Extended Non-negative Matrix Factorization for Face and Facial Expression Recognition

Humayra Binte Ali, David M. W. Powers, Xibin Jia, and Yanhua Zhang

***Abstract*—Face and Facial Expression Recognition is a broad research area for its diversified applicability in different applications from security, surveillance to medical diagnosis. The main challenge in this area is to decrease the recognition time as well as to increase the accuracy rate. In this paper, we propose face identification system and facial expression recognition system based on non-negative matrix factorization (NMF). As facial parts are more prominent to express a particular facial expression rather than whole faces and NMF performs part based analysis, so we get a significant result for face recognition. We test on CK+ and JAFFE dataset and we find the face identification accuracy is nearly 99% and 96.24%. But the facial expression recognition (FER) rate is not as good as it required to be. We propose fusion based NMF method and we name it as OEPA-NMF, where OEPA means Optimal Expression specific Parts Accumulation. Our experimental result shows that OEPA-NMF outperforms the predominant NMF.**

***Index Terms*—Non-negative matrix factorization (NMF), facial expression recognition (FER), optimal expression-specific parts accumulation (OEPA), face recognition (FR).**

I. Introduction

Face is one of the most prominent biometric traits for its uniqueness and robustness. For this reason face recognition has snatched the attention of researchers in the domain of person identification, speaker recognition, intruder detection, security enhancement as well as other domains of computer vision, psychology and physiotherapy. Face recognition covers both the area of Face Identification and Face Verification. Face Identification is widely used in video surveillance, information retrieval, video games and some other human computer interaction areas. On the other hand, to verify access control into computer or mobile device or building gate, and digital multimedia data access control, Face Verification technique is needed.

In parallel there are lots of applications where facial expression is highly needed than only face detection. As for example, pain estimations for patients by observing the movement of facial features, human machine interaction like online chat conversation or online teaching where users or students expression is needed to make the conversation more realistic and fruitful one.

In this research work, our focus is on face recognition as well as facial expression recognition. The most challenging part in these areas are to recognize faces or facial expressions with minimum time requirement and with minimum error rate. Our proposed approach with programming and mathematical analysis will focus on these constraints of minimum time requirement and with minimum error.

II. Research Background

Among appeareance based feature extraction subspace projection techniques are often used computer vision problem as an efficient method for both dimension reduction and finding the direction of the projection with certain properties. Usually, the face image is considered to lie in a high-dimensional vector space. The subspace projection techniques represent a facial image as a linear combination of low rank basis images. The popular subspace projection techniques are PCA, ICA and NMF. In the context of face recognition, we attempt to find some basis vectors in that space serving as much as important directions of projection in a low rank image subspace.

Turk and Pentland [1] first successfully used the Eigenface method for face recognition. Researchers in [2] used Eigenface by applying Bayesian method as an extension for similar application as [1]. The related Singular Value Decomposition (SVD) and Principle Component Analysis (PCA) have proven effective for face recognition [3]-[5]. Different versions of ICA can be successfully used for face recognition [6], [7].

Non-negative matrix factorization is another decomposition that is becoming important in face research. NMF, correntropy-based NMF (NMF-Corr) and PCA have been successfully implemented on ORL face dataset for occluded face recognition. The results show that the correntropy-based NMF has better recognition rate compared with PCA and NMF. In another work of face recognition [8] NMF has been used and the result shows average 75% recognition rate for face recognition. Ref. [9] also successfully implemented the similar approach of NMF with different versions. Part based decomposition is popular is object recognition area as it can successfully identify objects in occluded regions [6]. As LNMF, which is an extension of NMF, preserves the locality constraints by imposing on the factorized matrices from NMF, [6] successfully implemented

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the LNMF method for face recognition in occluded regions.

These research works show the success of NMF for face and facial feature recognition. Here in our work, we successfully implement NMF for face and facial expression recognition. Also we successfully compare our propose method with NMF method.

III. Non-negative Matrix Factorization

In the previous section, many machine learning research shows that Non-negative matrix factorization (NMF) is a useful decomposition for multivariate data like face and facial expression recognition. According to research studies [10] it is clear that NMF can be understood as part based analysis as it decomposes the matrix only into additive parts. This factorization technique of NMF is completely different of Principal Component Analysis (PCA) or Vector Quantization (VQ) in terms of the nature of the decomposed matrix. PCA and VQ works on holistic features where as NMF decomposes a part based representation of matrix.

Let us define the factorization problem for NMF by using the multiplicative update rule,

$$\begin{gathered} X \approx W.H \\ X \in R^{MxN,\geq 0}, W \in R^{MxR,\geq 0}, H \in R^{RxN,\geq 0} \end{gathered} \tag{1}$$

In the above equation, R defines the low-rank dimensionality. Here W and H are quite unknown; X is the known input source. Now we have to estimate the two factors. We have to start with random W and H. Columns of W will contain vertical information about X and the horizontal information will be extracted in the rows of H. NMF does additive decompositions and parts make this decomposition.

We first have to define the cost functions to solve an approximate representation of the factorization problem of $X \approx W.H$. By using some measure of distance between two non-negative matrices P and Q, such cost functions can be constructed. The square of the Euclidian distance between the matrices P and Q, is one fruitful measure

$$\| P-Q \|^2 = \sum_{i,j} (P_{ij} - Q_{ij})^2 \tag{2}$$

The above equation is lower bounded by zero and absolutely vanishes if and only if $P = Q$. To define the cost function, another usefull representation,

$$D(P \| Q) = \sum_{i,j} (P_{ij} \log \frac{P_{ij}}{Q_{ij}} - P_{ij} + Q_{ij}) \tag{3}$$

In the above equation, when $\sum_{ij} P_{ij} = \sum_{ij} Q_{ij} = 1$, it means that (3) reduces to Kullback-Leibler distance or relative entropy. Here P and Q can be regarded a normalized probability distribution.

Now, following the cost function of equation (2), we have to define it for the input matrix X and the non-negative decomposed matrix W and H. If we do that, the cost function would be,

$$\| V - WH \|^2 \tag{4}$$

The main goal is now to reduce the distance $\|V\text{-}WH\|$. To do that, first we have to initialize W and H matrix. Then we apply the multiplicative update rule, which is described in the paper of Lee and Seung [10]. They claim and prove that the multiplicative update rules minimize the Euclidean distance $\|P\text{-}Q\|$ (Equation (2)) and also the divergence, D $(P\|Q)$ (Equation (3)) is decreasing when multiplicative update rule is applied. In our programming here, we use the Euclidian distance as a cost function and apply the multiplicative update rule to minimize the distance. The rules are defined below,

$$H_{p\beta} \leftarrow H_{p\beta} \frac{(W^T V)_{p\beta}}{(W^T WH)_{p\beta}} \tag{5}$$

$$W_{\alpha p} \leftarrow W_{\alpha p} \frac{(VH^T)_{\alpha p}}{(WHH^T)_{\alpha p}} \tag{6}$$

According to the mathematical analysis, if we use the equation (5) and (6) to decrease the Euclidian distance $\|V\text{-}WH\|$, the distance $\|V\text{-}WH\|$ converges. Our experimental analysis also shows that and we get a significant output.

IV. Dataset

For evaluation purposes we benchmark our results on the Cohn-Kanade and JAFFE datasets. We used the both datasets for both face and facial expression recognition.

Cohn-Kanade has 2000 image sequences from over 200 subjects. For each expressed emotion we have a sequence from neutral. We took the two most expressive images for each subject and emotion across a validation sample of 100 subjects, for a total of 1200 images (100 subject × 6 expression × 2 emotions). There is a significant variation of age group, sex and ethnicity. In the JAFFE dataset, ten subjects posed for 3 or 4 examples of each of the six “basic" facial expressions (happiness, sadness, surprise, anger, disgust, fear) as well as a neutral face expression. Altogether JAFFE has 219 facial images, and we used all of these in our validation and comparison experiments.

The Fig. 1 and Fig. 2 show a portion of the dataset of our experiment. Fig. 3 is the prepared data to feed in our prposed mathod which we want to compare against the predominant NMF method.

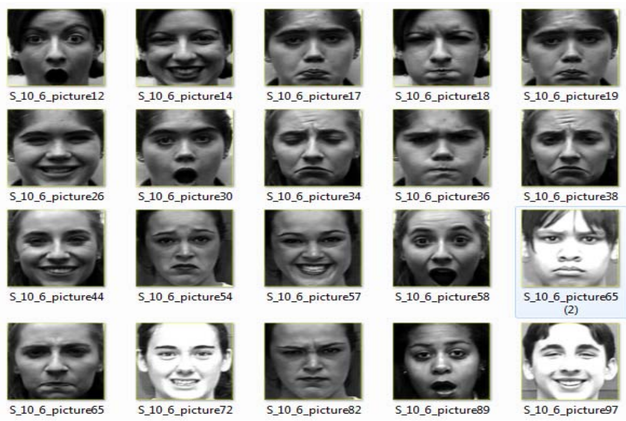

Fig. 1. CK+ facial expression data.

Fig. 2. A portion of data from JAFFE dataset.

Fig. 3. A portion of data that we segmented using our algorithm.

V. Experimental Setup

A. Face and Facial Parts Detection

In CK dataset, the background is large with all the face images. First we apply the Viola-Jones algorithm [11] to find the faces. For eyes, nose and mouth detection we applied cascaded object detector with region set on already detected frontal faces in Fig. 4. This cascade object detector with proper region set can identify the eyes, nose and mouth. Actually it uses Viola-Jones Algorithm as an underlying system. This object detection algorithm uses a cascade of classifiers to efficiently process image regions for the presence of a target object. Each stage in the cascade applies increasingly more complex binary classifiers, which allows the algorithm to rapidly reject regions that do not contain the target. If the desired object is not found at any stage in the cascade, the detector immediately rejects the region and processing is terminated.

Fig. 4. Face and facial parts detection.

B. Training and Testing Data

We benchmark our system on 1200 (100 subjects × 2 subject from each expression × 6 expression) face and facial expression images from CK+ and 219 face and facial expression images from JAFFE dataset. We performed 10 fold cross validation for both NMF and OEPA-NMF implementation. When nearly sixty percent data was used as training sample, the recognition rate started to achieve a good accuracy rate. The cross-validation result is given in the graph in result analysis section.

VI. Face vs. Facial Expression Recognition

We apply NMF using 10 fold cross validation. When the train sample is more than 60% then we are able to achieve a good recognition rate. For face identification using CK+ the result shows 99% accuracy and on JAFFE it is 96.24%. This accuracy is irrespective of facial expressions. May be this one of the reason of having good recognition rate for face identification that Non-negative matrix factorization (NMF) learns a parts-based representation of faces and part based representation is very suitable for occluded and low intensity or high brightness images.

On the other hand, for facial expression recognition the result is not as good as it should to be for real life use. Like some other subspace learning techniques, it tends to find similar faces rather than similar expression. We explain the situation more elaborately in the next section named problem specification and proposed solution section. To overcome this occurrence, we propose to perform NMF on different face parts rather than on holistic faces. Our proposed algorithm is discussed in the next section.

VII. Problem Specification and Proposed Solution

While working on facial expression recognition (FER) using recent and strong subspace learning techniques like NMF, we face a major problem. It finds the faces of similar appearance than the similar expression in some cases. The case is when a same person's face of test image in also in train folder and the expression of train and test image does not vary in a great extent, like disgust and sad. In this type of cases our system matches similar faces rather than similar expressions. The Fig. 5 clearly depicts it.

Fig. 5. Face A, B, C.

For clarification, let A= sad expression image of subject 20, B=sad expression of subject 30, C= disgust expression of subject 20. The system should match A with B (in the above figure) as they have same expression (sad) while our system is developed for facial expression recognition, but it matches A with C. It means the system finds similar person's face rather than similar expression for some specific images. Because A and C are the same person.

To solve this problem, we present part based NMF analysis and for fusion we proposed an algorithm, namely, Optimal Expression-specific Parts Accumulation (OEPA). The Fig. 6 depicts our proposed solution to overcome the issues that described in the previous figure. The brief algorithm is stated below.

In this proposed algorithm we accumulate only the subset of those facial parts, which gives a good recognition rate for facial expression. We divided the face images into four facial parts and calculate the most predominant part which are responsible for expressing a specific expression.

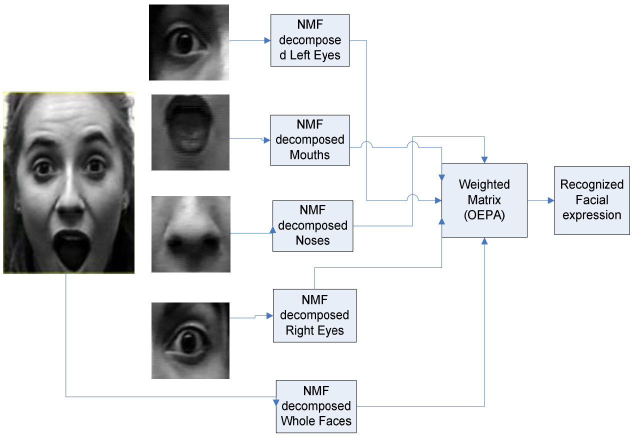

Fig. 6. Proposed Solution (OEPA-NMF).

Sometimes a subset of all the four parts of the face is optimal in terms of processing time and accuracy for identifying an expression. In this approach, we adapt similar approach and named it as Optimal Expression- specific Parts Accumulation (OEPA). In case of identifying an expression, if more than one subset of four parts give almost equal accuracy within a threshold value, this algorithm picks the subset of minimal number of parts in order to reduce the processing time. It increases the efficiency of the program in terms of time and as well as accuracy.

The analysis of faces and expressions using facial parts has been explored in our previous work [12]-[14], applying OEPA to improve on PCA and ICA based approaches. NMF however has been advocated as a promising alternative as reviewed above, and we explore OEPA in application to NMF in this paper.

Algorithm: Pseudocode for Optimal Expression-specific Parts Accumulation (OEPA) approach

Step 1: Initialization:

First we initialize the random population.

Step 2: Evaluation:

1. Let I be the vector [IL, IR, IM, IN] of subregions (Left eye, Right eye, Mouth, Nose).
2. For i in I evaluate fitness f(i) where f(i) is chance-corrected accuracy (kappa).
3. Let E be [Hap, Sad, Disgust, Anger, Fear, Surprise], a vector representing the six basic emotions.
4. For e in E,for k=1 to 4, for P in P(I), accumulate
   a. K (e,k) = argmax{P:|P|=k} f(P),
   the best set of k regions for e.
   L(e,k) = max{P:|P|=k} f(P)
   the corresponding fitness value
   b. K (e) = argmax{k:1-4,P:|P|=k} f(P),
   the best set of regions for e.
   L(e) = max{k:1-4,P:|P|=k} f(P)
   the corresponding fitness
   c. K = argmax{e:E,k:1-4,P:|P|=k} f(P),
   the best regions and emotion.
   L = max {e:E,k:1-4,P:|P|=k} f(P)
   the corresponding fitness.

VIII. Result Analysis

A. Performance Index

A well-known formula for measuring the separation performance is Performance Index (PI) which is defined as

$$PI(A) = \frac{1}{m(n-1)} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{[A]_{i,j}}{\max_j [A]_{i,j}} - 1 \right) \quad (7)$$

where $[A]_{i,j}$ is the (*i*, *j*)th-element of the matrix [A]. As because, the knowledge of the mixing matrix [A] is required, the smaller value of PI usually mentions the better performance evaluation for experimental settings. In this experiment the NMF Performance Index=0.313333.

B. NMF Visualization

Fig. 7 shows a portion of the NMF decomposed faces. For more clear view we take only two subjects image with several facial expressions. We find an interesting visualization in Fig. 8. Here we can see an interesting analogy that the images are grouped according to each subject with each expression or near similar expression. This approach of NMF is quite different from PCA and ICA.

Fig. 7. A portion of the NMF-decomposed faces from the whole dataset.

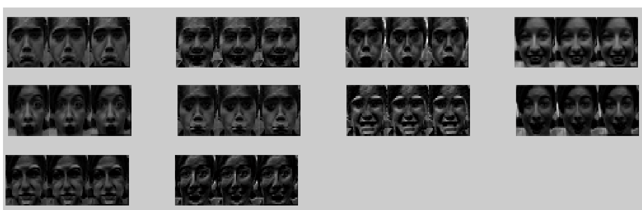

Fig. 8. Two subjects with several facial expressions (It clearly shows the grouping of subjects and expressions).

Now we present the tabular form of accuracy for face identification and facial expression recognition. The table presents the accuracy rate and the kappa value. For face identification, the accuracy rate is 99% for CK+ dataset and 96.24% for JAFFE dataset. As written before, we used the same data for face and facial expression recognition. Interestingly we have this result regardless of the presence of facial expressions. For facial expression recognition, the accuracy differs according to different facial expressions. The table also shows the kappa value for each expression recognition. As shown in Table I, the facial expression recognition rate is not as good as it is required for real time application. So we implemented OEPA-NMF on CK+ database and the result is described in Table II. We got a good recognition rate for facial expression recognition.

C. Overall Comparison

The average facial expression recognition rate versus training sample between NMF and OEPA-NMF is depicted in the following graph.

The recognition rate greatly depends on the volume of train and test set. Fig. 9 shows how is varies on the number of training sample. We divide the train and test set automatically by applying 10 folds cross validation. We plot the graph only for facial expression recognition rate as we are said before we are not interested to apply OEPA-NMF for face identification. For face identification we achieve a good result using NMF method without any extension.

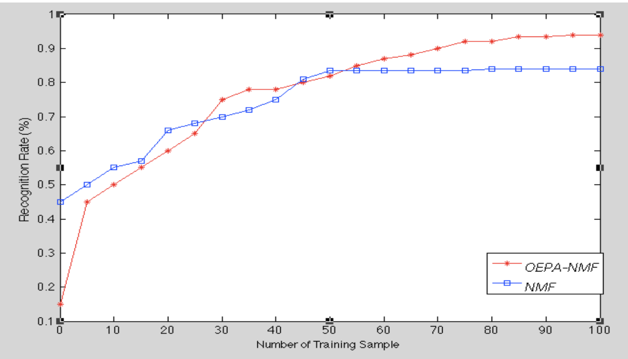

Fig. 9. Recognition Rate vs Number of Training Sample of NMF and OEPA-NMF.

D. Bookmaker Informedness

Where the number of classes can vary and where the biases of the system to particular classes do not match to the prevalence of the corresponding real classes, measurement techniques such as, Recall, Precision and Accuracy does not show reliable understanding. The work of [15] first introduces the concept of informedness which is a probabilistic measure based on decision, prediction or contingency is informed, rather than due to chance.

To estimate the informedness, bookmaker is an algorithm, which calculates from a contingency table based on the idea of betting with fair odds [16], [17]. It is shown that informedness subsumes chance corrected accuracy estimates based on other techniques that allow for chance, including Receiver Operating Characters (ROC), Correlation and Kappa, all of which are identical when bias is matched to prevalence.

In the dichotomous case (K = 2 non-empty classes), Bookmaker estimates Informedness as tpr-fpr (which is the True Positive Rate/False Positive Rate trade off investigated by ROC), and can also be expressed as B = Recall+InverseRecall−1 = Sensitivity+Specificity−1 = (Recall− Bias)/(1 − Prevalence) [16]. For K>2 classes, Informedness is a predic- tion bias weighted average of the Informedness for each case [16], like, $B=\sum_i (P_i X B_i)$

where P_i is the probability with which prediction i is made, and B_i is the calculated one vs. rest Bookmaker Informedness for prediction *i*. More information is described here [15]-[17].In order to provide better understanding of the results, the average of classification accuracy (%) and the informedness is given in Table I. JAFFE dataset has poor recognition rate than CK+ as the image quality is not good and the expression posing does not follow similar way for all the subjects.

TABLE I: COMPARISON OF FACE IDENTIFICATION AND FACIAL EXPRESSION RECOGNITION USING NMF

Face vs. Facial Expression Recognition	*Dataset / Method*	*Emotion*	*Accuracy with Brightness Adjust*	*Images/ Subject*	*Informedness*
Face	CK+/ NMF	N/A	99.00%	1500/100	**97.04%**
Face	JAFFE /NMF	N/A	96.24%	213/10	**94.94%**
Facial Expression	CK+/ NMF	Happy	**85.00%**	1200/100	82.17%
		Sadness	**83.00%**		80.16%
		Fear	**74.50%**		71.91%
		Surprise	**86.00%**		82.50%
		Disgust	**78.00%**		75.83%
		Angry	**83.50%**		80.71%
Facial Expression	JAFFE /NMF	Happy	**66.67%**	219/10	64.11%
		Sadness	**66.67%**		64.11%
		Fear	**33.33%**		30.21%
		Surprise	**70.00%**		67.90%
		Disgust	**33.33%**		30.21%
		Angry	**68.67%**		66.11%

The next table (Table II) is an average of all the two datasets of facial expression images.

TABLE II: EFFECTS OF FACIAL PARTS FOR EXPRESSION RECOGNITION WITH OPTIMA: LE=LEFT EYE, RE=RIGHT EYE, N=NOSE, M= MOUTH.

Facial Parts	**Surp.**	**Anger**	**Sad**	**Happy**	**Fear**	**Disg.**
LE	84%	67%	68%	72%	44%	57%
RE	84%	67%	68%	72%	44%	57%
LE+RE	84%	67%	68%	72%	44%	57%
N	18%	20%	57%	18%	36%	59%
M	***96%***	52%	58%	88%	84%	54%
LE+RE+N	64%	58%	52%	78%	60%	***89%***
LE+RE+M	89%	82%	78%	***92%***	***88%***	80%
N+M	74%	44%	44%	60%	40%	72%
LE+RE+N+M	86%	***90%***	***86%***	85%	83%	80%
OEPA-NMF	**96% M**	**90% LE+RE+N+M**	**86% LE+RE+N+M**	**92% LE+RE+M**	***88% LE+RE+M***	***89% LE+RE+N***

IX. Conclusion and Future Work

In this work, we implement NMF by using the multiplicative update rule to find face identification and facial expression recognition. Our research shows that for face identification NMF is very strong and much suitable method. We are not interested to apply OEPA-NMF for face identification as we get a good recognition rate for face identification using the predominant NMF algorithm. As shown in Table I, the facial expression recognition rate is not as good as it is required for real time application. To overcome the problem of same face recognition rather than same facial expression, we implemented our proposed algorithm OEPA-NMF (Optimal Expression-specific Parts Accumulation-NMF). Our experiment shows that OEPA-NMF performs better than prevalence NMF method.

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