NON-NEGATIVE MATRIX FACTORIZATION FOR FACE ILLUMINATION ANALYSIS

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ABSTRACT

Changing illumination causes severe problems for face recognition in uncontrolled environments. It might be helpful for illumination invariant face recognition if information about the illumination can be recovered from the given face image. In this paper an illumination classification method based on Non-negative Matrix Factorization(NMF) is proposed. The traditional NMF approach together with its few variants are investigated to classify an unknown illumination to one of the illumination conditions present in the training set. Encouraging results have been achieved on CMU-PIE face database which contains faces under various illumination conditions.

Keywords: Illumination, Non-negative Matrix Factorization, Face Recognition

1 INTRODUCTION

The performance of face recognition systems in controlled environments has now reached a satisfactory level for many applications [6]; however, there are still many challenges posed by uncontrolled environments. The effect of variation in the illumination conditions in particular, which causes dramatic changes in the face appearance, is one of those challenging problems [11] that a practical face recognition system needs to cope with. Fig. 1 shows how different a face can appear under different illuminations.

A number of illumination invariant face recognition approaches have been proposed in the past years. An extensive survey can be found in [12]. An important group of illumination invariant approaches is based on statistical modelling of illumination variation. From a face database containing various illuminations, a model is trained for each identity to obtain a subspace which covers all possible variations of illuminations. Then a probe face image under an unknown illumination will be projected into all these individual subspaces of different identities, and classified to the identify with the closest subspace to the probe image [1].

Figure 1: Examples of face images of the same subject while under different illuminations in Yale-B database[2].

Alternatively, instead of learning a person-specific subspace which contains the variations of this specific person's face due to all possible illumination conditions, we can learn an illumination-specific model which covers variation of faces belonging to all different identities under this specific illumination. The prerequisite of this approach is to classify the illumination of the probe face image to one of the illumination conditions in the training set. The face recognition can then be performed using the classifier specifically trained for all faces under a illumination condition. To the best of our knowledge, there has not been much work in this direction.

Non-negative Matrix Factorization(NMF) has been shown to be a useful decomposition approach for multivariate data. Its application in face recognition has received attention since it was introduced by Lee and Seung [4] for learning part-based representation of objects, including faces. In addition to the non-negative constraint of the standard NMF, new constraints have been proposed for the application in face recognition. Li et al. [5] proposed Local NMF in which constraint on the spatial locality is added to the standard NMF. Zhang et al. [10] introduced so-called Topology Preserving NMF. Wang and Jia presented Fisher NMF and PCA NMF in [8]. Hoyer extended standard NMF to control sparseness of the resulting matrix explicitly [3]. These variations of standard NMF have been shown to be more successful than PCA for face recognition, especially when occlusion is present in face images. Although in some of the work mentioned above a face database containing illumination change has been considered, the NMF methods have not been carefully investigated to analyse the illumination of a face image.

In this paper we investigate how NMF methods can help illumination invariant face recognition. More specifically the questions we intend to answer are:

1 Can NMF separate different illumination sources from a single face image under the combination of these illuminations?

2 Can NMF be used for illumination classification?

We conducted experiments on the CMU Pose Illumination and Expression(PIE) face database [7] which contains face images of 68 persons in various illumination conditions. The illumination classification results using NMF encourage further investigation in this direction. Section 2 describes the standard NMF and several variants considered in our experiments. In Section 3 the details and results of the experiments are presented. Conclusion is drawn in Section 4.

2 STANDARD NMF AND ITS VARIANTS

NMF is a recent method for learning latent structure of non-negative signals. For a given non-negative $N \times T$ matrix $\mathbf{V}$, NMF tries to find a factorization

$$\mathbf{V} \approx \mathbf{WH} \tag{1}$$

where $\mathbf{W}$ and $\mathbf{H}$ are two non-negative matrices with dimensions $N \times M$ and $M \times T$. The non-negativity of all three matrices makes NMF useful for describing decomposition with a potential physical meaning. The process of NMF is actually a learning process. Assuming $\mathbf{V}$ is the assembly of T samples, each represented by a N dimensional column vector $V_i, i = 1, ..T$, then $\mathbf{W}$ is the assembly of N dimensional column vectors $\{W_i\}_{i=1,..M}$, which are the basis vectors of an N dimensional linear space learnt from $\mathbf{V}$. And the projection coefficients of sample V_i are represented by the column vector H_i of $\mathbf{H}$. i.e.

$$V_i \approx \mathbf{W}H_i \tag{2}$$

Given a new N dimensional sample vector S, its projection coefficient vector L in subspace $\mathbf{W}$ can be obtained by

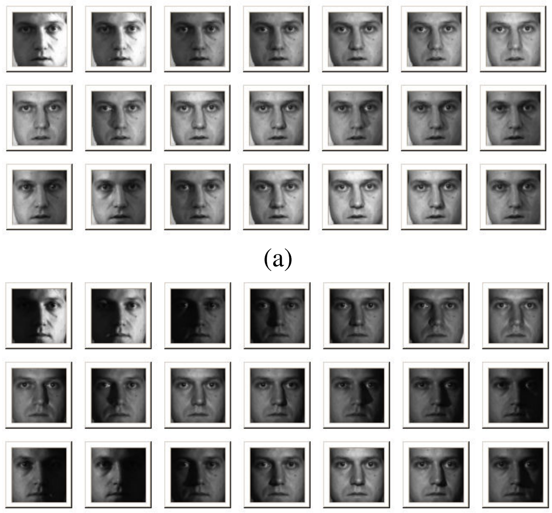
$$L = \mathbf{W}^{-1}S \tag{3}$$

where $\mathbf{W}^{-1}$ is the pseudo inverse matrix of $\mathbf{W}$. The traditional squared error cost function for NMF is given by [3]

$$E(\mathbf{W}, \mathbf{H}) = \|\mathbf{V} - \mathbf{WH}\|^2 \tag{4}$$

The sparseness constraint adopted in [3] is that the sparseness of each column vector of $\mathbf{W}$ and that of each row vector of $\mathbf{H}$ should be s_w and s_h, which are predefined values. Here, the sparseness of an n-dimensional vector X is defined as

$$sparseness(X) = \frac{\sqrt{n} - (\sum |x_i|)/\sqrt{\sum x_i^2}}{\sqrt{n} - 1} \tag{5}$$



(a)

(b)

Figure 2: Examples of cropped face images in PIE database. (a) the *light* set (b) the *illum* set.

where x_i is the nth element of X. In Local NMF approach [5] the cost function is given by

$$\sum_{i,j} (x_{ij} \log \frac{x_{ij}}{y_{ij}} - x_{ij} + y_{ij}) + \alpha \sum_{i,j} u_{ij} - \beta \sum_{i} v_{ii} \tag{6}$$

where $x_{ij}, y_{ij}, u_{ij}, v_{ij}$ are the (i, j)th element of $\mathbf{V}$, $\mathbf{WH}$, $\mathbf{W^TW}$ and $\mathbf{HH^T}$, respectively, and α ,β are small positive constraints.

3 EXPERIMENTS AND RESULTS

3.1 CMU-PIE face database

The CMU-PIE face database contains facial images of 68 persons with various pose, illumination conditions and expressions. In our experiments, we used a subset containing all the frontal faces in neutral expression. These faces are further divided into two subsets, the *illum* set and the *light* set. Each set contains face images captured under 21 different directional lighting conditions. The difference between these two subsets is that the images in the *light* set contain background lighting, while those in the *illum* set have no background lighting. The face images are normalized geometrically so that corresponding eye positions are consistent cross all images. Face regions are cropped and re-sized to an image with 64 by 64 pixels. Examples are given in Fig. 2. The locations of the flashes to generate directional illuminations is shown in Fig. 3.

3.2 Illumination source separation

In this experiment we are trying to see whether NMF can be used to decompose an image under combined illuminations into images each under one individual illumination source component of the combined illuminations. From the *light* set, we used 68 images to train the NMF. These images are captured under the same illumination conditions, which is a combination of background lighting and a directional lighting from the left. Examples of these images are shown in Fig. 4(a). In comparison, another set

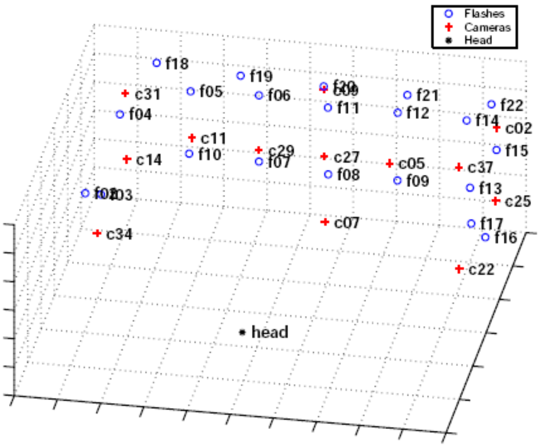


Figure 3: Locations of the flashes used for PIE face data.

(a)

(b)

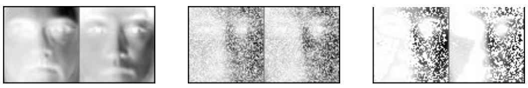
Figure 4: Examples of faces in the *light* set containing background lighting and identical directional lighting from (a) the left and (b) the right to train NMFs.

containing background lighting and a directional lighting from the right is used to train another NMF. Examples of these images are shown in Fig. 4(b).

In this experiment the number of basis images of NMF is set to two, since we have the prior knowledge that the training images contain two independent illumination sources. Ideally we hope the basis images will be two images, each under one of the two illumination sources in the training images. However this does not happen using standard NMF, Local NMF or Sparse NMF. Although the training images in Fig. 4(a) and those in Fig. 4(b) both contain background lighting as one of two illumination sources, the two NMFs trained from each of them do not share any common basis image which might correspond to the background lighting, see Fig.5 and 6.

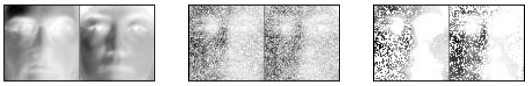
3.3 Illumination classification

In this experiment we tried to find out whether NMF can be used for illumination classification. NMFs are trained from the *light* set and the *illum* set respectively. Since each set contains 21 different illumination conditions, the number of basis images of NMFs is set to 21. For Sparse NMF



(a) (b) (c)

Figure 5: NMF basis images learnt from images in Fig. 4(a). (a) standard NMF (b) Local NMF and (c) Sparse NMF.



(a) (b) (c)

Figure 6: NMF basis images learnt from images in Fig. 4(b). (a) standard NMF (b) Local NMF and (c) Sparse NMF.

(a)

(b)

Figure 7: Examples of histogram equalized cropped face images in PIE database. (a) the *light* set (b) the *illum* set.

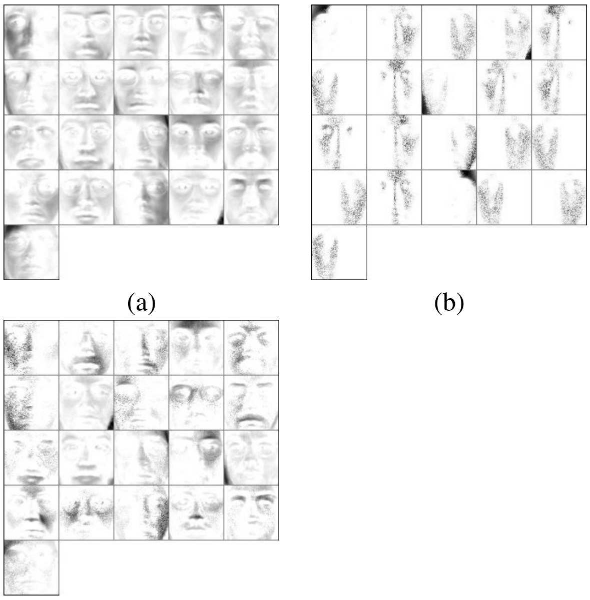
the sparseness constraint is set on W only, with s_w=0.5. We also repeated experiments on histogram equalized version of the images, see Fig. 7.

All images under the same illumination condition form a class. The classification is performed on the projection coefficients of each image on the learnt NMF. A machine learning toolbox named WEKA [9] developed by University of Waikato is used for the experiment. The classifier adopted here is Support Vector Machine(SVM) classifier with linear kernel. Pairwise classification is used for this SVM to solve the multi-class classification problem.

The illumination classification accuracy is shown in Table 1. The results do not seem to be impressive. However, from Fig. 3 we can see the location distribution of the flashes used to provide directional illumination for PIE face database is very dense. Therefore the images captured under under neighbour flashes have very minor difference and it is difficult, even for human, to tell the difference of the lighting directions(See Fig. 2). For the purpose of illumination invariant face recognition, it may not be necessary to have so many illuminaton classes; some of the 21 illuminations classes maybe be merged to form more compact and distinctive classes. Based on this consideration, we take it as a successful identification if the

Table 1: Illumination classification accuracy

	illum set		*light* set	
	orig img	histeq img	orig img	histeq img
NFM	59.45%	61.64%	50.49%	48.95%
LNFM	56.91%	46.78%	46.28%	48.95%
SNFM	63.72%	57.82%	51.68%	47.20%



(c)

Figure 8: 21 NMF basis images learnt from all images in the *light* set. (a) standard NMF (b) Local NMF and (c) Sparse NMF.

identified flash direction is the direct neighbour of the true flash. Then the accuracy rate becomes very encouraging, as shown in Table 2. Some observations can be derived from the results in Table 2:

1. Better results are achieved in the *illum* set than in the *light* set. This is reasonable because all images in the *light* set contain background lighting, and as a result these images exhibit less difference due to directional lighting changes than the images in the *illum* set which contain no background lighting.

2. Histogram equalisation does not necessarily bring any advantage. It helps for standard NMF, but not for Local NMF or Sparse NMF.

3. Standard NMF and Sparse NMF usually have a better performance than Local NMF.

4 CONCLUSION

In this paper we presented some preliminary investigation on standard NMF and a few variations for the problem of illumination variation in face recognition. We found that although the NMF methods are not able to separate individual illumination from their combinations, they can be useful for illumination classification. In our future work, we would like to investigate the performance of NMF when the number of basis vectors varies. And it will be interesting to see whether NMF methods have any advantages over other traditional subspace methods, such as PCA and ICA, for illumination classification.

Table 2: Illumination classification accuracy when identified illumination direction is near the true direction

	illum set		*light* set	
	orig img	histeq img	orig img	histeq img
NFM	89.71%	90.97%	86.76%	88.10%
LNFM	88.73%	87.04%	84.38%	83.26%
SNFM	91.95%	89.15%	86.62%	83.96%

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