression and customer impression of service quality. Based on the results, a facial expression warning system will be designed to improve the service quality of the Customer Service Representative when they practice in training sessions. The system, based on existing systems, has three modules: facial recognition, feature extraction and facial expression recognition. This paper also uses Haar-like features for face detection and a Support Vector Machine for facial expression recognition in an attempt to improve the recognition rate by using a novel feature extraction method. This paper also presents results of the method when tested on standard facial expression databases.**

I. Introduction

Today, many companies work for the same customers and the competition has become more and more fierce. As a result, each enterprise must try to give the best services to entice potential customers. Customer service has become one of the most important services and customer service representatives (CSRs) play a very important role. During a transaction, CSRs must have the right behaviors, outward emotions and facial expressions so their customers do not feel slighted.

Some researchers have mentioned the advantages of positive emotional expression in CSRs, and conversely for negative ones. For example, Brown et al [1] and Hennig-Thurau et al [2] indicated the relationship between this type of expression and customer satisfaction by concluding that employee smiling leads to more content customers. Ravid et al [3] studied the need to avoid expressing anger to customers. In order to assure the effectiveness of customer service operations, some have conducted research of emotion recognition from speech in customer service interactions. For instance, Pao [4] developed a real-time emotion detection system for use in the conversation between service representatives and customers. Commercial software for monitoring emotion has also been introduced, such as QA5 developed by Nemesyco [5].

Currently, many companies use not only call centers but also video support centers thanks to the development of software in this field, freeware such as Skype [6] or Hangouts [7] or commercial software such as Live Guide [8] or VeeStudio [9]. An example of this can be seen in the announcement of "Mayday" button links to video tech support for customers in a recent tablet from Amazon, the Kindle Fire HDX [10].

This paper tries to solve the research question of how to design a system which will give warnings to CSRs when their facial expressions may affect customer impressions during video customer service. The first part of the research reconfirms the hypothesis that negative expressions are not productive for customer service sessions, and vice versa. In this section, experiments of a customer service interaction by using Skype were carried out. Following Hodsoll et al [11], experienced CSRs were asked to express happy faces as positive expression or angry faces as negative expression. From recorded video sessions, a suitable online survey was developed to collect the opinion of observers about the facial expression of CSRs and their service quality in these videos. The final work of this stage was the correlation analysis between facial expression and customer service evaluation to investigate the hypothesis. The second part is devoted to developing a warning system by using the results of the experiments. This system is based on Piatkowska and Martyna's work [12], [13] but uses a novel feature extraction technique which includes the combination of Center-Symmetric Local Binary Pattern (CS-LBP) with Principal Component Analysis (PCA). To preserve holistic information and increase accuracy, the algorithm is used not only for the component regions (nose, eyes) but also for the whole face image. Comparison of the proposed algorithm to a previous method [12], [13] was conducted in a second experiment.

II. Facial expression and service quality

As mentioned above, previous research have suggested that negative facial expressions can affect the impressions of customers based on observations and experiments of direct interaction between customers and CSRs. Future system will use online video, an indirect interaction, so the first part of this paper attempt to reconfirm this hypothesis during video customer service by conducting experiments in this situation.

In this step, a simulation was done of customer service transactions using experienced people to perform the role of CSRs. Those CSRs are first instructed to express facial expressions during the interactions with customers. The facial expressions requested are representative of positive expression (happy), negative expression (angry), and neutral (example in Figure 1). Each session from ten to fifteen seconds was recorded and 72 videos were selected for survey with the attributes below:

- Audio:
  - Half of the videos have audio.
  - Half of the videos have no audio.
- Gender:
  - A male CSR appears in 36 videos.
  - A female CSR appears in 36 videos.
- The CSRs were instructed to express equal numbers of facial expressions:
  - Happiness in 24 videos.
  - Anger in 24 videos.
  - Neutral expression in 24 videos.

Fig. 1: Different facial expressions

These 72 videos were divided randomly into six sets which were shown to subjects to collect their responses. For this task, videos were published together with Likert scale questions in an online survey. Based on existing scales used to measure the quality of service [14], [15], questions were developed and divided into three groups, shown in Tables I, II, and III.

TABLE I: Questions about Facial expression of CSR

	5 Strongly agree	4 Agree	3 Neither	2 Disagree	1 Strongly disagree
Neutral					
Happy					
Angry					

TABLE II: Questions about service quality expressed by CSR in video

	5 Strongly agree	4 Agree	3 Neither	2 Disagree	1 Strongly disagree
The service quality is good					
Atitude of CSR is appropriate					
CSR is competent					

43 Vietnamese volunteers aged 24 to 62 participated as subjects. In total, 848 responses were received. In each video, statistical analysis was done for nine variables (the nine questions in the survey). The variables are labeled: happy, angry, neutral, Good Service, Appropriate Attitude, Competent, Interested, Pleased, Continue Service. For example, statistical analysis of one video which has thirteen responses is presented in Table IV.

TABLE III: Questions about service quality expressed by CSR in video

	5 Strongly agree	4 Agree	3 Neither	2 Disagree	1 Strongly disagree
Enjoyable					
Pleased					
Want to do this service again					

For verifying our survey, internal consistency reliability was tested by using Cronbach's alpha. The result are considered as follows:

- Acceptable if $0.6 \leqslant$ Cronbach's alpha < 0.7
- Good if $0.7 \leqslant$ Cronbach's alpha $\leqslant 0.9$
- Excellent if Cronbach's alpha > 0.9

The result in Table V shows that the questionnaire responses have good consistency.

TABLE IV: Statistical analysis of one example video

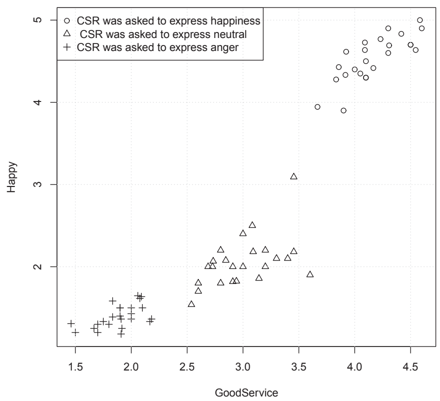
Variable	Number of responses	Mean	Std Dev	Minimum	Maximum
Neutral	13	1.6154	.6504	1.0000	3.0000
Happy	13	4.7692	.4385	4.0000	5.0000
Angry	13	1.8462	1.0682	1.0000	5.0000
GoodService	13	4.2308	.4385	4.0000	5.0000
AppropriateAttitude	13	4.3846	.5064	4.0000	5.0000
Competent	13	4.1538	.3755	4.0000	5.0000
Interested	13	4.2308	.4385	4.0000	5.0000
Pleased	13	4.2308	.4385	4.0000	5.0000
ContinueService	13	4.1538	.4755	4.0000	5.0000

TABLE V: Reliability test

Cronbach's Alpha	Number of Items	Cases Valid	Cases Excluded
.8196	9	72	0

From the mean of variables in all 72 videos, a correlation analysis was calculated between three variables of facial expressions and six variables of service quality. Thus 3x6 = 18 charts were built and each chart has 72 elements. Figure 2 is a sample of the result, two charts for the correlation between good service and happy/angry.

Statistical analyses for 3 different sets when CSR was asked to express angry, happy, and neutral are presented in Tables VI, VII, and VIII. Thus each set has $72/3 = 24$ videos. The maximum, minimum, and mean values were calculated for responses from 5 (strongly agree) to 1 (strongly disagree) in each set. The response for a given video was the average of all responses to that question. If result in one question is high, the subject agrees with this opinion and low if the subject disagrees (reference table in Table IX).



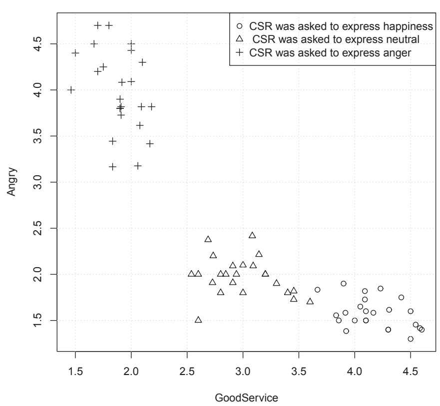


Fig. 2: Example of the result

TABLE VI: Results when CSR was asked to express happy face

	Minimum	Maximum	Mean
GoodService	3.6667	4.6000	4.169975
AppropriateAttitude	3.9000	4.8000	4.319979
Comptetent	3.5000	4.8000	4.052846
Interested	3.6111	4.7000	4.104008
Pleased	3.7778	4.8000	4.180654
ContinueService	3.6667	4.4167	4.030458

TABLE VII: Results when CSR was asked to express neutral face

	Minimum	Maximum	Mean
GoodService	2.5385	3.6000	3.000763
AppropriateAttitude	2.6000	3.7000	2.995283
Comptetent	2.7000	3.7000	3.072371
Interested	2.3077	3.3636	2.765729
Pleased	2.4615	3.6000	3.058250
ContinueService	2.6000	3.6364	3.115350

The distribution in Figure 2 and the results in Tables VI, VII, and VIII support the hypothesis of the relation between

TABLE VIII: Results when CSR was asked to express angry face

	Minimum	Maximum	Mean
GoodService	1.4615	2.1818	1.889783
AppropriateAttitude	1.4167	2.0833	1.757196
Comptetent	1.5833	2.4545	1.982588
Interested	1.4615	2.0000	1.776313
Pleased	1.6000	2.1000	1.819008
ContinueService	1.6667	2.6364	2.069888

TABLE IX: Reference table

5	4	3	2	1
Strongly agree	Agree	Neither	Disagree	Strongly disagree

facial expressions and customer service is still true with video interaction: in normal situations, CSR happy faces are interpreted as more positive than angry faces. This relation can be considered as one useful factor for improving service satisfaction.

III. Facial expression warning system

The results of the experiment described above will be used in the development of a warning system for use in CSRs training sessions. Practice with the warning system is intended to help CSRs learn to interact with customers without inappropriate expressions. In particular, this system warns CSRs when their expressions become angry, which is not productive and can affect the customer during the video customer service transaction.

The proposed warning system uses novel algorithms as well as algorithms from previous research on systems for facial expression recognition. Previous systems commonly have three different modules: face detection, feature extraction, and facial expression recognition. In the face detection module, one widely used method is comparison of Haar-like features, for example Paschero et al [16]. Facial extraction has two main approaches. One is to use geometric based features, the shape and location of components in the face, as in Tian et al [17]. Another method is to use appearance based features, for example facial texture such as Ou et al used Gabor wavelet for feature extraction [18]. In the facial expression recognition stage, a classifier is used to classify features which were extracted in previous steps. There are many different methods, such as a rule based classifier in Pantic and Rothkrantz [19], a neural network in Tian et al [17], and a Support Vector Machine in Bartlett et al [20].

We found that the system in Piatkowska and Martyna, as shown in Figure 3 [12], [13], could be developed to improve the recognition rate for use in the proposed warning system. This paper describes an improvement of the efficiency of this system by using a novel feature extraction method. An overview of the proposed system is shown in Figure 4.

The first component, face detection module, uses the Viola-Jones algorithm with Haar-like features [21]. The face is detected by matching the Haar-like features in the database

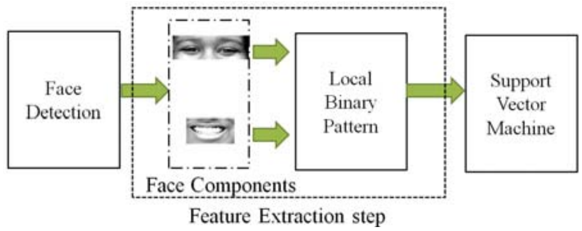


Fig. 3: Piatkowska's system

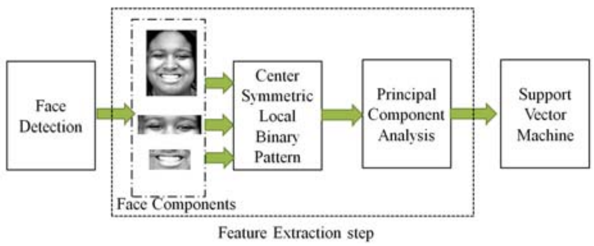


Fig. 4: Proposed system

with these features in testing image. The Database in this case is the Haar XML file provided by OpenCV library. A Haar-like feature is the difference between the sum of the pixels in different rectangular regions which can be seen as the black and white regions in Figure 5. There are three different types of this feature, as shown: 2-region features, 3-region features, and 4-region features. In 2-region features, the difference is calculated between two regions. In 3-region features, the difference is calculated by the subtraction between the sum of left and right regions and the center region. In 4-region features, the sums of two region pairs in the diagonal are calculated and the Haar-like feature is the difference of these two sums. These Haar-like features represent the characteristics of the face by interpreting the face has different light and dark areas. For example, the eye region is darker than the nose region. After detecting the face, for increased accuracy of the following steps, some components of the face are also detected, the components which greatly contribute to facial expression such as the eyes [22], and the mouth [23].

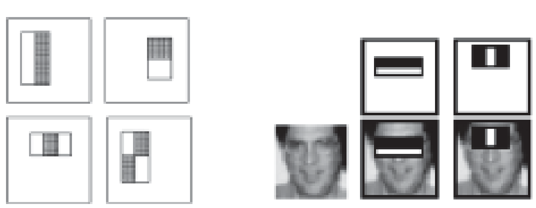


Fig. 5: Face detection by Haar-like feature

After face detection, the next step is dedicated to identifying the facial expression by comparing the test face image with the training face image. Questions arise in this step as to how to compare, and based on which criteria. One way would be to compare all pixels in two images but this method is too complex therefore takes too much CPU time. The work becomes easier if we choose only some features for comparison after feature extraction. For example, Piatkowska et al used Local Binary Pattern (LBP) method. The general idea of this method is to compare every pixel with all neighbors, in this case eight neighbors. If the intensity of the given pixel is greater than intensity of the neighbor pixel, the neighbor pixel is assigned the value zero and the value one if less than or equal. This procedure results in eight binary digits for each pixel in the image. For illustration, in the Figure 6, result of the LBP step is binary 00011110. After using LBP for all pixels, every pixel has the value in a range from 0 to $2^8 = [0, 255]$. A histogram is built with the x axis value of [0, 255] and y axis is number of pixels which have this value. This histogram is used to compare two images [13], [24].

The proposed system improves the feature extraction by using another method called Center Symmetric-Local Binary Pattern (CS-LBP). Instead of comparing center pixel with all neighbors, this algorithm uses only the comparison of four pairs: one pixel and it's symmetry pixel through the center. Thus the binary chain has only four digits and the value of the pixel is in a range zero to $2^4 = [0, 15]$. For example, in Figure 6, the binary is 0001 and decimal value after the conversion is one. Using this algorithm, the number of features is reduced sixteen times, reducing complexity. Researchers also indicated the advantage of CS-LBP when compared with LBP. For example, M.Heikkila et al said that CS-LBP gives a significant reduction in dimensions while preserving distinctiveness [25] or Zheng et al and Xiao et al stated that CS-LBP inherits the desirable properties of texture features but the computation becomes cheaper [26], [27].

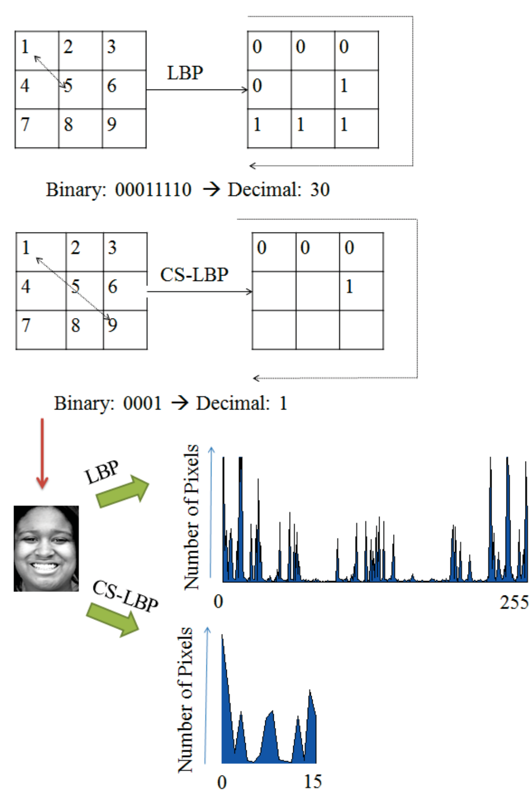


Fig. 6: Feature Extraction by using LBP or CS-LBP

After using LBP for each pixel, Piatkowska used only two small regions, eyes region and mouth region, and a histogram based on the LBP value is calculated in each region. In this case, only local information can be obtained. So, in order to encode the holistic information or enhance the holistic description of the face, the proposed system uses not only regions but also the whole face image in the CS-LBP algorithm.

To further increase accuracy, the proposed system does not build the histogram in big regions, such as the mouth region. Instead, the algorithm divides the eye region, the mouth region, and the whole face into smaller regions of 5x5, 4x4 and 6x9 pixels, respectively. A sub-histogram is computed for each smaller region and concatenated into one histogram as shown in (Figure 7).

Finishing the CS-LBP step, once again to improve the recognition rate and reduce the dimension of feature vector, Principle Component Analysis (PCA) is used. This famous technique removes noise and redundant information by finding features with high variance. From the result of PCA step, a histogram is built. This is the feature which was used in the last module of the algorithm, the facial expression recognition.

Fig. 7: Histogram built by using the combination of sub-histograms

In the facial recognition modules, to compare feature histogram of images in the database to histogram in the test images, a Support Vector Machine (SVM) is used. An SVM is a method of supervised learning for classification by using a hyperplane to divide the space into two regions, each region classifying one type of element. For training, from the negative training samples and positive training samples, a margin separator is defined by mathematical functions. Using this margin separator, the testing sample is considered as positive case or negative case. The SVM is an effective machine learning method when using a relatively small number of training data.

The proposed system was tested by using images come from Cohn-Kanade and FEED facial expression databases which have labeled images of seven facial expressions: anger, disgust, fear, happiness, sadness, surprise and neutral.

The Cohn-Kanade database has images from neutral to peak of the facial expression and has the following number of each facial expression as follow: disgust (59), happiness (69), anger (45), fear (25), surprise (82), sadness (28) [28], [29]. Thus 25 images of each expression were chosen randomly. This data was divided randomly into five different sets and each set has similar numbers of facial expressions, in this case five of each. With this data, four sets for training with 7x5x4 = 140 samples and one set for testing with 7x5 = 35 samples.

For each test, one set was removed as used as the test data, for all sets. Hence, number of test samples was 35x5 = 175 and the number of wrong detection for each of the image was counted, as shown in Table X:

TABLE X: Comparison the number of wrong detection between Piatkowska et al's algorithm and proposed algorithm with Cohn-Kanade database

Set 1	Piatkowska et al's algorithm	Proposed algorithm
Anger	2/5	1/5
Disgust	1/5	1/5
Happiness	0/5	0/5
Fear	3/5	2/5
Surprise	0/5	0/5
Neutrality	0/5	0/5
Sadness	5/5	2/5

Set 2	Piatkowska et al's algorithm	Proposed algorithm
Anger	2/5	2/5
Disgust	1/5	0/5
Happiness	0/5	0/5
Fear	2/5	2/5
Surprise	0/5	0/5
Neutrality	0/5	0/5
Sadness	2/5	3/5

Set 3	Piatkowska et al's algorithm	Proposed algorithm
Anger	0/5	1/5
Disgust	1/5	1/5
Happiness	0/5	0/5
Fear	1/5	0/5
Surprise	1/5	0/5
Neutrality	0/5	0/5
Sadness	5/5	4/5

Set 4	Piatkowska et al's algorithm	Proposed algorithm
Anger	2/5	2/5
Disgust	0/5	0/5
Happiness	0/5	0/5
Fear	4/5	2/5
Surprise	1/5	0/5
Neutrality	1/5	0/5
Sadness	1/5	1/5

Set 5	Piatkowska et al's algorithm	Proposed algorithm
Anger	1/5	0/5
Disgust	1/5	0/5
Happiness	1/5	1/5
Fear	3/5	2/5
Surprise	1/5	0/5
Neutrality	1/5	1/5
Sadness	5/5	4/5

Total	Piatkowska et al's algorithm	Proposed algorithm
Anger	7/35	6/35
Disgust	4/35	2/35
Happiness	1/35	1/35
Fear	13/35	8/35
Surprise	3/35	0/35
Neutrality	2/35	1/35
Sadness	18/35	14/35

The overall number of wrong facial expression recognition when use the Cohn-Kanade database can be seen in Table XI.

TABLE XI: Recognition rate with Cohn-Kanade database

	Piatkowska et al's algorithm	Proposed algorithm
Wrong detection	48	32
Correct detection	127	143
Number of testing	175	175
Recognition rate	75.57%	81.71%

The FEED database from Munich Technical University has nineteen subjects with ten males, nine females and each subject has three images of three videos in each facial expression [30]. So we can devise three images into three different sets. With this data: two sets for training with 2x19x7 = 266 samples and one set for testing with have 19x7 = 133 samples.

TABLE XII: Comparison of the number of wrong detections between Piatkowska et al's algorithm and the proposed algorithm in the FEED database

	Piatkowska et al's algorithm	Proposed algorithm
Neutral	4/19	3/19
Disgust	4/19	2/19
Happiness	3/19	2/19
Fear	9/19	5/19
Surprise	7/19	6/19
Anger	3/19	2/19
Sadness	6/19	5/19
Total of wrong	35/133	25/133

The number of wrong detections was counted as shown in Table XII. The overall number of wrong facial expression recognitions of using FEED database can be seen in Table XIII.

The results of testing with the Cohn-Kanade database and FEED database shows that proposed system has a better recognition rate than the system developed by Piatkowska.

TABLE XIII: Recognition rate with FEED database

	Piatkowska et al's algorithm	Proposed algorithm
Wrong detection	35	25
Correct detection	98	108
Number of testing	133	133
Recognition rate	73.68%	81.20%

IV. Conclusions

This paper described an experiment to examine the relation between the facial expression of customer service representatives and the impressions customers have about those representatives. As in previous research, without any additional instructions about the situation, customers tended to have lower impressions when the CSR expression was interpreted as more "angry" and more positive when the expression was interpreted as more "happy". The strength of that correlation suggests that this relation is an extremely important factor when training new CSRs. However, not every situation is likely to be evaluated in the same way, for example situations where empathy with a customer problem would be more appropriate. So a useful direction for future research would be to examine different situations and more nuanced expressions. Of course, since the experiments were conducted only with Vietnamese CSRs and subjects, future research will also investigate these retains in other cultures.

With the goal of detecting more nuanced differences in expression and developing a system to assist CSR training through facial expression recognition, this paper also described methods of improving existing methods of facial expression recognition. The system tested was based primarily on Piatkowska's method but with several novel differences. This system integrates Center-Symmetric Local Binary Pattern with Principle Component Analysis, preserving holistic information to increase accuracy for the whole face image. Results of testing on two facial expression databases, Cohn-Kanade and FEED, suggest that this method improves the existing algorithms to allow more nuanced facial expression recognition. Future research will confirm the new algorithm on real-life situations such as the proposed Customer Service Representative training system, intended to provide warnings to CSRs in training so they learn to have appropriate expressions for a more positive customer response.

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