Graph Manifold Clustering based Band Selection for Hyperspectral Face Recognition

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***Abstract*—Efficient band selection reduces the computational load associated with the processing of hyperspectral data. In this paper we propose a novel graph manifold approach based band selection framework for hyperspectral face recognition. In this work, we extract facial features by local binary pattern, which is a popular facial feature descriptor. In the next stage, we cluster the data points using graph manifold ranking method and select representative bands from each cluster. We also propose a band similarity index (BSI) for quantifying the consistency of band selection algorithms. BSI facilitates faster and efficient matching of HSI faces provided the selected bands capture inter and intra-subject variation. We compare the efficiency of the proposed framework with state of the art methods on two real hyperspectral face datasets.**

***Index Terms*—Hyperspectral Face Recognition, Band Selection, Graph Manifold Clustering, Band Similarity Index, Manifold Ranking.**

I. Introduction

Face recognition research has attained commendable height in last few decades [1]. Face recognition often encounters hurdle because intra-person differences can overrule inter-person differences, particularly when the number of subjects in the gallery increases. Therefore, new imaging modalities are being explored to increase facial discrimination. Recently, hyperspectral imaging has gained popularity among research community due to the consistently decreasing price of the imaging sensors. A hyperspectral image cube (HSI) comprises of two spatial and one spectral dimension, which contains the reflection pattern across several bands in the electromagnetic region. A hyperspectral face cube consists of several grayscale images across the visible spectrum and beyond, resulting in more secured biometric. HSI provides new opportunities for improving face recognition accuracy by revealing the information which is beyond the human eye or the conventional RGB camera. Inclusion of spectral dimension, in fact, increases the size of the face space leading to more considerable inter-person distances. Some researchers [2] have characterized the skin tissues and implemented face recognition using spectroscopy, which gives high inter-subject discrimination. In addition to the surface appearance, spectral measurements in the near-IR range can also sense the subsurface tissue features which are significantly different for each person.

We can improve the computational performance of processing the hyperspectral face cube by either dimensionality reduction or band selection. Since hyperspectral images generally form non-linear manifolds, we require to apply non-linear dimensionality reduction, which is computationally expensive. Hence we utilise band selection strategy before face recognition, motivated by its success in applications like target detection, classification and unmixing of remotely sensed hyperspectral image. Ideal band selection process does not degrade the accuracy significantly. Although band selection has been found to be effective in the remotely sensed hyperspectral images, researchers are yet to explore the proficiency of band selection in hyperspectral face recognition. To the best of our knowledge, there is no band selection method in literature, motivated for hyperspectral face image. In case of hyperspectral face cube, some specific bands highlight the distinct spatial structure of the human face, while other bands do not provide distinct spatial pattern suitable for better recognition. Hence, all the bands are not necessary for the recognition task, only a selected number of bands can be employed to obtain satisfactory face recognition performance.

The contributions of our work are as follows-

- We propose a novel, discriminative and representative feature based band selection approach for hyperspectral face recognition. The overall process involves feature extraction by local binary pattern (LBP) and band selection by manifold ranking (MR).
- We also propose a similarity measure called band similarity index (BSI), which calculates the similarity between the bands selected from two hyperspectral faces of the same subject, taken during different sessions. BSI measure also emphasizes the effectiveness of our proposed band selection technique for face recognition task.

The overall paper is organized in the following sections: Section II analyzes present state of the art band selection methods and their the pros and cons, section III presents a detailed account of our proposed work-flow, section IV specifies the experimental procedure, section V presents the results and section VI include incorporates conclusion and future work.

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II. Band Selection of Hyperspectral Data: Literature Review

Although hyperspectral images capture in-depth features, the sheer volume of the data creates a major inconvenience in processing the data. Band selection strategy is often incorporated as a pre-processing step to select the informative and discriminative spectral bands and obtain a compact representation of the data. Band selection reduces the computational burden associated with the previous stage without compromising the accuracy. Existing band selection strategies include: clustering approaches [3], [4], similarity-based approaches [5], [6], progressive BS [7], joint band prioritization (JBP-BS) [8], rank minimization approach (RM-BS) [9]. We have used JBP-BS [8] and RM-BS [9] for validating the performance of our algorithm. The JBP-BS [8] algorithm clustered the bands by orthogonal subspace projection and de-correlate the essential bands by mutual information measure. The work proposed in RM-BS [9] formulated the work in rank minimization approach. This method reduces the redundancy in the data by identifying the bands which lead to a low-rank representation of the linear coefficient matrix.

III. Proposed Work flow

In case of hyperspectral face recognition, both spatial and spectral information are of equal importance. In our proposed band selection framework, we extract facial features by LBP, which is widely used in face recognition and perform spectral embedding based manifold ranking.

A. Pre-processing

We employ the widely used face detection algorithm Viola et al. [10] which identifies the face part of size 100×100 employing Haar-like features.

B. Feature Extraction : Local Binary Pattern

The two primary attributes of a hyperspectral image: noise level and reflectance value vary across individual bands. We compute the noise index of each band according to Liu et al. [11] and quantify overall reflectance as par the works of Zhu et al. [12]. We display the variation of noise index and average reflectance of individual band images of a particular subject in Fig. (2). Fig. (2) shows the distinct band to band variation of noise index and average reflectance. We exploit Local Binary Pattern (LBP) feature because it is noticeably affected by the noise and reflectance pattern of the pixels. LBP is a popular texture based feature extraction method, which has been successfully applied in face recognition tasks [13]. LBP acquires a compact feature from the image and is noticeably affected by the noise and reflectance pattern of the pixels. The LBP operator labels the image by thresholding the neighbourhood of each pixel with the value of the central pixel and encodes it in binary number 0 or 1. The sting of 8-bits are converted to a single decimal number which replaces the original value of the central pixel. The histogram of the represented image serves as the feature for facial micro-patterns. We choose LBP features over raw pixels, because of its sensitivity to the change in the reflectance and noise variation for different band images. Thus LBP extracts discriminative features for individual band images and which enables efficient clustering of the bands.

Every time the ranking is done on whole manifold is reconsider the global relationship. The flowchart of the method is shown in Fig. 1.

Algorithm 1 Band selection by Manifold Ranking (MR-BS)

Input:

$X = \{x_1, x_2, ..., x_n\}, k, \alpha$

Note: $X = \{x_1, x_2, \cdots, x_n\} \in \mathbb{R}^m$,where m is the dimensionality of the data (the Local binary pattern histogram from each band) and n is the number of bands. k query bands according to which other bands are ranked. α is a convergence parameter in $[0, 1)$.

Output: K selected bands.

Initialization :

Initial band selection by simple clustering method using k-means and then choosing the centroid of each cluster as representatives. The query vector: $Y = [y_1, y_2, \cdots, y_n]$ with $y_i = 1$ means x_i is a query and $y_i = 0$ otherwise.

Note: Let $F : X \rightarrow R$ denote a ranking function that assigns every point x_i a ranking score f_i, leading to a vector of $F = [f_1, f_2, \cdots, f_n]$. For an appropriate measurement of the ranking function, a graph network is defined as $G = (V, E)$. Where the data points are X, V is the vertex set, and E is the edge set.

for until K bands selected **do**

Affinity matrix W obtained as

$$w_{ij} = \begin{cases} e^{-\|x_i - x_j\|^2 / 2\sigma^2}, & \text{if } x_i \text{ and } x_j \text{ are connected} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Degree matrix is obtained as $D = diag\{d_{11}, \cdots, d_{nn}\}$, where $d_{ii} = \sum_j w_{ij}$.

Note: In the context of HSI band selection, if the two bands are neighbor they are connected. The distance between two connected points $d(x_i, x_j)$ is computed as the Euclidean distance between them.

Construct the symmetrically normalize matrix $S = D^{-1/2} W D^{-1/2}$.

Iterate $F(t+1) = \alpha SF(t) + (1\alpha)Y$ until convergence.

Let F^* denote the limit of the sequence $F(t)$. Label each point x_i as a label $y_i = argmax_{j \leq c} F^*_{ij}$.

end for

return Rank of X based on which the K distinct bands chosen.

C. Graph Manifold Clustering

In this work, we identify the informative and discriminative bands from the hyperspectral face using manifold ranking. The graph manifold clustering framework identifies an initial subset of bands by an unsupervised algorithm like k-means algorithm [14]. Since the bands in the same cluster are highly similar, we can consider any informative band corresponding

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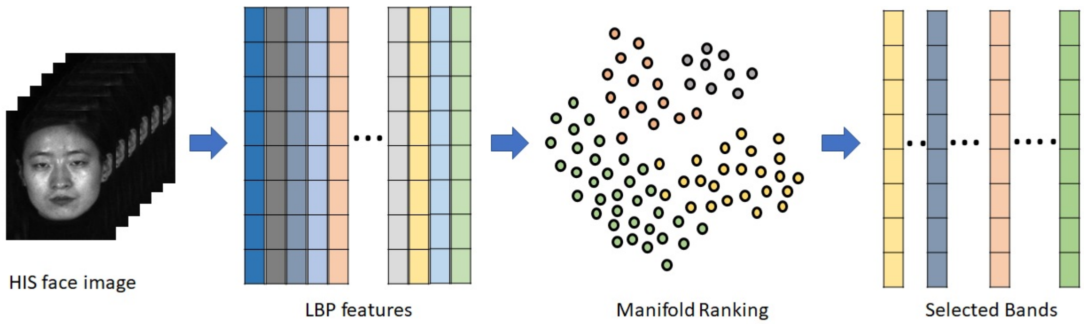

Fig. 1: Overall Layout of the band selection process

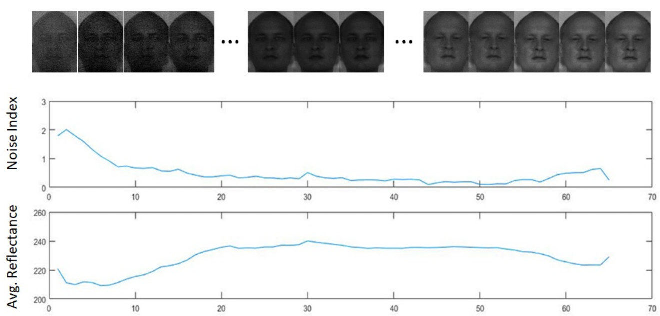

Fig. 2: Variation of noise level and average reflectance of the individual images in a HSI cube

to each cluster as a representative band. This framework considers the centroid of each group (cluster) as the initial representative band corresponding to each cluster or groups as a very natural choice. The manifold ranking strategy treats the representative bands as a query, and assigns a rank corresponding to the other bands. In the next iteration, the manifold ranking strategy [15] estimates the rank of the remaining bands based on the outcome of the previous iteration. In this process, manifold ranking formulation identifies the most dissimilar bands in each iteration and use it as a query in the next stage. We continue this iterative band selection by manifold ranking process until we identify the desired number of bands.

IV. Experiment

A. Dataset Description

We validate our proposed band selection performance of two hyperspectral face datasets- CMU Hyperspectral Face Database (CMU-HSFD) [16] and PolyU database [17]. Images of CMU-HSFD dataset are acquired with a spectro-polarimetric camera. Each hyperspectral face cube contains 65 bands which cover spectral range of $450 - 1090nm$ with a spectral resolution of $10nm$. The database contains 48 subjects; each subject has 4 to 20 cubes acquired at different sessions and different lighting combinations. PolyU dataset [17] contains 48 subjects of which we have chosen first 38 subjects for experimental purpose because of availability of more than one cube per subject. In PolyU dataset, each cube consists of 33 spectral bands from $400 - 720nm$ wavelength.

Algorithm 2 Band Similarity Index

Input:

Set of band selected from all subjects. Let, the training and testing bands selected from the i-th subject be- $\phi^i_{Tr} = \{B_1, B_2, \cdots, B_n\}$ and $\phi^i_{Ts} = \{B'_1, B'_2, \cdots, B'_n\}$ respectively.

Band Tolerance = ΔB

Output: BSI_i, BSI_{mean} and $BSI_{variance}$

Initialization :

$$\Phi^i_{Tr} = \{B_1, B_2, \cdots, B_n\}$$

$$\Phi^i_{Ts} = \{B'_1, B'_2, \cdots, B'_n\}$$

Note: The selected bands may not be the exact same in the case of training and testing. The perturbation of band selection is addressed using the tolerance limit. $B'_1 \in \langle B_1 \pm \Delta B\rangle$, $B'_2 \in \langle B_2 \pm \Delta B\rangle$, $B'_3 \in \langle B_3 \pm \Delta B\rangle$ $\cdots$ $B'_n \in \langle B_n \pm \Delta B\rangle$.

for $i < N$ and $i \leftarrow i + 1$ **do**

Calculate BSI for each subject

$$BSI_i = \frac{|\Phi_{train} \cap \Phi_{test}|}{|\Phi_{train}|}$$

end for

Calculate the mean of BSI for the overall dataset -

$$BSI_{mean} = \frac{1}{N}\sum_{i=1}^{N} BSI_i$$

Calculate the variance of BSI for the overall dataset -

$$BSI_{Variance} = \frac{1}{N}\left[\sum_{i=1}^{N}\Big(BSI_i - BSI_{mean}\Big)^2\right]^{\frac{1}{2}}$$

return BSI_{mean} and $BSI_{variance}$

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B. Band Selection Consistency

A cropped and pose specific hyperspectral face depends solely on the spectral characteristics of face parts. As a consequence, the hyperspectral face cube is unique for a particular subject. The bands selected from two different sessions of a subject, should either contain same bands or contain adjacent spectral bands because they are highly similar. The band selection algorithms to be used for face recognition purpose requires consistency and subject dependency.

We have proposed an evaluation criterion for band selection-band similarity index (BSI), which quantifies the similarity between the bands selected from two different faces, i.e., training and testing face of a particular subject. The proposed band selection index draws inspiration from the probability of detection measure which is widely used in dictionary pruning [18]. Our proposed band selection index performs an approximate matching between the bands selected from training and testing data. Assume that the number of bands retained after the band selection process is n and the bands selected from training subject and test subjects be ϕ_{train} and ϕ_{test} respectively. BSI calculates a score ranging between $0, 1$ for each pair of hyperspectral faces. Exact match yield $BSI = 1$, whereas, no match is indicated by $BSI = 0$. Higher BSI value indicates a good match. The BSI value for a particular pair is dependent on the number of selected bands and the selected tolerance value.

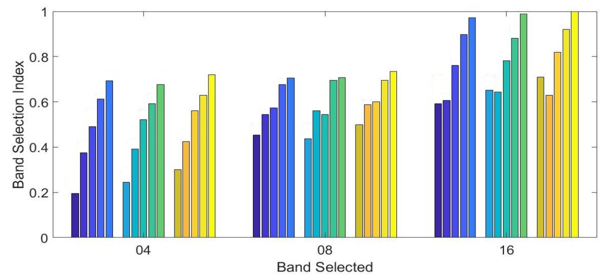
C. Relevant Algorithms

The proposed method is used for band selection to perform hyper face recognition using three state of the art recognition techniques : (i) $3D$-LBP [19] (ii) $3D$-Gabor Wavelet [20] (iii) $3D$-LDP [21]. These methods are based on simultaneous spatial and spectral domain feature extraction. As a result, the information contained in the $3D$ data is fully exploited.
Our proposed band selection strategy has been compared with-JBP-BS [8] and rank minimization (RM) BS [9]

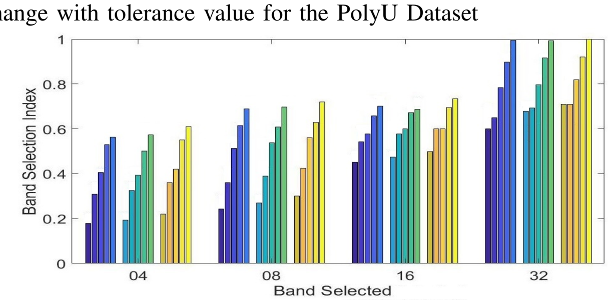
V. Result

A. Band Similarity Index computation

Fig.3a and Fig.3b shows variation in BSI with varying tolerance and selection of the different number of bands for PolyU and CMU datasets. We have chosen 16 out of 33 bands in PolyU and 32 out of 65 in CMU. Selection of the higher number of bands is futile because it does not significantly reduce the computational complexity which was the main objective of band selection. In both, the figures 3a and 3b, the *blue*, *green* and *yellow* set of bars represents the BSI for JBP-BS [8], RM-BS [9] and proposed method respectively. We display the BSI values corresponding to tolerance values 1 to 5 in the consecutive bars. The plot indicates a consistent increase in BSI with increasing tolerance. In case of both the datasets, the BSI value obtained by our BS framework is higher than others. The BSI value increases with the increase in tolerance value. All the methods show almost similar BSI values when the number of selected bands is high. However, the difference of the BSI for our proposed method in case of less number of band selection shows its superiority over other methods.



(a) The graph shows the performance of Band Selection and its change with tolerance value for the PolyU Dataset



(b) The graph shows the performance of Band Selection and its change with tolerance value for the CMU Dataset

Fig. 3: Band Selection Index for different methods for varying tolerance

B. State of the art Face Recognition Methods based on band selection

In table I and II face recognition accuracy for PolyU and CMU databases are reported. In this table band selection is performed by JBP-BS [8], RM-BS [6] and our proposed band selection. The face recognition task is carried out by 3D-LBP [19], 3D-GW [20] and 3D-LDP [21]. Our proposed BS results into superior face recognition compared to JBP-BS [8] and RM-BS [6] This result is consistent for all there FR algorithms in both the databases.

C. Runtime Comparison

The runtime performance is implemented on Matlab $2017a$. in a Quad Core desktop PC having an 8GB RAM. Fig. 4a and Fig. 4b shows average runtime performance of band selection algorithms on PolyU dataset and CMU dataset respectively. It evident from the graph that our proposed band selection leads to lower runtime compared to other band selection algorithms.

VI. Conclusion

This paper proposes, a face-specific band selection framework using the manifold ranking of feature data. The BS framework identifies the optimal band set that results in satisfactory face recognition performance. We also proposed an index (BSI) to quantify the performance of band selection for face recognition. We demonstrate that our proposed BS leads to higher BSI which implies the superiority of manifold

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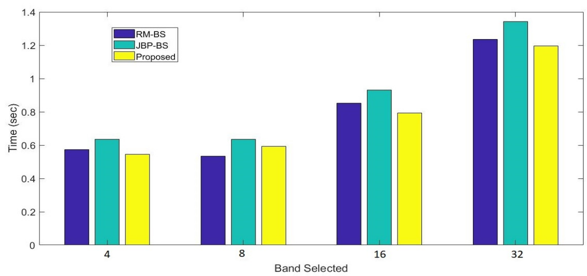
TABLE I: Percentage accuracy for face recognition after band selection for some state of the art algorithms on PolyU Dataset

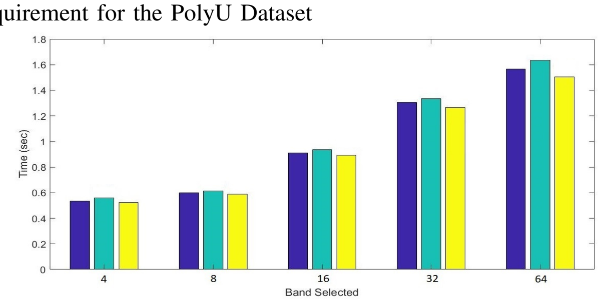
	No. of Selected Bands = 4			No. of Selected Bands = 8			No. of Selected Bands = 16			No. of Selected Bands = 32		
	JBP-BS	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**
3D LBP [19]	36.72	27.84	43.87	53.35	48.93	57.55	68.72	72.36	74.18	83.36	81.36	82.83
3D GW [20]	49.52	53.38	57.73	59.62	64.69	69.43	74.59	75.26	78.36	88.84	86.73	89.32
3D LDP [21]	56.47	51.46	61.64	69.28	73.48	77.48	79.48	84.53	86.67	91.57	96.77	96.15

TABLE II: Percentage accuracy for face recognition for different number of band selection using state of the art algorithms on CMU Dataset

	No. of Selected Bands = 4			No. of Selected Bands = 8			No. of Selected Bands = 16			No. of Selected Bands = 32			No. of Selected Bands = 64		
	JBP-BS	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**	**JBP-BS**	**RM-BS**	**Proposed**
3D LBP [19]	18.73	16.47	27.49	28.56	30.78	33.55	31.53	43.73	46.43	49.76	56.74	59.49	72.75	75.54	77.19
3D GW [20]	27.59	23.48	39.61	35.58	45.43	49.82	46.68	52.75	58.69	60.55	65.38	69.37	79.33	79.82	82.87
3D LDP [21]	33.38	34.61	42.37	43.64	49.38	53.27	53.85	61.53	68.18	68.71	73.89	76.41	83.79	83.75	87.48



(a) The graph shows the performance of Band Selection and time requirement for the PolyU Dataset



(b) The graph shows the performance of Band Selection and time requirement for the CMU Dataset

Fig. 4: Time consumption for some Band Selection methods

ranking BS in face recognition task. Though our proposed framework is designed explicitly for face recognition purpose, we can also use it for any generalised band selection task irrespective of the end application.

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