A COMPARISON OF TEXTURE FEATURE ALGORITHMS FOR URBAN SETTLEMENT CLASSIFICATION

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1. INTRODUCTION & OBJECTIVE

The use of image texture features to characterise urban environments is not new; for example, Benediktsson *et al.* have used morphological features to classify urban regions [1]. Pesaresi [2] investigated the effect of GLCM parameters on classification accuracy in urban environments.

The objective of the research presented here is to establish which texture feature extraction algorithms are most suitable for automatically classifying low-income settlement types using QuickBird imagery.

2. DATA & METHOD

The following settlements types were identified in Soweto (Gauteng province, South Africa) to be used as target classes:

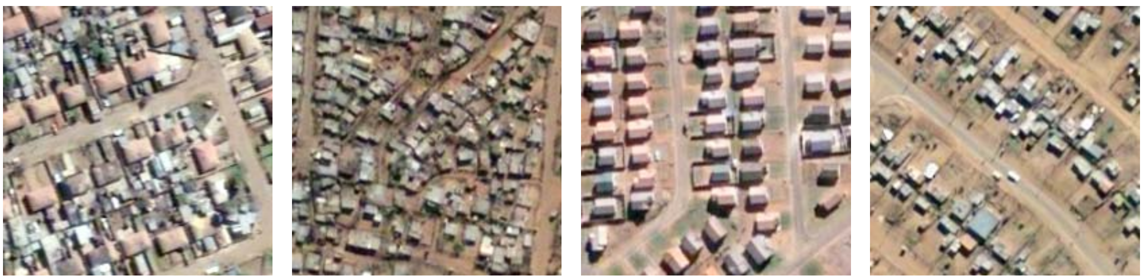
FT_Type1, FT_Type2: Formal Township. This type contains permanent (brick) structures. The buildings are laid out in a planned manner. Type 1 and 2 are differentiated on the homogeneity of the house sizes.

IS_Type1: Informal squatters. Non-permanent shack type dwellings (typically made out of tin, cardboard, wood, etc.) established on informal, non-serviced sites. Typically characterised by high building densities.

FTIS_Type1, FTIS_Type2, FTIS_Type3: Formal Township plus Informal Squatter. Any type of residential unit, of any density, can be found in this category, but buildings appear in pairs — a larger building will be accompanied by a backyard shack. The three sub-types are differentiated based on the size of the primary building.

Formal_suburb: Formal suburban regions, characterised by permanent residential structures, either single or multi-level, located in or near well-established residential areas.

Informal_township: Informal townships, characterised by permanent or semi-permanent shack type dwellings laid out in a planned manner, both on serviced and unserviced sites. Building density can vary from low to high.



(a) FTIS_Type1 (b) IS_Type1 (c) FT_Type1 (d) Informal_township

Fig. 1. Examples of some of the settlement classes found in Soweto

Table 1. Overall classification accuracy obtained with various texture algorithms

Texture algorithm	**# features**	**Classification Accuracy (%)**	**Reference**
Moran's I	1	25.64	[3]
Geary's C	1	27.74	[3]
G index	1	35.43	[3]
GLCM (11×11)	8	82.28	[4]
Lacunarity (3×3)	1	44.05	
Wavelet transforms	3	63.17	
Granulometrics	20	84.62	[5]
Local Binary Patterns	20	94.41	[6]

Panchromatic QuickBird imagery at a resolution of 0.6m over Soweto was collected. Polygons were extracted from the imagery for each of the target classes. From these polygons, $120m \times 120m$ tiles were randomly extracted and labeled by target class.

The various texture feature extraction algorithms listed in Table 1 were applied to the training tiles to obtain a set of labelled feature vectors for each algorithm. The discrimination ability of each texture feature extraction algorithm was then assessed by training a support vector machine to classify the labelled feature vectors. The values reported in Table 1 are the overall classification accuracy values obtained using 10-fold cross-validation, and should therefore be indicative of performance on unseen data.

3. DISCUSSION OF RESULTS

The best results were obtained with the Local Binary Pattern (LBP) method, producing an overall classification accuracy of 94%, followed by the granulometric pattern spectra, with 85%. The LBP algorithm produces a histogram of the occurrence of certain small-scale edge elements, which appears to capture much of the relevant information needed to distinguish the settlement types; in contrast, the granulometrics capture the distribution of object sizes in a histogram, which is an intuitively satisfying method of describing settlements. The Gray-Level Co-occurrence Matrix (GLCM) algorithm also performed quite well, but the spatial autocorrelation-based methods performed poorly.

4. CONCLUSION

Similar to the results obtained by Pesaresi [2], it was found that some of the texture features were able to separate the different settlement classes very well. In addition, it appears that the LBP features are more powerful than the commonly used GLCM features for this particular problem. Future work will focus on measuring the accuracy of these algorithms in a mapping application.

5. REFERENCES

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