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Automated identification of rivers and shorelines in aerial imagery using image texture

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ABSTRACT

A method has been developed which automatically extracts river and river bank locations from arbitrarily sourced high resolution (~1m) visual spectrum imagery without recourse to multi-spectral or even color information. This method relies on quantifying the difference in image texture between the relatively smooth surface of the river water and the rougher surface of the vegetated land or built environment bordering it and then segmenting the image into high and low roughness regions. The edges of the low roughness regions then define the river banks. The method can be coded in any language without recourse to proprietary tools and requires minimal operator intervention. As this sort of imagery is increasingly being made freely available through such services as Google Earth or Worldwind this technique can be used to extract river features when more specialized imagery or software is not available.

Keywords: rivers, banks, image analysis, edge finding, photography, satellite, texture, entropy

1. INTRODUCTION

Rivers have long served as important passages for shipping, as sources of fresh water for human and ecological needs and as conduits by which the contaminants and heat generated by modern industry may be dispersed. The need to accurately predict river stage and currents has led to the development of increasingly sophisticated river models.

Historically many of these models have been constrained by a lack of readily available computational power and, as such, have been either one-dimensional or else quasi two-dimensional,[1] requiring minimal information about the exact river geometry. However with the recent great increase in cheaply available computer power, more sophisticated two-dimensional, and even three-dimensional models are being developed based on finite element or finite volume techniques. These models require, a much more accurate description of the river channel geometry than have earlier models.

1.1 Motivation

A fundamental challenge in the rapid development of hydrodynamic river models is the lack of accurate information describing the river bank geometry. Unlike for coastlines, there is no readily accessible database of river bank locations and what information is available is often outdated and of questionable accuracy and resolution. With rivers of interest to the Navy often being located in denied access areas, it is generally not possible to obtain this information using traditional surveying techniques. However as high resolution satellite and aerial imagery is increasingly available for the entire globe, it is becoming more common to extract river bank locations from this imagery, thus generating an accurate and high resolution bank geometry.

Much of the globe is covered by various sorts of multi- or hyperspectral imagery and numerous techniques have been developed to use the wealth of information contained in these images to identify and extract river features. However these techniques are often closely tied to particular image sources and sensors or else require

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proprietary software packages and trained operator input. These tools and image sources may not always be readily available, particularly in civilian applications, so alternate techniques must be developed.

We have developed a method which automatically extracts river and river bank locations from arbitrarily sourced high resolution (~1m ground sample distance) visual spectrum imagery without recourse to multi-spectral or even color information. This method relies on quantifying the difference in image texture between the relatively smooth surface of the river water and the rougher surface of the vegetated land or built environment bordering it and then segmenting the image into high and low roughness regions. The interface between the low and high roughness areas defines the river banks.

This method can be coded in any language without recourse to proprietary tools and requires minimal operator intervention. As this sort of imagery is increasingly being made freely available through such services as Google Earth or Worldwind this technique can be used to extract river features when more specialized imagery or software is not available.

1.2 Background

The automated detection and extraction of features in remotely sensed imagery, including water and shorelines, is a major topic of ongoing research and development. Many methods have been proposed through the years, all of which perform well in certain circumstances and have certain limitations. One of the most common approaches is to use information encoded in multispectral imagery to, for instance, separate the differences in reflectivity between different surfaces, such as water and land.[2]

When such data is not available, as in cases where only visual spectrum imagery is available, other methods have been developed. The most common of these rely on segmenting the image based on differences in color, hue, saturation or intensity between the features of interest.[3-5] These methods are generally considered to be supervised classification techniques in that they require the active input of a trained analyst to define the characteristics of the regions of interest.

Often, however, only one image band is available, as in the case of grayscale imagery, or the features of interest are such that even a trained analyst has difficulty in defining the criteria for segmenting the image. For these cases certain automated, unsupervised (or minimally supervised), image classification schemes have been developed using the high resolution information encoded in a single channel image to segment it into finer blocks than a human can segment it.

Segmentation by image clustering, the location and definition of regions of similar characteristics, is quite common, especially using the K-Mean or ISODATA techniques. But these techniques suffer limitations in requiring significant operator input in the setup phase, requiring significant computation time and in having difficulty in identifying geometrically straight features.[6] While these techniques have been used successfully to segment water and land and determine the shoreline,[7] their use has been limited by speed and by the need for a trained operator. Certain more automated techniques, for example the Syneract method,[8] have been developed to reduce the need for operator input but they are still slow and have generally been used in segmenting land use and vegetation rather than in developing a shoreline.

The machine vision community has developed a number of powerful techniques based on the field of texture analysis[9] that have seen some adoption by the remote sensing community. Images may be segmented by breaking them down into fundamental units, or tokens,[10] or by comparing statistics of image roughness based on frequency domain transformation,[11] moment-based segmentation[12] or both Shannon and non-Shannon entropy[13,14] or a combination of techniques.[15]

Image entropy is a measure of the local variance in the image data that has many uses in image analysis. Entropy information is commonly used to aid in image enhancement.[16] Methods have been developed using image entropy, in combination with other information, in the semi-supervised analysis of remotely sensed images, including in the location and extraction of water points.[17,18] However, little success has been seen in developing entropy based techniques to quickly segment water and land with minimal supervision and without requiring any information in addition that which is available in a single band image (i.e. a grayscale image).

2. METHOD

A technique has been developed, as will be described below, which uses the concept of Shannon entropy[19] to automatically segment water from land in images of rivers or coastal regions and to locate the interface between the two, the river bank or coastline. This technique differs from prior art in being fully automated and requiring only minimal operator setup. Most importantly, it requires no information other than that contained in a single channel (i.e. grayscale) image. It is designed to work with high resolution imagery from any source, including such publicly available sources as Google Earth, Worldwind or Terraserver with no *a priori* requirements as to image format, size, color space or sensor used.

The technique exploits the fact that in imagery of many rivers of interest, generally coastal plain rivers winding through a vegetated or built environment, there is a clear difference in the roughness of the surface of the water and the roughness of the vegetated or built environment surrounding it. This difference is intuitively obvious to a human observer, allowing a human to perceive the river regardless of whether the imagery is in true color, false color, IR, grayscale or any other colorspace. The technique does have a limitation in that it cannot be applied when the surface roughness of the river is not distinguishable from that of the land. Examples of this would include whitewater rivers or rivers in morphologically smooth landscapes (i.e. featureless deserts, mud flats or ice sheets). These, however, represent a very small subset of rivers of interest.

Roughness in an image is represented by the local variance in the image color or gray level and can be expressed in several forms. Shannon entropy is a metric commonly used in information theory and texture analysis that lends itself well to classifying this sort of image.

Imagery must first be obtained from some source. This imagery must be of high enough resolution that the rough surface of the land can be readily observed. This required resolution will vary depending on the location of the area of interest but it will generally be in the range of 1-3 meters per pixel. There must be sufficiently defined features such that the location of two points, both in image coordinates and in geographic coordinates (i.e. UTC or lat/lon), is known precisely. This is necessary to map the extracted data back to Earth coordinates. Figure 1 shows an example of imagery obtained from Google Earth which meets these criteria.

The image is converted to grayscale, if needed, by converting gamma values to intensity.[20] It is then padded by adding an extra set of mirrored pixels surrounding the image (see Figure 2). This allows centered statistics to be calculated along the edges of the original image with no data loss.

Next for every pixel in the original image the local Shannon entropy is calculated for the nine pixel box surrounding, and including, the pixel of interest. Shannon entropy is defined as

$$H = -\sum_{i=1}^{N} p(X_i) log_2 p(X) \tag{1}$$

where H is the entropy of the gray level X, in the region of interest, with discreet values $X_1 - X_N$ where N is the number of possible gray levels, and p is the probability mass function of X.[19] The padded pixels are then discarded and the Shannon entropy is plotted for the original image (see Figure 3).

The image is then binarized by thresholding such that all pixels with gray levels greater than one half of the maximum gray level in the entire image are set to one and all others are set to zero. This is shown in Figure 4.

The image is next processed using two of the basic operations of mathematical morphology; dilation and erosion.[21] These are operations whereby a binary image is acted upon by a structuring element, in this case a circular element. In erosion, pixels are removed from a binary structure equivalent to those masked by the structuring element with the element center moving along the edges of the original structure. Dilation is the opposite operation. These form the basis of the operator pairs of closing and opening. Closing involves dilating and then eroding an image while opening involves eroding and then dilating an image. Closing serves to remove, or close, any small holes in the image while opening serves to despeckle, or remove noise from the image. Figures 5 and 6 illustrate these two operations.

In Figure 5 the element (a) represents a river segment (dark blue) spanning from the bottom to the top of the image frame. A small hole, either a small island or an image artifact, is seen in the white circle. In (b) we

Figure 1. Imagery of the Pearl River, LA obtained from Google Earth.

6	5	6	7	8	7
2	1	2	3	4	3
6	5	6	7	8	7
10	9	10	11	12	11
14	13	14	15	16	15
10	9	10	11	12	11

Figure 2. An example of image padding. The original image is shown by the intensity levels depicted in the gray cells. The clear cells represent mirrored image padding added around the edges of the original image.

Figure 3. The distribution of Shannon entropy calculated from Figure 1 using equation 1. Dark colors represent low entropy values (smooth regions) while light colors represent high entropy values (rough regions).

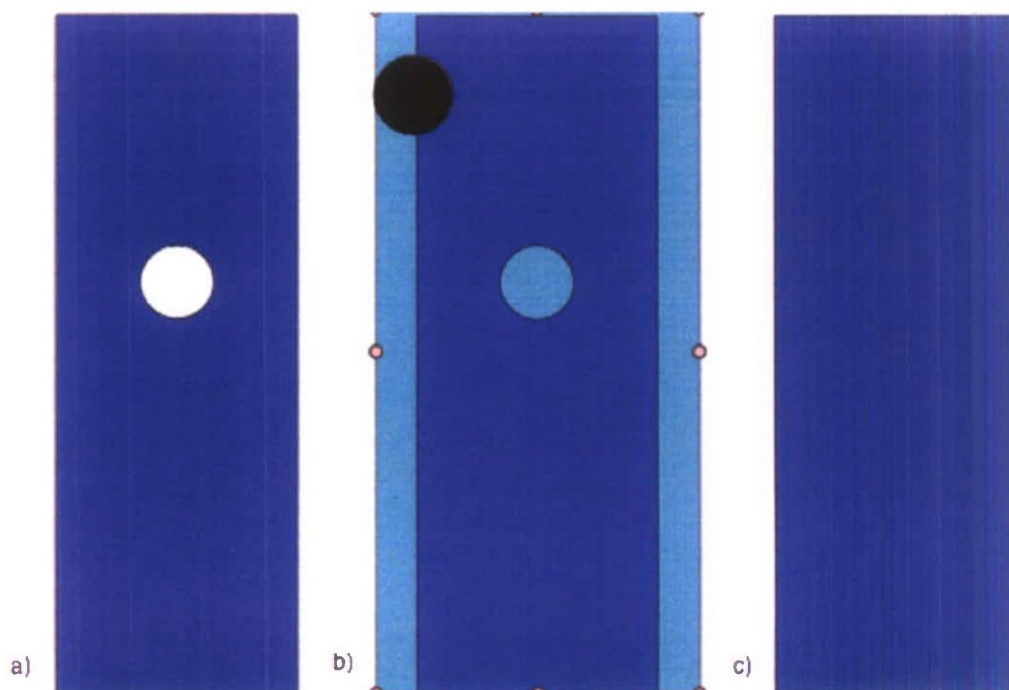Figure 4. Thresholded and binarized version of Figure 3.

Figure 5. The morphological closing of an image with a small hole.

see the result of dilating the image by moving a circular structuring element, shown by the black circle, around all edges in the image. This expands the element by the amount shown as light blue. In (c) we see the results of eroding the image (b) by the same structuring element, this time removing area around the element edge. As there is no longer an edge where the hole was, this returns the element (a) with the small hole removed, or closed.

In Figure 6 the element (a) represents a river segment (dark blue) spanning from the bottom to the top of the image frame. A small region, either an isolated smooth area such as a pond or mowed field or an image artifact such as a speckle, is seen in the adjacent dark blue circle. In (b) we see the result of eroding the image by moving a circular structuring element, shown by the black circle, around all edges in the image. This shrinks the elements by the amount shown as light blue. In (c) we see the results of dilating the image (b) by the same structuring element, this time adding area around the element edge. As there is no longer an edge where the small element was, this returns the element (a) with the small element removed. The image has been opened.

Figure 7 then shows the results of applying these two morphological operations to the image in Figure 4. The locations of the black (low entropy) pixels then can be returned as the location of the water. The river edges are then located by finding the interface between the low entropy (water) and high entropy (land) pixels by examining the local gradient. These edges are plotted in red on Figure 8. As can be seen the plotted edges show very good agreement with the edges as determined from visual inspection.

By referencing two distinct points in the image where both image coordinates (row and column) and geographic coordinates (UTC or latitude and longitude) are known, the edge and water locations can be converted into georeferenced coordinates for use in a numerical model.

3. VALIDATION

In addition to the presented test and development case using the Pearl River in MS and LA, this technique has been evaluated on a number of other rivers. An inland reach of the Snohomish River in Washington state is presented here to further validate the technique.

Figure 9 shows imagery of a 3.5 km reach of the Snohomish River south of Snohomish, WA. The ground sample distance is approximately 1 m at full resolution. Processing the entire image using the method described, the location of the water and the water's edges can be extracted. A detail of this is shown in Figure 10.

In this figure the water points are colored black while the edges, the river banks, are indicated with a thin red line. Due both to the nature of the image compression used and to the nature of the river banks, the actual banks are indicated by a several pixel wide gradient between land and water and so the precise bank location must be estimated by eye. At no point in this image is the calculated bank location more than 1 pixel off the authors' best visual estimate as to the bank location. This implies a maximum error in bank location of 1 m and a mean error much less than 1 m. Several small and isolated "edge" regions can be seen in the image, particularly on the north bank of the river. These represent small ponds or otherwise morphologically smooth features which present as water. These will easily be removed during the post-processing required to order the edge points and use them to generate a mesh.
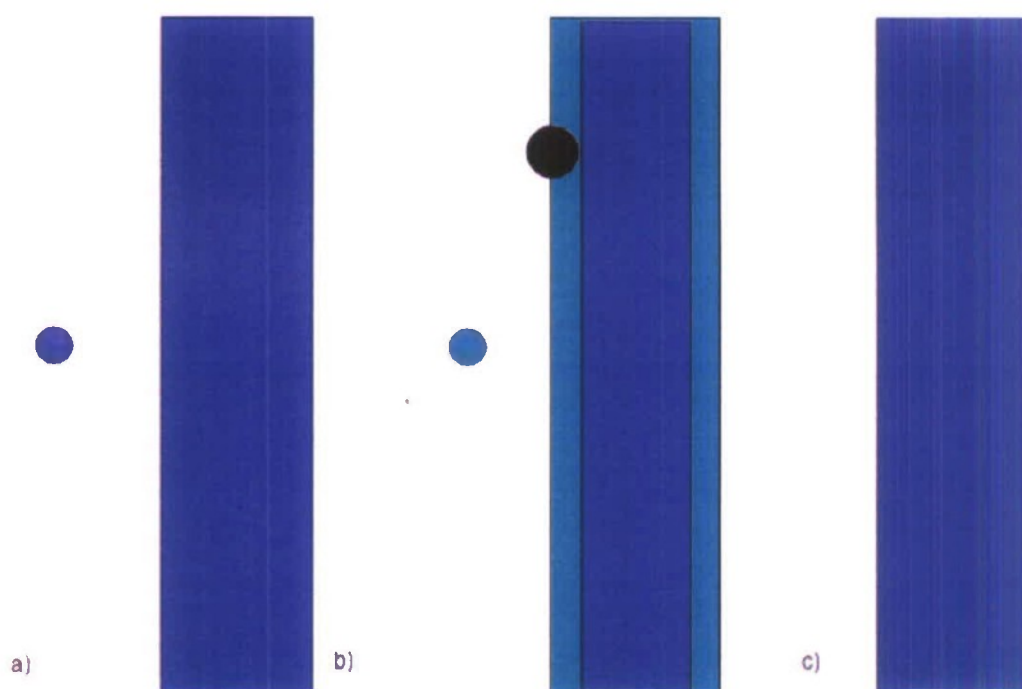
Figure 6. The morphological opening of an image with a small speckle.

Figure 7. Figure 4 after the basic mathematical morphology operations of closing and opening.

Figure 8. Edge pixels, shown in red, superimposed on the original image from Figure 1.
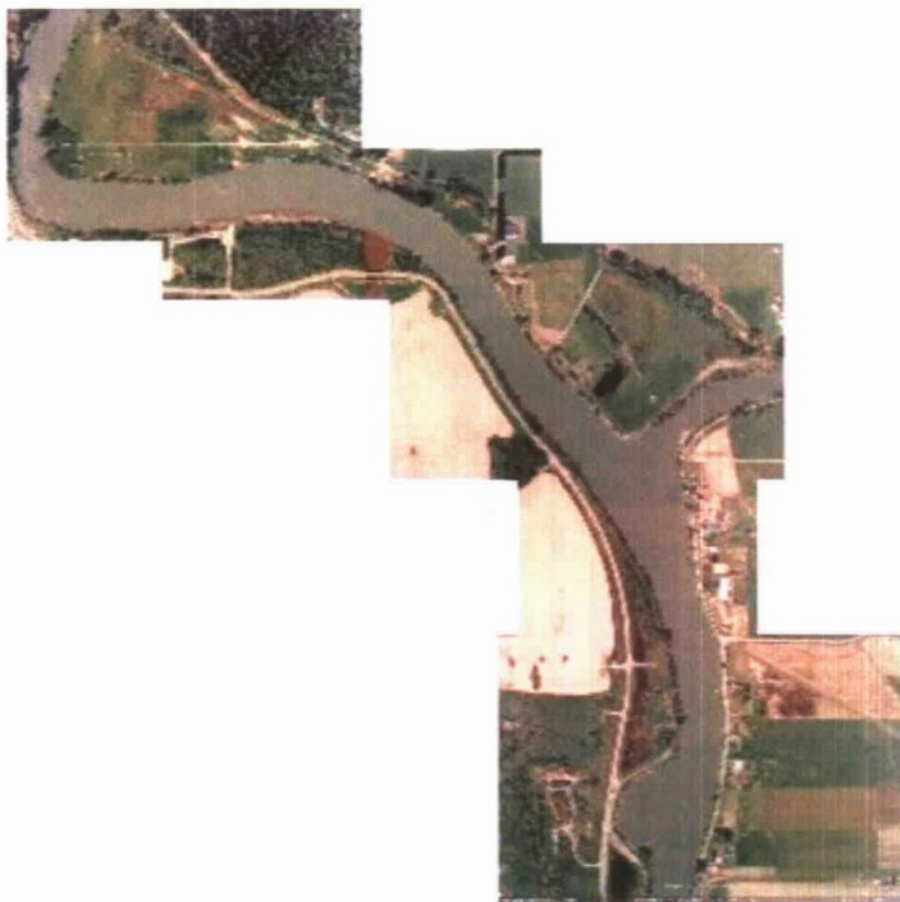
Figure 9. A 3.5 km reach of the Snohomish River south of Snohomish, WA. Ground sample distance is 1 m.

Figure 10. Detail of the processed Snohomish River imagery. Maximum error in edge location is approximately 1 pixel, or 1 m.

4. CONCLUSION

A method has been presented for the automated segmentation of an arbitrary high resolution aerial or satellite image into regions of land and regions of water and for locating the interface between them. This enables the rapid extraction of the information needed to develop a high resolution hydrodynamic mesh of the river without reliance on specialized sensor packages or platforms.

This method has been coded in Matlab$^{\circledR}$ in versions both tied to and independent of the routines in the Matlab Imaging Toolkit$^{\circledR}$. It can readily be ported to any programming language using standard library functions.

The method shows great promise and accurately determines the location of river banks and water in high resolution aerial imagery sourced from such publicly available sources as Google Earth. In tests on the Pearl River in MS and LA and the Snohomish River in WA, the method correctly located the river banks to an apparent maximum error of approximately 1 m.

The method does suffer from one basic limitation in that it can not distinguish between morphologically smooth river water and areas of mowed fields, standing water or built environments which have similar textural characteristics. This can be dealt with in the post-processing needed to prepare the output for meshgeneration.

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