Volume 3, Issue 4, April 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Face Tracking Technique Using CKE and CCA

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Abstract*: In video surveillance, the faces of interest are often of small size. Image resolution is an important factor affecting face recognition by human and computer. In existing system a feature extraction method called coupled kernel embedding (CKE) is used for LR face recognition. The final kernel matrix is constructed by concatenating two individual kernel matrices in the diagonal direction. CKE solves this problem by minimizing the dissimilarities captured by their kernel Gram matrices. In the proposed system canonical correlation analysis (CCA) algorithm, also called Local discrimination CCA (LDCCA) along with coupled kernel embedding (CKE) is used for LR & HR face image recognition. . LDCCA method considers a combination of local properties and discrimination between classes. CCA can extract the features even though there is a wound in the face . In the proposed system the time complexity will be reduced. Automatic face recognition has long been established as one of the most active research areas in computer vision

Keywords : Face Recognition, Feature Extraction, CKE, CCA, Low Resolution, Super Resolution.

INTRODUCTION

A database consists of static images of human faces. Images were taken in uncontrolled indoor environment using cameras of various qualities. Automatic face recognition has long been established as one of the most active research areas in computer vision. Face recognition in unconstrained environments remains challenging for most practical applications. In contrast to traditional still-image based approaches, recently the research focus has shifted towards video based approaches. Video data provides rich and redundant information, which can be exploited to resolve the inherent ambiguities of image-based recognition like sensitivity to low resolution, pose variations and occlusion, leading to more accurate and robust recognition. Face recognition has also been considered in the content-based video retrieval setup, for example, character-based video search.

Figure 1

The A video camera produces images at a certain frame rate and depth of field, which impose physical limits on the spatial density of image detectors. Intuitively, recovering the lost information of LR face images first is a promising solution for achieving better performance. In fact, most existing two-step methods of LR face recognition exploit a preprocessing of SR as the first step. The super-resolved face images are then passed to the second step for recognition and classification. During the past decade, a number of learning- based SR methods have been proposed to predict the corresponding HR image from a single LR image or multiple LR images. Almost all the learning-based methods consider a linear projection subspace to solve the problem of computing similarity metrics between HR and LR images projection subspace to solve the problem of computing similarity metrics between HR and LR images computing similarity metrics between HR and LR images projection subspace to solve the problem of computing similarity metrics between HR and LR images. A new efficient kernel method for LR faces recognition without any SR preprocessing. According to the aim of recognition, learn a coupled kernel embedding (CKE) method to map the face images with different resolutions onto an infinite subspace and carry out the recognition step in the new space.

RELATED WORK

During the past decade, a number of learning-based SR methods have been proposed to predict the corresponding HR image from a single LR image or multiple LR images. Baker and Kanade propose "face hallucination" to infer the HR face image from an input LR face image based on face priors. Chang et al. propose a method based on locality linear embedding. Jia and Gong propose a multi linear approach to hallucinate face images across multiple modalities (generalization to variations such as facial expression or pose) based on a unified global and local tensor space representation. Li et al. solve SR reconstruction using a sparse directional regularization strategy for color images. Recently, several algorithms have been proposed to avoid explicit SR in the image domain. Hennings–Yeomans et al. propose a joint objective function that integrates the aims of SR and face recognition, which indeed improves the recognition rate

figure 2

., "How to measure the similarity (distance)?" In their words, in many cases, the task of LR face recognition may be reduced to the finding of a proper distance measure between an LR face image $\mathbf{I_I}$ £ $\mathbf{R^m}$ and an HR face image $\mathbf{h_j}$ £ $\mathbf{R^M}$.

$$\mathbf{d_{ij} = dist(l_i, h_j)} \qquad \textbf{(1)}$$

Obviously, some common distances (e.g., Euclidean distance or Mahalanobis distance) cannot be calculated directly since he dimensions of the LR and HR features are not equal due to $m < M$. To solve this problem, the traditional two-step methods exploit super-resolution (SR) functions to project the LR image onto the target HR space, and then calculate the distance in the HR space as

$$\mathbf{d_{ij} = dist(f_{sr}(l_i),h_j)} \qquad \textbf{(2)}$$

To analyze the super-resolution reconstruction constraints, In particular, derive a sequence of results which all show that the constraints provide far less useful information as the magnification factor increases. Therefore propose an algorithm that learns recognition-based priors for specific classes of scenes, the use of which gives far better super-resolution results for both faces and text. Generally, all super-resolution algorithms are based on the fundamental constraints that the super-resolution image should generate the low resolution input images when appropriately warped and down-sampled to model the image formation process.

PROBLEM DEFINITION AND ARCHITECTURE

The word recognition plays an important role in our life, It is a basic property of human beings. When a person sees an object he/she first gather all information about the object and compress its properties and behavior with existing knowledge stored in the mind, If we find the proper match recognize it. Same way in the case of face recognition ,if the system find the exact match of the image from database recognize it.

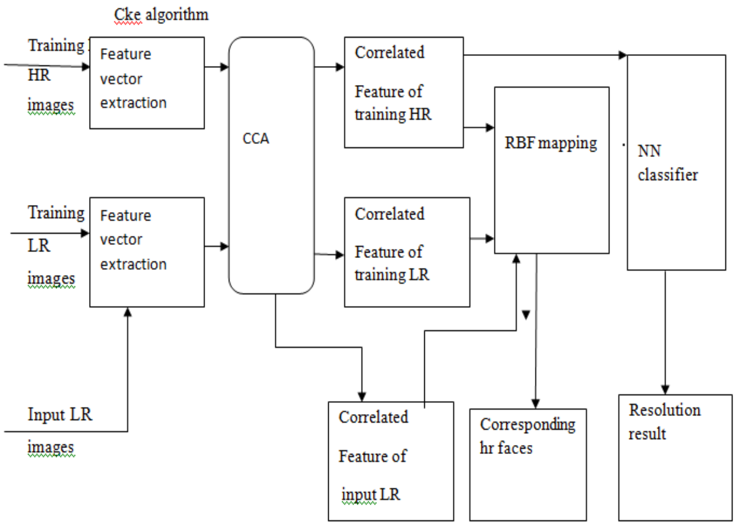

figure 3

Earlier there is pixel by pixel matching of images is considered..there is some problem when we consider the pixel by pixel mapping of images in the case of any missing parts of the images, or any wound present in the images etc..this is the main problem In the case of face recognition system..To overcome this we moves to the proposed system.

The architecture diagram of the project is given below.fig 3 Which describe the flow of the process..We are giving the input as the video and get the output as the exact match of the images. That is the exact recognition of the face. So here we are apply two algorithms coupled kernel embedding and the canonical correlation analysis algorithm. In the video there is high resolution and low resolution images are present. After the feature vector extraction we are applying the canonical correlation analysis algorithm into it. If any correlated feature is present between the images then makes a RBF mapping to the corresponding face.

ALGORITHMS

A. *Coupled Kernel Embedding (CKE)*

Kernel-based learning machines have aroused considerable interest in the fields of pattern recognition and machine learning. Kernel representation offers an alternative learning to nonlinear functions by projecting the data onto a high-dimensional Hilbert feature space to increase the computational power of the linear learning machines, though this still leaves unresolved the issue of how best to choose the features or the kernel function in ways that will improve performance.

$$\boldsymbol{\Phi}\colon \boldsymbol{R^M} \rightarrow \boldsymbol{V} \quad \boldsymbol{x} \rightarrow (x) \qquad \textbf{(3)}$$

Let $\boldsymbol{\Phi}$ be a nonlinear mapping, and the HR input data space $\boldsymbol{R^M}$ is mapped onto a (potentially much higher dimensional) feature vector in the feature space V.

CKE algorithm implemented on a binary classification problem. There are two modes including HR objects (squares and five-pointed stars) and their LR counterparts (triangles and circles) in the input space, where the squares and triangles belong to the first class, and the five-pointed stars and circles belong to the second class. It is well known that the nonlinear kernel mapping could transform complex distributed data onto high-dimensional.

Hilbert feature space where the data becomes linearly separable. Moreover, the kernel method and the inner product operation can be efficiently used to represent the nonlinear features in the reproducing kernel Hilbert space . The data points in the original individual input spaces onto different reproducible kernel Hilbert spaces by coupled nonlinear functions (fsr and gsr), i.e., At the same time, the samples coming from different modes or different classes may become more separable in the kernel spaces. Some special properties (e.g., isomorphic) may be endued to the Hilbert spaces V and W.

$$\boldsymbol{\Psi}\colon \boldsymbol{R}^{\mathrm{m}} \rightarrow \mathbf{w} \quad \mathbf{x} \rightarrow \boldsymbol{\psi}(\mathbf{x}) \qquad \textbf{(4)}$$

In the same way, let Ψ be another nonlinear mapping corresponding to LR images, and the input data $\boldsymbol{R}^{m}$ space with the other mode (m << M) can be mapped onto the feature space w. Then determine the embedding features using a locality-preserving projections (LPP) approach and implement the recognition stage in the learned embedding subspace by some classification procedure. It is worth noting that the target of implicit SR step is consistent with classification since the kernel mappings will be integrated well into a uniform objective function using the locality-preserving criterion, and the algorithm is very efficient and suitable for real-time applications.

CKE algorithm for recognition, and the detailed implementations are summarized as follows.

1)Compute the weight matrix. Use the HR samples hL(i =1, 2,...,N) to compute W.

2) Compute the kernels KH and K_L Compute the Gram matrices KH and KL using the kernel functions, where the super parameters are estimated by cross validation.

3) Generalized eigenvalue decomposition. Solve the 2N × 2N eigenvalue decomposition problem . Let u1,u2 ….ud be the leading eigenvectors associated with the first d smallest eigen values and denote which compose the optimal projection directions.

$$U^* = \begin{pmatrix} U_L^* \\ U_H^* \end{pmatrix} = [u_1, u_2, \ldots, u_d] \qquad \textbf{(5)}$$

4) Feature embedding.

$$z_t = U_L^{*T} \begin{pmatrix} \langle \Psi(l_1), \Psi(l_t) \rangle \\ \langle \Psi(l_2), \Psi(l_t) \rangle \\ \vdots \\ \langle \Psi(l_N), \Psi(l_t) \rangle \end{pmatrix} = U_L^{*T} \begin{pmatrix} \mathcal{K}_L(l_1, l_t) \\ \mathcal{K}_L(l_2, l_t) \\ \vdots \\ \mathcal{K}_L(l_N, l_t) \end{pmatrix}. \qquad \textbf{(6)}$$

5) Features matching and classification. We choose the Euclid distance as our similarity measure and use the nearest neighbor classifier as the final classification tool, then determine the predictive label of z

B. Canonical Correlation Analysis Algorithm (CCA)

A new feature extraction algorithm is developed based on canonical correlation analysis (CCA), called Local Discrimination CCA (LDCCA). The method considers a combination of local properties and discrimination between different classes. Not only the correlations between sample pairs but also the correlations between samples and their local neighborhoods are taken into consideration in LDCCA.

Effective class separation is achieved by maximizing local within-class correlations and minimizing local between-class correlations simultaneously. Besides, a kernel version of LDCCA (KLDCCA) is proposed to cope with nonlinear problems in experiments. The experimental results on an artificial dataset, multiple feature databases and face databases including ORL, Yale, AR validate the effectiveness of the proposed methods.

Canonical correlation analysis (CCA), just like Principal component analysis is an effective feature extraction method for dimensionality reduction and data visualization. PCA is a single-modal method, which deals with data samples obtained from a single information channel or view. In contrast, CCA is typically used for multi-view data samples. In order to improve the performance of CCA in classification tasks, so incorporate the idea of local discriminate analysis into CCA, which is referred to as LDCCA.

A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a database which contain facial images. It is typically used in security systems and can be compared to other biometrics such as fingerprint or eye iris recognition systems

V. Conclusion

This paper studied the impact of the number of learning based SR methods have been proposed to predict the corresponding HR image from a single LR image or multiple LR images. While the earlier existing algorithms are time consuming. Moreover these are not suitable for real-time application. In the proposed system Canonical Correlation Analysis (CCA) algorithm along with coupled kernel embedding (CKE) is used for LR and HR face image recognition. Semisupervised learning problems are the focus of our future work

ACKNOWLEDGMENT

I take this chance to express my deep sense of gratitude to our **Management**, our principal **Dr. B. Karthikeyan ,** for providing an excellent infrastructure and support to pursue this research work at our college. I express my profound thanks to Head of the department **Prof. J. Mercy Geraldine M.E.,(Ph.D)** for her administration and keen interest, which motivated me along the course as well as research work, and also thank to all staff members.

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