MATCHING AERIAL COASTLINE IMAGES WITH MAP DATA USING DYNAMIC PROGRAMMING

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ABSTRACT

Matching aerial images with map data is an important task in several remote sensing applications such as autonomous navigation, cartography, oceanography. The unique and distinctive shapes of coastlines can be effectively utilized to solve this problem. In this study a completely automatic scheme is proposed to detect coastlines using multi-resolution texture analysis and to match the detected coastlines to a map database. A shape matching method using dynamic programming is used and tested on the satellite images of the western coast of Turkey.

1. INTRODUCTION

Coastline extraction and coastline matching with map data are important issues in several applications and coastal studies such as autonomous navigation of aerial vehicles, cartography, geo-referencing satellite images and coastal geomorphology monitoring. In recent years, there has been an increasing focus of interest on coastline extraction and matching. In [1] and [2] fuzzy rules and textural features are used in a semiautomatic scheme to extract coastlines. In [3], [4] and [5] edge based extraction is done in high contrast aerial images. [6] uses Hausdorff distance to match coastal features found by edge detection. [7] employs a contour based matching to register aerial images. [8] uses spectral and textural features to extract coastlines in SAR images.

The common drawbacks of the existing techniques are the need for user interaction, high computational complexity and the sensitivity to noise. These problems should be solved especially for the real-time applications such as autonomous navigation of unmanned air vehicles (UAV). This kind of a navigation system can be very effective when no GPS data and no communication link are available. A passive navigation system is also very important in military UAV applications

In cartography, updating coastline maps and charts by using recent aerial coastline images requires extracting coastlines in the images and them matching with the old map data. Cataloging satellite images and monitoring coastal geomorphology, both use multitemporal, multisatellite and multisensor coastline images. In order to index and analyze these images, the images should be georeferenced by automatically matching images with the map data.

In this paper, problem of matching aerial coastline images with map data has been studied because of the needs described above. The problem has been studied in two main parts: Automatic multi-resolution coastline extraction and matching of extracted coastlines with map data.

For the proposed automatic coastline extraction method, first we implemented the wavelet decomposition of the coastline image to extract multi-resolution information and to highlight textural content. The wavelet image has been segmented into sea and land regions by using textural features. Multiscale segmentation of the wavelet image has been achieved by means of coarse to fine segmentation which employs co-occurrence features and histogram features of textures. Co-occurrence features have been selected by using a feature selection scheme based on Fisher's linear discriminant analysis (FLDA). Sea and land textures are classified by using the maximum likelihood classifier. After classification of sea region, boundary pixels are extracted as the coastline.

In order to develop a method that matches the extracted coastlines with map data, shape descriptors are studied. Commonly used contour-based shape descriptors such as chain code representation, curvature scale space descriptors and Fourier descriptors are discussed.

The coastline matching algorithm described in this paper is adapted from Petrakis, Diplaros and Millios' shape retrieval algorithm [9]. In the proposed method, extracted coastlines are segmented into convex and concave segments by finding inflection points of the coastlines. Features of the segments such as turning angle, length, and area are extracted from the coastline segments. Using dynamic programming table, extracted coastlines are matched with the map data. Automatic coastline extraction and matching methods are tested on a vector map of the Aegean coast of Turkey.

2. COASTLINE DETECTION

The aerial images of coastal areas can be visually identified easily due to the homogeneous nature of the regions occupied by sea. The complexity of the problem is directly related to the physical conditions such as the position of the imaging device, properties of image sensors, atmospheric events, etc. An aerial image captured by an infrared (IR) sensor array mounted on a high altitude satellite on a clear day could be considered as a best case scenario. In this case, sea region can be easily segmented by selecting the connected dark valued pixels. But in reality several difficulties arise. Low altitude aerial images often suffer from reflections and inhomogeneity due to windy conditions, local currents and change in depth. More complicated texture analysis is needed to segment regions covered by water in such

images. Atmospheric conditions such as haze and clouds may also complicate the problem. Using Synthetic Aperture Radar (SAR) images may alleviate the problem of blocked view but the captured SAR images are not easy to interpret without using special purpose texture analysis.

If no restrictions are imposed on the physical properties of image acquisition, we can consider the segmentation of water filled regions as a texture analysis problem. Textural features can be selected to represent characteristics of sea regions even if they are subject to the undesired conditions mentioned above. To implement texture analysis, we chose to apply Haralick's co-occurrence features [10] on images converted by Discrete Wavelet Transform (DWT) [11]. This combination is commonly used in texture analysis since DWT is an effective multiscale representation on which textural features are enhanced. The filterbank implementation shown in Figure 1 is applied to implement DWT. Separability property of DWT allows using one dimensional filters in row and column directions. In our implementation the 4-tab Daubechies [12] low (G) and high (H) pass filters are used with weights {0.4830, 0.8365, 0.2241, -0.1294} and {0.1294, 0.2241, -0.8365, 0.4829} respectively.

A representative set of patches taken from different coastal images are converted to DWT domain. Using the detail images (D_1-D_3) Haralick's textural features are computed. The importance of these features are tested and the most dominant ones are selected by analysing the projection in the pattern space by Fishers Linear Discriminant [13]. The distance between training samples corresponding to competing classes contribute to the confidence measure of the features being used. The training set is formed of 5000 sea and land patches from 15 different aerial images.
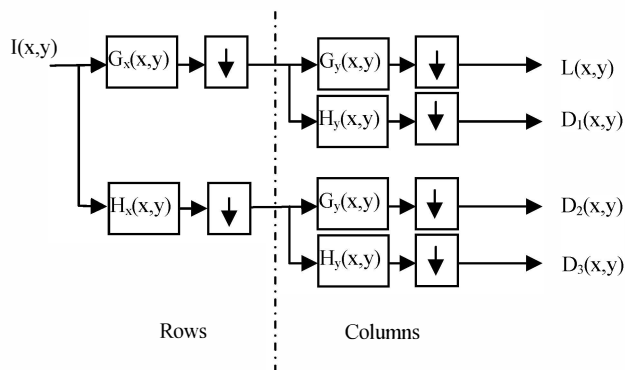

Figure 1 - Implementation of DWT using filterbanks

The selected co-occurrence features are used in combination with histogram features [11] in a quadtree structured course to fine approach using maximum likelihood classification [13] scheme. The details of the coastline detection procedure can be found in [14][15].

Figure 2b illustrates the segmented parts of the original image given in Figure 2a. The erroneously segmented parts are eliminated during coastline detection process which highlights bordering pixels and applies binary operations that thins the borders and rejects small segments.
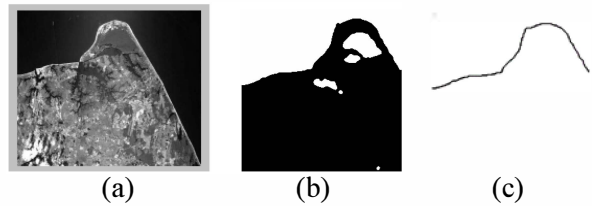

(a)   (b)   (c)

Figure 2 - (a) Original Image (b)Segmentation result (c) Detected coastline after binary post-processing operations

The coastal sketch illustrated in Figure 2c is a typical coastline segment with unique features. The problem of finding a match of this segment in a map database is similar to the problem of object recognition. The important difference of the coastline matching problem is that the contours are not closed contours making it difficult to represent shapes.

3. COASTLINE REPRESENTATION USING SHAPE DESCRIPTORS

In shape matching, a key issue is to extract the perceptually important shape features representing object boundary. These features are derived from a choice of a shape descriptors. They are used for computing similarities between the objects. For good retrieval accuracy, an algorithm based on a shape descriptor must be able to find perceptually similar shapes from databases, even if they undergo geometric transformations, this means that the shape descriptor must be invariant for translated, rotated, and scaled shapes. The descriptors must be robust to noise, distortion and deformations which are easily tolerated by human observers. They must be compact for indexing the database and computationally efficient for real-time applications.

Shape representation and matching techniques [16] in the literature can be generally classified into two class which are contour-based and region-based methods. Contour-based techniques only use object boundary information whereas region based techniques use all pixels within the object to obtain the shape descriptors. In coastline matching, extracted coastlines from aerial images are mostly open-curved and whole object information about sea and land regions cannot be captured. For these reasons, region-based techniques which need whole information about the object are not suitable for coastline matching.

Among contour-based methods, simple global descriptors such as area, circularity, eccentricity, and major axis orientation usually can only discriminate shapes with the large differences and ignore local deviations of the boundary which are important in coastline matching. Hausdorff distance is a correspondence-based shape descriptor using point-to-point matching which needs further improvement to achieve rotation/scale invariance and robustness to noise. Chain code representations, Fourier descriptors, and curvature scale space descriptors are commonly used shape matching methods in contour-based techniques. In this section, some of these methods will be briefly explained and advantages, disadvantages for coastline matching will be discussed.

3.1 Chain Codes

Chain codes are used to represent an object boundary by a connected sequence of straight-line segments with specified length and orientation. Chain code representations are mostly used in handwritten character recognition applications [17] The method was introduced by Freeman [18] who described a method permitting the encoding of arbitrary geometric configurations. Chain code representation is sensitive to noise and variations on the object boundary.

3.2 Curvature Scale Space (CSS) Descriptors

Curvature Scale Space (CSS) Descriptors are widely used in shape representation. CSSD describes local shape features. By representing shape boundary in scale space, not only the locations of convex (or concave) segments, but also the degree of convexity (or concavity) of the segments on the shape boundary are coded [19][20]. CSSDs can effectively represent closed curves but the open curves cannot be represented completely.

3.3 Fourier Descriptors

Fourier descriptors are derived from Fourier Transformation of the shape signatures. Global shape features are captured by the first few low frequency terms, while finer features of the shape are captured by higher frequency terms.

Different types of FDs are used in the shape recognition literature such as complex coordinates, centroid distance, curvature, and cumulative angular function [21]. For closed boundaries, FDs have properties similar to CSSD. They are usually meaningful and they capture structural features of the shape boundary. They are robust to boundary noise and irregularities. They can be calculated with low computational complexity. However, for the case of open curved boundaries, FDs are not suitable because the periodicity of the whole boundary contour is essential in their computation.

Extracted coastlines from aerial coastline images usually match a part of the coastlines in the map data. This means that most of the extracted coastlines are open curves. For this reason, a coastline matching method must be suitable for open curve matching. Also, a coastline matching method must be invariant to geometric transformations and must be robust to noise and deformations. The commonly used representations of shape described above are very effective for closed contours but they are not very useful for open curves.

A dynamic programming method which is particularly useful for the case of open curves is described in the next section

4. COASTLINE MATCHING USING DYNAMIC PROGRAMMING

The coastline matching algorithm using dynamic programming is adapted from Petrakis, Diplaros and Millios' algorithm [9] which was originally described for object recognition. The algorithm is applicable to distorted and noisy coastlines by allowing matching of merged sequences consecutive segments in a coastline with the segments of another coastline. The algorithm is also invariant to translation,

scale, rotation and starting point selection. The main idea of this method is to represent each coastline by a sequence of concave and convex segments and allow the matching of merged sequences of small segments in a deformed or noisy coastline with larger segments in the other coastline. Merging shows similar effect to that of smoothing several small segments in a coastline to form a single larger segment without performing the costly smoothing operations. The algorithm selects most promising merges based on local information.

4.1 Segment Features

Concave (V) and convex (C) segments of a coastline which are the parts of the coastline between the consecutive inflection points can describe visually prominent parts of the coastline. After finding inflection points of the coastlines, the coastlines are segmented into concave and convex segments according to the signs of the segment curvatures. The part of the coastlines between the consecutive inflection points are selected as coastline segments.
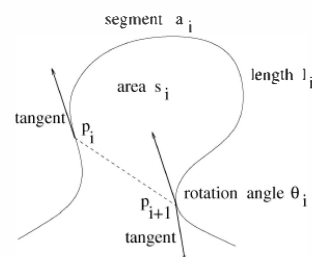

Figure 3- Segment features defining the importance of a segment [9]

In the specification of visual prominence of a segment, three segment features (Rotation Angle θ_i, Length l_i ,and Area S_i) shown in Figure 3 are employed.

4.2 Dynamic Programming (DP) Algorithm

In matching of two coastlines, A and B, the algorithm builds a dynamic programming (DP) table (Figure 4), where rows and columns correspond to inflection points of A and B, respectively. By starting at any cell at the bottom row, going upwards and to the right, the table is filled with the cumulative cost of the partial match of the segments between the inflection points (rows and columns) passed. Only about half of the cells are assigned cost values, in DP table, as convex segments cannot match concave ones. Merges can take place when a segment sequence of one coastline matches a single segment or a group of segments of the other coastline. Merges make "jumps" in the DP table. Reaching the top row (termination area) implies a complete match, when all inflection points of coastline are visited.

Additional information is stored in each cell to allow the backtracking of a path. The backtracking of a path shows segment associations between the two coastlines. Dynamic Programming is used to find the minimum cost path from a cell in the initialization area to one in the termination area.
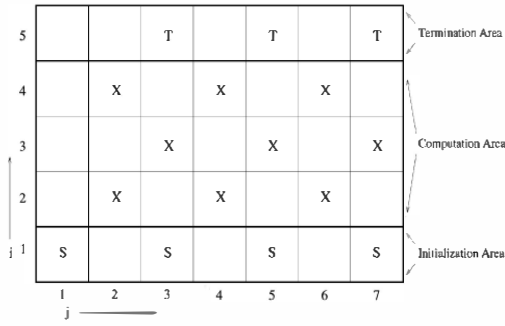
Figure 4 – An illustration of DP table [9]

4.3 Matching Segments

A complete match is a correspondence between the sequences of segments in order, so that no segments are left unmatched in coastline A and there are no crossovers. A complete match is characterized by a complete path $((i_0,j_0), (i_1,j_1), ...,(i_T,j_T))$, which is a path that starts from the initialization area and ends at the termination area. The cost (distance) $D(A,B)$ of matching coastline A with coastline B can be defined as:

$$D(A,B) = \min_{T}\{g(i_T, j_T)\} \tag{7}$$

where $g(i_T,j_T)$ is the cost of the complete match. $g(i_T,j_T)$ is defined by:

$$g(i_T, j_T) = \min_{i_w, J_w} \sum_{w=1}^{T} \psi(a(i_{w-1}+1|i_w), b(j_{w-1}+1|j_w)). \tag{8}$$

The term $\psi(a(i^{w-1}+1\,|\,i^w), b(j^{w-1}+1\,|\,j^w))$ representing the similarity cost of two arguments is computed by:

$$\begin{aligned}\psi(a(i_{w-1}+1|i_w), b(j_{w-1}+1|j_w)) = \\ \lambda.(M_C(a(i_{w-1}+1|i_w)) + M_C(b(j_{w-1}+1|j_w))) \\ + D_C(a(i_{w-1}+1|i_w), b(j_{w-1}+1|j_w))\end{aligned} \tag{9}$$

where M_C is merging cost and D_C is dissimilarity cost. The first two terms in (9) represent the cost of merging segments $a(i_{w-1}+1\,|\,i_w)$ in coastline A and segments $b(j_{w-1}+1\,|\,j_w)$ in coastline B respectively while last term is the cost of matching the merged sequence $a(i_{w-1}+1\,|\,i_w)$ with the merged sequence $b(j_{w-1}+1\,|\,j_w)$. Constant λ denotes the relative importance of the merging costs. Low values of λ encourage merging and high values of λ inhibit merging. Low values of λ should be used while matching the coastlines with a high amount of detail.

Merging should follow the grammar rules (i.e. recursive applications of CVC→C or VCV→V).

4.4 Scale Factor

Scale invariance in matching can be achieved by incorporating a scale factor that can be computed as the ratio of the lengths of the matched parts of coastlines A and B respectively:

$$\rho_t = \frac{\sum_{w=1}^{t-1} \sum_{i=i_{w-1}}^{i_w-1} l_i(A)}{\sum_{w=1}^{t-1} \sum_{j=j_{w-1}}^{j_w-1} l_j(B)} \tag{10}$$

where $2 \le t \le T$ and $l_i(A)$ and $l_j(B)$ are the lengths of a_i and b_j, respectively. This value is an approximation of the actual scale factor of a complete match. The value ρ_1 is set to 1.

4.5 Dissimilarity Cost:

The dissimilarity cost of matching a group of the segments from coastline A with a group of the segments from coastline B is computed by:

$$D_C = U.\max_{f}\{|d_f|\}. \tag{11}$$

The term d_f is the cost associated with the distance in feature f (i.e., length, area or angle). d_f may take negative values when f is the angle.

$$d_f = \frac{|F_A - S_w(f)F_B|}{F_A + S_w(f)F_B} \tag{12}$$

where, $F_A = \sum_{i=i_{w-1}+1}^{t_w} |f_i|$, $F_B = \sum_{j=j_{w-1}+1}^{J_w} |f_j|$, and

$S_w(f)$ is a parameter depending on the feature f. $S_w(f)=\rho_{w-1}$ for f = length and $(\rho_{w-1})^2$ for f = area. For f = rotation angle, $S_w(f) =1$ because angle does not depend on the scale. ρ_{w-1} is computed according to (10) for global and local matching respectively.

U is a weight term associated with the dissimilarity of the partial match such that: U emphasizes the importance of matching large parts from both coastlines, in a similar way that humans pay more attention on large coastline parts when judging the quality of matching. Without U, the matching of very small coastline parts contributes to the cost of matching equally with the matching of large parts. U is defined as the maximum of two proportions of the matched coastline length with respect to the total length:

$$U := max \left\{ \frac{\sum_{i=i_{w-1}+1}^{t_w} l_i(A)}{l_A}, \frac{\sum_{j=j_{w-1}+1}^{J_w} l_j(B)}{l_B} \right\}. \tag{13}$$

4.6 Merging Cost

Let the types of the segments being merged be CVC → C, Segments are merged to a single merged convex segment C by absorbing the concave segments between convex segments. The opposite case is obtained by exchanging C and V. The merging cost can be defined by:

$$M_C = \max_{f}\{U_f C_f\} \tag{14}$$

where f represents a feature (length, area or rotation angle).

For all features:
$$C_f = \frac{\sum_{\text{V segs of group}} |f|}{\sum_{\text{all segs of group}} |f|} \quad (15)$$

where the sum in the numerator is for the absorbed concave segments, while the sum in the denominator is for all merged segments of the group. The weight term of merging cost is defined as:

$$U_f = \frac{\sum_{\text{V segs of group}} |f|}{\sum_{\text{V segs of coastline}} |f|} \quad (16)$$

where the sum in the numerator is for the absorbed concave segments, while the sum in the denominator is for all concave segments of the coastline.

5. RESULTS AND CONCLUSIONS

In order to test the proposed coastline matching method, a 1/250000 vector map of Aegean coast of Turkey was constructed to be used as a reference map. As test images, 20 Aerial coastline images were acquired from an internet search site for aerial images (a.k.a Google Earth). Coastlines of the images were extracted by using proposed coastline extraction method described in Section 2. The longest coastline segments detected in the coastline images are selected as match candidates. Segment features for the images and the map have been calculated as described in section 4.1. By using the proposed DP coastline matching method (adapted from [9]), 9 out of 20 images were matched with the map data correctly. A typical example of a correct match of a coastline image and the map is illustrated in Figure 5. The accuracy of the match can be further improved by incorporating more data such as reference directions, scale, etc. when available.

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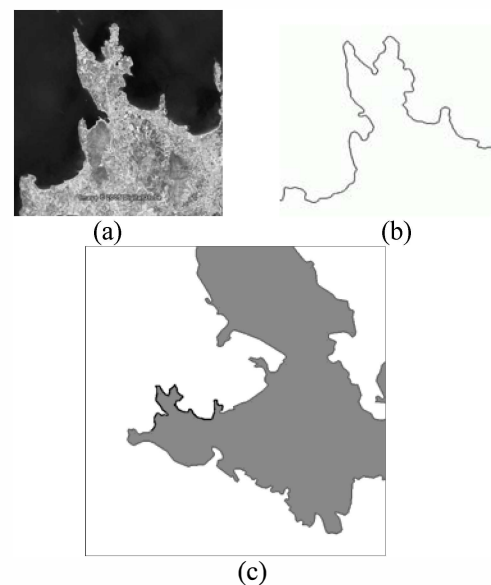
Figure 5 - (a) Aerial image of Çeşme (b) Corresponding partial map (c) Match of the coastline (coastline segment is highlighted in black).