



An Efficient Tool Identification System Using Principal Component Analysis

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Abstract: An efficient implementation of tool identification system based on feature extraction technique is proposed and validated. Principal Component Analysis (PCA) is used for extracting features from a large training database images of different classes of tools like spanner screwdriver, knife and hammer. Original image from each class is rotated by 5° to obtain 72 training images for each individual class of tools. In the proposed method, the initial computation of features of the training images using PCA is computed for the entire database and is saved in the memory. Computed results are loaded from memory when a test image is provided to the system for identification. Simulation results shows that proposed method can recognize a tool within 15 seconds from the database containing 288 training images and hence the proposed method can be used for real time tool identification systems.

Keywords: Principal component analysis; eigen values; eigenvectors; covariance matrix.

I. INTRODUCTION

Object recognition systems [1] are employed in many applications, such as industry and assembly lines, robotics, object grouping, object tracking, face recognition etc. All of these applications require a computer vision program able to recognize different types of objects. The recognition of objects in an assembly line or objects travelling on a conveyor belt requires that the training database and all relevant information for recognition be previously stored in the machine memory and loaded when required in order to ensure fastest response. Machines, unlike humans need the translation of pictures into a machine understandable format. This is achieved by extracting features from images, and then the features are used to classify and recognize objects. This is done by comparing these features with previously stored database of known features of different objects.

Principal Component Analysis (PCA) [2] is one of the most successful techniques that have been used in image recognition, feature extraction and compression. PCA is a statistical method under the broad title of factor analysis. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables. The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc.

Rest of the paper is organized as follows. Section II deals with PCA and its mathematical background. Proposed method and simulation results are discussed in section III. Section IV compares three different implementation methods of the proposed tool identification system and finally section V concludes the paper.

II. PRINCIPAL COMPONENT ANALYSIS

Much of the work in automatic object detection has focused on extracting the dimensional properties of the object to be recognized. The use of edges, control points etc to measure lengths, angles etc lead to complex and time consuming techniques of pattern recognition. The relevant information in the image of an object is to be extracted, encode it as efficiently as possible, and compare one object encoding with a database of models encoded similarly. Capture the variation in a collection of images and use this information to encode and compare the objects. In mathematical terms, find the principal components of the distribution of the objects (tools in this case), or the eigenvectors of the covariance matrix of the set of tool images, treating an image as a point (or a vector) in a very high dimensional space. The eigenvectors are ordered, each one accounting for a different amount of the variation among the images of the tools. These eigenvectors can be thought of as a set of features that together characterize the variation between the images of tools. Each image location contributes more or less to each eigenvector so that an eigen image can be compiled. Each individual image in the database can be represented exactly in terms of a linear combination of the eigen images. In principle any collection of images of the tools [3] can be approximately reconstructed by storing a small collection of weights for each object. The weights describing each image of a tool are found by projecting the face image onto the eigen image.

This approach to object recognition involves the following initialization operations:

1. Acquire an initial set of training images
2. Calculate the eigen images from the training set, keeping only the M images that correspond to the highest eigen values. These M images define the image space.



3. Calculate the corresponding distribution in M-dimensional weight space for each known object, by projecting its image onto the image space.

Having initialized the system, the following steps then used to recognize new test images:

1. Calculate a set of weights by projecting the input image onto each of the eigen images.
2. Determine if the image is a known object at all, by checking to see if the image is sufficiently close to image space.
3. If it is an object, classify the weight pattern as either a known object or as unknown.

A. Mathematics behind PCA

A 2-D image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Consider M vectors of size N (rows of image \times columns of image) representing a set of sampled images. p_j s represent the pixel values.

$$\mathbf{x}_i = [p_1, \dots, p_N]^T; \quad i = 1, 2, \dots, M \quad (1)$$

The images are mean centered by subtracting the mean image from each image vector where mean m of an image can be calculated as in (2).

$$m = \frac{1}{M} \sum_{i=1}^M \mathbf{x}_i \quad (2)$$

Mean centered image can be represented as (3)

$$\mathbf{w}_i = \mathbf{x}_i - m \quad (3)$$

To find a set of M orthonormal vectors \mathbf{e}_i , the quantity λ_i given in (4) is maximized with the orthonormal constraint given in (5).

$$\lambda_i = \frac{1}{M} \sum_{i=1}^M (\mathbf{e}_i^T \mathbf{w}_i)^2 \quad (4)$$

$$\mathbf{e}_i^T \mathbf{e}_k = \delta_{ik} \quad (5)$$

\mathbf{e}_i s and λ_i s are given by the eigenvectors and eigen values of the covariance matrix (C) defined in (6).

$$C = \mathbf{W}\mathbf{W}^T \quad (6)$$

where \mathbf{W} is a matrix composed of the column vectors \mathbf{w}_i placed side by side. The size of C is enormous for images of small size. If the image is 64×64 , the covariance matrix will be 4096×4096 in size. Hence it is not feasible to solve for the eigenvectors of C directly for implementing a system with fast response time. From the principles of linear algebra, the vectors \mathbf{e}_i and scalars λ_i can be obtained by solving for the eigenvectors and eigen values of the $M \times M$ matrix $\mathbf{W}^T\mathbf{W}$. If \mathbf{d}_i and μ_i be the eigenvectors and eigen values of $\mathbf{W}^T\mathbf{W}$, then

$$\mathbf{W}^T\mathbf{W}\mathbf{d}_i = \mu_i\mathbf{d}_i \quad (7)$$

Left multiplying by \mathbf{W} , (7) becomes

$$\mathbf{W}\mathbf{W}^T(\mathbf{W}\mathbf{d}_i) = \mu_i(\mathbf{W}\mathbf{d}_i) \quad (8)$$

The first $M - 1$ eigenvectors \mathbf{e}_i and eigen values λ_i of $\mathbf{W}\mathbf{W}^T$ are given by $\mathbf{W}\mathbf{d}_i$ and μ_i respectively. $\mathbf{W}\mathbf{d}_i$ needs to be normalized in order to be equal to \mathbf{e}_i . Since we only sum up a finite number of image vector, M , the rank of the covariance matrix cannot exceed $M - 1$.

The eigenvectors corresponding to non zero eigen values of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted in descending order according to their corresponding eigen values. The eigenvector associated with the largest eigen value is one that reflects the greatest variance in the image[3].

An image can be projected onto M' ($\ll M$) dimensions by computing

$$\Omega = [\mathbf{v}_1 \mathbf{v}_2 \dots \mathbf{v}_{M'}]^T \quad (9)$$

where $v_i = e_i^T w_i$, v_i is the i^{th} coordinate of the image in the new space, which is the principal component thus obtained. The vectors e_i are called eigen images. So Ω describes the contribution of each eigen image in representing the object image by treating the eigen images as a basis set for object images. The simplest method for determining which object class provides the best description of an input test image is to find the object class k that minimizes the Euclidean distance (ϵ_k) given in (10).

$$\epsilon_k = \|\Omega - \Omega_k\| \quad (10)$$

where Ω_k is a vector describing the k^{th} object class. If ϵ_k is less than some predefined threshold θ_c , an object is classified as belonging to the class k .

III. PROPOSED METHOD: IMPLEMENTATION AND RESULTS

The block diagram of the proposed method is shown in Fig. 1. Features are extracted and stored in the memory and loaded for identifying a feature when a test tool is provided. For the implementation of the tool identification system, tools belonging to 4 different classes namely spanner screwdriver, knife and hammer. 72 rotated samples of each class made up the training database, making a total of 288 training images. Each training image in a class differs from its adjacent samples by a rotation angle of 5° .

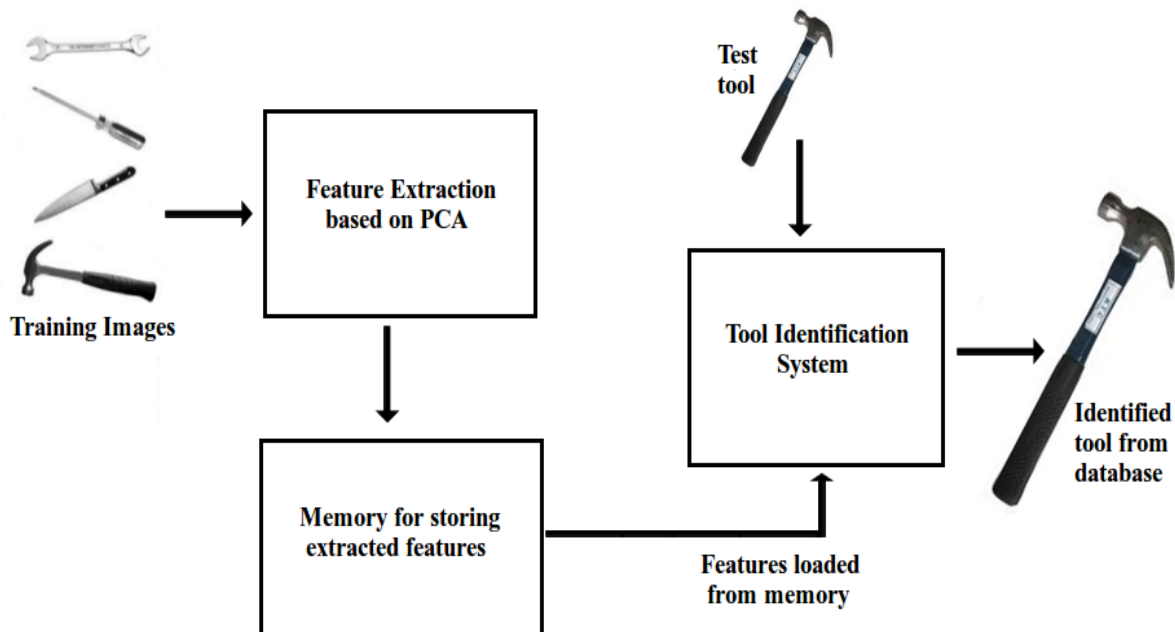


Fig. 1. Algorithm for FECEG Extraction

Sample images from the training database for the four different classes of tools are shown in Fig. 2. To create a set of images for testing, the original non rotated sample from each class is rotated [4] 72 times, each time by 5° . Test samples for each class were chosen randomly from these rotated images.



Fig. 2. Training database images (a) Class 1: Spanner (b) Class 2: Screwdriver (c) Class 3: Knife (d) Class 4: Hammer

The database was loaded on to the computational software, MATLAB in this case, and all the required features were extracted. The features used for the recognition of the class or tool are the weights of projection of the images [5],[6] on to the eigen image space. These features were calculated for the existing training database and stored for use in recognition. The number of eigen images required to perform accurate recognition is much lesser than the number of training images. From 288 images that were included in the training database, only 146 eigen images were required to accurately identify the equivalent of the test image in the training database. Simulation results of the proposed method indicating true identification of test image from database is shown in Fig. 3.

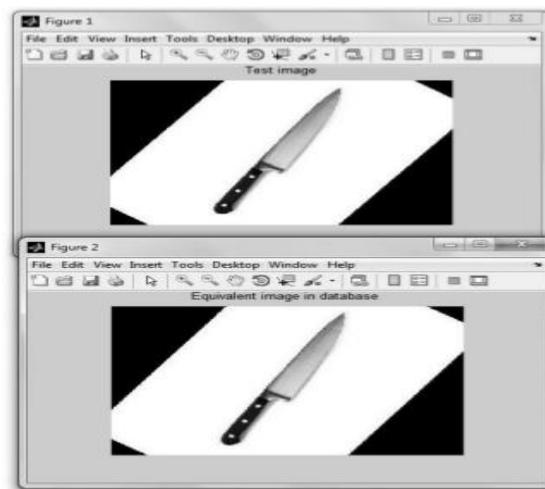


Fig. 3. Simulation results for tool identification of class 3: Knife

IV. COMPARISON OF TOOL IDENTIFICATION TIME

Object identification time of the proposed method (Method II and Method III) is compared with the existing method (Method I). Method I performs all the computations including, database creation, PCA feature extraction and object recognition for a test image. The existing method requires more computation time and hence it is less efficient. Method II saves the entire database in a memory and loads the database from the memory when a test image is applied to the system for identification thereby reducing execution time. All the initial computations including database creation and PCA feature extraction are saved in a memory location in Method III making proposed system more efficient and suitable for real time applications. Fig. 4 shows the simulation results for tool identification where first one is the test image and second one is the identified tool from the database..

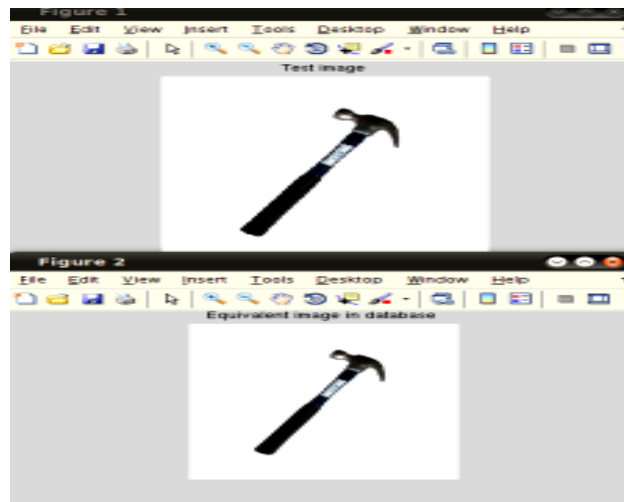


Fig. 4. Simulation results for tool identification of class 4: Hammer

The initial computation of features of the training images is the most time consuming part of the system. Once these computations are saved, they have to be updated only when new training images are encountered. For recognition, these features are simply loaded from memory. The time required to identify a tool after navigating through the projections of 288 training images only comes to about 15 seconds. Thus the proposed system serves as quite an efficient system for recognizing the objects in the image. If only the database is saved according to Method II, the program execution time is about 55 seconds. If the database is computed every time the test image is given as per Method I, the program execution takes about 5 minutes as shown in Table I. Instead of using a threshold value to determine the class of a test image, Euclidean distance between weights of projection of the eigen image to the projection of the test image is used.

TABLE I
COMPARISON OF PROPOSED METHOD WITH EXISTING METHOD

Methods	Time taken
Method I (Existing)	5 minutes
Method II (Proposed)	55 seconds
Method III (Proposed)	15 seconds

To improve the accuracy of the system in practical applications, the training database can be expanded to include other variations that may be present in the image, in terms of skew, position etc. Imposing a threshold will also improve the accuracy of the system. This will enable the test object to be rejected on ground of not being close enough to any of the training images. A neural network implemented to perform the same task with the same accuracy will be overly complex and will take a large time to train. This is particularly disadvantageous in case of an expanding training database. Also the extraction of features that could effectively characterize these images will also prove difficult. One of the simplest methods require determining the outermost edges of the object in the image. The centroid of the object is calculated and the distance of the edges from this point at different angles can be combined to a feature vector. These vectors for different images can be mapped to respective targets based on their classes. This approach does not guarantee the accuracy that PCA does.

V. CONCLUSION

An efficient tool identification system using Principal Component Analysis is proposed and validated. Simulation results shows that the proposed method is most effective and accurate approach to identify and classify tools. Proposed method takes only 15 seconds to identify a tool from the database. This has been more apparent after an attempt to use a traditional neural network for achieving the same task. The same technique can be adapted into object recognition systems of differing capacities depending on the functionality required.



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