SAR AND OPTICAL DATA FUSION BASED ON ANISOTROPIC DIFFUSION WITH PCA AND CLASSIFICATION USING PATCH-BASED SVM WITH LBP

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ABSTRACT

SAR (VV and VH polarization) and optical data are widely used in image fusion to use the complimentary information of each other and to obtain the better-quality image (in terms of spatial and spectral features) for the improved classification results. The optical data acquisition depends on whether conditions while SAR data can acquire the data in presence of clouds. This paper uses anisotropic diffusion with PCA for the fusion of SAR (Sentinel 1 (S1)) and Optical (Sentinel 2 (S2)) data for patch-based SVM Classification with LBP (LBP-PSVM). Fusion results with VV polarization performed better than VH polarization using considered fusion method. Classification results suggests that the LBP-PSVM classifier is more effective in comparison to SVM and PSVM classifiers for considered data.

Keywords— Fusion, SVM, Anisotropic Diffusion, Principal Component Analysis, Local Binary Pattern

1. INTRODUCTION

Image fusion aims to merge the data acquired using different sensors to provide an improved image with spectral and spatial features [1]. Image fusion with SAR and optical data is widely used in the field of remote sensing due to their different physical and chemical characteristics [2]. In literature, various image fusion methods were implemented such as dictionary fusion, sparse representation fusion, bayesian fusion, component substitution, multi-resolution analysis, etc., using panchromatic/multispectral and hyperspectral data [1-3]. Various other methods such as bilateral filter, weighted square filter, Anisotropic diffusion, 3-D Anisotropic diffusion, PCA, Anisotropic diffusion were also introduced to fuse the data and these methods acts as well as edge preserving methods and feature extraction [4-5]. After fusion, the classification of the fused images is considered to be the necessary step. Classification in remote sensing involves grouping the pixels having similar characteristics for different land cover types and is widely researched area in the field of remote sensing using satellite imagery. Various classification methods such as Support Vector Machines (SVM) and random forest classifiers are the most researched classifiers by the remote sensing community due to their improved classification results [6,7]. Local Binary Pattern is also being used for classification purposes [8]. A recent study for hyperspectral dataset reported the higher performance by PSVM in comparison to other classifiers, namely Naïve Bayes, Linear discriminant analysis, K-nearest Neighbors, and Decision Tree classifier [6,7].

Keeping in view the effectiveness of Anisotropic diffusion, Anisotropic diffusion with PCA was used to fuse S1 and S2 datasets over an agricultural area in India. In addition to fusion, LBP-PSVM for classification was used to compare the performance with SVM and PSVM to extract both spatial and spectral features of the fused image.

2. METHODS USED

In this study, Anisotropic Diffusion with PCA was used for fusion and SVM classifier was used for classification.

2.1. Fusion: Anisotropic Diffusion with PCA

Anisotropic Diffusion technique aims to reduce noise (without removing significant features), preserves the edges in an image and smoothen the images at homogeneous distributed regions or edges and preserves the heterogeneous regions with the help of partial differential equations. It is advantageous in the filtering of optical data as it preserves the edges at coarser resolution. It uses flux function which includes the gradient operator and Laplacian operator to preserve the image diffusion of the image [5].

PCA is the linear transform method which is also proposed for fusion and is extremely useful in the image decomposition into low and high frequency components [9]. Anisotropic diffusion with PCA is helpful in performing the fusion to extract the useful spatial features.

2.2 Feature Extraction: Local binary pattern (LBP)

LBP is known to be the circular derivative patterns of first-order, obtained by concatenating the binary gradient directions for the image classification. LBP acts as a feature
extraction method or a visual descriptor that consists of micropatterns [8]. The histogram of micropatterns generated from LBP contains the image information regarding edge distribution as well as local features. The traditional LBP operator [8] helps in extracting the image information for the constant local grayscale variations. At each pixel location, radius of the neighborhood pixels around the central pixel is calculated to deriving the features.

2.3 Classification: SVM
SVM is an optimization technique based on statistical learning which determines the boundary location for each class. Generally, it is designed and considered for the two-class problems which selects the decision boundaries linearly for the separation of the classes [4]. SVM selects a hyperplane for the non-linear separable classes which widens the margin and reduces the misclassification errors simultaneously. A user-defined parameter i.e., regularization parameter (C) acts as trade-off between margin as well as misclassification error. To minimize the excessive computational cost, kernel functions were used in the high dimensionality feature space [4]. Therefore, combination of LBP and SVM are widely used to classify the satellite image because of their variant ability [10-11].

3. DATASET USED
The study area used in this work is located in Central State farm in Hisar, Haryana (India). Sentinel 1 and Sentinel 2 images of size 964 rows and 1028 columns were acquired on 23 March 2019 and 24 March 2019. VV and VH polarized images from Sentinel 1 and four bands (Red (R), Green (G), Blue (B) and Near Infrared (NIR)) from Sentinel 2 images at 10 m resolution were considered. A total of twelve land cover types, namely, Built-up-area (1), Dense Vegetation (2), Fallow land (3), Fenugreek (4), Fodder (5), Gram (6), Mustard (7), Oat (8), Pea (9), Sparse Vegetation (10), Spinach (11) and Wheat (12) were identified after a field visit to the study area on 6 April 2019.

4. METHODOLOGY
This section describes the adopted methodology used in this paper for fusion and classification of S1 and S2 data.

For the fusion of both Sentinel 1 and Sentinel 2 data, preprocessed data was considered in this study. 3-D Anisotropic diffusion with PCA was used to fuse Sentinel 1 (VV and VH polarization) and Sentinel 2 data in a band-wise manner. Firstly, the base and details layers from S1 and S2 are extracted using 3-D anisotropic diffusion. Secondly, detail layers are fused using PCA transform and base layers using weighted method. Finally, based layers and detail layers are layer-stacked to form the final fused image.

The quality of the fused images was evaluated using considered fusion indicators [12], namely, Erreur Relative Globale Adimensionnelle de Synthese (ERGAS), Spectral Angle Mapper (SAM), Relative Average Spectral Error (RASE), Universal Image Quality Index (UIQI), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR) and Correlation Coefficient (CC).

Once the fused images were obtained, feature extraction on the fused images were performed using pixel-wise Local Binary Pattern for patch-wise SVM classification i.e., LBP-PSVM. The training and testing of LBP-PSVM classifier, image patch of similar size (i.e., p×p) was extracted with help of ground reference image. During classification, only patches of central pixels whose value is non-zero were assigned a class number in the ground reference image else no class number was assigned. RBF kernel function, optimal values of regularization parameters (C and γ) using a suitable patch size were considered for LBP-PSVM classifier. The performance of the classification is measured in terms of overall accuracy (OA).

5. FUSION AND CLASSIFICATION RESULTS
This section describes the fusion and classification results of S1 and S2 data and the experimental setup was performed using MATLAB and Python 3.0.

Table 1 provides the fusion results of Anisotropic diffusion using PCA in terms of considered fusion indicators for S1 and S2 data. The comparison of other traditional fusion methods such as Brovey, Ehlers, IHS, etc., has not been performed due to their lower performance [13-15]. IHS transform can only be performed for three bands and in this study fusion of four bands has been performed.

S2 fused with S1(VV) data achieved higher performance in comparison to the S2 fused with (VH) data (Table 1). According to the above details of the fusion indicators, VV polarization depicted the higher fusion results (Table 1). For VV polarization, lower value of ERGAS, higher value of UIQI, SSIM, CC, indicates higher fusion quality in comparison to VH polarization. Lower value of RASE and ERGAS indicates less spatial and spectral distortion in the VV polarized fused image.

Table 1: Fusion evaluation using various fusion indicators; P (Polarization)

| P | Fusion Parametric value obtained using Anisotropic Diffusion with PCA |
|---|---------------------------------------------------------------|
| VV | ERGAS | SAM | UIQI | SSIM | CC | RASE | PSNR |
|   | 0.14 | 0.16 | 0.99 | 0.99 | 0.99 | 0.57 | 50.95 |
| VH | 4.13 | 5.69 | 0.91 | 0.98 | 0.98 | 19.76 | 29.46 |
Figure 1 provided the input images and the fusion results for the visually interpretation. The results are provided for both VH and VV polarized images of S1 (Figures 1). The images obtained after fusion with both VH and VV polarization are displayed using three bands (NIR, R, and G). VV polarization of S1 data is sensitive towards the roughness of the surface and VH polarization provides more detailed information about canopy cover and vegetated areas. The VV polarized fusion (Figure 1(d)) indicates the better tone and texture of the image than VH polarized fusion in terms of visual interpretation.

Table 2 provides the classification results in terms of overall accuracy using PSVM, SVM and LBP-PSVM for the obtained fusion results and original data i.e. S2 layerstacked with S1 (VV and VH) separately (SVM). Table 2, LBP-PSVM classifier achieved the better classification results with 98.69% and 97.82% for VV and VH polarization respectively, in comparison to SVM and PSVM classifier. For SVM classifier, S2 layerstacked with S1 (VV and VH) shows poor performance in comparison to Anisotropic diffusion with PCA fusion (AWP) results. Therefore, S2 layerstacked with S1 is not shown with PSVM and LBP-PSVM classifiers (Table 3).

Table 3: Accuracy metrics of LBP-PSVM classifier for VV polarization

| Class | Omission error (%) | Commission error (%) | Class-wise Accuracy (%) |
|-------|--------------------|----------------------|-------------------------|
| 1     | 0.00               | 1.36                 | 99.00                   |
| 2     | 0.00               | 0.00                 | 100.00                  |
| 3     | 0.00               | 1.38                 | 99.00                   |
| 4     | 5.75               | 2.38                 | 98.00                   |
| 5     | 0.00               | 12.5                 | 88.00                   |
| 6     | 1.97               | 1.97                 | 98.00                   |
| 7     | 0.51               | 0.00                 | 100.00                  |
| 8     | 1.96               | 3.11                 | 97.00                   |
| 9     | 5.18               | 2.89                 | 97.00                   |
| 10    | 3.06               | 1.33                 | 99.00                   |
| 11    | 3.15               | 0.40                 | 100.00                  |
| 12    | 5.26               | 9.24                 | 91.00                   |

Tables 3 and 4 provides the accuracy metrics i.e., omission error, commission error, and class-wise accuracy of LBP-PSVM classifier for VV and VH polarization. Only results of LBP-PSVM classifier has been provided because it achieved maximum classification accuracy in terms of overall accuracy (Table 2). The omission error for VH polarization is more than VV polarization for class 9. It means class 9 is more incorrectly classified in VH polarization. On the other hand, commission error for class 5 is more in VH polarization.

The results of class-wise accuracy for VH and VV polarization has been compared. Results from Tables 3 and 4 indicates an increase of 0% to 12% for different classes by VV polarization. It means that VV polarization achieved better classification result (Tables 2, 3, and 4).
Table 4: Accuracy metrics of LBP-PSVM classifier for VH polarization

| Class | Omission error (%) | Commission error (%) | Class-wise Accuracy (%) |
|-------|-------------------|----------------------|-------------------------|
| 1     | 0.23              | 0.45                 | 100.00                  |
| 2     | 0.00              | 0.00                 | 100.00                  |
| 3     | 0.00              | 0.69                 | 99.00                   |
| 4     | 2.63              | 11.90                | 88.00                   |
| 5     | 4.17              | 17.86                | 82.00                   |
| 6     | 5.12              | 0.85                 | 99.00                   |
| 7     | 0.80              | 0.15                 | 100.00                  |
| 8     | 7.81              | 2.69                 | 96.00                   |
| 9     | 5.40              | 6.28                 | 94.00                   |
| 10    | 0.00              | 5.78                 | 94.00                   |
| 11    | 3.79              | 7.69                 | 92.00                   |
| 12    | 4.39              | 8.40                 | 92.00                   |

6. CONCLUSION

This study reports the anisotropic diffusion using PCA to fuse the SAR and optical data. Based on the fusion results, major conclusion drawn from the study is that VV polarized fused images resulted in better performance in comparison to the VH polarized fused images in terms of image analysis for the considered dataset. Another conclusion is that out of PSVM and SVM, only LBP-PSVM were able to improve the classification accuracy by extracting more spectral and spatial features acquired from considered patch size. The different classification accuracy of SVM using different approaches suggests that the classifiers are assigning different classes for the same region, therefore more ground data collection is required as well as other deep learning approaches like Convolutional Neural Networks can be used for the comparison of the classification accuracy.

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