Object Recognition using Appearance based Techniques

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Abstract—In this paper results of object recognition using some appearance based techniques such as Principal Component Analysis (PCA), Kernel PCA and Linear Discriminant Analysis (LDA) has been presented. Detecting the objects and extracting the features of unconstrained images is a challenging task in Image Processing and Pattern Recognition. High-dimensional data are common in many domains, and dimensionality reduction is the key to cope up with the curse-of-dimensionality. Two benchmark object databases namely Coil-20 database and ORL databases were used for experiment. Principal Component Analysis is a statistical tool used to analyze data sets. PCA is a very popular technique for dimensionality reduction and feature extraction. PCA attempts to find a linear subspace of lower dimensionality of the original feature space in which the new features have the largest variance. The Kernel principal component analysis is a non-linear version of principal component analysis, where the original image space is mapped in to non-linear feature space using kernel trick which produces the symmetric kernel matrix. Linear Discriminant Analysis considers the classes of different objects and it works on the basis of scatter matrix. It considers the scatter within the class and outside the class. In this project, for classification, the minimum distance classifier is used to classify unknown sample. The Euclidean distance measure is used to measure similarity between the trained images and the test image. The results shows that the Linear discriminant analysis has better performance than Principal component analysis and Kernel principal component analysis.

Index Terms—Appearance Based, Principal Component Analysis, Kernel PCA, Linear Discriminant Analysis, Object Recognition and Euclidean Distance.

I. INTRODUCTION

Computer vision is concerned with modelling and replicating human vision using computer software and hardware. It combines knowledge in computer science, electrical engineering, mathematics, physiology, biology, and cognitive science. It needs knowledge from all these fields in order to understand and simulate the operation of the human vision system. As one of the most fundamental and active areas in computer vision, object recognition is commonly used as the general term for the problems of automatically categorizing an object in an image into a set of predefined classes. Visual object recognition is a very important and challenging problem for multiple every-day applications including security, robot navigation, character recognition, clinical image understanding and many others. Therefore, it remains an important area...
of intense research in computer vision[1].

The study of object recognition concerns itself with a two-fold problem. First, the problem of visual object representation. Second, the problem of matching objects percepts to visual object representations. Object recognition algorithms rely on matching or learning algorithms using appearance-based or feature-based techniques. Common techniques include edges, gradients, Histogram of Oriented Gradients (HOG), Haar wavelets, and linear binary patterns. Object recognition is useful in applications such as video stabilization, automated vehicle parking systems, and cell counting in bio-imaging. Appearance-based techniques can also be used for recognizing objects in a cluttered environment and for tracking long image sequences or sequences across views.

II. APPLICATIONS OF OBJECT RECOGNITION

Biometric recognition and optical character/digit/document recognition are the most widely used applications. In particular, face recognition has been studied extensively from 1960’s and with large scale ongoing efforts. On the other hand, biometric recognition systems based on iris or fingerprint [2] as well as handwritten digit has become reliable technologies. Other object recognition applications include surveillance, industrial inspection, content-based image retrieval (CBIR), robotics, medical imaging, human computer interaction, and intelligent vehicle systems. Object recognition plays an important role in a vast diversity of robotic applications.

III. LITERATURE REVIEW

Appearance based techniques have been successfully employed for object recognition and pose estimation but most of this work has been performed under constant illumination conditions. In a robot was used to vary the direction of illumination on an object but only from five different light source positions. In this work the PCA and LDA methods are used for object Recognition with different angles or orientations of different objects. Appearance-based methods emphasize the use of view-based representations of objects, which are constructed from a set of views of an object in a pre-processing (or learning) stage, for object recognition or tracking. The collection of views is usually recorded in a compact way through principal component analysis (PCA), support vector machine (SVM) or neural networks. Murase and Nayar [3] observed that all the training feature vectors (e.g., vectors in association with a PCA representation) of an object consist of a manifold in the feature space. Hitoshi Sakano et.al [5], have presented the kernel mutual subspace method. The mutual subspace method proposed by Maeda is a superior technique for implementing robust object recognition by performing a principal component analysis on multiple input images. This technique could be effective for large scale recognition problems. Ching-Liang Su [6], have presented Edge distance extraction and orientation invariant transform for object recognition. The “vector magnitude invariant transform” technique can solve the image rotation problem.

Daniel L. Swets and John (Juyang) Weng [7], describes the automatic selection of features from an image training set using the theories of multidimensional discriminant analysis and the associated optimal linear projection. They demonstrate the effectiveness of these Most Discriminating Features for view-based class retrieval from a large database of widely varying real-world objects presented as "well-framed" views, and compare it with that of the principal component analysis. The combination of databases are considered to conduct experiments, trained the system on a diverse set of objects from natural scenes, ranging from human faces to street signs to aerial photographs. Universum linear discriminant analysis (ULDA) by X.H. Chen, S.C. Chen and H. Xue [7]. The experiment was done on UCI database. They have used 1NN classifier to perform final classification and repeated the process 10 times. [Universum the samples that belong to the same application domain as the training data, but do not belong to either target classes]. Here ULDA has been compared one-against-one(OAO-LDA) and LDA. Generalized Discriminant Analysis: A Matrix Exponential Approach by Bin Fang et.al [8]. They have proposed a method called exponential discriminant analysis (EDA) technique to overcome the under sampled problem. Conducted experiments on four different databases (Yale, PIE, Synthetic and Digit). Local Linear Discriminant Analysis with Composite Kernel for Face Recognition by Zhan SHI, et.al [9]. In this paper, a
local linear discriminant analysis method with composite kernel for face recognition. Yale and synthetic database has been used.

Nonlinear Component Analysis as a Kernel Eigenvalue Problem is presented by Bernhard Scholkopf, Alexander Smola and Klaus-Robert Muller [10]. A new method for performing a nonlinear form of principal component analysis is proposed. By the use of integral operator kernel functions, principal components in high-dimensional feature spaces can be computed by using this technique. Kernel PCA can be applied to all domains where traditional PCA has so far been used for feature extraction and where a nonlinear extension would make sense.

IV. PRINCIPAL COMPONENT ANALYSIS

Principal Components Analysis (PCA) is a technique that can be used to simplify a data set. It is a linear transformation that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a data set while retaining those characteristics of the data set that contribute most to its variance, by keeping lower order principal components and ignoring higher-order ones. The idea is that such low-order components often contain the “most important” aspects of the data.

The steps in the PCA algorithm are as follows

1. Prepare the data: The first step is to obtain a image matrix X with M images.

\[ X = \{x_1, x_2, \ldots, x_M \} \] .............(1)

2. Obtain the mean The mean image \( \mu \) has to be obtained as,

\[ \mu = \frac{1}{M} \sum_{n=1}^{M} X_n \] .................(2)

3. Subtract the mean from original image: The difference between the input image and the mean image has to be calculated and the result is stored in \( \varphi \).

\[ \varphi_i = X_i - \mu_i \] .................(3)

4. Calculate the covariance matrix: The covariance matrix C is calculated in the following Manner

\[ C = \frac{1}{M} \sum_{n=1}^{M} \varphi_n \varphi_n^T \] ...........(4)

5. Calculate the Eigen values and Eigen vectors of the covariance matrix and select the principal components: In this step, the Eigen values and the corresponding Eigen vectors (Eigen images) should be calculated. Then From M Eigen vectors \( \sigma \), only k should be chosen, which have the highest Eigen values. The higher the Eigen value, the more characteristic features of a object does the particular Eigen vector describe. Eigen images with low Eigen values can be omitted, as they explain only a small part of the characteristic features of the images.

6. Finding the weights of the database images.
7. Follow the same procedure for input image and finding the weights of the database image.
8. Calculate the Euclidean distance between the input image and all the images of database.
9. If the distance between any image is minimum then the input image is matched to the corresponding database image.

V. LINEAR DISCRIMINANT ANALYSIS

The objective of LDA is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible LDA and FLDA(Fisher's Linear discriminant analysis) are the methods used in statistics, pattern recognition and machine learning to find a linear combination of features which characterize or separate two or more classes of objects or events. LDA takes the consideration of scatter within-classes but also the scatter between-classes. It is also more capable of distinguishing image variation due to identity from variation due to other sources such as illumination and expression.
The steps in the LDA algorithm are, the first two steps are same as PCA after calculating the overall mean of database images the mean of each class s calculated as
\[ \mu_i = 1/N \sum_{i=1}^{C} Xi \] .................................(1)
where N is number of images in the class. Then the within class and between class scatter matrices are determined as
\[ S_w = 1/n \sum_{i=1}^{C} \frac{1}{N} \sum_{j=1}^{N_i} (X_{ij} - \mu_i) \cdot (X_{ij} - \mu_i)^T \] .............(2)
Between class matrix as,
\[ S_b = \frac{1}{n} \sum_{i=1}^{C} (\mu_{i} - \mu) \cdot (\mu_{i} - \mu)^T \] .................................(3)
The main objective of LDA method is to maximize the between class scatter and minimize the within class scatter. In order to achieve this find the ratio of \( S_b/S_w \) or \( S_bS_w^{-1} \). After this eigen images and weights of training set has been calculated and test the input image using the weights of the training image and test image.

VI. KERNEL PRINCIPAL COMPONENT ANALYSIS

Kernel Principal Component Analysis (KPCA) is a popular generalization of linear PCA that allows non-linear feature extraction. In KPCA, data in the input space is mapped to higher (usually) dimensional feature space where the data can be linearly modelled. The feature space is typically induced implicitly by a kernel function, and linear PCA in the feature space is performed via the kernel trick. However, due to the implicitness of the feature space, some extensions of PCA such as robust PCA cannot be directly generalized to KPCA. Principal Component Analysis (PCA) is one of the primary statistical techniques for feature extraction and data modelling. One drawback of PCA is its limited ability to model non-linear structures that exist in many computing applications. Kernel methods enable us to extend PCA to model non-linearities while retaining its computational efficiency. In particular, Kernel PCA (KPCA) has repeatedly outperformed PCA in many image modelling tasks.

The kernel Principle Component Analysis is extension and application of PCA in kernel defined feature space. The Principle Component Analysis has not facility to handle dual representation. It provides non-linear function for features analysis. Projections onto feature space eigen vectors is computed through the dual representation. It is computed from the eigen values and eigen vectors from Kernel matrix.
Steps in the KPCA algorithm are as follows

1. Prepare the data: The first step is to obtain a image matrix X with M images.
\[ X = \{ x_1, x_2, \ldots, x_M \} \] ........................................(1)

2. Map the data X into a feature space F via non-linear mapping f using Kernel trick. This mapping produce a symmetric kernel matrix K.
\[ X \rightarrow \phi(X) \] ..................................................(2)

3. K is M x M square matrix by
\[ K_{i,j} = \phi(X_i), \phi(X_j)) = k(X_i,X_j) \] ..........(3)

4. Assuming Mapped data is centered and Perform PCA on K.
\[ \sum_{i=1}^{M} \phi(X) = 0 \] ..........................................(4)

5. If \( Sm_i = 1f(X) \neq 0 \), then centering is done by
\[ K_{center} = K - K_{1:N} \cdot K_{1:N}^{-1} \] ....................(5)

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where, \((1)_{i,j} = 1/N\).

Apply normal PCA on kcenter and determine the weights of training database images.

VII. EXPERIMENTAL RESULTS

To conduct experiments and test object recognition algorithms, the Coil-20 (Columbia Object Image Library) database and Olivetti Research Laboratories (ORL) database of faces are used. Columbia Object Image Library (COIL-20) is a database of gray-scale images of 20 objects. ORL is a database of gray scale images with 40 individuals. Experiments are conducted in two sets using two benchmark databases. The first set of experiment is conducted for varying principal components versus recognition rate whereas second set is number of training samples per class versus recognition rate. The comparative results of all the three algorithms for first set of experiments with variable number of principal components for Coil-20 database is shown in the Figure 3 and for ORL database it shown in the Figure 4. The second set of experiments with variable number of training images per object for Coil-20 database is shown in the Figure 5 and for ORL database it shown in the Figure 6.

![Figure 1. Sample images of Coil-20 Database](image1)

![Figure 2. Sample images of ORL Database](image2)

![Figure 3. Plot of PCA, KPCA and LDA for Coil-20 Database with variable principal components](image3)

![Figure 4. Plot of PCA, KPCA and LDA Coil-20 Database with variable training images per object](image4)
VIII. CONCLUSION

Appearance based methods namely Principal component analysis (PCA) Kernel Principal Component Analysis (KPCA) and Linear Discriminant Analysis (LDA) are gaining attention as efficient techniques for Object Recognition. The advantage of PCA method is dimensionality reduction and the recognition is good when the training database size is small. By using the kernel method the performance of PCA is enhanced in non-linear space. The Kernel methods provide a modular way of analysis of patterns in data. Especially when data is of high dimensions like image the computational efforts are considerably reduced by use of kernels. LDA technique produces better performance than the other two techniques for both Coil-20 and ORL database.

REFERENCES

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