EXPLOITING SPATIAL PATTERNS FOR INFORMAL SETTLEMENT DETECTION IN ARID ENVIRONMENTS USING OPTICAL SPACEBORNE DATA

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ABSTRACT

In this paper human settlement detection using SPOT data in arid environments is addressed, with stress on informal settlement analysis. We show that a proper use of spatial patterns may improve the delineation of the extent of these areas and the discrimination between formal and informal settlements. A comparison with existing global data sets shows the potentials of this approach for human settlement mapping in arid environments.

1 INTRODUCTION

Unstructured human settlement mapping and monitoring is an important topic for many national and international initiatives including the European Global Monitoring for Environment and Security (GMES) initiative and the humanitarian and development aid policies of the United Nations. Also, monitoring settlements is useful to acquire information on phenomena, like illegal immigration, that are very high-ranked on any current political agenda. The application of these techniques has a global scope and would be particularly relevant for the developing world.

Unstructured ("informal") human settlements are usually defined (Mason and Fraser, 1998) as dense settlements with groups living in self-constructed shelters without any formal structure which is usual in urban areas. Often, no real subdivision of the land is done, and these areas are characterized by rapid, unstructured and unplanned development.

Spatial technology may help a lot in analyzing the patterns of these settlements, forecasting their possible changes and provide information on how to make the living conditions in these areas much better than they are today. However, for spatial technology to be effective in informal settlement environments, it has to be cheap, both in data acquisition and processing, as automated as possible to achieve faster and more reliable results, simple to use and largely based on tested routines and algorithms. Nevertheless, traditionally, field survey and visual interpretation of satellite data are used to produce reliable information. These are, to a large extent, manual operations and require a wide expertise; moreover, besides the operator skill bias, they are time-consuming and hard to catch up with the rapid developing pace.

The aim of this research is to develop a semi-automatic algorithm for the extraction of such human settlements.

2 STRUCTURED AND UNSTRUCTURED SETTLEMENT DISCRIMINATION

The overall problem discussed in this paper may be subdivided into two sub-problems. The first one is the discrimination of human settlements against their surrounding natural environment. The second one is the detection of informal settlements as a subset of the previously identified areas. According to this scheme, the challenge of informal settlement detection using satellite remote sensing data is also twofold. On the one hand, a robust algorithm for detecting human settlement areas in these images is required. On the other hand, the methodology must be flexible enough to incorporate very different settlement environments, and be able to discriminate among them.

A first comment, based on current technical literature and the long term aim to exploit all available sources of data, is that spatial patterns more than spectral features have to be investigated. With the improvement in spatial resolution, between-class spectral confusion and within-class spectral variation were found to increase for land cover/ land use studies (Barnsley and Barr, 1996). Thus, spatial information gets essential to reduce mapping confusion, especially in areas where the settlements are realized using locally available and very diverse materials.

A second comment is that simple classification procedures are highly desirable, but very complex to design, due to the wide variety of settlement characteristics, both spatially and spectrally. Even working at a regional level, where significant correlation between settlement areas exists, the goal of a uniquely tailored automatic algorithm may be very difficult to achieve.

A general overview of literature survey about this topic shows a sort of rift within the choice of sensors to be used for urban detection, as described hereafter. Before the launch of VHR satellites one of the most employed sources of data were SPOT satellites. For such imagery it is impossible to identify every single house because of the small size of the objects, and the most common approach is based on statistical textures, which take into account the spatial distribution and variation of neighborhood pixel values within an appropriate moving window. There are a few methods to quantify them, from Grey-Level Co-occurrence Matrix (GLCM) (Haralick *et al.*, 1973) to Markov Random Fields (MRF) (Descombes *et al.*, 1999). Even though the MRF approach provides good performances, it is not considered here, since it requires a significant computational part that does not fulfil the aforementioned requirement of easiness. Proposed algorithms based on the GLCM com-

putation cause instead other remarks. First of all, they basically focus on single locations (Zhang *et al.* (2001)-Shaban and Diksit (1999)), and thus they do not allow any generalization of the results. Moreover, they are based on supervised techniques, make use of very diverse texture sets, and lead to overall accuracies widely variable between 40% and 80%.

Since 2000, despite the launch of the fifth satellite of the family, SPOT spatial capabilities have been overshadowed by the availability of the aforesaid VHR sensors: in the urban analysis field, researchers are more interested in exploiting the sources that can theoretically lead to best performances. Some internationally funded projects are at the moment providing satellite data to extract suitable information about settlements from remotely sensed imagery. For example, informal settlement detection, such as the mapping of refugee camps, has been addressed within the *GMOSS* (Global Monitoring for Stability and Security) network. In the framework of this project the assessment of suitable indicators for refugee camp detection were computed by means of night-time sensors' data or VHR satellite imagery. Moreover, the European Union Joint Research Center carried out a comparison among four different methods (supervised and unsupervised classification, multi-resolution segmentation and morphological analysis) aiming at single tent detection in order to deduce the population of the Lukole camp, Tanzania (Giada *et al.*, 2003). For this task, methods based on interpretation by a human operator are practically not feasible because of the large number of tents, and computer-based techniques are the only alternative.

Nevertheless, it is worthwhile to consider that, in many cases, the full spatial resolution available from VHR sensors is not really required, and a trade-off among accuracies, tasks, easiness and generalization should be addressed.

3 ALGORITHM OVERVIEW

An interesting technique developed for urban settlement detection and characterization in the past and applied mainly to satellite SAR data is based on a supervised neural network classification chain, with spectral and spatial analysis steps (Gamba and Dell'Acqua, 2003). Additionally, spatial analysis, according to previous comments, may be performed using textural features, possibly extracted using a locally adaptive window width (Gamba *et al.*, 2006).

In this work a simpler, but equally effective, methodology has been developed and tested for arid environments, with the aim of a better automatization of the process. The procedure is intended to a general purpose detection of settlements, therefore, besides the simplicity, it is fast and easily repeatable. In particular, the co-occurrence matrix textural features suggested by Haralick (Haralick *et al.*, 1973) form the basis for the analysis. On the one hand, they allow adopting an unsupervised approach (and thus to cope with the significant problems due to the lack of knowledge about most of the developing areas), but, on the other hand, they reduce the application fields of the system, since they
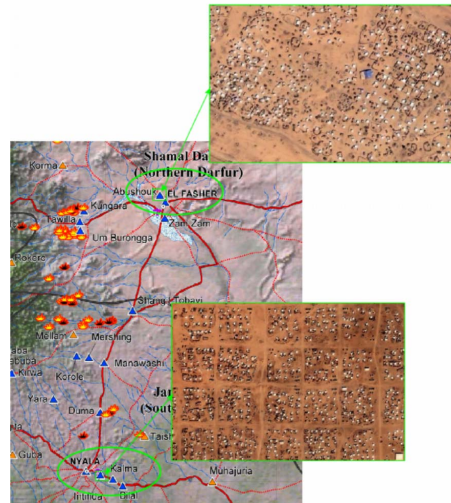

Figure 1: The urban test areas in Sudan considered in this work.

only permit a very poor (in terms of class number) land-use classifications of the images. Actually they allow to detect with high precision the boundaries and the extent of the settlements, both formal and informal; to some extent it is possible to separate this two classes, but just in case they present different building densities. In general this condition is verified, even if there are some cases where this density threshold is not clear-cut, for example in the city boundaries. Anyway, such a confusion in the results does not necessarily imply they are useless, since they give a first screening of the data and have an important role in assisting human experts.

The algorithm is modular, but sequential. The basic step - the detection of the settlements - starts from the computation of the Grey Level Co-occurrence Matrix (GLCM) of the original SPOT-5 image - resized by a factor of 2 to reduce computational cost - with moving window 21×21 and displacement vector (1,1). The choice of the moving window size (no considerations have been made upon the standard displacement) comes from the evaluations of the average dimensions of usual building blocks in many towns all over the world.

Among the eight most common co-occurrence features, *Homogeneity* is required. It belongs to the "contrast" group and it assigns high values to homogenous areas. In arid backgrounds, which are very uniform, it points the settlements out very efficiently.

This feature is then fed to an unsupervised classifier (*K-Means*) with a fixed number of output classes. This number is expected to range between 3 and 10, a good choice being 5. The crucial point is the merging of the output classes into the two macro-classes *City* and *Soil*, which represent the settlements and the background. The required knowledge about the test area for this merging operation is very scanty, especially in respect with the number of training points needed by supervised classifiers. In any case a good choice is to merge into the *City* category the first two classes

found by the K-Means algorithm, if the order is defined by increasing values of class centroids.

The second step of the algorithm tries and discriminates the city core from the refugee camp. Since the scale and the resolution do not allow to detect the single building (or tent), the only way for this purpose is to find differences in the texture properties of building agglomerations. From a theoretical point of view, buildings - in the common sense of the word - and tents or shacks have different geometrical properties and texture features. Actually, at this resolution, they are not properly defined, thus there is an objective difficulty in finding selection criteria. To this aim, the algorithm exploits one more feature, computed using the same parameters as before: *Variance*. Variance measures the dispersion of the values around the mean,and is useful since, in general, the impact of the camp on the environment is lower than the town. This implies that variations around the mean of the camp are not significant, and it appears darker than the city, which is more heterogenous. By classifying this feature using once again the *K-Means* algorithm it is possible to extract the informal settlement position.

4 EXPERIMENTAL RESULTS

The proposed procedure was evaluated using a test set composed by panchromatic SPOT-5 images of informal human settlements areas. The test sites are the towns of Al-Fashir and Nyala, respectively the capitals of Northern and Southern Darfur, Sudan, Africa (see Fig. 1). As a result of the war situation in that region since 2003, vast tent camps has been organized to accommodate thousands of refugees. The Abu Shok camp is located North-West from Al-Fashir, and its development is still occurring. Similarly, the refugee camp of Intifida is located East of Nyala, far away from the town center.

A visual analysis of the data sample in Fig. 2(a) shows that there is confusion among the materials of the human settlements (both formal and informal) and the surrounding natural environment. Therefore, it confirms that pixel values might not be enough to detect urban areas, let alone to efficiently discriminate more structured urban areas from informal settlements. As proposed in the previous section, more refined results may come from an analysis including spatial relationships between intensity values.

In the Al Fashir area the data set consists of two panchromatic SPOT-5 images with 2.5 m spatial resolution that were acquired on November 14, 2004 and April 7, 2005.

Results presented in Table 1 show that both images can be used to detect human settlements with very high precision, over 90%, fully exploiting arid background, with completely different pattern than the populated area.

Even with worse results, the obtained map would be at present the best chart available for such territories, as shown in Fig. 2(c) and (d), which depicts the existing maps of the

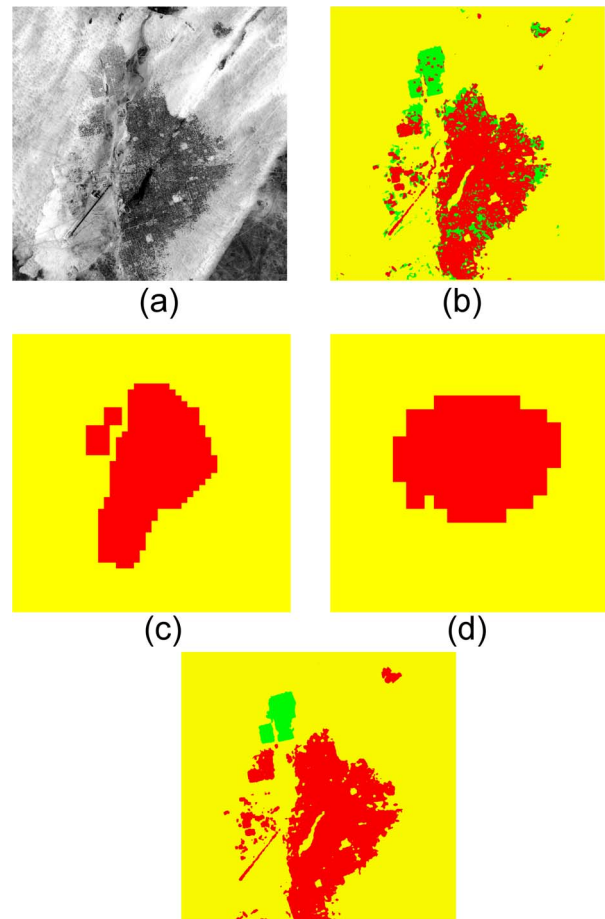

(a)　　　　　　(b)

(c)　　　　　　(d)

(e)

Figure 2: Al Fashir: (a) SPOT image, (b) classification results (green = camp, red = city, yellow = desert), to be compared with Africover (c) and GRUMP (d) maps, as well as the manually extracted ground truth in (e).

K=0.90	City	Soil
91.65%	1195580	108951
98.08%	95035	4850434
96.73%	92.64%	97.80%

K=0.97	City	Soil
95.43%	1290284	61793
99.99%	331	4897592
99.00%	99.97%	98.75%

Table 1: Confusion matrices for the two SPOT images of Al Fashir (2 classes), using the manually extracted GT.

K=0.87	City	Soil	Camp
92.82%	1064235	72814	9452
98.08%	74114	4850416	20939
47.37%	47046	36133	74851
95.83%	89.78%	97.80%	71.12%

K=0.87	City	Soil	Camp
97.64%	991209	13483	10504
99.99%	309	4897592	22
28.12%	193877	48288	94716
95.73%	83.62%	98.75 %	90.00%

Table 2: Confusion matrices for the two SPOT images of Al Fashir (3 classes), using the manually extracted GT.

city obtained from global and regional databases, Africover and GRUMP (Global Rural-Urban Mapping Project).

After detecting the settlement position, the algorithm tries and identifies different building densities (Fig. 2b). The quantitative evaluation in Table 2 shows that, as before, the classifier suffers the intrinsic confusion between shacks and outskirts, and there is a high commission error for the *Camp* class.

As for the Nyala area a second data set was employed: a panchromatic SPOT-5 image and a Quickbird image. The main difference with the first data set consists in the presence of more arid land vegetation. Unfortunately, shrubs have the similar texture properties than settlements at SPOT spatial resolution, leading to a significant mix-up even in case of two classes. The numerical evaluations of the confusion matrix in the upper part of Table 3 confirms the high commission error for the *City* class. As the first algorithm step is not effective, also the Formal/Informal discrimination cannot give useful outcomes. Lower part of Table 3 indeed reports an overall accuracy of 72% and a very low *K* index.

The first comment relates to the fact that the only available input was a panchromatic SPOT image: spatial resolution is high but, conversely, spectral information is poor. Besides ancillary data like GIS data and cadastral maps, a basic way to improve detection results would be more spectral information. Unfortunately, the only multi-spectral available data was a Quickbird pan-sharpened image that was acquired one year before and does not cover the exact zone (see Fig. 3a). Anyway, since refinement procedure described afterwards is very general, it is possible to process the QB image and then extend the results to the SPOT

K=0.40	City	Soil	
36.84%	759676	1302505	
97.55%	102699	4092982	
77.54%	88.09%	75.86%	

K=0.32	City	Soil	Camp
36.32%	382299	661907	8372
97.55%	55821	4092982	46878
8.48%	283354	640598	85651
72.88%	52.99%	75.86%	60.79%

Table 3: Confusion matrices for SPOT data of Nyala, with two or three classes, using the manually extracted GT.

K=0.55	City	Soil
52.97%	353481	313895
96.57%	45710	1286914
82.01%	88.55%	80.39%

K=0.66	City	Soil
64.32%	347753	192939
96.48%	51438	1407870
87.78%	87.11%	87.95%

Table 4: Confusion matrices for Quickbird data of Nyala without and with NDVI masking.

data. Basically, the trick is to mask the vegetation pixels within the original scene, first evaluating the NDVI index, then removing noise blobs (in our case those with area less then 100 pixels) and finally computing the *Homogeneity*. The further testing data set results are depicted in Fig. 3(b) and (c): the refugee camp is not included and the whole city has been captured. Confusion matrix In Table 4 shows the results after the original processing scheme, and (lower part) after the masking procedure. With respect to the previous case, overall accuracy is better, since the considered scene contains less textural zones that can lead to confusion in the final classification. In any case, the purpose of this section is to evaluate the quality of the refinements: the percentage comparison points out an effective improvement of the accuracy and the *K* coefficient, that approaches the typical quality gauge of 0.7.

5 CONCLUSIONS

In this paper we proposed a semi-automatic procedure to detect settlements in arid environments exploiting spatial patterns.

The results of this work show that panchromatic information by the sensors mounted on SPOT satellites are not immediately suited for our aim. The introduction of textures, however, considerably improves results, especially in differentiating settlements from arid areas. The main shown drawback is the confusion in classification between the patterns of groups of buildings and shrubs and/or rock aggregate ones. A first attempt to avoid this problem has been addressed, lacking SPOT multi-spectral information, by means of a Quickbird pansharpened image. More tests on SPOT imagery must be carried out to confirm the achieved improvements.
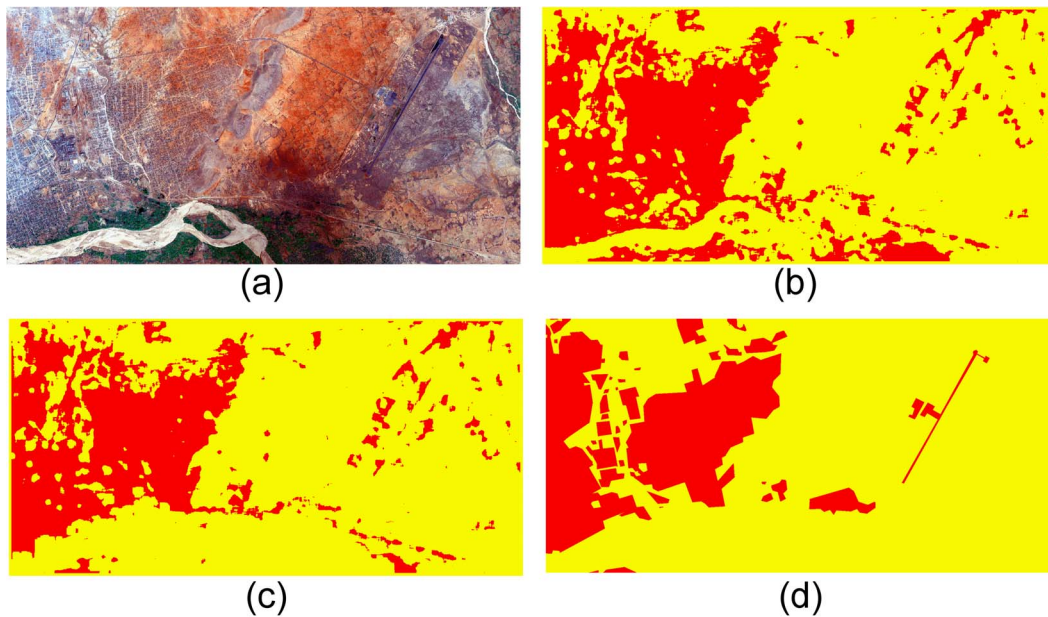
Figure 3: Nyala: (a) Quickbird image, and classification results (red = city, yellow = desert) without (b) and with (c) vegetation masking using NDVI, to be compared with the manually extracted ground truth in (d).

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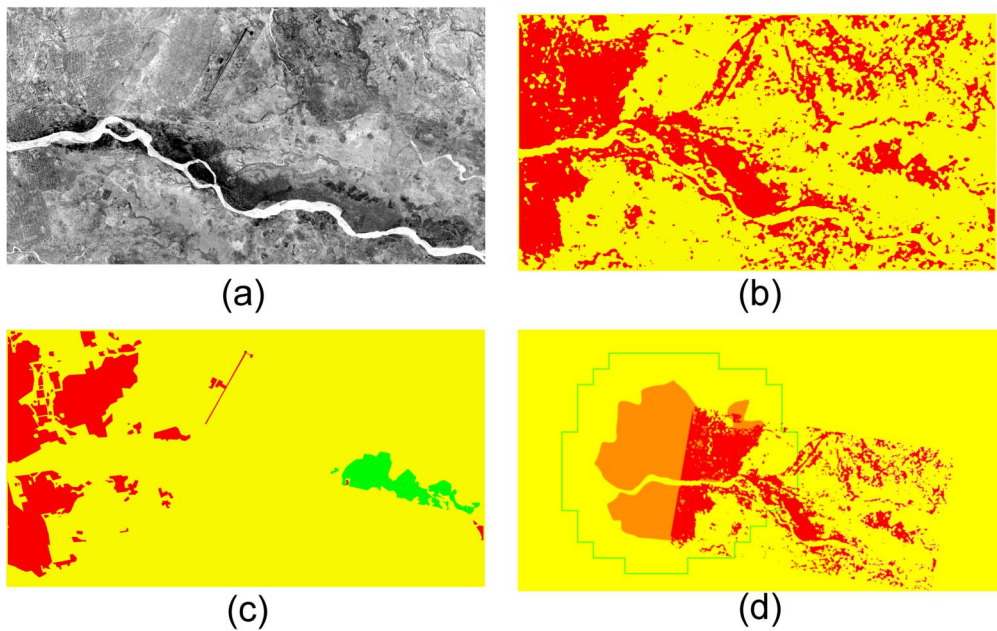GRUMP, http://beta.sedac.ciesin.columbia.edu/gpw/

Figure 4: Nyala: (a) Spot image, and (b) classification results (red = city, yellow = desert), to be compared with the manually extracted ground truth in (c), and GRUMP/Africover (blu/red) urban extents in (d).