Pose Invariant Generic Object Recognition with Orthogonal Axis Manifolds in Linear Subspace

Manisha Kalra, P. Deepti, R. Abhilash, and Sukhendu Das

Visualization and Perception Laboratory
Department of Computer Science and Engineering
Indian Institute of Technology - Madras, Chennai - 600 036, India

Abstract. This paper addresses the problem of pose invariant Generic Object Recognition by modeling the perceptual capability of human beings. We propose a novel framework using a combination of appearance and shape cues to recognize the object class and viewpoint (axis of rotation) as well as determine its pose (angle of view). The appearance model of the object from multiple viewpoints is captured using Linear Subspace Analysis techniques and is used to reduce the search space to a few rank-ordered candidates. We have used a decision-fusion based combination of 2D PCA and ICA to integrate the complementary information of classifiers and improve recognition accuracy. For matching based on shape features, we propose the use of distance transform based correlation. A decision fusion using Sum Rule of 2D PCA and ICA subspace classifiers, and distance transform based correlation is then used to verify the correct object class and determine its viewpoint and pose. Experiments were conducted on COIL-100 and IGOIL (IITM Generic Object Image Library) databases which contain objects with complex appearance and shape characteristics. IGOIL database was captured to analyze the appearance manifolds along two orthogonal axes of rotation.

1 Introduction

Existing object recognition systems [1][2][3][4] focus on recognition of a particular object class as well as its pose only along one axis of rotation. Such systems fail if they are given an object image from an arbitrary viewpoint. It is tough to capture the 3D appearance model of an object using a limited set of 2D views only along a single axis. Also, creation and storage of 3D models of objects poses a problem to the existing 3D model-based recognition systems. The problem we address is not restricted to a single class of objects, say only face recognition or vehicle recognition. Rather, it involves recognition across multiple categories of objects. Content based image retrieval, infant perception and recognition are the potential areas of its application. The goal of this work is to design a framework for generic object recognition (GOR) from arbitrary viewpoints and poses, using a limited set of 2D views of objects along multiple orthogonal axes of rotation.
The various approaches for object recognition can be grouped into the following categories based on the type of features and matching strategies used: a) Structural Decomposition: Recognition-by-components [5], 3-D part-based methods;

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b) Appearance Based Approaches: Principal Component Analysis [1], [2], [6], Support Vector Machines [7], [8]; c) Shape Based Approaches: Shape Context [9], Moment-based methods 4) Model Based Approaches: Geometric Invariants, CAD Model Based approach [10].

Murase and Nayar [1] have addressed the problem of automatically learning object appearance models for recognition and pose estimation using 1D PCA. From the set of 100 objects in COIL database, the authors have picked 20 objects (COIL-20 database) that do not possess pose ambiguities and have reported a recognition rate of 100% on these 20 objects. The object pose estimation is reported to have a mean absolute error of 2.02 degrees and standard deviation of 16.7 degrees. Nagabhushan et al. [2] have experimented the use of 2D Principal Component Analysis (2D PCA) on COIL-20 database for object recognition and have reported that 2D PCA gives a better recognition accuracy than 1D PCA. They also report a 100% recognition rate on the 20 object database for noise-free test samples. However, they did not report their results on COIL-100 database. The existing appearance based techniques (1D and 2D PCA) summarized above try to recognize object class and pose from only one axis of rotation and also do not use any shape cues for verification.

2 Proposed Framework

We propose a two stage framework based on the studies in cognitive psychology where we try to model the 'human visual-pathway' starting with low-level processing like feature extraction (using appearance based cues), to high-level object representation in the human brain, such as perception (using shape cues) and recognition. The flowchart of the overall framework for generic object recognition is shown in Fig. 1. The entire framework can be logically divided into three phases: *(a) Memory, (b) Representation and Classification, (c) Shape Perception.* Below, we describe the three phases.

2.1 Memory : 2D Image Gallery with Multiple Axes Views

The image gallery contains the 2D views of objects from multiple (orthogonal) axis of rotations. These views represent the objects already seen by human beings. This aspect of the framework models the recollection ability of the human beings to retrieve exemplars from the memory on seeing an object and studying its appearance from different poses and viewpoints [11]. A subset of this database is used to train the system, rest of the samples are used for testing.

2.2 Appearance Based Representation and Classification

According to neurological studies, the initial phase of object recognition uses the fact that people might initially characterize the objects using some set of rules or features. The human brain extracts a set of statistical features or cues from images of 3-D objects to represent or recognize it [11][13]. Based on this hypothesis, we propose a method which uses second and higher order statistics

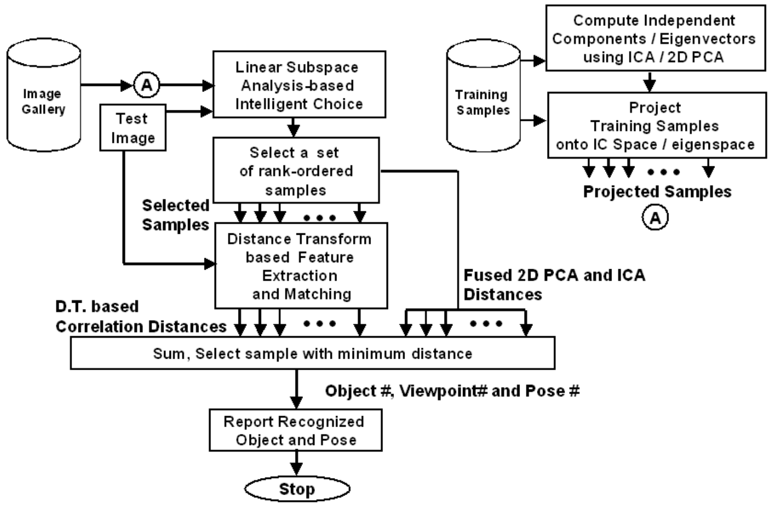


Fig. 1. Flowchart for Generic Object Recognition framework combining appearance (Linear Subspace Analysis) and Shape (DT based matching) cues

[13] to represent objects in a high dimensional space. We use a fusion of two linear subspace analysis based classifiers: 2D PCA [2] and ICA [14] for this task. Both 2D PCA and ICA are shown to capture the appearance manifold of the object from multiple orthogonal axis of rotations. The appearance representation of each object i is defined by a manifold set $M_i = \{o_{ij} | j = 1..K\}$ where o_{ij} is the manifold of the object i captured by rotating the object along the j^{th} orthogonal axis, and K (=2) is the total number of orthogonal axes along which the object is rotated. The manifold curves for an object lie on a manifold surface which is unique for an object. A typical manifold set for an object is shown in Fig. 2. Since consecutive poses (θ) of an object along a particular axis of rotation are close in appearance to each other, they lie close to each other in the manifold.

Decision Fusion of 2D PCA and ICA: Second order statistics (PCA) capture the amplitude spectrum of images but not their phase spectrum. The higher order statistics (ICA) capture the phase spectrum. However, both amplitude and phase spectrum contain important information that drives human perception [14]. The advantages of ICA over PCA have been quoted in [14]. 2D PCA on the other hand, preserves the column-wise or row-wise adjacency of pixels [15]. Each classifier shows different level of performance on different subsets of images, suggesting that different classifiers contribute complementary information to the classification task. A combination scheme involving both 2D PCA and ICA is likely to improve the recognition accuracy.

We use the decision level combination that is more appropriate when the component classifiers use different types of features. We use Sum rule (observed to work the best among all six combination strategies) for combining the two appearance-based object recognition methods : 2D PCA and ICA since it is

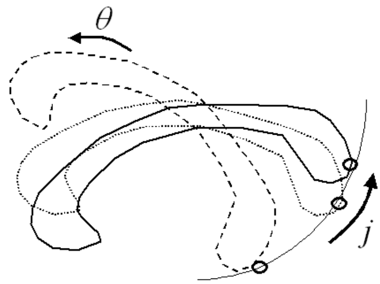


Fig. 2. Expected manifold set for an object in the linear subspace. j represents the axis of rotation (viewpoint), θ represents the pose number.

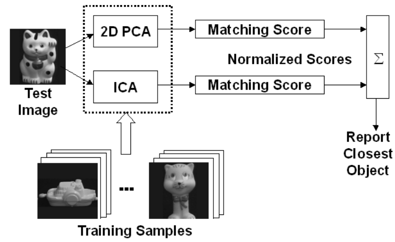


Fig. 3. Appearance-based Classifier Combination System Framework

the most robust classifier combination strategies [16]. Our combination strategy (shown in Fig. 3) is designed at decision level, utilizing the confidence value, called the matching score provided by each of the two appearance-based recognition schemes. The criterion for appearance-based object recognition is

$$D_{comb} = \frac{D_{2DPCA} + D_{ICA}}{2} \tag{1}$$

where D_{2DPCA} and D_{ICA} are euclidean distances between the test and training features in the 2D PCA Eigenspace and ICA Space respectively. Since each classifier uses its own representation of input patterns, the distances extracted from the patterns are unique to each classifier. Thus, before computing D_{comb}, the matching scores (D_{2DPCA} and D_{ICA}) are normalized using Max normalization, as in [16]. Use of the fused generic classifier helps to reduce the search space for objects, to a few rank ordered similar (in appearance) samples in the gallery. Shape matching is required to verify the object and it helps to improve the recognition accuracy.

2.3 Shape Perception for Verification

Since psychological findings indicate that shape dominates other cues in human object recognition, we suggest a shape perception stage in our framework which tries to imitate the visual similarity detection capability of the human brain. Once a set of rank ordered samples has been selected from the image gallery using appearance cues, the next step is to verify and match it with the test image using shape-based features (distance transform (DT) based matching). As the knowledge about the foreground pixel is stored around it at many positions by the DT, this representation of a bitmap gives the process of matching a high degree of tolerance to noise and discontinuities. DT based features have been preferred over moments and shape context [9] due to reduced computational cost and robustness against noise and discontinuities in edgemaps [17].

Shape Matching using Distance Transform based Correlation: Let $b_{x,y}$ be a bitmap with feature pixels of value 1 and background pixels with value 0. Consider a second bitmap b' and let $d_{x,y}$ be the DT of b'. Let the cross-correlation between DT d and the bitmap b be given as $R(b, d)$. If two samples (test and target shapes) are similar, we obtain small value of correlation indicating a higher degree of match. Instead of using R(b, d) as the distance measure between two bitmaps b and b', we use an average distance of the cross correlations of DT of b with bitmap b' [17]; and that of DT of b' with the bitmap b. Thus the distance measure for choosing the best sample based on the shape of the object is given as

$$DT_{Corr} = \mathrm{avg}(R(T, D(b_i)), R(b_i, D(T))) \tag{2}$$

where b_i is the edge map of the i^{th} training sample, T is the edge map of the test image and $D(.)$ is the DT function. This criterion works better than just using R as the shape similarity measure, as it is unbiased to T or b_i.

2.4 Combining Appearance-Based Generic Classifier and Shape Perception

The two stage approach (Fig. 1) based on linear subspace analysis (using fusion of 2D PCA and ICA) and DT based correlation attempts to imitate some perceptual properties of the human brain. For each object to be stored in the database, a large set of images from different poses and along multiple orthogonal viewpoints of the object are obtained. The set of images is normalized with respect to scale and projected into the universal linear subspace constructed using 2D PCA and ICA from the set of all object images. Each object is then defined by a manifold set in the universal linear subspace, where each manifold of the object corresponds to a single orthogonal axis of rotation (viewpoint). Given a test image, it is first projected onto the universal linear subspaces (separately for 2D PCA and ICA) and a few rank ordered samples closest to the test sample are selected based on the fused decision given by 2D PCA and ICA classifiers. These objects have overall similarity in appearance with respect to the input test sample. Linear subspace analysis thus acts as a generic classifier to identify such closely appearing objects. Shape matching is then performed using DT based correlation. The object with the minimum value of a sum of (a) appearance based fused ICA and 2D PCA distance (Eq. 1) and, (b) shape (rule as in [16]) cues using DT based matching (Eq. 2) is selected as the best match. The statistical analysis tool represents objects using second and higher order features, and DT based matching takes care of the response of the brain to boundaries of objects and shape features which match the test object with samples in memory. The manifold set of the object captures the perceptual properties of the human brain keeping the images of consecutive poses of objects which are visually similar in appearance, close to each other in the manifolds. The proposed criterion (for detailed flowchart, refer to Fig. 1) is evaluated on the COIL-100 [18] and IGOIL databases, and results are presented in the following section.

3 Experimental Results

We have conducted experiments using our proposed approach on two databases: COIL-100 (Columbia Object Image Library) [17] and IGOIL (IITM Generic Object Image Library) [19]. COIL-100 has been previously used by [1], [2], [7] to test the performance of their appearance based systems. To compare the performance of our proposed approach with the existing state-of-art techniques, we have used COIL-100 Database which contains color images of 100 objects. Images are taken at pose intervals of 5 degrees (72 poses per object). A part of the gallery used has been shown in Fig. 4. However, COIL-100 gallery contains images of objects along only one axis of rotation. To analyze the performance of the proposed methodology for recognition from arbitrary viewpoints, we have generated our own image gallery of objects along two orthogonal axes of rotation. The details of the experimental set up and the results of the application of fused appearance and shape classifier is presented in this section.

IITM Generic Object Image Library (IGOIL): [19] We have captured images of 20 objects along two orthogonal axes of rotation. In general, more than two orthogonal axes of rotation can be used to increase the robustness of the classifier to recognize from arbitrary viewpoints. However, since most of the objects in our gallery have similar appearance along two out of the three axes, we have used only two axes of rotations to capture the object appearances from several viewpoints. Images are taken at pose intervals of 5 degrees along each axis. This corresponds to 144 images per object. The images of objects were taken using a 35mm Sony CCD camera. Ambient light was used to avoid strong shadows. Each object's images along two orthogonal axes of rotation were taken by placing it on a turnable. The images taken by the camera were cropped and size normalized and rescaled to 128 × 128. The images had uniform black background and there was no occlusion. The 0 degree pose angle views of some objects along two orthogonal axes of rotation is shown in Fig. 5. Experiments

Fig. 4. Sample Objects from COIL-100

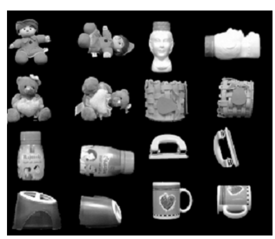


Fig. 5. Sample Objects from IGOIL

were conducted separately for both the databases with a part of the gallery chosen for training and the rest for testing. Different experiments were performed with training samples chosen for all objects from each database in the gallery, obtained at increments of every 10, 15, 20, 25 and 30 degrees. The framework was trained (separately for each experimentation) using each of these five training sets. The performance was analyzed using four and eight test samples (4 test samples from each orthogonal axis) per object for COIL-100 (400 test samples) and IGOIL (160 test samples) respectively, selected at random from the rest of the gallery.

3.1 Appearance Based Recognition

Fig. 6 show images of an object from IGOIL database along three orthogonal axes of rotation along with its corresponding manifold set captured using 2D PCA and ICA. For ease of visualization, we have displayed the manifolds using only the first three eigenvectors/ICs. For rest of the experimentation, we have used 10 eigendimensions for 2D PCA on both COIL-100 and IGOIL databases for better separability. We have selected 110 and 45 ICs for ICA on COIL-100 and IGOIL databases respectively. These dimensions was selected empirically by running experiments for 3-20 dimensions with 2D PCA and 10-125 ICs with ICA on both the databases. In order to have control over the number of ICs extracted by the algorithm, we have adopted the method used on face images in [13] for ICA. Given that the two linear subspace analysis based classifiers provide comparable

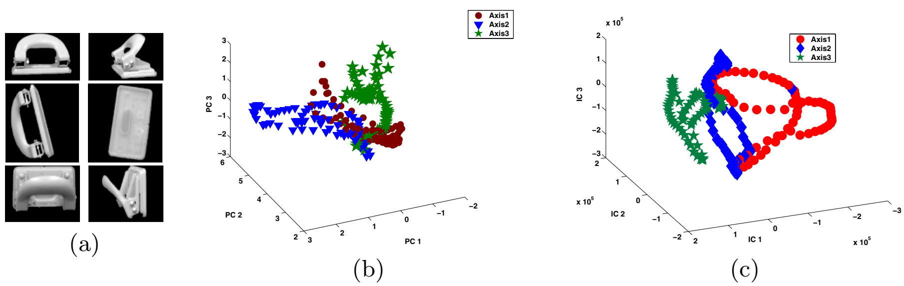


Fig. 6. (a) An object from IGOIL database along three orthogonal axes of rotation (only two views shown for each axis). (b) Parametric Eigenspace (2D PCA) for an object in (a). (c) Parametric IC Space (ICA) for an object in (a). Appearance is represented by a Manifold Set where each manifold corresponds to one axis of rotation.

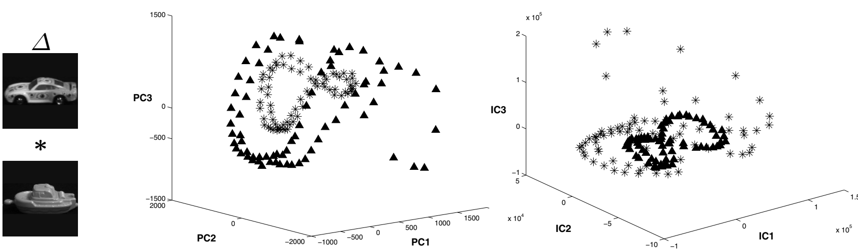
recognition performances, we examined whether the two representations gave similar patterns of errors on object images. There are objects which only either of the two classifiers are able to recognize. Fig. 7 (a) shows some objects for which 2D PCA worked but ICA failed. Fig. 7 (b) shows a set of objects for which ICA worked but 2D PCA failed. When the two algorithms made errors, however, they did not assign the same incorrect identity. Because the errors made by the two algorithms differed, a combined classifier was employed in which the similarity between a test image and a gallery image was defined by D_{comb} (Eq. 1). The comparison of percentage accuracy of the fused classifier (using D_{comb}), 2D PCA (D_{2DPCA}) and ICA (D_{ICA}) on COIL-100 database has been shown in Fig. 9.

(a) (b)

Fig. 7. Set of Objects from COIL-100 Database for which (a) 2D PCA succeedes but ICA fails and (b) ICA succeedes but 2D PCA fails

The recognition accuracies using D_{2DPCA}, D_{ICA} and D_{comb} on IGOIL database for 160 test samples (8 test samples per object) are shown in Table 1.

Need for Shape Matching: Linear Subspace analysis techniques (2D PCA and ICA) give good results for objects having distinct appearance and shape characteristics but fail for objects which are similar in appearance, but with minor differences in shape. Fig. 8 (a) and (b) show manifolds of two objects from COIL-100 database generated using (first three eigenvectors) 2D PCA and ICA respectively. The linear subspace techniques show an overlap in the eigenspace/IC space (i.e. both methods fail to discriminate). In such cases, use of shape properties gives an advantage over appearance based schemes to recognize objects from multiple viewpoints. We hence propose the use of shape properties to discriminate such objects and verify the results obtained by 2D PCA/ICA.



(a) (b)

Fig. 8. a: Universal Eigenspace (2D PCA) of two objects from COIL-100 database with similar appearance properties; b: IC Space of two objects showing an overlap. Overlap in both 2D PCA and ICA space suggests the use of a shape verification stage.

3.2 Improving Recognition Performance Using Shape Matching

Using linear subspace analysis we first select a set of rank-ordered samples (10 and 3 for COIL-100 and IGOIL respectively) based on their distances in eigenspace / IC Space. Increasing the number of rank-ordered samples does not alter the performance of the system by much, but increases the computational complexity. The number of rank-ordered samples selected is empirically set to approximately 10% of the total number of objects in the database. These samples are then matched with the test object based on shape features and the object with minimum distance of appearance and shape cues is returned as the best match. The criterion for object recognition using combination of 2D PCA and DT based correlation with 2D PCA and ICA are:

$$\mathbf{D}_{\xi} = D_{2DPCA} + DT_{corr} \quad \mathbf{D}_{\rho} = D_{ICA} + DT_{corr} \tag{3}$$

The values of D_{2DPCA}, D_{ICA} and DT_{corr} are normalized using Max normalization, before D_{ξ} and D_{ρ} are computed. Analysis is also conducted for recognition from arbitrary viewpoints on IGOIL database.

Fusion of combined 2D PCA and ICA system with Shape cues for Recognition: The proposed criterion for object recognition using combination of 2D PCA, ICA and DT based shape cues is

$$D_{\lambda} = D_{comb} + DT_{corr} \tag{4}$$

where D_{comb} and DT_{corr} are defined in Eq. 1 and 2 respectively. Fig. 10 shows the comparison of recognition accuracies using D_{ξ} (2DPCA and Shape), D_{ρ} (ICA and Shape) and D_{λ} on COIL-100 Database. Table 1 shows the comparison of recognition accuracies of D_{ξ}, D_{ρ} and D_{λ} on IGOIL database for recognition along multiple orthogonal axes. Note (in Fig. 10 and Table 1) that neither D_{ξ} nor D_{ρ} performs consistently better than the other. However, D_{λ} works better than both D_{ξ} and D_{ρ} for varying number of training samples given to the classifiers on both COIL-100 and IGOIL databases. The proposed approach gives peak recognition accuracies of 96.375% using 2DPCA, 97.675% with D_{ξ}, 97% using

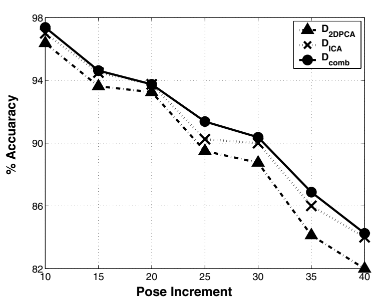


Fig. 9. Comparison of performance of D_{2DPCA} (EigenDimensions=10), D_{ICA} (No. of ICs=110) and D_{comb}. The percentage accuracy is shown as a function of the number of training samples (pose interval).

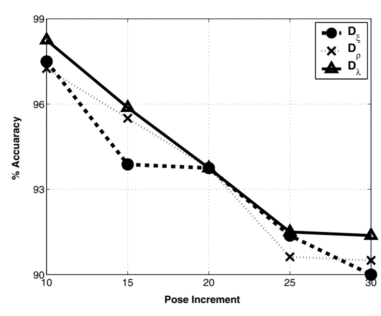


Fig. 10. Comparison of performance of the proposed method using D_{λ} , D_{ρ} and D_{ξ} on COIL-100 Database in case where the number of Independent Components=110 and Number of eigenvectors=20

ICA, 97.25% using D_ρ and 98.25% using D_λ, when tested with 400 samples on the entire COIL-100 database (pose interval of 10 degrees) containing 100 objects. The method provides a recognition rate of 91.375% with D_λ even when a sparse database was used for training. We compare the performance of our proposed method with that of Murase and Nayar [1] and Nagabhushan [2] as benchmarks which report a 100% recognition performance on 20 objects preselected from the COIL database. Most methods in the literature use only a subset of the 100 objects (typically 20 to 30) from COIL-100 database for experiments. Table 2 shows a comparision of recognition rates of techniques proposed by [1], [2] and [7] with our proposed framework. Our results provide better performance than those reported in [1], [2] and [7], given the fact that we have tested our approach on the entire 100 objects in the COIL database. Fusion of 2D PCA, ICA and DT based shape matching (D_λ) is shown to perform better than all other techniques. The comparison of recognition accuracies of D_{2DPCA}, D_{ICA}, D_ξ, D_ρ and D_λ on IGOIL database is shown in Table 1.

3.3 Results in Cluttered Background

To recognize objects from a cluttered background, we segment the given test image to extract the required object from the cluttered background (selective visual attention) and then recognize it. In segmentation phase, GrabCut [19] is used to extract the required foreground image from background with minimum user interaction. Results are shown in Fig. 11(a) and 11(b) for two different objects with varying background. Failures in segmentation can occur in two cases (i) regions of low contrast at the transition from foreground to background (ii) camouflage, in which the true foreground and background distributions overlap partially in color space (iii) background material inside the user rectangle but not belonging to the object of interest. Recognition is then performed using the technique explained in Fig. 1. The proposed approach gives good results in recognizing objects from highly cluttered backgrounds. We have tested our approach on 10 cluttered scene images. Fig. 11 shows the scenes, the extracted foreground object and the recognized object from the gallery.

(a) (b) (c) (d) (e) (f)

Fig. 11. (a) and (d) Cluttered scenes with user selected ROI. (b) and (e) Extracted object using GrabCut. (c) and (f) Recognized object from IGOIL.

Table 1. Comparison of recognition accuracies of D_{2DPCA}, D_{ICA}, D_{comb}, D_{ξ}, D_{ρ} and D_{λ} on IGOIL database with number of independent components=45 and number of eigenvectors for 2DPCA=15 using 160 test samples (8 test samples per object)

Pose	**Recognition Criterion**					
Interval	D_{2DPCA}	D_{ICA}	D_{comb}	D_{ξ}	D_{ρ}	D_{λ}
10	98.75	98.75	98.75	99.375	99.375	**99.688**
15	96.25	95.875	96.875	95.938	96.25	**96.875**
20	92.813	95.625	95.625	95.625	96.563	**96.563**
25	91.25	91.875	91.875	92.5	91.875	**92.813**
30	90.625	91.563	91.75	93.438	92.813	**93.75**

Table 2. Comparison of Recognition Rates of 1D PCA, 2D PCA, SVM, ICA and proposed framework (with D_{λ} as distance measure) on COIL-100 Database with 10 degree pose interval (36 training samples per object for training)

Technique	Reference	No. of Objects	No. of Test Samples	%Accuracy
IDPCA	[1]	20^a	720	100
2DPCA	[2]	20^a	720	100
		100^b	400	96.375
			3600	95.468
SVM	[7]	32^a	1152	96.03
ICA		100^b	400	97
			3600	96.639
Proposed (D_{λ})		100	400	**98.25**
			3600	**97.694**

^{a}results reported in literature; ^{b}our implementation

4 Conclusion

We present an efficient framework to Generic Object Recognition from arbitrary viewpoints using a combination of appearance and shape features. We use a fusion of two linear subspace analysis (2D PCA and ICA) techniques to reduce the search space to a few objects and then select the closest match using a sum of distances in linear subspace and DT based shape matching. The proposed method outperforms the recognition accuracy of the existing schemes of using only 1D PCA, 2D PCA and SVM for object recognition and also can capture the appearance manifold set of objects along multiple axes. There is however, a scope for analysis of the performance of the proposed technique for generic object recognition in presence of illumination variance and occlusion.

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