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Swarm based Image Fusion Technique for Change Detection using Remote Sensing Images

Ashok Kumar Panda[1], Chinmayee Pati[2]

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Abstract: In satellite monitoring, change detection may be crucial. Change detection is regarded as a challenging job in the realm of satellite applications due to the availability of satellite photos of a given geographic region acquired at various times. This study suggests a novel image fusion method based on optimization for spotting changes in satellite photos. Tests are run on two satellite photos taken in two separate time instances on a specific geographic region to show the effectiveness of the technique. The effectiveness is verified using change detection accuracy. Results are superior to those of currently used techniques.

Keywords: remote sensing, grey wolf optimization, image fusion, change detection, optimizations

1. Introduction

In remote sensing, image processing, categorization, and the detection of changes play an extremely important role [2, 3]. Change detection may be a very useful tool in a wide variety of diverse applications [2]. By using the technique of remotely detected multi-temporal picture segmentation, this change detection method may be used to determine changes in land cover.

Environmental and meteorological events, such as earthquakes, severe snowfall, and coastal erosion, may be responsible for some of the causes of change [4]. Within the realm of remote sensing application domains, change detection is regarded as one of the most difficult subjects to tackle [5, 6]. Change detection is of significant relevance in a variety of applications, including the research of land cover dynamics, monitoring of shifting agriculture, forest fire, and so on [7]. In order to solve these issues, which need an examination of bigger geographic regions, the development of an automated change detection approach is important. This will help reduce the amount of time and human labor required for these applications. Change detection is used to determine whether or whether there has been a change in a certain region by compiling numerous pictures that were captured at various points in time [8, 9].

Image fusion is an established approach in the field of image processing that is used to combine the data from two or more individual images into a single composite frame [10, 11]. In change diagnosis, a method known as multi modal picture fusion is a reliable strategy. A single picture may be created by fusing the results of many imaging modalities using the multimodal fusion technique [12, 13]. In change detection strategies, fusion procedures are often used to translate functional images into structural images [14].

[1]*Dept. of CSE, College of Engineering, Bhubaneswar-751024*
Email: ashopanda@gmail.com
ORCID ID: 0000-0003-4655-0449

[2]*Dept. of IT, Odisha University of Technology & Research*
Email: chinu2983@gmail.com
ORCID ID: 0000-0002-1865-9327

In this research work, an optimization algorithm-based image fusion technique is proposed to identify the changes that happens with respect to time in satellite images. The rest of the paper is organized as follows: Section 2 covers all that has been done before in the field of change detection using remote sensing photos. This section may be found here. In Section 3, you will also find the problem description and the specification of the objective function. This section also contains the formulation of the problem. We can find the optimization method that's being recommended in Section 4. In Section 5, we addressed how to set up the experiment, and in Section 6, we drew a conclusion to the research and spoke about how to make the procedure more efficient in the future.

2. Related Works

Applying a thresholding strategy to the magnitude of the DI pixels led to the development of a number of unsupervised methods that were proposed [2,15,16]. These methods were based on change vector analysis. The magnitude operator will lose some information regarding the direction of the difference if this technique is used, which is a restriction of the method. Some of the studies use a clustering strategy as a solution to the issue; nevertheless, in many practical situations, the accuracy is inferior to that which is offered by thresholding approaches [17]. To reiterate, the clustering algorithms need an extra physical post-processing step for labelling the clusters with modified and unchanging labels. This step prevents the procedure from being fully automated. As a result, a number of additional excellent unsupervised techniques have been devised and published in the relevant academic literature [18, 19]. Although the supervised method performs far better than the unsupervised method, it calls for a significant quantity of labelled data, which is not really accessible in practice.

This study addresses the aforementioned issue by developing a hybrid approach to the problem of change detection in satellite pictures by combining optimal support vector machines with fuzzy c-means. To generate a fuzzy set for altered pixels using the degree of change as the fuzzy membership function, the planned approach's goal is to apply an important unsupervised methodology, which is the technique's intended method. In addition, it makes use of an a-cut in order to automatically label the dataset with an appropriate value. Then, it makes use of supervised approaches using the automatically labelled data together with a little bit of ground reality data that was obtained beforehand (through sensors or through manual surveillance). [18, 19] Research has shown that the Support Vector Machine, often known as SVM, is one of the most successful techniques among supervised methods. The accuracy of SVM is dependent on using an appropriate kernel and properly configuring the kernel parameters. An optimization strategy based on a genetic algorithm (GA) may be used in this scenario in place of a heuristic-based kernel and kernel parameter setting in order to pick the most optimal kernel and kernel parameter settings possible. The literature [20] has information on SVM optimization via the use of GA. The GA optimized SVM (O-SVM) classifier is used in this method for the purpose of managing the supervised learning.

On the other hand, image fusion techniques that can merge the two different images of same landscape are used to merge one with other to identify the missing out parts between two images. In this model we intend to use the image fusion technique to identify the dissimilarity between images and to bring out the structural changes of landscape. In the past decade, the proposed image fusion techniques are as follows: Remote sensing image classification uses supervised and unsupervised techniques. Non artificial classifications employ these approaches. Random woods are also popular. It classes stochastic feature space indexes. Picture classification accuracy can be increased; however complicated background performance needs work. ML supervised and classified satellite photos of national forest land usage across three time periods. This technique yielded accurate classifications. The business claims multisensor data can classify semi-arid areas. To evaluate the feasibility and value of using Sentinel-1A data's extracted backscatter intensity, texture, coherence, and color features for urban land cover classification and to compare multisensory land cover mapping techniques for improving accuracy, different permutations of the following were considered: Backscatter has strength, uniformity, smoothness, and color. Wavelet transform-based multispectral picture classification offers good accuracy. RF-based classifiers classified land photographs in multidata fusion with complicated backdrops. Real-world applications need algorithm parameter settings.

3. Climatic Change Detection using Image Fusion

The model is intended to fuse the two images in which one is the ground truth image and the other is false color decomposed image. The false color decomposed image will represent the water in blue color, the vegetation in red color and the landscape as green color. When this image is fused to the other image the difference between the images are easily identified. The fusion of two images are carried out in the following section.

Table 1. Nomenclature

Sl. No	Acronym	Abbreviation
1	LL	Low, Low
2	LH	Low, High
3	HL	High, Low
4	HH	High, High
5	DWT	Discrete Wavelet Transform
6	GWO	Grey Wolf Optimization
7	CM1	Change Vector Analysis
8	CM2	Erreur RelativeGlobale Adimensionnelle De Synthese
9	CM3	Spectral Angle Mapping
10	CM4	IR-MAD
11	OA	Overall Accuracy
12	KC	Kappa Coefficient
13	CR	Correctness
14	FAR	False Alarm Rate
15	CE	Commission Error
16	OE	Omission Error

1.1 Discrete Wavelet Transform

Multimodal image fusion often uses DWT image decomposition. DWT decomposes images without gaps or overlap and recovers them with low loss. DWT uses low and high pass filters to split the picture into several sub-bands. The second level decomposition divides the LL band into four sections. Hence, a picture decomposed at "l" level has $3l+1$ sub-bands. $LH_n, HL_n, and\ HH_n$ are detail coefficients for $n = 1,2,\ldots l-1$.

1.2 Optimization of Weights using Evolutionary Algorithm

The approximate and detailed components of the input picture may be obtained via the use of multi-level decomposition. To combine the coefficients of various components into a single value, fusion rules such as the average or maximum fusion are often used. Since they each include complimentary information and a different representation of characteristics, the coefficients of approximation and detailed components of multi modalities may have a greater degree of variance. Nevertheless, traditional approaches such as average fusion and maximum fusion could not produce effective complementary fusion. Moreover, these methods might have a possibility of producing artefacts and losing information regardless of the modality they are applied to.

Weights, which helped overcome the aforementioned obstacles, were employed for the selection of coefficients. Due to the set weight value for fusion, primary weighted average fusion may not deliver an effective fusion. As a result, optimal weight selection may improve performance by choosing effective weights for multi-level decomposition components.

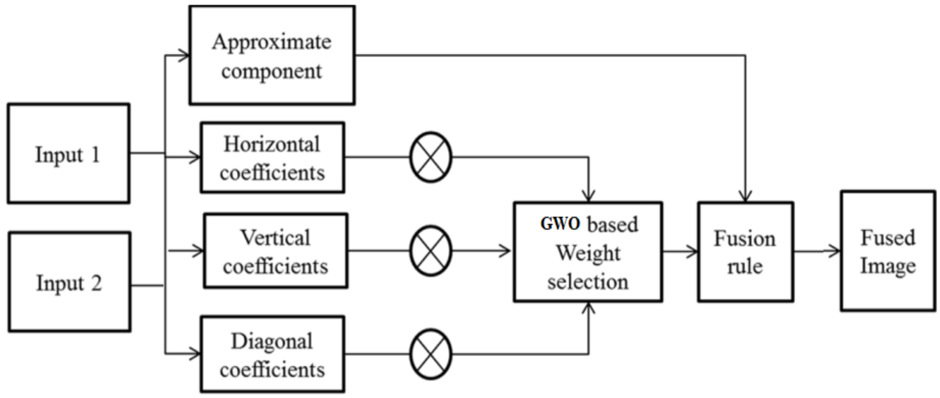

Fig 1. GWO optimized Image fusion using DWT

1.3 Grey Wolf Optimization algorithm

As it uses a group hunting technique, the GWO algorithm is one of the most fascinating kinds of algorithms. According to Muro et al., there are two different types of hunting that grey wolves engage in: i) tracking, chasing, and approaching the prey; and ii) pursuing, surrounding, and tormenting the prey until it stops moving. iii) Make an assault on the target animal. The optimization of the grey wolf makes a contribution both in the exploration and the exploitation phase. The goal of exploitation is to find the best possible solution within a restricted search area. In the case of the grey wolf, the exploitation phases of surrounding prey and assaulting for prey are employed to look for the best possible solution within a small search region. The exploration phase is represented by the quest for prey, during which the grey wolves look for their prey throughout an expansive global search arena.

In Grey wolves will detect the position of their prey and then surround them when they have located them. During this phase, the location vector of the prey is determined, and the positions of the other search agents are adjusted depending on the best solution that has been found. The prey encircling will use the following equation.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(k) - \vec{X}(k)\right| \quad (1)$$

$$\vec{X}(k+1) = \overrightarrow{X_p}(k) - \vec{A}.\vec{D} \quad (2)$$

4. Experimental Analysis

1.4 Dataset description

The datasets are collected from Mexico and Sardinia Island [1]. The details of the dataset are given in Table 2.

Table 2. Dataset Description

Sl. No	Location	Date of Input 1	Date of Input 2
1	Mexico	April 4th 2000	May 20th 2002
2	Sardinia Island	September 1995	July 1996

The results are tabulated in Table 3 and 4.

Table 3. Results on Image 1

Algorithms	OA (%)	KC	CR	FAR	CE (%)	OE (%)
CM1	70.23	0.66	0.90	0.47	35.04	54.26
CM2	70.41	0.65	0.87	0.46	34.28	51.04
CM3	65.26	0.56	0.80	0.65	46.80	34.35
CM4	79.16	0.74	1.00	0.27	7.48	51.91
Proposed Method	80.99	0.77	1.00	0.26	12.30	42.97

Table 4. Results on Image 2

Algorithms	OA (%)	KC	CR	FAR	CE (%)	OE (%)
CM1	48.39	0.32	0.34	0.82	1.00	0.77
CM2	48.39	0.26	0.28	0.77	1.00	0.74
CM3	64.81	0.28	0.26	0.58	1.00	0.71
CM4	98.37	0.76	1.00	0.36	0.30	0.91
Proposed Method	98.45	0.87	1.00	0.31	0.32	0.69

From the results 3 and 4 it is evident that the proposed model outperforms the existing techniques. Figures 4 and 5 show change detection results for the two research locations. Our technique accurately identified complicated landscape and line feature changes. The proposed change detection approach yields superior CE findings, while the suggested method yields more accurate results. The initial M4 approach produced good results, but it was difficult to remove certain non-sensitive elements (e.g., regions combining vegetation and barren ground or vegetation and water bodies) due to their comparable spectral characteristics and effect. Our technique can enhance change information extraction from cross-fused pictures from the high-resolution NIR band and low-resolution MS bands.

5. Conclusion

Within the scope of this research, we suggested a technique for multimodal picture fusion that makes use of GWO. In both the quantitative and qualitative evaluations, the suggested technique demonstrated superior performance when compared to the state-of-the-art fusion methods. When compared with well-known current methods, the suggested model demonstrated superior performance across all six of the investigated dimensions of effectiveness. The computational complexity of optimization algorithms is measured by the amount of time spent on computing in seconds; however, the computational time required by our suggested technique using GWO is much less than that required by traditional procedures. Within this strategy, we made use of a normalized and registered public picture dataset; however, in the future, we will need to further improve registration algorithms for the purpose of multi-central applications.

References

[1] S. Ghosh, L. Bruzzone, S. Patra, F. Bovolo, A. Ghosh, A context-sensitive technique for unsupervised change detection based on hopfield-type neural networks, IEEE Trans. Geosci. Remote Sens. 45 (3) (2007) 778–789.

[2] S. Ghosh, L. Bruzzone, S. Patra, F. Bovolo, A. Ghosh, A context-sensitive technique for unsupervised change detection based on hopfield-type neural networks, IEEE Trans. Geosci. Remote Sens. 45 (3) (2007) 778–789.

[3] L. Xu, H. Zhang, M. Zhao, D. Chu, Y. Li, Integrating spectral and spatial features for hyperspectral image classification using low-rank representation, in: Proceedings of IEEE International Conference on Industrial Technology (ICIT), IEEE, 2017, pp. 1024–1029

[4] A.M. Roy, S. Ghosh, A. Ghosh, A neural approach under active learning mode for change detection in remotely sensed images, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 7 (4) (2014) 1200–1206.

[5] M. Zanetti, L. Bruzzone, A generalized statistical model for binary change detection in multispectral images, in: Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International, IEEE, 2016, pp. 3378–3381.

[6] A.P. Tewkesbury, A.J. Comber, N.J. Tate, A. Lamb, P.F. Fisher, A critical synthesis of remotely sensed optical image change detection techniques, Remote Sens. Environ. 160 (2015) 1–14.

[7] S. Ghosh, L. Bruzzone, S. Patra, F. Bovolo, A. Ghosh, A context-sensitive technique for unsupervised change detection based on hopfield-type neural networks, IEEE Trans. Geosci. Remote Sens. 45 (3) (2007) 778–789

[8] L. Bruzzone, D.F. Prieto, An mrf approach to unsupervised change detection, in: Proceedings of International Conference on Image Processing: ICIP 99, IEEE, 1999, pp. 143–147.

[9] K. Islam, M. Jashimuddin, B. Nath, T.K. Nath, Land use classification and change detection by using multi-temporal remotely sensed imagery: the case of chunati wildlife sanctuary, bangladesh, Egypt. J. Remote Sens. Space Sci. 21 (1) (2018) 37–47

[10] H.T. Mustafa, J. Yang, H. Mustafa, M. Zareapoor, Infrared and visible image fusion based on dilated residual attention network, Optik 224 (2020) p. 165409, 2020/12/01.

[11] H. Yan, Z. Li, Infrared and visual image fusion based on multi-scale feature decomposition, Optik 203 (2020) 163900, 2020/02/01.

[12] S.M. Darwish, Multi-level fuzzy contourlet-based image fusion for medical applications, IET Image Process. 7 (7) (2013) 694–700.

[13] J. Du, W. Li, K. Lu, B. Xiao, An overview of multi-modal medical image fusion, Neurocomputing 215 (2016) 3–20, 2016/11/26.

[14] L. Wang, B. Li, L.-f. Tian, Multi-modal medical image fusion using the inter-scale and intra-scale dependencies between image shift-invariant shearlet coefficients, Inf. Fusion 19 (2014) 20–28, 2014/09/01.

[15] L. Bruzzone, D.F. Prieto, Automatic analysis of the difference image for unsupervised change detection, IEEE Trans. Geosci. Remote Sens. 38 (3) (2000) 1171–1182.

[16] F. Bovolo, L. Bruzzone, A theoretical framework for unsupervised change detection based on change vector analysis in the polar domain, IEEE Trans. Geosci. Remote Sens. 45 (1) (2007) 218–236.

[17] F. Bovolo, L. Bruzzone, M. Marconcini, A novel approach to unsupervised change detection based on a semisupervised svm and a similarity measure, IEEE Trans. Geosci. Remote Sens. 46 (7) (2008) 2070–2082.

[18] C. Cortes, V. Vapnik, Support-vector networks, Mach. Learn. 20 (3) (1995) 273– 297.

[19] E. Tuba, M. Tuba, M. Beko, in: Support Vector Machine Parameters Optimization by Enhanced Fireworks Algorithm, Springer, 2016, pp. 526–534

[20] C.-L. Huang, C.-J. Wang, A ga-based feature selection and parameters optimizationfor support vector machines, Expert Syst. Appl. 31 (2) (2006) 231–240.