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RESEARCH ARTICLE

PATTERN RECOGNITION FROM FACE IMAGES

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ABSTRACT

In this article, we use projected gradient descent nonnegative matrix factorization (NMF-PGD) method and make pattern recognition analysis on ORL face data set. Face recognition is one of the critical issues in our life and some security, daily activities and operations use this well known application area. NMF-PGD is a type of nonnegative matrix factorization (NMF) which defined in the literature. In the study, derived NMF-PGD definition and algorithm has been used in order to classify the ORL face images. We give the experimental results in a table and graph. According to experiments, face recognition accuracy rates have different accuracy values because of the k - lower rank value. We change k-values between 25 and 144 to see the performance of NMF-PGD. At the end, we make some analysis and comments on the recognition rates. Additionally, NMF-PGD can also be used for different kind of pattern recognition problems.

Keywords: *Pattern Recognition, Classification, Face Recognition, Nonnegative Matrix Factorization.*

ÖZ

Bu makalede, iz düşüm eğimli azatlım negatif olmayan matris ayrıştırma (NMF-PGD) yöntemi kullanılmış ve ORL yüz veri kümesi üzerinde örüntü tanıma analizleri yapılmıştır. Yüz tanıma, güvenlik ve günlük aktivitelerde kullandığımız hayatımızdaki önemli ve iyi bilinen alanlardan bir tanesidir. NMF-PGD, literatürde tanımlanmış bir negatif olmayan matris ayrıştırma yöntemidir. Bu çalışmada, elde edilmiş NMF-PGD tanımı ve algoritması, ORL yüz veri imgelerini sınıflandırmak için kullanılmıştır. Deneysel analiz ve sonuçlar tablo ve grafik halinde sunulmuştur. Deneysel sonuçlara göre, yüz tanıma doğruluk oranları k-düşük rank değeri nedeniyle farklı değerlere sahip olmaktadır. k-düşük rank değerlerini 25 ve 144 arasında olacak şekilde değiştirip seçerek, NMF-PGD yönteminin performansını test ettik. Son kısımda, bu oranlar hakkında çeşitli analizler ve yorumlarda bulunduk. Ek olarak, NMF-PGD diğer çeşitli örüntü tanıma problemlerinde de kullanılabilir.

Anahtar Kelimeler: *Örüntü Tanıma, Sınıflandırma, Yüz Tanıma, Negatif Olmayan Matris Ayrıştırma.*

1. INTRODUCTION

Nonnegative matrix factorization (NMF) is a well known and popular algorithm in pattern recognition. It is one of the machine learning algorithms, which has many application areas. NMF has been introduced by Lee and Seung in the literature [6, 7]. The authors define this method as part learning approach, because of its learning approach. There are many NMF derived type of algorithms and applications published in the literature [1-5, 8, 9-13]. Especially, image and signal processing, bioinformatics, robotics, finance and other application areas are popular for NMF. There are several studies published in these issues [1-7, 9-13]. Among pattern recognition methods, it is one of the unsupervised learning based type method [8]. k-lower rank values can be defined k-cluster values. Using different values and objective functions affects the performance of NMF and other derived NMF methods. Related studies in the literature are being published in these years. For example, face recognition, voice recognition, microarray data classification, some churn analysis are some of them.

2. PROJECTED GRADIENT DESCENT NONNEGATIVE MATRIX FACTORIZATION (NMF-PGD)

In this article, we use NMF-PGD for ORL face data set and get recognition results for face images. Firstly, we give a definition of Nonnegative matrix factorization (NMF). NMF proposed by Lee and Seung in 1999. It can be defined approximation between *A* matrix and products of *W* and H matrices. The authors use multiplicative update rule in their publication and show efficiency and derivation of this algorithm. They prove that NMF especially gives better accuracy results for part based learning [2, 3, 6, 7].

In NMF structure, *A* is called nonnegative data matrix, *W* and *H* are called lower rank matrix representations. Let *A* matrix has $m \times n$ dimension. We can define the rank of *A* as $k \leq min\ (m, n)$. Therefore in this condition, $m \times k$ and $k \times n$ are the dimensions of *W* and *H* matrices', respectively. The factorization process of NMF can be calculated with Eq (1).

$$A \approx W \, . \, H \qquad (1)$$
$$\text{subject to } W \geq 0 \text{ and } H \geq 0$$

Here, we define Obj(A, WH) as an objective function (calculation of error). We optimize and make it smaller in order to get good factorization of the matrices. In the literature, authors generally use Euclidean, Kullback-Leibler divergence and Itakura-Saito divergence as an objective function. Proposed different kind of objective functions has a good accuracy rates on different kind of several NMF studies. Projected gradient descent NMF (NMF-PGD) is also a kind of NMF which derived from NMF algorithm with projected descent approach. Lee and Seung use multiplicative update algorithm and we can state it below [6, 7].

$$H_j^{k+1} = H_{bj}^k \frac{((W^k)^T A)_j}{((W^k)^T W^k H^k)_j}, \quad \forall j.$$

$$W_i^{k+1} = W_i^k \frac{(A\,(H^{k+1})^T)_i}{(W^k H^{k+1} (H^{k+1})^T)_i}, \quad \forall i.$$

Multiplicative algorithm and also its stability and analysis have been proved analytically in the literature. Analysis shows its efficiency and mathematical background of derivations.

3. EXPERIMENTAL RESULTS

There are 400 faces in ORL face data set and we use them for NMF- PGD (Figure 1.). Accuracy metric with error analysis has been made. We change k-lower rank value from 25 to 144 basis images and we give recognition accuracy results in terms of accuracy for each k-value. We use k-nearest neighbor to classify faces after NMF-PGD algorithm. Classification results have been illustrated in Table 1 and Figure 2. We test NMF-PGD method running it one time.

Figure 1. ORL face data set sample images

We divide the data asset for training and testing phases. These images (faces) can be seen from Figure 1.

Table 1. Classification accuracy rates according to k-values for ORL face data set

Method	**Accuracy with k-values (%)**							
	k=25	**k=36**	**k=49**	**k=64**	**k=81**	**k=100**	**k=121**	**k=144**
NMF-PGD	77,3	78,1	79,8	78,9	80,3	82,4	83,3	82,8

After experimental analysis, we show that when we increase the k-lower rank value, then recognition rate accuracy also increases. But it is not general rule for other NMF based approach. Even for other applications it can be different. NMF-PGD reaches 83,3 % as the highest accuracy value when k-lower rank value is 121.

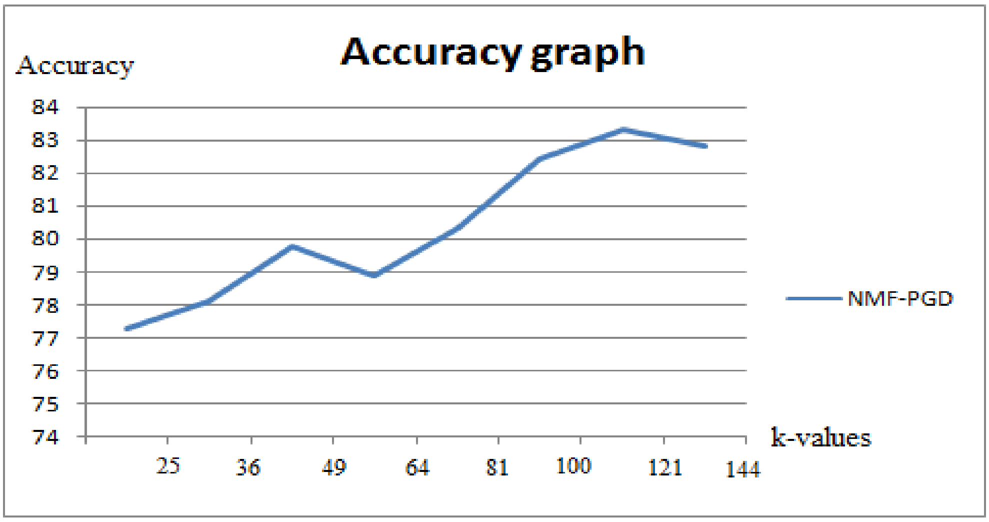

Figure 2. Classification accuracy rates graph according to k-values

The graph illustrated in Figure 2 for different k-lower rank values. These rates can be seen from Figure 2 for NMF-PGD method.

4. CONCLUSION

In this study, we use NMF-PGD for face recognition application area. ORL face data set has been chosen for the experimental analysis. We analyze patterns in faces with NMF-PGD and calculate their accuracy rates for each k-lower rank value. When k-lower rank value changes, the recognition accuracy also changes. NMF-PGD is derived from NMF and uses its approach into pattern recognition and part based learning. We show accuracy values of ORL face data set using NMF-PGD. The figures and the table illustrate our applications and recognition rates. Different kind of NMF algorithms and different kind of application areas can be tested in this context for future studies.

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