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Recognition of face images using Canonical collection

Gompanabilli Hema Latha & Prof. K.V. Ramana
(M.Tech,) Department of CST, A.U.College of Engineering (A) Andhra University, Visakhapatnam
(B.E, M.E,Ph.D)
Department of CST, A.U.College of Engineering (A) Andhra University, Visakhapatnam

Abstract

We address the problem of comparing sets of images for object recognition, where the sets may represent variations in an object's appearance due to changing camera pose and lighting conditions. Canonical Correlations (also known as principal or canonical angles), which can be thought of as the angles between two d-dimensional subspaces, have recently attracted attention for image set matching. Canonical correlations offer many benefits in accuracy, efficiency, and robustness compared to the two main classical methods: parametric distribution-based and nonparametric sample-based matching of sets. Here, this is first demonstrated experimentally for reasonably sized data sets using existing methods exploiting canonical correlations. Motivated by their proven effectiveness, a novel discriminative learning method over sets is proposed for set classification. Specifically, inspired by classical Linear Discriminant Analysis (LDA), we develop a linear discriminant function that maximizes the canonical correlations of within-class sets and minimizes the canonical correlations of between-class sets. Image sets transformed by the discriminant function are then compared by the canonical correlations. Classical Orthogonal Subspace Method (OSM) is also investigated for the similar purpose and compared with the proposed method. The proposed method is evaluated on various object recognition problems using face image sets with arbitrary motion captured under different illuminations and image sets of 500 general objects taken at different views. The method is also applied to object category recognition using ETH-80 database. The proposed method is shown to outperform the state-of-the-art methods in terms of accuracy and efficiency.

KEYWORDS

Object Recognition, Face Recognition, Image Sets, Canonical Correlation, Principal Angles, Canonical Correlation Analysis, Linear Discriminant Analysis, Orthogonal Subspaces

1. INTRODUCTION

This project represents a novel method of object recognition using image sets, which is based on canonical correlations. The previous conference version has been extended by a more detailed discussion of the key ingredients of the method and the convergence properties of the proposed learning, as well as by reporting the results of additional experiments on face recognition and general object category recognition using the ETH80 database. The main contributions of this paper are as follows: First of all, as a method of comparing sets of images, the benefits of canonical correlations of linear subspaces are explained and evaluated. Extensive experiments comparing canonical correlations with both classical methods (parametric model-based and nonparametric sample- based matching) are carried out to demonstrate these advantages empirically. A novel method of discriminant analysis of canonical correlations is then proposed. A linear discriminant function that maximizes the canonical correlations of within-class sets and minimizes the canonical correlations of between-class sets is defined, by analogy to the optimization concept of LDA. A novel iterative optimization algorithm finds the linear mapping. Image sets transformed by the discriminate function are then compared by canonical correlations. The discriminative capability of the proposed method is shown to be significantly better than both, the method that simply aggregates canonical correlations andthe kNN method applied to image vectors transformed by LDA. Interestingly, the proposed method exhibits very good accuracy as well as other attractive properties: low computational matching cost and simplicity of feature selection. The proposed iterative solution is further compared with classical orthogonal subspace method (OSM), devised to make different subspaces orthogonal to each other. As canonical correlations are only determined up to rotations within subspaces, the canonical correlations of subspaces of between-class sets can be minimized by orthogonal zing those subspaces. To our knowledge, the close

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relationship of the orthogonal subspace method and canonical correlations has not been noted before. It is also interesting to see that OSM has a close affinity to CMSM. The proposed method and OSM are assessed experimentally on diverse object recognition problems: faces with arbitrary motion under different lighting, general 3D objects observed. From different viewpoints, and the ETH80 general object category database. The new techniques are shown to outperform the state-of- The-art methods, including OSM/CMSM and a commercial face recognition software, in terms of accuracy and efficiency.

II. EXISTING SYSTEM

Relevant previous approaches to set matching for set classification can be broadly partitioned into parametric model-based [17, 34] and non-parametric sample-based methods [12, 14]. In the model-based approaches, each set is represented by a parametric distribution function, typically Gaussian. The closeness of the two distributions is then measured by the Kullback- Leibler Divergence (KLD) [6]. Due to the difficulty of parameter estimation under limited training data, these methods easily fail when the training and novel test sets do not have strong statistical relationships.Rather more relevant methods for comparing sets are based on matching of pairwise samples of sets, e.g. Nearest Neighbour (NN) and Hausdorff distance matching [12, 14]. The methods are based on the premise that similarity of a pair of sets is reflected by the similarity of the modes (or NN samples) of the two respective sets. This is certainly useful in many computer vision applications where the data acquisition conditions may change dramatically over time. For example, as shown in fig. 1 (a), when two sets contain images of an object taken from different views but with a certain overlap in views, global data characteristics of the sets are significantly different making the model-based approaches unsuccessful. To recognise the two sets as the same class, the most effective solution would be to find the common views and measure the similarity of those parts of data. In spite of their rational basis, the non-parametric sample-based methods easily fail, as they do not take into account the effect of outliers as well as the natural variability of the sensory data due to the 3D nature of the observed objects. Note also tha t such methods are very time consuming as they require a comparison of every pair of samples drawn from the two sets.The above discussion is concerned purely with how to quantify the degree of match between two sets, that is, how to define similarity of two sets. However, the other important problem in set classification is how to learn discriminative function from training data associated with a given similarity function. To our knowledge, the topic of discriminative learning over sets has not been given a proper attention in the literature. In this paper, we interpret the classical

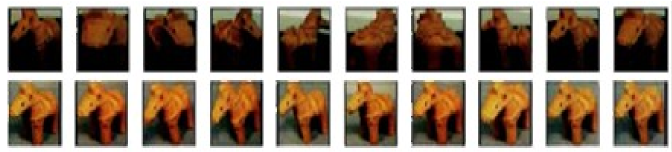

Fig. 1: Two Sets (Top and Bottom) Contain Images of a 3D Object Taken From Different Views But With a Certain Overlap in Their Views

Fig. 2: Two Face Image Sets (Top and Bottom) Collected From Videos Taken Under Different Illumination Settings. Face Patterns of the Two Sets Vary in Both Lighting and Pose.

Linear Discriminant Analysis (LDA) [14], [7] and its non-parametric variants,analogy to the optimization concept of LDA. The linear mapping is found by aNon-parametric Discriminant Analysis (NDA) [19], as techniques of discriminativenovel iterative optimization algorithm. Image sets transformed by the discriminantlearning over sets (See Section II-A). LDA has been recognizedas a powerfulfunction are then compared by canonical correlations. As canonical correlationsmethod for face recognition based on a single face image as input. The methodsare only determined up to rotations within subspaces, the canonical correlationsbased on LDA have been widely advocated in the literature [7], [9], [29], [30],of subspaces of between-class sets can be minimized by orthogonal zing those[35], [18]. However, note that these methods do not consider multiple input images. Subspaces. To our knowledge, the close relationship of the orthogonal subspacewhen they are directly applied to set classification based on sample matching, method and canonical correlations has not been noted before. It is also interestingthey inherit the drawbacks of the classical non-parametric sample-based methods to see that OSM has a close affinity to CMSM. The proposed method and OSM areas discussed above. Relatively recently the concept of canonical correlations has assessed experimentally on diverse object recognition problems: faces with arbitraryattracted increasing attention for image set matching in [36], [8], [23], [24], [37],motion under different lighting, general 3D objects observed from different view[27], [39], following the early works [1], [3], [5], [2]. As a method for comparing points and the ETH80 general object category database. The new techniques aresets, the benefits of canonical correlations over both parametric distribution-based shown to outperform the state-of-the-art methods, including OSM/CMSM and aand sample-based matching, have been noted in our earlier work [36] as well as commercial face recognition software, in terms of accuracy and efficiency.in [34]. They include efficiency, accuracy and robustness. This will be discussed Discriminant-Analysis of Canonical Correlations (DCC)and demonstrated in a more detailed and rigorous manner. Canonical correlations, which are cosines of principal angles.

K-Nearest Neighbor Features

All instances correspond to points in an n-dimensional Euclidean space

Classification is delayed till a new instance arrives

Classification done by comparing feature vectors of the different points

Target function may be discrete or real-valued

An arbitrary instance is

represented by

$(a_1(x), a_2(x), a_3(x),.., a_n(x))$

$a_i(x)$ denotes features

Euclidean distance between two instances

$d(x_i, x_j)$=sqrt (sum for r=1 to n (ar (x_i) - $a_r(x_j))^2$)

Continuous valued target function

mean value of the k nearest training examples.

III. PROPOSED SYSTEM

A nonlinear extension of canonical correlation has been proposed in [36], [23], [26] and a feature selection scheme for the method in [36]. The Constrained MutualSubspace Method (CMSM) [24][37] is the most related to the approach of this paper. In CMSM, a constrained subspace is defined as the subspace in which the entire class population exhibits small variance. The authors showed that the sets of different classes in the constrained subspace had small canonical correlations.However, the principle of CMSM is rather heuristic, especially the process of selecting the dimensionality of the constrained subspace. If the dimensionality is too low, the subspace will be a null space. In the opposite case, the subspace simply captures all the energy of the original data and thus cannot play the role ofa discriminant function. This paper presents a novel method of object recognition using image sets, which is based on canonical correlations. The previous conferenceversion [38] has been extended by a more detailed discussion of the key ingredients of the method and the convergence properties of the proposed learning, as wellas by reporting the results of additional experiments on face recognition and general object category recognition using the ETH80 [25] data base. The main contributions of this paper are as follows: First of all, as a method of comparing sets of images, the benefits of canonical correlations of linear subspaces are explained and evaluated. Extensive experiments comparing canonical correlations with both classical methods (parametric model-based and non-parametric sample-basedmatching) are carried out to demonstrate these advantages empirically. A novel method of discriminant analysis of canonical correlations is then proposed. A lineardiscriminant function that maximizes the canonical correlations of within-class sets and minimizes the canonical correlations of between-class sets is defined, byanalogy to the optimization concept of LDA. The linear mapping is found by a novel iterative optimization algorithm. Image sets transformed by the discriminant function are then compared by canonical correlations. As canonical correlations are only determined up to rotations within subspaces, the canonical correlations of subspaces of between-class sets can be minimized by orthogonalizing those subspaces. To our knowledge, the close relationship of the orthogonal subspace method and canonical correlations has not been noted before. It is also interesting to see that OSM has a close affinity to CMSM. The proposed method and OSM are assessed experimentally on diverse object recognition problems: faces with arbitrary motion under different lighting, general 3D objects observed from different view points and the ETH80 general object category database. The new techniques are shown to outperform the state-of-the-art methods, including OSM/CMSM and a commercial face recognition software, in terms of accuracy and efficiency.

Discriminant-Analysisof Canonical Correlations (DCC)

canonical correlations, which are cosines of principal angles

$0 \leq \theta_1 \leq \ldots \leq \theta_d \leq (\pi/2)$

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between any two d-dimensionallinear subspaces L1 and L2 are uniquely defined as:

$$\cos\theta_i = \max_{\mathbf{u}_i \in \mathcal{L}_1} \max_{\mathbf{v}_i \in \mathcal{L}_2} \mathbf{u}_i^T \mathbf{v}_i$$

As shown in Fig 3 canonical correlations of two different image sets of the same object acquired in different conditions proved to be a promising measure ofsimilarity of the two sets. This suggests that by matching based on image sets one could achieve a robust solution to the problem of object recognition even whenthe observation of the object is subject to extensive data variations. However, it is further required to suppress the contribution to similarity of canonical vectors of two image sets due to common environmental conditions (e.g., in lightings, view points, and backgrounds) rather than object identities. The optimal discriminantfunction is proposed to transform image sets so that canonical correlations of within-class sets are maximized while canonical correlations of between-class setsare minimized in the transformed data space.

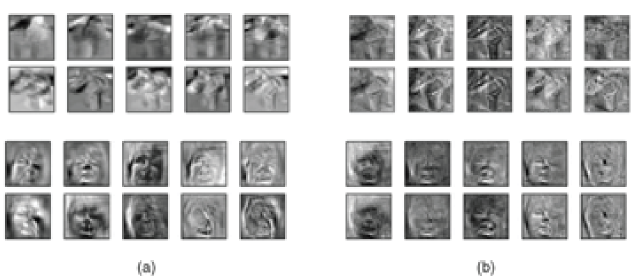

Fig. 2: Principal Components Versus Canonical Vectors. (a) The First Five PrincipalComponents Computed from the Four Image Sets Shown in fig. 1.The principal components of the different image sets are significantly different.(b) The first five canonical vectors of the four image sets, which are computed foreach pair of the two image sets of the same object. Every pair of canonical vectors(each column) U;V well captures the commonmodes (views and illuminations) of the two sets containing the same object. The pairwise canonical vectors are quite similar. The canonical vectors of differentdimensions u1; . . . ; u5 and v1; . . . ; v5 represent different pattern variations, e.g.,in pose or lighting.

IV. PROBLEM FORMULATION

Assume sets of vectors are given as {X1; . . . ;Xm}, where Xi describes a data matrix of the ith set containing observation vectors (or images) in its columns. Each set belongs to one of object classes denoted by Ci. A d-dimensional linear subspace of the ith set is represented by an orthonormal basis matrix , where A,i;Pi are the eigenvalue and eigenvector matrices of the d largest eigenvalues, respectively, and N denotes the vector dimension. We define a transformation matrix where n <N The matrix T transforms images so that the transformed image sets are class-wise more discriminative using canonical correlations.

Representation. Orthonormal basis matrices of the subspaces of the transformed data are obtained from the previous matrix factorization of $\mathbf{X}_i\mathbf{X}_i^T$:

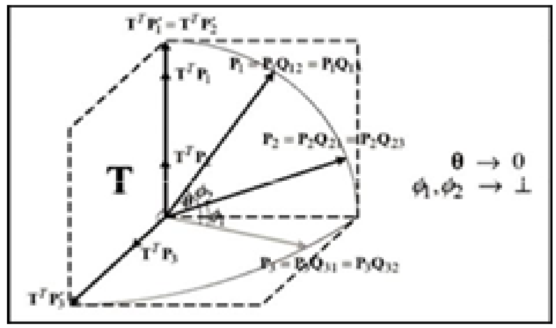

Fig. 3: Conceptual Illustration of the Proposed Method.

Here, the three sets represented by the basis vector matrices P_i; i= 1; . . . ; 3 are drawn.

We assume that the two sets P_1; P_2 are within-class sets and the third one is coming from the other class. Canonical vectors P_iQ_{ij}; i=1. . . ; 3; j ≠ i are equivalent to basis vectors P_i in this simple drawing where each set occupies a one-dimensional space. Basis vectors are projected on the discriminative subspace by T and normalized such that |T T P ‘|=1. Then, the principal angle of within-class sets, θ becomes zero and the angles of between-class sets, Φ_1 Φ_2 are maximized.

$$\mathbf{Y}_i\mathbf{Y}_i^T = (\mathbf{T}^T\mathbf{X}_i)(\mathbf{T}^T\mathbf{X}_i)^T \simeq (\mathbf{T}^T\mathbf{P}_i)\mathbf{\Lambda}_i(\mathbf{T}^T\mathbf{P}_i)^T.$$

Except when T is an orthogonal matrix, TT Pi is not generally an orthonormal basis matrix. Note that canonical correlations are only defined for orthonormal basis matrices of subspaces. Any orthonormal components of TT Pi now defined by TTP’$_i$ can represent an orthonormal basis matrix of the transformed data. Set Similarity. The similarity of any two transformed data sets represented by T TP$_i$’ ,TTP$_j$’ is defined as the sumof canonical correlations by

$$F_{ij} = \max_{\mathbf{Q}_{ij},\mathbf{Q}_{ji}} \mathrm{tr}(M_{ij}),$$

$$M_{ij} = \mathbf{Q}_{ij}^T\mathbf{P}_i'^T\mathbf{T}\mathbf{T}^T\mathbf{P}_j'\mathbf{Q}_{ji} \text{ or } \mathbf{T}^T\mathbf{P}_j'\mathbf{Q}_{ji}\mathbf{Q}_{ij}^T\mathbf{P}_i'^T\mathbf{T},$$

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astr(AB)=tr(BA) for any matrix A;B. Qij;Qji are therotation matrices similarly defined in the SVD solution of canonical correlations with the two transformed subspaces.

Discriminant Function. The discriminative function (or matrix) T is found tomaximize the similarities of any pairs of within-class sets while minimizing the similarities of pairwise sets of different classes. Matrix T is defined with the objective function J by

$$\mathbf{T} = \arg\max_{\mathbf{T}} J = \arg\max_{\mathbf{T}} \frac{\sum_{i=1}^{m} \sum_{k \in W_i} F_{ik}}{\sum_{i=1}^{m} \sum_{l \in B_i} F_{il}},$$

where the indices are defined as W_i ={ $j|X_j \in C_i$} and B_i = {$j|X_j \notin C_i$}. That is, the two index sets Wi; Bi denote, respectively, the within-class and between-class sets for a given set of class i, by analogy to [19]. See Fig. 3 for the concept of the proposed problem. In the discriminative subspace represented by T, canonical correlations of within-class sets are to be maximized and canonical correlations of between-class sets to be minimized

Table 1: Proposed Iterative Algorithm for Finding T, Which Maximizes Class Separation in Terms of Canonical Correlations?

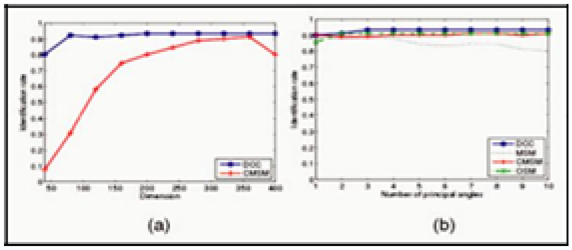
Algorithm 1. Discriminant-analysis of Canonical Correlations (DCC)

Input: All $\mathbf{P}_i \in \mathbb{R}^{N \times d}$ **Output:** $\mathbf{T} \in \mathbb{R}^{N \times n}$

1. $\mathbf{T} \leftarrow \mathbf{I}_N$
2. Do iterate the following:
3. For all i, do QR-decomposition: $\mathbf{T}^T\mathbf{P}_i = \mathbf{\Phi}_i\mathbf{\Delta}_i \rightarrow \mathbf{P}'_i = \mathbf{P}_i\mathbf{\Delta}_i^{-1}$
4. For every pair i, j, do SVD: $\mathbf{P}'^T_i\mathbf{T}\mathbf{T}^T\mathbf{P}'_j = \mathbf{Q}_{ij}\mathbf{\Lambda}\mathbf{Q}^T_{ji}$
5. Compute $\mathbf{S}_b = \sum_{i=1}^{m}\sum_{l \in B_i}(\mathbf{P}'_l\mathbf{Q}_{li} - \mathbf{P}'_i\mathbf{Q}_{il})(\mathbf{P}'_l\mathbf{Q}_{li} - \mathbf{P}'_i\mathbf{Q}_{il})^T$, $\mathbf{S}_w = \sum_{i=1}^{m}\sum_{k \in W_i}(\mathbf{P}'_k\mathbf{Q}_{ki} - \mathbf{P}'_i\mathbf{Q}_{ik})(\mathbf{P}'_k\mathbf{Q}_{ki} - \mathbf{P}'_i\mathbf{Q}_{ik})^T$.
6. Compute eigenvectors $\{\mathbf{t}_i\}_{i=1}^{N}$ of $(\mathbf{S}_w)^{-1}\mathbf{S}_b$. $\mathbf{T} \leftarrow [\mathbf{t}_1, \ldots, \mathbf{t}_N]$
7. End
8. $\mathbf{T} \leftarrow [\mathbf{t}_1, \ldots, \mathbf{t}_n]$

V. K-NEAREST NEIGHBOR FEATURES

We have collected a database called the Cambridge-Toshiba Face Video Database with 100 individuals of varying age and ethnicity and, equally, represented genders. For each person, 14 (seven illuminations two recordings) video sequences of the person in arbitrary motion were collected. Each sequence was recorded in a different illumination setting for 10 s at 10 fps and at 320 x240 pixel resolution. an original image sequence and seven different lightings. Following automatic localization using a cascaded face detector [31] and cropping to a uniform scale of 20x20 pixels, images of faces were histogram equalized. Note that the face localization was performed automatically on the images of uncontrolled quality. Thus, it was not as accurate as any conventional face registration with either manual or automatic eye positions performed on high quality face images. Our experimental conditions are closer to the conditions given for typical surveillance systems.



(a) The effect of the dimensionality of the discriminative subspace on the proposed iterative method (DCC) and CMSM. The accuracy of CMSM at 400 is equivalent to that of MSM, a simple aggregation of canonical correlations.

(b) The effect of the number of canonical correlations on DCC

VI. CONCLUSIONSAND FUTURE WORK

A novel discriminative learning framework has been proposed for set classification based on canonical correlations. It is based on iterative learning which is theoretically and practically appealing. The proposed method has been evaluated on various object and object category recognition problems. The new technique facilitates effective discriminative learning over sets and exhibits an impressive set classification accuracy. It significantly outperformed the KLD method representing a parametric distribution-based matching and kNN methods in both PCA/LDA subspaces as examples of nonparametric sample-based matching. It also largely outperformed the method based on a simple aggregation of canonical correlations The canonical-correlation-based methods including the proposed method were also shown to be highly time efficient in matching, thus offering an attractive tool for recognition involving a large-scale database.

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