Rebuilding the Cadastral Map of The Netherlands: The Artificial Intelligence Solution

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SUMMARY

The Dutch Cadastral Map does fit its design goal; it is a complete and topologically correct index to the cadastral registration. However, its graphical quality of about 0.5 meter doesn't seem to be accurate enough in a future where people want to zoom in and establish the exact location of their boundaries themselves. The related uncertainty of the parcel size is also becoming a problem.

After a market survey, the Dutch Cadastre started a research project in 2017 where many different aspects (legal, communication, geodetic, organizational, etc.) of rebuilding the map were studied. The focus however was on the most critical aspect: the question whether the millions of field sketches could be read automatically. Two companies (KPMG and Sioux LIME) realized a proof of concept in which they have proven that it is possible up to a certain level of accuracy. We continued by contracting experts from both companies who, together with our own staff, succeeded in building a prototype that is capable of reading the documents and connecting them together to a new geometry of a cadastral map. In the solution artificial intelligence is widely used.

The content of a field sketch is very complex, usually handwritten and with a flexible map scale. Extracting structured information from such documents demands several algorithmic steps: image quality improvement, line and point detection, recognition of measurement numbers, actually reading these numbers, and linking these numbers to two points (begin & end). The numbers represent tape measurements between these points. The result of this process is a drawing on scale and structured measurement data. In this process manual checking and correction is needed.

A second large process is that of positioning the resulting line pattern in the national reference system and connecting the different line patterns to each other. The resulting network of sketches can be re-calculated with every new extension and forms the basis of the new cadastral map. The architecture of the solution will be shown and discussed.

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1. INTRODUCTION

The Dutch Cadastre offers legal certainty for every piece of land in the Netherlands: the cadastral parcels. When new parcels come into existence, their borders are measured accurately by surveyors. These measurements are then secured in surveying field sketches, which are usable to reconstruct terrain borders later on. The measurements have been processed on scale in the past to form the cadastral map (scale 1:1000/1:2000), which visualizes the location of all cadastral parcels in the Netherlands.

Because of the (old-fashioned) methods and scale of production utilized during construction, the current cadastral map is of a graphically adequate quality only. As a result of this limited quality (characterized by border standard deviations of approximately 20 cm in urban and 40 cm in rural areas), the cadastral map is currently unsuitable for the task of reconstructing an object's precise location in the field. Furthermore, with the progressive increase in digitisation and open data policies, combining multiple information sources (e.g. aerial imagery and digital maps) becomes increasingly accessible to a wider range of people. Obtaining inaccurate data frequently causes inconvenience, and even leads to feelings of incomprehension among citizens.

To overcome these limitations, a new cadastral map needs to be developed. Research has been started with the goal to create a new map whose increased border accuracy makes it suitable for developments like combining data sources, 3D-objects and digitalization. To achieve this goal, almost all available (historical) field sketches must be processed. Due to time and cost constraints, this enormous task requires far-reaching automation. In order to investigate how an accurate cadastral map with a preset geometric quality can be created while making use of recent developments in Artificial Intelligence (AI), a research programme has been set up in 2017. In cooperation with companies specializing in AI solutions (Sioux LIME and KPMG), the method for creating the new so-called reconstruction map has been developed. During the research, issues like automatically extracting measurements from field sketches, combining information and redetermining border positioning have been investigated.

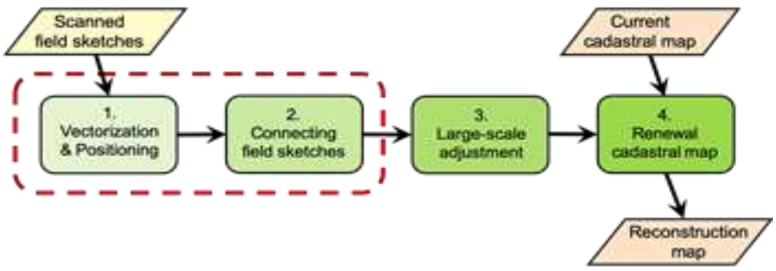

Figure 1: Overview of the four-step approach to renewal of the cadastral map.

The method developed for creating an accurate reconstruction map from field sketches is schematically presented in Figure 1. This paper discusses primarily the first 2 steps: vectorisation & Positioning and Connecting field sketches. The follow-up steps 3 and 4 are detailed in the FIG contribution by Van den Heuvel et al. (Van den Heuvel et al., 2020). Furthermore, the work by Hagemans et al. sketches the overall concept and motivation behind rebuilding the cadastral map (Hagemans et al., 2020).

1.1 Related work

A similar undertaking has been performed in some other countries, for instance New South Wales, Australia, where a large archive of drawings is being digitised. However, Dutch sketches show significantly different structure and conventions. Another key difference is the focus on AI and deep learning in our solution.

Using deep learning to vectorise cadastral plans has been proposed before, for example by (Ignjatić et al., 2018), (Oliveira et al., 2017) and (Oliveira et al., 2019). The vectorisation of sketches is significantly different from plans: the former is a schematic drawing, where the dimensions of objects are written down and need to be recognized and interpreted one by one. Cadastral plans on the other hand already are to scale, and here it is only the line structure and parcel numbers that need to be recognized. A key novelty in our approach is also the development of a bespoke pipeline of many different deep learning and custom computer vision algorithms, combined with a specialised user interface to allow efficient human correction.

Figure 2: Example of a field sketch.

2. PROBLEM STATEMENT

A large part of the information required to build the "Reconstruction map" is hidden in hand-drawn historic sketches, like the one shown in Figure 2. This paper details the challenge of extracting this information. The problem at hand can be formulated in two questions:

1. How can we extract high-quality geometrical relations and semantic information from an archive of millions of field sketches, with minimal human supervision?
2. Can we geographically place the geometrical networks on top of a reference map by linking to common features such as parcel boundaries, buildings, and other sketches?

In order for the reader to appreciate the scope of this challenge, we describe the structure of the Dutch cadastral field sketches in more detail below. In section 3, we introduce the AI-based solution "VeCToR" that has been developed to vectorise, position, and link the sketches at large scale.

2.1 Field Sketch Breakdown

Figure 2 shows a large chunk of a typical field sketch. This example is from the 1980s, but we should note that examples from other eras or made by other artists can look significantly different, which complicates the development of a generic solution. Conceptually, all sketches contain two layers of information:

– Geometrical relations: mostly distances and angles between points.
– Semantic interpretation: parcel number annotations, building shapes, parcel boundaries, etc.

In the current investigation, we have focused on extracting almost all geometrical relations, while ignoring some of the semantic interpretation. This leads to the following breakdown of items to be vectorized, visualized in Figure 3:

a. Lines and points: The network of points and lines forms the backbone of the sketch, as many other graphical elements are attached to it. A line is not simply a visual connection between points. It carries important geometrical information, because collinearity of all points on a line is usually implied. We therefore define a line as a sequence of visually connected points in a straight line. The challenge is to find the starting point, end point, and all intersections of these lines, even if the line is interrupted (dashed).
b. Measurements: these are annotations of line segment lengths, like '84.88'. We need to identify: (1) the value, (2) the intersection it applies to, which can be ambiguous, and (3) the starting point (origin) for the measurement, indicated by an arrowhead. Adding to the challenge, the origin can actually be a point that is very far away from the text. Another difficulty is to distinguish the measurement textboxes from other elements that look similar, like free-form text, special annotations like 'yz.bs' (iron tube), or small line structures.
c. Parcel numbers: these contain information for the placement of the sketch on a reference map. They can be red, black or blue.
d. Buildings: these are very important carriers of geometrical as well as semantic information. Semantically, they are important reference structures for connecting field

sketches to existing map data. Geometrically, the orthogonality of building corners has to be implied when doing a geometric adjustment. Buildings are either indicated by hatching (diagonal stripes) or a pink background colour. We represent buildings as an open or closed polygon connecting points from the network in a certain order.

e. Symbols: a wide variety of symbols can occur. Since we focus on extracting geometrical information from the sketches, we only consider the orthogonality and collinearity symbols.

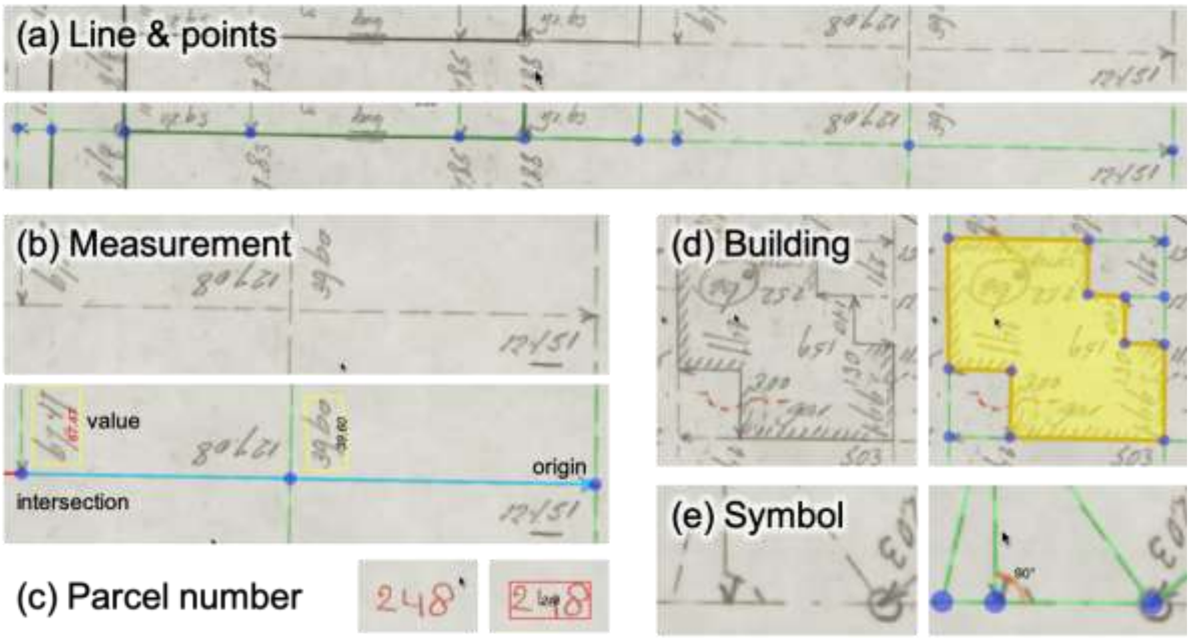

Figure 3: Information units extracted during vectorisation using the AI-based solution.

The following items can be seen on the sketch but have been left out of scope:

– Handwritten references to other sketches,
– Freeform text, like names of owners, house numbers,
– Line-styles (dashed or dotted, colour) and their semantic meaning,
– Northern arrow,
– Cadastral stones, iron tubes, etc, sometimes labelled with an ID number,
– Page headers.

3. **VeCToR – OVERVIEW**

In order to overcome the challenge proposed in section 2, the Dutch Cadastre developed a data processing platform called VeCToR. VeCToR stands for: Vectorisation and Coupling Tool for Reconstruction. This platform provides a structured workflow to convert a JPEG picture to a digital (vectorised) network of geometric observations, coupled to other sketches at overlapping points.

Previous feasibility studies have shown that the vectorisation process can be automated to a large extent, but realistically human corrections will always be needed to achieve sufficient quality. The feasibility is then ultimately determined by the labour costs per field sketch. It is therefore important to reduce labour costs by making human tasks as simple and fast as possible. This is where AI comes into play. To make efficient use of AI, the problem is broken down into sub-steps, and for each step an AI can be developed. One key insight from the feasibility studies is that AI will not obtain perfect results, and defects from the first step propagate into the next step. To mitigate this, a human-validated workflow has been proposed. This alternating machine-human pipeline concept is illustrated in Figure 4. Since errors are fixed by humans before they propagate, the next AI step can do a better job, ultimately leading to reduced human effort. Furthermore, this approach automatically structures the human tasks into manageable chunks, which is crucial for effective quality control and allows for specialisation of workers.

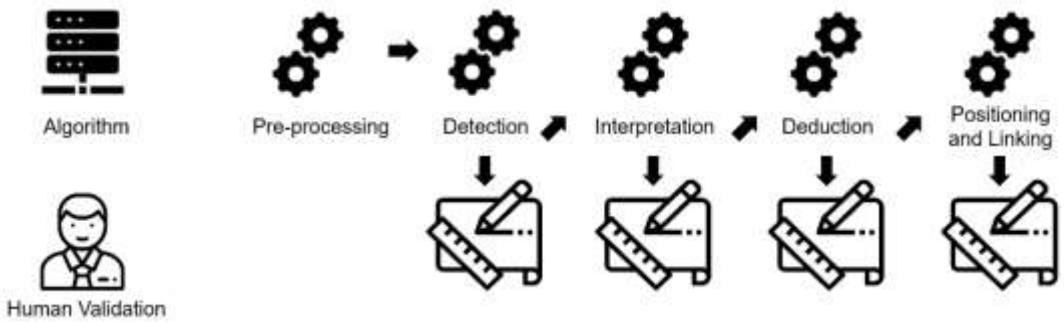

Figure 4: Global pipeline stages used for field sketch processing.

A fully functional prototype of this pipeline has been developed. We opted for a bottleneck-driven way of developing. Periodically, the human effort per task was measured on a small test group, and the task that demonstrably cost the most time was consequently improved. This could be improvement of the AI algorithm, improvement in user experience, or both. This way, the actual time per field sketch was measured a few times during the project and pushed further and further down, in order to arrive at a reliable upper limit. The lower limit in terms of labour time has however not been reached yet. In the next section, we detail each step in the VeCToR pipeline.

4. VeCToR – PIPELINE

The proposition of VeCToR is that the usage of AI algorithms helps in reducing human processing time. While algorithms do not always achieve perfect results, it is easier for humans to validate and correct results than having to produce them from scratch. In this section, the individual pipeline steps are presented which contribute to achieving the goal of reducing field sketch processing time.

In the pipeline, field sketches need to be pre-processed first. When the pre-processing step has been completed, a series of AI steps is executed, each followed by a validation step performed by a person. Where possible, the performance of the AI steps is measured on a validation set. When field sketches have been vectorized, they are positioned on the map and linked to neighbouring field sketches in order to form the geometric base for the improved cadastral map.

4.1 **Pre-processing**

The field sketches which need to be vectorized are only available in the JPEG format. The compression induced by the JPEG format decreases the clarity of the field sketches, which coherently reduces the performance of (certain) AI algorithms. These limitations result in the need for a robust pre-processing algorithm, which is able to remove noise and irregularities introduced by JPEG-compressing the images. A literature study has been performed in order to find the state of the art in the area of image compression artefact suppression.

CAS-CNN (Cavigelli et al., 2017) has achieved excellent results on the task of compressed image artefact suppression. A Convolutional Neural Network (CNN) is a neural network (NN) type which opposed to other NN variants requires minimal pre-processing, because it is able to learn filters from the input data. CAS-CNN makes use of hierarchical skip connections and a multi-scale loss function in order to effectively train a large NN while avoiding the problem of vanishing gradients. More recently, ZHENG et al. have proposed S-NET (Zheng et al., 2018), which is also a CNN-based approach. S-NET uses an architecture based on residual blocks, which enables training deeper models leading to an improvement on the previous state-of-the-art. Fewer residual blocks imply greater speed, at the price of reduced quality. Ultimately, the choice has been made to settle on S-NET with 4 residual blocks as JPEG artefact removal algorithm. The enhancement of image quality on a compressed JPEG is clearly visible from Figure 5.

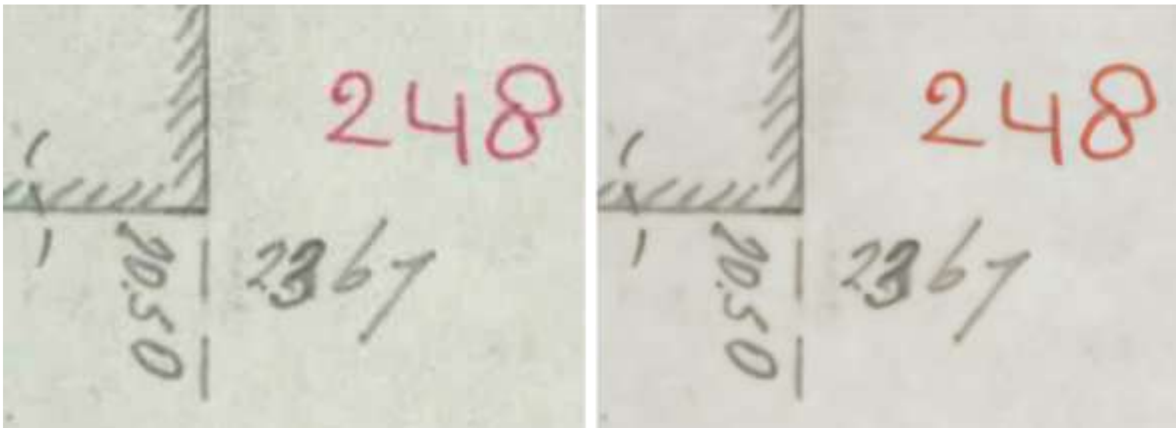

Figure 5: Comparison between original JPEG (left) and enhanced by S-NET (right).

4.2 **Line and Point Detection**

The possibility to automate the detection of lines present on field sketches has also been researched. Lines on field sketches hold important information because they consist of measurement lines (section 2). A line is represented by the coordinates $[(x^1, y^1), .. , (x^n, y^n)]$ of both its endpoints and optional intermediate points. Intermediate points are present on the intersection of lines. Many line detection algorithms have been created over the last decades, most notably Line Segment Detector (LSD), Hough Transform (HT) and Random Sample Consensus (RANSAC). LSD is a linear-time line segment detector which delivers accurate results, a controlled number of false detections, and does not require parameter tuning (Von Gioi et al., 2008). HT on the other hand is a technique which is able to find objects within a certain class of shapes by making use of a voting procedure (Hough, 1959). Finally, RANSAC is an iterative method used to estimate parameters of a mathematical model (Fischler and Bolles, 1981), which is suitable to detect lines (optionally from line segments). More recently however, NN based architectures (Lui et al., 2019), (Li et al., 2020) have been created which achieve state-of-the-art results. A NN-based method (U-NET), together with the LSD and RANSAC line detection algorithms has been found most suitable for this task. The chosen approach is as follows: First of all, segmentation is performed using U-NET. The model features an EfficientNetB5 (Tan et al., 2019) backbone, and has been trained using combinations of augmented field sketches and masks with field sketch lines. It is then able to predict a matrix with dimensions equal to the input sketch, where the value of elements in the matrix depends on the presence of a line on the corresponding input image coordinate. The task of the U-NET model is thus to generate a de-noised matrix with only lines present, for use in downstream algorithms. This matrix is then used by LSD to detect line segments, while finally RANSAC is used for constructing the coordinates of entire lines out of free line segments. The usage of a NN which is able to understand the wide variety of field-sketches, combined with proven static methods for line extraction, has been proven to deliver great results. A pixel-level F-score of 0.84 has been measured on the test set for the line segmentation task. Due to the nature of the approach, the score may be improved further by expansion and optimization of the train set.

When lines have been detected by the algorithm, they are presented to the user for validation. Lines are visualized as an overlay placed directly on top of the field sketch, which allows users to quickly inspect the results of the algorithm. The process of creating and deleting lines has been streamlined in order to minimize the human interaction needed.

4.3 **Parcel and Measurement Detection**

When lines and points have been detected, the skeleton of the field sketch is known. As mentioned in section 2, field sketches also contain measurements which indicate the distance from the start of the measurement line to the point closest to the measurement. The problem of measurement detection can be generalized to an object detection problem. Recently, a lot of research has been performed in the area of object detection, in a wide range of domains. Nugraha et al. have used a You Only Look Once (YOLO) model based on Convolutional NN layers to detect objects from images in order to guide self-driving vehicles (Nugraha et al., 2017), while Sun et al. have used a Region Convolutional NN (RCNN) approach to solve a face detection problem (Sun et al., 2018). Both techniques have in common that they combine convolutional layers with additional layers to effectively recognize object regions in images, characterized by a rectangular bounding box. However, normal bounding boxes are problematic in the case of field sketch measurements, because they cannot provide information on the orientation of the text, and often overlap. Therefore, the technique most suitable for the measurement detection problem has been found to be a RCNN variant: mask-RCNN. Invented by Facebook AI Research, mask-RCNN extends a regular RCNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition (He et al., 2017).

A visualization of masks obtained on a field sketch is presented in Figure 6. We use post-processing to extract more information from the mask regions. Fitting a tight rotated bounding box on the masks provides a hint on the orientation of the boxes. The location and orientation of the boxes is used to select the most likely point and line. Some boxes can be filtered out, because they cannot be associated to any point or line, reducing false positives.

Figure 6: The Mask-RCNN model applied to a field sketch (left). After post-processing (right), blue-coloured masks are associated to a line and point, and red-coloured masks are disregarded.

Because only a small training set is available, transfer learning in combination with train-set augmentation has been used to obtain optimal results. Transfer learning is a technique which takes a model that has been trained on a large domain-independent data set, and fine tunes it on domain-dependent data. This way a relatively small fine tuning dataset is sufficient to obtain good model results. A ResNet (He et al., 2016) backbone trained on the Microsoft Common Objects in Context (COCO) (Lin et al., 2014) dataset has been used to initialize the model weights. The Mask-RCNN model has been evaluated on the test set, and obtains a F-score of 0.85 when detecting measurement ROIs. Like the other NNs, the obtained results will likely improve when more training data becomes available. When the measurements have been detected, they are presented as a layer placed on top of a field sketch for human validation.

4.4 **Parcel and Measurement Interpretation**

Finally, when the location of measurements has been detected in field sketches, their actual value needs to be extracted. The value of a measurement denotes the distance between the start of the measurement line to the measurement point. Measurements consist of handwritten digits optionally separated by a comma or point. Handwritten text recognition is a challenging task, because every writer has a different handwriting. Different approaches to solve the handwritten text problem have been proposed. First of all, handwritten text can be classified letter-by-letter by performing word segmentation. Low error rates have been achieved by applying NNs or CNNs on the task of digit classification (Cireşan et al., 2010), (Pratt et al., 2019). Recently, a novel technique has been proposed which combines convolutional layers, recurrent layers and a CTC loss to classify entire words. Based on these results, a segmentation-free end-to-end algorithm has been implemented in order to recognize measurement values. The algorithm consists of a single network consisting of 5 CNN layers, 2 RNN (LSTM) layers and the CTC loss and decoding layer. A dataset consisting of 550k annotated measurements and parcel numbers has been used to train the NN. The vocabulary of the dataset consists of the numeric characters together with the decimal separator, and two symbols indicating the image orientation (up / down). The dataset is split into train and test sets, with the train set being augmented during training. Instances are duplicated (the original image and the original rotated by 180 degrees, with the orientation included in the label). Following this approach, a word-level F-score of 0.88 is obtained on the test-set.

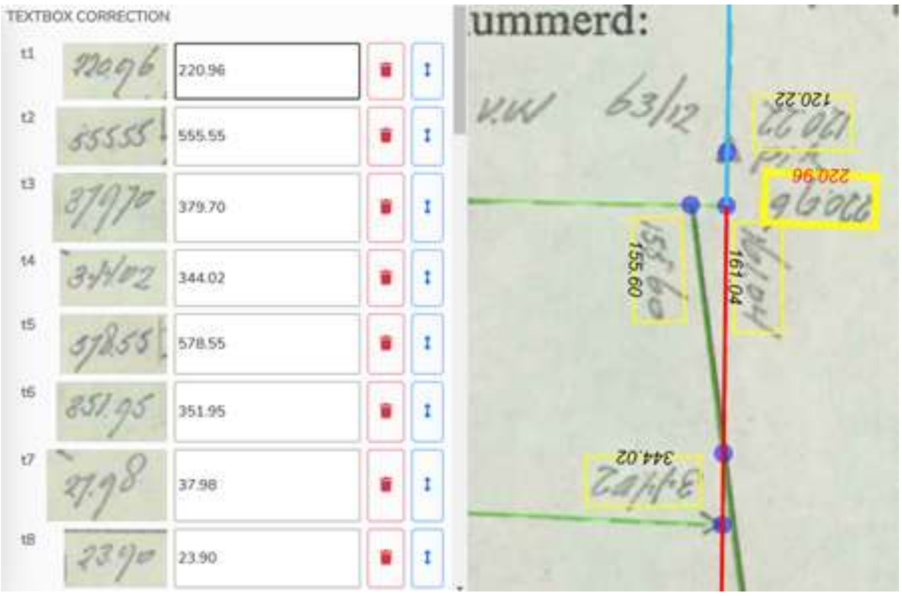

Figure 7: Optimized workflow for interpretation correction.

An optimized human validation workflow has been created, presented in Figure 7. Each measurement is cut out of the field sketch, and presented together with its interpretation as a row in a table. Human validators can quickly skim through the table using key combinations and quickly correct misinterpreted parcel numbers and measurements.

4.5 **Cadastral Correction**

When measurements and lines have been detected and validated, they are decomposed into measurement lines. A vectorized line does not necessarily correspond to a single measurement line: it might be comprised of multiple measurement lines with different orientations. In order to detect the start of a measurement line, the global field sketch scale is calculated by averaging the scale of all individual line segments. For each vectorized line, measurement line starting points are predicted by making use of the scale factor between consecutive increasing or decreasing measurements on the line. Using the line scale (the global scale is used when the line scale could not be determined), the starting point of a measurement line is predicted. While not having been formally evaluated, the estimated accuracy of this method lies around 80 percent. Measurement lines are presented as a sketch overlay for human validation, where users can correct the origin of the measurement line as needed.

4.6 **Building Detection and Symbol Deduction**

The goal of building detection is to find sets of points which together define the contour of a building. An approach based on image processing and heuristics has been adopted to detect buildings on top of field sketches. The (human-validated) line structure is used to generate candidate building polygons, and each candidate is individually classified as a building or not. Classification is based on either background colour of the polygon, or shading around the contour of the polygon (example: Figure 3d). The detected buildings are presented for human validation as an overlay over the field sketch.

When building validation is finished, symbols are deducted. Symbols are used to validate the structural integrity of the field sketch. Symbols are deducted from buildings by making use of the fact that the angles of building walls are commonly 90° (degrees). Where the angle between lines making up a corner of a building is approximately 90°, a symbol indicating a 90° angle is created. Furthermore, symbols indicating a 180° angle are added to intersections located on measurement lines, because measurement lines are straight by definition. The deducted symbols are presented as a sketch overlay for human validation. Furthermore, the user adds any additional symbols that were explicitly marked on the sketch by the land surveyor.

With all measurements and geometric symbols detected, a coordinate adjustment can be done. This significantly transforms the points from arbitrary pixel locations to a properly scaled metric geometry. Since some measurements are redundant, this also provides an effective way of error-checking. The user is actively pointed to the most likely mistakes. Further details on the geodetic concept is presented in the contribution of Van den Heuvel et al. (Van den Heuvel et al., 2020).

4.7 **Field Sketch Positioning**

When all sketch items described in previous subsections have been determined, a digital projection of a field sketch is known. This digital projection needs to be mapped to a geographical location, in order to be of use for reconstruction surveyors and for the cadastre to reach its goal of a more accurate cadastral map. From this point, the digital projection taken from a field sketch is referred to as local geometry, while a geographic location positioned on a map is referred to as global geometry. Mapping the local geometry to a valid global geometry by hand is a rather time consuming process, so solving it as well as possible by adopting AI functionality is essential when seeking to minimize the field sketch processing time needed. In this subsection, the algorithms used to map a local geometry to a global geometry are set out. An example of a positioned field sketch is presented in figure 8a.

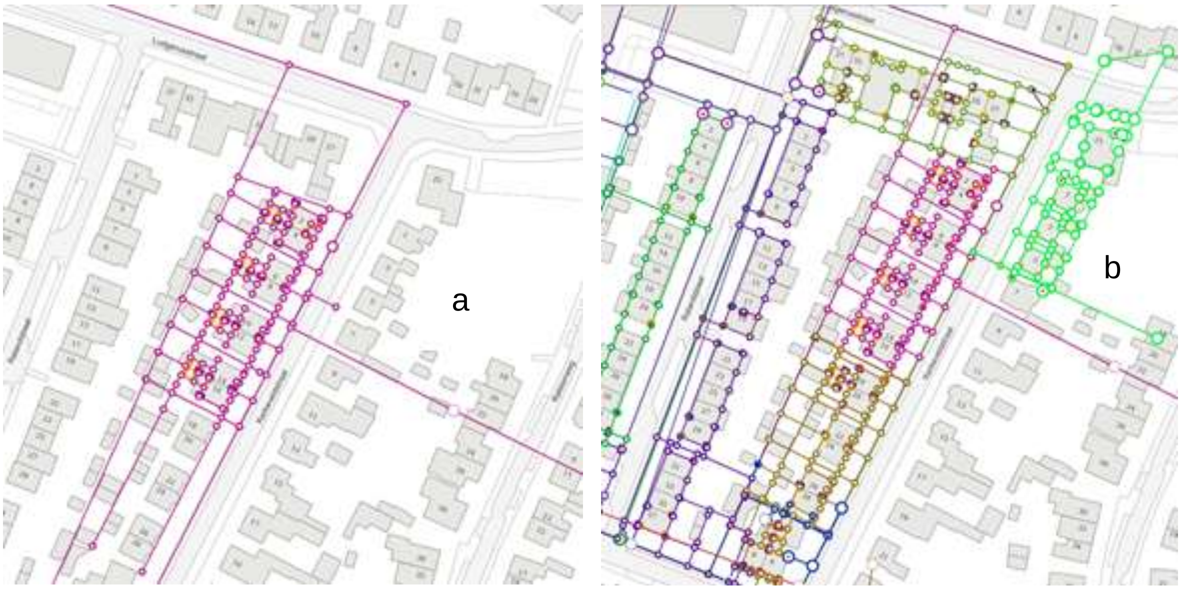

Figure 8: Illustration of workflow steps: (a) a single sketch positioned on the map; (b) multiple linked sketches.

Initially, an edge-matching algorithm is executed. This method searches for an optimal rigid transformation from local to global geometry by finding all possible equivalences between local edges and global edges, based on edge length. The global edges to match with are selected from a reference map based on the parcel numbers present in the field sketch. For every match between a local edge and a global edge, a vector containing the x translation (Δx), y translation (Δy) and the rotation (ϕ) is determined: [Δx, Δy, ϕ]. The set of vectors of all matches is clustered using the k-Nearest Neighbours algorithm, resulting in clusters of edges with similar transformations. The optimal Euclidean transformation which satisfies all links between points is selected using a least-squares approach.

A positioning accuracy of 52 percent is obtained in rural areas, while the positioning accuracy improves to 87 percent in urban areas. Incorrectly positioned field sketches are usually located closely to their actual location, requiring minimal human interaction.

4.8 **Field Sketch Linking**

Finally, when a group of neighbouring field sketches has been positioned, the goal of a more accurate cadastral map is within reach. An example of a group of positioned neighbouring sketches is presented in figure 8b.

In order to connect neighbouring field sketches, point equivalences between the different sketches are sought. Points are deemed equal when the distance between their geometries is less than or equal to a specified threshold. Points originating from different field sketches positioned very closely on the map are automatically linked. Using the same method, links between field sketch points and measured GPS-points are added. These equalities are used when adjusting the set of field sketches. The adjustment process and the approach for using the results to improve the cadastral map are described in more detail in (Van den Heuvel et al., 2020).

5. CONCLUSION

In this paper, we have introduced VeCToR, a bespoke workflow combining artificial and human intelligence to vectorize, position, and link historic field sketches with the aim of rebuilding the Dutch Cadastral map. The AI components serve to reduce the human labour that is required to get close to 100% accuracy.

Although improvements to the workflow are still possible, a pilot program has been carried out by two independent companies, in order to establish a robust baseline. The pilot has delivered promising results: it is feasible to effectively vectorize field sketches using the methods proposed in this paper. The data gathered during the pilot is used to rebuild a small area on the cadastral map, following the procedure of (Van den Heuvel et al., 2020). Taking into account the potential of the used algorithms, the goal of processing the field sketches required for rebuilding the Dutch cadastral map is achievable.

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BIOGRAPHICAL NOTES

Jeroen Franken is Architect and Technology Manager of scientific computing at technology firm Sioux LIME in Eindhoven, the Netherlands. He is overseeing the development of a pipeline for Kadaster that combines AI and human tasks. His drive is to use mathematics and physics to solve problems in software or hardware. He obtained a PhD degree in Applied Physics at Eindhoven University of Technology.

Wim Florijn has been working since 2019 as a machine learning engineer and software developer at Kadaster. He is working on the entire KKN application stack, and is specifically interested in creating and improving its machine learning components. After receiving his master's degree in computer science specializing in machine learning and data science, he has previously worked as a machine learning engineer at a company specializing in big data analysis.

Maarten Hoekstra is an Independent Cloud Architect and Big Data expert. He uses novel technologies for large scale processing and solving data challenges. He previously worked for KPMG as a Senior Manager and spearheaded the Architecture and Engineering team.

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