Cross-cultural emotion analysis a clustering approach

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Summary

It is stated that the various studies on the facial expression representations are varies from one culture to another culture and these facial expression are not universal. There exist different facial expression recognition (FER) systems that are suitable for the small size of datasets and generate good results. If same these experiments are perform on the different cultural datasets or large size of data sets the efficiency decrease radically. To maintain accuracy for a large datasets and different cultures, we used a novel hybrid clustering approach that is combination of the k-means and self-organizing map (SOM) clustering. In this research we used the local Binary Pattern and Histogram of Oriented Gradient for extraction of facial expression. We studied six common emotions such as anger, disgust, fear, happiness, sadness, and surprise of different cultures. In this research we used the following datasets for experiment to get our results. JAFFE, KDEF, TFEID, RadBoud, CK+, which originate from different cultures such as Japanese, Taiwanese, Moroccans, Caucasians, Afro-American, Euro-American, Asians, and Europeans. By applying this clustering approach we got 85% average Accuracy.

Keywords:

FER, K-means, SOM, LBP, HOG

1. Introduction

Facial expressions are much effective and normal implies that individuals use for impart their feelings and intensions. Automatic facial emotion analysis is an intriguing and much difficult issue in the research field. The location of face and the recognition of facial expression under fluctuating conditions is a regular undertaking for people, which we satisfy without exertion. The character, age, sexual orientation and in addition the enthusiastic state can be seen from a few ones face. The impression we get from facial expression will influence our understanding of the talked word and even our state of mind towards the speaker himself. Consequently, they have a high significance for our every day of life despite the fact that we frequently don't know about it. Facial felling recognition has some essential uses in numerous zones, for such as, human–computer interaction and information driven activity feeling examination, manufactured face liveliness, security access control frameworks, law requirement, intelligent video, and picture understanding. Inferring a viable facial representation from unique face pictures is fruitful facial appearances recognition.

Even though distinctive strategies for facial expression recognition have accomplished great outcomes, there still stay diverse issues that should be tended to by the exploration group.

For the most, we have found that all the surveyed strategies for programmed outward appearance acknowledgment are computationally costly and more often than require large feature vector to complete the job. Our purposed approach is much powerful and for constant uses, in spite of the fact that they create great outcomes on different databases.

Objective of this study is to the investigation of individuals' facial feelings from a facial appearance utilizing k-means and SOM a hybrid approach to deal with changes of facial expression of diverse cultures, which is another contribution of this paper. In spite of the fact that perceiving individuals' facial expression is a testing assignment, we reflect it can prompt numerous fortifying improvements in human-computer interaction.

2. Review of literature

Faces are a standout amongst the most critical channels to nonverbal communication. Since 150 years back experimental scientists have been done on the Facial expression. [1] Ekman et al.describe the noteworthy step in the exploration on facial expression originated from Paul Ekman they have chip away at fundamental feelings. [2] Ekman and Friesen, work on the Facial Action Coding System (FACS).[3] Elfenbein et al. used the analytical methodology for considering the cross cultural communication of feeling utilizing constrained decision experimental design. The author done the exploration on the American, Indian, and Japanese members judged facial appearances from every one of the 3 societies. [4] Ahonen et al. purposed a novel Face Recognition procedure by utilizing Local Binary Patterns which considers both shape and surface data to demonstrate the face pictures. The face range is at first isolated into small area from which Local Binary Pattern (LBP) histograms are removed and associated into a solitary, spatially overhauled highlight histogram adequately exhibit to the face pictures. The acknowledgment is performed using a nearest neighbor classifier as a part of the processed element space with Chi square as a uniqueness measure. The exactness, straightforwardness of the proposed

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method thinks about speedy component extraction. [5] Jiang and Zhou, describe a picture division technique in light of group of SOM neural systems. The trial results demonstrate that the proposed technique performs superior to anything some current grouping based picture division strategies. [6] Orrite et al. work on the HOG Based Decision Tree for Facial Expression Classification. The Finally Support Vector Machine (SVM) is reflected for the choice procedure in each cluter. This present technique has been completed on the Cohn-Kanade AU-Coded Facial Expression Database, seeing unmistakable passionate states from single picture and it performs amazingly well. [7] Dailey et al. work on two cultural facial feelings are all inclusive. In these explorations, the author have exhibited proportional in-group points of interest for Japanese and American judges of enthusiastic facial expression and appeared, with the model, how the distinctions may emerge in various social learning situations. The author fined that numerous aspects of generation of facial expression might be innate and universal over cross cultural societies.

[8] Tarek, et al. the purposed a Kohonen Maps Joined to K-means in a Two Level approach for Time Series Clustering use to Meteorological and Electricity Load data. In this research the authors first apply the SOM technique for clustering. The K-means algorithm with SOM units various k-values for the quantity of groups in which information are parceled.

[9] Huang et al. Authors to purposed the facial image analysis based on Local Binary Patterns. This research demonstrates a comparison study of LBP technique in context of facial image recognition.

[10] Arai, work another strategy for image clustering by using density maps got from Self-Organizing Maps. The suggested SOM based image clustering technique shows better clustering result for both reenactment and genuine satellite symbolism data.

[11] Su, et al. Introduced a SOM based automatic facial appearance recognition framework, which perform effectively to the previously stated three sub-issues, for example, face identification, facial appearance feature extraction, and expression classification of facial.

[12] Xu, et al. they purposed Gabor wavelet transform and Histogram of Oriented Gradients for Facial appearance recognition. HOG is used for reducing the dimensionality of the element vector. Authors got test results with a typical acknowledgment rate of 92.5%, which reveals that the proposed procedure is superior to anything other Gabor Wavelet change based approaches under the same exploratory environment.

[13] Dhanachandra, et al. these authors utilized K-means clustering algorithm for Image segmentation is the arrangement of a picture into various groups. Numerous examines have been done in the territory of picture division utilize for clustering.

[14] da Silva, et al. work on the multicultural facial feeling recognition by using HOG filter and the local binary filter, with Support vector machines, k-nearest neighbors and neural network (NNs), on the following datasets MUG + CK+ and JAFFE and they got 42 % exactness.

[15] Zia, et al. work on the culturally diverse emotion classification in view of incremental learning and LBP-features. Most facial expression recognition (FER) frameworks utilize on the small datasets for training and testing and show great outcomes. Whereas the execution embarrass profoundly when datasets from various societies were displayed. The proposed system has ability to learn incrementally and can suit future data.

[16] Ali, et al. works on the boosted NNE accumulations based methodology for multicultural facial expression recognition. The boosted NNE accumulations based group classifier it includes three stages: initial step is the preparation of parallel neural systems, second step is to join the forecasts of binary neural systems to form NNE, and third step is to consolidate the expectations of NNE accumulations with a specific end goal to recognize the presence of an expression. The pictures were collected from three different datasets belonging Taiwanese, Caucasians Japanese, and Moroccans are consolidated to build up the culturally diverse facial appearance dataset. These cross cultural facial databases are utilized for the training and testing of parallel neural systems in every NNE collection. The test result demonstrates that expressions joy and shock are the general expressions which are anything but difficult to identify on culturally diverse databases.

Our proposed clustering approach is the combination of two well-known clustering approaches, which are, SOM and K-means clustering by applying over the five different databases JAFFE, KDEF, TFEID, RadBoud, and CK+, we use HOG and LBP for feature extraction. We got 85% accuracy over five cross cultural databases.

3. Material and methods

The main objective of our methodology is to recognize facial emotion; by using various filters and machine learning algorithms, we used a hybrid clustering technique which is combination of two K-means with SOM has capacity to correctly clustering emotions on facial images of multicultural facial appearance. We focused six common emotions such as (sadness, disgust, anger, fear, surprise and happiness) of different cultures. In this research we used the following datasets for experiment to get our results. JAFFE, KDEF, TFEID, RadBoud, CK+, which originate from different cultures such as Japanese, Taiwanese, Moroccans, Caucasians, Afro-American, Euro-American, Asians, and Europeans.

Our methodology contain following steps:

3.1 Preprocessing

This process concentrates on noise reduction on facial image, normalization, and trimming the face area. Normalization aims is planning face for representations. Diverse cultural databases are not in uniform size. In normalization we make face area resized and in uniform size.

3.2 Feature Extraction

The second step is features extraction after preprocessing we get the feature from the facial images of diverse culture. We used the Local Binary pattern (LBP) and Histogram of Oriented gradient (HOG) for feature extraction.

3.2.1 Local Binary Pattern

There are several method exist for facial feature extraction. One of these methods is LBP it is exceptionally basic and proficient operator that is utilized to separate the feature from face. [17] Ojala, et al. presents the LBP operator. The LBP operator utilized Zia and Jaffar, is represented by $\mathrm{LBP}_{\mathrm{P,R}}^{\mathrm{U2}}$ where P shows the quantity of neighbor pixels, R represents the radius of neighbor circle and U2 for uniform shape. The picture is distributed into cells and every cell contains 3×3 pixels. Every pixel with in a cell, contrast the pixel with its 8 neighbors to its left side top, left-center, left-base, right-best, and so forth. Take after the pixels along a circle clockwise counter. The inside pixel value used as threshold. If a neighbor pixel value is higher than the center pixel than we assign one value that pixel otherwise assign zero as shown below fig.

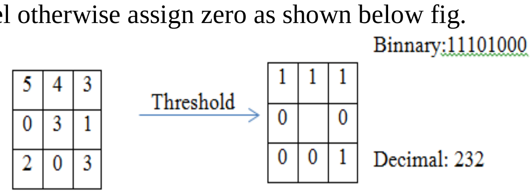

Fig. No.1. LBP Work

Where LBP is used to get feature from area of concern. In this research we use five different datasets such as d = (1,2,3,4,5). And $D_d = \{I_{d1}, I_{d2}, I_{d3}, \ldots\ldots, I_{dmd}\}$ are the arrangements of face pictures in each dataset d, where md number of pictures in each dataset d.
I divide each image into 5×6 weighted region as shown in fig 1. The result of image is represented by $J_{d,i}^{r,c} = div(I_{d,i})$ and its corresponding feature of every region is computed as follows:

$$H_{d,i}^{r,c} = LBPH(J_{d,i}^{r,c}) \qquad (1)$$

Where r = 1,2,3,4,5,6, and c = 1,2,3,4,5. The each $H_{d,i}^{r,c}$ size is 1×59, and 5×6 (30) such histogram feature for every image $I_{d,i}$. The concatenated histogram size 1×1770 is computed.

$$H_{d,i} = NORM([h_{d,i}^{r,c}]_{r=1,c=1}^{r=6,c=5}) \qquad (2)$$

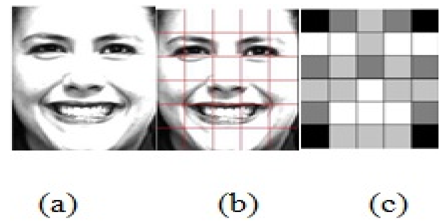

Fig. No.2 LBP Effects

(a) Face image from cohn-kanade, and (b) image divide 5×6 and (c) show the weighted regions.

3.2.2 Histogram of oriented gradient (HOG)

Histogram of oriented gradient is shape descriptor and it is used to localization of facial image. [18] Dalal and Triggs introduced HOG descriptor. This system counts occurrence of gradient in localize portion of an image. By utilizing histogram of oriented gradient presence of item with in a facial picture can be depicted by conveyance of intensity gradient or edge direction.

3.2.2.1 Gradient computation

In HOG first step is calculation of gradient computation.

3.2.2.2 Orientation Binning

Second step is Orientation Binning in this phase perform calculation to create cell histograms. Every pixel with in a cell cast a weighted vote in favor of orientation construct histogram channel based with respect to the qualities found in angle calculation. The blocks are rectangular and the histograms networks are spread 0 to 1800 or 0 to 3600 these angle are depend on where the gradient are unsigned or signed.

3.2.2.3 Similarity Measure

There exist different methods for measuring the similarity of two vectors.

3.2.2.3.1. Euclidian Matrix

There are two vectors $P = (p_1, p_2, p_3, \ldots\ldots\ldots, p_n)$ and $Q = (q_1, q_2, q_3, \ldots\ldots\ldots, q_n)$ the distance is calculated as:

$$d = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_n - q_n)^2}$$

3.2.2.3.2. Cosine Similarities

It measure the relationship of two vector which having n measurement for result of the cosine angle between the two vectors , lets A and B are two vector and cosine similarity is θ it characterized with dot products as given below.

$$Similarity = \cos(\theta) = \frac{A.B}{\|A\| . \|B\|}$$

Let vector $A = (p_1, p_2, p_3, ..., p_n)$ and $B = (q_1, q_2, q_3, ..., q_n)$ then the correspondence between them is given as below

$$\cos(\theta) = \frac{p_1 q_1 + p_2 q_2 + ... + p_n q_n}{\sqrt{p_1^2 + p_2^2 + ... + p_n^2} . \sqrt{q_1^2 + q_2^2 + ... + q_n^2}}$$

3.3 Clustering

The third step of our methodology is clustering the data. Our purposed clustering technique that is a combination of K-means and SOM is used for cross cultural facial expression recognition. Self-organizing map is type of artificial neural network. SOM consist nodes or neurons and these nodes are connected with other node and the weight vector of the same measurement. Artificial neural network, SOM uses two steps training and mapping/testing. First we train the data after training process map the testing data with training data. The k-means clustering algorithm is efficient and widely used for clustering. The K-means clustering algorithm has less computational cost for large number of cluster data. It produces different cluster result for different cluster data.

3.3.1 SOM Training Process

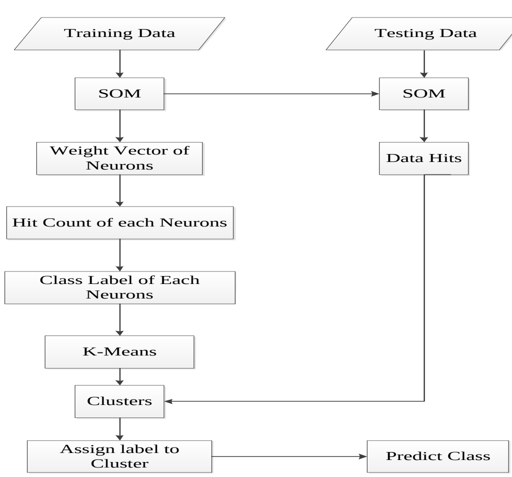

Fig. No.3 SOM Training

In the SOM training process we divide the data set into two groups one is the training data set and the other is testing data set. On the training data set we apply the SOM method and get the weight vectors of each neuron. After getting the weight vector of neurons counts the hits of each neuron for computing number of hits of each neuron on Training Data X and gets the class information of each neuron on the basis of hits and assigns the class label to every neuron. When labels are assigned to each class then we apply the K- Means clustering algorithm to make cluster. After applying the k- means clustering algorithm we Get neurons list in each cluster, and get class labels of all data neurons hits, on these basis it assign the label to cluster, finally predict the class. When the training process is completed then we take the other data set known as testing data set. On the testing data set we apply the SOM method and get the hits of testing data. After getting the hits it go to specific cluster and assigned label to the cluster. Finally it predicts the class.

We used 1406 images for training purpose and 600 images for testing purpose of diverse cultures.

Algorithm 1

Begin: Training samples {x1, y1, t1}, . . .,{xN, yN; xi ε X, yi ε {1,2, . . .,M}, ti ε T

Construct Self organizing map

Train SOM (X)

Initialization: W = get the weight vector of neurons

Evaluate network using test data

Get neuron hits on Test Data (T)

HitCount (HitList, TargetClass)

Compute number of hits of each neuron on Training Data X

Get class information of each neuron on the basis of hits

Apply K-Means clustering algorithm to form clusters

K-Means (No of Clusters)

Get neurons list in each cluster

GetClusterNeuron (Clusters, HitCount)

Get class labels of all Data neurons Hits

GetClassLabel (NeuronClass)

Get hits of Test Data

GetTestHits (THits)

Final Prediction

Prediction ()

End

Algorithm 1:

Initially assigns equal weights to all training samples {x1, y1, t1}, . . .,{xN, yN; xi ε X, yi ε {1,2, . . .,M}, ti ε T Choose random values for the initial weight vectors w_j. Construct Self organizing map Train SOM (X). Then Compute number of hits of each neuron on Training Data X and get the information about each neurons on the basis if hits. Find the winning neuron $I(X)$ that has weight vector closest to the input vector, i.e. the minimum value of the weight vector is represented as below equation:

$$d_j(X) = \sum_{i=1}^{D} (x_i - w_{ji})^2$$

And assign the class label to the wining neurons on the basis of hits.

After this step update the weight of winning neurons by applying this equation.

$$\Delta w_{ji} = \eta(t) T_{j,I(X)}(t)(x_i - w_{ji})$$

$T_{j,I(X)}(t)$ is a Gaussian neighborhood and η(t) is the learning rate. When the class labels are assigned to different neurons then we applied the k-means clustering algorithm. The k-means clustering algorithm as following these steps

1. Initialize the k number of clusters and Centre.
2. For every pixel of an image we calculate the Euclidean distance d, from center to every pixel of an image by using this equations
$$d = \| p(x, y) - c_k \|$$
3. On the base distance d, assign all the pixel to the nearest center
4. After assigning the all pixel we recalculate the new position by using this equation
$$c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{y \in c_k} p(x, y)$$

Repeat all the process until to get desire clustering result when the clustering process is completed then we have to assign cluster label. After assigning the cluster label we predict the class.

In this research first we trained the Self Organizing Maps (SOM) and get result. After getting the SOM result we apply k-means clustering algorithm on every SOM unit with various k value. The k-means performed better and generated number of cluster according to the value of k.

4. Results and discussion

In this research we used five diverse society databases for facial expression recognition. We apply our purposed SOM with k-means clustering technique on datasets for clustering. Each of these datasets contains several pictures. The five datasets utilized as a part of this study are JAFFE, KDEF, TFEID, RadBoud, CK+, which are originated from various societies, for example, Japanese, Taiwanese, Moroccans, Caucasians, Afro-American, Euro-American, Asians, and Europeans. Face pictures from these datasets are showed in below figure.

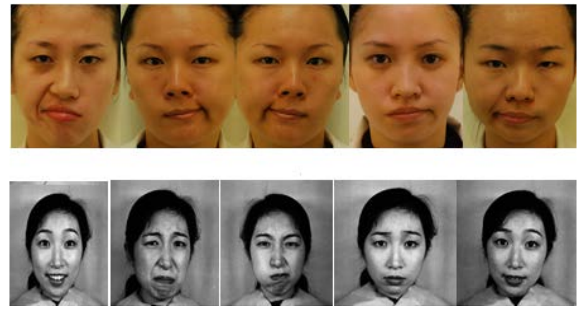

Fig. No.4 Diverse cultural Images

Row 1 TFEID and Row 2 JAFFE Datasets.

4.1 Experiments 1

We train the SOM with k-means and measure the accuracy on the different five databases. First we trained JAFFE database only and give the name its J1. After this we check the performance of JAFFE with other four databases and evaluate the accuracy. The results are shown in table 1 of this experiment. We train KDEF dataset and give its name (J2). We take trained KDEF dataset and measure its accuracy along with other datasets and its result shown in table 2. Similarly we trained TFEID, Radbound and CK+ datasets and give its name (J3), (J4), and (J5) respectively. The performance results of (J3) with other five datasets are shown in table 3. While the performance results of (J4) and (J5) with other five Datasets are shown in table 4 and table 5 respectively.

The accuracy of different datasets in column and expression in rows has been shown in percentage (J1)

Table 1 JAFFE Database Results

Ex\DS	JAFFE	KDEF	TFEID	Radbd	CK+
Ang	87.5	67.2	75.3	66.2	69.7
Dis	86.1	72.3	78.2	64.5	65.3
Fear	85.7	56.2	75.9	69.7	71.9
Hap	88.2	62.5	73.2	77.2	85.2
Sad	87.3	68.3	69.6	62.5	70.2
Sur	84.6	71.4	69.8	65.7	73.2
Ave	86.5	66.3	73.6	67.6	72.5

The accuracy of different datasets in column and expression in rows has been shown in percentage (J2).

Table 2 KDEF Database Results

Ex\DS	JAFFE	KDEF	TFEID	Radbd	CK+
Ang	86.2	87.5	73.8	69.3	67.2
Disg	86.1	86.1	67.2	67.2	72.3
Fear	85.7	85.7	70	65.3	56.2
Hap	88.2	83.7	73.2	73.2	62.5
Sad	87.3	87.3	71.1	71.1	68.3
Sur	89.2	84.6	77.2	77.2	71.4
Ave	87.1	85.8	72.08	70.5	66.3

The accuracy of different datasets in column and expression in rows has been shown in percentage (J3)

Table 3 TFEID Database Results

Ex\DS	JAFFE	KDEF	TFEID	Radbd	CK+
Ang	87.5	87.5	81.2	73.8	66.2
Disg	86.1	86.1	77.8	67.2	64.5
Fear	85.7	85.7	80.5	71.2	69.7
Hap	88.2	83.7	79.3	73.2	77.2
Sad	87.3	87.3	85.2	71.1	62.5
Sur	85.1	85.3	84.6	77.2	65.7
Ave	86.6	85.9	81.4	72.2	67.6

The accuracy of different datasets in column and expression in rows has been shown in percentage (J4)

Table 4 Radbound Database Results

Ex\DS	JAFFE	KDEF	TFEID	Radbd	CK+
Ang	88.2	87.5	86.4	86.4	73.8
Dis	86.1	86.1	80.2	80.2	67.2
Fear	85.7	85.7	80.5	80.5	72.3
Hap	88.2	84.2	79.3	87.2	77.5
Sad	87.3	87.3	85.2	85.2	71.1
Sur	85.1	84.6	84.6	84.6	77.2
Ave	86.7	85.9	82.7	84.01	73.1

The accuracy of different datasets in column and expression in rows has been shown in percentage (J5)

Table 5 CK+ Database Results

Ex\DS	JAFFE	KDEF	TFEID	Radbd	CK+
Ang	88.2	87.5	86.4	86.4	85.1
Dis	86.1	86.1	80.2	83.5	83.2
Fear	85.7	85.7	80.5	80.5	80.5
Hap	88.2	85.1	87.2	87.2	82.4
Sad	87.3	87.3	85.2	85.2	85.2
Sur	86.2	84.6	84.7	84.6	84.6
Ave	86.9	86.05	84.03	84.5	83.5

4.2 SOM Clustered results

The clustering results of cross-cultural database are shown in below figures

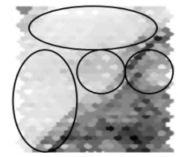

Fig. No.5 U Matrix

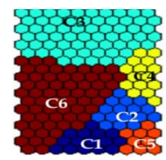

Fig. No.6 Clustering Results

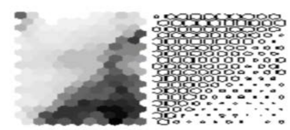

Fig. No.7 Average Version of U Matrix

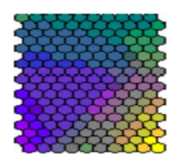

Fig. No.8 Color coding Scheme

In the above Fig. No.5 U-matrix which shows a comparative measurement of distance between the networks colored units, whereas the grey color shows the distance measure of the node to its neighboring. More dark color shows large distance between the networks. Fig. No.6 shows the clustering result of diverse cultural datasets for emotion recognition. Fig. No.7 Average Version of U Matrix shows the size of SOM map and its usual distance of its neighbor. The Fig. No.8 shown the color scheme which is used for different cluster the similar node automatically come its same color scheme.

5. Conclusion

There exist different facial expression recognition (FER) systems that are suitable for the small size of datasets used for training and same datasets for testing and got good results. If same these experiments are perform on the different cultural datasets or large size of datasets reduce the efficiency badly. To maintain accuracy for a large size and diverse culture datasets we used a novel hybrid clustering approach that is combination of the k-means and self-organizing map (SOM) clustering. We studied six common emotions such as anger, disgust, fear, happiness, sadness, and surprise of different cultures. In this research we used the following datasets for experiment to get our results, JAFFE, KDEF, TFEID, RadBoud, CK+. By applying this clustering approach we got 85% average Accuracy. We observed after performing the experiment the JAFFE Database show high performance over the other databases that's we used in the this research.

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