DOI: 10.21917/ijivp.2015.0156

COLOR IMAGE RETRIEVAL BASED ON FEATURE FUSION THROUGH MULTIPLE LINEAR REGRESSION ANALYSIS

K. Seetharaman[1] and R. Shekhar[2]
[1]*Department of Computer Science and Engineering, Annamalai University, India*
E-mail: kseethadde@yahoo.com
[2]*Department of Computer Applications, Manonmaniam Sundaranar University, India*
E-mail: shekhar.aims@yahoo.co.in

Abstract

This paper proposes a novel technique based on feature fusion using multiple linear regression analysis, and the least-square estimation method is employed to estimate the parameters. The given input query image is segmented into various regions according to the structure of the image. The color and texture features are extracted on each region of the query image, and the features are fused together using the multiple linear regression model. The estimated parameters of the model, which is modeled based on the features, are formed as a vector called a feature vector. The Canberra distance measure is adopted to compare the feature vectors of the query and target images. The F-measure is applied to evaluate the performance of the proposed technique. The obtained results expose that the proposed technique is comparable to the other existing techniques.

Keywords:

Regression, Fusion, Feature, F-measure, Least-Square Estimate

1. INTRODUCTION

Information fusion technique plays a noteworthy role in computer vision and information retrieval for the last ten years. Fusion techniques are applied in various application domains, namely object detection, recognition, identification and classification, object tracking, change detection, decision making, etc. It has been successfully applied in various areas, i.e. space and earth observation domains, computer vision, medical image analysis and defense security, etc. Data fusion combines data from various sources, and facilitate to improve the results and interpretation, performances of the source data, and to produce a high-quality visible representation of the data [1]. A review of literature reveals that information fusion is performed at pixel level, feature level, and decision level. The pixel level fusion combines the pixels of two or more number of images, or different parts (region of interest) of the same image and the outcome results of the fused images are more informative. The feature level fusion extracts various features like boundaries, edges, texture orientations, color features, etc. from different images, and then combines them into one or more feature maps that may be used instead of original image for further processing or analyses. The decision level fusion merges the results obtained from various algorithms, and produces a final fused decision. The results obtained from different algorithms are expressed as confidences (or scores) rather than decisions, which are known as soft fusion; otherwise, it is called hard fusion [1]. Methods of decision fusion include voting methods, statistical methods, and fuzzy logic based methods. Among them, the decision level fusion is one of the hottest techniques adopted in application areas like pattern recognition, multispectral image mining, and has got successful results specifically in handwritten, and face recognition. In recent years, the feature level fusion has turned the attention of the researchers in the area of computer vision to the recognition and classification. Sun et al. [2] report that different features extracted from the same pattern always reflects different characteristics of the pattern. The effective discriminant information on multi-features is maintained as it is, and also the redundancy of information is eliminated by optimizing and merging the different features. There are two kinds of feature fusion methods: one method groups two sets of feature vectors into one-union vector, and then extracts the features in higher dimensional real vector space [3]; and the other combines two sets of feature vectors by merging two complex vectors [4].

The image or data fusion methodology is mostly adopted in multi-spectral or hyper-spectral remote sensing satellite image processing or analysis, since that type of images contain complicated structures and also they are captured through infrared apparatus. Thus, by combining the features of various images or data sources into a single image or data, it yields better results. Since 1990s it has got fruitful results and developments in remote sensing image analysis. A number of researchers have shown interest in remote sensing image analysis.

The algorithms for analyzing the remote sensing image fusion can be divided into three categories such as component substitution fusion [5], [6], modulation based fusion technique [7], [8], [11], and multi-scale analysis based fusion technique [9], [10], [13], [14]. Yocky [15] applies discrete two-dimensional wavelet transform image fusion techniques to combine Lands at TM data and SPOT panchromatic data. The "standard" TMISPOT wavelet merges is then presented and compared to the IHS merging technique. They also introduce algorithms called "additive" and "selective resolution" wavelet mergers, and compare the new wavelet techniques to the IH-merging algorithm. A literature survey reveals that a number of transform based fusion algorithms have been developed such as Principle Component Analysis transform based fusion algorithm [5], Local Correlation Modeling (LCM) fusion algorithm [6], and Regression Variable Substitute (RVS) based fusion algorithm [5]; the fusion algorithms of the modulation based technique include Brovey transform fusion algorithm [11], Smoothing Filter Based Intensity Moulation (SFIM) based fusion algorithm [7], and high pass filter fusion algorithm [12]; the fusion algorithms based on the multi-scale analysis mainly include wavelet decomposition based fusion technique [9], [10], [13], and Laplacian pyramid decomposition based fusion technique [14].

Nevertheless, a number of fusion based algorithms have been studied in the literature, a doubt arises that whether the algorithm described are in a manner of generalized mathematical model [16], [17]. Also, there arises a qualm that most of the researchers have ignored the concept of generalization of the fusion based algorithm for the image retrieval. Sun et al. [2] proposed a technique, in which, they extract features based on feature fusion using canonical correlation analysis. The model can reflect the main features of the fusion process by a simple mathematical formula. The establishment of a generalized model will contribute to relatively theoretical analysis and fusion algorithm design in the light of a specific application. Also the model is beneficial to qualitative and quantitative analysis of fusion technology from different aspects. Recently, Diogone et al. [18] extend the pan-sharpening ARSIS method to the fusion of two multispectral images and to compare it with two other existing methods: the couple non-negative matrix factorization (CNMF), and a Multisensor and multiresolution technique. Saulquin et al. [19] consider one-dimensional (1-D) geophysical time series as series of significant time-scale events, and they combine a wavelet-based analysis with a Gaussian mixture model to extract characteristic time-scales of 486 144 detected events in the Sea Surface Temperature Anomaly (SSTA) observed from satellite at the global scale from 1985 to 2009. In [19], it retrieves four low-frequency characteristic time-scales of Niño Southern Oscillation (ENSO) in the 1.5 to 7-year range and show their spatial distribution.

2. PROPOSED FUSION MODEL

The regression analysis plays a significant role in combining various features. Thus, in this paper, we have made an attempt to combine the features of various parts of a query image and then it compares with the features of the target image in the feature database using the multiple linear regression (MLR) model. To achieve this, the MLR model expressed in Eq.(1) is adopted.

$$FU_i = C_{ij} + \lambda_{ij} FE_{ij} + \varepsilon_{ij} \tag{1}$$

where, the error term ε_{ij} is assumed to have the following properties:

$$\left.\begin{aligned} &E(\varepsilon_{ij}) = 0 \\ &Var(\varepsilon_{ij}) = \sigma^2, \text{ and} \\ &Cov(\varepsilon_i, \varepsilon_j) = 0, \quad i \neq j \end{aligned}\right\} \tag{2}$$

ij - i^{th} feature of the j^{th} region

FU_i - response variable of the i^{th} fused feature vector

C_{ij} - constant of the i^{th} feature of the j^{th} region

λ_i - coefficient of the i^{th} feature of the j^{th} region

FE_{ij} - feature vector of the ij^{th} feature of the j^{th} region

ε_{ij} - error term of the j^{th} feature of the i^{th} region

σ^2 - variance of the error term ε_{ij}.

The complete model of the compact model expressed in Eq.(1) can be written in the expanded form as in Eq.(2) with n independent feature vectors on FU and the associated values of FEs.

$$\left.\begin{aligned} FU_1 &= C_{11} + \lambda_{11}FE_{11} + \lambda_{12}FE_{12} + \ldots + \lambda_{1m}FE_{1m} + \varepsilon_{11} \\ FU_2 &= C_{22} + \lambda_{22}FE_{21} + \lambda_{22}FE_{22} + \ldots + \lambda_{2m}FE_{2m} + \varepsilon_{22} \\ &\vdots \\ FU_n &= C_{n2} + \lambda_{n2}FE_{n1} + \lambda_{n2}FE_{n2} + \ldots + \lambda_{nm}FE_{nm} + \varepsilon_{nn} \end{aligned}\right\} \tag{3}$$

The above Eq.(2) can be written in the matrix form as follows:

$$\begin{bmatrix} FU_1 \\ FU_2 \\ \vdots \\ FU_n \end{bmatrix} = \begin{bmatrix} 1 & FE_{11} & FE_{12} & \ldots & FE_{1m} \\ 1 & FE_{21} & FE_{21} & \ldots & FE_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & FE_{n1} & FE_{n1} & \ldots & FE_{nm} \end{bmatrix} \begin{bmatrix} \lambda_{11} \\ \lambda_{21} \\ \vdots \\ \lambda_{n1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{n1} \end{bmatrix} \tag{4}$$

and the specifications in Eq.(2) become

$$\left.\begin{aligned} E(\varepsilon) &= 0, \text{ and} \\ Cov(\varepsilon) &= E(\varepsilon\varepsilon') = \sigma^2 I \end{aligned}\right\} \tag{5}$$

Note that "1" in the first column of the design matrix FE is the multiplier of the constant term 'C'. It is customary to introduce the artificial variable $Z_{j0} = 1$.

The given input query image is segmented into various regions according to its nature or structure of the image. Each region of the segmented color image is modeled to HSV color space, where H represents hue of the color and it ranges from 0°to 360°; S represents saturation of the color, namely the magnitude of the color with which the amount of white is mixed; V is attributed to the pixel values, and it contains the texture primitives and magnitude of the intensity value of the pixels. Both S and V range from 0 to 1, which are, generally, represented in per cent. In this research work, the color features and texture orientations are considered and those are fused based on the expression given in Eq.(1). According to the features considered in this article, the model in Eq.(1) is restructured as follows.

The main objective of the MLR analysis is to develop a regression model based on the image features, which is used to predict the response of the various fused features of the query and target images using the MLR model presented in Eq.(6).

$$FU_{r_i} = C_{r_i} + \lambda_{r_iH}FE_{r_iH} + \lambda_{r_iS}FE_{r_iS} + \lambda_{r_iV}FE_{r_iV} + \lambda_{r_iT}FE_{r_iT} + \varepsilon_{r_i} \tag{6}$$

where,

r_i - i^{th} region of the segmented image

FU_{r_i} - response variable of the features fused from r_i^{th} region

C_{r_i} - constant term of the i^{th} region

λ_{r_iH} - coefficient of the feature vector of the H component of the i^{th} region

FE_{r_iH} - predictor variables of feature vector of the H component of the i^{th} region

Similarly, the λ_{r_iS}, λ_{r_iV} represent the coefficient of the feature vectors of S and V components of the HSV color space of the i^{th} region, and λ_{r_iT} represents the texture features of the i^{th}

region of the segmented image; FE_{r_iS}, FE_{r_iV} represent the feature vectors of the *S* and *V* components of the *HSV* color space, and FE_{r_iT} represents the texture feature of the i^{th} region of the segmented image.

3. PARAMETER ESTIMATION

In order to fuse the different kinds of futures extracted from a region of an image, the parameters of the MLR model have to be estimated. To estimate the parameters λ_{r_i}, the least square estimation (LSE) method is adopted. The LSE method selects $\hat{\lambda}$ by which the sum of the squares of the differences between the response variable and the predictor variables can be minimized. λ_{r_i} is the estimate of the λ_{r_i}, which is estimated as follows:

$$S(\lambda_{r_i}) = \sum \begin{pmatrix} FU_{r_i} - C_{r_i} - \lambda_{r_iH} FE_{r_iH} - \\ \lambda_{r_iS} FE_{r_iS} - \lambda_{r_iV} FE_{r_iV} - \lambda_{r_iT} FE_{r_iT} \end{pmatrix}$$

$$S(\lambda_{r_i}) = (FU - Z\lambda)'(FU - Z\lambda) \tag{7}$$

The deviation between the response variable and the predictor variables is called residuals. The vector of residuals ε_{r_i}, contains the information about the unknown parameter σ^2.

$$\begin{aligned} \varepsilon_{r_i} &= FU_{r_i} - C_{r_i} - \lambda_{r_iH} FE_{r_iH} - \\ &\lambda_{r_iS} FE_{r_iS} - \lambda_{r_iV} FE_{r_iV} - \lambda_{r_iT} FE_{r_iT}, i = 1,2,\ldots,n \end{aligned} \tag{8}$$

The least square estimate of λ is given by,

$$\hat{\lambda}_{r_i} = \left[(FE)'(FE)\right]^{-1}(FE)'(FU) =$$

$$\begin{bmatrix} C_{r_i} \\ \hat{\lambda}_{r_iH} \\ \hat{\lambda}_{r_iS} \\ \hat{\lambda}_{r_iV} \\ \hat{\lambda}_{r_iT} \end{bmatrix} = \left[(FE)'(FE)\right]^{-1}(FE)'(FU) \tag{9}$$

$$\left[(FE)'(FE)\right]^{-1} =$$

$$\left(\begin{bmatrix} 1 & FE_{r_1H} & FE_{r_1S} & FE_{r_1V} & FE_{r_1T} \\ 1 & FE_{r_2H} & FE_{r_2S} & FE_{r_2V} & FE_{r_2T} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & FE_{r_nH} & FE_{r_nS} & FE_{r_nV} & FE_{r_nT} \end{bmatrix}' \begin{bmatrix} 1 & FE_{r_1H} & FE_{r_1S} & FE_{r_1V} & FE_{r_1T} \\ 1 & FE_{r_2H} & FE_{r_2S} & FE_{r_2V} & FE_{r_2T} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & FE_{r_nH} & FE_{r_nS} & FE_{r_nV} & FE_{r_nT} \end{bmatrix} \right)^{-1} \tag{10}$$

where,

$$\left[(FE)'(FE)\right]^{-1}$$

$$\begin{bmatrix} 1 & FE_{r_1H} & FE_{r_1S} & FE_{r_1V} & FE_{r_1T} \\ 1 & FE_{r_2H} & FE_{r_2S} & FE_{r_2V} & FE_{r_2T} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & FE_{r_nH} & FE_{r_nS} & FE_{r_nV} & FE_{r_nT} \end{bmatrix} \begin{bmatrix} 1 \\ FU_{r_1H} \\ FU_{r_2H} \\ \vdots \\ FU_{r_nH} \end{bmatrix} \tag{11}$$

For example, let us take $i = 1$,

$$\hat{\lambda}_{r_1} = \begin{bmatrix} \hat{\lambda}_{r_1H} \\ \hat{\lambda}_{r_1S} \\ \hat{\lambda}_{r_1V} \\ \hat{\lambda}_{r_1T} \end{bmatrix} =$$

$$\left(\begin{bmatrix} 1 \\ FE_{r_1}H \\ FE_{r_1}S \\ FE_{r_1}V \\ FE_{r_1}T \end{bmatrix} \begin{bmatrix} 1 & FE_{r_1}H & FE_{r_1}S & FE_{r_1}V & FE_{r_1}T \end{bmatrix} \right)^{-1} \tag{12}$$

$$\begin{bmatrix} 1 \\ FE_{r_1}H \\ FE_{r_1}S \\ FE_{r_1}V \\ FE_{r_1}T \end{bmatrix} \begin{bmatrix} FU_{r_1} \end{bmatrix}$$

Similarly, the parameters can be estimated for other regions, i.e. $i = 2, 3, \ldots, n$.

4. MEASURE OF PERFORMANCE

In order to measure the performance of the proposed method, the F-measure [20] is adopted, which is calculated based on the precision and recall values [21], and that are given in Eq.(13), Eq.(14) and Eq.(15).

$$F - \text{measure} = \frac{(1+\alpha)(\text{Precision})(\text{Recall})}{(\alpha)(\text{Precision}) + (\text{Recall})} \tag{13}$$

where,

$$\text{Precision} = \frac{\left|\{\text{Relevant Images}\} \cap \{\text{Retrived Images}\}\right|}{\left|\text{Retrived Images}\right|} \tag{14}$$

$$\text{Recall} = \frac{\left|\{\text{Relevant Images}\} \cap \{\text{Retrived Images}\}\right|}{\left|\text{Relevant Images}\right|} \tag{15}$$

5. EXPERIMENTS AND RESULTS

In order to examine the proposed MLR model, different types of images considered from the well-known image databases such as Brodatz Album, Corel image database, and VisTex image database as proposed in [21], and are used in the experiment. The given input query image is segmented into various regions according to its structure. For a sample, the segmented rabbit image is presented in the Fig.1.

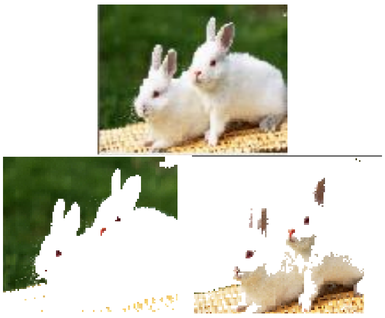

Fig.1. Segmented Rabbit image: First row – actual image; first image in the second row – rabbit is segmented from background; second image in second row – background is segmented from rabbit

The segmented image is modeled to *HSV* color space. The texture features are extracted from the *V* component of the *HSV* space. The color features *H*, *S*, *V* and the texture feature are considered as observation and used in the MLR model expressed in Eq.(6). The parameters λ_{r_i} are estimated, based on the feature observations, using the Eq.(9). Using the estimated parameter values, the features are fused and it results in the response variable FU_{r_i}. Similarly, the same procedure is adopted in all the regions of the query image. After fusing the features of each region of the query image individually, it is formed as a feature vector, f_v. The feature vector is compared with the feature vectors in the image feature database based on the Canberra distance metric. Kokare et al. [22] performed a comparative study among the nine distance metrics, and report that the Canberra distance metric yields better results. Thus, in this research work the Canberra metric is used to measure the distance between the query and target images. The Canberra metric is presented in Eq.(16).

$$d_c\left(f_v^q, f_v^t\right) = \sum_{i=1}^{r} \frac{\left|f_v^{q_i} - f_v^{t_i}\right|}{\left|f_v^{q_i}\right| + \left|f_v^{t_i}\right|} \tag{16}$$

where,

f_v^q and f_v^t - feature vectors of the query and target images respectively

i - i^{th} feature

r - r^{th} image region

In order to validate the proposed system, the images in Fig.3(a) are given as input query image, for which the system retrieves the images in the rows against them in Fig.3(b). The retrieved output images show that the proposed MLR model based feature extraction, and fusion of the features is robust for scaling and rotation for both types of images such as texture and structure. Since the proposed system extracts the features from the fused feature, based on the MLR model, almost it serves same as the distributional approach. Thus, the proposed system acts as an invariant for scaling and rotation.

On trial and error basis, a rigorous experiment is conducted on the fused features between the query and target images to arrive a significant threshold (*t*) value for Canberra distance metric. The experiments result in a range from 0 to 0.15, and the retrieved images in the range of 0 to 0.15 are presented Fig.2. For this range (t<= 0.15), the proposed system retrieves the images which are same or very similar. The user can fix (either increase or decrease) the t value according to his requirement of a number of images.

At various levels of significance the test is conducted, and the obtained output results are graphically represented, which is presented in Fig.3. It is observed from the experiments that the proposed fusion method yields better results for structure images compare to the texture, but for fine texture images it gives a good result compared to the semi-texture (like stone and brick-wall). Since the structure images are segmented into various regions according to its nature, the image data become homogeneous and so the model parameters are estimated more precise than the texture images. The semi-texture images are mixed image data than the fine texture. In the case of semi-textured images, the images are not segmented so the data are mixed (either not homogeneous or heterogeneous). Thus, the fused data yield better results for structure and texture (fine) images.

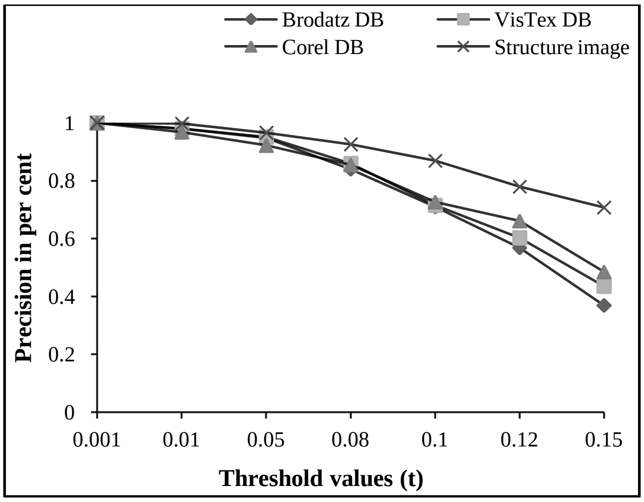

Fig.2. Threshold (*t*) vs. Precision

6. CONCLUSION

In this paper, a multiple linear regression based fusion method has been adopted and different kinds of images both texture and structures have been included in the experiment. The model parameters are estimated based on the least-square estimation method. If the image is structure, then it is segmented; otherwise, the image is considered as a whole image. The fused feature vectors of the query image are compared with the target images features using the F- measure. The fusion based method yields better results for structure images.

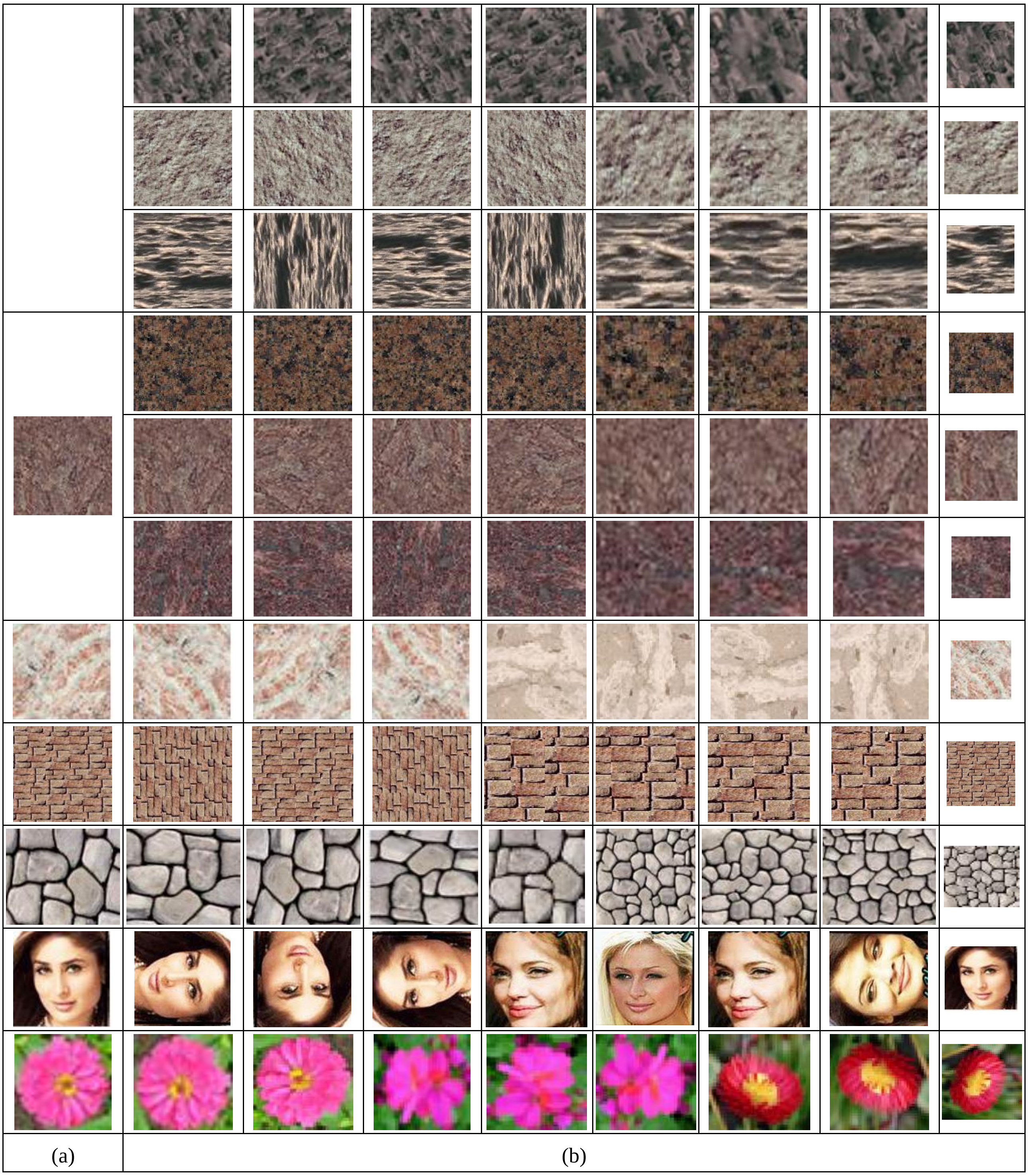

Fig.3. Texture (collected from Brodatz Album, Structure images: Images in column 1 – input query images; the images in the row(s) against them are retrieved output images; images in the last row are scaled. Images presented in some columns are rotated through a 90 degrees or 180 degrees or 260 degrees

REFERENCES

[1] Jixian Zhang, "Multi-source remote sensing data fusion: status and trends", *International Journal of Image and Data Fusion*, Vol. 1, No. 1, pp. 5-24, 2010.

[2] Quan – Sen Sun, Sheng- Gen Zeng, Yan Liu, Pheng - Ann Heng and De- Shen Xia, "A new method of feature fusion and its application in image recognition", *Journal of Pattern Recognition*, Vol. 38, No. 12, pp 2437-2448, 2005.

[3] Chengjun Liu and H. Wechsler, "A shape and texture based enhanced Fisher classifier for face recognition", *IEEE Transaction on Image Processing*, Vol. 10, No. 4, pp. 598-608, 2001.

[4] J. Yang and J. Yang, "Generalized K-L transform based combined feature extraction", *Pattern Recognition*, Vol. 35, No. 1, pp. 295-297, 2005.
[5] V. K. Shettigara, "A generalized component substitution technique for spatial enhacement of multispectral images using a higher resolution data set", *Photogrammetric Engineering and Remote Sensor,* Vol. 58, No. 5, pp. 561–567, 1992.
[6] J. Hill, C. Diemer, O. Stöver and Th. Udelhoven, "A Local Correlation Approach for the Fusion of Remote Sensing Data with Different Spatial Resolutions in Forestry Applications", *International Archives of Photogrammetry and Remote Sensing*, Vol. 32, pp. 1-8, 1999.
[7] J. G. Liu, "Smoothing Filter-based Intensity Modulation: a spectral preserve image fusion technique for improving spatial details", *International Journal of Remote Sensing*, Vol.21, No. 18, pp. 3461-3472, 2000.
[8] Jixian Zhang, Jinghui Yang, Zheng Zhao, Haitao Li and Y. H.. Zhang, "Block-regression based Fusion of Optical and SAR Imagery for Feature Enhancement", *International Journal of Remote Sensing*, Vol. 31, No. 9, pp. 2325-2345, 2010.
[9] Thierry Ranchin, Bruno Aiazzi, Luciano Alparone, Stefano Baronti and Lucien Wald, "Image fusion—the ARSIS concept and some successful implementation schemes", *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 58, pp. 4-18, 2003.
[10] P. S. Pradhan, R. L. King, N. H. Younan and D. W. Holcomb,"Estimation of the Number of Decomposition Levels for a Wavelet-Based Multiresolution Multisensor Image Fusion", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 44, No. 12, pp. 3674 – 3686, 2006.
[11] Jim Vrabel, "Multispectral imagery advanced band sharpening study", *Photogrammetric Engineering and Remote Sensing*, Vol. 66, No. 1, pp.73-79, 2000.
[12] Pat. S. Chavez, Stuart C. Sides and Jeffrey A. Anderson, "Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT panchromatic", *Photogrammetric Engineering and Remote Sensing*, Vol. 57, No. 3, pp. 295-303, 1991.
[13] J. Zhou, D. L. Civco and J. A. Silander, "A Wavelet Transform Method to Merge Landsat TM and SPOT Panchromatic Data", *International Journal of Remote Sensing*, Vol. 19, No. 4, pp. 743-757, 1998.
[14] B. Aiazzi, L. Alparone, S. Baronti and S. Garzelli, "Context-driven fusion of high spatial and spectral resolution images based on oversampled multiresolution analysis", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 40, No. 10, pp. 2300-2312, 2002.
[15] David A. Yocky, "Multiresolution Wavelet Decomposition ImeMergerof Landsat Thematic Mapper and SPOT Panchromatic Data", *Photogrammetric Engineering & Remote Sensing*, Vol. 62, No. 9, pp. 1067-1074, 1996.
[16] Te - Ming Tu, Shun - Chi Su, Hsuen – Chyun Shyu and Ping S. Huang, "A new look at IHS-like image fusion methods", *Information Fusion*, Vol. 2, pp. 177-186, 2001.
[17] Zhijun Wang, D. Ziou, C. Armenakis, Deren Li and Qingquan Li, "A Comparative Analysis of Image Fusion Methods", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 43, No. 6, pp. 1391-1402, 2005.
[18] D. Sylla, A. Minghelli-Roman, P. Blanc, A. Mangin and O. H. Fanton d'Andon, "Fusion of Multispectral Images by Extension of the Pan-Sharpening ARSIS Method, *IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing*, Vol. 7, No. 5, pp. 1781 – 1791, 2014.
[19] B. Saulquin, R. Fablet, G. Mercier, H. Demarcq, A. Mangin and O. H. Fanton d'Andon, "Multiscale Event-Based Mining in Geophysical Time Series: Characterization and Distribution of Significant Time-Scales in the Sea Surface Temperature Anomalies Relatively to ENSO Periods from 1985 to 2009", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 7, No. 8, pp. 3543-3552, 2014.
[20] Xiao Li, Ye – Yi Wang and Alex Acero, "Learning Query Intent from Regularized Click Graphs", *31st Annual International ACM SIGIR conference on Research and Development in Information Retrieval*, pp. 339-346, 2008.
[21] K. Seetharama and M. Jeyakarthic, "Statistical Distributional Approach for Scale and Rotation Invariant Color Image Retrieval Using Multivariate Parametric tests and Orthogonality Condition", *Journal of Visual Communication and Image Representation*, Vol. 25, No. 5, pp. 727-739, 2013.
[22] M. Kokare, B. N. Chatterji and P. K. Biswas, "Comparison of similarity metrics for texture image retrieval", *Conference on Convergent Technologies for Asia-Pacific Region TENCON 2003*, Vol. 2, 571-575, 2003.