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Heterogeneous Feature Fusion-Based Recognition Framework with LBP

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Abstract : *A technique is proposed to extract system requirements for a maritime area surveillance system, based on an activity recognition framework originally intended for the characterization, prediction and recognition of intentional actions for threat recognition. To illustrate its utility, a single use case is used in conjunction with the framework to solicit surveillance system requirements. Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement, surveillance and more generally image understanding. In this paper we combine KLDA (combination of LBP and GABOR features) with gradient face features(which are more resistive to the noise effects) for more effective recognition process. Specifically, we make three main contributions: (i) we present a simple and efficient pre-processing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition; (ii) we introduce Local Ternary Patterns (LTP), a generalization of the Local Binary Pattern (LBP) local texture descriptor that is more discriminate and less sensitive to noise in uniform regions, and we show that replacing comparisons based on local spatial histograms with a distance transform based similarity metric further improves the performance of LBP/LTP based face recognition; and (iii) we further improve robustness by adding Kernel PCA feature extraction and incorporating rich local appearance cues from two complementary sources – Gabor wavelets and LBP – showing that the combination is considerably more accurate than either feature set alone.*

Keywords: *GABOR features, Local Ternary Patterns, LBP, face features.*

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I. Introduction

Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement, surveillance..Numerous approaches[1] have been proposed, including eigen faces, fisher faces, nearest feature line-based subspace analysis, neural networks, elastic bunch graph matching wavelets and kernel methods. Most of these methods were initially developed with face images collected under relatively well-controlled conditions and in practice they have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc Within the past decade, major advances have occurred in face recognition. Many methods [2] have been proposed for face recognition. However, the performance of most existing face recognition methods is highly sensitive to illumination variation. It will be seriously degraded if the training/testing faces under variable lighting. Thus, illumination variation is one of the most significant factor affecting the performance of face recognition and has received much attention in recent years. Many methods have been proposed to handle the illumination problem. In general, these methods can be divided into three main categories. The first approach uses image processing technique/model to normalize ace images under different illumination conditions. For instance, histogram equalization (HE) ,logarithm transform are widely used for illumination normalization. However, it is difficult for these image processing techniques to account for different lighting conditions. There have been models developed to remove lighting effects from images under illumination conditions. In this paper we combine LBP, LTP patterns GABOR FEATURES [3] and GRADIENT FACE features for face recognition purpose under difficult varying lighting conditions.

For visual recognition tasks, batch mode solution has been used for heterogeneous feature fusion. It is well known that batch solution approach has the limit of poor scalability, low efficiency, and high cost. It even becomes impractical to use batch solution approach when one has to handle millions of image samples. As a result, online learning algorithms have gained popularity for their high efficiencies in large-scale data analysis. Another advantage of online algorithm is the ability to “include human in the loop” with robotic vision. In this paper, we describe a novel online algorithm called in multiple Reproducing Kernel Hilbert Spaces [4] that combines group LASSO sparse method and dual averaging sub-gradient learning technique. This online algorithm is used to solve HFFM model efficiently and it can be used for a wide range of visual recognition tasks such as event recognition, object categorization and so on. Different than standard online MKL, the solution of HFFM tends to depend on a subset of low-noise samples. Group LASSO is used to select explanatory samples and remove noisy samples in HFFM model for the classifying function. In this paper, we propose a new unsupervised heterogeneous structure fusion (HSF) [5] algorithm which explicitly preserves and balances the two kinds of feature variability's by finding a unified feature projection. In the proposed HSF algorithm, we refer inter and intra-variability of feature sets as the external and internal feature structures, respectively, which are jointly formulated in one optimization framework. The objective function of HSF combines two features structures in a closed form which can be optimized alternately via linear programming and eigenvector methods. The HSF solution provides not only the optimal feature projection but also the weight coefficients that encode the relative importance and relevance between two kinds of structures and among multiple feature sets. The main contribution of this work is to explicitly and directly mine the relationship between internal and external feature structures by finding a unified feature projection that not only preserves the two kinds of structures and but also allows them to complement each other in an optimal way.

II. Methodology

Making recognition more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. We tackle this by combining the strengths of robust illumination normalization, local texture based face representations, and distance transform based matching, kernel-based feature extraction and multiple feature fusion.

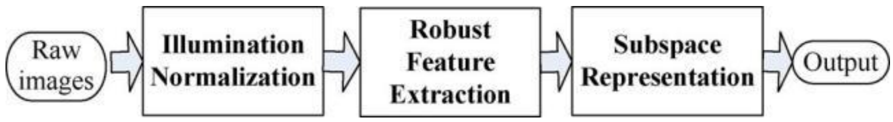

Figure 1: Stages of Full Face Recognition method

The proposed face recognision system consists of image normalization, feature extraction and subspace representation. Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. The method centres on a rich set of robust visual features that is selected to capture as much as possible of the available information. A welldesigned image preprocessing pipeline is prepended to further enhance robustness. The features are used to construct illumination-insensitive subspaces, thus capturing the residual statistics of the data with relatively few training samples.

III. HSF Algorithm

1. Structure Metrics

Given M data samples each of which is represented by N-channel D-dimensional feature vectors, we can encapsulate the input data in a matrix $X=[X_1,X_2, ...,X_N]^T$ (ND×M), where $X_k=[x_{k1},x_{k2}, ...,x_{kM}]^T$ (k=1,2, ..., N) is the k-th feature channel where $x_{kl}\in R^D$ is the kth-channel feature of the l-th sample. Similar to CCA or LPP, a feature projection of X_k is represented by $Y_k=[y_{k1},y_{k2}, ...,y_{kM}]^T$ where $y_{kl}\in R^d$ (d<<D) and which is expected to preserve certain feature structure, i.e., feature correlation in CCA or data similarity in LPP. Given a projection matrix A(ND×d), the input data X is projected to the fused data Y(d×M) via $Y=A^T X$.The goal of HSF is to find the optimal A that preserves internal and external feature structures with appropriate weighting coefficients. We will discuss some structure metrics used for two kinds of feature structures below.

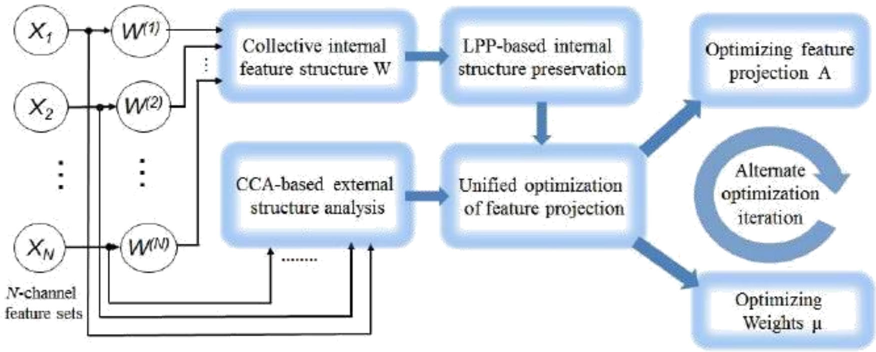

Figure 2: The internal and external feature structures are represented by LPP-based and CCA-based approaches and unified in one projection optimization framework.

The internal structure is represented by the similarity between data samples within the same feature set. Although the Euclidean metric is an often distance measurement for computing the data similarity, it is not suitable here due to the lack of the consideration of possible disconnected distribution in the feature space. On the other hand, the $\chi 2$ metric is more appropriate to capture the internal structure because it involves a normalization factor to cope with different distribution scales. Thus we adopt the $\chi 2$ metric as one option here due to easiness and convenience.

2. HSF Algorithm

The pseudo code of the proposed HSF algorithm is presented in Algorithm. N is the number of feature sets or channels, and Xp, Xq (p, q = 1, 2, ...,N) respectively is any feature set. Firstly, the similarity matrix of each feature set is computed to describe the internal structure from step 1 to step 3. Secondly, the orthonormal basis matrixes is calculated to encode the following the external structure from step 4 to step 9. At last, the weight of structures and projection matrix is solved by alternately iterative optimization from step 10 to step 17.

ALGORITHM: The pseudo code of the HSF algorithm
Input: $\mathbf{A} = I$ and $\mathbf{X} = [\mathbf{X}1,\mathbf{X}2, ...,\mathbf{X}N]^T$
Output: fused feature $\mathbf{Y} = \mathbf{A}^T\mathbf{X}$

1: **for** $0 < i < N$ **do**
2: Compute$\mathbf{W}^{(i)}$ according to (1)
3: **end for**
4: **for** $0 < p < N$ **do**
5: **for** $0 < q < N$ **do**
6: Compute $\mathbf{P}p$ from $\mathbf{X}p\mathbf{X}^Tp = \mathbf{P}p\mathbf{\Lambda}p\mathbf{P}^Tp$
7: Compute $\mathbf{P}q$ from $\mathbf{X}q\mathbf{X}^Tq = \mathbf{P}q\mathbf{\Lambda}q\mathbf{P}^Tq$
8: **end for**
9: **end for**
10: **for** $0 < i < T$ (T is the iteration number) **do**
11: $\mathbf{R}p$ and $\mathbf{R}q$ respectively are computed by the upper triangular matrixes of $\mathbf{A}^T\,\mathbf{P}p$ and $\mathbf{A}^T\,\mathbf{P}q$
12: $\mathbf{P}p$ and $\mathbf{P}q$ are normalized by $\mathbf{P}p\mathbf{R}^{-1}\,p$ and $\mathbf{P}q\mathbf{R}^{-1}q$
13: $\mathbf{Q}pq\mathbf{\Lambda}0\mathbf{Q}^Tqp$ is the SVD of $\mathbf{P}^Tp\,\mathbf{P}q \in R^{M\times M}$
14: Compute $\mathbf{O}$ according to (9)
15: Solve μ by optimizing (16)
16: Solve $\mathbf{A}$ by optimizing (14)
17: **end for**

IV. Experiments

In this section, we evaluate the performance of HSF in the ATR task on the Comanche IR database. In this database, there are 10 different military targets, and there are 72 orientations for each target (0°, 5°, ..., 355°). In addition, the database includes 874 to 1518 IR chips (40×75) for each target class, totaly 13859 chips.In Fig. 3, some chips is shown. The rows and columns are respectively the different targets and orientations. The experimental analysis has three aspects. First, the performance of different feature fusion methods are compared regarding the recognition accuracy to show their advantages to enhance the discrimination of features by mining their intrinsic structures. Second, we compare the HSF algorithm with the SRC-based methods which are considered as the-state-of-the-art ones in the field. Third, we further conduct the detailed analysis on the accuracy of pose estimation between HSF and SRC methods. Specifically, we extract two kinds of features from each IR chip, HOG (Histogram of Oriented Gradients) and LBP (local binary pattern) [1]. More features are possible, but these two are found to be more effective ones.

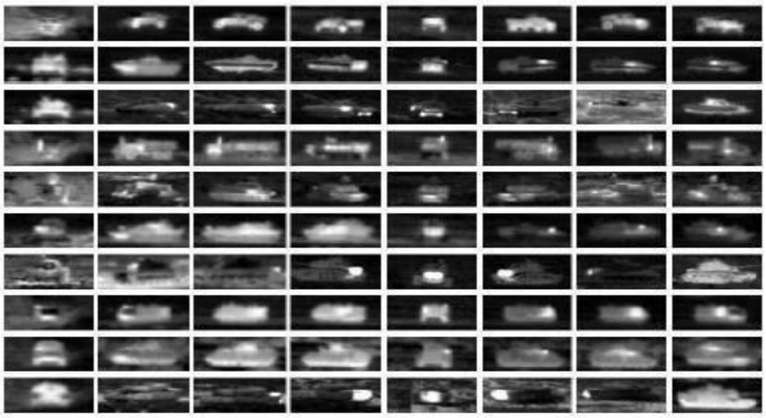

Figure 3: IR chips of 10 targets (row-wise) in 8 orientations in the Comanche database

V. Conclusion

We have presented a new unsupervised feature fusion algorithm for ATR in IR imagery, called Heterogenous Structure Fusion (HSF), which jointly and explicitly takes advantage of heterogenous structures among multiple feature sets, namely the internal and external structures. Specifically, the former one characterizes the distribution structure in each feature channel, and the latter one represents the correlation among all feature channels.

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