Hyperspectral Face Recognition using 3D-DCT and Partial Least Squares

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Hyperspectral imaging offers new opportunities for inter-person facial discrimination. However, due to the high dimensionality of hyperspectral data, discriminative feature extraction for face recognition is more challenging than 2D images. For dimensionality reduction and feature extraction most of the previous approaches just sub sampled the hyperspectral data [5, 6, 9] or used simple PCA [3]. In contrast, we propose the three dimensional Discrete Cosine Transform (3D-DCT) for feature extraction (Fig. 1). Exploiting the fact that hyperspectral data is usually highly correlated in the spatial and spectral dimensions, a transform such as DCT is expected to perform information compaction in a few coefficients by providing maximal decorrelation. DCT transform being an approximation of the KL-Transformation optimally compacts the signal information in a given number of transform coefficients. Moreover, compared to other transforms, such as the Fourier transform, the transformed coefficients are real and thus require less data to process.

The Discrete Cosine Transform (DCT) [1] expresses a discrete signal, such as a 2D image or a hyperspectral cube, as a linear combination of mutually uncorrelated cosine basis functions [4]. DCT generates a compact energy spectrum of the signal where the low-frequency coefficients encode most of the signal information. A compact signal representation can be obtained by selecting only the low-frequency coefficient as features.

The 2D-DCT of a 2D image $h(x,y)_{N_1 \times N_2}$, and the 3D-DCT of a hyperspectral cube $H(x,y,\lambda)_{N_1 \times N_2 \times N_3}$ are given by

$$C(u,v) = \Omega_1(u)\Omega_2(v) \sum_{x=0}^{N_1-1} \sum_{y=0}^{N_2-1} h(x,y)\{cos[\frac{\pi(2x+1)u}{2N_1}]cos[\frac{\pi(2y+1)v}{2N_2}]\} \tag{1}$$

$$F(u,v,w) = \Omega_1(u)\Omega_2(v)\Omega_3(w) \sum_{x=0}^{N_1-1} \sum_{y=0}^{N_2-1} \sum_{\lambda=0}^{N_3-1} H(x,y,\lambda) \tag{2}$$

$$\{cos[\frac{\pi(2x+1)u}{2N_1}]cos[\frac{\pi(2y+1)v}{2N_2}]cos[\frac{\pi(2\lambda+1)w}{2N_3}]\}$$

where $u = \{0,1,...,N_1-1\}$, $v = \{0,1,...,N_2-1\}$, $w = \{0,1,...,N_3-1\}$ and $\Omega_i(u)$ is defined as

$$\Omega_i(u) = \begin{cases} \sqrt{\frac{1}{N_i}} & \text{if } u\text{=0;} \\ \sqrt{\frac{2}{N_i}} & \text{otherwise} \end{cases} \tag{3}$$

The low frequency coefficients near the origin of $F(u,v,w)$ represent most of the energy of the hyperspectral cube (Fig. 1), therefore, the high-frequency coefficients can be discarded. In order to construct our proposed feature vector, we sample a frequency sub-cube $\Gamma(u,v,w)$ of dimensions $(\alpha \times \beta \times \gamma)$ by retaining only the low-frequency elements around the origin of $F(u,v,w)$ i.e., $\{(u,v,w)|u \leq \alpha, v \leq \beta, w \leq \gamma\}$ (Fig. 2). The sub-cube $\Gamma(u,v,w)$ is vectorized and normalized to unit magnitude to obtain the final feature vector $f \in \mathcal{R}^d$, where $d = (\alpha\beta\gamma)$, which is used for classification. For the purpose of classifying the 3D-DCT features, we propose Partial Least Square (PLS) regression.

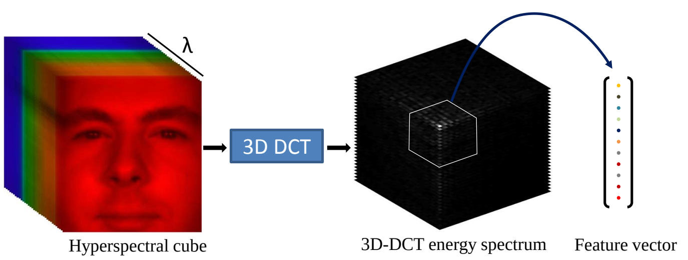

Figure 1: 3D-DCT based feature extraction. A hyperspectral cube (each band is rendered as RGB) and the corresponding 3D-DCT energy spectrum. It can be seen that only few coefficients around the origin contain most of the energy.

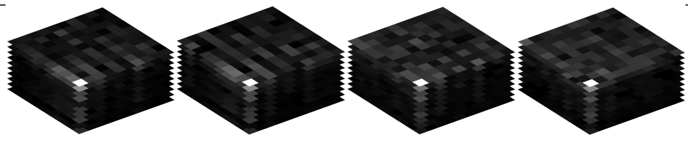

Figure 2: Sub-cubes of size $10 \times 10 \times 10$ sampled around the origin of the 3D-DCT energy spectrum of four different subjects of the UWA Hyperspectral Database.

We perform experiments on three standard hyperspectral face databases including the PolyU Hyperspectral [3, 7], CMU Hyperspectral [2] and UWA Hyperspectral databases. The results are compared with five existing hyperspectral face recognition algorithms. Table 1 shows that the proposed algorithm out-performed five existing hyperspectral face recognition algorithms on all three databases. We observe that PLS regression performed better than SRC. It is because PLS basis projects the feature vectors into a latent space in which feature vectors corresponding to the same subject are closer than the feature vectors corresponding to different subjects.

Table 1: Average recognition rates and standard deviations (%) for ten fold experiments on three databases.

Algorithm	PolyU Database	CMU Database	UWA Database
Hyperspectral			
Spectral Signature [5]	24.63±3.87	38.18±1.89	40.52±1.08
Spectral Angle [8]	25.49±4.36	38.16±1.89	37.95±4.15
Spectral Eigenface [6]	70.30±3.61	84.54±3.78	91.51±3.07
2D PCA [3]	71.11±3.16	72.10±5.41	83.85±2.42
3D Gabor Wavelets [9]	90.19±2.09	91.67±2.86	91.50±3.07
Proposed			
2D-DCT + SRC	75.86±2.92	97.44±1.24	97.00±1.29
2D-DCT + PLS	91.43±2.10	97.78±1.28	97.25±1.87
3D-DCT + SRC	87.02±1.72	98.10±0.69	98.00±1.84
3D-DCT + PLS	**93.00±2.27**	**99.00±0.85**	**98.00±1.39**

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