Local ontologies for object-based slum identification and classification

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ABSTRACT:

One of the consequences of rapid urbanization in developing countries is the proliferation of slums. Lack of quantified, updated and spatially disaggregated information on slums contributes to incomplete intervention and monitoring. The identification, delineation and characterization of slums spatially in a consistent manner will make it possible to target slum intervention programs as well as improve understanding of the phenomena geographically. We propose an ontological approach to define slums based on indicators related to the morphology of the built environment and address the issue of varying conditions by comparing two completely different contexts. The ontological indicators form the basis of object-oriented image analysis (OOA) and classification of slums. Examples from Kisumu (Kenya) and Ahmedabad (India) illustrate how these indicators might be applied.

1. introduction

Rapid urbanization has led to the migration of people from rural to urban areas in search of better opportunities like employment and services. This has increased the demand of affordable housing in these areas. However, most of the urban economies of the developing countries are unable to meet these demands leading to movement of people to the affordable slum areas, further contributing to the growing number of slum population. According to UN-HABITAT (2003), the biggest proportion of world's total slum population is from the developing world. Every year, world's slum population is increased by about 6 million people leading to greater demand of provision for shelter, employment and urban services. To achieve improvement in conditions, there is a need to have adequate information.

Remote Sensing (RS) based methods can help to get spatially disaggregated and updated information through effective detection at different spatial scales. With the increasing availability of VHR satellite imagery, avenues are open for better analysis and automation. (Sliuzas et al., 2008). But, the first step towards this is to deal with the variability of slums across the world and have a comprehensive definition as a basis for image-based identification and characterization. This step calls for formulation of a standardized definition first, which could make international comparisons and monitoring possible.

2. generic ontology of slums

Kohli et al. (2012) proposed an ontological framework for defining slums as a basis for image-based classification that recognized the variability in definitions and type of slums across different contexts. The authors identified classes at three levels to conceptualize slums using the morphological indicators, in addition to site conditions (see Figure 1). In this paper, we adapt the generic ontology proposed by their work to two completely different contexts, i.e. Kisumu, Kenya and Ahmedabad, India. These localized slum ontologies are used as a basis for object-based image classification of slums in both areas.

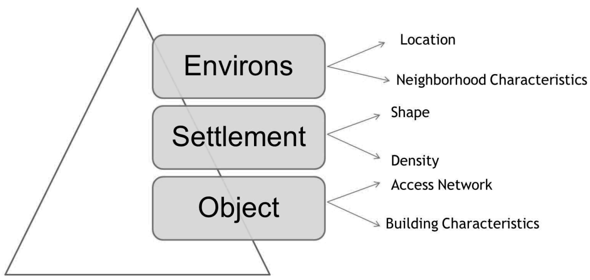

Figure 1 Concepts of ontology at three levels (after Kohli et al. (2012))

3. local adaptation of generic ontology

Image analysis should be based upon a sound concept translated into methodological steps which is used to recognize the objects of interest. To formulate a strategy to extract slums from the image it is important to answer the question: what characteristics of the slums can be derived from the image? To retrieve the necessary information to describe a slum relevant for a specific study area, the generic slum ontology was adapted to each local context, by combining knowledge from input from local experts and visual interpretation of the image. As shown in Figure 1, slum indicators are identified at three levels: object level, settlement level and environs level. Object level comprises of building characteristics observable via VHR images, such as roof material, footprint, shape, orientation, type, height, access network characteristics such as connected/not connected with surroundings, regular/irregular structure, and type and width of roads. Settlement level consists of the development characteristics of the settlement referring to overall shape and density. Environs comprise the location of slums with respect to socio-economic status and hazard-prone areas.

We test the generic ontology on the two cities from completely different contexts in order to test the robustness of the developed method. Indian cities are experiencing tremendous growth, but due to the lack of infrastructure, the slum population is continuously increasing. The mega cities, but most importantly medium and small cities, lack sufficient data about slum areas and thus require an efficient system for monitoring of physical development of slums. In Kenya, on the other hand, slum-like conditions often form a dominant component of cities, and data availability and human resources are often scarce. In the following sections, we discuss the application of the ontological concepts for the two study areas.

3.1 Kisumu

In Kisumu, slum settlements display a clear contrast to the planned areas (Figure 2). The characteristics at three spatial levels are explained as follows:

3.1.1 Object level

- The majority of the roofs are constructed from rusty iron sheets. The colour of the roofs mostly range from bright grey to dark brown, few have bright blue and red.
- Shape of roof is mostly L-shaped, U-shaped.
- Type of housing: row houses most common.
- Most of the houses are single storied.
- Irregular patterns of buildings with variable orientation.
- Internally the slums are connected with irregular, unpaved road network.

3.1.2 Settlement level

- Irregular shape of the overall settlements, basically encircling the planned centre areas.
- Variable densities among various slum-clusters.
- Some slum-clusters on swampy areas.

Figure 2 A subset of 2009 GeoEye image of Kisumu city. The highlighted area shows the slum area.

3.1.3 Environs

- Towards the lake and south of the old town is a permanent swamp, periodically linked to the lake during rainy season. These plains comprise of Nyalenda, Chiga and Nyalunda slums.
- At the hinterland of Kisumu there is mushrooming of unplanned settlements that are surrounded by farmlands.

3.2 Ahmedabad

Ahmedabad slums have the following characteristics:

3.2.1 Object level

- Roofs are overlapping for different dwellings and generally less bright than formal settlements generally gray, dark gray or bluish gray in color.
- The roof material is generally tin, thatched or mangalore tiles.
- The relatively small footprint of houses is also good distinguishing characteristic from planned buildings.
- The building type of slum in most of the cases is attached.
- Most of the slums comprise of just irregular access roads or footpaths with a variable widths.

3.2.2 Settlement level

- Shape of the slums at settlement level is irregular
- Highly dense compared to formal settlements

3.2.3 Environs

- Most of the slums are connected with surrounding areas.
- Located close to highways, major roads, railways and particularly along river which may be prone to seasonal flooding.
- Small pockets located close to employment opportunities such as CBD, middle/high socio-economic status areas.

4. Linking ontology and ooa based image classification

4.1 Local ontology

Ontology integrates subjectivity with objectivity by implementing an explicit cognitive structure that facilitates accurate and effective communication of meaning in a domain (Gasevic et al., 2009). This concept is being explored in the field of remote sensing also, to address the uncertainty in object-reconstruction in an image based on knowledge of real-world. Agouris et al.(1999) suggest that it is important to have an ontological understanding of the clear definitions and relations of objects on image and real world so as to address the uncertainties in spatial analysis. We use local ontologies as a basis for identification and classification of the slums (Table 1). The ontological framework helped to create rules to be applied in object-oriented classification.

The process included converting prior knowledge to methodological steps which can be fed into the computer for it to recognize the object of interest and in a way, imitating the human visual interpretation process. Since the ontology is defined at three levels it can establish different relations with neighboring areas and thus help to determine relevant parameters for creating set of rules in OOA. The local ontology guided the OOA parameterization in Definiens software (Definiens, 2009). The relevance of indicators in classifying meaningful objects for different subsets of the image is discussed in the subsequent section. Some indicators proved to be important in identifying relevant objects, whereas others did not produce good results.

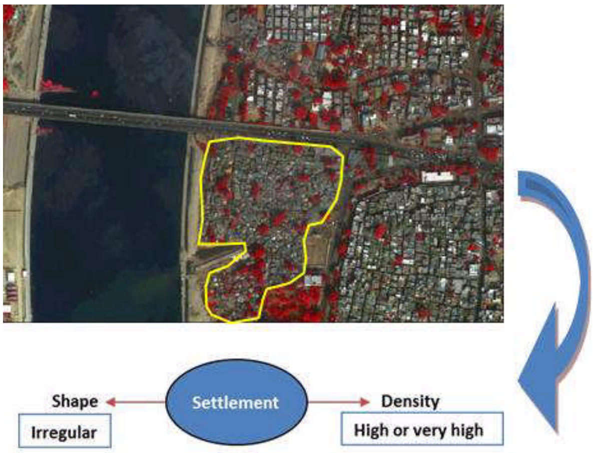

Figure 3 Integrating knowledge from local ontology of Ahmedabad at settlement level

4.2 Segmentation

The first step in OOA is image segmentation, i.e. dividing the image into regions or objects of homogeneous pixel values within the segmented objects. Multi-resolution segmentation is a type of bottom-up segmentation method based on a pair wise region merging technique, which for a given number of image objects minimizes the average heterogeneity and maximizes their respective homogeneity (Definiens, 2009). A sequence of steps using feature properties can be repeated number of times till all the objects are classified or desired results are obtained. To make an objective choice of scale parameter that controls the amount of heterogeneity within segments, ESP (Estimating Scale Parameter) tool (Dr•gu• et al., 2010) was used. ESP tool can be used to find the thresholds in the rate of change of local variance at appropriate scales.

This process generated image objects representing individual buildings in planned areas, building clusters in slums in addition to other classes. This later helped in classification based on the area feature in Ahmedabad as the slum segments tended to be larger than individual formal buildings. For Kisumu, we used trial and error to guide the segmentation. Three scale factors were used to classify objects at three levels. Small scale factor and higher weight on shape factor was assigned to level 1 so as to target shadow, buildings and vegetation. In the second level, segmentation based on multi-resolution segmentation was increased to classify roads. In the third level chessboard segmentation was carried out targeting the settlements and to investigate the possibility of differentiating slum from non-slum by using texture.

4.3 Classification results

4.3.1 Ahmedabad

An image subset comprising the centre part of the city was used for classification. It comprises of vegetation, river, residential, commercial buildings and slums. Due to high variability in the built-up area of the image it was difficult to classify the built-up area using spectral values of the blue, green or red bands alone or any combination of these bands. The GLCM Entropy of the red band was used to classify the built-up area. In the formal settlements individual buildings could be detected; however, the dwellings in slums, being attached and closely packed (Table 1), were detected at settlement level. This fact

Table 1 Analyses of local slum characteristics at the three ontological levels and translation into indicators for OOA

Level	Indicators	Interpretation element	Observation (Ahmedabad)	Observation (Kisumu)	Indicators for OOA
Environs	Location	Pattern, secondary data	Close to highways, major roads, railways, lakes and along river which may be prone to seasonal flooding	On flood zones, marshy areas, close to farmlands, and along highways	Association
	Neighborhood characteristics	Pattern, secondary data	Close to employment opportunities such as CBD, middle/high socio-economic status neighborhoods.	Surrounding the planned areas, close to employment	Association
Settlement level	Shape	Pattern	Irregular shape, elongated along river	Encircling the major ring road	Geometry
	Density	Texture	Denser compared to planned Low/No vegetation and open spaces	Denser compared to planned Low vegetation and open spaces	Texture
Object level	Building	Shape Size Material Color Orientation	variable Range of values - 10 to 40 m^2 Roofs-corrugated iron sheets, tin, concrete, plastic, thatch Range-grey, brown, white Haphazard, clumped together	Rectangular forming L/U shapes Range of values - 10 to 40 m^2 Roofs-corrugated iron sheets, tin Range-grey, brown, red and blue Haphazard arrangement	Spectral/ Geometry
	Access network	Shape Type Width	Irregular Paved/unpaved access streets Range – variable	Irregular Unpaved access paths Range – 1 to 3 m	Spectral/ Geometry

is also supported by the local ontology of slums for Ahmedabad (Fig 3).

The local ontology of Ahmedabad (Table 1) has slums located particularly along the river. We created a buffer of 500 pixels along the river to analyse the built-up area in this buffer and to extract slums within it. Misclassifications were removed by applying additional criteria for refining the classification results. Most of the slums were detected as different patches along the river by using the following parameters: relative border to shadow, GLCM Contrast of blue and red bands. The logic behind using relative border to shadow is that, since the slum buildings are closely packed as mentioned in the ontology, they cast very small shadows compared to the formal settlement buildings or multi-storey buildings. GLCM Contrast of blue and red bands clearly showed different contrast between slums and formal settlements. A vector layer, digitized by a local planner with boundaries of slums within the image subset was used to verify the results. The overall accuracy before clean-up was 76 percent. Clean-up was done using Rel. border to shadow, vegetation and area. Area of segments was very good indicator for clean-up, since slum segments were mostly in the form of relatively large patches and not as individual buildings. Area was also used outside the buffer to find any slum patches away from the river (Fig 4). The overall accuracy after clean-up was 92 percent.

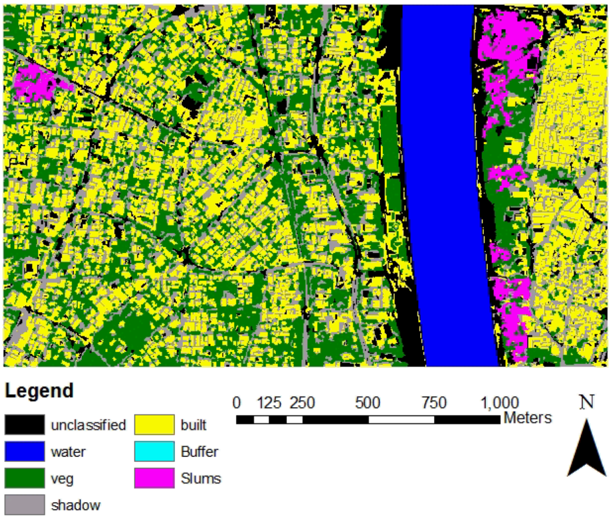

Figure 4 Classified image of Ahmedabad, with most slums forming a strip along the river

4.1.2 Kisumu

As shown in figure 2, slums in Kisumu display a clear contrast as compared to the planned areas. For classification, building and road characteristics were very important as evident from the local ontology. Layer brightness values and shape features were used to classify buildings. There was a lot of mixing between bare-soil and rusted iron sheets. To identify slum buildings based on their shadow, relation between sunlight and building was analysed. Angle to a single object was used to locate buildings on the sun side of shadow. In combination, the irregularity of access network, using the "branches of order" feature, could be used to classify slum and non-slum roads. This is because the roads in planned areas are regular and symmetric compared to slum roads. The distance from slum roads was then used to classify slum buildings. GLCM Contrast was used to refine the results as there is a difference in texture between the planned and the slum areas. The buildings in the planned areas have a regular orientation and appear to be homogeneous in character, while in the slums the buildings are haphazard and heterogeneous. Another reason explaining the difference in texture is the difference in the density of buildings. The planned areas have a low density, while the slum areas have high density with clustering of buildings. Areas with low texture were associated with planned areas and areas with high texture were associated to slum areas. This analysis demonstrates that texture is robust enough as regards the detection of the slum areas, despite of some noise that appeared in the results (Fig 5).

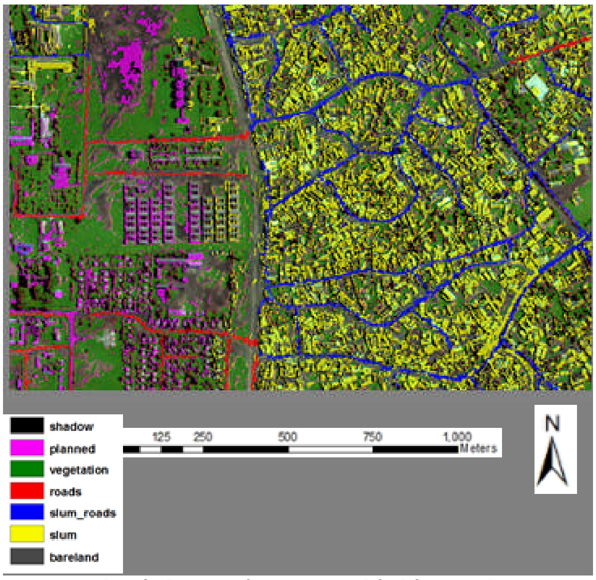

Figure 5 Classified image of Kisumu (modified from Mathenge (2011))

5. conclusion and research direction

Slum definitions and appearances vary in different contexts. This makes transferability of an approach from one area to another a major concern. In this paper we provide a systematic approach for identification and classification of slums. The OOA parameterization is based on the knowledge about slums from local ontology. In our study, we have considered two aspects of slum ontology: generic and local ontology. The former describes the general characteristics of all slums at the global level. In the latter, the generic ontology is adapted to the characteristics of the slums in Kisumu and Ahmedabad. By exhibiting two examples, we have shown that local ontologies guided slum identification in a systematic way by providing a comprehensive framework which integrates context specific knowledge.

The two above examples display two completely distinct case studies. The lack of reference data for accuracy assessment still remains a challenge. In Ahmedabad, knowledge from a local planner could be used for this purpose. A question that remains is - Can such reference data be used as benchmark for accuracy assessment? This problem is accentuated by the fact that there are political, administrative as well as physical aspects related to slum definitions. For e.g. the old city cores of most Indian cities are dense neighborhoods with dilapidated housing conditions. How do they differ from slums? These questions constitute our research in investigation.

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