NOVEL DLBP FEATURE EXTRACTION FOR SATELLITE IMAGE CHANGE DETECTION

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Abstract: With the use of remote sensing imagery to model the natural phenomena such as disaster management mitigation, urban development etc., the need to assess the changes due to this phenomena is highly critical. The remote sensing data is complex in terms of the color and textural variations. Feature extraction is a crucial step in remote sensing image classification which directly affects the classification accuracy. The extraction of textural features on such images which are rich in spatial information is extremely important. There are many feature extraction techniques already available in the literature. But the main drawback of the existing techniques is the lack of obtaining the minute information embedded in the image. This is a critical stage in enhancing the change detection result. This paper presents a Dynamic Local Binary Pattern (DLBP) for textural feature extraction for satellite image change detection. The quantitative analysis of the proposed method is carried out by computing the kappa coefficient, false alarm and missed alarm.

Keywords: Multispectral; change detection; local binary pattern; local ternary pattern; change map .

1. Introduction

Multispectral images play a significant role in remote sensing. These images consist of three to four bands and are rich in spatial information, spectral properties and rich in textural details. The presence of these features make multispectral images suitable for applications such as land use and land cover change detection, surveillance, agricultural analysis etc. The increased complexity of satellite images makes the change detection difficult.

Textural feature extraction is applied in many areas such as medical imaging, computer vision, remote sensing, signal analysis etc. Texture serves as a major descriptor of the homogeneity in images especially in remote sensing imagery which is rich in textural variations. Statistical analysis is mainly done for textural feature extraction. It mainly represents the spatial properties of texture primitives to convey the differences in regions. Gray Level Co-occurrence Matrix(GLCM) is a statistical textural extraction method which is widely used. It is specified by the spatial relationship between the pixels in the image [Parveen *et al.* (2019)]. Haralick feature extraction to extract texture from ultrasound images is proposed in.It computes the spatial properties of GLCM using four angular mean as a function of the angular relationship and their distance. Feature extraction using HOG features, color moment feature and Gabor feature in MR images is presented in [Jeslin *et al.* (2020)]. Here the image features are detected using the Harris detector. Earth quake induced building detection with textural feature extraction is used for SAR image change detection [Li *et al.* (2018)]. Multi textural feature extraction for SAR image change detection using homogeneity, mean and variance based GLCM features is explained in [Li *et al.* (2019)].A Radian Mean Local Binary Pattern(RMLBP) based descriptor for color image retrieval is developed for extracting features from individual color spaces and concatenating the histograms form individual color channels to form a single feature vector [Sotoodeh*et al.* (2019)]. LBP feature extraction is also used to analyze the features in energy transformation in machines for bearing fault diagnosis [Kaplan *et al.* (2019)]. Gabor and GLCM for texture analysis in multispectral image is presented in [Cirisa *et al.* (2017)]. Here Gabor magnitude is calculated from curvelet decomposed images and GLCM features are extracted from this Gabor magnitude. This improves the retrieval rate for images. Plane based wavelet features are extracted from agricultural image databases along with GLCM features to improve the selection rate of the features [Sudheer *et al.* (2019)]. A GLCM and LBP fused feature extraction for content based image retrieval is proposed in [Garg *et al.* (2019)]. Discrete Wavelet Transform (DWT) is applied on the RGB channels and rotational invariant Dominant-Rotated Local Binary Pattern is performed. A central pixel selection strategy to enhance the LBP based feature extraction is presented in [Pan *et al.* (2019)]. Here, the concept that different central pixels have varying gray level distribution is taken into consideration and sampling radius is selected differently for different pixels. An improved joint local ternary pattern for target recognition in infrared images is presented in [Sun *et al.* (2016)]. When compared to the conventional LBP, this method can extract both the macroscopic and microscopic details by fusion of different scales.

Facial expression recognition is another predominant area where feature extraction is prevalent. Different variants of LBP and LTP are developed for feature extraction in facial images. Local Directional Ternary Pattern(LDTP) for facial expression recognition is explained in [Ryu *et al.* (2017)]. Here emotion related features are extracted using directional details and ternary pattern by utilizing the edge information. Multi-Stage Binary Pattern (MSBP) for facial expression recognition is proposed in [Arshid*et al.* (2018)]. While LBP discards the important textural information by considering only the sign difference between the central pixel and the neighboring pixels, MSBP takes into account the gradient difference along with the sign difference to extract the important information. An Improved Adaptive LTP (IALTP) with two dimensional Principal Component Analysis(PCA) for facial feature extraction is explained in [Luo *et al.* (2018)].Here gradient descend iterative function finds the difference coefficients which is considered as the threshold for IALTP. An Improved Complete Dynamic LTP for textural feature extraction is proposed in [Parveen *et al.* (2018)]. Image local features such as sign, magnitude and center complementary details are extracted in this method and Weber's law is used for selecting the threshold value.

Water and non-water textural feature extraction for water area recognition is proposed in [Chen *et al.* (2018)] .An optimal mask is developed by maximizing the texture energy using Cuckoo Search algorithm. Urban area classification using Histograms of Equivalent Patterns for extracting textural feature is explained in [Aguilar *et al.* (2016)]. The feature space is divided into image patches of definite shape and size where the division is based on local and global functions of intensities of pixels. In this work, a textural feature extraction using Dynamic Local Binary Pattern is introduced and applied on each individual channels and fused for change analysis. The remaining sections divided as: Section 2 explains the materials and methods, section 3 gives the experimental results and section 4 concludes the work.

2. Materials and Methods

To analyze the proposed work, a sample set of 60 images are selected from https://www.digitalglobe.com.Of these samples, two image sets are used for change detection. The proposed work is executed in MATLAB 2018a . The database comprises of Landsat and optical images.

2.1. *Methodology*

In this research, a set of LANDSAT images of the same area acquired at different times are taken for analysis and given for textural feature extraction using DLTP. Once the features are extracted from each channel , difference image is generated and classified into changed and unchanged regions. The overall block diagram of the proposed feature extraction based change detection is shown in Fig. 1.

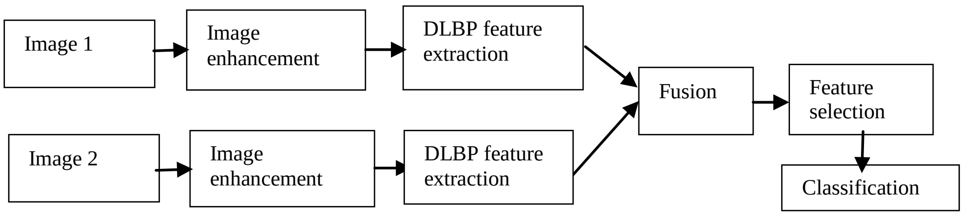

Fig. 1. Overall block diagram of feature extraction based change detection

2.2. *Image enhancement*

It is a smoothing filter which works on the principle of convolution of a mask with the input image. The filter mask is applied as a sliding window over the whole image. The convolution can be represented using Eq. (1) and Eq. (2)as:

$$g(x,y) = f(x,y) * w(x,y) \qquad (1)$$

$$g(x,y) = \sum_{i=-1}^{1}\sum_{j=-1}^{1} f(x+i, y+j)w(i,j) \qquad (2)$$

where f(x,y) is the input image, w(x,y) is the filter mask and g(x,y) is the output image after spatial filtering.

The RGB spatial filter is an averaging filter which smoothens the image by averaging over the sum of pixels with its neighbors.

2.3. *Feature extraction*

Feature extraction creates a set of new features from a dataset and focuses on reducing the number of features. The new set of features should encapsulate all the information present in the original set of features and help in easier and faster classification. Features extracted can be texture, color, shape etc. Texture analysis is extensively employed in image segmentation, classification, and pattern recognition. Textural feature extraction is an important part of texture analysis which can solve the problems of spectral heterogeneity and complexity in spatial distribution. It is thus important to measure the texture accurately since the extracted texture features affect the outcome of subsequent stages. Of the different textural feature extraction techniques available, Local Binary Pattern(LBP) is the most commonly used method. Variants of LBP have been explored and developed by researchers.

2.3.1. *Local Binary Pattern*

LBP is a simple and effective texture descriptor. It labels the pixels in the image on thresholding the pixel neighborhood and represents the result in binary code. In LTP, the neighboring gray valued pixels are compared with the central pixels using a threshold value. Once the comparison is performed, the neighboring pixels are allocated with one of the two values 0 and 1. By taking a circular neighborhood with radius 1, the LBP code for the center pixel (x,y) is measured using Eq. (3) and Eq. (4)as:

$$LBP_{P,R} = \sum_{i=0}^{p-1} L * 2^{i}, \quad (3)$$

where

$$L = \begin{Bmatrix} 1, (C_i - C_c) \geq 0 \\ 0, (C_i - C_c) < 0 \end{Bmatrix} \quad (4)$$

where R denotes the distance of the neighboring pixel from the central pixel, P represents the count of the number of pixels. C_c gives the central pixel and C_i gives the neighboring pixel. The LBP operation can be depicted using Fig. 2.where the center pixel has a value 85 .

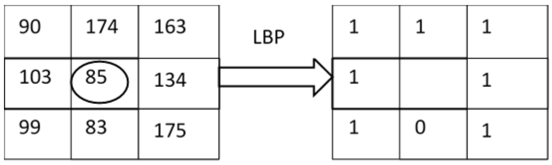

Fig. 2. LBP calculation illustration

LBP compares the central pixel to the neighborhood pixels and quantifies the value to 1 or 0 depending on whether the central pixel or neighborhood pixel is greater. LBP is an effective texture feature extraction technique and can give a reliable feature extraction even in the presence of noise. But the main drawback in LBP method is the manual selection and fixing of threshold. As the threshold value is fixed manually, there are chances that the intensity and brightness variations in the image are incorrectly interpreted as a texture and extracted. Hence the selection of threshold plays a critical role in proper textural feature extraction. To overcome his limitation, Dynamic Local Ternary Pattern is developed which uses dynamic threshold selection.

2.3.2. *Dynamic Local Binary Pattern*

In traditional LBP, the threshold needs to be manually set and the textural complexity of satellite images vary from image to image. A manually set threshold cannot be directly applied to all the satellite images. To solve this, a dynamic threshold selection method called Dynamic Local Binary Pattern is introduced. In DLBP, region based mean is computed and this mean value is compared with the central pixel and further with the neighboring pixels. This is binary coded and represented. The region based mean is computed using Eq. (5) as:

$$Mean_{Region} = \frac{\sum_{i=1}^{n} C_i}{n} \quad (5)$$

Where C_i represents the neighboring pixels, n is the number of neighboring pixels. For 3x3 neighborhood, n=8. The DLBP is calculated using Eq. (6) and Eq. (7) as:

$$DLBP = \sum_{i=1}^{8} L * 2^{i-1} \tag{6}$$

Where L is computed as:

$$L = \begin{Bmatrix} 1, if\ (Mean_{\text{Region}} \geq C_c) and (Mean_{\text{Region}} \leq C_i) \\ 0, elseif\ (Mean_{\text{Region}} \geq C_c) and (Mean_{\text{Region}} > C_i) \\ 1, elseif\ (Mean_{\text{Region}} < C_c) and (Mean_{\text{Region}} \leq C_i) \\ 0, otherwise \end{Bmatrix} \tag{7}$$

Where C_c represents the central pixel and C_i gives the neighboring pixel. Here the $Mean_{\text{Region}}$is compared with the central pixel and the DLBP code is generated on comparing with the neighboring pixels. Fig. 3. illustrates concept of DLBP.

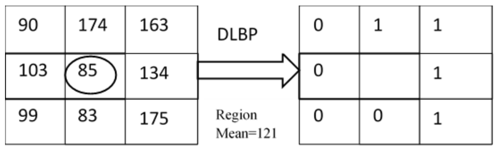

Fig. 3. DLBP representation

Consider that the $Mean_{\text{Region}}$ is 121. This mean value is compared with the central pixel and since it is greater than the center pixel, it is directly compared to the neighboring pixel. DLBP is less sensitive to noise than the original LBP.

2.4. *Feature fusion and optimal feature selection*

Feature fusion involves combining the feature vectors from individual channels into a single feature vector. On performing feature fusion, all the discriminant information on combining feature sets obtained from different channels can convey more textural information than from individual channels . Here, feature vectors from the individual channels are fused end-to-end to get the final feature vector. Here, the final feature vectors is a combination of textural features from individual channels in bitemporal images. The textural features are extracted for individual multispectral images and the combined feature vector contain the spatial neighborhood information. Let T_1 = [T_{11},T_{12}…. ,T_{1N}] and T_2= [T_{21},T_{22}…. ,T_{2N}] be the textural features extracted from the two channels in bitemporal images. To fuse the corresponding level of features in individual channel, the textural features are merged feature fusion concatenation as given in Eq. (8)

$$F = Concat(T_1, T_2) \tag{8}$$

where F represents the fused feature map.

Feature extraction and selection play an important part in binary classification. It is important to note that proper selection of features is essential in predicting the different classes in the image. The concatenated features in each channel in the multispectral image results in redundant data along with discriminative information. Researchers have explored the importance of feature selection methods to detect redundant features and it is observed that proper feature selection can improve the accuracy of classification and save time. The feature selection criteria forms a set of feature subsets which contain highly correlated features in the target class and uncorrelated with each other. Therefore, Correlation Feature Subset Selection (CFS) finds feature subsets that have high feature to feature and feature to class correlation. Let n be the number of subsets. The CFS criteria is evaluated for each subset Y where the average feature to class correlation r_{cf} (with f ЄY and c is target class) and average feature to feature correlation r_{ff} is low. The CFS criteria is depicted using Eq. (9) as :

$$CFS = Max_{Y_n}\left[\frac{r_{cf1} + r_{cf2} + ...+ r_{cfn}}{\sqrt{k + 2(r_{f1f2} + ...+ r_{fifj})}}\right] \tag{9}$$

r_{cfi} and r_{fifj} are the correlation variables. The best feature subset X is formed over each iteration and for the entire dataset. The optimal feature subset X is given to the classification module for accurate classification.

2.5. *Classification and change map creation*

On generation of the final feature vectors, the change map is created on classifying the feature vector of each pixel into changed and unchanged classes by applying the FCM algorithm. FCM is an effective clustering algorithm where every data point may belong to one or more clusters .The reduced feature vector corresponding to all pixels is the input to FCM clustering. Fuzzy partitioning is done by modifying the membership grade μij and the cluster centroids ν by applying optimization iteratively on the objective function J shown in Eq. (10).

$$J(U,V)=\sum_{i=1}^{n} \sum_{k=1}^{n} (\mu_{ij})^m \|x_i-v_j\|^2$$

(10)

where $\|x_i-v_j\|$ denotes the Euclidean distance between i^{th} data and j^{th} cluster center. After every iteration, membership and cluster centers are modified using Eq. (11) and Eq. (12)as

$$\mu_{ij}=1/\sum_{k=1}^{c}(d_{ij}/d_{ik})^{(2/m-1)} \tag{11}$$

$$v_j=(\sum_{i=0}^{n}(\mu_{ij})^m x_i)/(\sum_{k=1}^{n}(\mu_{ij})^m), \text{ for all values of } j =1,2,\ldots c \tag{12}$$

where n denotes the data points and m represents the degree of fuzziness and it is considered that m ∈ [1, +∞). μij gives the membership grade for the ith data and jth cluster center. d_{ij} gives the Euclidean distance between ith data and jth cluster center. $v_j$gives jth cluster center,c gives the number of cluster centers. By taking d = 2, number of clusters, c = 2 and initializing the iteration procedure at l = 0, the centroids and membership grades are computed .

In accordance with the maximum value of membership grade, the pixels are allotted to the corresponding classes to generate the binary change map .

3. Experimental Results

The experiments are performed on two data samples to analyze the performance of the proposed method.

3.1. *Dataset Description*

For analysis, two pairs of multispectral image datasets were employed. The first image set contains SPOT-5 multispectral images of Guangzhou city, China acquired during 2006 and 2007. The second image set contains GF-1 multispectral images of Huangyan Country province, China acquired during 2013 and 2015. The size of each image in this database is 1242x1086 pixels. The ground truths for each of the image sets are also available in the database. Fig. 4. shows a sample database with the ground truth.

Fig. 4. (a) Sample image 1(year: 2006) (b) Sample image 2(year:2007) (c) Ground truth

3.2. *Quantitative and qualitative results and discussion*

Both qualitative and quantitative results reflect the analysis of the change map. The performance of the proposed technique is compared with two other state of art techniques: LBP, LTP and proposed DLBP based texture feature extraction. Fig. 5. shows the textural feature extraction output for various techniques. The results of dataset I and II are shown in Fig. 6. and Fig. 7., respectively, with white pixels representing the unchanged areas and black pixels representing the change areas. By visualizing the qualitative results of the textural feature extraction, it is obvious that the proposed feature extraction can extract texture features effectively by differentiating between the plain and extremely textured regions in the remote sensing image by utilizing gradient dynamic threshold selection using the mean and variance of the image. This is a more effective in texture feature differentiation over the random threshold selection in LBP and LTP where the extremely high variations are identified and the nearest regions with minute textural variations cannot be distinguished and grouped as a single textural variations omitting the minute variations.

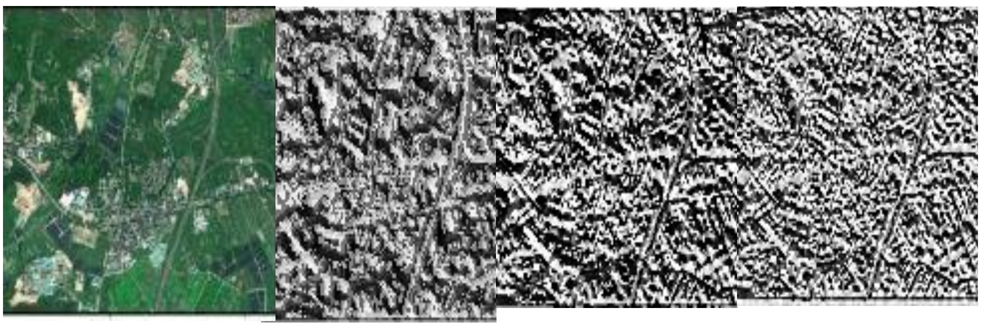

Fig. 5. (a) Sample image 1(year: 2006) (b) LBP output (c) LTP output (d) DLBP output

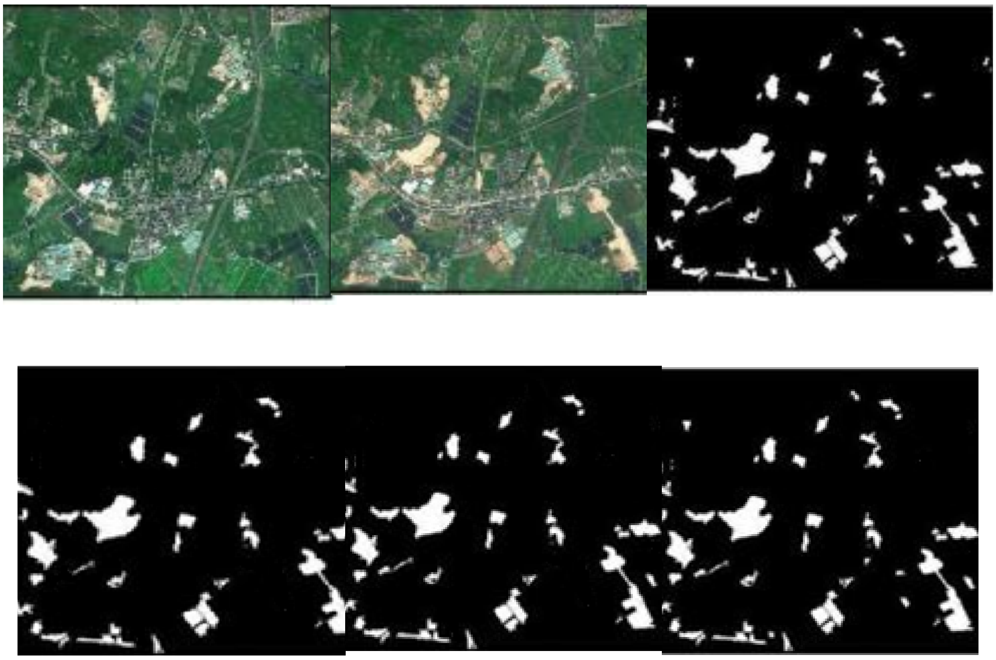

Fig. 6. (a) Sample image 1(year: 2006) (b) Sample image 2(year:2007) (c) ground truth (d) Change map for LBP feature extraction (e) Change map for LTP feature extraction (f) Change map for DLBP feature extraction

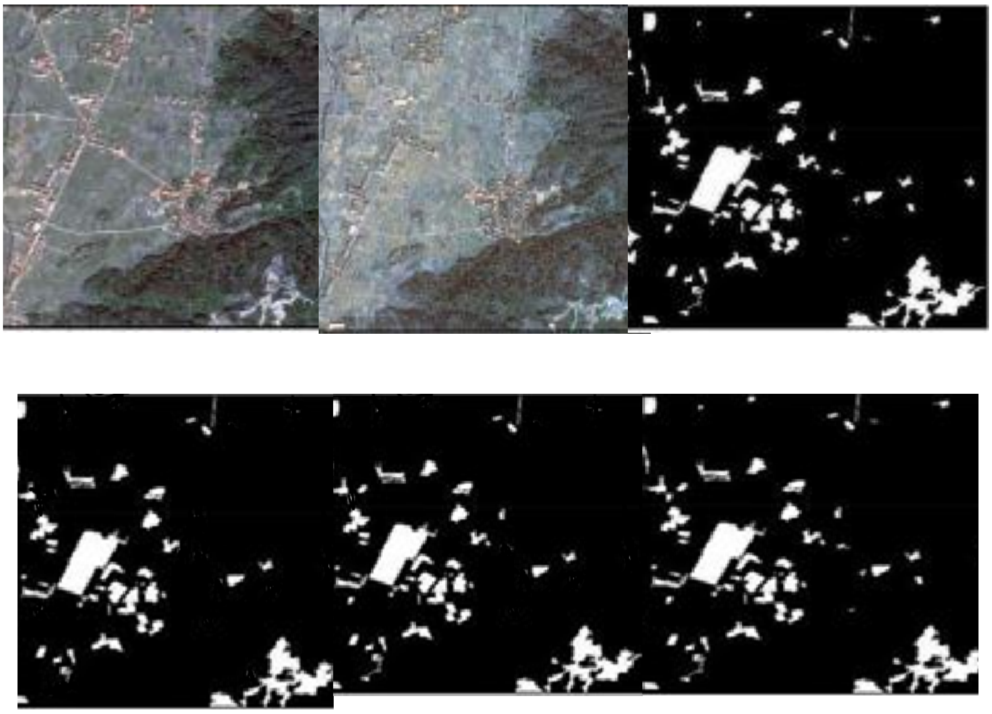

Fig. 7. (a) Sample image 1(year: 2006) (b) Sample image 2(year:2007) (c) ground truth (d) Change map for LBP feature extraction € Change map for LTP feature extraction (f) Change map for DLBP feature extraction

This effect is evident from the binary change map that there are more false alarms on feature extraction using LBP and LTP over the proposed textural feature extraction. Also the proposed textural feature extraction based change detection detects more changed pixels with high false alarms. To evaluate the quantitative performance, some performance metrics are calculated to compare with the ground truth result. The performance metrics evaluated are: Overall accuracy (OA), False alarms (FA), Missed Alarm (MA) and Kappa coefficient(k). The quantitative measures for the methods are shown in Table 1. When compared to the state-of-art techniques in Table 1., the proposed technique yields better performance in terms of overall accuracy . Also, the proposed method gives a lesser total error value with minimum false alarms. The advantage of the proposed method lies in the utilization of the feature fusion of textural feature vectors in each channel. DLBP extracts information pertaining to the local spatial neighborhood which reduces the noise effects. Further, applying feature fusion on the individual channel images provides abundant spatial neighborhood information that produces more distinguished and discriminant features.

Table 1. Quantitative metrics for classification

	DATASET 1	DATASET 2
ue		
Alarms(%)		
arms(%)		
Accuracy(%)		
:)		

It is evident form the table that using the proposed textural feature extraction for change analysis results in a better output both quantitatively and qualitatively compared to the traditional feature extraction based change analysis.

4. Conclusion

This paper proposes an efficient textural feature extraction based change analysis using Dynamic Local Binary Pattern. By applying textural feature extraction on the individual image channels and fusing them results in reinforcing the information in each channel thereby strengthening the textural attributes in the fused image. On the one hand, with respect to the standard textural feature extraction methods, the proposed technique properly exploits the information present in the original images by employing region based mean for thresholding the image. The empirical study confirms that by applying the proposed textural feature extraction based change analysis in the ability to detect change with an accuracy of up to 92% on an average. As future developments of the proposed work, we are considering the following: to extend the change-analysis technique to images requiring some methodological modifications for taking into account the multiscale properties of such data and to consider multiclass problems.

References

1. Parveen, R. and Kulkarni, S.(2019) Vegetation Discrimination and Change Analysis Using Multi-temporal IRS-1C LISS III Imagery. *ACTA Scientific Agriculture*, **3**: 163–171.
2. Mugasa, H., Dua, S., Koh, J.E.W., Hagiwara, Y., Lih, O.S., Madla, C., Kongmebhol, P., Ng, K.H., Acharya, U.R., Dua, S. et al.(2019) An Adaptive Feature Extraction Model for Classification of Thyroid Lesions in Ultrasound Images. *Pattern Recognit. Lett.*
3. Jeslin, T. and Linsely, J.A.(2020) A novel method for classification using multi class-SVM classifier with multi features. *J. Crit. Rev.*, **7**: 155–159.
4. Li, Q., Gong, L. and Zhang, J. (2018) Earthquake-induced building detection based on object-level texture feature change detection of multi-temporal sar images. *Bol. Ciencias Geod.* , **24**: 442–469.
5. Li, Q., Gong, L. and Zhang, J. (2019) A correlation change detection method integrating PCA and multi-texture features of SAR image for building damage detection. *Eur. J. Remote Sens.*, **52**: 435–447.
6. Sotoodeh, M., Moosavi, M.R. and Boostani, R.(2019) A novel adaptive LBP-based descriptor for color image retrieval. *Expert Syst. Appl.* ,**127**: 342–352.
7. Kaplan, K., Kaya, Y., Kuncan, M., Minaz, M.R. and Ertunc, H.M.(2019) An improved feature extraction method using texture analysis with LBP for bearing fault diagnosis. *Appl. Soft Comput. J.* , **108565.**
8. Sudheer, D. and Krishnan, R.(2019) Multiscale texture analysis and color coherence vector based feature descriptor for multispectral image retrieval. *Adv. Sci. Technol. Eng. Syst.* , **4**: 270–279.
9. Ciriza, R., Sola, I., Albizua, L., álvarez-Mozos, J. and González-Audícana, M.(2017) Automatic detection of uprooted orchards based on orthophoto texture analysis. *Remote Sens.* , **9**.
10. Garg, M., Malhotra, M. and Singh, H.(2019) A Novel CBIR-Based System using Texture Fused LBP Variants and GLCM Features. *Int. J. Innov. Technol. Explor. Eng.*, **9**: 1247–1257.
11. Pan, Z., Wu, X. and Li, Z.(2019) Central pixel selection strategy based on local gray-value distribution by using gradient information to enhance LBP for texture classification. *Expert Syst. Appl.* , **120**: 319–334.
12. Sun, J. and Wu, X.(2016) Infrared target recognition based on improved joint local ternary pattern. *Opt. Eng.* , **55**, 053101.
13. Ryu, B., Rivera, A.R., Kim, J. and Chae, O.(2017) Local Directional Ternary Pattern for Facial Expression Recognition. *IEEE Trans. Image Process.*, **26**: 6006–6018.
14. Arshid, S., Hussain, A., Munir, A., Nawaz, A. and Aziz, S.(2018) Multi-stage binary patterns for facial expression recognition in real world. *Cluster Comput.*, **21**: 323–331.
15. Luo, Y., Wang, B. yu, Zhang, Y. and Zhao, L. ming (2018) A novel fusion method of improved adaptive LTP and two-directional two-dimensional PCA for face feature extraction. *Optoelectron. Lett.*, **14**: 143–147.
16. Parveen, S., Rehman, S. M. S. A. A., Naeem, N., Devi, J. and Ahmed, M. (2018) The Improved Complete Dynamic Local Ternary Pattern Texture Descriptor for Face Spoof Attacks. *Int. J. Comput. Sci. Netw. Secur.*, **18**: 102–110.
17. Chen, Z., Peng, K., Huang, L., Wang, Y., Wu, X. and Xiao, Z.(2018) A Water-Area Recognition Approach Based on " Tuned " Texture Mask and Cuckoo Search Algorithm. *Comput. Intell. Neurosci.*, **2018**: 1–8.
18. Aguilar, M.A., Fernández, A., Aguilar, F.J., Bianconi, F. and Lorca, A.G.(2016) Classification of urban areas from geoeye-1 imagery through texture features based on histograms of equivalent patterns. *Eur. J. Remote Sens.*, **49**: 93–120.
19. Wu, Y. and Qiu, W.(2017) Facial expression recognition based on improved local ternary pattern and stacked auto-encoder. *AIP Conf. Proc.*, **1864**.
20. Wang, J., Zhang, R., Wu, T., Ok, S. and Lee, E.(2018) Face Recognition Based on Improved LTP., **134**: 6–10.
21. Jothibasu, M., Karthik, M., Malar, E., Boopathy, S., Senthil Kumar, M.Improved reversible data hiding through image using different hiding and compression techniques(2018) International Journal of Innovative Technology and Exploring Engineering, 8 (2 Special Issue2), pp. 327-330.
22. Arulkumar, V., Vivekanandan, P.An intelligent technique for uniquely recognising face and finger image using learning vectorquantisation (LVQ)-based template key generation(2018) International Journal of Biomedical Engineering and Technology, 26 (3-4), pp. 237-249
23. Premkumar,M., Ashokkumar,S.R., Mohanbabu,G., Jeevanantham,V., Jayakumar, S., "Security behavior analysis in web of things smart environment using deep belief networks", International Journal of Intelligent networks, Vol.3, pp.181-187, 2022
24. Haldorai, A., Ramu, A. "Security and channel noise management in cognitive radio networks", Computers and Electrical Engineering, vol. 87, art. no. 106784,2020