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Developing Intelligent Surveillance System

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Abstract. This paper describes a real time feature extraction for realtime surveillance system. We use incremental KPCA method in order to represent images in a low-dimensional subspace for realtime surveillance. In the traditional approach to calculate these eigenspace models, known as batch PCA method, model must capture all the images needed to build the internal representation. Updating of the existing eigenspaceis only possible when all the images must be kept in order to update the eigenspace, requiring a lot of storage capability. Proposed method allows discarding the acquired images immediately after the update. By experimental results we can show that incremental KPCA has similar accuracy compare to KPCA and more efficient in memory requirement than KPCA. This makes pro-posed model is suitable for real time surveillance system. We will extend our research to realtime face recognition based on this research.

Keywords: Intelligent Monitoring System, Eigenspace Update, Kernel PCA

1 Introduction

Unsupervised surveillance gadgets aided by hi-tech visual information retrieval and indexing systems use computerized face recognition techniques that can recognizes faces from an image. There are two main approaches for face recognition [1]. The first approach is the feature based matching approach using the relationship between facial features [2]. The second approach is the template matching approach using the holistic features of the face images [2]. Template based techniques often follow the subspace method called eigenface originated by Turkand Pentland [3]. This technique is based on the Karhunen-Loeve transformation, which is also referred as PCA. It has gained great success and become a de facto standard and a common performance benchmark in face recognition. One of the attractive characteristics of PCA is that a high demension vector can be represented by a small number of orthogonal basis vectors. The conventional methods of PCA such as singular value decomposion(SVD) and eigen-decomposition, perform in batch-mode with a computational complexity of $O(m^3)$whenm is the minimum value between the data dimension and the number of training examples. Undoubtedly these methods are computationally expensive when dealing with large scale problems where both the dimension and the number of training examples are large. To address this problem, many researchers have been working on incremental algorithms. Among them Chandrasekaran et al presented an

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incremental eigenspace update method using SVD [4]. Hall et al derived aneigen-decomposition based incremental algorithm and later extended their work to merge and split eigenspace models [5]. Another problem of PCA is that it only defines a linear projection of the data, the scope of its application is necessarily somewhat limited. It has been shown that most of the data in the real world are inherently non-symmetric and therefore contain higher-order correlation in-formation that could be useful[6]. PCA is incapable of representing such data.

For such cases, nonlinear transforms is necessary. Recently kernel trick has been applied to PCA and is based on a formulation of PCA in terms of the dot product matrix instead of the covariance matrix [7]. Kernel PCA(KPCA), however, requires storing and finding the eigenvectors of a $N \times N$ kernel matrix where N is a number of patterns. It is infeasible method for when N is large. This fact has motivated the development of incremental way of KPCA method which does not store the kernel matrix. In this paper we propose a method that allows for incremental eigenspace update method by incremental kernel PCA for vision learning and recognition. Paper is organized as follows. In Section 2 we will briefly explain the incremental PCA method. In Section 3 KPCA is introduced and to make KPCA incrementally, empirical kernel map method is explained. Experimental results to evaluate the performance of proposed method are shown in Section 4. Discussion of proposed method and future work is described in Section 5.

2 Updating Image Representations

The incremental PCA [8] represents the input image with principal components $a_{i(N)}$ and it can be approximated as follows:

$$x_{i(N)} = \hat{U} a_{i(N)} + \bar{x} \quad (1)$$

To update the principal components $a_{i(N)}$ for a new image x_{N+1}, computing an auxiliary vector η is necessary. Detailed description is in[8].

3 Experiment

To evaluate the performance of accuracy on eiegnspace update for incremental data we take nonlinear data. The disadvantage of incremental method is their accuracy compared to batch method even though it has the advantage of memory efficiency. So we shall apply proposed method to a simple toy data which will show the accuracy and memory efficiency of incremental KPCA [9][10][11][12] compared to APEX model proposed by Kung[13] and batch KPCA. Next we will use images from the Columbia Object Image Library (COIL-20). The set is consisted of images of 20 objects rotated about their vertical axis, resulting in 72 images per objects. We used these images for testing the performance of incremental KPCA.

4 Reconstruction Ability

To compare the reconstruction ability of incremental eigenspace update method proposed by Hall [8] to APEX model we conducted experiment on face data. Applying this data to incremental eigenspace update method we finally obtain30 Eigenvectors. As earlier experiment we set 30 output nodes to standard method.

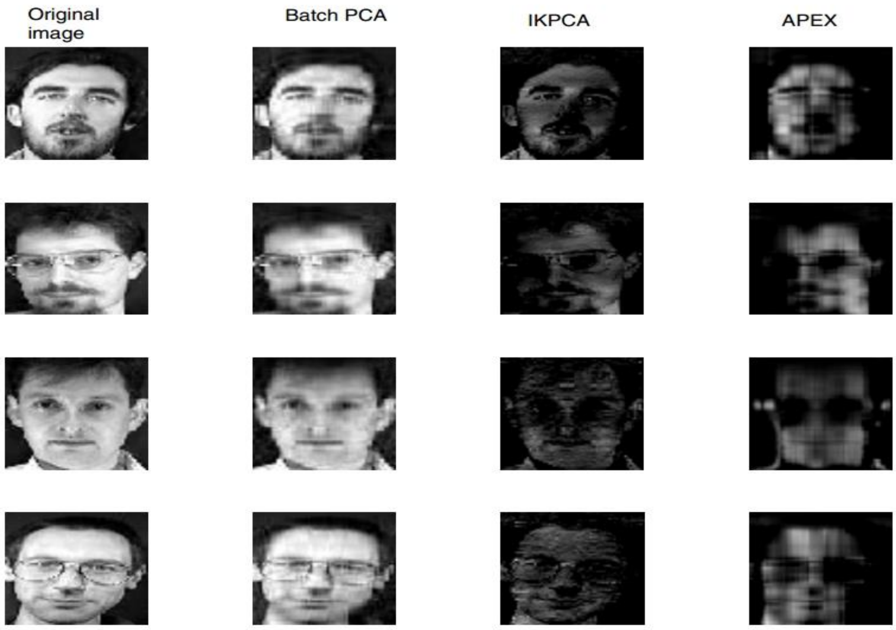

Fig. 1. Shows the original data and their reconstructed images by incremental KPCA method, batch PCA and APEX respectively.

The MSE (MeanSquare Error) value of reconstruction error in APEX is 10.159 whereas incremental KPCA is 0.26941 and KPCA is 0.15762. This means that the accuracy of incremental KPCA is superior to standard APEX and similar to that of batch KPCA. We can see that reconstructed images by incremental KPCA update method is similar to original image and more clear compared to APEX method.

5 Conclusion and Remarks

A real time feature extraction for realtime surveillance system is proposed in this paper. We use incremental KPCA method in order to represent images in a low-dimensional subspace for realtime surveillance. Proposed method allows discarding the acquired images immediately after the update. By experimental results we can show that incremental KPCA has similar accuracy compare to KPCA and more efficient in memory requirement than KPCA. This makes pro-posed model is suitable for real time surveillance system. We will extend our research to realtime face recognition based on this research.

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