Combining Multiple Classifiers for Automatic Road Extraction from Lidar Data

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Abstract:

The ultimate goal of pattern recognition systems in remote sensing is to achieve the best possible classification performance for recognition of different objects such as buildings, roads and trees .Extracting of road from newer Lidar data is one of the main challenge in photogrammetry and computer vision. Roads in Lidar data appear as homogenous area in same height. In this paper the idea is to combine classifiers with different error types by a learnable combiner which is aware of the classifiers' expertise, so that the variance of estimation errors are reduced and the overall classification of road accuracy is improved. In this paper we used Naïve Bayes and Weighted Voting Method as classifier fusion methods. The results quality was assessed for each classification method with the same validation set of pixels computing the confusion matrix. Experimental results show that the proposed model outperforms results with higher accuracy rather than single classifiers.

Keywords: Road Extraction, Classifier Fusion, Weighted Voting, Naïve Bayes, Diversity, Correlation

1 Introduction

Extraction of roads in complex environments as urban areas is one of the challenging issues in photogrammetry and computer vision, since many tasks related to automatic scene interpretation are involved.Auclair-Fortier et.al (2000) divide road characteristics in four different types: spectral, geometric, topologic and contextual and many different road detection techniques used this characteristics for its methodology. Compared to the relatively high number of research groups focusing their work on road extraction in rural areas, only a few groups work on the automatic extraction of roads in urban environments. Different methods used different data like high and low resolution image, Lidar, RADAR… and different level of automation for its algorithm. The recognition and accurate localization of objects in digital imagery has attracted considerable attention in the past in photogrammetry and computer vision. In semi-automatic schemes an operator selects an initial point and a direction for a road tracking algorithm (McKeon and Denlinger, 1988, Vosselman and de Knecht, 1995).Snake as a most important semi-automatic method used for detection and extraction of road. A few years ago many fully automatic road extraction proposed that minimized the role of operator. The fusion of different scales helps to eliminate isolated disturbances on the road while the fundamental structures are emphasized .In the coarse resolution, roads are modeled as bright lines and in fine resolution roads are assumed to have two parallel edges that be bright, and have a homogenous texture (Mayer and Steger, 1998). Road extraction in complex urban scenes was performed by Hinz and Baumgartner [4] from multi-view aerial images with a high ground resolution. They use a road model exploiting knowledge about the radiometric, geometric, and topological characteristics of roads, making use not only of the image data, but also of a Digital Surface Model (DSM). Lidar sensor technology is evolving rapidly and now allows the acquisition of very dense point clouds in a short period of time (Kraus, 2002). Alharthy and Bethel (2003) present a simple and fast method to detect roads in urban areas from Lidar data. The main aim of the work was to exclusively use Lidar data so that limitations of availability of other sources such as ground plans could be avoided. Both the intensity and height information were used to filter the raw Lidar data and remove “noise” that was unrelated to the road. Clode [1] implement road classification in a manner similar to Alharthy and Bethel (2003) .Again, both intensity and height information are used in the classification but the idea of a local point density is introduced. The local point density is an indicator of how many neighboring Lidar points have similar spectral and geometric properties to the Lidar point in question. The fact that roads are consistent in nature is an important model assumption.
Approach proposed in this paper used Lidar data in urban area for automatic extracting of road network based on multiple classifier systems.

2 Multiple Classifiers system(MCS)

Combining multiple classifiers is one of the most important topics in pattern recognition. Combining classifiers to achieve higher accuracy is an important research topic with different names such as combination of multiple classifiers, committee machine, classifier ensembles and classifier fusion. Multiple classifier fusion may generate more accurate classification than each of the constituent classifiers. Methods that used for combination of classifiers is depended output type of single classifier that these included: 1) abstract level: a classifier only outputs a unique class, 2) rank level: the classifier ranks all the class in a queue with the label at the top being the first choice, 3) measurement level: the classifier in this case associates a confidence measurement for each class and produced a vector for every classifier and a matrix for ensemble of classifier at the end.
Performances of MCS method depend on selected classifiers that were used for fusion. Two main concepts that influence in selection of classifiers are correlation between them and diversity. The correlation between the classifiers to be fused needs to be small to allow performance improvement in classifier fusion. [2].For each classifier, a confusion matrix ***M*** can be generated using the labeled training data .The confusion matrix lists the true classes' *c* versus the estimated classes' $\hat{c}$ .Result of this matrix states correctly classified (N^{00} and N^{11}), also the false positives (N^{01}) and false negatives (N^{10}). The top-left entry of the confusion matrix is dedicated to the normal case N^{00} . The first row – except for the first entry – contains the N^{01} . The off-diagonal elements except for the first row – contain the N^{10} .By using of this matrix, correlation index (ρ) is defined as:

$$\rho = \frac{2 \times N^{FF}}{N^{TF} + N^{FT} + 2 \times N^{FF}} \qquad \textbf{(1)}$$

Where N^{TT} implies both classifiers classified correctly, N^{FF} means both classifiers classified incorrectly, N^{TF} represents the case of the 1st classifier classified correctly and
2nd classifier classified incorrectly, and N^{FT} stands for the 2nd classifier classified correctly
and 1st classifier classified incorrectly.
Diversity among the ensemble of classifiers is deemed to be a key issue in classifier combination. However measuring diversity isn't straightforward because there is no generally accepted formal definition. Kuncheva,[6],suggested ten statistics which can measure diversity among binary classifier outputs (correct or incorrect vote for the class label). In this paper we used disagreement measures as one of the main pair wise diversity measures (diversity between i, k classifier) It is the ratio between the number of observations on which one classifier is correct (N^{10} , N^{01}) and the other is incorrect to the total number of observation. In this measure N^{00} is number of observation on which two classifiers are incorrect and N^{11} is number of observation on which two classifiers are correct.

$$Dis_{i,k} = \frac{N^{01} + N^{10}}{N^{11} + N^{10} + N^{01} + N^{00}} \qquad \textbf{(2)}$$

Classifiers producing crisp, single class labels (SCL) provide the least amount of useful information for the combination process. However, they are still well performing classifiers, which could be applied to a variety of real-life problems. Two methods of this type used in this paper are the Weighted Voting method and the Naïve Bayes method.

2.1 Weighted Voting Method

Voting strategies can be applied to a multiple classifier system assuming that each classifier gives a single class label as an output and proposed by Kuncheva[7].Assume that the label outputs of the classifiers are given as c-dimensional binary vectors $[d_{i,1},...,d_{i,c}]^T \in [0,1]^c, i = 1,..,L$ where $d_{i,j} = 1$ if D_i labels x in w_j ,and 0 otherwise.

$$\sum_{i=1}^{L} d_{i,k} = \max_{j=1}^{c} \sum_{i=1}^{L} d_{i,j} \tag{3}$$

This rule is often called in the literature the majority vote. If the classifiers in the ensemble are not of identical accuracy, then it is reasonable to attempt to give the more importance to better classifiers in making the final decision. The label outputs can be represented as degrees of support for the classes in the following way:

$$d_{i,j} = \begin{cases} 1 & \textit{if } \mathrm{D_i \text{ labels } x \text{ in } w_j} \\ 0 & \textit{otherwise} \end{cases} \tag{4}$$

The discriminant function for class w_j obtained through weighted voting is:

$$g_i(x) = \sum_{i=1}^{L} b_i d_{i,j} \tag{5}$$

2.2. Naïve Bayes Method

In this method classifiers must be mutually independent. [7] Denote by $p(s_j)$ the probability that classifier D_j labels x in class $s_j \in \Omega$.The conditional independence allows for the following representation

$$p(S \backslash w_k) = p(s_1, s_2, ..., s_L \backslash w_k) = \prod_{i=1}^{L} p(s_i \backslash w_k) \tag{6}$$

Then the posterior probability needed to label x is

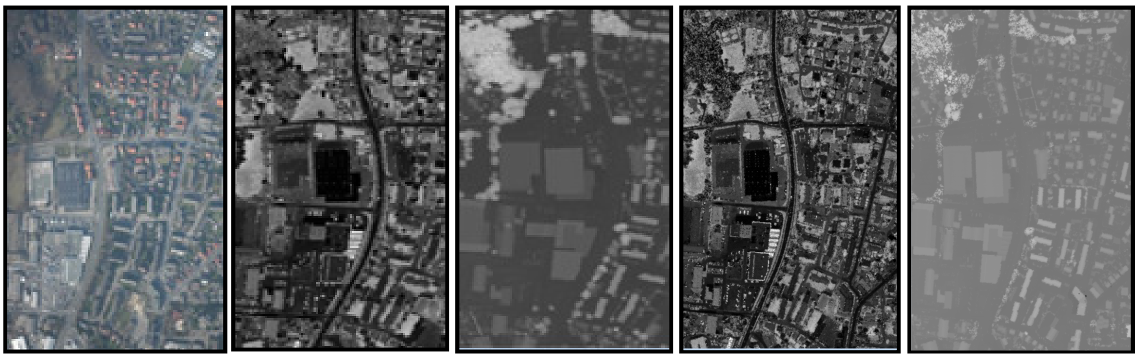
$$p(w_k \backslash S) = \frac{p(w_k)p(S \backslash w_k)}{p(S)} = \frac{p(w_k)\prod_{i=1}^{L} p(S_i \backslash w_k)}{p(S)}, k = 1,...,c \tag{7}$$

Final support for class w_k

$$\mu_k(x) \propto p(w_k)\prod_{i=1}^{L} p(s_i \backslash w_k) \tag{8}$$

3 Data set

The potential of two mentioned classifier fusion methods evaluated for road extraction from Lidar data. The data is related to an urban area with different combination of Tree, road and building ad grass land objects (Figure 1).



a b c d e

Figure1. Data set, a) digital image, b) first pulse intensity, c) first pulse range, d) last pulse intensity, e) Last pulse range

Figure 2 shows the general structure of our strategy in assessment of Majority voting and Naive Bayes methods in classification of road object using Lidar data.

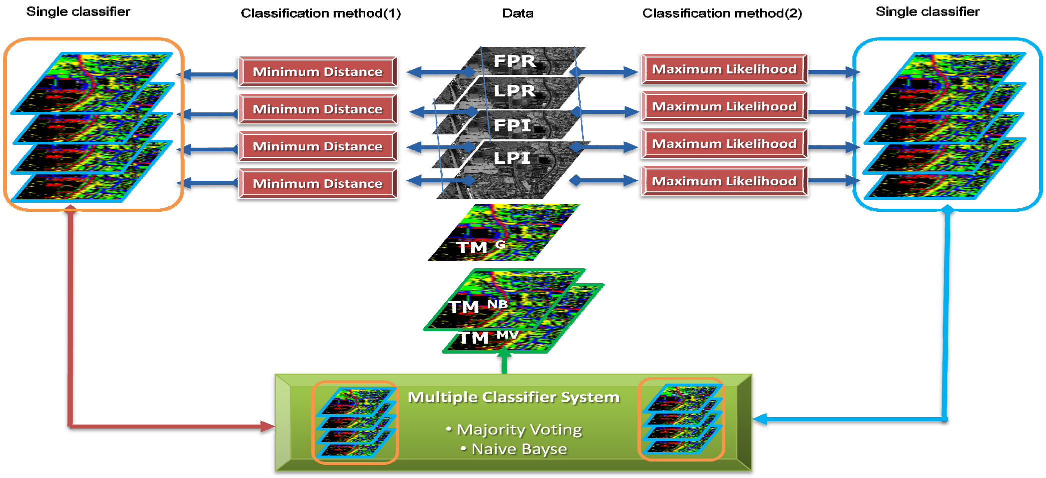


Figure 2. Evaluation Strategy of assessment of Majority voting and Nave Bayes methods

4.2 Experiment and Results

For four types of data set we used two classification methods like Minimum Distance and Maximum Likelihood.Figure3 show the result of this single classifier.

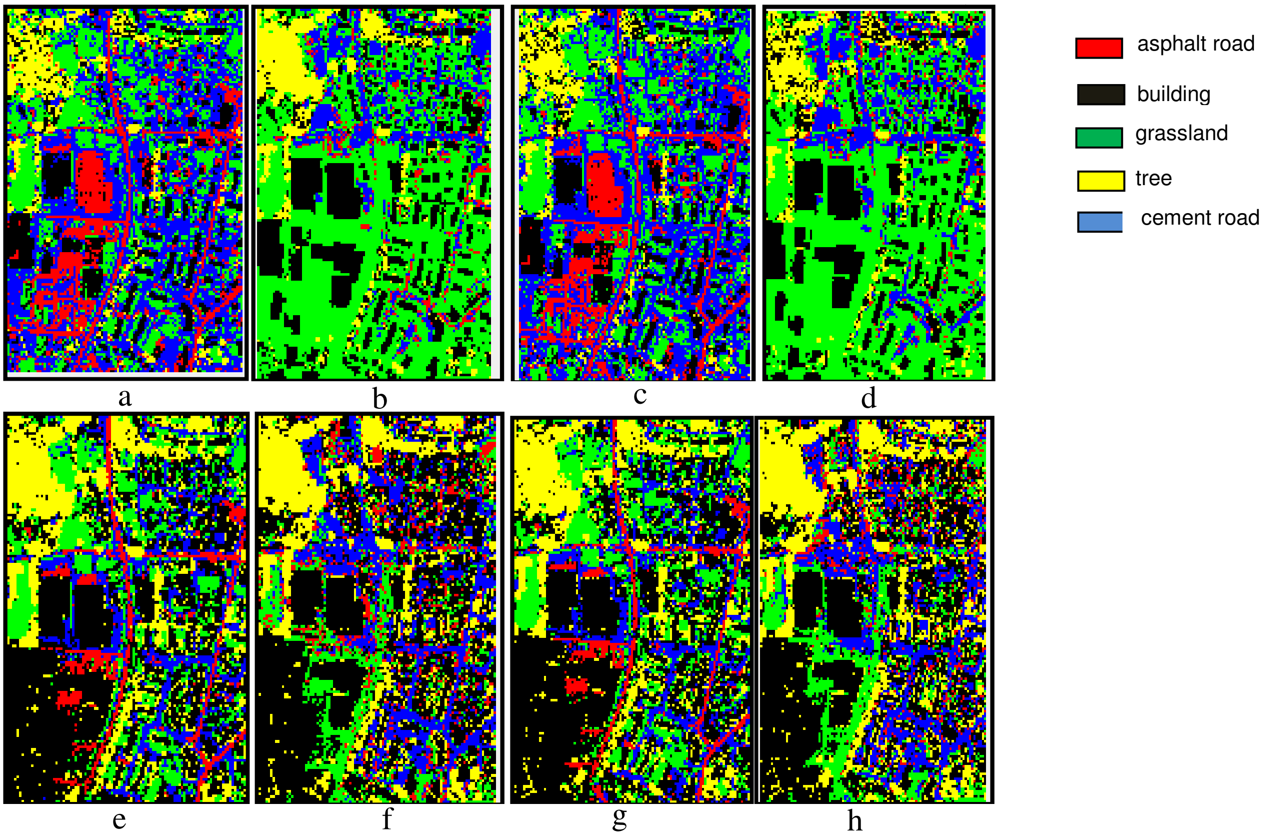


Figure3. Result of classification by Minimum Distance, first pulse intensity (a), first pulse range (b), last pulse intensity(c),last pulse range(d),result of classification by Maximum Likelihood, first Pulse intensity (e), first pulse range (f), last pulse intensity (g), last pulse range (h).

Then we used Weighted Voting and Naïve Bayes methods for fusing different classifiers. For evaluation and comparison of result we produced three measures in the last step. These three measures used by Clode and Rottenstiener [1] are:

$$completeness = \frac{TP}{TP+FN} \qquad correctness = \frac{TP}{TP+FP} \qquad quality = \frac{TP}{TP+FP+FN} \qquad \textbf{(9)}$$

For each pairs of classifier we computed diversity and correlation and in the end two classifiers that produced higher diversity, used for Naïve Bayes Method. In the two below table:max(Maximum Likelihood),min(Minimum Distance),FI(first intensity),LI(last intensity),FR(first range),LR(last range).

Table 1. The correlation coefficient between classifiers for the road class

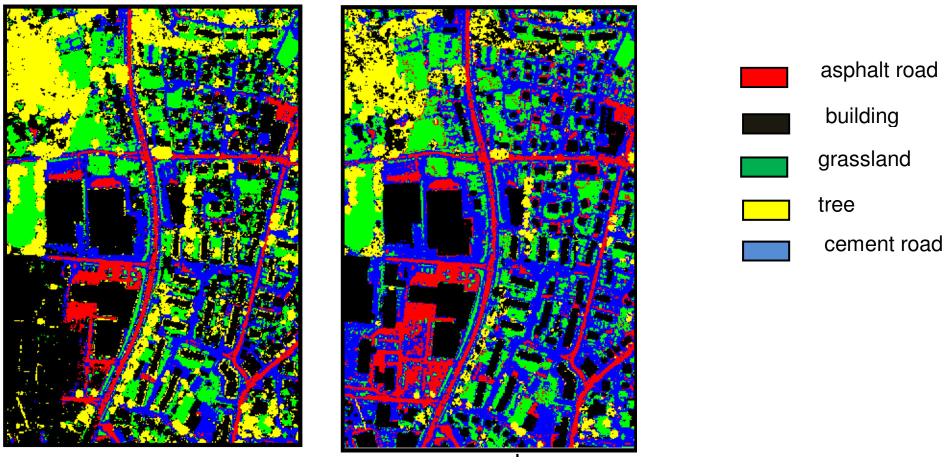
	FImax	FRmax	LImax	LRmax	FImin	FRmin	LImin	LRmin
FImax	1	0.1322	0.9804	0.1290	0.6486	0.1236	0.6111	0.1326
FRmax	0.1322	1	0.1375	0.8294	0.0597	0.8410	0.0539	0.8830
LImax	0.9804	0.1375	1	0.1345	0.6316	0	0.5946	0.1376
LRmax	0.1290	0.8294	0.1345	1	0.0549	0.8624	0.0489	0.9371
FImin	0.6486	0.0597	0.0316	0.0549	1	0.0525	0.9565	0.0659
FRmin	0.1236	0.8410	0	0.8624	0.0525	1	0.0468	0.9283
LImin	0.6111	0.0539	0.5946	0.0489	0.9525	0.0468	1	0.0606
LRmin	0.1326	0.8830	0.1376	0.9371	0.0659	0.9238	0.0606	1

First table shows that LImax and FRmin have higher correlation and this coefficient between FImax and LImax is smaller than others. Correlation only between intensity data or range data is big but between mixtures of these two data is smaller.

Table 2. The diversity coefficient between classifiers for the road class

	FImax	FRmax	LImax	LRmax	FImin	FRmin	LImin	LRmin
FImax	0	0.7968	0.0026	0.7836	0.0343	0.8232	0.0369	0.8628
FRmax	0.7968	0	0.7942	0.2876	0.8311	0.2744	0.8041	0.2084
LImax	0.0026	0.7942	0	0.7810	0.0369	0.8736	0.0396	0.8602
LRmax	0.7836	0.2876	0.7810	0	0.8179	0.2348	0.8206	0.1108
FImin	0.0343	0.8311	0.0369	0.8179	0	0.8575	0.0026	0.8971
FRmin	0.8232	0.2744	0.8736	0.2348	0.8575	0	0.8602	0.1293
LImin	0.0369	0.8041	0.0396	0.8206	0.0026	0.8602	0	0.8997
LRmin	0.8628	0.2084	0.8602	0.1108	0.8971	0.1293	0.8997	0

The second table shows that diversity measure between FImax and LImax is smaller than others and between LImin and LRmin is bigger than others. Using results of these two tables, we select two classifiers having higher diversity for using in the Naïve Bayes method.



a b

Figure4. Results of fusion, a) Weighted Voting Method) Naïve Bayes Method

Table3. Results of single classifiers and fusion methods for the road class (%)

data	Classification method	completeness	correctness	quality	Producer accuracy	User accuracy
First intensity	Maximum likelihood	89.47	100	89.47	89	100
	Minimum distance	100	90.47	90.47	100	90
Last intensity	Maximum likelihood	89.47	100	89.47	89	100
	Minimum distance	100	90.47	90.47	100	90
First range	Maximum likelihood	11	40	9	10	40
	Minimum distance	5	17	4	50	16
Last range	Maximum likelihood	21	61	19	21	61
	Minimum distance	8	75	8	70	75
8 data	Weighted	88	95	92		
8 data	Naïve Bayes	95	95	100		

In the range data we have smaller completeness, correctness and quality rather than intensity data. These measures computed with 170 check points that distributed between all classes. In this paper we used producer and user accuracies of each classifier as weights for the Weighted Voting Method. Producer accuracy represents how many percent of training data are classified correctly and user accuracy represent how many correct samples exist in special class. Results of this table show that Naïve Bayes Method had better results than Weighted Voting Method in this data set.

5. Conclusion

Road extraction from Lidar data is one of the challenging issues in photogrammetry and remote sensing. In this paper the idea is to combine different classifiers and compared result with single classifiers. Naïve Bayes and Weighted Voting are two methods that used for classifier fusion. Results of Weighted Voting and Naïve Bayes in these data show that fusion of classifiers produced better result rather than single classifiers.

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