Data Fusion for Urban Feature Extraction from LiDAR and Hyperspectral Data

Dr. Seyed Yousef Sadjadia  
Geomatics Department, School of Civil Engineering, Tafresh University, Tafresh, I.R. Iran  
Emails: sysadjadi@hotmail.com

Omid Aienehb  
Geomatics Department, School of Civil Engineering, Tafresh University, Tafresh, I.R. Iran  
Email: aieneh.omid@gmail.com

Abstract – The main problems of hyperspectral data are the large number of bands, high dependency between them and different signal to noise ratio in each band. In order to reduce the dimensions of the feature space, minimizing noise and spectral dependence between bands, the MNF method has been used for achieving better results in this paper. Finally, by applying this algorithm, the 144 bands of hyperspectral data was reduced to 19 suitable bands. Then from LiDAR data, the image height and intensity of the return signal produced from the first and the last pulse of the laser were produced by LiDAR sensor. At last, The 19 spectral bands extracted from hyperspectral data have been fusion with 4 images of LiDAR data at the pixel level to create 23 suitable spectral bands. In order to detect and extract any feature study of the area on 23 spectral bands, seven different SVM method were applied and finally by majority voting in the decision level between 7 obtained results, the class of each pixel was turned out. Then, morphology closing transform for repairing buildings and Hough transform for reconstructing the network effects of the fragmentation of land transportation were used on the results of pixels basis SVM method to disciplined side structure built by man as well as the individual pixels is reduced. The results in this paper indicates the 99.52% overall accuracy and .958 kappa coefficient which compared to the GRSS chosen institution method .6 Kappa coefficient has been improved. The data used in this paper are air-borne LiDAR and hyper-spectral scenes requested and downloaded from the organized of a recent contest in data fusion domain. The data have been gathered and are available from Houston University in 2012 by Geoscience and Remote Sensing Society (GRSS), a branch of IEEE institute.

Keywords – MNF, SVM, LiDAR, Hyperspectral, Majority, Voting, Fusion, Extraction.

I. INTRODUCTION

One of the powerful methods for improving classification performance is data and sensor fusion. In recent years, different remote sensing sensors are provided a wide spectrum of data. For many applications, the information provided by single sensors are incomplete and imprecise, multiple sensors can provide complementary data and fusion of information from different sensors can provide the better information from desired area which is not possible with individual sensors (Simon, 2002. Pohl and Van Genderen, 1998). Fusion of multiple datasets can be performed at the signal, pixel, feature and decision level (Esteban, 2004. Pohl, 1998). In signal level fusion, signals from multiple sensors are combined together to create new signal with a better signal-to-noise ratio than the input signals. In pixel level fusion, the information from different images on a pixel by pixel are merged to improve detection of objects in some tasks such as segmentation. Feature level fusion consists of merging features extracted from different images. In this level of fusion, features are extracted from different sensors are combined to create a feature vector for classified using a classifiers methods. In decision level fusion, different datasets are combined at a higher level of integration. In this level of fusion, at first the data from each single sensor is classified, then fusion consists of merging the output from the classification (Du et al. 2013, Dong et al. 2009, Yan, 2004). Decision-level fusion consists of merging information at a higher level of abstraction, combines the results from multiple algorithms to yield a final fused decision. Input images are processed individually for information extraction. The obtained information is then combined using decision fusion methods. Decision-level fusion was chosen against pixel level fusion and feature-level fusion in the three-level fusion hierarchy, because of its feasibility, lower computational complexity and robustness to the removal or addition of individual data sources. An extensive literature is available on the decision fusion approaches. As one of the most important techniques in decision fusion, voting has been applied in different applications. In voting-based fusion, the class assigned by a classifier is considered as a vote for that class. Applications of majority voting techniques to combine classifiers can be found (in Lam and Suen 1997), (Rahman and Fairhurst 2000 and Lin et al. 2003). A comprehensive review of majority voting and its variants for combining multiple classifiers in character recognition has been presented in (Rahman et al 2002) and (Kuncheva 2004). International Journal of Image and Data Fusion 197 Downloaded by [DLR-Bibliotheken] at 09:23 30 August 2014 In weighted version of voting method, usually a weight is assigned to each classifier. Detailed discussion of weighted voting can be found in Littlestone and Warmuth (1994). Benediktsson and Kanellopoulos (1999) used a weighting-based approach to combine the classification results from multiple neural networks and statistical models. The weights of the individual classifier reflected the reliability of the sources and were optimized in order to improve the combined classification accuracy during training. Tsoumakas et al. (2005) combined weighted voting with the classifier selection step so that only the results from a subset of the classifiers were used for fusion. Such selective fusion was shown to be a generalization of weighted voting. In addition, Bayesian decision fusion strategy has been successfully applied in diverse fields ranging from pattern recognition (handwritten digit/character recognition and image recognition), to
medical diagnosis and machine fault diagnosis (fault diagnosis in transformer and induction motor). Zheng et al. (2005) used Bayesian-based fusion to integrate results from different image processing approaches for diagnosing diseases. McArthur et al. (2004) combined k-means clustering, back-propagation neural network and userwritten rules based on Bayesian approach to diagnose faults in a power transformer. Dempster–Shafer-based fusion has also been widely used in various fields. Parikh et al. (2001, 2003) used the Dempstert–Shafer evidence theory to combine the outputs of multiple primary classifiers to improve overall classification performance. The effectiveness of this approach was demonstrated for detecting failures in a diesel engine cooling system. There are several other decision fusion strategies including behavior knowledge space (Huang and Suen, 1993, 1995) which uses a lookup table that lists the most common correct classes for every possible class combinations given by the classifiers, decision templates (Kuncheva et al. 2001) which compute a similarity measure between the current decision profile of the unknown instance and the average decision profiles of instances from each class. A detailed overview of various decision fusion strategies is available in Kuncheva (2004). With the development of the remote sensing imaging technology, application of decision fusion approaches for fusion of images from different sensors is becoming more and more widespread in remote sensing. Recently, new researches focus on decision fusion strategies to overcome the weaknesses of single remote sensing sensors (Simone et al. 2002, Hsu and Burke 2003). As hyperspectral images provide a detailed description of the spectral signatures of classes without any height information, fusion of this data with LiDAR data may improve classification results. In Lidar data object detection is possible as well as prediction about height of objects. Fusion of these both datasets is expected to increase the classification accuracy. Simental et al. (2003) showed that fusion of hyperspectral and LiDAR data can enhance overall detection and classification performance in vegetation classes. As HSI provide a widespread description of the spectral information in some classes without any height information such as building, street and vegetation, fusion of this data with LiDAR data may improve classification results in areas with different height. Lemp et al. (2005) fused hyperspectral and LiDAR data for improving classification of urban areas. They used LiDAR data for segmentation and hyperspectral data for classification tasks. Delponte et al. (2008) investigate the joint of hyperspectral and LiDAR data with classification based on SVM for rainforest areas. They applied a band reduction strategy to select the best features from hyperspectral data. Then, they added a LiDAR data to selected features from hyperspectral data for the classification. In recent years, Zhao et al. (2013) applied four features: Principal Component Analysis (PCA), Minimum Noise Fraction (MNF), Normalized Difference Vegetation Index (NDVI) and GLCM on hyperspectral data. Next, non-ground and ground points on LiDAR data are separated based on the algorithm proposed by Axelsson (Zhao, 2013). After that they applied three classifiers on features of hyperspectral data and LiDAR data. Finally, they fused all classifiers using majority voting (Zhao, 2013). This paper proposes a classifier fusion system based on SVM classifier and dimension reduction methods for fusion of hyperspectral and LiDAR data. At first, different features are extracted from both datasets to generate features spaces on hyperspectral and LiDAR data. Then, classification based on SVM is applied on hyperspectral and LiDAR data features and by using a classifier fusion method, the outputs of SVM classifiers for producing final image will be fused. At last, final image will be reconstructed.

II. PROPOSED METHOD

This paper proposes a classification method based on SVM and dimension reduction for fusion of hyperspectral and LiDAR data. In first section, Minimum Noise Fraction (MNF) method is applied on hyperspectral images for dimensionally reduction and then several features are extracted from LiDAR data. In second section, Features extracted from the LiDAR data and hyperspectral images are fused at the pixel level and then, Support Vector Machine method for classification is applied on features fusion. In third section, the classifiers which are obtained from SVM method will be fused together by using a fusion method and then final image will be provided. In final section, morphology closing transform for repairing buildings and Hough transform for reconstructing the network effects of the fragmentation of land transportation will be used on the final image to discipline side structure built by man. General diagram for proposed method is shown in figure 1.

2.1 Feature Extraction

In this step, as shown in the figure 1, different features are extracted from LiDAR and hyperspectral data. These features must contain useful information for improving accuracy of classification process.

2.1.1 Dimension Reduction on Hyperspectral Data

![Fig.1. Proposed method for Lidar and hyperspectral data fusion](image-url)
One of the main steps of classification process on hyperspectral is extraction of proper features from dataset. These features must contain useful information to identify different regions of the surface. MNF have been utilized to reduce the dimension of spectral bands. The first 19th features or bands contain the most information of the hyperspectral images. Because the variances of bands in the first 19th ones are higher than the others.

2.1.2 Feature extraction on LiDAR data

Extraction of proper features from LiDAR data is one of main steps in classification process. On LiDAR data, the image height and intensity of the return signal received from the first and the last pulse of the laser were produced by LiDAR sensor.

2.2 SVM based classification

One of the most popular classification methods are SVMs defined by Vapnik (1998), a large margin-based classifier with a good generalization capacity in the small-size training set problem with high-dimensional input space. SVMs discriminate two classes by fitting an optimal linear separating hyper-plane to the training samples of two classes in a multidimensional feature space. The optimization problem being solved is based on structural risk minimization and aims to maximize the margins between the optimal separating hyper-plane and the closest training samples – the so-called ‘support vectors’. A detailed description on the general concept of SVM is given by Burges (1998) and Schölkopf and Smola (2002). It is worth underlining that the kernel-based implementation of SVMs involves the problem of the selection of multiple parameters, including the kernel parameters (e.g., parameters for the Gaussian and polynomial kernels) and the regularization parameter C. In our proposed method, the kernel of each individual classifier is adjusted according to the corresponding feature space properties. This paper utilized one-against-all multiclass SVM with RBF kernel (RBF is one of the most popular kernel function for SVM classifier) as base classifier.

\[ k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0 \]  

(1)

Grid search is a well-known technique for model selection which performs exhaustive search and selects a set of parameters values with the best fitness (Hsu et al. 2010). In this paper, LIBSVM software has been used for multi-classification.

2.3 Fusion of Hyperspectral and LiDAR data

In first section, after producing Hyperspectral images with suitable bands and producing images height and intensity of the first and the last return from LiDAR data, SVM classifiers are applied on features fusion. For this purpose, seven different methods of machine learning SVM on the images are used. Finally by majority voting in the decision level between SVM obtained results from seven different methods, the class of each pixel is turned out.

III. RESULT

3.1 Data Set

In this paper, we present a fusion method for improvement of classification results on urban areas. The proposed approach was applied on two data sets. A Hyperspectral and a LiDAR derived digital surface model (DSM); both data sets with spatial resolution of 2.5 m which is shown in figure 2. The Hyperspectral consists of 144 spectral bands. The data sets have captured over the University of Houston campus and the neighboring urban area and have been acquired by the National Science Foundation (NSF)- funded Centre for Airborne Laser Mapping (NCALM). The ground truth of this data set which was provided by NCALM have 15 different land cover classes; grass healthy, grass stressed, grass synthetic, tree, soil, water, residential, commercial, road, highway, railway, parking lot 1, parking lot 2, tennis court, running track. These classes are shown in table 1.

![Fig.2. Data sets: a) hyperspectral Image, b) LiDAR derived DSM](image)

![Table 1: Classes, Training and Test Samples, and Color Code](table)

3.2 Results and Experiment

In first step of proposed method, feature spaces on Hyperspectral and LiDAR data have been produced independently. Features extracted from the LiDAR data are illustrated in Figure 3.
In next step, classification based on SVM is applied on hyperspectral and LiDAR data. After classification of hyperspectral and LiDAR data, majority voting will be applied on the outputs of the classifiers as classifier fusion method.

To investigate the effects of mining in data fusion and using them individually, the results of feature extraction are investigated in four different modes: (a) feature extraction from hyperspectral images with 19 spectral bands with the voting results of the class of seven different method of SVM, (b) feature extraction from four images LiDAR data with voting between seven different methods of SVM, (c) feature extraction from LiDAR and hyperspectral image data fusion using a SVM, (d) feature extraction from LiDAR and hyperspectral image data fusion with voting between seven different methods of SVM, are illustrated in Figure 4. Table 2 and 3 illustrates the accuracies of classification results on all fifteen classes of data sets in four different modes. Figure 5(d) demonstrates the classifier fusion strategy on hyperspectral and LiDAR data.

In final section, the connection between discrete and also removing the effects of the additional duty irregular data must be made. For this purpose, an image of edges of 15th features classes is needed which can be done by using canny edge extraction method. Then, after finding the edges, the lines which are along together and are 10 pixels or more far from each other will be find and connected together by using Hough transform and also intersected lines with 3 pixels spaces will be find and connected together. Since the structural features have geometrically regular and rectangular, in order to restore regular geometric shape of them, morphology close transform with structural elements with dimensions of 3 square pixels will be used. By using structural elements, discrete
The trees can be divided into two distinct classes: the individual tree and rows of trees. The rest of the vegetation, such as green plants and plant vegetation dry and combination of green and dried plants can be considered in the category of green space that surface range. In order to determine the point or row linearity of the trees, a neighborhood radius around of 5 pixels is considered around each tree. If at least three trees are in a row by using Hough transform, they are as a row of trees. Also, another method for identification of row of rows, is the number of pixels forming the side of the tree considering length to width ratio. If the number of pixels forming the feature of the tree is more than 5 and its width ratio is greater than 3, In that case, this feature is considered as a row of trees. The result is illustrated in Figure 5.

![Image](image.png)

**Figure 5.** (a) Classify images to proposed method, (b) Restorative complications are extracted using the definition of the object instead of feature. The only difference is that the feature of tree rows are shown in blue.

### IV. Conclusion

Fusion of hyperspectral and LiDAR data in decision level is the important aim of our proposed method. In this level, complexities of hyperspectral and LiDAR data are considered. Because HSIs provide a detailed description of the spectral signatures of objects but no information on the height of ground covers, whereas LiDAR data provide detailed information about the height of objects but no information on the spectral signatures. So the elevation information of LiDAR data is very effective for the separation of objects with similar spectral signatures. Also the spectral information of hyperspectral data is very effective for discrimination of similar elevation objects but different spectral information. Based on the results of our proposed method, fusion of classifiers on two data sets improves classification accuracy. The overall accuracy (OA) and kappa coefficient of this strategy are shown in Table 4. Based on these results, proposed classifier fusion on hyperspectral and LiDAR data improves the classification accuracy. The object-based feature extraction in image, of the individual pixels is prevented. In other words, it is possible that pixel-based SVM method consider different classes for a few pixels that are adjacent to each other, this leads to a rupture in the results. But by using feature extraction method based on object for each individual pixel class finds the nearest neighbors. Because SVM classification method cannot extract the feature continuously. Therefore, due to the reasons provided, to regulate the construction feature and also the extracted continuous road, morphology close transform used with Hough transform. Then be sure to check whether adding images LiDAR to hyperspectral image data is improving or not. If you use the LiDAR image, overall accuracy and kappa coefficient for the classification of 93.03 and .431 respectively and the use of hyperspectral images to a classification of 98.62 and .899 respectively, were calculated. As a result, an increase from .899 to .958 kappa coefficient of hyperspectral image by adding LiDAR data, show a broadly favorable effect of using LiDAR imagery to improve the results of the classification. A comparison of the proposed method and tournament favorite institution is given in Table 4.

- a. The selected method of data integration in international competition IEEE.
- b. Hyperspectral imaging with seven SVM.
- c. LiDAR imaging with seven SVM.
- d. Hyperspectral and LiDAR imaging with one SVM.
- e. Hyperspectral and LiDAR imaging with seven SVM.

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<td>Overall Accuracy</td>
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### REFERENCES


