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The Organic Perspective To Cape Town-South Africa Shack Extraction

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Abstract

The spatial reconstruction of man-made objects from urban imagery for use in management and emergency reconnaissance has been a growing research area for over two decades. Informal settlements are an example of man-made objects and they also represent one of the greatest modern challenges of developing countries. Urban governors constantly require up to date spatial and attribute information on the state of development in these settlements. The challenge with data capture in slums lies in the numerous contextual and societal complexities that characterize these unplanned environs. Several ground and image based techniques have been tested in data creation and unlike ground-based data collection techniques, image based techniques have proved superior. The evolution of sensors, data specifications and user requirements however, create a need to revisit existing spatial reconstruction approaches. This study addresses some of the contextual and approach based limitations to data collection by proposing an organically inspired perspective to shack extraction. It uses very high resolution aerial image datasets as input in a novel multi-scale framework that employs a watershed segmentation to inform on optimum locations and split complex shack candidates. Both the outer settlement boundary (macro) and the individual shack unit candidates within that boundary are identified and traced (micro scale) at a detection rate of 94%. The results are proposed for inclusion in larger scale urban planning architectures that include social and environmental parameters.

Keywords

Organic; Shack; Image-processing; Multi-scale; Boundary

Introduction

Motivation and objectives

The dramatic increase of the world's population from three and a half (3.5) to seven point four billion (7.4) since the 1970"s, has together with other forces driving urbanization increased urban populations worldwide significantly (World population | UNFPA). In developing countries, the construction of formal residential living spaces cannot keep up with the urban-driven migrant influx and the demand for shelter, resulting in the development of slums in urban and peri-urban areas. In order to address the problematic associate with informal settlements through town planning processes, organizations involved require access to up to date information on both the "seeding" and proliferation of slums as well as their inhabitants. They require answers to questions such as: - "Are there any slums in this city? If so, where are they located? How many settlements are there in the city? What is their coverage area and extent? Are these settlements located in risk prone areas? Are there any new isolated settlements developing within the city? How many households are there per settlement? What configurations, shapes, sizes, locations, orientations exist in these settlements?" The answers to these questions can take the form of social statistics, slum household's data, settlement location data, dwelling counts, census demographics amongst other details. In essence they can assume a spatial or attribute nature and this information is optimal in the creation of data repositories for planning.

The main objective of the study is therefore to extract the spatial extent of informal settlement units in from imagery at both what can be described as "Macro" and "Micro" level based on methods inspired by organic processes. "Macro" will be understood as referring to entire informal settlements while "Micro" refers to the environment at the level of individual shacks. An image processing based approach will be tested which recognizes the organic nature of settlements and emulates human ability to detect, isolate clusters within the informal settlement layout (Macro) as well as individual roof scapes or shacks (Micro).

Overview

Urban development processes are dynamic hence the planning repositories that aid decision support for the management of these processes, require up to date spatial information continuously. Different techniques have been employed in collecting the spatial and attribute components of slum data. The techniques have either been ground-based (e.g. field surveys, sketch mapping, mobile mapping, community-based surveys) or space based (e.g. earth observation (EO) techniques). Ground-based techniques can extract much detail including information about individual dwellings, although the data collection process can be very expensive, unsafe and time-consuming. EO techniques present image detail at different resolutions and they are highly efficient in capturing large-scale datasets in minimal time. New EO technologies such as Airborne Laser Scanning (ALS) provide additional information and can thus contribute to the automation of the acquisition of spatial data. The datasets generated from EO can easily be incorporated into spatial planning architectures for decision support tool creation [1]. As the advantages of EO continue to increase in comparison to ground-based techniques, imagery, therefore, becomes a key input choice for spatial reconstruction initiatives. Products from both 2D and 3D reconstruction of slums are useful in emergency or service driven reconnaissance, detection of infills/open spaces, land use classification as well as environmental protection [2]. This increased need for data, together with the possibilities of new, faster and more reliable acquisition methods suggests the need for further research in this area. Geo-information scientists are therefore faced with the need to continuously develop reconstruction tools that meet the demands of present day slum challenges.

References to related work

Several scholars have studied urban dynamics using image based

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approaches. The distinction of a built area (formal or informal) from other land cover classes is itself an interesting application of remote sensing. In the case of informal settlements, various techniques have been used to identify built area including region based analysis, texture analysis, statistical techniques and support vector machines e.g. Anthony et al. [3] amongst other approaches. This section reviews the work of earlier scholars in both large and small scale identifications of built areas for reconstruction. In a study by Louw et al. [4], an automated land use classification method based on high level contextual characteristics is described. This classification uses high resolution RGB image data. Training samples are selected for different land use types and used to calculate high level feature indices relating one feature to the other. An automated algorithm is then crafted that calculates contextual characteristics from the feature indices and creates feature vectors to classify the image content. An overall classification of 82% is recorded which is a moderate classification accuracy. This approach can be described as a supervised classification technique as it involves using pre-determined feature information to influence the assigning of pixels to classes. It reports promising results with 82% accuracy, however it is one of the purely pixel based approaches which have been criticised as not adequately capturing complex detail. In an unpublished thesis study by Mathenge et al. [5] ontology based object oriented techniques are used to map the location of Informal settlements from very high resolution imagery of Kisumu Kenya. Three-stage chessboard segmentation is chosen to identify informal and non-informal areas. An eCognition based segmentation scale parameter of 10 and 40 are tested. Thereafter building densities, characteristics and irregular roads are used as cues in verifying an area as informal. The research outcome is promising in its use of a modern approach of object oriented analysis. In the specific area of individual shack detection, snakes or active contours are often used. Researchers such as Mayunga et al. [6], Barry et al. [7], Rüther et al. [8] evaluate how level edge based techniques may not optimize boundary delineation in complex areas. The researchers argue that unlike common building detection systems, shacks lack regularity and common orientation hence require an adaptive model to their complexities such as the active contours. They argue that using generic models alone, in areas where buildings are not well structured does not provide realistic results [8]. In studies such as Mayunga et al. [6] study a radial casting algorithm was used to initiate the snakes on Quick bird RGB and NIR data and the output of they reported the output of their study as satisfactory. No qualitative evaluation data is given in the paper on actual accuracies.

Materials and Methods

Study area and data description

A case study of the City of Cape Town (CoCT) in the Western Cape Province (WCP) of South Africa is used in this study. Cape Town is the principal city of the Western Cape Province, located approximately at latitude of -33.55°S and a longitude of 18.25°E along the south-western coast of South Africa. It is also known as Ikapa or Kaapstaad in IsiXhosa and Afrikaans respectively as stated by Spocter et al. [9]. The overall population was estimated at approximately 3.7 million people as per Census 2011. The data tested in this study included a collection (1998-2012) of optical aerial imagery ranging from 50cm to 8cm in resolution that covered the entire administrative area of the City of Cape Town. For a visual location impression of the local Cape Town in South Africa see (Figure 1).

Object detection strategy: The organic perspective

Information contained in imagery can be described as either expressing the world domain, the scene domain, or the image domain. McKeown et al. [10] defines the world domain is the broadest abstraction that includes all physical objects that constitute a scene. According to McKeown et al. [10], the scene domain contains objects that are semantically related to one another. It can be described using terms such as complex, dense, rugged, flat, sparse etc. depending on the quality and resolution of the representation they are contained in. The image domain is the lowest level of abstraction that reduces the scene to a collection of digital pixel intensities that can be interpreted. The objective of any successful man-made object extraction system is to accurately interpret the image domain in a manner that best matches the world domain. In the case of urban areas, the world domain is a complex environment with a rich spectral palette.

This creates a diverse, heterogeneous pixel configuration in the image domain that cannot easily be related to object primitives.

In order to design a successful image processing strategy a user requires a set of low, medium or high level concepts driving a sequence of operations towards the isolation of a feature [11]. Due to the predominance of diverse roof detail there are very few areas with uniform texture, causing low level algorithms, such as the edge detectors, to perform poorly in shack extraction domain. Figure 2 shows an informal area image scene and the corresponding Sobel edge filter output.

In support of the view proposed by Mayer et al. [11], the researcher thus proposes a strategy based on a combination of mainly medium level concepts for shack extraction. The selected concepts

Figure 1: City of Cape Town on the South West coast of South Africa (Image source: Google Maps).

Figure 2: a) Original informal settlement scene and b) Sobel edge extraction.

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were characteristic of an object based framework in the sense as they are based on pre-determined models of shack units (micro) and informal settlements (macro) models. The research concepts propose that shack roofs can be accurately separated on the basis of shape in cases where uniform or similar textures of attached roofs of different units make distinction by texture impossible. In addition, shack areas differ significantly from formal build up areas. A hybrid structure of model and data driven reconstruction prescribed this set of techniques and parameters for optimal shack reconstruction using organicism. The concept of "Organicism" is incorporated through postulating that individual elements in systems such as informality interact organically with each other and with the system as whole thus developing and growing the system organically. Organicism was originally derived from Wrights philosophies in architecture and town planning, where organic layouts or designs are part of century-old paradigms emphasising architectural flexibility and freedom. Organic designs are also defined as components of a philosophy which promotes harmony between human habitation and nature [12-16]. According to Steffes et al. [17] this philosophy can be applied to several architectural aspects and settlement layouts.

Three organic phenomena were thus be applied to, or emulated in the extraction of shacks from images, the human vision system, the human ability to notice and recognise patterns and the organic nature of the shack- scape as summarised in Table 1. The organic research design was based on the outcomes of rigorous tests conducted by a combination of optical and ALS image data.

Index based shack detection and shack boundary outlining

In line with organicism, the researcher applied scale-space to the shack roof problem in order to reduce roof detail at an each decomposition The Daubechies wavelet was found suited for the decomposition that optimises the isolation of the strongest shack edges. It also offered significant blurring which is a desired effect in reducing undesired detail (Figure 3).

All input image were therefore decomposed into child datasets and it was expected that weaker boundaries and smaller object are more likely to disappear with decomposition. The multi scale pyramid was subjected to an RGB to HSV transform and later a de correlation stretch as part of pre-processing to reduce the amount of image detail. Thereafter the researchers developed a normalized shack index (NSI) to identify shack roofs in imagery. This NSI index is developed by testing and recording the general spectral behavior of shack roofs and a few other prominent land cover types (vegetation, roads, and building roofs) within the HSV color model. The researchers achieved this by studying the histograms and pixel values across vegetation, road, shack and building roof areas and recording common trends in these land covers. An optimum performance threshold was established by shifting the (normalized) scaling across from -1 to 1 and evaluating the performance of the index as the ratio changes. This NSI resulted in a binary output of shack and non-shack candidates and was defined in Equation 1.

$$\text{Normalized Shack Index (NSI)} = \frac{Hue - "Value"}{Hue + "Value"} \quad (1)$$

The shack candidates emerged to foreground and the rest of the image remained background. However, the foreground pixels may be connected and need splitting further and the watershed transform were utilized. The watershed transform is described as a region based segmentation technique and is useful in splitting connected polygons in binary images. The operation of the watershed is analogous to establishing "catchment" areas in a river basin. These are represented by intensity minima"s in the image space where water would accumulate if poured over the image "terrain", with the intensity values as "elevation" equivalents. Watershed lines are commonly defined on nodes, edges, corners and lines. These edge, corners or "catchment" areas are identified by computing the gradient changes and using a distance transform. Methods used to compute a distance transform include the Euclidean, Quasi-Euclidean, city block and chessboard. The difference between these techniques is the manner in which the algorithms compute the distance to boundary elements.

The following methods are used as extracted from Guide:

The analogy	The hypothesis	The perspective for shack reconstruction
The human eye: The fact: The human eye uses a system similar to HSV to differentiate colours	Some image processing techniques use this analogy and researcher wants to apply it to the shack problem	The use of HSV transform in pre- processing informal settlement imagery imitates the HSV that resembles human color perception strongly
Human cognition or The recognition process: The fact: Humans are able to recognise objects due to cognitive processes that help interpret scenes	Image analysis can emulate this process and researcher tests its application to shack reconstruction	The use of background subtraction, wavelet transforms and MSER algorithm. These imitate human cognitive abilities. These techniques are selected as they are usually applied to bioinformatics for medical cell/organ boundary delineation from imagery is tested for suitability in slum or shack extraction.
The nature of shacks: The fact: Shacks have an unplanned layout that is migrant driven	The growth of shacks is an organic process similar to the other natural growth	Deriving cues from biological image extraction for applications that can be relevant to shack extraction

Table 1: The organic perspective for shack reconstruction.

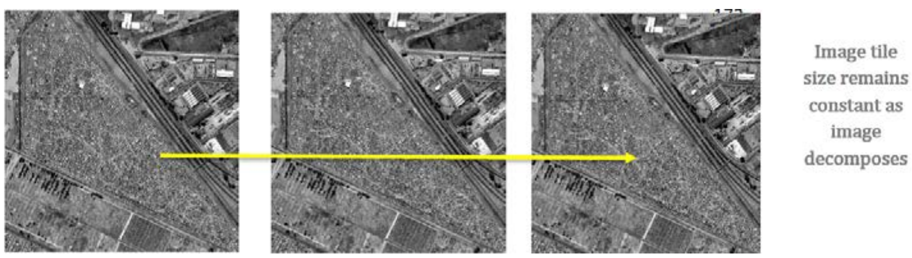

Figure 3: Generations of Debauchee's Wavelet decomposition at iteration 1,3,5 respectively.

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i) City block- distance between (x_1, y_1) and (x_2, y_2) is $|x_1 - x_2| + |y_1 - y_2|$.

ii) Chessboard- distance between (x_1, y_1) and (x_2, y_2) is $\max(|x_1 - x_2|; |y_1 - y_2|)$.

iii) Euclidean- distance between (x_1, y_1) and (x_2, y_2) is $\sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2}$

iv) Quasi Euclidean - distance between (x_1, y_1) and (x_2, y_2) is $|x_1 - x_2| + \sqrt{2} - 1|y_1 - y_2|$ for

$|x_1 - x_2| > |y_1 - y_2|; | + \sqrt{2} - 1 |x_1 - x_2| + |y_1 - y_2|$, otherwise (Figure 4)

The watershed algorithm involved a pre-step which yielded output a distance operation in form of a grey scale image. This image closely resembled the original image except that the recorded intensities represent proximity values to the nearest boundary point. Thereafter the water shed transformation was applied and the final output is a binary image with polygons split at watershed points. The shack candidates were regularised using morphological operators like the Pixel Fill, Structuring elements and Pixel Erosion (thinning algorithm). The boundary tracing algorithm used in the experiments for this study implements the Moore-Neighbour tracing algorithm modified by Jacob's stopping criteria. The algorithm traces the exterior boundaries of objects, as well as boundaries of holes inside these objects, in the input binary image. It also descends into the outer objects (parents) and traces their children (objects completely enclosed by the parents). The input binary image must be structured such that nonzero pixels belong to an object and 0 pixels constitute the background. The researcher also tests the performance of a modified tracing algorithm also by Sardella which uses a three-element vector of the initialisation coordinates and direction for the tracing operation and searching for a boundary by moving directionally away from the seed pixel [18-22].

Performance metrics of extracted polygons

An empirical discrepancy based evaluation is used which validates both the boundary localization and the planimetric accuracy. The percentage overlap between a corresponding manually digitized reference area between two polygons and the algorithm result is used as an indication of overall XY location fixing. On the other hand, the planimetric accuracy is computed by finding the root mean square value of the non-overlapping areas between two polygons that delineate the same shack unit. The polygon area comparison approach is illustrated in Figure 5.

Shufelt proposes confusion matrix computation to evaluate a detection system. Based on Shufelt's proposal, the researcher adapted these to match the informal settlement context. A True Shack Positives (TSP) are those shack candidates that have been correctly identified by the shack extraction algorithm as being a shack unit and are in fact labeled as a shack unit in the reference data. True Shack Negatives (TSN) are those shack candidates that have been correctly identified by the given algorithm as being a shack environment background and are in fact labeled as a shack environment background in the reference data. False Shack Positives (FSP) are those shack candidates that have been incorrectly identified by the given algorithm as being a shack

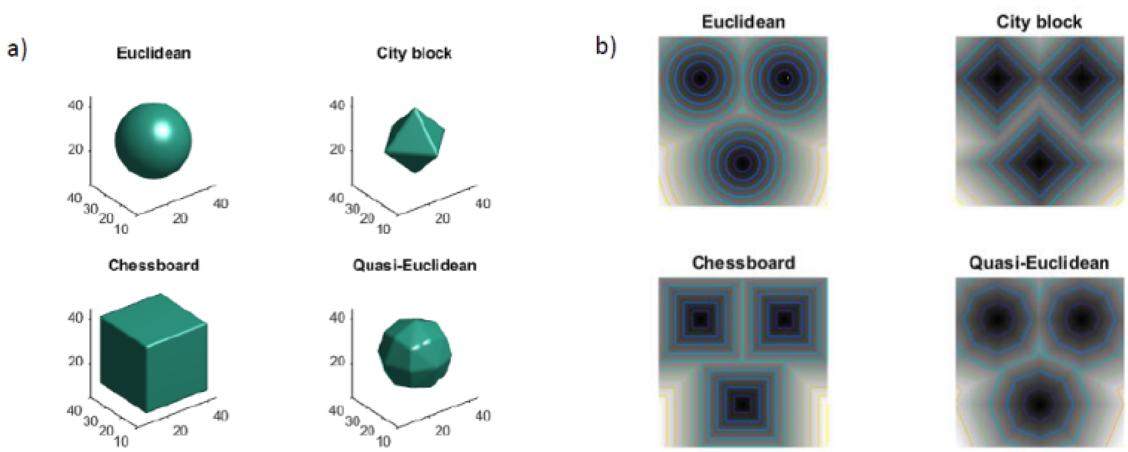

Figure 4: Iso surface plots illustrating the distance transforms in three dimensions as well as b) two dimensional representations of how each method computes distance. (Source: Matlab Documentation).

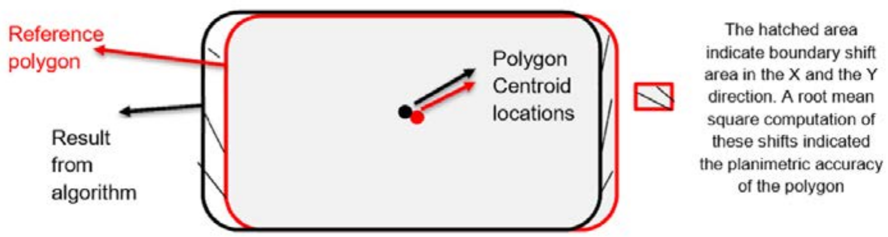

Figure 5: Locality and plan metric assessment of resulting polygon.

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unit and are in shack environment background in the reference data. False Shack Negatives (FSN) is those shack environment background details that have in fact been identified as shack units in the reference data. Missed shack factor (MSF) refers to a ratio that compares the false shack negative versus true shack positive ratio.

Results and Discussion

The following shack reconstruction steps were conducted at multiple scales and within the constraints of the macro and micro outline. These were computed through the development and application of the normalized shack index (NSI) to identify the initial shack candidate candidates in the pre-processed aerial imagery. The researchers developed the NSI through exploring spectral characteristics of shacks in the HSV channel. This was based on sampling and identifying the common characteristics and average spectral properties per land cover type. An original concern arose from the fact that there are two distinct groups of shack roof types: one with higher saturation value than the other (Figure 6). In order to investigate further some sampling and studying of the band values of the slum areas is conducted. During the sampling stage these two roof types are easily distinguishable by visual inspection where they clearly have different spectral appearance in the RGB image. However once the NSI is developed the visual dissimilarities between these two roof types in the HSV channel are overcome by the correlation between their bands that enabled the ratio relating their bands to allow for the automatic identification of both roof types. It is observed that, their average ratios in the hue and "value" channel are comparable, and allowed for a uniform index to identify them. Band ratios between the saturation, hue and "value" for the two slum roof types are 12.7; 0.9 and 0.6 respectively. Thus suggesting that only hue and saturation channel should be used to characterize shacks (Figure 7). The entries of Table 2 are then plotted into a comparison bar graph as shown in Figure 8.

Figure 6: Illustration of high saturation roofs (type 1) highlighted in red and light saturation roofs (type 2) in yellow highlight.

Hue	Saturation	"Value"
0.6092	0.2544	0.8941
0.5333	0.1818	0.4314
0.6176	0.1538	0.8667
0.5707	0.2619	0.4941
0.5942	0.1804	1.0000
0.5714	0.0400	0.6863
0.6010	0.6600	0.1961
0.5833	0.0870	0.8118
0.5709	0.1843	1.0000
0.5521	0.0821	0.7647
0.6181	0.1943	0.9686
0.6111	0.0252	0.9333
0.6087	0.1150	0.7843
0.7292	0.0460	0.6824
0.5667	0.0829	0.7098
0.0714	0.0402	0.6824
0.5104	0.2581	0.2431

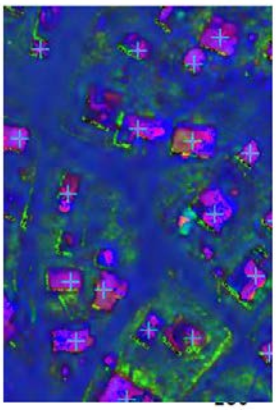

Figure 7: Extraction of values across the three bands (HSV).

It was observed that a similar spectral behavior to that of the ratios of the two shack roof types prevailed for values of dark and light roofed building types although the ratio values are less comparable. The NSI values between 0.5 and 0.8 proved to be the most reliable range for shack detection. These values could vary in extreme illumination situations. In the Figure 9 darker and lighter roof shacks are clearly identified at the suggested thresholds. The index proved to over detect shacks for lower thresholds and showed improved performance as the threshold value increased. This confirmed that in slum areas hue values tend to be significantly larger than "value" values. This index emulated a background foreground separation as it would occur for a human observer searching for shacks in an image who would identify shack candidates as foreground while ignoring the rest of the land covers in the slum area as irrelevant background.

This process was repeated several times on the background image (iterated) with a slightly adjusted NSI threshold for each run (adjusted by 0.5) until no new shack regions merged into the fore. This was substantially done in order to minimise the percentage of error resulting from slum areas being wrongly classified as background. The researcher also observed that even after "iteratively" updating the fore ground, some small portions of background are included with the shack areas. The opposite process to the background updating described above, was likewise computed. The application of the NSI on aerial imagery resulted in shack candidates that contained one or more units within their extent (Figure 10).

This was not the desired outcome for the micro reconstruction as the aim is to design an optimal technique for the isolation of single units. The NSI derived candidates were split by watershed transformation. The outlines from this macro settlement identification became seed areas for the micro reconstruction. NSI method was applied to each of the stack levels individually then once the individual shack units are identified per level their boundaries are traced. The final polygons to be traced are derived from the intersection of the strongest oultiles across the child images as computed in the image stack. This was determined by the application of the intersection function on the stack that allowed for the strongest polygon features to be identified and cleaned in order to be upheld as true shack roof edges.

These are then used for boundary tracing. The boundary tracing tool applied in the study used a clockwise tracing approach based on searching and enveloping the closest polygon vertex within an 8-pixel

Land Cover	Hue Range	Saturation Range	"Value" Range
Road	0.05-0.1	0.2-0.3	0.6-0.7
Tarred Road	0.3-0.4	0.2-0.3	0.1-0.2
Sluml1 (lighter roof)	0.5-0.8	0.2 -0.3	0.8-1.0
Slum 2 (darker roof)	0.6-0.8	0.04-0.08	0.5-0.7
Vegetation	0.1-0.2	0.4-0.5	0.1-0.2
Shadow	0.1-0.2	0.9-1.0	0.2-0.3
Building roof 1	0.4-0.6	0.1-0.2	0.7-0.8
Building roof 2	0.05-0.1	0.1-0.2	0.4-0.5

Table 2: Spectral properties of various land covers in HSV channel.

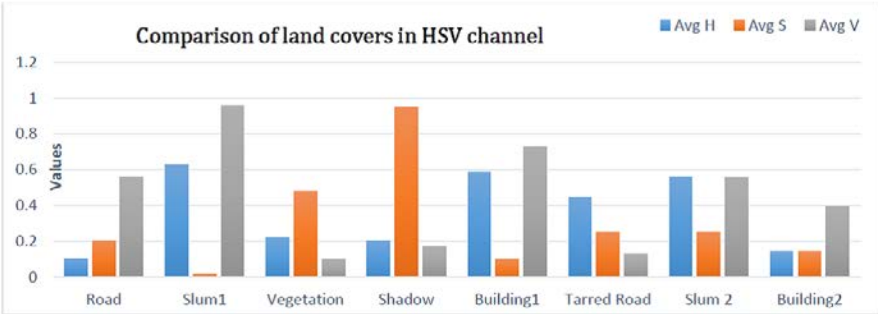

Figure 8: Graphical comparison of image land covers in Hue, Saturation “Value” channel.

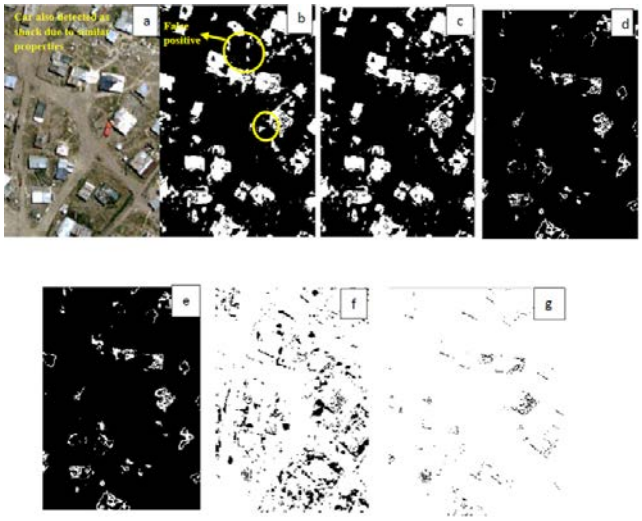

Figure 9: Original image and detected shack candidates using NSI at thresholds sequentially at b) 0.8, c) 0.7, d) 0.5, e) 0, f)-0.5 g) -1 (shacks are white).

Figure 10: Shack candidates constituting the foreground in larger scene.

search neighbourhood. The tracing resulted in snapped or closed boundary polygons for defined polygons and did not trace holes within the parent polygons. Afterwards simple shape fitness heuristic was computed to validate that the geometry of the derived polygons was near regular. This shape heuristic is commonly applied to establish the nature of shapes in medical image processing and its suitability to shack reconstruction is found to be favourable. The shape metric tests whether derived polygons are more square or rectangular in nature. Figure 11 shows some outputs of different distance transform effects on the splitting process.

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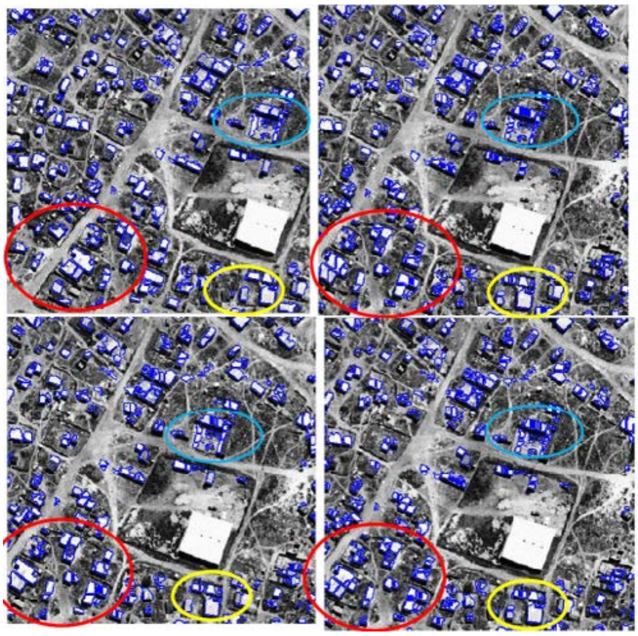

Figure 11: Circles highlighting different splitting scenarios based on the watershed segmentation output to split shack polygons using a) Chessboard b) City-block c) Quasi-Euclidean d) Euclidean distance transform.

The research showed that a multi scale approach to shack extraction improves the likelihood of identifying shack roof outlines. The detection performance of the proposed strategy was found to be 94.43% when compared to a manually digitized reference layer. In summary the research achieved its objectives. It displayed that an informal settlement layout can be inspirational and useful to developing a methodology for shack extraction at both macro and micro level in aerial imagery.

Conclusion

This study developed a method employing ALS and aerial photography to identify and locate slum areas, as well as map the individual shack units within the CoCT settlements. On computing accuracy metrics, the following outcomes for different sample scenes were obtained. The high shack detection percentage shows a high shack identification rate by the proposed method with an average of 94.43% as compared to the total number of shacks identified in the manually generated layer. The limitations of the study included the fact that the prescribed method is resolution dependent and will display less reliable results when computed at coarser resolutions. Some tweaking would be necessary to adjust it accordingly should a change be required. Another limitation of the research was that there was no ground-truthing which could be carried out to confirm that the identified units are in fact household units. This was due to poor accessibility and security concerns in conducting a ground survey in the informal neighborhoods on a door to door basis. This limited access to some ground data reduces the possibility of discarding non-shack entities among the units identified as shacks. This limited access to ground data made it impossible to detect units which were incorrectly identified as shacks, among these the roofs of "tuck" shops and service providing units. Moreover, the derived slum signature is not valid for double storey or complex shaped shacks which occur in rare cases.

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