Practical Sketch Recognition Approaches for Land Tenure Mapping

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Summary

SmartSkeMa is a system for recording land tenure information using sketch maps. We present in this paper SmartSkeMa's methodology for producing sketches which is both practical for undertaking fieldwork and facilitates accurate recognition of drawn objects. We justify our approach by presenting results of an empirical evaluation of two prominent computer vision methods in the context of geographic sketch recognition.

KEYWORDS: sketch maps, community mapping, land tenure, object detection.

1. Introduction

Hand drawn sketch maps have been considered a particularly useful tool in community mapping as they facilitate collaborative map creation among participants involved in the exercise [4]. Current approaches using sketch maps have limitations. In some approaches sketch maps are stored as is and are used as sources of reference information within the community. Such data invariably lack the contextual details required to make them interoperable with other data sources. Yet other approaches go further and involve the manual digitization of the sketch maps into a GIS system, enriching the data with a geographic context. However, even in this case the data may fail to accurately capture significant social values and norms that govern human relationships on land. Firstly, if the sketches are not standardised, their interpretations may be inaccurate. Secondly, the manual digitization and interpretation task is arduous and prone to human error.

To deal with these challenges we present a system called the Smart Sketch Maps tool, SmartSkeMa (pronounced smärt skē-mə) in short, for recording land tenure information within the context of rural and peri-urban communities based on sketch maps. Our tool is composed of several components that come together to provide a single function: integrating the user's sketch into a base topographic dataset. Figure 1 gives an overview of the SmartSkeMa workflow.

In this expose we present a combination of methods used in SmartSkeMa to facilitate automatic recognition and interpretation of useful objects in sketch maps. Our main contributions are:

1. a methodology for producing sketches that is both practical for undertaking fieldwork and facilitates accurate recognition using techniques from computer vision (Sections 2 and 3).
2. an empirical evaluation of two prominent computer vision methods (HOG and SVM) in the context of geographic sketch recognition; we also compare practicality and ease of deployment and use of these methods (Section 4).

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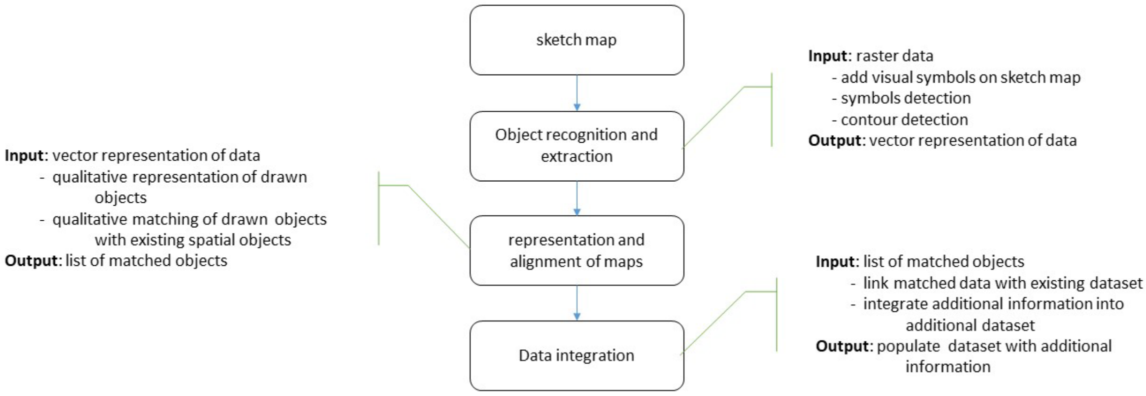

Figure 1 Overview of the SmartSkeMa workflow

2. Smart Sketch Maps: A comprehensive system for community based land tenure recording

The SmartSkeMa system is being designed to support a bottom-up approach to land tenure recording. In particular, the system is evolving to target local authorities and non-governmental organizations in the use of sketching as a method for creating land tenure, land use and land resource maps.

In our work we assume that sketching is completely analogue in that no digital sketching tools are used. Sketches can be drawn on a piece of paper (Figure 2a), or on the ground using white or colored chalks (Figure 2b). The two example sketches are drawn during sketching session with the Massai community of Southern Kenya. Shapes and symbols used to communicate information through sketches vary widely between participants, introducing challenges for both sketch interpretation and the technical computer vision challenge of automatically identifying meaningful objects.

(a) (b)

Figure 2 (a) Sketch map drawn on a pioece of paper, (b) sketch on the ground using white and colord chalks by the Massai community

To address these practical issues, both for producing useful sketches quickly in a workshop environment and for ensuring satisfactory recognition accuracy, we have developed an approach of using stamps to place visual language symbols into the map. Stamps are cheap to make and once a community has committed to mapping the land using sketch maps stamps can be used repeatedly. For SmartSkeMa, stamps are a powerful tool that greatly simplify the interpretation of the sketch map. Figure 3 presents a subset of stamps used during our workshops.

The particular visual language we employ is based on an ontology that we developed for land use concepts of Massai community. Our ontology consists of 280 concepts, 17 of which are assigned visual symbols for sketching. Further details of the ontology are beyond the scope of this paper (the latest publically available version of the ontology can be downloaded as an owl ontology at http://www.sketchmapia.de/its4land-domain-model).

Figure 3 Set of symbols extracted from the Masai ontology. From left to right: marsh, mountain, olopololi, otilinka, house, boma

This paper focuses on demonstrating how the image processing modules of SmartSkeMa perform object recognition and interpretation. Object recognition and interpretation facilitate the extraction of meaningful objects from the sketch maps. In next sections we present the workflow used for symbol detection and object extraction followed by an evaluation to demonstrate the performance of the different approaches used.

3. Object Recognition in Land Tenure Sketch Maps using Symbol and Contour Detection

In SmartSkeMa, object recognition is based on the structure of the sketch maps that we anticipate. In general, a sketch is considered as a set of strokes configured in such a way that groups form an object. The task is to interpret these objects in terms of particular concepts. SmartSkeMa begins by identifying the position of symbols which can be used to apply labels to sketched objects. Afterwards, the drawn objects are identified by detecting the outer contours around the identified symbols (Figure 4).

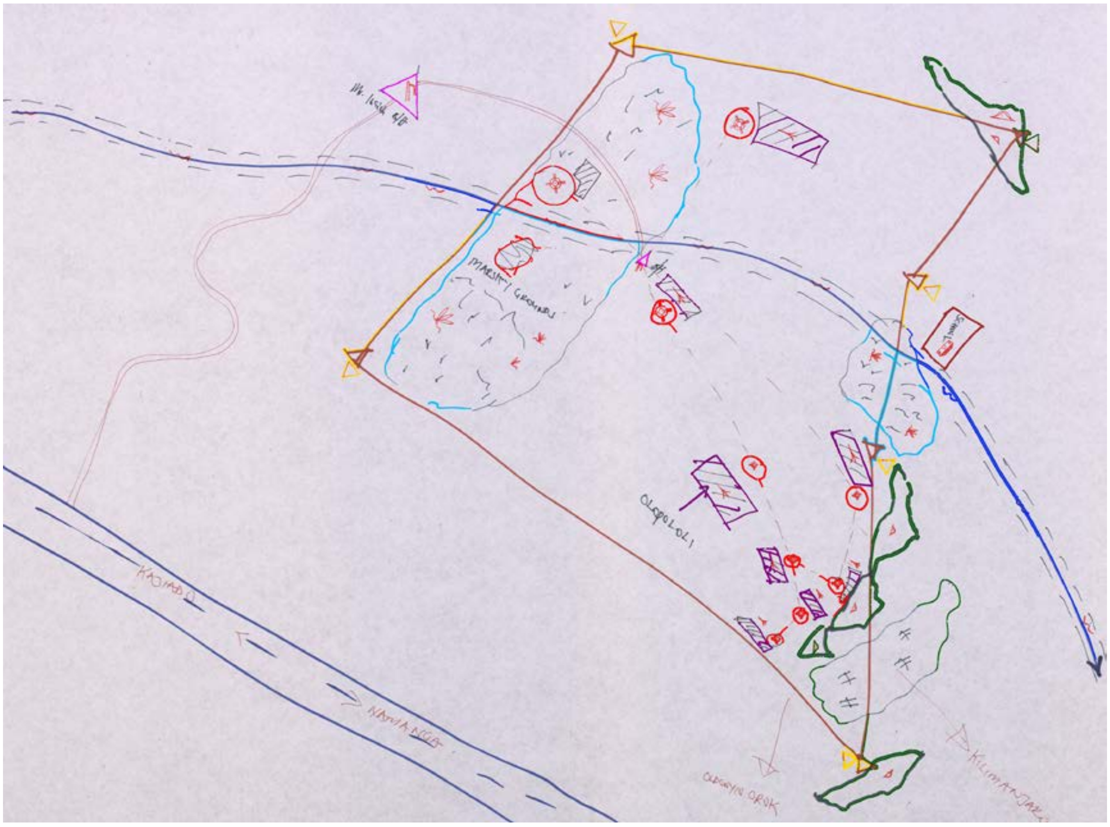

Figure 4 Contour detection – light blue for marsh-land symbol, green for mountain symbol, red for homestead symbol, dark blue for water (river section), and yellow for boundary beacon.

For detecting drawn objects, we have explored three well known matching approaches in the area of computer vision. Initially, a template based matching method was used. Because of its poor performance the method was then extended to supervised learning using Haar cascades [2] and Histogram of Oriented Gradients (HOG) together with Support Vector Machines (SVM) [1]. In the HOG feature descriptor, the distribution of the magnitudes and orientations of gradients over differences in pixel intensities are used as features [2]. The HOG descriptors for object recognition are a relatively new approach, capable of providing high accuracy of recognition with a small training dataset. The dlib library‡‡ provides the function **fit** which does the heavy work of fitting the model (i.e. generating the HOG descriptors) to the training data. Dlib also creates **detector**s, which are objects that implement the scanning of an image for occurrences of the objects of interest as prescribed by the HOG descriptors. For evaluation we have implemented prototypes for two of the approaches as python Jupyter notebooks using the OpenCV library.

4. Evaluation

To train the haar like cascade classifiers, 6 datasets with 550 positive samples containing the object of interest and 1100 negatives were used. The symbols used in the evaluation are shown in Figure 3. In contrast, due to the low structural variability of the stamps, we noticed that there was not a significant performance improvement on the HOG classifiers when using a large amount of samples, hence, the datasets used to train them, only contained 30 positive images. Classifiers were evaluated on a testing dataset of 350 images. Figure 5 shows an example result of the symbol detection phase.

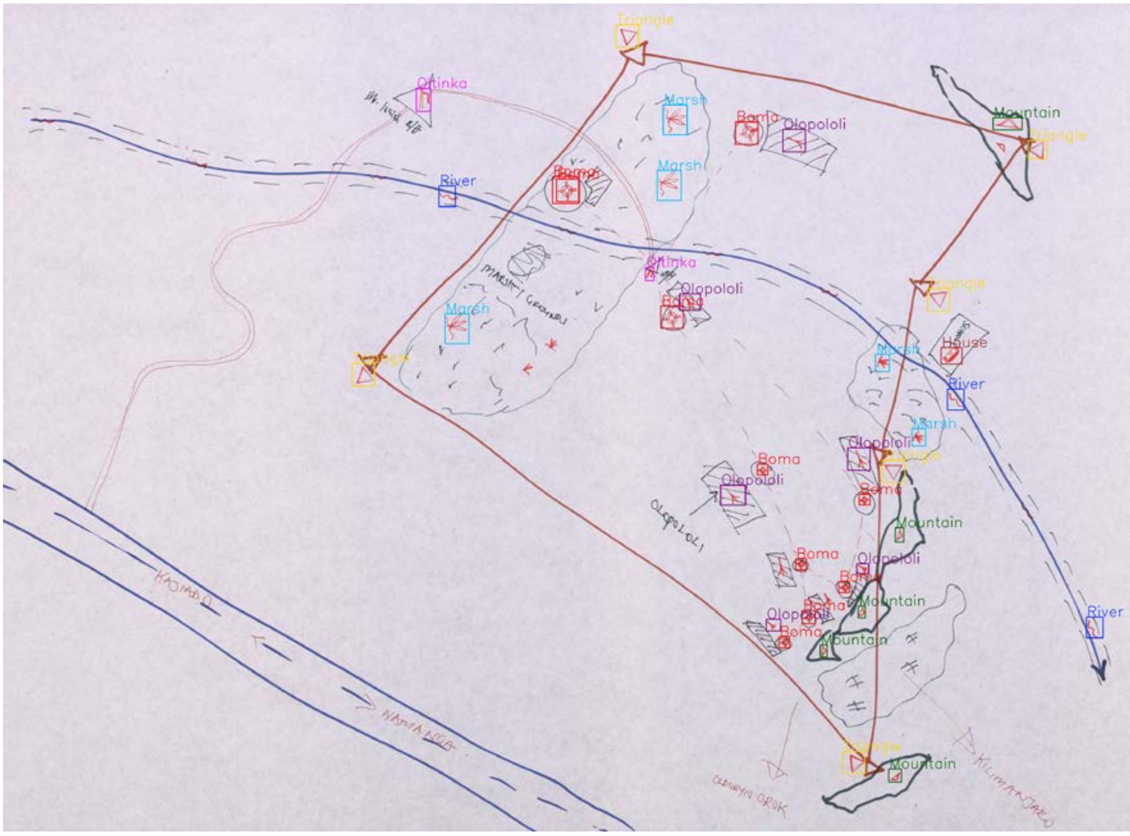

Figure 5 Example output of the HOG object detectors

Based on the testing results, four metrics were computed to measure the classifier's performance: True Positive Rate, False Negative Rate, Precision and number of False Positives; see Tables 1, 2.

Overall, the evaluation shows that HOG is more suitable for object detection in sketches. HOG gives higher True Positive Rate and Precision with a lower False Negative Rate (Tables 1 and 2), meaning

‡‡ http://dlib.net/imaging.html

that there is high likelihood of both, detecting almost all the objects of interest [3]. Moreover, HOG required shorter training times (~20 seconds) than Haar Cascades (~30 minutes) per symbol.

Table 1 HOG performance metrics.

HOG				
	Total no of positive symbols			
Object	True Positives	False Negatives	False Positive	Precision
Mountain	66 (91.7%)	6 (8.3%)	1	98.5%
Olopololi	50 (100%)	0 (0.0%)	1	98.0%
Marsh	67 (97.1%)	2 (2.9%)	0	100%
Boma	74 (96.1%)	3 (3.9%)	0	100%
House	22 (66.7%)	11 (33.3%)	0	100%

Table 2 Haar cascades performance metrics.

Haar-Cascade				
	Total no of positive symbols			
Object	True Positives	False Negatives	False Positive	Precision
Mountain	43 (59.7%)	29 (40.3%)	11	59.7%
Olopololi	45 (90%)	5 (10.0%)	4	90.0%
Marsh	65 (85.5%)	11 (14.5%)	9	85.5%
Boma	74 (96.1%)	3 (3.9%)	10	96.1%
House	24 (72.7%)	9 (27.3%)	1	72.7%

5. Conclusion

In this paper we examined two object detection approaches. We identified HOG as a suitable method for detecting drawn objects in sketch maps. The evaluation shows that HOG together SVM enables object detection with higher accuracy. This enables SmartSkeMa to automatically digitize drawn objects and assign meaningful interpretations to them.

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