An Efficient Method for Texture Feature Extraction and Recognition based on Contourlet Transform and Canonical Correlation Analysis

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Abstract

Feature extraction is an important processing step in texture classification. For feature extraction in contourlet domain, statistical features for blocks of subband are computed. In this paper, we present an efficient feature vector extraction method for texture classification. For more discriminative feature a canonical correlation analysis method is propose for feature vector fused to the different sample of texture in the same cluster. The KNN (K-Nearest Neighbor) classifier is utilizing to perform texture classification.

Key word: Texture features, Contourlet transform, Canonical Correlation Analysis.

Introduction

Texture classification is one of the fundamental issues in computer vision and image processing. Various approaches for texture feature extraction as well as classification have been proposed during the last two decades, but the texture analysis and classification problem remains difficult and needs intensive research [1]. Texture represents the coarseness and statistical characteristics of the local variation of brightness between neighboring pixels, and plays an important role in image analysis and pattern recognition. Texture analysis is indispensable for important applications, such as in medical image analysis, document analysis, target detection, industrial surface detection, and remote sensing. The texture model involves basic texture primitives that form texture elements, called *textons* or *texels* and there are four major issues in texture analysis, namely texture feature, texture discrimination, texture classification, and shape from texture [2]. Texture analysis plays an important role in computer vision and image processing. Numerous algorithms of textural features extraction have been presented during the past decades [3] , which can be divided mainly into statistical approaches and structural approaches. The former, including co-occurrence matrix [4], wavelet transform [5], and Gabor filter [6], are the most commonly used in practice. Texture is an important feature of an image that can be extracted for the purpose of image retrieval. Image texture refers to surface patterns which show granular details of an image. It also gives information about the arrangement of different colours. There exist two main approaches for texture analysis. They include structural and statistical approaches. In structural texture approach, the surface pattern is repeated such as floor design that contains the same pattern. In statistical texture, the surface pattern is not regularly repeated in the same pattern such as different flower objects in a picture that normally contains similar properties but not exactly the same [7]. Texture is an inherent property of entities or scenes, which has the characteristics of brightness, color, shape, scale, etc. Texture analysis aiming to interpret and understand real-world visual patterns is an active and challenging research field. Texture classification, as one of the major problems in texture analysis, has been studied for several decades and shows striking improvements; however, the extraction of effective features for texture image representation is still considered as a challenging problem [8]. In [9] the researcher focuses on the use of image-based techniques for classifying, in particular they compare several texture descriptors based on

Local Binary Patterns (LBP), and they proposed some combination of new texture descriptors: the Elongated Ternary Pattern (ELTP) and the Elongated Binary Pattern (ELBP). These two variants of the standard LBP are obtained by considering different shapes for the neighborhood calculation and different encodings for the evaluation of the local gray-scale difference. In [10] the researcher present a color image retrieval scheme for combining all the three color, texture and shape information. Firstly, the image is predetermined by using fast color quantization algorithm with clusters merging, and then a small number of dominant colors and their percentages can be obtained. Secondly, the spatial texture features are extracted using steerable filter decomposition. Thirdly, the pseudo-Zernike moments of an image are used for shape descriptor. In [11] the researcher presents a color image retrieval method based on texture, which uses the color co-occurrence matrix to extract the texture feature and measure the similarity of two color images. In [12] the researcher proposes a hierarchical approach to retrieve an iris image efficiently from for a large iris database. This approach is a combination of both iris color and texture. Iris color is used for indexing and texture is used for retrieval of iris images from the indexed iris database. Kd-tree is used for real-time indexing based on color indices. The iris texture features are obtained through Speeded Up Robust Features (SURF) algorithm. In [13] the researcher proposes a multiscale texture classifier which uses features extracted from both magnitude and phase responses of subbands at different resolutions of the dual-tree complex wavelet transform decomposition of a texture image. The mean and entropy in the transform domain are used to form a feature vector. In [14] The researcher presents a method to extract color and texture features of an image First, HSV color space is quantified rationally. Color histogram and texture features based on a co-occurrence matrix are extracted to form feature vectors. Then the characteristics of the global color histogram, local color histogram and texture features are compared and analyzed for CBIR. 2. Preliminaries In this section, the theoretical foundations for the expert system used in the presented study are explained in the following subsections.

2.1 Contourlet Transform

Contourlet transform is a kind of double iterative filter structure that combined Laplacian pyramid(LP) with direction filter Bank (DFB), developed on the basis of wavelet transform, which is another image representation method of multi-resolution, time-frequency local features and multi-direction. Due to contourlet transform can extract the very important intrinsic geometric structure of image; it can describe the edge detail and texture of image with the best way. With constantly enrich and improve of Contourlet theory and algorithms, it gradually reflect a better advantage in image denoising, enhancement and fusion [15]. Multiscale and time-frequency localization of an image is offered by wavelets. But, wavelets are not effective in representing the images with smooth contours in different directions. Contourlet Transform (CT) addresses this problem by providing two additional properties viz., directionality and anisotropy. Contourlet transform can be divided into two main steps: Laplacian pyramid (LP) decomposing and directional filter banks (DFB) as shown in the Figure 1. The original image is divided to a lowpass image and a bandpass image using LP decomposing. Each bandpass image is further decomposed by DFB. Repeating the same steps upon the lowpass image, the multiscale and multidirection decomposition of the image will be obtained. Contourlet transform is a multi scale and directional image representation that uses first a wavelet like structure for edge detection, and then a local directional transform for contour segment detection. A double filter bank structure of the Contourlet is shown in Figure 1 for obtaining sparse expansions for typical images having smooth contours. In the double filter bank structure, Laplacian Pyramid (LP) is used to capture the point discontinuities, and then followed by a Directional Filter Bank (DFB), which is used to link these point discontinuities into linear structures. The Contourlet have elongated supports at various scales, directions, and aspect ratios. This allows Contourlet to efficiently approximate a smooth contour at multiple resolutions. In the frequency domain, the Contourlet transform provides a multiscale and directional decomposition [16-18].

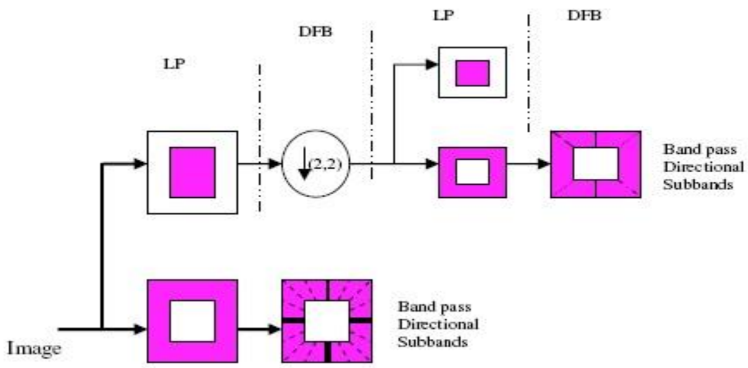

Figure 1 Double Filter Bank Decomposition of Contourlet Transform

One way of achieving a multiscale decomposition is to use a Laplacian pyramid (LP) as introduced by Burt and Adelson [19]. Figure 2 shows this decomposition process, where H and G are called (low pass) analysis and synthesis filters, respectively, and M is the sampling matrix. LP in the PDFB uses orthogonal filters and down sampling by two is taken in each dimension. The LP decomposition at each level generates a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image [20]

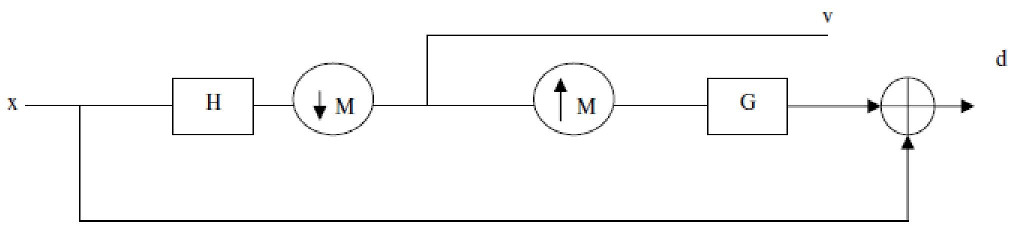

Figure 2 Laplacian Pyramid

2.2 Canonical Correlation Analysis

The feature fusion has become one of the important and hot research fields in pattern recognition. Multiple features can be extracted from the same patterns by using different methods. They give different characteristics of the same pattern. After effectively fusing multiple features through some given methods, we are not only able to obtain the effective discriminant information between multiple features, but also eliminate the redundant information between features in a certain extent. Therefore, the feature fusion is highly significant for recognition. The information fusion is generally divided into three levels in pattern recognition, i.e, pixel level fusion, feature level fusion, and decision level fusion. Taking HIS transformation method and principal component analysis (PCA) as the representation, the pixel level fusion has been widely studied and applied in image fusion, especially in remote sensing image fusion. The decision level fusion, represented by combination classifiers of Bayesian methods, or neural network, has been successfully applied to hand writing numerals and face recognition. While the feature level fusion is between pixel level fusion and decision level fusion. In contrast, although the research of feature level fusion does not start as early as other two fusion methods, it plays a very important role in the process of information fusion. The advantages of feature level fusion are in two aspects: first, it can eliminate redundant information between original multiple features; second, it is able to derive effective discriminant information from multiple feature sets and improve the accuracy in recognition. Therefore, feature level fusion as obtained researchers' wide attention and some delightful researches [21].

Canonical correlation analysis has been widely used to analyze associations between two sets of variables. Suppose that $X \in R^{p\times n}$ and $X \in R^{q\times n}$ are two matrices each contain n training feature vectors from two different modalities. In other words, there are n samples for each of which $(p \times q)$ features have been extracted $S_{xx} \in R^{p\times p}$and $S_{yy} \in R^{q\times q}$denote the within-sets covariance matrices of X and Y and $S_{xy} \in R^{p\times q}$ denote the between-set covariance matrix (note that $S_{yx} = S_{xy}^T$). The overall $(p+q)\times(p+q)$ covariance matrix, S, contains all the information on associations between pairs of features:

$$S = \begin{pmatrix} cov\,(x) & cov(x,y) \\ cov(y,x) & cov(y) \end{pmatrix} = \begin{pmatrix} S_{xx} & S_{xy} \\ S_{yx} & S_{yy} \end{pmatrix} \qquad \text{Eq. 1}$$

However, the correlation between these two sets of feature vectors may not follow a consistent pattern, and thus, understanding the relationships between these two sets of feature vectors from this matrix is difficult. CCA aims to find the linear combinations, $X^* = W_x^T X$ and$Y^* = W_y^T Y$, that maximize the pair-wise correlations across the two data sets:

$$corr(X^*, Y^*) = \frac{cov(X^*, Y^*)}{var(X^*).var(Y^*)} \qquad \text{Eq.2}$$

Where $(X^*, Y^*) = W_x^T S_{xy} W_y$, $cov(X^*) = W_x^T S_{xx} W_x$, $cov(Y^*) = W_y^T S_{yy} W_y$. Maximization is performed using Lagrange multipliers by maximizing the covariance between X^* and Y^* subject to the constraints$var(X^*) = var(Y^*) = 1$. The transformation matrices $W_X$andW_y, are then found by solving the eigenvalue equations:

$$\begin{cases} S_{xx}^{-1} S_{xy} S_{yy}^{-1} S_{yx} \widehat{W}_x = \gamma^2 \widehat{W}_x \\ S_{yy}^{-1} S_{yx} S_{xx}^{-1} S_{xy} \widehat{W}_y = \gamma^2 \widehat{W}_y \end{cases} \qquad \text{Eq.3}$$

Where $\widehat{W}_x$ and $\widehat{W}_y$are the eigenvectors and $\gamma^2$is the diagonal matrix of eigenvalues or squares of the *canonical correlations*. The number of non-zero eigenvalues in each equation is $d = rank(S_{xy}) \leq \min(n, p, q)$ which will be sorted in decreasing order, $\delta_1 \geq \delta_2 \geq \cdots \geq \delta_d$. The transformation matrices, W_x and W_y consist of the sorted eigenvectors corresponding to the non-zero eigenvalues $X^*, Y^* \in R^{d\times n}$ are known as canonical variates. For the transformed data, the sample covariance matrix defined in Eq. (1) will be of the form:

$$S^* = \begin{pmatrix} \begin{pmatrix} 1\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0\ 0 & \cdots & 1 \end{pmatrix} & \cdots & \begin{pmatrix} \delta_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \delta_d \end{pmatrix} \\ \vdots & \ddots & \vdots \\ \begin{pmatrix} \delta_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \delta_d \end{pmatrix} & \cdots & \begin{pmatrix} 1\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0\ 0 & \cdots & 1 \end{pmatrix} \end{pmatrix} \qquad \text{Eq.5}$$

The above matrix shows that the canonical variates have nonzero correlation only on their corresponding indices. The identity matrices in the upper left and lower right corners show that the canonical variates are uncorrelated within each data set. As defined in, feature-level fusion is performed either by concatenation or summation of the transformed feature vectors:

$$Z_1 = \binom{X^*}{Y^*} = \begin{pmatrix} W_x^T \\ W_y^T \end{pmatrix} = \begin{pmatrix} W_x & 0 \\ 0 & W_y \end{pmatrix}^T \binom{X}{Y} \qquad \text{Eq.6}$$

$$Z_2 = X^* + Y^* = W_x^T X W_x^T Y = \begin{pmatrix} W_x \\ W_y \end{pmatrix}^T \binom{X}{Y} \qquad \text{Eq.7}$$

Where $Z1$ and $Z2$ are called the Canonical Correlation Discriminant Features (CCDFs)[21, 22].

3. Methodology

In this study, a new texture classification algorithm which uses Contourlet transform with canonical correlation analysis for efficient texture characterization was proposed. The block diagram of the proposed model is shown at figure 3. The stages involved in texture classification are as follows;

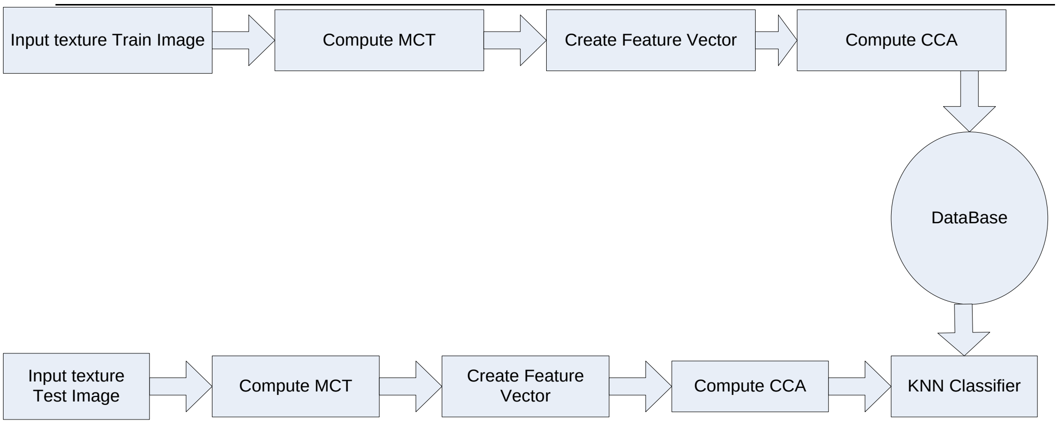

Figure 3 Block Diagram of the proposed model

3.1 Contourlet Transform

The primary goal of the contourlet construction was to obtain a sparse expansion for a typical image that is piece wise smooth. Two dimensional wavelets are only good at catching the point discontinuities, but do not capture the geometrical smoothness of the contours [1]. The contourlet transform is good at capturing multi-scale and multi-orientation features, which are very important for invariant pattern recognition. In the propose work, we applied the multilevel contourlet transform (MCT) Figure 4 show the result of the MCT for the texture image.

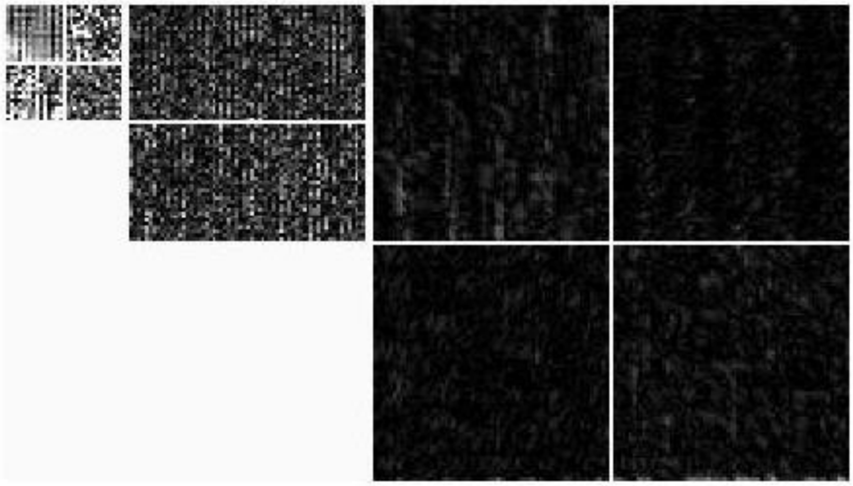

Figure 4 Texture MCT

3.2 Create Feature Vector

The universality of feature extraction is very important for defect classification of metals as different production lines may generate different surface defects. So the image information should be extracted as much as possible to improve the universality of the method. Feature detection is the primary question to be solved in the image process and pattern recognition. In the propose work, some statistical features are computed. After compute the MCT for the texture image, we divided the result of the MCT subband to NxN nonoverlap blocks and compute mean, standard deviation and norm for each blocks.
From these statistical, we create the feature vector.

3.3 Canonical Correlation Analysis

The information fusion method is one of the emerging technologies of data processing. There are three levels of information fusion (pixel level, feature level, and decision level). The advantage of the feature level fusion is obvious. Different feature vectors extracted from the same pattern always reflects the different characteristic of patterns. By enhancing and combining these different features, it not only keeps the effective discriminant information of multi-feature, but also eliminates the redundant information to certain degree. This is especially important to classification and recognition. Canonical correlation analysis (CCA) is one of the statistical methods dealing with the mutual relationships between two random vectors [23]. We combine the two feature vectors to obtain a single feature vector, which is more discriminative than any of the input feature vectors. This is achieved by using a feature fusion technique based on Canonical Correlation Analysis (CCA). Figure 5 show how create the texture feature vector

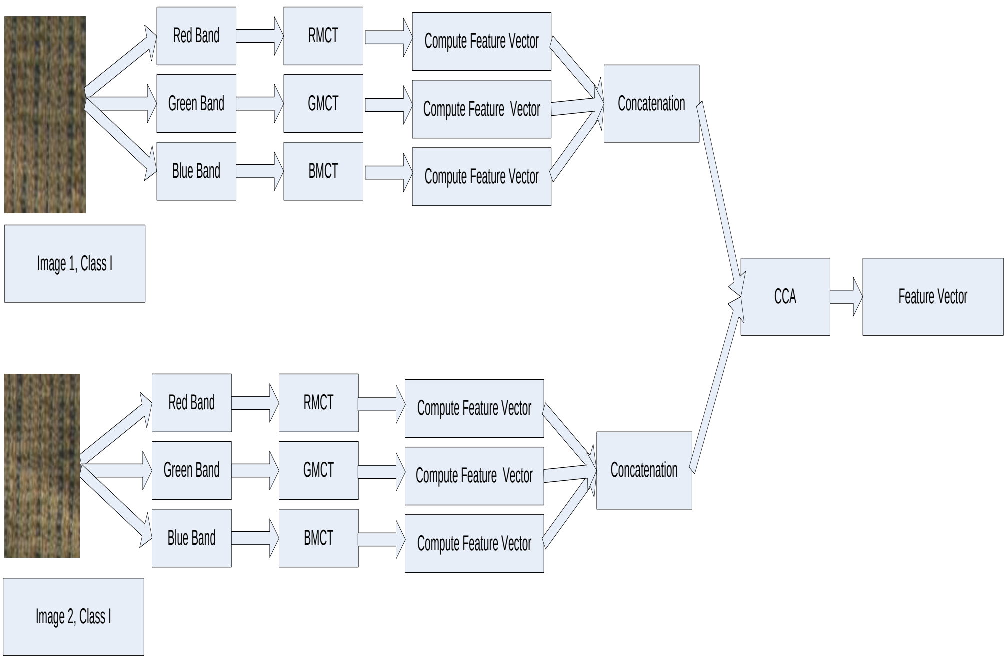

Figure 5 Create Texture Feature Vector

4. Experimental Results and Analysis

For experiments we used images from the Outex Color version of Outex_TC_00034 database [24]. This database contains 68 textures. The type of the texture image is color bmp format. For each band of the texture color image, firstly we applied the MCT then compute the statistical feature. Finally, fusion all the features vectors for each image based on concatenation. Based on CCA, we fusion the feature vectors from different images but for the same class as show in figure 5. For each class of the 68 texture images, we selected number of images for training and testing.

The KNN classifier is used for texture classification. Table 1 shows the classification result (CR):

Level	Block Size	CR for 2X2	Block Size	CR for 4X4
0	2X2	95.1471	4X4	94.7059
0, 1	2X2	95.8824	4X4	94.5588
0, 1, 2	2X2	95.4412	4X4	95.4412

From the Table 1, we can show the best classification result when the contourlet level is 0, 1 and the block size is 2x2; that give the best descriptor features when the block size is not high.

5. Conclusions

In this paper, we have investigated the texture classification problem and established a novel texture classification method via nonparametric modeling through contourlet domain as well as extracting statistical features then applied CCA to create a new feature vector. According to the distance between feature vectors, a new distance between two images is defined, with which a k-nearest neighbor classifier is utilized to perform supervised texture classification. The various experiments have shown that our proposed method significantly improves the texture classification accuracy.

References

[1] Y. Dong and J. Ma, "Feature extraction through contourlet subband clustering for texture classification," *Neurocomputing,* vol. 116, pp. 157-164, 2013.

[2] K. M. Saipullah and D.-H. Kim, "A robust texture feature extraction using the localized angular phase," *Multimedia Tools and Applications,* vol. 59, pp. 717-747, 2012.

[3] H. Zhou, R. Wang, and C. Wang, "A novel extended local-binary-pattern operator for texture analysis," *Information Sciences,* vol. 178, pp. 4314-4325, 2008.

[4] A. Samal, J. R. Brandle, and D. Zhang, "Texture as the basis for individual tree identification," *Information Sciences,* vol. 176, pp. 565-576, 2006.

[5] K. Jafari-Khouzani and H. Soltanian-Zadeh, "Radon transform orientation estimation for rotation invariant texture analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 27, pp. 1004-1008, 2005.

[6] F. Y. Shih and C.-F. Chuang, "Automatic extraction of head and face boundaries and facial features," *Information Sciences,* vol. 158, pp. 117-130, 2004.

[7] K. Iqbal, M. O. Odetayo, and A. James, "Content-based image retrieval approach for biometric security using colour, texture and shape features controlled by fuzzy heuristics," *Journal of Computer and System Sciences,* vol. 78, pp. 1258-1277, 2012.

[8] Y. Guo, G. Zhao, and M. PietikäInen, "Discriminative features for texture description," *Pattern Recognition,* vol. 45, pp. 3834-3843, 2012.

[9] L. Nanni, S. Brahnam, and A. Lumini, "A local approach based on a Local Binary Patterns variant texture descriptor for classifying pain states," *Expert Systems with Applications,* vol. 37, pp. 7888-7894, 2010.

[10] X.-Y. Wang, Y.-J. Yu, and H.-Y. Yang, "An effective image retrieval scheme using color, texture and shape features," *Computer Standards & Interfaces,* vol. 33, pp. 59-68, 2011.

[11] X.-y. Wang, Z.-f. Chen, and J.-j. Yun, "An effective method for color image retrieval based on texture," *Computer Standards & Interfaces,* vol. 34, pp. 31-35, 2012.

[12] U. Jayaraman, S. Prakash, and P. Gupta, "An efficient color and texture based iris image retrieval technique," *Expert Systems with Applications,* vol. 39, pp. 4915-4926, 2012.

[13] T. Çelik and T. Tjahjadi, "Multiscale texture classification and retrieval based on magnitude and phase features of complex wavelet subbands," *Computers & Electrical Engineering,* vol. 37, pp. 729-743, 2011.

[14] J. Yue, Z. Li, L. Liu, and Z. Fu, "Content-based image retrieval using color and texture fused features," *Mathematical and Computer Modelling,* vol. 54, pp. 1121-1127, 2011.

[15] Z. Luo, "Iris feature extraction and recognition based on wavelet-based contourlet transform," *Procedia Engineering,* vol. 29, pp. 3578-3582, 2012.

[16] N. Chitaliya and A. Trivedi, "An efficient method for face feature extraction and recognition based on contourlet transforms and principal component analysis," *Procedia Computer Science,* vol. 2, pp. 52-61, 2010.

[17] M. N. Do and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation," *IEEE Transactions on image processing*, vol. 14, pp. 2091-2106, 2005.

[18] G. Chen and B. Kégl, "Invariant pattern recognition using contourlets and AdaBoost," *pattern recognition*, vol. 43, pp. 579-583, 2010.

[19] P. Burt and E. Adelson, "The Laplacian pyramid as a compact image code," *IEEE Transactions on communications*, vol. 31, pp. 532-540, 1983.

[20] C. M. Patil and S. Patilkulkarni, "An efficient process of recognition of human iris based on contourlet transforms," *Procedia Computer Science*, vol. 2, pp. 121-126, 2010.

[21] Y.-H. Yuan, Q.-S. Sun, Q. Zhou, and D.-S. Xia, "A novel multiset integrated canonical correlation analysis framework and its application in feature fusion," *Pattern Recognition*, vol. 44, pp. 1031-1040, 2011.

[22] M. Haghighat, M. Abdel-Mottaleb, and W. Alhalabi, "Fully automatic face normalization and single sample face recognition in unconstrained environments," *Expert Systems with Applications*, vol. 47, pp. 23-34, 2016.

[23] Q.-S. Sun, S.-G. Zeng, Y. Liu, P.-A. Heng, and D.-S. Xia, "A new method of feature fusion and its application in image recognition," *Pattern Recognition*, vol. 38, pp. 2437-2448, 2005.

[24] Outex Color version of Outex_TC_00034 database: http://lagis-vi.univ-lille1.fr/datasets/outex.html.