Identification of Objects using Data Fusion of LiDAR and Hyperspectral Data

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***Abstract*—With the advent of diverse sensor systems and image processing algorithms that allow very accurate analysis of parametric features application based algorithms to integrate features of multiple data systems. Complimentary features used are capable of overcoming physical limitations set by Light Detection and Ranging(LiDAR) and hyperspectral data.A graph based fusion approach which is able to integrate feature fusion while also accommodating feature reduction as implemented by a variable kernel based component analysis model. Stacked spatial, elevation and spectral features form the weighted edges which improves the identification accuracy over binary edges. This letter focuses on the improvement in identification accuracy over isolated LiDAR and Hyperspectral Data.**

***Index Terms*—Data Fusion, Hyperspectral Imaging(HSI), Kernel, Light Detection and Ranging(LiDAR)**

I. INTRODUCTION

The following article delineates the data fusion algorithm of LiDAR and hyperspectral based data on a suitable graph based fusion method. The spectral, spatial and elevation features are combined to give an improved association result in contrast with the accuracy of individual LiDAR and hyperspectral based data. The graph based fusion process ensures and enhances the temporal, spatial, and spectral comparison of two different sensor systems and is, in addition to the geometric alignment, one of the essential steps for comprehensive data fusion. An added advantage to this method includes the increased accuracy as well reduced number of decision making stages.

The features from the data sets are processed and normalized using a succession of different kernels, mainly Gaussian and a linear kernel utilized in Principle Component Analysis(PCA). The normalized form, the data is roughly integrated into the fusion algorithm in order to generate a weighted transformation factor and variable. This weighted transform is then used to fuse

the characteristic features of the data providing a data fused graph. The graph obtained, it is then processed using a weighted support vector machine to clearly identify and associate the data with the training set thereby generating a higher accuracy.

Hyperspectral images(HSI) provide the spectral and spatial characteristics while the elevation characteristics are obtained from the LiDAR based images. The implementation of HSI images for identification is well documented in Sierra Nevada[1]. Despite the vast amount of information provided in these images, there is still the question automatic interpretation of such complicated data on a large scale. As LiDAR provides the elevation characteristics of the given topological features, LiDAR based imagery is used in a variety of applications in remote sensing. Hyperspectral imagery or HSI images are basically images which contain the features in the respective bands of information present. The complexity of high spectral data contained in these spectral bands is filtered through the decision making stages allowing for the accurate classification and mapping. The fusion of data for identification of objects is well documented in[2] however a graph based fusion technique with variable kernels for the processing of data is untested.

This method of data fusion requires building a morphological profile based on the features[3],[4]. This morphological profile built is used as the backbone of association and classification of data. Each morphological profile contains the data set in the form of a matrix. This matrix is the collective set of data points which basically points towards the indexing of information on the respective LiDAR and hyperspectral based data.

II. INPUT DATA

Data sets utilized in the identification algorithms was collected over Houston and was provided by sensors positioned approximately 2000 feet off the ground for LiDAR and 5500 feet for HSI. The data was collected by the Centre for Airborne Laser Mapping which consequently sponsored by NSF.

The data sets constitute a LiDAR normalized digital surface modeland HSI image which has a spectral range from 380nm - 1050nm and consists of 144 bands. The training data contains the structural analysis of the various classes of data as presented.

Figure 1is a collection of the various data sets considered and shows the various classes considered in the identification process.

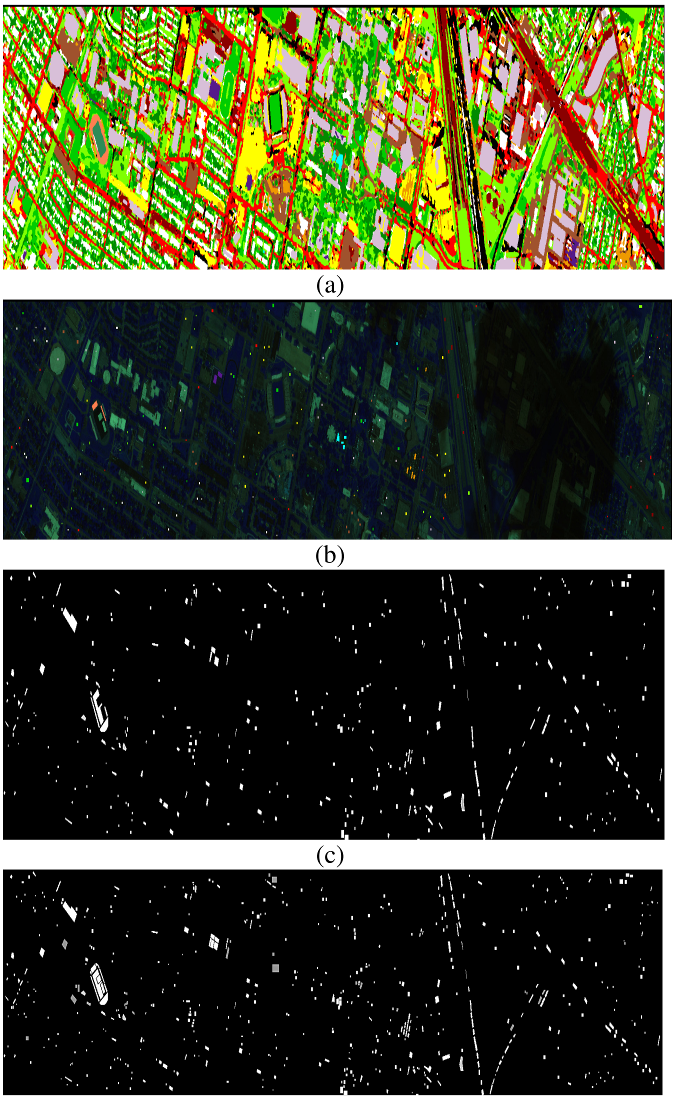

Fig. 1. Data sets used (a)LiDAR Image (b) False Color representation of Hyperspectral Image (c)Training Samples (d) Testing Sample.

Fig.1. (d) contains a higher number of data sets as this is the testing data in stark contrast to Fig.1. (c) which is the training data representation of the following data set.

III. DATA NORMALIZATION

Normalization of data is necessitated due to varying dimensionality of the LiDAR and Hyperspectral Data sets. Normalization has the added benefit of greatly mitigating the computational cost as well as the minimization of the run time. Normalization is achieved by variation of the kernel function adaptive to the data set where linear data takes precedence over the Gaussian function for similar data type.Linear kernel is a parametric model whereas a Gaussian kernel isn't, and the complexity of the latter grows with the size of the training set [5]. Furthermore, the storage of the kernel matrix and projection into a broad number of dimensions to attain linear separation of the data set is computationally taxing.

However, a linear kernel is fallible to non linear sets of data and accommodation for the Gaussian or Radial Basis Function(RBF) was necessitated at this juncture.A RBF creates non-linear combinations of the features to map the data points onto a higher-dimensional feature space where a linear decision boundary is used to separate the classes [6].

The hyperspectral image contained 144 spectral bands and the DSM based LiDAR image contained 70 bands, for effective and streamlined computation normalization to standardize the dimensions achieved standard dimension for both LiDAR and HSI images dimension D as =70.

IV. GRAPH BASED DATA FUSION

Several mathematical parameters used in the fusion of data can be given as below.

$X^{Spe} = \{x^{Spe}{}_i\}^n{}_{i=1}$: Defines the Spectral elements with each data point represented as x .A total of n spectral points.

$X^{Spa} = \{x^{Spa}{}_i\}^n{}_{i=1}$: Defines the Spatial elements with each data point represented as x .A total of n spatial points.

$X^{Ele}=\{x^{Ele}{}_i\}^n{}_{i=1}$: Defines the Spatial elements with each data point represented as x .A total of n spatial points.

$[X^{Spe}; X^{Spa}; X^{Ele}]=\{ x^{Sta}{}_i = [x^{Spe}{}_i; x^{Spa}{}_i; x^{Ele}{}_i]\}^N{}_{i=1}$:The following is the two dimensional stacked matrix of the data points .N represents a dimensionally stable number of data points from the each of the elements of the stacked matrix.The issue at hand is the computation of the transformation matrix $W \in R^{3D\times d}$[7]. The transformation matrix is fundamental for feature fusion in a way of $Z_i = W^T x_i$ (x_i is a data variable, it can be used to represent $x^{Sta}{}_i$, $x^{Spe}{}_i$, etc.),where $Z_i$represents the fused features in lower dimensional feature space.The transformation matrix W has three essential functions in the data fusion operation: Fuse different features in a lower dimensional feature space. Secondly, maintain local neighborhood information.Finally detect the primary edges in the high-dimensional feature space.

The transformation matrix can be made defined by the following mathematical function as given by [8]

$$\arg \min \left\{ \sum_{i,j=1}^{n} \left\| W^T x_i - W^T x_j \right\|^2 A_{ij} \right\} \qquad (1)$$

In the given function the terms can be defined as follows:
W: Transformation matrix
X_i: Data point in the co-ordinate x dimension
A: The edge of the graph

The above mathematical function essentially computes the Euclidian distance of each data point. This distance is then a function of the relative 'closeness 'of data points with respect to a probabilistic function. To compute the normalized weight simply multiply the transpose of the transformation matrix with each individual data point from the stacked matrix which is given by[9]

$$Z_i = W^T .X_{ij} (2)$$

With the help of the transformation matrix, Eigen vectors which form the edges or weights of the data graph G can be successfully computed.Graph,G is defined as (Xi,Q^{Fus})Where $Q_{ij,\ defines}$ the relationship between the different nodes .The parameter can be defined in (3) [10]

$$Q^{Fus} = Q^{Spe} \Theta Q^{Spa} \Theta\ Q^{Ele} (3)$$

Each of the Q^{ij}parameters represents the individual relationship between each point. Where 'ϴ' represents the element wise multiplication of each of the elements in each of the three parameters – Spectral, Spatial and Elevation.

This element wise multiplication is thereby the practical embodiment of data fusion as these features are multiplied integrating different data sets into one common factor defined by Q^{Fus}. A pair wise distance matrix between the stacked elements X^{Sta}tosuccessfully define Q^{Fus}. The distance matrix by Δ .Based on the fusion of parameters a definition for fused distance matrix in (4) [9]

$$\Delta^{GFus} = \ + A^{Neg} \max (\Delta) \qquad (4)$$

Based on the fused data matrix part a formal definition of the Q^{Fus} can be defined in (5). Where Ni: Neighborhood of the stacked matrix.

$$Q^{Fus} = \begin{cases} e^{||xi-xj||^{\ 2}} \text{ if } x_i \in Ni \\ 0 \text{ , otherwise} \end{cases} \qquad (5)$$

The fused neighborhood segregates between data points with significant variation and ensures that the points which vary significant variation in terms of spectral, spatial or elevation parameters.Such data points aren't joined in the fused graph .This degree of correlation and variance between the points allows us to distinguish between fine features.One such instance is the ability of the algorithm to distinguish between similarly size objects thus reiterating the need of data fusion .The separation occurs as a result of the hyperspectral parameter which can distinguish between objects based on the spectrum of their wavelength [11].

A degeneracy constraint as defined in [10] is used to boost overall accuracy is given as :

$$X^{Sta} LG^{Fus} (X^{Sta})^{T} w = I \qquad (6)$$

D^{Fus} is the diagonal fusion matrix and I is the identity matrix. The transformation matrix W=(w1,w2,.....,wr) which is made of r eigenvectors associated with the least r Eigen values λ1 <λ2 <λ3.....<λr. Where Lis the Laplacaian matrix as given by (7).

$$L^{GFus} = D^{fus} - W \qquad (7)$$

The Eigen Problem is then defined as:

$$X^{Sta} L^{GFus} (X^{Sta})^{T} w = \lambda X^{Sta} D^{Fus} (X^{Sta})^{T} w \ (8)$$

$L^{GFus}$is the fused Laplacian Distance which differentiates a single data point from the fused stack points. The Eigen Vectors so obtained are used in the definition of the weights in the fused graph. Classification is done based on these weights.

V. RESULTS

In this experiment, a radial based function is employed with the support vector machine classifier. The purpose of this radial function is to generate a Euclidean based system which allows for accurate values and more level of approximations. As mentioned earlier, a Graph based fusion algorithm is used to fuse the characteristic features.

The GGF algorithm is used to compute the fused matrix of features. This proposed GGF is compared with 1) the original HSI image 2) the original LiDAR image 3) Morphological profile built using the spectral , spatial and elevation characteristics 4) Fused data matrix 5)Stacked data matrix from all relevant features extracted using PCA.

The graph is constructed using the weighted edges principle where each weight is assigned based on the Euclidean distance. In order to obtain the relevant features from the data set, KPCA normalization is performed. The normalized features are then subject to GGF. Quantitative evaluation of the results is performed by measuring the overall association accuracy of the test samples. It was observed during the test cases, a 12% increase in the data fused value in contrast with the individual morphological profiles. The test case generated an accuracy of about 82.5% for LiDAR and 81.5% for HSI images.

The various regions of interests were considered and an overall accuracy was generated. The improvements in the weighted fusion concept of GGF increased the process time to generate a better and accurate value of identification.

As observed the input data is a combination of various natural and manmade structures with different levels of elevation. Hence it is impossible to correctly establish the identification using Hsi imagery exclusively. Combination of LiDAR based data is a must at it provides the correct and useful elevation characteristics required to identify the differences.

The GGF algorithm establishes a relationship between the nodes by assigning weights to it. These weights are assigned using the distance function which happens to be the Euclidean distance function. The normalized method of fusion assigns the same weight to all edges, this however is not ideal as the stacking of all features provides for unbalance of information. Hence the GGF is used in order to stabilize these unbalances.

TABLE II

X	Y	Accuracy
1	100	81.57%
2	101	77.5%

The X and Y coordinates represent the matrix range of values which are taken into consideration. It can be observed from

TABLE III

SAMPLE	Accuracy
1	97.5%
2	95%
5	97.5%
10	97.5%
20	92.5%

the table that the accuracy values depend on the attributes present in that particular region of interest.

At the given sample points, the accuracy was generated using the weighted SVM. From the table it is observed that the data fused values have an average accuracy of 95%

TABLE IV

System	Overall Accuracy	Processing time(sec)
LiDAR	82.5%	163
Iyperspectral	79.54%	258
Data Fused	95	429

This table represents the identification accuracies of the system along with the processing time of the independent algorithms and the identification accuracy of the graph based data fused system.

VI. CONCLUSION

The following paper explicates the data fusion and processing steps to successfully extract principal components from HSI and LiDAR data. Section III documents the data normalization technique used to obtain the PC's which selects a block of data and uses either linear or radial based kernel. This is followed by the graph based fusion technique based on a weights set as given in (5). Finally a radial based classifier is used to obtain the association accuracy and thereby demonstrate a quantitative improvement in the system over similar data fused systems [3][9]. In terms of scope work focused on the reduction of complexity in terms of space as well as time and the manual interpretation and modification of parameters.

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