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Fusion of UAVSAR and Quickbird data for Urban Growth Detection

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Abstract: Urban areas are rapidly changing all over the world and therefore, continuous mapping of the changes are essential for urban planner and decision makers. Urban changes can be mapped and measured by using remote sensing data and techniques along with several statistical measures. The urban scene is characterized by very high complexity, containing objects formed from different types of man-made materials as well as natural objects. The aim of this study is to detect the urban growth which can be further utilized for urban planning. Although high-resolution optical data can be used to determine classes more precisely, it is still difficult to distinguish classes such as residential regions with different building type due to spectral similarities. SAR data provide valuable information about the type of scattering backscatter from an object in the scene as well as its geometry, and its dielectric properties. Therefore, the information obtained using the SAR processing is complementary to that obtained using optical data. This proposed algorithm has been applied on multi sensor dataset consisting of the optical QuickBird images (RGB) image and full polarimetric L-band UAVSAR images data. After preprocessing data, the coherency matrix (T), and Pauli decomposition are extracted from multi temporal UAVSAR images. Next, SVM (Support vector machines) classification method is applied to the multi-temporal features in order to generate two classified maps. In the next step, post classification based algorithm was used for generating the change map. Finally, the results of the change maps are fused by majority voting algorithm to improve the detecting of the urban changes. In order to clarify the importance of using both optical and polarimetric images, the majority voting algorithm was also applied to change maps of optical and polarimetric images, separately. In order to analyze the accuracy of the change maps, the ground truth change and no-change area that gathered by visual interpretation of Google earth images were used. After correcting the noise generated by the post-classification method, the final change map was obtained with an overall accuracy of 89.81% and Kappa of 0.8049.

Keywords: Synthetic aperture radar (SAR), High resolution optic image, Multi-temporal analysis, Change detection, Support vector machines, Fusion.

1. Introduction

An urban area is a location characterized by high population density and many built-up features in comparison to the areas surrounding it [1]. Due to the expansion of urbanization over the past few decades, changes in the urban area are evident through the application of change detection techniques. Urban change detection is used for urban planning. Using different methods of change detection and applying them to radar and optical data has advantages and disadvantages. Combining these methods and data sets can allow us to overcome their disadvantages and complement each other. For this purpose, in this paper, a decision-level fusion method based on the majority voting algorithm is proposed to combine the change maps made by different methods applied to two optical and polarimetric data sets.

It has been stated that due to the ability of radar satellite to acquire data in every pass and regularly, SAR data are suitable for analyzing the changes. By using optical sensors with moderate resolution such as LandSat in urban areas, many of man-made features spectrally appear similar. Also, optical sensors with high resolution such as QuickBird are not efficient in discriminating among man-made objects which are constructed by using different materials [2]. On the other hand, several of these objects can be distinguished based on their geometrical and dielectical properties by using Radar images. Walls of buildings for example have relatively strong backscattering signal due to the corner reflectors as these wall oriented orthogonally on the radar look direction while surface of bare soil has low backscattering signal because it acts as a specular surface which reflects the signal away from the radar [3].

Post-classification change detection is carried out after classification into land cover or land use. In this method of change detection, the classification results of two imageries are compared. Because of that the accuracy of postclassification change detection is strongly depends on the accuracy of classification [4]. The post classification change detection results contained large amount of noise due to classification errors of individual images [5].

In 2008, Sanli et al. [6] determined land use changes using polarimetric and optical images and monitored their environmental impacts. In this research, the urban development of the Admiralty region in Turkey between 1971 and 2002 was determined using remote sensing techniques. To improve the accuracy of land use/cover maps, the contribution of SAR images to optic images in defining land cover types was investigated. Landsat-5 and Radarsat-1 were fused to prepare the land use map for 2002. Comparisons with the ground truth reveal that land use maps generated using the fuse technique are improved about 6% with an accuracy of 81.20%.

In 2012, Longbotham et al. [7] conducted research on the discovery of flooded areas by fusing optical and polarimetric images with high spatial resolution. In this research, the goal was not only to identify the best algorithms (in terms of accuracy), but also to investigate the further improvement derived from decision fusion. The goal was not only to identify the best algorithms (in terms of accuracy), but also to investigate the further improvement derived from decision fusion. The method applied is the majority voting algorithm. The majority voting will improve all the results provided. The statistical significance of the change detection maps was evaluated with the McNemar test and all the results were statistically significant (to the 95% confidence level).

In 2014, Mishra and Susaki [8] applied Landsat, PALSAR and AVNIR-2 images between 2007 and 2011 to automatically detect patterns of change using optical and SAR data fusion. The experiment was carried out in an outskirts part of Ho Chi Minh City, one of the fastest growing cities in the world. The improvement of the change detection results by making use of the unique information on both sensors, optical and SAR, is also noticeable with a visual inspection and the kappa index was increased by 0.13 (0.75 to 0.88) in comparison to only optical images.

Optical images have been applied independently in most studies to detect urban changes or determine urban growth. Improvements have been made in research that exploits both optical and radar data. In this research, a new Post-Classification approach has been presented to extract urban land use/cover changes information from UAVSAR imagery. Also, the change maps obtained from optical and polarimetric images with high spatial resolution were fused together to achieve better results.

2. Experiments

After applying the necessary preprocessing, optical and polarimetric data are classified using the SVM algorithm and then the change detection is performed using a number of conventional methods. After obtaining the change maps, they are fused with the majority voting method and the final change maps is obtained.

In order to improve the accuracy of the urban change detection and the application of both optical and polarimetric data, a suitable method is proposed, as shown in Figure 1.

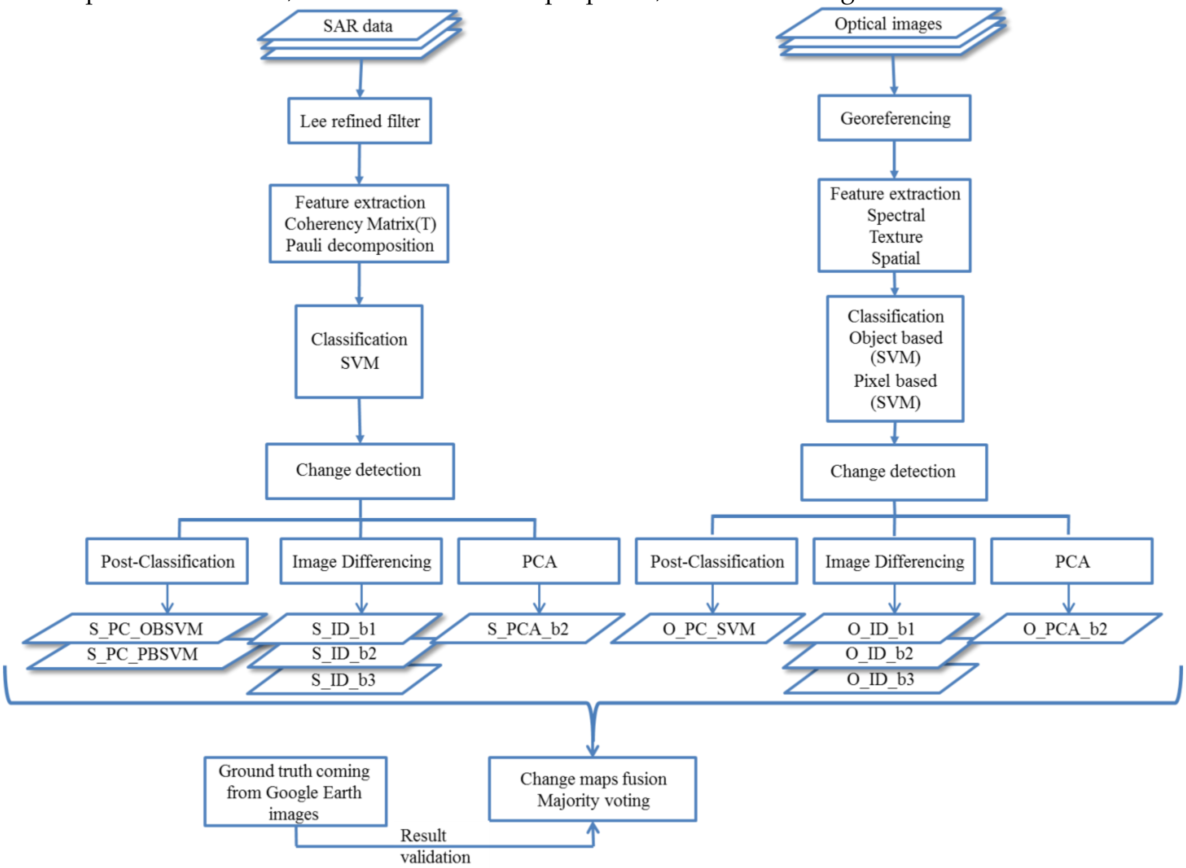


Figure 1. The proposed framework of the change detection algorithm

For a preliminary validation of the proposed CD strategy, we investigate two datasets from Oakland in California. In the period 2010 to 2017, the region was affected by urban expansion, deforestation and land use change. We consider the pair of SAR data acquired by the UAVSAR satellite mission and the pair of optic data acquired by the QuickBird satellite over the region in 2010 and 2017, respectively, as the input dataset. Table 3 lists the data specification such as acquisition date (before and after changes), band spcifications and spatial resolution.

Table 1. Data specification

Dataset	Acquisition date (before changes)	Acquisition date (after changes)	Band	Spatial resolution (m)
QuickBird	06.06.2010	12.03.2017	R,G,B	0.75 x 0.6
UAVSAR	23.04.2010	03.04.2017	L-Band(Fully polarimetric)	6.2 x 6.2 (GRD)

Change detection in urban areas is difficult due to the high degree of similarity between some classes, including bare land, building and road. The probability of an error in the separation between these ground cover classes increases because of the high spectral similarity between these classes and the low number of bands. In this research, the feature extraction is used to increase the number of bands and the ability to separate classes. For each data set used in this study, different features are produced. Spectral, textual and spatial features can be used to improve the separation of classes in optical data due to limitations in the number of bands, and the provision of indices such as NDVI is not possible due to lack of NIR bands. The features provided for polarimetric data are the coherency matrix and Pauli target decomposition. Coherency matrix elements are applied to classify polarimetric images. Pauli target decomposition is used to detect changes by image differencing and principal components analysis methods.

After providing the multi-temporal optical and polarimetric images, the optical images were coregistered to each other and the refined Lee filter is used to reduce the noise in the polarimetric data. Two classification methods for optical images are applied. In the pixel based method, the train sample for the five classes for each date is selected separately and then classified using the support vector machine algorithm. In the object based method, the images are first segmented, then by selecting segments of the five classes as a train sample, the images are classified using the support vector machine algorithm using the spatial, textual and spatial features of the images.

In order to classify the polarimetric images, the train samples for the three classes were extracted using the Pauli decomposition technique. Then, using the components of the coherency matrix and using the support vector machine algorithms, the polarimetric images are classified.

In the final stage, the obtained change maps are fused by the majority voting method into four forms. These four categories are selected as follows:

1. All maps of the changes obtained from optical and polarimetric images
2. All maps of changes made from optical images
3. All maps of changes made from polarimetric images
4. Chart maps are carefully evaluated

The pixel-level classification produces maps producing a sort of "salt and pepper" noise driven by valid spectral information. This noise can be eliminated through the methods such as morphological post processing or the removal of clusters of pixels smaller than certain values [21]. At the end, the final change map is improved by removing pieces less than 300 pixels and noise on the map is deleted.

3. Results and discussion

The change maps obtained from image differencing, principal components analysis and post-classification methods were evaluated using two Kappa coefficients and overall accuracy. In the change maps of post-classification derived from the object based method, there are segments that have been mistakenly identified as a change due to errors in the classification of these pieces. This is not the case, however, in the change maps made by the pixel based methods. According to the results shown in the Table 2, the urban change detection using the post-classification method with the pixel-based algorithm is more accurate.

Table 2. Evaluation of optical image change detection.

Methods	Overall Accuracy	Kappa
Post Classification-OBSVM	67.48%	0.4409
Post Classification-PBSVM	80.59%	0.6767
PCA-band2	71.91%	0.5216
Image Differencing-band1	70.44%	0.4839
Image Differencing-band2	71.01%	0.5285
Image Differencing-band3	76.68%	0.6183

The limitation of polarimetric images is the low spatil resolution than the optical images. The advantage of these images is the number of bands and polarizations and the ability to detect and differentiate the features. This limitation and advantage of polarimetric images have made the range of precision in polarimetric and optical images close to each other.

Table 3. Evaluation of PolSAR image change detection.

Methods	Overall Accuracy	Kappa
Post Classification-svm	70.02%	0.4727
PCA-band2	71.73%	0.5184
Image Differencing-band1	70.96%	0.4903
Image Differencing-band2	70.72%	0.4736
Image Differencing-band3	70.46%	0.4745

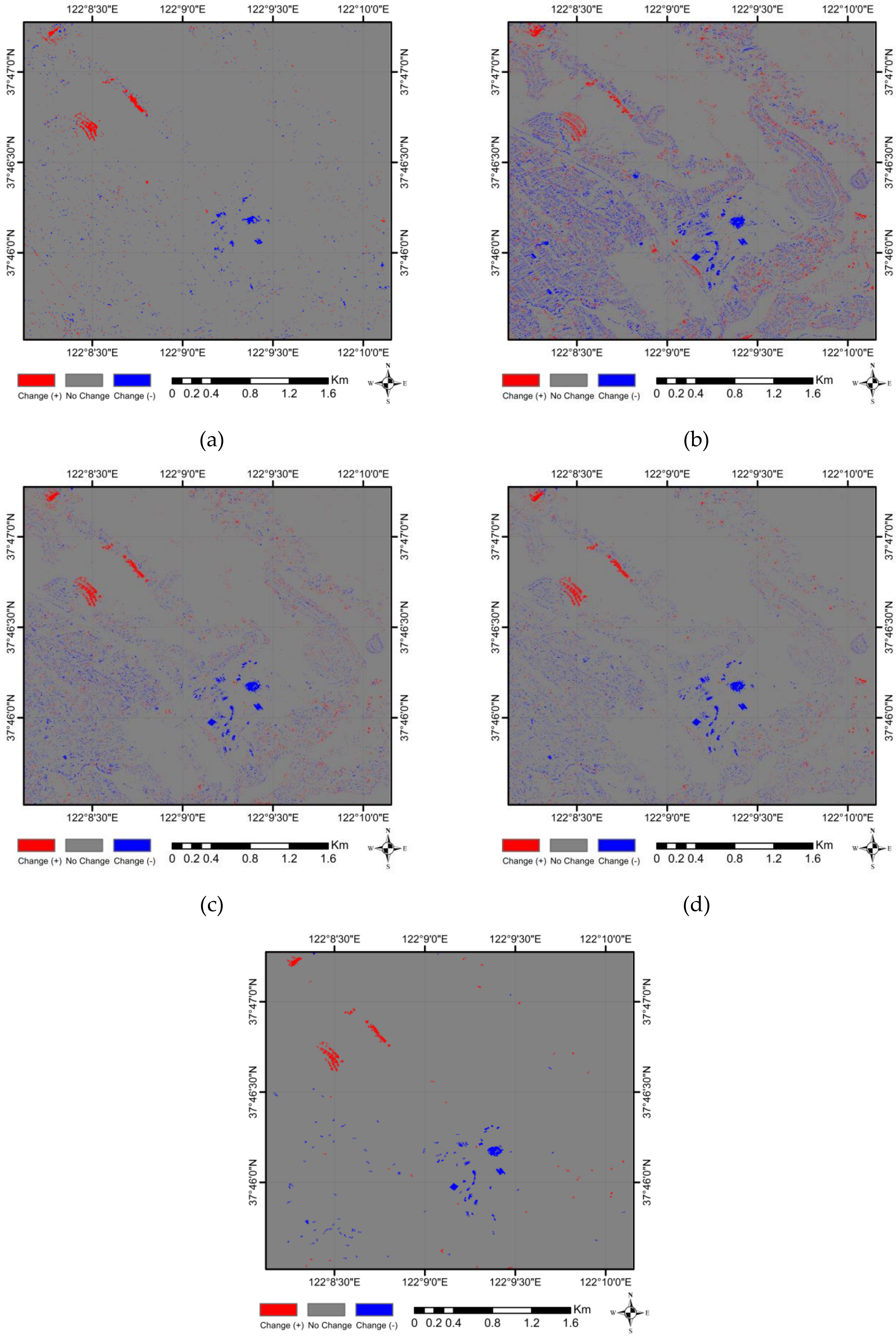
Assessing the accuracy of the results shows that by fusion of the change maps obtained from the polarimetric images, the accuracy is better than the individual methods of change detection. In the fusion of optical images, the precision will also produce the best results. The results showed that fusing the change maps obtained from different algorithms will cover the defects and take advantage of these methods.

Fusing all change maps of polarimetric and optical images gives better results than fusing only the change maps made by polarimetric or optical images. This shows that the results of combining two optical and polarimetric data sets give better precision than the results of combining only one optical or polarimetric data. In order to achieve the best combination for fusing change maps, two kappa coefficients and overall accuracy criteria are used to select the best change map. The five change maps that have been selected for the best combination include a post-classification map derived from the pixel based algorithm, and the object based algorithm, and the image differencing of band 3 from the optical and the post-classification map derived from polarimetric image. Also the salt&pepper noise reduction can be seen caused to increase the accuracy of the final change map.

Table 4. Evaluation of fused change maps.

Methods	Overall Accuracy	Kappa
Optic-Post Classification-PB	80.59%	0.6767
PolSAR-Post Classification	70.02%	0.4727
Majority Voting-All	88.18%	0.7792
Majority Voting –Optic	80.56%	0.6581
Majority Voting –PolSAR	75.22%	0.4958
Majority Voting –Best	88.61%	0.7829
Majority Voting-Best-Improvement	89.81%	0.8049

The final change maps derived from fusing different combinations of change maps are shown in Figure 2. As can be seen, since two change maps are derived from the post-classification method the change map obtained from the fusion of optical images, salt&pepper noise is most observed. While in the change maps resulting from the polarimetric images, one change map is derived from the post-classification method. In the improved change map, the level of noise reduced significantly.



(e)

Figure 2. Change maps: (a) Majority voting PolSAR; (b) Majority voting optic; (c) Majority voting best; (d) Majority voting all; (e) Majority voting best improvment.

5. Conclusions

In this paper, the goal is to detect changes in the urban area and improve the results by fusion at the decision level by majority voting meethod. Fusion of images with just one source and achieving better results suggests that fusing different algorithms will cover defects and take advantage of different methods. The results of fusing two types of optical and polarimetric data give better accuracy than the results of the fusion of only one optical or polarimetric data. Polarimetric images reveal better the changes caused by variations in geometric structure and physical properties of the features, and optical images better reveal changes resulting from spectral variation. Therefore, by fusing optical and polarimetric data at the decision level, different changes can be identified.

By analyzing the accuracy of the classification methods, we find that the object-based method results is better than the pixel based method because of the high resolution of the optical images.

If change detection methods are independent of each other, by increasing the number of methods and increasing the accuracy of the methods, the majority voting algorithm increases the accuracy of the change detection.

As a suggestion, the application of more than one fused image (optic-polarimetric) as well as the application of the fused time series of images will improve the level of monitoring of the land cover/use change.

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Abbreviations

The following abbreviations are used in this manuscript:

PolSAR: Polarimetric Synthetic Aperture Radar
OBSVM: Object Based Support Vector Machine
PBSVM: Pixel Based Support Vector Machine

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