

Homography and Image Processing Techniques for Cadastre Object Extraction

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Abstract: In this paper we propose a simple, low-cost, fast and acceptable method of surveying which contributes to the cost reduction of the service and makes it affordable for all citizens. The approach described in this paper results in taking semi-automatically the geometry of a spatial object in a parcel for cadastre purposes, namely swimming pool. The most innovative part of this approach is that we extract the geometry from images using an uncalibrated camera. Normally for professional tasks we use metric or stereo cameras. The approach is focused on simplicity and automation and little intervention of the user is required. It takes into account images taken with an uncalibrated digital camera and cadastral spatial data. The camera is like an input device for spatial data acquisition. Digital images acquired by a non-professional camera are usually taken by a person, without any specific knowledge for the images or usage of the cameras. The basic concept is that the owner of a parcel can update the data of his property by himself. The data are imported at the cadastre maps at the end.

1 INTRODUCTION

The methods used today for carrying out a cadastral survey rely mainly on classical survey tools and photogrammetry. These include Electro optical Distance Measurement Equipment (EDM), the Global Navigation Satellite Systems (GNSS) and Total Stations. The results of such measurements have to comply with high accuracy. Photogrammetric methods have been applied to cadastral surveying in the last decades.

Modern photogrammetric techniques have been proved to be as accurately as the classical surveying methods. Photogrammetry uses metric cameras that means elements of the internal orientation are known. These include the image coordinates of the principal point, the focal length of the camera, the fiducial marks and the lens distortion. Photogrammetric techniques for cadastral was first introduced in Switzerland (Weissmann, 1971). Aerial photography has been used for the identification of land parcels (Siriba, 2009) then the parcel boundaries are identified and scaled off the orthophotographs monoscopically, and therefore sufficient for cadastral purposes (Konecny, 2008). The identification of land

parcel boundaries using digital photogrammetric method can be extracted by on Digital Photogrammetric Workstation (DPW) (Kyutae and Song, 2011). Unmanned Aerial Vehicles have been used for cadastral mapping extracting line features from images [UAV] (Crommelinck et al., 2016).

In our approach we try to obtain accurate information about land from interpretation and measurements taken from images. The images are obtained from amateur, uncalibrated cameras. Amateur cameras have been used since 1990s and this approach was either single image analysis or bundle block adjustment for relative orientation and the creation of stereo models. Extracting a spatial object from images taken from an uncalibrated camera is inherently ambiguous and not trivial. The algorithms developed require no knowledge of the camera's internal parameters (focal length, aspect ratio, principal point) or external ones (position and orientation). We use only some scene constraints such as planarity of points, parallelism of lines and perpendicularity of lines. The geometric constraints are derived directly from the images due to special markers. A hierarchy of the algorithms to calculate points measurements is investigated and different

cases are taken into account. This leads to extremely flexible method which can be applied to different images. In order to achieve the goal of this project, a number of research areas had to be addressed. The main idea was to extract the outer contour of the house with interesting outlines, and the contour of the swimming pool. This method has been used to update the cadastre maps from any user and it is mainly concerned to identify each user's own new spatial object, mainly swimming pool, in the cadastre map and not to survey it with high accuracy.

Our framework is based on the principals of single or multiview geometry, which is the concept of acquiring metric information from a perspective view of a scene given only minimal geometric information determined from the image (Criminisi et al., 2000). The method provides us with data from a simple image, without prior knowledge of the camera parameters (intrinsic parameters), its exact position and free of camera synchronization or calibration. The implemented techniques aim to increase the level of automation, making the framework as free of user input as possible and independent of special equipment.

In a typical photogrammetric process stereo vision has been used to compute depth, but, in our case monocular vision proves to be sufficient.

2 PROPOSED METHODOLOGY

Our goal is to create a service for any user with a high level of automation. We want to keep the user interaction at the minimum and have the smallest amount of photographic input. The approach presented here uses single image analysis and involves the steps segmentation, clustering, and edge detection to minimize the user intervention.

Images are characterized by perspective distortion which refers to the transformation of objects by appearing significantly different than in the real life form. This is due to the angle of view of the image capturing. Shape is distorted in perspective imaging. Parallel lines can look as if they meet in images and rectangles appear as quadrilaterals. In order to obtain accurate geometric information of the real world space via an image, it is mandatory to eliminate the perspective distortion. To that aim we need to create a relation between the image and the real scene depicted. Such relations often refer to the existence of a known shape, which is in our approach a rectangle, in the real world which is used as a reference on the image. By knowing an area on the image which in real life represents a rectangle, can help us make the

required association to correct the distortion. Having considered the above, we need to create a rectangle on the scene, which will be included on the image.

2.1 Homography

The connection of real world data with their image representations or how the scenes depicted in images correspond to the real world are topics that concern a wide range of scientific fields, from computer vision to topography. The digital depiction of the real world has its base on perspective geometry. The distortion that physical scenes have in images is represented in perspective transformation. Perspective transformation maps points to points or lines to lines in different spaces with often non equal dimensions. This transformation is known as homography. Given an image of a planar surface, points on the image plane can be mapped into corresponding points in the world plane by means of homography (Hartley and Zisserman, 2000). The relation between real world and image points is

$$X = Hx \quad (1)$$

where x is an image point and X is the corresponding point in real world (Criminisi, 2002). This relation is defined by the 3×3 matrix H . The matrix H holds the information of the transformation and therefore can relate any image point to its position on the physical space.

As it has become clear the main problem is the estimation of the homography matrix H . There is a variety of algorithms developed for estimating the H matrix e.g. RANSAC. They are categorized based on three methods for acquiring H , using nonhomogeneous linear solution, homogeneous solution, non-linear geometric solution (Criminisi et al., 1999).

In our case we used a linear solution. The method for computing H is based on the Direct Linear Transformation (DLT) algorithm which solves a set of variables from a set of similarity relations such as $x=Ay$ where A contains the unknowns. The algorithm implemented is described by Hartley & Zisserman in (Hartley and Zisserman, 2000), which is a normalized DTL for 2D homographies. In order for these algorithms to work for uncalibrated cameras, the estimation of the homography can be achieved directly from a set of known image-world correspondences, such as points. The homography transformation is described as

$$x' = \frac{H_{11}x + H_{12}y + H_{13}z}{H_{31}x + H_{32}y + H_{33}z} \quad (2)$$

$$y' = \frac{H_{21}x + H_{22}y + H_{23}z}{H_{31}x + H_{32}y + H_{33}z} \quad (3)$$

where

$$H = \begin{bmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{bmatrix}, \quad (4)$$

x', y' are the image coordinates, x, y are the real world coordinates and $H_{11}, H_{12}, H_{13}, H_{21}, H_{22}, H_{23}, H_{31}, H_{32}, H_{33}$ the unknown parameters. There are eight degrees of freedom for that transformation. This means that for four different pairs of corresponding (x', y') and (x, y) points, we obtain a system of eight equations which leads to the unique determination of the transformation of all the points.

The algorithm solves the problem which is stated as

Given $n \geq 4$ 2D to 2D point correspondences $\{x_i \leftrightarrow x'_i\}$, determine the 2D homography matrix H such that $x'_i = Hx_i$.

There is a need of 4 known points (markers) with real coordinates system. We found out that not every combination of 4 points on the ground can solve the above problem. The four points can create any geometrical shape in the reality and this problem must be tackled. We have tried many different geometrical shapes in the reality and we finalize that only a rectangle results in the best solution. The algorithm also applies normalization of the initial data which makes the technique independent of scale choices, coordinate origin choices or changes. This provides also results with higher accuracy.

The corners of a rectangle are going to be used as the four correspondences required to compute the homography transformation. This is a method to create the four pairs of image to world points, while fulfilling the requirement for perspective correction.

2.2 Automatic Swimming Pool Extraction

2.2.1 Color based Segmentation

The identification of the pool on the image is crucial in order to obtain information about its location. The position of the corner pixels can be extracted if the system can recognize the pool. Image segmentation techniques are achieving that aim. The property that distinguishes the pool from its neighboring environment is its color, therefore the image is analyzed with color-based segmentation (Cheng et al., 2001). By performing color based segmentation, the image is partitioned in chromatically homogeneous regions. Each identified region has

pixels with the same chromatic values. For this purpose, our framework used the K-means clustering algorithm for image content classification.

2.2.2 K-means Clustering

K-means Clustering in digital imaging is a region formation technique which relies on common patterns in specific values within a group of neighboring pixels (Sharma et al., 2012). Clustering distinguishes and classifies samples with similar properties (Phyo et al., 2015). Color based clustering creates clusters, each one consisting of pixels with similar chromatic properties and the goal of the segmentation algorithm is to create clusters according to their color homogeneity. Given an image this method splits it into K clusters. The number of clusters (k) is decided beforehand. Each cluster is defined by its center. Every point is associated to the cluster where the difference between the point and the center is smallest. The mean is considered the center of each cluster. After an initial assignment of all the data points, the new means of the clusters are recalculated and the data are reassigned to the new clusters. This iterative process is finished when no new changes occur in the cluster means. The objective of the algorithm is defined as:

$$\operatorname{argmin} \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2 \quad (5)$$

where S_i is a cluster and μ_i is its mean.

2.2.3 Clustering Implementation

In order to chromatically segment the image, it was transformed in the CIE $L^*a^*b^*$ color space. This color space approximates the human vision. It includes all perceivable colors and its coverage exceeds those of other models, such as the RGB color model. The $L^*a^*b^*$ space consists of a luminosity channel L^* and the color channels a^* and b^* . Channel a^* indicates where color falls along the red green axis, and blue yellow colors are represented along the b^* axis. The color information is on the a^* and b^* channels. Each image point is regarded as a point in the $L^*a^*b^*$ color space and the difference between two colors can be calculated as the Euclidean distance between two color points (SCIMS 2019). The ability to express color difference as Euclidean distance is of great importance in color segmentation.

After converting the image in the $L^*a^*b^*$ color space the k-means clustering algorithm is implemented with 3 initial mean values. The pixels are assigned in clusters according to their a^* and b^* values. The result are three clusters, each with similar

color values. We are interested in the cluster containing the blue objects in the image. It is determined that the blue cluster has the smallest mean a^* and b^* values, making this a criterion to distinguish the cluster (Figure 1).



Figure 1: Input images and the identified blue cluster.

Further processing is required to define the pool. After removing the small objects from the image, we identified all the connected image components. It is observed that the pool is always the biggest component, thus removing all the other components we refined the result which depicts only the pool in a binary black-white image (Figure 2).



Figure 2: Final feature extraction, the pool is identified.

2.3 Corner Points Detection

Detecting corners of a quadrilateral or a rectangle in a binary image, is a common process and a variety of solutions are provided. There is a variety of algorithms for that purpose, such as the Harris – Stephens corner detector algorithm (Harris and Stephens 1998) or the FAST algorithm (Rosten and Drummond 2005). However, these algorithms work better with perfectly shaped features consisting of straight lines. Our cases involve rectangles formed by edges with irregularities, as it is expected in images depicting outdoor scenes. Our initial approach was based on the Hough transform (Kovesi, 2019), which is a feature extraction technique used to identify lines, circles or curves. Its characteristic is that it can find imperfect instances of those features and perform a robust detection under noise. Hough transform detects lines based on their polar form. Our aim was identifying the meeting points of lines as corners after

line detection. Unfortunately even that robust approach was unsuccessful in our cases due to the line imperfection (Figure 3).

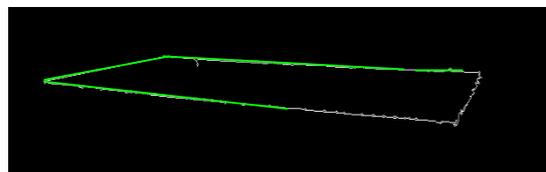


Figure 3: The Hough transform implemented on one of our cases. The lines are not identified in the parts with irregularities

Considering the unsuitability of the known algorithms for our case, we implemented a different method for identifying the corners. Using the binary image from the pool extraction method, we scan the image for the outmost occurrences of the points belonging to the swimming pool. In this part of the framework the input is a binary image with zeros everywhere except the section of the swimming pool which is represented with pixel value 1. The image is scanned in order to find the first and last occurrences of non zero elements belonging to the swimming pool, in the vertical and horizontal direction. Those are considered corners. More specifically, the image is scanned vertically returning the row and column pixel position of all the occurrences of the non zero elements. The pixel position of the first and last of those occurrences are the leftmost and rightmost corners.

Then we single out the first and last row which have occurrences of the non zero elements. We identify all the non zero elements that belong in those two rows and we sort them by their pixel values separately in two arrays, one representing the non zero occurrences of the first row and the other those of the last row. The pixel position of the first element in the first row array is the uppermost corner and the pixel position of the last element of the last row array is the lowermost corner. The method considers special cases, such as rectangles or shapes with horizontal or vertical lines which is a rare occurrence in images due to the perspective distortion and recognizes the real corner points from the side points where the swimming pool is cut out of the image (Figure 4).



Figure 4: The identification of the corners.

2.4 Georeferencing

The resulting pixel positions of the previous step are computed with the homography matrix and the geographic coordinates are calculated. Our aim is to calculate the geographic coordinates of all four swimming pool corners. There are several approaches to achieve that. An image with all swimming pool corners visible along with the aforementioned rectangle for the perspective correction can be put as input in the framework and have immediate results. Another approach is the input in the framework of an image with three corners visible. The fourth corner can be calculated via Euclidian geometry. One other method involves the use of two images one with the correction rectangle and one with all the corners of the swimming pool. The two pictures can be related with a homography matrix, essentially computing the final geographic coordinates via a proxy image. All three approaches were implemented.

Approach A: Image with Four Visible Swimming Pool Corners



Figure 5: Image with four swimming pool corners visible as input.

This straight forward approach uses one image to identify both the perspective correction rectangle formed by the red dots on the image and the four swimming pool corners (e.g. Figure 5). This technique is the least accurate. The results are presented below.

Real Geographic coordinates	Results	Error (distance in m)
2490643.605, 1114391.994	2490643.254, 1114391.621	0.513
2490636.025, 1114399.984	2490636.336, 1114399.791	0.366
2490632.345, 1114396.534	2490632.993, 1114397.344	1.037
2490639.925, 1114388.524	2490639.917, 1114388.631	0.108

It can be observed that the points further from the perspective correction rectangle (e.g the third coordinate above which represents the leftmost corner in the image) are those with the biggest deviation from the real coordinates. It was determined

experimentally that as we move further from the rectangle the accuracy of the results diminishes.

Approach B: Two Images



Figure 6: Two images as input. The corners are calculated based on the second image, whereas the perspective correction rectangle is acquired from the first image.

The geographic coordinates in this method are calculated from the second image using as a proxy for the perspective correction the first image (e.g. Figure 6). In order to minimize the deviation of the results from the first approach, the input for the initial rectangle and the four points to be computed were separated in two images. To be more specific, the image which has the closest depiction of the initial rectangle, in our case the first image above is used to calculate the homography matrix relating the image with the geographic coordinates. The points to be computed are extracted from the second image which depicts all four corners. A second homography matrix is computed based on four random point pairs in the two images. This matrix relates the two images. In summation, the points are extracted from the second image, they are transformed in the coordinate system of the first image via the homography matrix relating the two images and then the geographic coordinates are computed via initial homography matrix.

Real Geographic coordinates	Results	Error (distance in m)
2490643.605, 1114391.994	2490643.136, 1114391.425	0.737
2490636.025, 1114399.984	2490636.035, 1114399.393	0.592
2490632.345, 1114396.534	2490632.379, 1114397.022	0.489
2490639.925, 1114388.524	2490639.780, 1114388.351	0.225

The overall accuracy of the results is improved in comparison to the previous method. There is a definite rectification of the third coordinate, but a loss in accuracy of the others. This may be due to the errors in the point pair selection, the extra step which involves external input.

3 CONCLUSIONS

This paper presented a simple, low-cost and fast technique of acquiring metric information via the use of images. This method has the potential to substitute classic methods of surveying, in the sense that results in obtaining geometric information at minimum cost. It extracts information from images using an uncalibrated camera. Utilizing the principals of single or multiview geometry, we are provided with data without prior knowledge of the camera intrinsic parameters, position or orientation and free of camera synchronization or calibration.

The algorithms developed detect automatically the geometry of an object and compute spatial data with the requirement of minimum scenes constraints and user input. The principals of homography were utilized to relate image information with geographic coordinates. Image segmentation techniques and morphological image processing were combined to achieve the required automation in geometric data extraction. Depending on the combination of the algorithms and the variation of input, three methods were presented to compute the final geographic coordinates. The framework created is considered a flexible, automatic and accurate way of acquiring spatial data with no use of special equipment. However, the flexibility of the framework can be further increased by developing the methodology to include detection of random shape spatial objects.

As further work we would like to fully automate the approach, the user hasn't to do any intervention. We envision an open, interoperable application environment for spatial information processing, empowering the user and providing the cadastre office with new services. The services are fed with spatial information input, which comes from the uncalibrated digital cameras, as well as from the cadastre data. We are currently investigating more algorithms and technologies for extracting spatial information from the images independent of the geometry of the spatial object.

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