15TH ARSPC, Alice Springs, Australia, 13- 17 September 2010

**COMBINING STATISTICAL AND NEURAL CLASSIFIERS USING**

**DEMPSTER-SHAFER THEORY OF EVIDENCE FOR IMPROVED**

**BUILDING DETECTION**

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**Abstract**

This paper describes an approach for building detection from multispectral

aerial images and lidar data by combining the results derived from statistical

and neural network classifiers, which offer complementary information, based

on Dempster-Shafer Theory of Evidence. Four study areas with different

sensors and scene characteristics were used. First, we filtered the lidar point

clouds to generate a Digital Terrain Model (DTM), and then the Digital Surface

Model (DSM) and the Normalised Digital Surface Model (nDSM) were

generated. After that a total of 25 uncorrelated feature attributes have been

generated from the aerial images, the lidar intensity image, DSM and nDSM.

Then, three different classification algorithms were used to detect buildings from

aerial images, lidar data and the generated attributes. The classifiers used

include: Self-Organizing Map (SOM); Classification Trees (CTs); and Support

Vector Machines (SVMs). The Dempster-Shafer theory of evidence was then

applied for combining measures of evidence from the three classifiers. A

considerable amount of the misclassified building pixels were recovered by the

combination process.

**Introduction**

Research on building detection from aerial images and lidar data fusion has

been undertaken so that the strengths of each data type can compensate for

the weaknesses of the other. Low contrast, occlusions and shadow effects in

the images can be compensated by the accurately defined planes in the lidar

data. On the other hand, the poorly defined edges in the lidar data can be

compensated by the accurately defined edges in the aerial images. Matikainen

et al. (2007) applied the Gini splitting criterion for CT for building detection from

aerial images and lidar data. Rottensteiner et al. (2007) evaluated the

Dempster-Shafer based fusion of multispectral aerial images and lidar data for

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building detection. Salah et al. (2009) tested the Self-Organizing Map (SOM) for

building detection from aerial images and lidar data.

Kanellopoulos et al. (1997) have demonstrated the complementary behaviours

of neural and statistical algorithms in terms of classification errors. The efficient

combination of such classifiers, should achieve better classification results than

any single classifier, even results obtained with the best classifier used

individually. In the simplest implementation of the hybrid concept, predictions of

different classifiers were averaged (Breiman, 1996). Many other methods have

also been used to combine classifiers, such as Bagging (Breiman, 1996) and

Boosting (Freund and Schapire, 1997). Applications of majority voting (MV) for

pattern recognition have already been studied in detail in Lam and Suen (1997).

Another technique which is widely studied in classical classifier fusion but less

addressed in remote sensing is Dempster-Shafer (*D-S*) theory (Shafer, 1976).

*D-S* theory has already been investigated in handwriting recognition, in

automatic disambiguation of word senses, in human speech perception but this

is probably the first attempt to use it for combining information derived from

different classifiers for improvement of land cover mapping.

After introducing *D-S* theory in the following section, the methods are described,

and then the results are presented and evaluated. Finally, the results are

summarised.

**Overview of Dempster-Shafer Theory**

The theory of evidence was introduced by Shafer (1976) as a mathematical

framework for representation and combination of different measures of

evidence. It can be considered as a generalization of the Bayesian framework

and permits the characterization of uncertainty and ignorance. In outlining the

Dempster-Shafer theory, we consider a classification problem where the input

data are to be classified into *n* classes *Cj*∈*θ*, *θ* is referred to as *the frame of*

*discernment*. The power set of *θ* is denoted by *2θ* i.e. the set of all subsets of *θ*.

A probability mass *m (A)* is assigned to every class *A*∈*2θ* by a classifier such

that *m (Ø) = 0*, *0 ≤ m (A) ≤ 1*, and *Σ m (A) =1*, where the sum is to be taken over

all *A*∈*2θ* and *Ø* denotes the empty set. *m (A)* can be interpreted as the amount

of belief that is assigned exactly to *A* and not to any of its subsets. Imprecision

of knowledge can be handled by assigning a non-zero probability mass to the

union of two or more classes *Cj*. The *support Sup (A)* of a class *A*∈*2θ* is the

sum of all masses assigned to that class. The plausibility *Pls (A)* sums up all

probability masses not assigned to the complementary hypothesis *Ā* of *A* with

*A*∩ *Ā =Ø* and *A*∪ *Ā = θ*:

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*Sup A m B Pls A m B Sup A*

*B A A B*

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*Sup (A)* is also called *dubiety*. It represents the degree to which the evidence

contradicts a proposition. If *z* classes are available, probability masses *mi (Bj)*

have to be defined for all these classes *i* with *1 ≤ i ≤ z* and *Bj*∈*2θ*. From these

probability masses, a combined probability mass can be computed for each

class *A* ∈ *2θ* through an *orthogonal summation* process as follow: