Horizon 2020
European Union funding
for Research & Innovation

ITS4LAND
innovations for land tenure

Deliverable 3.2

Semantic recognition of sketched objects

1st August 2017

Version 1.0

Abstract:
This report documents its4land tools for semantic recognition of objects in hand-drawn sketch maps

Project Number: 687828
Work Package: 3
Lead: WWU Münster
Type: DEC
Dissemination: Public
Delivery Date: August 01 2017
Actual Delivery Date: August 01 2017

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Executive Summary

This documents reports the outcomes of work leading to deliverable D3.2 which is the second deliverable for work package WP3, Draw and Make. D3.2 consists of a set of methods and software implementations for extracting the geometric representations of conceptual objects drawn in sketch maps. In order to address the overall challenge of automatic understanding of land tenure sketch maps, we were required to consider three separate problems: i) understanding the structure of the images to be processed including the underlying semantics, ii) developing unified methods of sketching including a visual language and simplified sketching modalities, and iii) developing the required image processing workflows using existing techniques. During the first year of WP3 we used two distinct approaches to collect land tenure sketch maps; we experimented with three different sketching modalities from the participatory mapping literature; and we explored three different methods from the area of computer vision to perform symbol detection and object classification in sketch maps. As such D3.2 represents a multi-disciplinary approach to capturing land tenure related land use information.
Instructions for installation and use of the software delivered are given in the README files included in the software submission. An outline of the processes is given in the appendixes.

Data collection for D3.2 consisted of engaging participants in sketching exercises, first in an unconstrained setting at their homes and subsequently in a formal workshop at a meeting facility away from their homes. The initial sketch maps were used to develop the visual language which was verified in the second, follow up, data collection phase.

The semantic recognition system consists of set of modules each implemented as a standalone system for a specific part of the semantic sketch recognition task. The modules are i) an image pre-processing module which transforms the image into a format suitable for subsequent processing ii) a module for recognition of symbols symbols iii) a module for the extraction of contours and regions.

In this report we briefly outline the methods employed towards the realization of D3.2 and give a detailed description of the contents of the deliverable. The report is intended as a descriptive document of the tools delivered as D3.2 and at the same time as a preliminary user reference for readers wanting to test any of the tools.

Contents

1. Introduction

its4land is a European Commission Horizon 2020 project funded under its Industrial Leadership program, specifically the 'Leadership in enabling and industrial technologies – Information and Communication Technologies ICT (H2020-EU.2.1.1.)', under the call H2020-ICT-2015 – and the specific topic – 'International partnership building in low and middle income countries' ICT-39-2015.

its4land aims to deliver an innovative suite of land tenure recording tools that respond to sub Saharan Africa's immense challenge to rapidly and inexpensively map millions of unrecognised and/or unrecorded land rights in the region and register them in formal land administration systems. ICT innovation is intended to play a key role. Many existing ICT-based approaches to land tenure recording in the region have not been successful: disputes abound, investment is impeded, and the community's poorest lose out. its4land seeks to reinforce strategic collaboration between the EU and East Africa via a scalable and transferrable ICT solution. Established local, national, and international partnerships seek to drive the project results beyond R&D into the commercial realm. its4land combines an innovation process with emerging geospatial technologies, including Smart Sketch Maps, UAVs, automated feature extraction, and geocloud services, to deliver land recording services that are end-user responsive, market driven, and fit-for-purpose. The transdisciplinary work also develops supportive models for governance, capacity development, and business capitalisation. Gender sensitive analysis and design is also incorporated. Set in the East African development hotbeds of Rwanda, Kenya, and Ethiopia, its4land falls within TRL 5-7: 3 major phases host 8 work packages that enable contextualisation, design, and eventual land sector transformation. In line with Living Labs thinking, localised pilots and demonstrations are embedded in the design process. The experienced consortium is multi-sectorial, multi-national, and multidisciplinary. It includes SMEs and researchers from 3 EU countries and 3 East African countries: the necessary complementary skills and expertise is delivered. Responses to the range of barriers are prepared: strong networks across East Africa are key in mitigation. The tailored project management plan ensures clear milestones and deliverables, and supports result dissemination and exploitation: specific work packages and roles focus on the latter.

This document is directly linked to WP3 – "Draw and Make" of the its4land project. The primary objective of the work package is to develop a software tool (the Smart Sketch Maps or SSM system) for recording land tenure information within the context of rural and peri-urban communities based on hand-drawn sketch maps. The tool is composed of several components including a specialized domain model and a visual language for sketching, a system for automated recognition and extraction of objects in sketch maps, qualitative representation, and qualitative alignment of sketched information with underlying geo-referenced datasets. All these component come together to provide a single function: integrating the user's sketch into a base topographic dataset.

Work packages in the its4land project are organized into distinct tasks. D3.2 is one of three planned outputs of task T3.2 of WP3. This document seeks to represent D3.2: it intends to provide the results of the semantic recognition part of the overall Smart Sketch Maps system.

The “smart” in smart sketch maps is only realizable after explicitly drawn spatial object are identified and assigned a semantic category. Our system will allow users to submit a hand drawn sketch map produced during a community mapping exercises and then the semantic recognition tool will extract the boundaries of drawn objects and classify them into some semantic categories. For classifying the drawn objects, we have opted for prescribing a visual language as a set of symbols. The symbols are generated each of which represents a specific class of features (e.g. tree, dwelling, etc.). The predefined symbols will help to detect drawn features as well as categorizing them into semantic categories.

For matching symbols and recognizing contours of each drawn feature, we have explored three main approaches. We have implemented a prototype symbol recogniser that is capable of identifying a variety of symbols (trees, houses, water body symbols, grazing symbols, etc.). Our prototype is implemented on top of OpenCV, using the Histogram of Oriented Gradients (HOG) approach for image features together with linear Support Vector Machines (SVMs) [2]. The HOG features together with the SVMs (abbreviated HOG+SVM) form the model for detecting spatial objects in the input maps while OpenCV provides a set of tools for manipulating the images throughout the object detection process. Objects that are not interpreted as symbols arise only as regions. For recognizing these regions, we have used the sketch segmentation approach developed by Broelemann and Jiang [3, 4]. The approach extracts regions and classifies them into polygonal and linear features such as landmarks and line segments.

This report is structured as follows. Section 2 presents the use case scenario against which we are designing, Section 3 gives an overview of the study areas where data developing the SSM system were collected, and Section 4 presents the Data collection methodology. The main outcomes of our research in task T3.2 are discussed in Section 5 results of the research work, methodologies adopted in recognition spatial objects (Section 6), and conclusions (Section 7).

2. Sketching land tenure maps: use case scenario

In the Draw and Make work package (WP3), we aim at providing tools to collect and disseminate land use and land tenure information. The SSM system is being designed to support a bottom-up approach to land tenure and land use mapping. In particular SSM is evolving to target non-governmental organizations such as Namati and Water Aid in the use of sketching as a method for creating land tenure, land use and land resource maps.

The general use case scenario is one where members of a community are supported to create land use maps by hand and an organization (which may be private, non-governmental, or a government department) working with the community operates the SSM system making it available to the community as a service. Such a model fits well with some of the existing operational models of organizations involved community based participatory mapping work[1].

In such a model, the organization would engage the community to establish a standard for creating their maps specifying both the symbols and some rules about how the symbols are allowed to be composed into a map.

The mapping itself then occurs in several iterations starting with completely free hand drawn maps and evolving towards a standardized map in each iteration. To make the mapping more effective a few members of the community could be trained as volunteer mappers for the community and would be responsible for producing the final standardized maps.

[1] See http://spatialcollective.com/, https://namati.org/ourwork/communityland/, or http://www.landcoalition.org/ for example approaches.

3. Study Areas

We focused on two study areas within the context of rural and peri-urban communities in Kenya and Ethiopia. The Ethiopian cases focus on peri-urban and rural land certification. Meanwhile, the Kenyan cases address pastoralist land rights registration in the context of subdividing group ranches into private holdings – and associated land disputes with other land uses. We have selected one study area in each country based on the relevance of the tool for end-users. In Kenya, we have selected Kajiado County – Mailua ranch, while in Ethiopia we focus on Robit Bata kebele, a rural village near Bahir-Dar city.

Kajiado County is located between Nairobi County and the Republic of Tanzania. In Kajiado, land is mainly used for livestock rearing and crop growing. Nomadic pastoralism is still predominant throughout this county. Maasai pastoralists mainly occupy the area. In this specific area, the land tenure system is dominated by group ranches. Mailua ranch is one of the group ranches located in Kajiado Central. This use case area is selected because many people have embarked on the subdivision of group ranches without adequate survey control and without proper land use planning. In Ethiopia, Robit Bata rural kebele is selected because of the issues related to the high degree of land degradation and fragmentation. In order to tackle these problems, land tenure information via a community mapping is vital as input information for land consolidation purposes.

4. Data Collection

4.1. Field visits to Kajiado, Kenya

We have organized different workshops during our field visits to Kenya. In the first visit, we conducted experiments to collect freehand sketches from two families of Maasai pastoralists at Mailua ranch. Focusing on land issues, spatial information was collected via freehand sketches. A total of 20 participants (11 male and 9 female) participated in the experiments, and 20 sketch maps were collected in total. We also collected data from a third Maasai family living near Kajiado town (peri-urban), the site was selected because of their land issues, particularly, conflicts on the parcel boundaries. There were 12 participants (five female and seven male) and we have collected 12 land use sketch maps with parcel boundaries from this site.

In the second field visit, we organized two different workshops. The first workshop was organized with male community member of the Maasai tribe. During the workshop we showed different maps to raise awareness about different types of maps that can be used to present boundaries of the group ranches and privately owned land bordering the ranches, social facilities, land uses, and resources including wildlife. Afterwards, participants were asked to individually draw a large area sketch map including the spatial features such as mountains near and far, rivers, roads, marsh lands, thick forest and all man-made resources such as boma, water holes, olopololi, manyata (for young warriors), schools, hospitals, etc. From this workshop, 13 large-area sketch maps were produced.

The second workshop was conducted with female community members of the Maasai tribe. Participants were asked to draw a small-area sketch map focusing on drawing details inside the structure of the boma and mapping other man made resources around the boma such as water holes, olopololi, the manyata, schools, hospitals, etc. After mapping spatial features within and outside the boma, participants were asked to explain their individual sketch maps to other participants. Participants were actively involved in the group discussion and contributed additional information or missing information in the presented maps. Finally participants were asked to jointly draw large-area group sketch maps. We collected 13 individual sketch maps and two group sketch maps (contributed by all participants).

4.2. Field Visits to Bahir-Dar Ethipoia

In the first field trip, we visited different sites in Bahir-Dar city. The main purpose of these visits was to learn about the study sites and examine the feasibility of each site for our field work and to meet stakeholders. Following the visit, the Rural Kebele of Robit Bata was selected as a study area. Robit Bata is a rural area outside Bahir-Dar city experiencing a high level of land fragmentation. The farms have visible boundaries but there are also ditches used to create terraces because of the undulating terrain and sometimes these are not boundaries. There are also a lot of natural features including hills, rivers and Lake Tana. The morphology also presents good conditions for conducting UAV flights to collect orthophotos (WP4 and WP5).

In the second field visit, we conducted data collection workshop with the local community. The workshop was organized with 10 male and three female participants.

Similar to the Kenyan workshops, we initially introduced different types of maps to raise awareness about maps in general. Afterwards, participants were divided into groups according to where they lived so that nearby neighbours worked together. The participants were asked to draw a large-area group sketch map of their part of the kebele showing among other things their homes, church, hospital/clinic, schools, farms, and grazing areas. We collected 13 individual sketch maps and three detailed group sketch maps (contributed by all participants).

5. Results

During the execution of T3.2 a total of 73 sketch maps were collected across seven different sketching exercises. These data have informed our approach to sketch recognition and the design of an initial visual language for sketch maps. Data from the second round sketching exercises will be used to derive a revised version of the symbols in the visual language.

In addition to the identification of a suitable symbology, we experimented with different approaches to sketching, namely, simple pen and paper sketching, using stamps for sketch annotation, and sketching in the ground. Each of these methods has its own pros and cons, and the choice of which approach to employ depends on factors which are outside the scope of this work [8, 9].

At the end, the system for recognition of objects in sketch maps is informed by the experiences of the research team during the data collection phases of the project. The resulting system while based in part on the data collected from the field also constrains the types of sketch maps that can be used mostly for practical reasons. For example, symbols such as the small ticks representing grass in Figure 1 cannot be recognized and must therefore be ignored by the system.

In this section we summarize the outcomes of the research in task T3.2 that contributed to the realization of the deliverable D3.2. First we present an overview of the data collected during the field visits to Kenya and the innovations derived from that experience. Then we give a summarized description of the visual language developed from these data. Finally we describe the sketch recognition system at a high level.

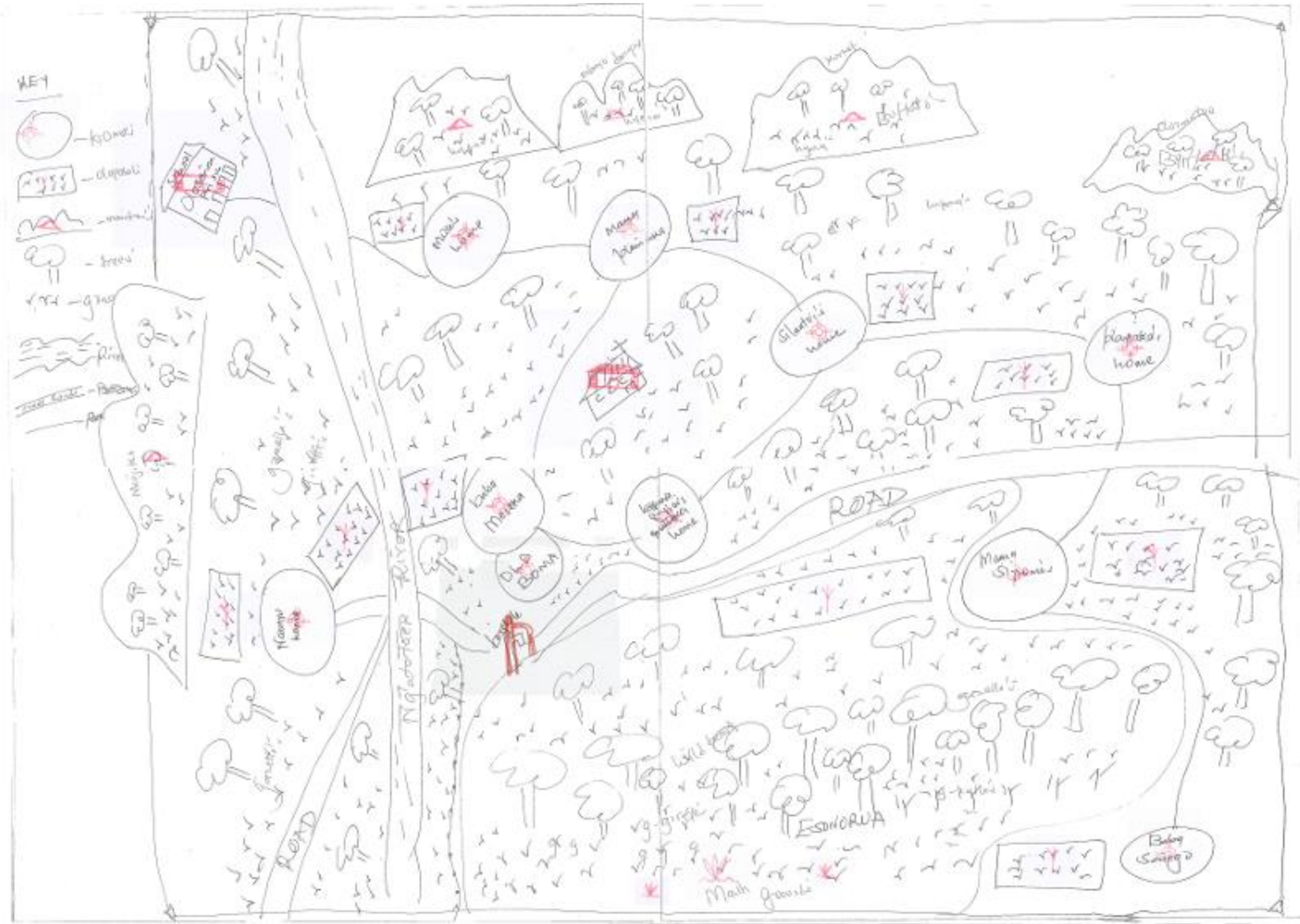
5.1. Collected Sketch Maps

From our two different field visits in Kenya and Ethiopia, we have collected a total of 73 sketch maps at two different scales. Out of 73 sketch maps, 44 are large area sketch maps containing spatial features such as mountains near and far, rivers, roads, marsh lands, and all man-made resources while the remaining sketch maps contains detail information about the internal structure of the boma and mapping other man made resources around.

The initial data collection exercises conducted in March 2017 provided insight into the sketching process and the workflows within which sketching can be suitably applied. All sketch maps collected were survey sketch maps. In addition, all but four of the sketch maps focussed on the homestead. Of the four sketch maps that covered a large area beyond the homestead only two were truly survey type maps showing details of resources between the different homesteads and other landmarks of interest.

A total of 28 sketch maps were collected during the second field visit to Kajiado, Kenya in June 2017. Of these 28 sketch maps, 13 sketch maps were drawn by male participants and were mostly a depiction of the boma locations within the sketcher’s ranch and the paths connecting the a boma to others. The female participants drew 13 individual sketch maps of their boma. All of these maps showed the actual dwellings (enkaji in Maasai), animal pens, and the entrances to the boma as common features.

Figure 1: Example sketch map from Kajiado, Kenya. This sketch map is included as an example to demonstrate the SSM object recognition tools



The female participants were also asked to prepare two joint sketch maps. The joint maps showed the configuration of all bomas in their respective group ranches as well as other features of interest within the group ranch such as wild life territories, hills or mountains and man-made water points where either a borehole or dam has been installed. The submitted software sources contain one of the joint maps (Figure1) as an example.

5.2. Visual language

The visual language consists of a set of symbols corresponding to relevant concepts in the Southern Kenya Maasai Ontology (see D3.1). The set of symbols identified so far is shown in Figure 2. The symbols were identified by extracting all the objects drawn in the sketch maps from Mailua and listing those that occurred in more than one sketch map. We then chose an arbitrary number of those as a way to initially minimize the amount of data used for subsequent development of the sketch recognition system.

The visual language is a dynamic object and can be modified by assigning new symbols to concepts or by defining rules that combine existing symbols to define new symbols. This is part of the work to be performed during task T3.3 as part of deliverable D3.3 of its4land.

5.3. Sketching modalities

During the data collection phase 3 main sketching modalities were explored based, partly, on ideas found in the literature. The standard sketching approach using pen and paper has been used by the team at WWU in several previous projects as evidenced in the extensive sketch map database of the Spatial Intelligence Lab[2]. This was the primary sketching approach to which our study participants were exposed.

The first alternative approach we introduced was the use of coloured chalk powder to draw large sketch maps in the ground (See Figure 3 for an example). This approach was chosen because we expected that it would be useful to foster interaction between members of the community during the sketching process. This method had already been documented in the participatory mapping training program by the EU-ACP Technical Centre for Agricultural and Rural Cooperation and the International Fund for Agricultural Development.3 As expected the ground sketching brought the group participants together to comment on the outcome including a woman who joined in to make her contribution to the map. One disadvantage of the ground sketches is that they may quickly expand to cover large areas that are then difficult to capture digitally, e.g. with a handheld camera. This was the main drawback to using this modality in the context of D3.2.

The final innovation introduced is the use of stamps to annotate sketch maps drawn on a piece of paper (see Figure 1 for an example of the idea). This addition was a novel contribution in that we have not seen it used elsewhere in the literature. The advantage it brings is technical.

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[2] https://www.uni-muenster.de/Geoinformatics/en/sketchmapia/sketch-map-database.php

[3] http://pgis-tk-en.cta.int/info/index.html

Figure 2: Symbols from the sample visual language developed from sketches and discussions held in Kajiado, Kenya

Figure 3: Ground sketch map drawn during sketching session at Mailua, Kajiado

Due to the great variations in the choice of symbols used by participants during sketching, it was necessary to find alternative ways to standardize some of the symbols used. Since not all symbols may come across as natural to all participants, the research team introduced the stamps in order to annotate important objects in the sketch maps. The advantage of using stamps is that stamps are relatively inexpensive to obtain and will ensure more similarity in symbols corresponding to important concepts across users. This ensures that the system's users can produce highly accurate classifiers with relatively little data.

5.4. Object recognition system

The main outputs of task T3.2, to date, are the two image classification tools forming deliverable D3.2. The first tool is a symbol detection software program that accepts as input an image and identifies the locations all symbols detected in the image. The second tool takes the output of the first tool and extracts regions of the sketch map corresponding to different types of objects.

5.5. Sketch recognition in sketch maps: a workflow

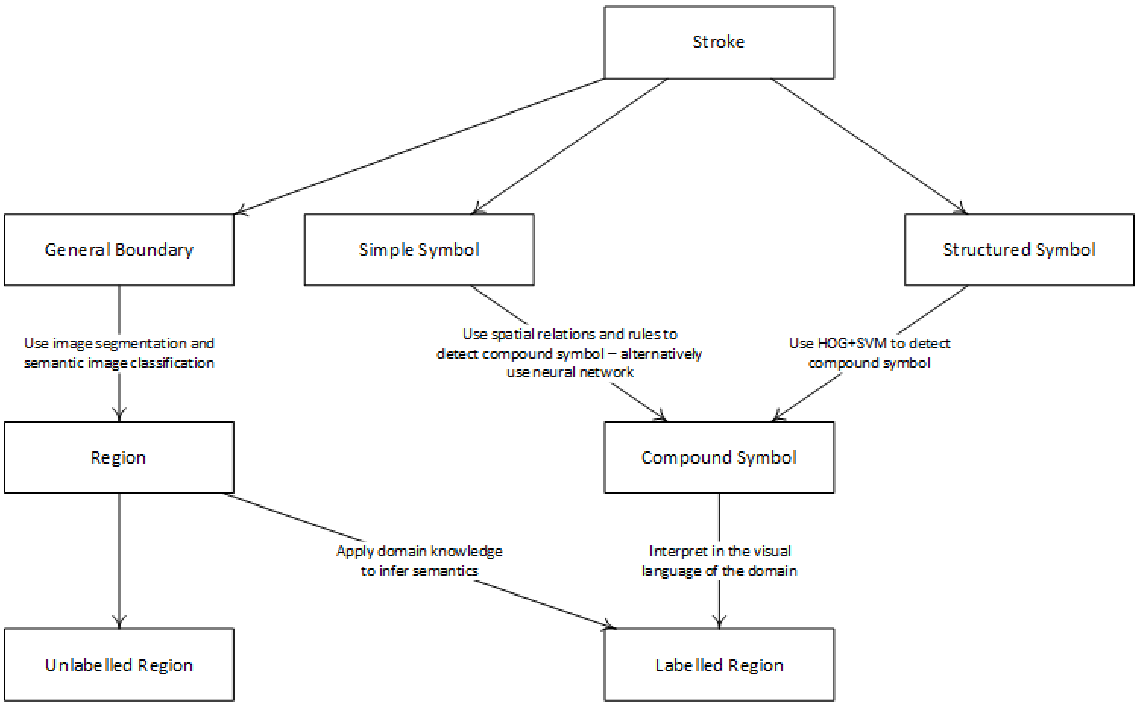
Our workflow for object recognition in a sketch map is based on the structure of the sketch maps that we anticipate. In general, a sketch is considered as a set of strokes configured in such a way that groups of strokes form an object. The object may be a symbol or it may represent a region. In both cases, the objects refer to specific concepts in the domain of application. The concepts may be specific or abstract. For example, a house symbol may represent a dwelling or in general a building.

In order to successfully detect all the objects in the image our workflow follows the structure shown in the Figure 4. The image is viewed as an array of pixels. The task is to identify sets of pixels in the image that form strokes and group the strokes into objects which can then be interpreted as representing particular concepts.

There are two kinds of objects as identified in the Sketchmapia project [7]. Those that play the role of containers are akin to Sketchmapia's city blocks. They form a global structure within which other objects are organized. The other kind of object of interest in

Sketchmapia is the landmark which can loosely be interpreted as those objects that are neither city blocks nor line-like features such as streets or rivers.

Figure 4: High-level view of the workflow for semantic object recognition in sketch maps

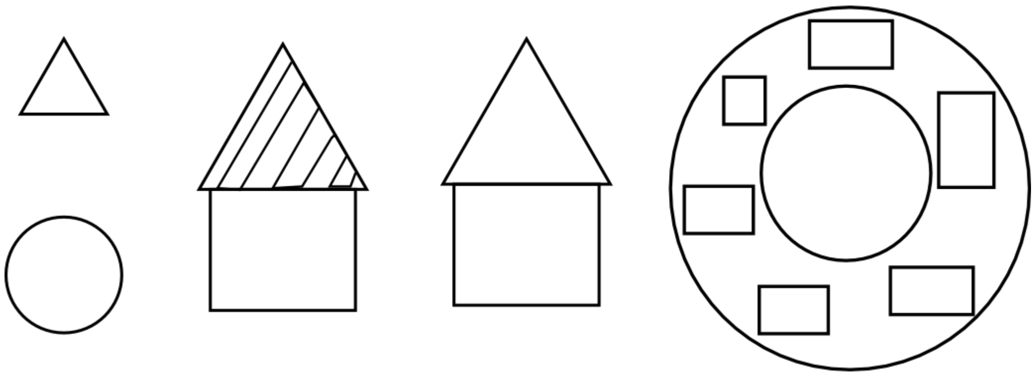


SSM begins by identifying symbols which can be used to apply labels to sketch objects. Once symbol positions are known, the associated concepts can then be assigned to regions of the image that have been recognized as objects. This two-step process is achieved by two independent systems.

Symbol detection

- For symbol detection, we classify symbols into two main groups. Atomic symbols and compound symbols (See Figure 5).
- Atomic symbols are symbols that are not ordinarily interpreted on their own but only in the context of their local surroundings.
- Compound symbols are composed of groups of atomic symbols and are interpreted relative to their contents as opposed to their surroundings.
- Atomic symbols can in turn be simple (e.g. triangle, oval, rectangles, etc.) or structured with complex configurations of strokes (window, hatched roof etc.).
- For compound symbols composed of structured atomic symbols, we use a HOG+SVM object detector to classify the drawn object. At the moment we use HOG+SVM for both, however
- For compound symbols composed of simple atomic symbols we will use qualitative spatial representations and spatial rules to classify the drawn object. Alternatively we may also explore a neural networks approach to detect the objects directly.

Figure 5: (left to right) Examples of simple atomic symbols, compound symbol with a structured atom, and compound symbols with simple atoms.



Region detection

- Objects that are not interpreted as symbols arise only as regions. The first step to the identification of such regions is the identification of their boundary. Here we employ an image segmentation based on edge detection followed by a classification that uses knowledge of the domain to obtain regions with particular semantics.

Assigning semantics

- Semantics are applied to a detected object in two ways. First when a symbol is detected, it can be assigned to its surrounding region provided the shape of the region satisfies the constraints determined by the symbol (e.g. mountains can be open on one end and streams must be line-like in that their lengths must be at least twice as large as their widths).

6. Methodologies for Object Recognition

For matching predefine symbols, we have adopted three well known matching approaches in the area of computer vision. We have implemented prototypes for each considered approach using the OpenCV technology. OpenCV[4] (Open Source Computer Vision Library) is released under a BSD license and hence it is free for both academic and commercial use. During our work a number of approaches to symbol detection were explored. Initially, a template based matching method was used. The method was then extended to supervised learning using Haar cascades to generate object classifiers [1]. Because both approaches proved to inefficient and inappropriate for object detection in hand drawn images, particularly given the variations in drawing symbols, we explored a the third approach, HOG+SVM.

6.1. Template Matching

Template Matching [5] is a high-level machine vision technique that identifies the parts on an image that match a predefined template. We have implemented a prototype for template matching using OpenCV (Java version). We created a catalogue of symbols from hand drawn sample images and expanded the set by rotating, scaling and blurring the original symbols. The expanded set of images was then used as the templates for our prototype. The prototype takes one template at a time and tries to match the corresponding symbols in the sketch map. After matching, the system captures the actual contour of the drawn object as a boundary. One of the main drawbacks of template matching is that the approach does not allow finding variations of the templates resulting from such as rotation, skewing and scaling.

6.2. Supervised Learning using Haar Cascades

As an alternative we also considered supervised learning using Haar cascades [1]. Haar classification is a tree-based technique where in the training phase, a statistically boosted rejection cascade is created. Boosted means that one strong classifier is created from weak classifiers, and a weak classifier is one that correctly gets the classification right in at least above fifty percent of the cases. The cascade itself is a structured set of feature descriptors. A feature descriptor can be thought of as a summary of some important feature in an image such as an intersection of two strokes (lines).

Cascades are useful if we want to match different occurrences with variations in factors like scale, rotation, and/or skewness of objects in the image. However, the approach requires very large datasets and computational time for training its descriptors, also known as cascades. For training a particular cascade, we need a huge number (at least 4000) of training samples. So we created a tool to automatically generate large datasets from a small number of samples and created cascades from our expanded sample sets (i.e. house, trees, building, etc.) to match different symbols in sketch maps. Despite these efforts, even with a carefully curated sample set, the approach produced a very large number of incorrect matches.

[4] http://opencv.org/

6.3. Histogram of Oriented Gradients (HOG)

In OpenCV, to detect symbols you will need to spend a lot of time tuning the parameters particularly in detecting multi-scale symbols and again there is no guarantee that the exact same parameters will work from image-to-image. In order to detect symbols with variations in size, orientation, skewness, we have adopted a Histogram of Oriented Gradients (HOG) descriptor used with linear Support Vector Machines (SVMs) [2]. 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. The dlib library[5] 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.

6.4. Region Detection

In order to transform the input sketch map into grayscale image with homogeneous illumination, we used the standard algorithm [6] and separated the texts from the drawn symbols. To identify the remaining sketched elements such as linear and polygonal regions, the image is partitioned into regions (segmentation) and then objects are classified based on their geometric appearance (semantic recognition) using the algorithm proposed in [3]. The used algorithm [3],[4] also deal with visual artifacts (e.g., as a result of noise in the original image) and typical drawing effects found in hand-drawn sketch maps such as small gaps between lines, and streets with open ends or closed streets where side streets start. The method recognizes and interprets the depicted objects, and then transfers them into a digital format, i.e. shape file. In order to access these methods publicly, we packaged them and developed a Java based plugin for geographic information systems (GISs), i.e. plugin for the OpenJump software (open source Java based GIS application). The plugin enables ordinary users to access, process and extract drawn spatial information in sketch maps.

[5] http://dlib.net/imaging.html

7. Conclusion

In this section we make concluding remarks about the work presented in this report. In task T3.2 we have developed a robust system for object recognition in sketch maps. During the work of T3.2, however, we encountered several challenges which we outline below. After the challenges we make recommendations for improvements on our work and outline the path of our research going forward.

7.1. Challenges

One of the greatest challenges faced by WP3 in T3.2 is the shortage of data for designing the intended system. Although many maps were collected not all maps could be used as example inputs to an automated image interpretation software tool. This is due to several related factors which we consider as challenges in their own right:

- Extremely variable symbols used: because some of the participants preferred different symbols there was not enough data for training a sophisticated recognition system such as neural networks.
- We also found that many participants did not find the concept of a map particularly interesting or familiar. It took several visits and discussions with the community before many were convinced of what a map could be used for.
- Time for community engagement was limited – significantly more time than was available is required to develop a relationship with the community that is conducive to sketch mapping research purposes.
- Finally we believe that lack of writing skills among some of our participants impeded on the drawing abilities of participants which was perhaps a major cause of extreme variations in the way symbols were drawn.

7.2. Recommendations

Our experience over the past year has made it clear that for the project to successful, it must tap into the experience of the users that we expect will use our system. For smart sketch maps the majority of users may be non-governmental organisations that conduct participatory rural mapping using sketch maps. As such we recommend that work during the system validation phase should involve such partners in order to ensure that the output of our work is relevant to the problems identified at the beginning of the project. Working with experts in the area also promises to help us maximize the volume and quality of data collected.

For organizations that use the SSM system a recommended model is one where selected members of the community are trained to be the community's mappers. A mapper in the community can continuously produce maps which can then be collected periodically to become part of a rich dataset. The dataset would then be used to generate further samples for training SSMs object classifiers.

The second recommendation we make for our work is that the system must be deployed within a custodian organisation which will be responsible for developing the visual language in conjunction with the community and also training the system to recognize sketch maps for the particular domain in which they are working.

7.3. Future directions

Going forward we will continue to focus our effort on task T3.2 which includes the work on sketch map representation. In this phase we will also solve some of the problems faced during the recognition phase (e.g. recognition of complex symbols as groups of simple symbols using rules constructed with spatial constraints). In addition it may be useful for the work coming up in WP6 to provide a simple user interface for introducing new symbols and training the system with the new symbols.

Bibliography

[1] S. Reinius, “Object recognition using the OpenCV Haar cascade-classifier on the iOS platform,” in Institutionen för Informationsteknologi, Uppsala Universitet, 2013.

[2] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” in 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05), 2005, vol. 1, pp. 886–893.

[3] K. Broelemann and X. Jiang, “A region-based method for sketch map segmentation.,” in Graphics Recognition. New Trends and Challenges. LNCS, Vol. 7423, Berlin Heidelberg: Springer-Verlag, 2013, pp. 1–14.

[4] K. Broelemann, “A System for Automatic Localization and Recognition of Sketch Map Objects,” in Workshop of Understanding and Processing Sketch Maps, 2011, pp. 11–20.

[5] N. Perveen, D. Kumar, and I. Bhardwaj, “An overview on template matching methodologies and its applications,” Int. J. Res. Comput. Commun. Technol., vol. 2, no. 10, pp. 988–995, 2013.

[6] M. Sezgin and B. Sankur, “Survey over image thresholding techniques and quantitative performance evaluation,” J. Electron. Imaging, vol. 13, no. 1, pp. 146–168, 2004.

[7] Schwering, A., Wang, J., Chipofya, M., Jan, S., Li, R., & Broelemann, K., 2014. SketchMapia: Qualitative representations for the alignment of sketch and metric maps. Spatial Cognition & Computation, 14(3), pp. 220-254.

[8] Knight, R., Brinkhurst, M., & Vogelsang, J. (2016) Community land protection facilitators guide. [Online] Available from: https://namati.org/resources/community-land-protection-facilitators-guide/ [Accessed 17th July 2016].

Appendices

In these appendices we describe how to install and try the two sketch map processing tools. The tools require at least Windows 7.

Appendix 1. Installation and workflow for recognition of individual symbols

Step 1: To use the symbol recognition software we recommend that you download and install anaconda2 from the anaconda website (unless you know what you are doing). We recommend installing anaconda2 as it installs python2.7 together with many of the dependencies that the libraries we are building on require.

Step 2: copy the entire folder SymbolRecognition (in which this file is located) to your preferred location. We recommend placing directly on the root of your hard-drive (e.g. C:\)

Step 3: copy the files inside the folder 'site-packages' to the site-packages folder of your anaconda installation (by default this will be at C:\ProgramData\Anaconda2\Lib\site-packages).

Step 4: install dlib

To install dlib you must first give all users read/write rights for the 'site-packages' folder

- In Windows explorer right-click on the folder icon for the 'site-packages' folder then select properties. This will open the Properties window of the folder.
- In the folder Properties select the 'Security' tab and select each user in the Group or user names list in turn and select 'Full control' in the 'Allow' column followed by a click on the 'Apply' button at the bottom of the window.
- Click OK when done

Open the command line terminal and install dlib with the following command

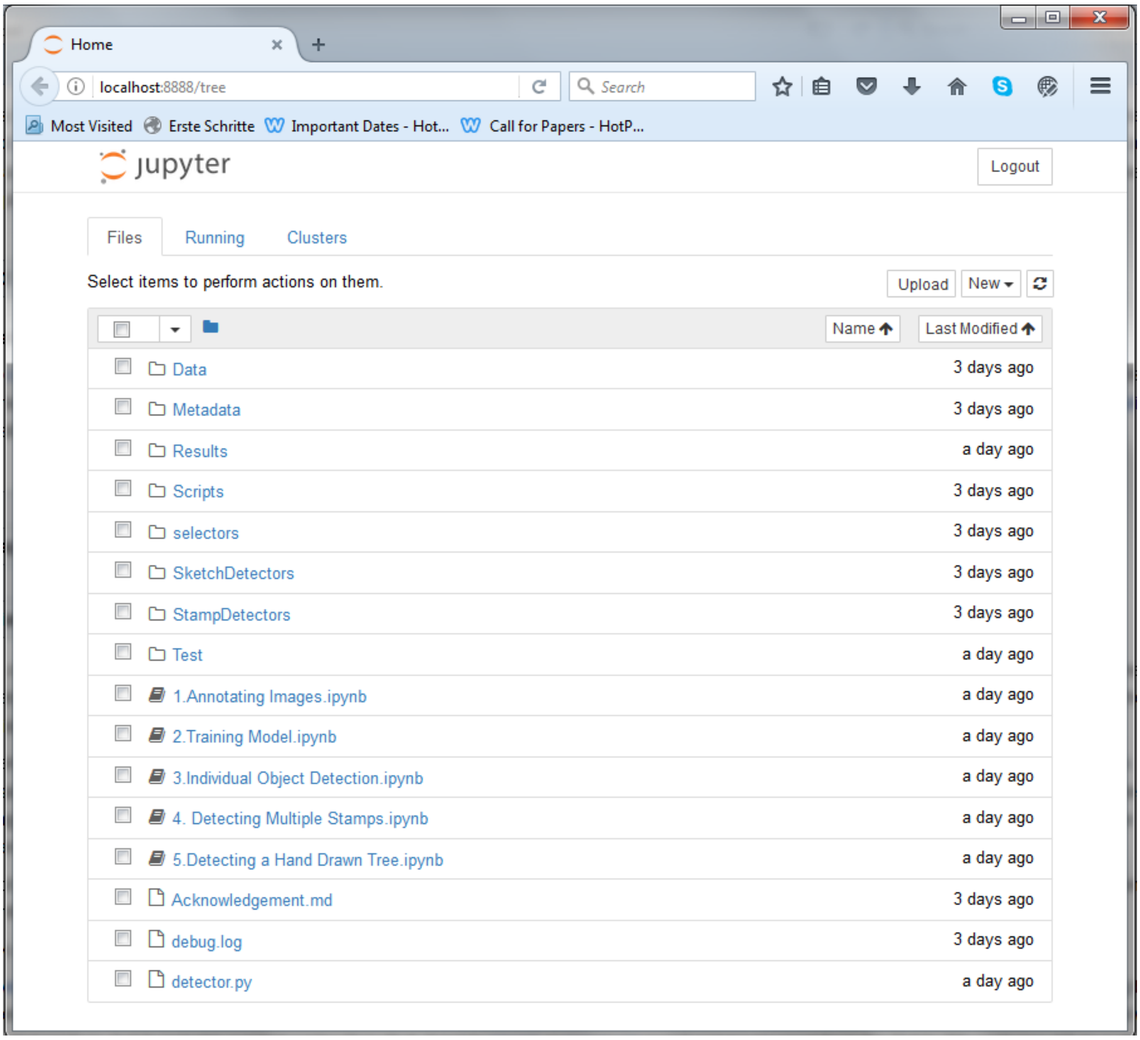
conda install -c conda-forge dlib=19.0

Step 5: in the command line terminal navigate to the SymbolRecognition folder.

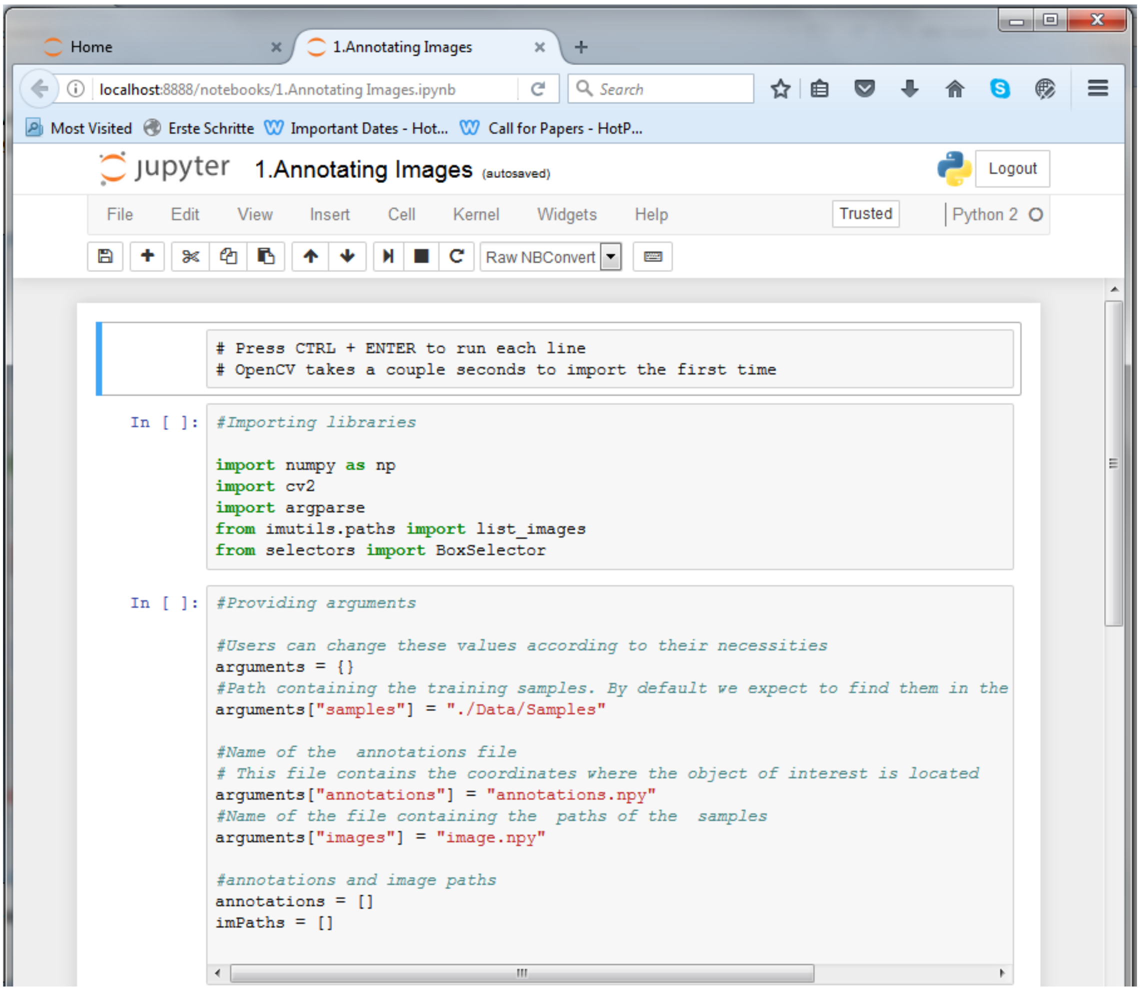
Step 5: at the command prompt now type jupyter notebook and hit Enter. This starts the jupyter server and opens your browser.

```
> jupyter notebook
[I 08:49:37.334 NotebookApp] Serving notebooks from local directory: C:\[redacted]\Object
Detection.0.2
[I 08:49:37.335 NotebookApp] 0 active kernels
[I 08:49:37.336 NotebookApp] The Jupyter Notebook is running at: http://localhost:8888/?token=39ccaa054d
8c953578549a33eb73af33a4afb85f53f16bb2
[I 08:49:37.336 NotebookApp] Use Control-C to stop this server and shut down all kernels (twice to skip
confirmation).
[C 08:49:37.339 NotebookApp]

    Copy/paste this URL into your browser when you connect for the first time,
    to login with a token:
        http://localhost:8888/?token=39ccaa054d8c953578549a33eb73af33a4afb85f53f16bb2
[I 08:49:39.790 NotebookApp] Accepting one-time-token-authenticated connection from ::1
```



Step 6: to begin exploring how the tool works click on one of notebooks labelled 1. through 5. Upon clicking one of the notebooks, e.g. number 1. Annotating Images.ipynb, a new browser tab will open and load the notebook.



Step 7: you can run the notebook by clicking in each cell (to make it the window's focus) and pressing CTRL+ENTER. An IPython notebook in jupyter is executed cell by cell. This means that if you change something in any of the cells you have to rerun that cell (but you do not have to rerun all preceding or subsequent cells unless the changed cell has side-effects on the other cells)

Note: please read comments in the code shown in the notebook to follow what is going on.

Note: for the first time please run the notebooks in the order in which they are listed (1 – 6).

Appendix 2. Workflow for Region Recognition

Step 1: Download OpenJump application for Windows-64-bit

Web-link: http://openjump.org/

OR

Download and extract OpenJump_v1.8 application from the given package (.zip)

Step 2. Extract the application on your local derive

C:\\ or D:\\

Step 3. You need to install the Matlab Compiler Runtime 2014a for Windows 64-bit.

http://www.mathworks.com/products/compiler/mcr/

OR

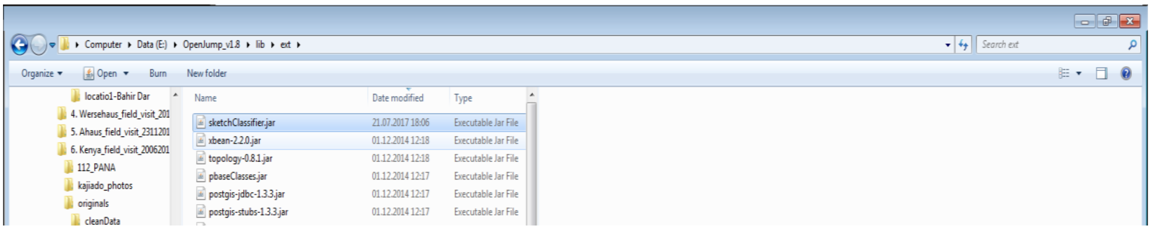
Download and install Matlab Compiler from the given zip package recognition of individual symbols

Step 4. Extract the recognition system (files) from the package and store on your local derive

e.g. C:\\sketchClassifer\

Step 5. Download also the plug-in (sketchClassifier.jar) and put the jar file in the folder:

\OpenJump_vx.x\lib\ext



Step 6. Create file "info" on your C: derive

C:\\info

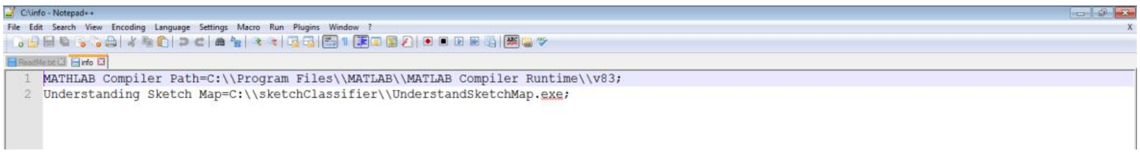
Step 7. Add the following paths in the info file

1. MATLAB compiler

   e.g. C:\\Program Files\\MATLAB\\MATLAB Compiler Runtime\\v83

2. UnderstandSketchMap.exe (inside the sketchClassifier folder)

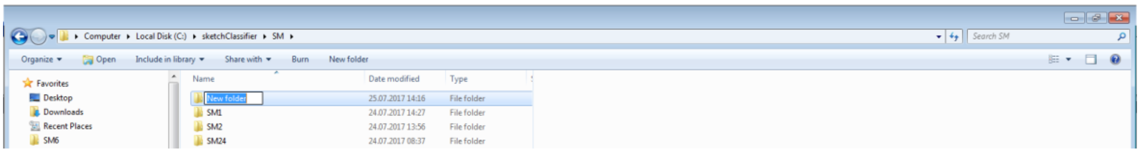
   e.g. C:\\sketchClassifer\UnderstandSketchMap.exe



Step 8. Go to the sketchClassifer\SM folder and create one folder

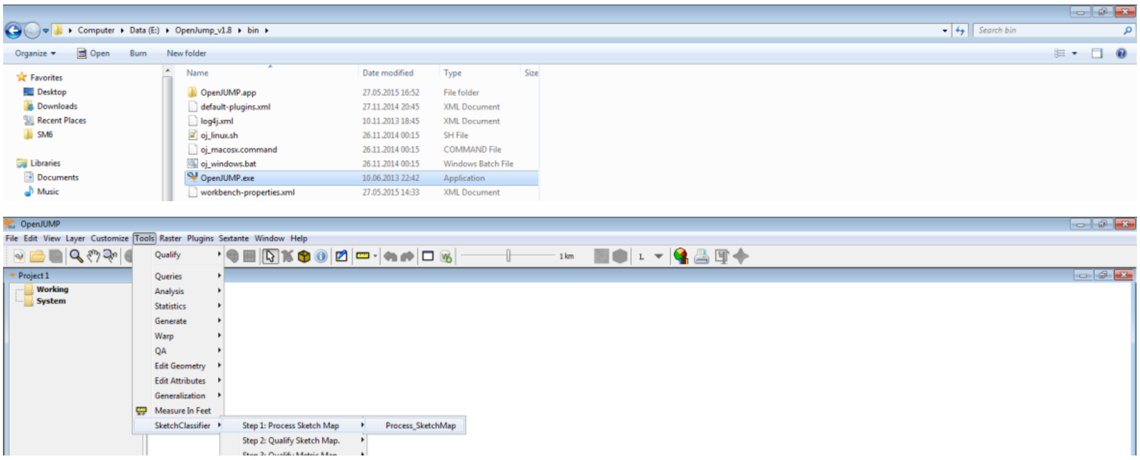
Step 9. Put the sketch map (.png) in the created folder.

NOTE: (the file name must be same as folder name), i.e. SM\SM1\SM1.png

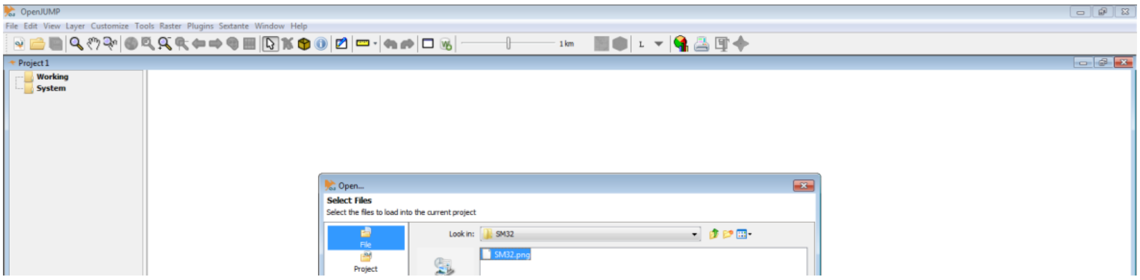


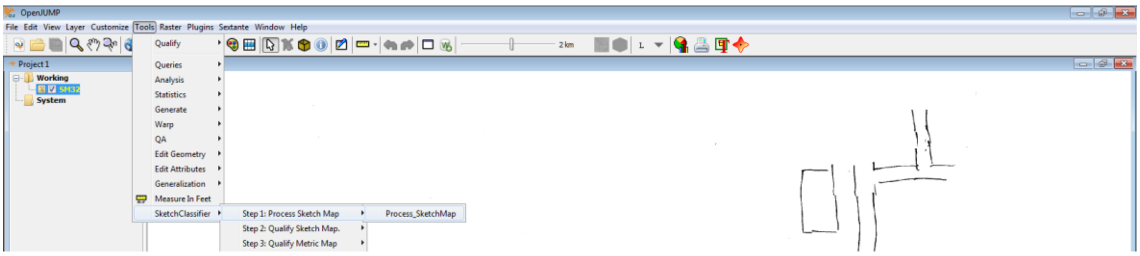
Step 10. Open the OpenJump application by double clicking on OpenJUMP.exe

- you will see sketchClassifier under the "TOOL" menu
- Menu: \Tools\sketchClassifer\Step 1: process Sketch map\

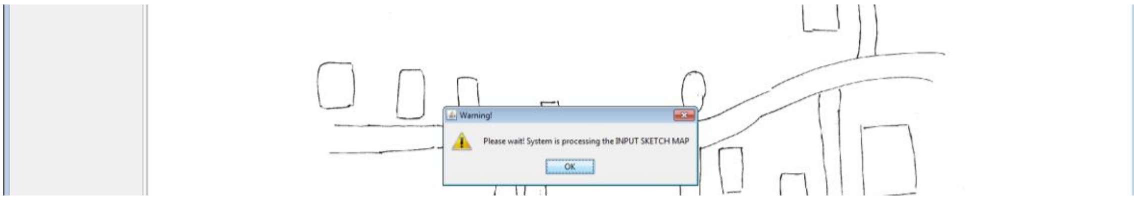


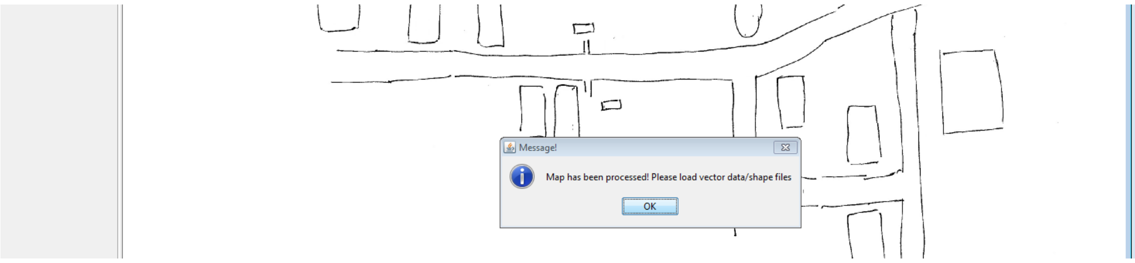
Step 11. To process, load the sketch map in the OpenJump layer
e.g. file\open and select the SM1.png
Step 12. After loading the sketch map, click
\Tools\sketchClassifer\Step 1: process Sketch map\



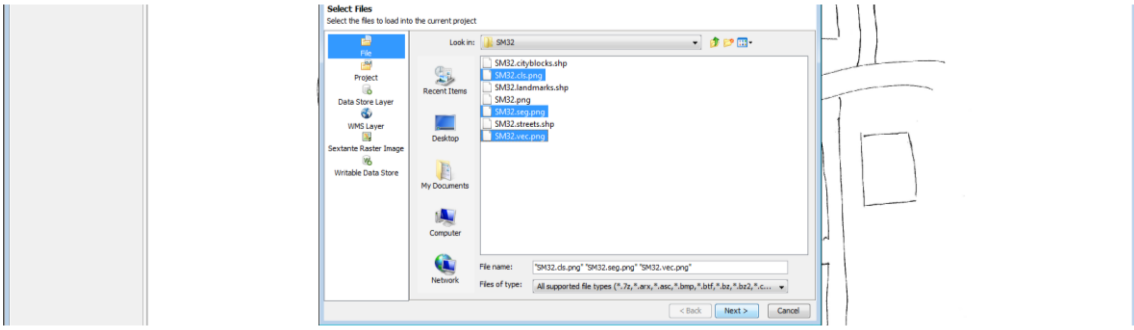


Step 13. You will receive message, please click on the massage and wait!





Step 14. The process will create shape files of the recognized objects in the same folder where you have saved your sketch map.



Step 15. To see the recognition results, you can load shape files or segmentation and classification images in the OpenJUMP layers.

Figure 6. shows image segmentation, classification, and vectorization of sketched elements.