FROM A PHYSICAL SCANNED MAP TO A DIGITAL ELEVATION MODEL USING THE LEGEND AND KRIGING

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ABSTRACT

The objective of this paper is the development and analysis of methods for producing digital elevation models from physical scanned maps having as little as possible human interaction. The elevation layers are identified based on the map's legend using the CIE L*u*v* color space, the mean shift filtering and the randomised local search color clustering. The nonelevation layers within the map image generates unclassified pixels. Their values are estimated using geostatistics (i.e. kriging). In the end, the elevation contours are extracted and interpolated.

1. INTRODUCTION

The manual digitization process of the paper maps is costly and tedious. An automatic or semi-automatic method increases the efficiency, but it is a challenging problem. A solution that works in the gray scale domain can be found in [1]. An approache in the color domain is offered by ref. [2]. None of the methods is fully automated.

A digital elevation model (DEM) is a basic geographical data type, stored using an ASCII or binary file and it allows the generation of 3D renderings for a specific earth surface area. Remote sensing and satellite imagery are used to obtain high quality DEMs. But this is not an affordable solution for each case. The elevation data extracted from a scanned map can offer a cheaper way to produce DEMs.

Arrighi et al. in [3] use topographical maps to obtain the altitude information.This paper focuses on physical maps where colors are used to express the elevation. The map's legend shows the colors that are used to symbolize the altitude data within the map and also the elevation ranges denoted by each color.

This work proposes an approach for producing digital elevation models based on the map's legend and geostatistics. The paper is organized as follows. We start in Section 2 by giving details about the method used to extract the elevation layers from the scanned map that includes conversion into CIE L*u*v* color space, mean shift filtering and RLS clustering. An approach for estimating the unclassified pixels based on kriging is presented in Section 3. Also, this section summarizes the methods used for the contours extraction and interpolation. Conclusions are drawn in Section 4.

2. LEGEND BASED ELEVATION DETECTION

The identification of the elevation layers within a physical scanned map is not an easy task. Usually, a paper map combines more information layers. The printing process uses the dithering effect [4]. The lines, the text and the edges within the map image after scanning may be anti-aliased. Anti-aliasing is a method used in graphics for smoothing the jagged edges in order to do them pleasing to the human eye. But from our problem's point of view, we can say that anti-aliasing introduces a lot of unwanted colors.

2.1 The color space

The RGB color space is widely used for digital images and it is compatible with digital displays, but it is not perceptually uniform. CIE L*a*b* and CIE L*u*v* color spaces were developed to be perceptual uniform. The differences in color are represented by the Euclidean metric [5]. The method described in this paper uses color similarity measurements, hence, we consider CIE L*u*v* color space [6] for all the steps used to identify the elevation layers.

Two adjacent colors in the map's legend may have small dissimilarities and CIE L*u*v* space is efficient in the measurement of small color differences. The main drawback of the CIE L*u*v* is that it contains a singularity and the near values are numerically unstable [5].

2.2 Mean shift filtering

The algorithm used in this work and proposed in [7] employs a 5-dimensional feature space: the first three dimensions are the L* u* v* coordinates, and the last 2 dimensions denote the position of the pixel within the image. The quality of filtering can be controlled using 2 resolution parameters: h_r, and h_s - the radius of the analyzing window in the color domain, respectively, in the spatial domain.

The mean shift filtering method searches for the local maxima of density by moving iteratively a 5D analyzing window by the mean shift vector, until the magnitude of the shifts becomes less than a threshold. Local maxima of density are called *modes*. The mean shift filtering method ends by replacing the value of each pixel with the 3D color component of the 5D mode it is associated to.

Mean shift filtering reduces the number of colors within an image and offers a discontinuity preserving smoothing. We used this type of filtering in order to reduce the dithering effect within the scanned map.

In our experiments we considered the spatial resolution $h_s = 7$. For filtering the crop image that contains the legend, we used a higher value for the color resolution (i.e. $h_r = 6.5$) in order to eliminate as many as possible from the artifacts created by the dithering effect. The map test image is filtered using a smaller value for the h_r (i.e. 2) for avoiding the distortions over the elevation layers (i.e. small area elevation regions).

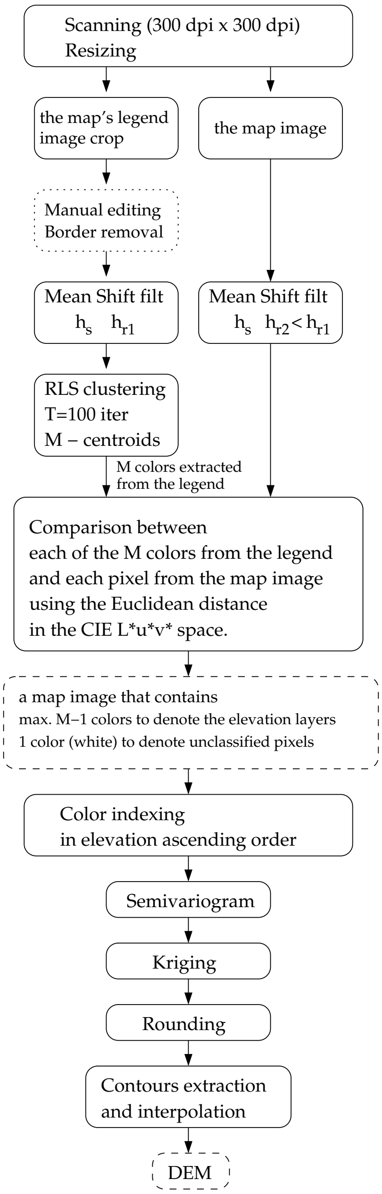


Figure 1: The diagram for the proposed approach for producing a digital elevation model from a physical scanned map.

2.3 Color clustering using the RLS algorithm

Randomised Local Search (RLS) approach for color clustering was proposed in [8] and it was designed to be insensitive to the initialisation.

The *RLS* method has as input the color image (X), the number of clusters (M) and the number of iterations (T). The initial values for the centroids (C) are generated by taking randomly values from the image. P is the partition array containing integers pointing from X to C. An optimal partition (P) is generated by finding the nearest centroid for each element in X. An iterative process is used to generate global changes to the clustering structure and to perform local fine-tuning. It is a three-step procedure: *the random swap* modifies the centroid structure by changing one value per iteration, *the local repartition operation* adjusts the partition array in respect to the modified set of centroids, and *the k-means* enhances the the local refinement. The objective function (obF) is used to appreciate the quality of the new solution, which is accepted only if it improves the current solution.

In our work we use the *RLS* color clustering method for extracting the colors from the map's legend. This method is less sensitive to initialisation than the *k-means* method. We run the algorithm using $T = 100$ and $M = [elevColors + 1]$ - the number of elevation layers denoted by the map's legend plus one - the white color, which appears in the legend crop image after manual border removal step that is done in order to reduce the distortions.

2.4 Identification of the elevation layers

Our approach for identifying the elevation layers from a color-coded relief scanned map is described in Figure 1.

The colors extracted from the legend and the preprocesed map image are converted from RGB into CIE L*u*v* color space, where Euclidean distance is computed between each color from the legend and each pixel within the map image. If h is the height of the map image, and w is the width, the result will be a $h \times w \times M$ matrix structure storing the distances relative to each color from the legend that contains M colors.

The elevation layers are identified by means of a threshold operation over the $h \times w \times M$ matrix. After the threshold process, the $h \times w \times M$ matrix contains only zeros (denoting nonlayer regions) and ones (denoting the elevation layer). We tried to apply the same threshold value to all the layers. However, due to small dissimilarities between some colors of the legend, we used two threshold categories.

Median filtering is applied for removing the isolated values caused by the dithering effect and generates a $h \times w \times M$ matrix denoted TM.

In order to reduce errors we identify the overlaps between the extracted elevation layers by making the sum of the M matrices of size $h \times w$ contained by TM and finding the values greater than one.

In the end all the layers are combined together using the related colors from the map's legend. Values corresponding to overlaps are associated to white.

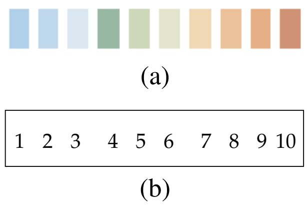


Figure 2: The legend. (a) After MEAN SHIFT filtering (spatial resolution $h_s = 7$, color resolution $h_r = 6.5$), manual border removal and RLS color clustering (T = 100 iterations, M = 11 centroids); (b) The index of colors in elevation ascending order.

3. KRIGING BASED GAP FILLING

3.1 The semivariogram

An intrinsic statistical model assumes that there is a stationary variance of differences in a random variable between positions separated by a given distance and a given direc-

(a) (b)

Figure 3: The map image. (a) After MEAN SHIFT filtering (spatial resolution $h_s = 7$, color resolution $h_r = 2$). (b) The identified altitude layers - a map image that contains 4 colors to denote the elevation layers plus white to denote unclassified pixels.

tion.The semi-variance of difference is called the semivariogram [9], and is defined as follows:

$$\gamma(h) = \frac{1}{2} \cdot E[(z(x_1) - z(x_2))^2], \quad ||h|| = ||x_1 - x_2|| \qquad (1)$$

where h is called *the lag*. Experimental semivariograms are usually fitted with theoretical models. In our work, we used a general version of the exponential-Bessel, as a theoretical model:

$$\gamma(h) = C_0 \cdot [1 - J_0(b \cdot h) \cdot exp(-\left(\frac{h}{L}\right)^p)] + \gamma_0 \qquad (2)$$

As an example, Figure 4 shows the experimental and the theoretical semivariograms associated with the sparse test map image.

Semivariograms shows how the averrage difference between values at pairs of points changes with the distance between points. Semivariograms are used further for weighting individual sample points in the neighborhood of the locations to be estimated.

3.2 The kriging

Kriging was developed by D.G.Krige (1962) and is an optimal method for estimation of the unknown values within an originally sparsely sampled data assumed to be characterized by an intrinsic statistical model [9].

The input data, $z(x_s)$, exists at sampled locations x_s, where $s = 1, 2, \ldots, N$. Kriging estimates the value at a specified location x_E where the value $z(x_E)$ is unknown using a weighted sum of the observations:

$$\hat{z}(x_E) = \sum_{s=1}^{N} \lambda_s z(x_s), \quad \sum_{s=1}^{N} \lambda_s = 1 \qquad (3)$$

where λ_s is the weight corresponding to the sample located at x_s.

By minimizing the variance of the estimation error, we obtain the kriging weights and, hence, the kriged estimate, $\hat{z}(x_E)$. The kriging variance , σ_E^2, is expressed as:

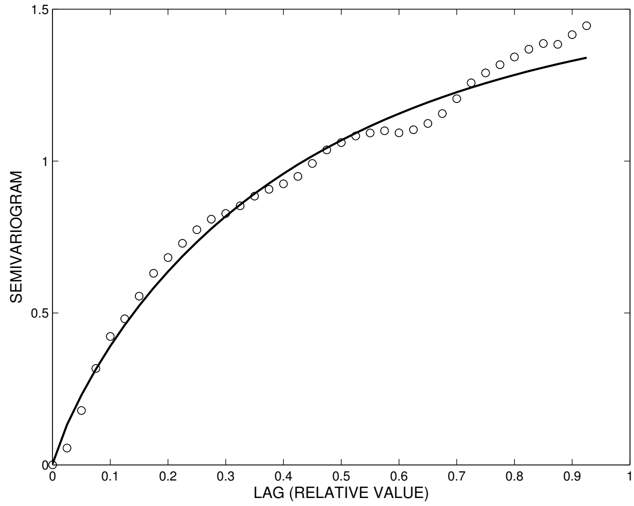


Figure 4: Semivariogram for the sparse map image (Fig. 3b). The dots simbolized by 'o' denote the computed semivariogram. The solid line refers to the theoretical model given by equation (2) fitted to the experimental semivariogram using the following parameters: $\gamma_0 = 0.0035$, $C_0 = 1.5516$, $L = 0.4216$, $b = 4.4408 \cdot 10^{-14}$, and $p = 0.8671$.

$$\sigma_E^2 = E[z(x_E) - \hat{z}(x_E)]^2 =$$
$$= 2\sum_{s=1}^{N} \lambda_s \gamma(||x_E - x_s||) - \sum_{s=1}^{N}\sum_{q=1}^{N} \lambda_s \lambda_q \gamma(||x_s - x_q||) \qquad (4)$$

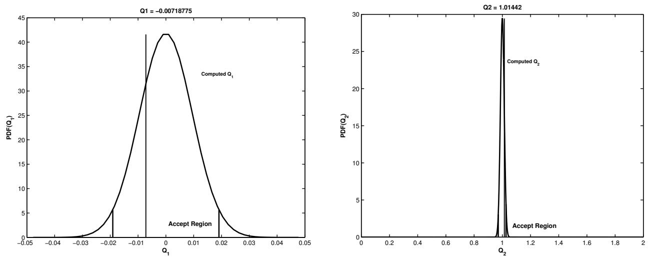
A physical paper map includes non-elevation layers and after scanning some artifacts may appear near the edges due to anti-aliasing. These yields gaps (denoted by white colored pixels) within the resulting image after elevation layers identification step. In this work, kriging was used to estimate the value of those unclassified pixels.

First, the colors within the sparse map image are indexed in elevation ascending order based on the map's legend. Then, kriging is applied. The resulting values are rounded to the nearest integers. After this step, we have a solid-colored physical map image that contains only elvation data (Figure 6a).

In order to evaluate the results obtained after kriging (i.e. how well the experimental semivariogram was fitted to the theoretical one), we used Q_1 and Q_2 cross validations. Q_1 checks the statistics of the mean of the E_r (approximately, follows the normal distribution) [[10]]. Q_2 checks the statistics of the variance of E_r (approximately, follows the chi-square distribution). E_r is an array that contains the normalized residuals between the observed data and the kriged values at the original observation locations (by using the same semivariogram model parameters and kriging parameters). Q_2 rule is a more strictly validation rule than Q_1. Figure 5 shows an example of Q_1 and Q_2 cross-validations.

3.3 The interpolation

Color-coded contours are extracted from the solid-colored physical map image by detecting the borders between colors through a sliding-neighborhood operation. Next, using



(a) (b)

Figure 5: Cross-validation results after kriging the map image in Figure 3b using the theoretical semivariogram model in Figure 4. (a) Q_1 cross-validation; (b) Q_2 cross-validation. The computed cross-validation values are located within the coresponding accepted region, for both cross-validation methods

the information offered by the map's legend, the contours are converted into a sparse altitude data set.

The sparse DEM is interpolated using a Laplacian system of equation, based on the following relations:

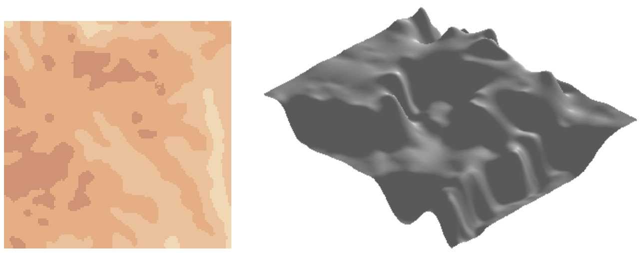
$$z_{i,j} = \frac{z_{i,j-1} + z_{i,j+1} + z_{i+1,j} + z_{i-1,j}}{4}, \qquad z_{i,j} = e_{i,j} \quad (5)$$

where $z_{i,j}$ - denotes an altitude sample and $e_{i,j}$ expresses the known value for an elevation sample.

For solving the system, the LSQR iterative solver - an algorithm developed by Saunders and Paige [11] - is applied.

More details on contours extraction and interpolation are included in [12].

Figure 6b shows the 3D representation of the interpolated DEM obtained for the test map image (Figure 3a).



(a) (b)

Figure 6: (a) The resulting image after kriging and rounding; (b) The 3D representation of the interpolated DEM.

4. CONCLUSIONS

In this paper, we tried to find a solution for each of the steps necessary for obtaining a digital elevation model from a physical paper map. In order to identify the altitude layers, the scanned map is processed in the CIE-L*u*v* space using the map's legend. The method offered good results with no wrong classified pixels next to white regions. A kriging based approach is used in order to automate the gap filling process (a process that estimates a color from the legend for each unclassified pixel - denoted by white). The estimation may be difficult for map images that contain a lot of unclassified pixels and we can say that the method worked well for this kind of situations, too.

The problem is that the whole process is computational intensive, and processing large maps needs a significant amount of time. Our future work may be concerned with development of fast algorithms for processing large map images.

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