Improving the automated classification of aerial imagery[1]

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Abstract. One of the main practical issues when applying data mining techniques for land cover classification of aerial imagery is the large amount of attributes used for describing the data. In addition to the increase of the learning time, another drawback is that this represents a source of noise. But, are all these attributes necessary to learn a good classifier? In this paper, we carried out an experimental analysis trying to improve the land cover classification of aerial imagery. We focused on urban and peri-urban areas, used an object-oriented image segmentation approach in order to better face the classification problem, and tested three different spatial resolutions (0.5, 1, and 2 m/pixel). Then, we analysed the attributes that were more relevant for the classification and how they improved the performance of the model. However, once the model has been learnt, a new question arises: can we reuse it in a different place? In a second experiment, we investigated whether the models that have been generated in a particular location can be used to classify a new geographical area with similar land cover types. The results show that the model reusing performs quite well for some type of classes.

Keywords: Data mining, remote sensing, aerial image classification, LiDAR, attribute selection, reusing of models.

1 INTRODUCTION

Data acquisition for mapping has experimented many changes throughout history. Whereas in ancient times was just necessary an eye to observe and to make a draft, later appeared instruments capable of measuring angles and distances. As a result, geometry became an effective tool for calculation and cartographic representation.

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These techniques have survived to our days, but human necessity of conquering the sky and space has led to the emergence of new technologies like GNSS, photogrammetry and remote sensing. Remote sensing consists on the acquisition of imagery and other data from objects without being in contact. These images not only convey information from the visible spectrum, but also from other wavelengths (near infrared, thermal, etc.), making the classification of objects easier. As result, land cover maps can be generated or it can be used to detect different objects on the terrain.

Image classification done by experts is a long and costly task. This is well known problem in database domain, where large amount of data available to organisations has led to emergence of data mining techniques [6]. These data provide valuable information that can be used for decision making, which is sometimes hard to extract by a human expert (and may miss some details), or even by classical statistic techniques of data analysis [2][12]. During the last years machine learning techniques have been successfully applied for image classification [10][12][13] (see [9] for a comparison between classical statistic and data mining techniques).

Our paper aims to tune and assess a classifier in order to improve the results for a Mediterranean environment. In addition to initial attributes generated with ENVI FX5 software[2], we added new ones calculating ratios from the initial, which is not mentioned in previous literature. These new attributes created from two initial variables can discriminate better a class from the others, as described in Section 3. In order to reduce the number of attributes, we will also apply attribute selection methods [3].

On the other hand, most of the previous studies made do not work with high resolution imagery, using resolutions of 10 and 30 meters [4][8]; only [11] works with a resolution of 1.5 meters. However, in this paper we worked with three different high resolutions (0.5, 1 and 2 meters) in order to know if some classes are better classified with a lower resolution, meaning a bigger size of pixel. The experiments in Section 3 show that some objects present in a beach, like parasols, could disappear when the resolution changes, and thus classification improves.

Usually, in imagery classification each model is learnt and applied for the imagery at hand. So, when other images arrive, a new model has to be learnt, and so on. However, there are landscapes and areas that share some characteristics not only geographical but also related to land use. A possible alternative could be to reuse or adapt the models learnt from an area to be applied the imagery belong to another area.

Therefore, the aim of this paper is twofold:

- To study the significance of attributes for image classification testing several resolutions. For this purpose:
  - New attributes derived from initial attributes (spectral, textural and spatial attributes) are defined, in order to improve classification accuracy.
  - Attribute selection is done by analysing correlation between all the variables in order to reduce noise and processing time, and to obtain a more robust model. Then several machine learning techniques are compared to determine the most

[2] [http://www.exelisvis.com]

appropriate classifier adapted to the selected attributes and to the land cover classification problem.

- To analyse the performance of the reuse of a model when applied to classify a different area (Zone B) to the one used for learning (Zone A).

The rest of the paper is organised as follows: Section 2 describes the process of generating the data set that has been used for the analysis. Section 3 presents the experimental analysis performed to determine the most significant attributes for the classification of aerial imagery for each image resolution, as well as the results obtained when we reuse a model for a different area. Finally, section 4 highlights the main conclusions of the paper.

2 DATA EXTRACTION

Two study areas were defined, the area A is located between Puerto de Sagunto (Sagunto) and Canet d'en Berenguer, in the North of the province of Valencia (Spain). The area B is located in the North of the city of Valencia. These areas were chosen because of their diversity in terms of urban, agriculture, industry, forest and coastal land-uses.

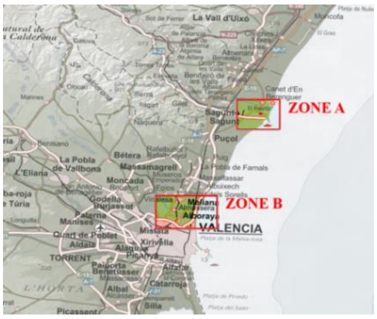


Fig. 1. Location of the study areas. Source: IGN

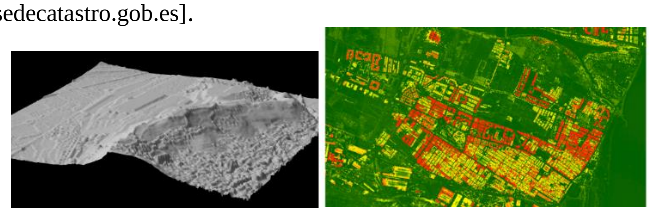
LiDAR (Light Detection and Ranging) data[3] and high resolution ortoimages (0.5 m/pixel) were used in this work. LiDAR data required a filtering process to reduce noise, and the extraction of the Digital Terrain Model (DTM) and the Digital Surface Model (DSM)[7]. Then, the normalised model was obtained as the difference between both, showing the height of all the objects with respect to the terrain (see Fig. 2).

The image segmentation from ortoimages and a normalised surface model, as well as the attributes extracted from these images, were obtained using ENVI FX5 software. Three different types of attributes were computed: spectral, textural and spatial [http://www.exelisvis.com/portals/0/pdfs/envi/FXExampleBasedTutorial.pdf]. When working

[3] LiDAR data was acquired by Instituto Geográfico Nacional (IGN) in the Plan Nacional de Ortofotografía Aérea (PNOA) in 2009 with a resolution of 0.5 points/m^2.

with objects instead of pixels, each object has a different area. Since an object with an area of 1 m^2 cannot have the same weight that one with 1000 m^2, objects have to be weighted according to their area.

Finally, the cadastral use was included in the database as a new external attribute. This new variable informs if the objects are in urban, agricultural or another use. This information was downloaded from the Spanish Cadastre database [http://www.sedecatastro.gob.es].



a *b*

Fig. 2. DSM (a) and normalised surface model (b)

3 EXPERIMENTAL ANALYSIS

The study area was divided in 20 zones of approximately equal-size. Each zone corresponds to a data set. This division is used in order to carry out a statistic test and to get statistically more robust results [11]. Training data were selected manually, choosing and tagging each object according to its class. Classes were: building, water, beach, vegetation, barren land and road. This process was carried out with all the 20 data sets. Additionally, we used a cross validation evaluation with 10 folds, giving 200 repetitions in total. The experiments were performed in a server with 64 GB RAM.

We used the following learning techniques implemented in Weka [5]: Support Vector Machine (SMO), the k Nearest Neighbours (IBk), Decision Tree method (J48) and an Ensemble method (Random Forest, denoted as RF in the tables of results).

Firstly, we worked with all the original attributes generated by ENVI FX5. Next, the correlation among attributes was analysed, deciding if the ratio between two ENVI variables improved the discrimination of a class; in this case, this ratio was added as a new attribute to the original attribute list. This analysis was carried out analysing several scattergrams of the variables (see Fig. 3). After this, cadastral information was included in all the instances to the extended scenario.

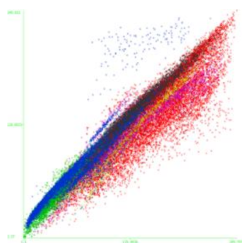


Fig. 3. Example of scattergram of the instances displayed in different colours according to its class

Once the attributes were added, different feature selection methods were applied in order to decrease the number of attributes, reducing the noise and the processing time. We used the following methods implemented in Weka: GreedyStepwise and RaceSearch [https://dataminingntua.files.wordpress.com/2008/04/weka-select-attributes.pdf]. The notations used in the tables of results for denoting the different scenarios are: Original (O) when all the attributes generated by ENVI are used; Extended (E) are the Original attributes plus the new attributes added after studying their correlation, Cadastre scenario (C) are the Extended attributes plus the cadastral use; and Greedy Stepwise (G) and Race Search (R) are the selected attributes using respective methods from the Cadastre scenario attributes list.

		0.5 m		1 m		2 m	
Alg.	**Meth.**	**Accuracy**	**Kappa Weighted**	**Accuracy**	**Kappa Weighted**	**Accuracy**	**Kappa Weighted**
SMO	**O**	77.6897%	31090.6	69.8445%	38644.1	91.2302%	64965.2
	E	83.3650%	33908.3	71.3971%	40088.7	91.8569%	65725.3
	C	81.8922%	32494.4	71.3219%	44146.1	97.0912%	70842.3
	G	95.6068%	44114.4	96.8299%	63192.2	97.4376%	71243.9
	R	96.5165%	45045.8	94.9764%	61055.9	95.2561%	68622.8
kNN	**O**	81.5816%	31968.4	69.4415%	36702.2	88.6846%	60518.2
	E	86.6459%	35951.5	70.0101%	37463.8	90.4471%	62697.0
	C	86.6307%	35957.2	87.7282%	52193.0	90.8543%	63194.4
	G	91.1762%	41485.4	91.9647%	58662.0	95.0745%	68593.6
	R	91.2117%	41436.4	91.7211%	58248.4	94.2228%	67509.1
RF	**O**	88.6169%	37826.3	88.5172%	52893.0	89.8002%	61134.6
	E	87.8729%	37173.9	77.8626%	45984.4	94.9448%	68091.6
	C	88.1734%	37201.8	78.3712%	46707.6	89.0143%	62699.0
	G	91.0420%	39689.3	82.0746%	48365.5	93.2509%	66760.8
	R	95.1226%	43785.8	94.4985%	60435.6	90.5096%	63040.4
J48	**O**	92.6059%	41655.8	86.5309%	51306.3	78.5007%	51161.2
	E	80.8054%	32135.7	75.6536%	47328.8	83.2301%	56274.9
	C	79.6052%	31236.1	76.3288%	44929.2	84.0350%	56359.5
	G	90.3872%	39018.8	93.5446%	60071.0	91.7935%	64012.7
	R	93.6807%	42408.2	93.7985%	60002.7	85.9940%	59431.1

Table 1. Average of the accuracy and Kappa area-weighted indexes for the 20 data sets for the different algorithms and methods in all the resolutions

Model evaluation was done using two measures: accuracy and Kappa. Table 1 shows the average of the accuracy and Kappa area-weighted (according to the respective training sample area) index for the 20 data sets for the different combination of learning algorithms and methods. To determine the statistical significance of the results, Friedman and Nemenyi post-hoc tests (both non-parametric tests have been performed using software in [1]) were applied. Values inserted into the test analysis for this paper were just the Kappa area-weighted indexes of each data set. Friedman test was applied in order to verify if differences between methods were statistically significant. This test also calculates average ranking for methods (see Table 2) being methods with lowest rankings those that had the best performance. After confirming this dissimilarity, Nemenyi post-hoc test was used to verify pairwise dissimilarities (see Table 3).

		Ranking		
Alg.	**Meth.**	**0.5 m**	**1 m**	**2 m**
SMO	**O**	11.25	10.45	13.175
	E	8.45	13.175	14.825
	C	8.275	13.85	16
	G	9.525	15.225	16.875
	R	8.275	11.7	15.7
kNN	**O**	15.45	5.2 (1)	4.55 (2)
	E	13.45	7.175 (2)	6.55 (3)
	C	13.225	8.1	6.6
	G	6.5 (1)	13.075	13.5
	R	12.875	11.05	12.3
RF	**O**	10	9.35	8.15
	E	9.325	11.7	10.4
	C	6.75 (2)	12.35	9.975
	G	9.05	10.3	10.8
	R	7.025 (3)	12.35	9.7
J48	**O**	14.1	7.25 (3)	4.4 (1)
	E	11.7	7.925	7.625
	C	12.35	9.325	9.225
	G	10.2	10.15	10.05
	R	12.225	10.3	9.6

Table 2. Method average ranking for the spatial resolutions after applying the Friedman test. Rankings are showed in brackets for the top 3 methods of each resolution.

Alg.	Meth.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
SMO	O (1)		- - -	- - -	- - -	- - -	- - x	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - x	- - -	- - -	- - -	- - -
	E (2)	- - -		- - -	- - -	- - -	o x x	- - x	- - x	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - x	- - x	- - -	- - -	- - -
	C (3)	- - -	- - -		- - -	- - -	o x x	- - x	- - x	- - -	- - -	- - x	- - -	- - -	- - -	- - -	- - x	- - x	- - -	- - -	- - -
	G (4)	- - -	- - -	- - -		- - -	- x x	- x x	- x x	- - -	- - -	- - x	- - -	- - x	- - -	- - x	- x x	- x x	- - x	- - -	- - x
	R (5)	- - -	- - -	- - -	- - -		o - x	- - x	- - x	- - -	- - -	- - x	- - -	- - -	- - -	- - -	- - x	- - x	- - -	- - -	- - -
kNN	O (6)	- - o	x o o	x o o	- o o	x - o		- - -	- - -	x o o	- - o	- - -	- - -	x o -	- - -	x o -	- - -	- - -	- - -	- - -	- - -
	E (7)	- - -	- - o	- - o	- o o	- - o	- - -		- - -	x - o	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -
	C (8)	- - -	- - o	- - o	- o o	- - o	- - -	- - -		- - o	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -
	G (9)	- - -	- - -	- - -	- - -	- - -	o x x	o - x	- - x		- - -	- - -	- - -	- - -	- - -	- - -	o - x	- - -	- - -	- - -	- - -
	R (10)	- - -	- - -	- - -	- - -	- - -	- - x	- - -	- - -	- - -		- - -	- - -	- - -	- - -	- - -	- - x	- - -	- - -	- - -	- - -
RF	O (11)	- - -	- - -	- - o	- - o	- - o	- - -	- - -	- - -	- - -	- - -		- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -
	E (12)	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -		- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -
	C (13)	- - -	- - -	- - -	- - o	- - -	o x -	- - -	- - -	- - -	- - -	- - -	- - -		- - -	- - -	o - -	- - -	- - -	- - -	- - -
	G (14)	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -		- - -	- - -	- - -	- - -	- - -	- - -
	R (15)	- - -	- - -	- - -	- - o	- - -	o x -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -		o - -	- - -	- - -	- - -	- - -
J48	O (16)	- - o	- - o	- - o	- o o	- - o	- - -	- - -	- - -	x - o	- - o	- - -	- - -	x - -	- - -	x - -		- - -	- - -	- - -	- - -
	E (17)	- - -	- - o	- - o	- o o	- - o	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -		- - -	- - -	- - -
	C (18)	- - -	- - -	- - -	- - o	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -		- - -	- - -
	G (19)	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -		- - -
	R (20)	- - -	- - -	- - -	- - o	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	

Table 3. Summary of the Nemenyi post-hoc test making a pairwise comparison for the different methods in each spatial resolutions. o = the method in the row improves the method of the column. x = the method in the row does not improve the method of the column. - = the method of the row and the one of the column are not significantly different. Each cell shows comparison for 0.5, 1 and 2 meters of resolution, respectively.

According to Table 2, for the next experiment we selected the three classifiers with the best average rankings, and a method with an attribute selection (Greedy or Race) if no one of these methods was in the top 3 of the ranking. Therefore, for a resolution of 0.5 meters the method that achieves the best performance is kNN-Greedy. RF-Cadastre and RF-Race were also selected, because their distance was very close and they are in the top 3. For 1 meter resolution, kNN-Original and kNN-Extended performed the best results but J48-Greedy was also selected because the difference with kNN-Original was not significant and the scenario had fewer variables. For 2 meter resolution J48-Original and kNN-Original obtained the best results. Here we had the same case that for 1 meter resolution, in this case J48-Race was the method with fewer attributes chosen. We can observe that kNN (k=5) is the most frequent selected classifier, therefore nearest neighbour algorithm is the technique we recommend for classifying this kind of landscapes.

Resolution	**Methods**	**Accuracy**	**Kappa Index**
0.5 m	**kNN - Greedy**	96.2599%	0.9519
	RF - Cadastre	98.1754%	0.9765
	RF - Race	96.4333%	0.9542
	SVM - ENVI	96.4630%	0.9545
	kNN - ENVI	95.0592%	0.9363
1m	**kNN – Original**	95.157%	0.9372
	kNN - Extended	94.2411%	0.9253
	J48 - Greedy	96.5293%	0.9552
	SVM - ENVI	97.9550%	0.9736
	kNN - ENVI	95.7523%	0.9447
2m	**J48 – Original**	95.2285%	0.9385
	kNN - Original	93.0347%	0.9101
	J48 - Race	96.2999%	0.9524
	SVM - ENVI	97.2760%	0.9649
	kNN - ENVI	93.1418%	0.9109

Table 4. Overall accuracy and Kappa index comparison in a test sample between generated models and those generated by ENVI.

To introduce a different vision of how well our models work, we decided to unify the 20 data sets and compare the results with two methods implemented in the commercial software ENVI: SVM and kNN. Table 4 shows that with a resolution of 0.5 meters, RF-Cadastre increases ENVI results, while the other models have a similar Kappa index. Considering that the last two models use 6 and 8 attributes, respectively, and ENVI models use 54, the results are very good. On the contrary, with 1 meter resolution, our models do not improve the best performance generated with ENVI, but the differences are narrow. Finally, with 2 meter resolution, we also observe very similar results, either working with all the attributes or with a selection of them.

Comparing results of our models with those generated by ENVI we can affirm that ours achieved the best performance using the highest resolution (0.5 meters). It is also demonstrated that working with all the variables the results are similar or even better than those generated by ENVI, and they are still similar when working with fewer attributes. The use of less data is relevant in practice.

As an example, Fig 4. shows the classification of the study area using the RF-Race classifier and the 0.5 meter resolution; buildings are displayed in red, water in blue, beach in yellow, vegetation in green, barren land in brown, and roads in grey.

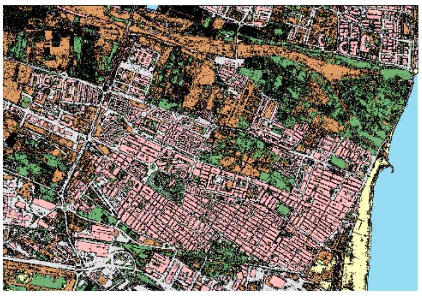


Fig. 4. Study area classification using the Random Forest-Race classifier and the 0.5 meter resolution image.

Finally, we proceeded to analyse if a model trained with data from a zone A could be reused to classify a zone B with similar features. The aim was to explore how a classification model behaves when the context of application changes, and if model retraining can be avoided. This kind of model reusing can be seen as a particular case of a more general approach called reframing (http://www.reframe-d2k.org/index.php/Project_description). We compared the results with those obtained by training a model with data from zone B using the ENVI software (the results of SVM-ENVI and kNN-ENVI methods in Table 4). We denote this approach as the direct approach.

	0.5 m			**1 m**			**2 m**		
	kNN-G	**RF-C**	**RF-R**	**kNN-O**	**kNN-E**	**J48-G**	**J48-O**	**kNN-O**	**J48-R**
Water (%)	97.49	98.45	98.38	92.26	97.79	97.16	85.02	83.16	97.82
Buildings (%)	96.24	98.49	97.36	76.43	74.76	96.47	88.84	78.47	92.18
Vegetation (%)	97.44	78.54	97.58	62.74	75.65	93.60	88.03	70.41	98.91
Accuracy (%)	50.86	62.17	50.17	64.63	67.54	49.91	65.64	75.33	60.42
Kappa Index	0.4264	0.5493	0.4223	0.5606	0.5978	0.4141	0.5647	0.692	0.5338

Table 5. Results of applying over the testing area B the three best models trained in zone A.

As expected, in general the reframing approach performed worse than the direct approach. This is explained by radiometric differences between both images, due to atmospheric scattering and sensor calibration differences. However, even carrying out radiometric corrections models are different depending on the zone. There are some seasonal soil moisture differences, or variations in shadows due to higher buildings. On the contrary, in other classes, such as buildings, water or vegetation, the differences between images are negligible. Hence, the reframing approach provides good accuracies (between 62.74% and 98.91%) for these classes. This process could be operative in practice if our goal would be to classify only these classes. For all the study area, only the kNN-Original classifier with 2 meter resolution had a good accuracy (see Table 5).

4 CONCLUSIONS

The addition of new attributes (ratios, cadastral information) has been proved to improve land cover classification results. In fact, these new attributes were not removed in any of the selection tests performed. At least in this type of landscapes kNN (k=5) classifier performed better. Regarding the method used to obtain the different resolutions, we have confirmed that the proposed method of constructing first the highest resolution (0.5m) and then to generalised it to generate the other resolutions, reduced in fact the time of generation and a non-significant effect in the results (99.97% accuracy comparing selection by hand and generalising). In that model, reusing concerns (the last experiments performed) showed that in general this approach is only competitive for some kind of objects. An alternative to improve the classification results could consist on updating the model of zone A with some data from zone B, in order to better adapt it to the new context of application.

After showing the relevance of the new attributes and the potential of Geographical Information Systems, a new attribute indicating adjacency of classes to each object could be included in future works. In this way, models would be able to learn, for instance, that a beach object can be adjacent to another object of the same class or an object belonging to the class water.

In this study, image classification using generic classes, such as buildings or roads, has been performed. A future line could be focused to obtain different models according to the level, in order to classify more specific objects and classes. For example, a new model could be generated from objects classified as buildings. This new model would distinguish between different buildings like industrial, row houses, historical, etc. Thus, this classification could be used for cadastral update, for detection of building types or urban land-uses. On the other hand, shadows generated by buildings can appear on the images. It would be interesting to preprocess these shadows in order to increase the accuracy,

Finally, in this paper we worked with three different resolutions. It would be recommended to carry out new tests to analyse if changes in spatial resolution could improve classification in all the areas or just in one class. This is important because working with high-resolution imagery, sometimes provides more detail than needed. For example, when classifying a road, we do not want to identify a bench or a car. Reducing spatial resolution these details may disappear, improving the overall classification.

5 REFERENCES

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