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CLASSIFIED EIGEN BLOCK: LOCAL FEATURE EXTRACTION AND IMAGE MATCHING ALGORITHM

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ABSTRACT

This paper introduces a new local feature extraction method and image matching method for the localization and classification of targets. Proposed method is based on the block-by-block projection associated with directional pattern of blocks. Each pattern has its own eigen-vertors called as CEBs(Classified Eigen-Blocks). Also proposed block-based image matching method is robust to translation and occlusion. Performance of proposed feature extraction and matching method is verified by the face localization and FLIR-vehicle-image classification test.

1. INTRODUCTION

In general pattern recognition, feature extraction part (or feature extractor) must be able to select discriminative characters of target pattern and extract them robustly to the various noises and distortions.

2D-DCT(Discrete Cosine Transform) and VQ(Vector Quantization) - based feature extraction methods[2][3] are kinds of localized methods based on block-by-block processing. Since localized normalizations of global distortions are available with these methods, they have been variously studied for feature extracting that are robust to the directional changes of illumination in frontal face recognition. Moreover very fast recognition processes are available because block-by-block processing needs very low computational loads comparing to global feature extraction methods, like a PCA or FLD [4][5]. Additionally they have compatibilities with various image compression methods.

Main question in previous DCT or VQ-based methods is how to select and arrange the coefficients to reduce the dimensionality. Most of methods select low frequency coefficients with zig-zag scanning or use codevectors that are built up using a few low frequency coefficients in DCT domain. But the higher frequency coefficients may be valuable for discrimination according to the characteristics of training patterns. For some images with more complex edges or textures, higher frequency coefficients are more valuable for their discrimination. In these senses, coeffi-cients selecting and arranging method should be varied by the block-size and characteristics of training data.

Eigenpaxel[1] is kind of localized method that can extract features in block region using statistical information of training data. This method consists of block-by-block local PCA with various block-sizes. In Eigenpaxel method, the block-basis are very similar with the basis of 2D-DCT with specified block-size. It means that expressional ability of Eigenpaxels will be limited to that of 2D-DCT due to their limited basis number.

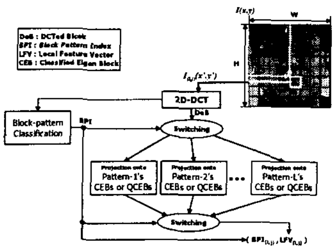


Fig.1 Block-based local feature extraction method

To get local features with more plentiful expression ability, proposed local feature extraction method showed in Fig.1, firstly, classifies blocks as their directional patterns. And it finds the eigen-vectors associated with each block patterns separately using block-based PCA. Every block patterns have its own eigen-vertors and limited expression ability can be expanded by more detail and plentiful eigen-vectors associated with various block patterns. We call these block-pattern-based eigen-vectors as CEBs (Classified Eigen-Blocks). Proposed method is performed on the DCT domain and CEB can be represented by weighted sum of a few DCT-coefficients with quantization and compatibility with various image compression methods makes proposed method more valuable for target recognition in compressed images.

When there are not enough training data to estimate a probability model for classification, Template matching and nearest neighbor classification are classical but most widely-used methods[6]. In chapter 5, we propose a new local-feature-based image matching method. Proposed matching method effectively utilizes proposed local features and is robust to translation and occlusions.

Performance of proposed feature extraction and matching method is verified by face-localization test and FLIR- vehicle-image classification test.

2. 2D-DCT

2.1 Block-by-block N-point 2D-DCT

We divide a given raw image into square blocks with size of $N \times N$ and apply N-point 2D-DCT to each block. For a given image block ***I(x,y)***, *DCT-ed-block(DeB)*, ***B(u',v')*** is transformed block from image-domain to DCT-domain.

For $0 \le u' \le N-1$, $0 \le v' \le N-1$

$$B(u',v') = \alpha(u',v') \sum_{y=0}^{N-1}\sum_{x=0}^{N-1} I(x,y) \cos\left(\frac{(2x_1+1)\pi t_1}{2N}\right) \cos\left(\frac{(2x_2+1)\pi t_2}{2N}\right) \quad (1)$$

$$\text{where } \alpha(t_1,t_2) = \begin{cases} 1/N & \text{if } t_1=0 \text{ or } t_2=0 \\ 2/N & \text{otherwise} \end{cases}$$

2.2 DC-rejection and energy normalization

Some localized processing, DC-coefficient rejection and energy normalization in a block can reduce the effect of global intensity changing caused by lighting condition changes. Set $\boldsymbol{B}(0,0)=0$ and

$$B_{normalized}(u',v') = \frac{\alpha(u',v') \sum_{y=0}^{N-1}\sum_{x=0}^{N-1} I(x,y)\beta(x,y,u',v')}{\sqrt{\sum_{u'=1}^{N-1}\sum_{v'=1}^{N-1} B(u',v')^2}} \quad (2)$$

3. BLOCK PATTERN CLASSIFICATION

3.1 Directional Pattern Descriptor(DPD)

In a block region, directions of edges or textures are most discriminative and noise-robust features. To catch and preserve these directional features, block patterns are classified by proposed direction descriptor.

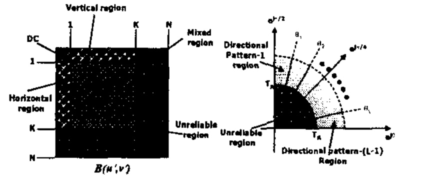
For a given DeB - ***B(u',v')***, three transitional energy terms of E_H, E_V and E_M are calculated by squared summing of DCT-coefficients located at specified regions (Fig. 2.(a)). Energy in unreliable region is rejected because information in that region is thought as useless noisy one. Proposed *directional pattern descriptor (DPD)* is the mixed vector of three energy terms with their eigen-directions; $e^{j\pi/2}, e^{j\pi/4}, e^{j0}$. ***DPD*** represents the dominant direction of transition in a block and is utilized to classify the patterns of block.

$$DPD = E_V e^{j\pi/2} + E_M e^{j\pi/4} + E_H e^{j0} \quad (3)$$

and

$$|DPD| = \sqrt{E_H^2 + E_M^2 + E_V^2 + \sqrt{2}(E_H E_M + E_V E_M)} \quad (4)$$

$$\angle DPD = \arctan\left((E_H + E_M/\sqrt{2})/(E_V + E_M/\sqrt{2})\right) \quad (5)$$



(a) (b)

Fig.2. (a) Division of block on the DCT-domain, (b) Directional classification of block pattern by angle of ***DPD***

3.2 Block pattern classification

Using DPD, block pattern classifying is very simple task, but in which various parameters are available. Number of classes (L), decision level ($\theta_1, \theta_2, \ldots, \theta_L$), window sizes (K) and threshold value (T_R), showed in Fig.2.(a) and (b), are adjustable variously with its applications.

< *BPI (·)* operation : Block pattern classification using *DPD*>
if ($|DPD| \le T_R$) , ***BPI*** $\Leftarrow$ 0 (unreliable pattern) $\Rightarrow$ reject
else if ($0.5*|DPD| < E_M$) , ***BPI*** $\Leftarrow$ L (mixed pattern)
else { if ($\theta_1 \le \angle DPD < \pi/2$) , ***BPI*** $\Leftarrow$ 1 (directional pattern-1)
else if ($\theta_2 \le \angle DPD < \theta_1$) , ***BPI*** $\Leftarrow$ 2 (directional pattern-2)
...
else if ($0 \le \angle DPD < \theta_{L-1}$) , ***BPI*** $\Leftarrow$ L-1 (directional pattern-L)
}
return ***BPI***

4. CLASSIFIED EIGEN BLOCK

*Classifed Eigen Block (**CEB**)* is new type of projection basis for the dimensionality reduction in small image-block area. The concept of applying PCA to block region is similar with Eigen paxel method, but CEB method is block-level PCA on DCT-domain and is based on multi-spaces separated by directional block patterns. Block-level PCA on DCT-domain can be coped with quantization because the most energy compacted in a few positions in eigen-blocks. *Quantized CEB(**QCEB**)*, in equation (13), will reduce the computational loads.

4.1 pattern-based block-PCA on DCT domain

operation "$\rightarrow$" is column-by-column scanning to make a matrix to a single column vector and "$\leftarrow$" is inverse. Operation "***BPI(·)***", showed in chapter 3.2, returns index of block pattern. $\boldsymbol{S}$ is set of DeBs gathered through all training images and S_1 , S_2,..., S_L are the classified sets of DeBs by their block-patterns.

$$S = \{\vec{B}_i \in \Re^{N^2 \times 1} \mid i=1,\ldots,M\} = S_1 \cup S_2 \cup \ldots \cup S_L \quad (6)$$

$$\text{where } S_k = \{\vec{B}_j^k \mid BPI(B_j^k)=k,\ \vec{B}_j^k \in S,\ j=1,\ldots,M_k\} \quad (7)$$

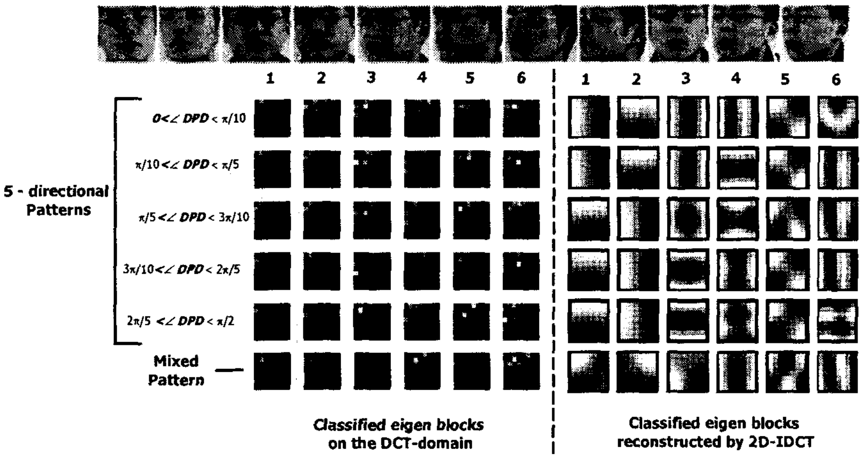


Fig.3. Examples of training data (real image-size =(64~80)×40))(top) and estimated CEBs for 5-directional patern & mixed pattern (Block-size=8×8 , K=4, $N_1,N_2,..,N_6$=6) (bottom)

for $k = 1, \dots, L$,

$$\bar{m}_k = \frac{1}{M_k}\sum_{j=1}^{M_k}\vec{B}_j^k \qquad (8)$$

$$\Xi_k = \frac{1}{M_k}\sum_{j=1}^{M_k}(\vec{B}_j^k-\bar{m}_k)(\vec{B}_j^k-\bar{m}_k)^T \qquad (9)$$

get (u_c^k,λ_c^k) satisfies , $\Xi_k u_c^k = \lambda_c^k u_c^k$

(10)

where $c=1,\dots,N^2$, $\lambda_1^k \ge \lambda_2^k \ge \dots \ge \lambda_{N^2}^k$, $N_k << N^2$

pattern-k's *CEBs* = $\{\bar{u}_j^k | j=1,\dots,N_k\}$

(11)

CEB consists of eigen-vectors associated with large k eigen-values for every block patterns except unreliable pattern. Examples of CEBs are showed in Fig.3. Transition -directional characteristics of each pattern are well-preserved in each pattern's CEBs.

With two quantization parameters - quantization level(T_Q) and Threshold level(T_s) and operator - ***quo(a,b)*** which means the quota got by dividing ***a*** by ***b*** , QCEBs can be obtained as a set of pairs made up with position index(*l*) and quantized value(*c*). Using QCEB, local features can be extracted with just a few calculation at a non-zero positions.

$$Q(\bar{u}_j^k=[u_1\ u_2 \dots u_{N_k}]^T, T_Q) = \{(l,c) | c=quo(u_l,T_Q) \ge T_s\} \qquad (12)$$

pattern-k's *QCEBs* = $\{Q(\bar{u}_j^k, T_Q) | j=1,\dots,T_k\}$

(13)

4.2 Local feature extraction using CEB or QCEB

For a given DCT-ed block ***B(u',v')*** of which block-pattern is ***k***, local feature vector(***LFV***) is extracted as *z* by projection block onto pattern-k's CEBs.

If ***BPI(B(u',v')) = k***

where $U_k^T = [u_1^k\ u_2^k \dots u_{N_k}^k]^T$, $z_{(i,j)} \in \Re^{N_k}$

$$LFV = z = U_k^T(\vec{B} - \bar{m}_k) \qquad (14)$$

Extracted local feature; block-pattern-index and local feature vector can be utilized for various partial target matching or occluded target classification applications.

5. MATCHING STRATEGY

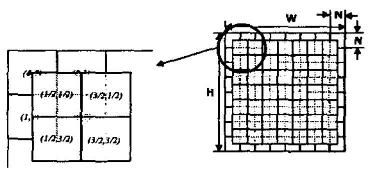


Fig.4.Concept of overlapped block analysis

Proposed matching method is based on the localized block-matching. Matched blocks are constrained as block-pairs of same block-pattern-indexes within input image and templates. Matching measure(***MD***) is calculated for all matched blocks and accumulated at the point of positional difference(***PD***) in accumulation map, ***A(m,n)***. To avoid errors caused by misaligned block-processing, templates must be analyzed by overlapped blocks (in Fig.4).

Position of max-accumulated value in ***A(m,n)*** means translations and max-value itself means matching degree between input and templates. By comparing max-values about various templates, we can find the template that is most well-matched with input pattern.

<Block-based matching algorithm >

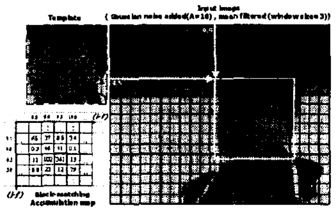
Reset accumulation map , ***A(m,n) =0*** for all ***(m,n)***

where $m = \ldots,-1,-1/2,0,1/2,1,\ldots$, $n = \ldots,-1,-1/2,0,1/2,1,\ldots$
For $i=0,\ldots,W/N-1$ and for $j=0,\ldots,H/N-1$
  $B_{(i,j)}$ is came from input image.
  For $i'=0,\ldots,W'/N-1$ and for $j'=0,\ldots,H'/N-1$
    $B'_{(i',j')}$ is selected from template.
    If $BPI(B_{(i,j)}) = BPI(B'_{(i',j')})$
      Calculate $MD = K_o / \left\| LFV_{B(i,j)} - LFV_{B'(i',j')} \right\|^2$ (18)
      and $PD = (i,j)-(i',j') = (i-i', j-j')$ (19)
      $A(PD)$ += MD
Find max-value and its position in $A(m,n)$
  Matchness ⇐ max-value
  Translation ⇐ position of max-value

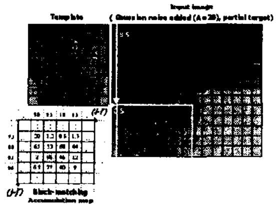
6. RESULT

6.1 Face-localization test

Target localization performance was tested by full- or partial-face included images and face-templates. Max-value points in accumulation map indicate the positions where targets (=templates) are in Fig.5.(a) and (b).



(a)



(b)

Fig.5. Result of face localization test : (a) target in input is fully available case, (b) is partially available case

6.2 Target classification test

In order to evaluate the target classification performance, we used a dataset of 900 FLIR-vehicle-images[7] which is polluted by serious spot-noise and global or local intensity changes smeared in real condition. 800 images were used as templates and 100 images were tested. The hit rate result with various dimensions showed in Fig.7. Proposed method showed higher performance than the various another local or global feature extraction methods coped with nearest neighbor classifier. It's because that the proposed method is robust to small misalignment errors in images and intensity variations.

Fig.6. FLIR(Forward Looking InfraRed)-vehicle images

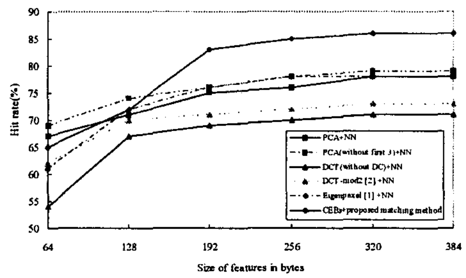


Fig.7. Result of image classification test (NN: Nearest Neighbor classification method)

7. DISCUSSION

Proposed local feature extraction and block-based matching method is adequate for occluded or partial-polluted target-image localization and recognition. Performance of proposed method was verified by localization and recognition test using face images and FLIR-vehicle images. Development of fast image matching algorithm utilizing introduced QCEB can be inspired as a further work.

8. ACKNOWLEDGEMENT

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