SENTIMENTAL ANALYSIS USING CNN TO RECOGNIZE HUMAN FACES

Kejal Chintan Vadza, Research scholarDepartment of Computer Science, Sabarmati University, Ahmedabad, Gujarat : kejalpatel2004s@gmail.com
Dr. Mukta Agarwal Head,Department of Computer Science, Sabarmati University, Ahmedabad, Gujarat : mukta.agarwal@sabarmatiuniversity.edu.in
Dr. Hitesh H. Vandra Principal, Shree Swami Narayan Institute of technology- Bhat, Gandhinagar, Gujarat : hhwandra@gmail.com

Abstract:
Facial expression recognition, commonly referred to as emotion recognition, is a useful tool for boosting the functionality of current human-computer interaction technology. In this paper, we have build a facial expression recognition system by first detecting the face from the background, rooting interesting features from it, and then classifying the face into one of five feelings: happy, horselaugh, sad, nausea, and neutral. We use the AdaBoost algorithm to determine class function parameters, and then we use a Fuzzy Conclusion System to develop the system. We had a success rate of 92.42 percent with our outfit, which is incredibly encouraging. The faces should all be in near-anterior exposures with the proper picture brightness. The Indian Face Database, created in 2002 by a group from IIT Kanpur, was utilized.

Keywords: Facial expression, Expression Recognition, Emotion recognition, Fuzzy Inference System, AdaBoost

1. INTRODUCTION

Mortal Researchers are experimenting in the relatively new subject of facial expression recognition. By extending commerce beyond textbooks, clicks, and touches, it has the potential to elevate the human computer interface to a completely new level if correctly implemented. Everything from games to online businesses can use it. Face identification from an image/videotape stream, facial point-of-birth, and finally interpreting those features to derive emotion make up the technique's three primary components. We cover all three phases of our research, concentrating on the final phase, which involves extrapolating sentiments from raw data. This study seeks to describe the five fundamental emotions of neutral, happy, laughing, sad, and nauseated. We used the Haar cascade training, which Viola-Jones first proposed.

2. FACE DETECTION

This is the initial stage in which the human face in a given image is recognised and distinguished from the rest of the background. We used Viola-Jones' Haar classifiers, which result in a boosted rejection cascade, to detect faces [1]. This method for detecting faces is now the most well-known because to its great calculation speed and accuracy. To put it briefly, this method begins by converting a pixel image into an integral image by summing the pixel intensities to the left and above of each pixel and giving that pixel an integer value. The Haar-like characteristic of each segment of the input image is then computed by moving numerous rectangular sections of increasing widths across the image in the detection window fashion. A Haar-like point is used to determine the difference between the pixel values of consecutive thickish portions at a certain location in a discovery window. Subdivisions of print are typically categorized using this distinction. For instance, it's common to observe in a collection of mortal faces that the area around the eyes is always darker than the area nearby the cheeks. As a result, the impertinence area and the brace of two adjacent blocks over the eye serve as the haar point for face detection.

Adaboost algorithm is used to organise these weak Haar-like features into a classifier cascade, producing a strong classifier, because such a feature is only a weak classifier. [1] Figure 1 displays the results of using this method on a test image. The classifier found the face, which is indicated by the green rectangle.

ISSN: 2278-4632
Vol-12 Issue-09 No.01 September 2022

3. FEATURE POINT EXTRACTION

Due to the fact that such a Haar-like feature is only a weak classifier, Adaboost algorithm is used to group these weak Haar-like features into a classifier cascade, which produces a strong classifier. [1] Figure 1 depicts what happened when this process was used on a test image. The face was picked up by the classifier and is indicated by the green rectangle.

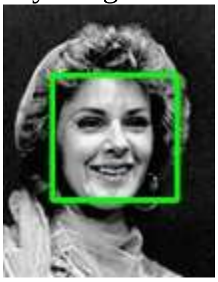

Figure 1 shows that a face may be seen in the test image. Green indicates the face border as determined by the Viola-Jones Method. Source: https://morioh.com/p/e38983d2c4ec

$$CrEyeMap\ 1\ 3[\ Cb^{2}\ (255\ Cr^{2}\ )\ Cb\ Cr\ ]$$

Figure 2: An intriguing feature point on a face from the Indian Face Database. Source: https://www.pluralsight.com/guides/face-recognition-walkthrough-facenet

To compute the retrieved characteristics, we utilise the following 7 equations, as proposed by [3]:

A. Eye Width

$we=((x11 — x10)+(x5 — x6))\sim 2$

B. Eyebrow Height 1:

$he1 = ((y15 - y4) + (y15 - y2)) \sim 2$

C. Eyebrow Height 2:

$he2 = ((y15 - y3) + (y15 - y1)) \sim 2$

D. Mouth Width

$wm = x\ 19 \sim x\ 18$

E. Mouth openness

$om = y21 - y20$

F. Tip-lip corners of Nose

$nl = ((y18 — y15)+(y19 — y15))-2$

G. Check EYE Distance:

$ec = ((y16 — y9)+(y17 - y\ 14))\sim 2$

We integrate the Edge and Skin Detection Algorithms to increase the precision of our feature values. [2] For instance, before calculating eye opening, we first identify the eye by changing the image's colour scheme from RGB to YCbCr. We then generate a chrominance eye mapping based on the hypothesis that high-Cb and low-Cr values may be present nearer to eyes. You might write this map as follows:

The brightness component is then used to construct a new eye map. Using the fact that eyeballs include both dark and bright pixels, we highlight these contrasting regions with grayscale operators. You might write this map as follows:

$$LEyeMap\ Dilate\ Y\ x\ y \qquad Erosion\ Y\ x\ y$$

where Y(x, y) denotes the face images.

ISSN: 2278-4632
Vol-12 Issue-09 No.01 September 2022

The two eye maps are now combined using an AND operator. The resultant eye mapping is dilated and normalised to lighten both eyes and lessen other face features. A threshold that is appropriate for the circumstance is used to monitor the location of the ocular region. Once the eye region has been located, the window that the eye is located in is determined using a template matching method. We have used the correlation and coefficient techniques for template matching [2]. One has slid the window open. Gradually around the eye areas, until the window with the maximum correlation and coefficient is selected. The Canny Edge Detector method is now used in conjunction with a skin detection approach to identify the eye centre, eyelids, and right and left edge points of the eye. Similar techniques are used to determine the other facial feature points. The standard procedure for identifying the region that contains features and then extracting the crucial feature points is shown in Figure 3.

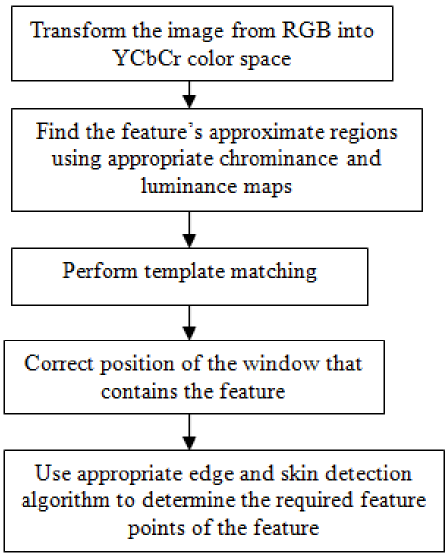

Figure 3. A generic approach for recognising a feature-rich region and extracting the needed feature points Source: own photo

4. FACIAL EXPRESSION RECOGNITION

For each extracted characteristic, we define our fuzzy set as a grouping of 5 values: Very Large, Large, Medium, Small, and Very Small. For a more precise result, we can compare the values of the extracted features to the values obtained by the former if we have a neutral face image. In this example, the discrepancy between the seven feature values produced by the two photos is fuzzified. In addition to the classifier's efforts, all feature values are normalised to a range of [0, 1] and classified using Gaussian membership functions. The AdaBoost technique is used to find the parameters of the class functions. Based on the rule matrix in Table 1 and observation, we manually develop weak classifiers to categorise the colorful components of feelings. The AdaBoost Algorithm is also used to give robust classifier parameter values for the distribution. This approach offers benefits in terms of computation speed and delicateness.

It's important to note that the outcomes would alter depending on whether or not we had a neutral face image available. Utilizing the collection of practise photos, they are both decided. When defuzzifying, we determine the degree of class of each data item in relation to the relevant emotion using the fuzzy rules derived from the rule matrix in Table 1.

	we	*he1*	*he2*	*wm*	*om*	*nl*	*ec*
Happy	*M*	*M*	*M*	*VL*	*S*	*S*	*S*
Laugh	*M*	*M*	*M*	*M*	*VL*	*L*	*VS*
Sad	*S*	*M*	*L*	*M*	*VS*	*M*	*M*
Disgust	*M*	*VS*	*S*	*M*	*S*	*S*	*S*
Neutral	*M*	*M*	*M*	*M*	*M*	*M*	*M*

M: Medium, S: Small, VS: Very Small, L: large, VL: Very Large

Table1: Rule Matrix - Fuzzy Inference System Classifier Source: Own Photo

The feeling that has the greatest number of characteristics identifying it as its own is known as the resultant emotion. In the event of a tie, the candidate with the highest overall probability of belongingness is chosen.

5. RESULT AND CONCLUSION

The Fuzzy Inference System is an effective technique for determining emotion in terms of calculation time and real-time accuracy. The identification rates for various emotions by our fuzzy classifier are displayed in Table 2. A 92.42 percent identification rate seems to be really impressive. It should be emphasised, though, that this proportion would almost probably decline, albeit not significantly, if other emotions were discovered. An emotion that has been correctly identified is shown in Figure 4.

Emotion	**Recognition Rate (in %)**
Happy	93.6
Laughter	96.2
Sad	94
Disgust	89.7
Neutral	88.6
Average Recognition Rate	92.42

Table 2: Recognition rates of different emotions by the Fuzzy Classifier

REFERENCES

[1]. Paul Viola, Michael J. Jones (2004), “Robust Real-Time Face Detection”, International Journal of Computer Vision, 2004
[2]. Mahdi Illbeygi, Hamed Shah-Hosseini, “A novel fuzzy expression recognition system based on facial fature extraction from color face images”, Engineering Applications of Artificial Intelligence., 2011
[3]. Vidit Jain, Amitabha Mukherjee, “The Indian Face Database”, http://vis-www.cs.umass.edu/~vidit/IndianFaceDatabase/ , 2002
[4]. Hadi Seyedarabi, Ali Aghagolzadeh, Sohrab Khanmohammadi, “Recognition of Six Basic Facial Expressions by Feature-Points Tracking using RBF Neural Network and Fuzzy Inference System”, IEEE International Conference on Multimedia and Expo, 2004
[5]. R. G. Harper, A. N. Wiens, and J. D. Matarazzo, Nonverbal communication: the state of the art. New York: Wiley, 1978.
[6]. P. Ekman and W. V. Friesen, “Constants across cultures in the face and emotion,” Journal of Personality and Social Psychology, vol. 17, no 2, p. 124-129, 1971.
[7]. C. Tang, P. Xu, Z. Luo, G. Zhao, and T. Zou, “Automatic Facial Expression Analysis of Students in Teaching Environments,” in Biometric Recognition, vol. 9428, J. Yang, J. Yang,Z. Sun, S. Shan,
[8]. W. Zheng, et J. Feng, Éd. Cham: Springer International Publishing, 2015, p. 439-447.
[9]. A. Savva, V. Stylianou, K. Kyriacou, and F. Domenach, “Recognizing student facial expressions: A web application,” in 2018 IEEE Global Engineering Education Conference

(EDUCON), Tenerife, 2018, p. 1459-1462.
[10] J. Whitehill, Z. Serpell, Y.-C. Lin, A. Foster, and J. R. Movellan, "The Faces of Engagement: Automatic Recognition of Student Engagementfrom Facial Expressions," IEEE Transactions on Affective Computing, vol. 5, no 1, p. 86-98, janv. 2014.
[11]. N. Bosch, S. D'Mello, R. Baker, J. Ocumpaugh, V. Shute, M. Ventura, L. Wang and W. Zhao, "Automatic Detection of Learning-Centered Affective States in the Wild," in Proceedings of the 20th International Conference on Intelligent User Interfaces - IUI '15, Atlanta, Georgia, USA, 2015, p. 379-388.
[12]. Krithika L.B and Lakshmi Priya GG, "Student Emotion Recognition System (SERS) for e-learning Improvement Based on Learner Concentration Metric," Procedia Computer Science, vol. 85, p. 767-776, 2016.
[13]. U. Ayvaz, H. Gürüler, and M. O. Devrim, "USE OF FACIAL EMOTION RECOGNITION IN E-LEARNING SYSTEMS," Information Technologies and Learning Tools, vol. 60, no 4, p. 95, sept. 2017.