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 action recognition framework originally intended for the categorization, prediction and recognition of intentional actions for threat detection. To illustrate its utility, a single use case is used in concurrence with the framework to solicit surveillance system requirements. Face recognition has expected a great deal of consideration from the scientific and industrial community over the past several decades owing to its wide range of applications in information security and access control, law enforcement, observation and more generally image understanding. In this article we combine KLDA (combination of LBP and GABOR features) with incline face features(which are more resistive to the clamor effects) for more effective recognition process. Specifically, we make three main contributions: (i) we present a plain and efficient preprocessing chain that reduce most of the effects of changing enlightenment even as still preserving the important facade details that are needed for recognition; (ii) we set up Local Ternary Patterns (LTP), a simplification of the Local Binary Pattern (LBP) local texture descriptor that is more differentiate and less responsive to noise in consistent regions, and we show that replace contrast based on local spatial histograms with a reserve transform based correspondence metric additional improves the recital of LBP/LTP based face recognition; and (iii) we additionally improve strength by adding together Kernel PCA feature extraction and incorporating rich local appearance cues from two balancing sources – Gabor wavelets and LBP – showing that the mixture is considerably more accurate than either feature set alone.

I. INTRODUCTION

Face recognition has acknowledged a great deal of consideration from the scientific and industrial communities over the past numerous decades owing to its wide range of applications in information security and access control, law enforcement, surveillance. Several approaches have been expected, including eigenfaces, fisherfaces, laplacianfaces, nearest feature line-based subspace analysis, neural networks, elastic cluster graph matching wavelets and kernel methods. Most of these methods were in the beginning developed with face images collected under relatively well-controlled conditions and in practice they have difficulty in dealing with the series of facade variations that usually occur in unconstrained natural images due to enlightenment, pose, facial expression, aging, partial occlusions, etc. Within the past decade, major advances have occurred in face recognition. Many methods have been proposed for face recognition. However, the performance of most existing face recognition methods is highly responsive to enlightenment variation. It will be seriously degraded if the training/testing faces under variable lighting. Thus, enlightenment variation is one of the most significant factor affecting the performance of face recognition and has received much consideration in recent years. Many methods have been proposed to handle the enlightenment 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 enlightenment conditions. For instance, histogram equalization (HE) ,logarithm change are extensively used for enlightenment normalization. However, it is not easy for these image processing techniques to report for different lighting conditions. There have been models developed to remove lighting effects from images under enlightenment conditions. In this article we mingle LBP, LTP patterns GABOR FEATURES and GRADIENT FACE features for face recognition purpose under difficult varying lighting conditions. For visual recognition tasks, batch mode key 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 explain a novel algorithm called in numerous Reproducing Kernel Hilbert Spaces that combines cluster LASSO sparse method and twin averaging sub-gradient learning technique. This algorithm is used to resolve HFFM model professionally and it can be used for a wide range of visual recognition tasks such as event recognition, object categorization and so on. Unlike than standard online MKL, the solution of HFFM tends to depend on a split of low-noise samples. Group LASSO is used to choose illustrative samples and remove noisy samples in HFFM model for the classifying function. In this article, we recommend a new unproven heterogeneous structure fusion (HSF) algorithm which explicitly preserves and balances the two kinds of feature variabilities by discovery a united feature projection. In the proposed HSF algorithm, we pass on inter and intra-variability of aspect sets as the external and internal feature structures, respectively, which are jointly formulated in one optimization framework. The intention 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 best feature projection but also the load 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 gratitude more consistent under uncontrolled lighting conditions is one of the most significant challenges for practical face recognition systems. We deal with this by combining the strengths of robust enlightenment normalization, local texture based face representations, and distance transform based matching, kernel-based feature extraction and multiple feature fusion.

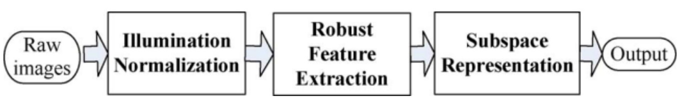

Fig.1: Stages of Full Face Recognition process

The proposed face recognition system consists of image normalization, feature mining and subspace representation. Each stage increases resistance to enlightenment variations and makes the information needed for recognition more manifest. The method centers on a rich set of robust visual features that is selected to capture as much as possible of the available information. A well considered image preprocessing pipeline is pretended to further improve robustness. The features are used to build enlightenment-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 $X=[X_1,X_2, ...,X_N]^T(ND\times M)$, 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 $A(ND\times d)$, the input data X is projected to the fused data $Y(d\times M)$ via $Y=A^TX$.The goal of HSF is to find the best possible 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.

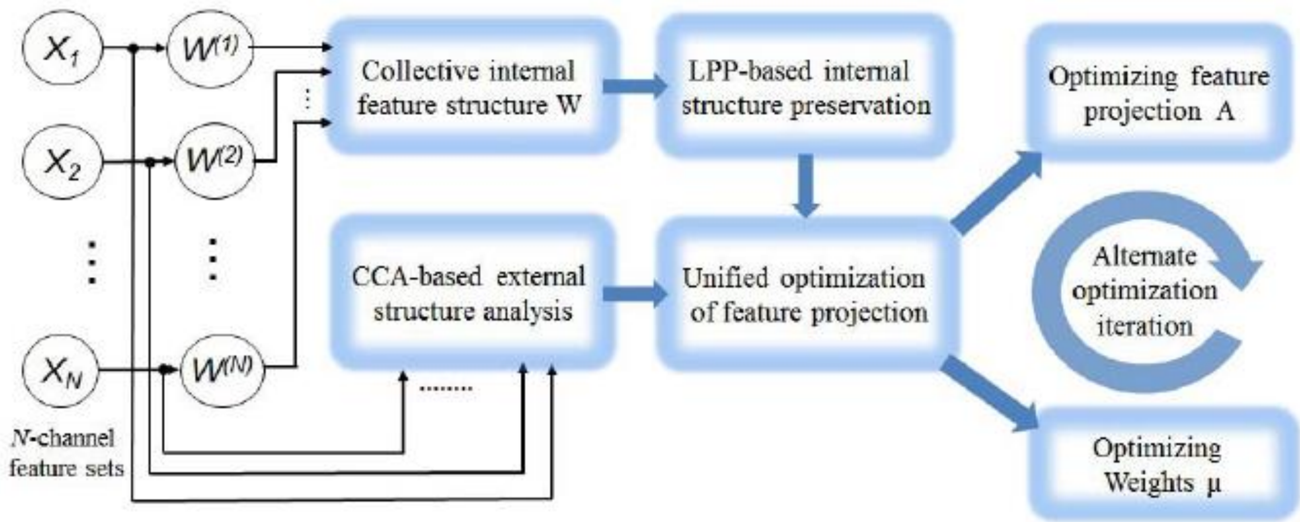

Fig.2: The internal and external feature structures are represented by LPP-based and CCA-based approaches

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 compute the information 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 suitable 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 $\mathbf{X}p,\mathbf{X}q$ (p, q = 1, 2, ...,N) respectively is any feature set. Firstly, the similarity matrix of every feature set is computed to portray the internal structure from step 1 to step 3. Secondly, the orthonormal base matrixes is calculated to encode the subsequent the external structure from step 4 to step 9. At last, the weight of structures and projection matrix is solved by alternately iterative optimization fromstep 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 $\mathbf{X}_p\mathbf{X}^T_p= \mathbf{P}_p\mathbf{\Lambda}_p\mathbf{P}^T_p$
7: Compute $\mathbf{P}_q$ from $\mathbf{X}_q\mathbf{X}^T_q= \mathbf{P}_q\mathbf{\Lambda}_q\mathbf{P}^T_q$
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: $\mathbf{Q}_{pq}\mathbf{\Lambda}_0\mathbf{Q}^T_{qp}$ is the SVD of $\mathbf{P}^T_p\ \mathbf{P}_q \in R^{M\times M}$
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

Here, we evaluate the performance of HSF in the ATR task on the Comanche IR database. There are 10 dissimilar military targets, and there are 72 orientations for each target (0∘, 5∘, ..., 355∘). In addition, the record includes 874 to 1518 IR chips (40×75) for every target class, totally 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 evaluate 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 mine 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.

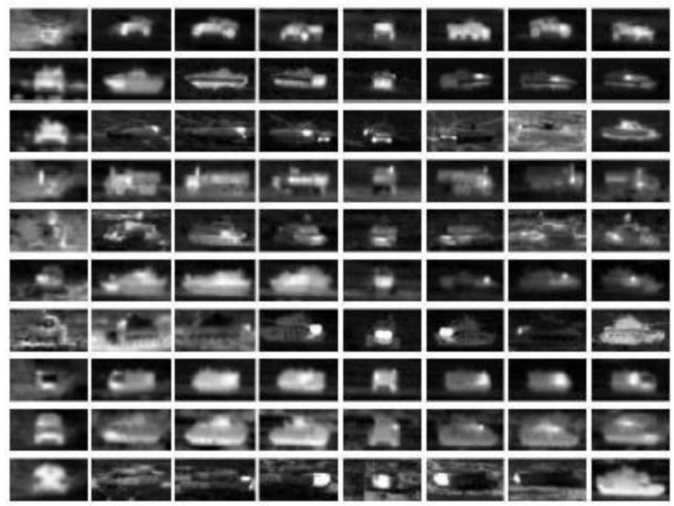

Fig.3: IR chips of 10 targets in 8 orientations in the Comanche database

V. CONCLUSION

We have accessible a new unsubstantiated feature fusion algorithm for ATR in IR imagery, called Heterogenous Structure Fusion (HSF), which jointly and explicitly takes advantage of heterogenous structures among numerous 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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