# FROM IMAGE CONTOURS TO PIXELS 

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#### Abstract

: This paper relates to the reconstruction of digital images using their contour representations. The process involves determining the pixel intensity value which would exist at the intersections of a regular grid using the nodes of randomly spaced contour locations. The reconstruction of digital images from their contour maps may also be used as a tool for image compression. This reconstruction process may provide for more accurate results and improved visual details than existing compressed versions of the same image, while requiring similar memory space for storage and speed of transmission over digital links. For the class of images investigated in this work, the contour approach to image reconstruction and compression requires contour data to be filtered and eliminated from the reconstruction process. Statistical tests which validate the proposed process conclude this paper.


## 1. INTRODUCTION

An important area of digital image processing is the segmentation of an image into various regions to separate the objects from the background. Image segmentation can be categorised by three methods.

The first method is based upon a technique called image thresholding (Russ, 2007), which uses predetermined grey levels as decision criteria to separate an image into different regions based on the grey levels of the pixels. The second method uses the discontinuities between grey levels regions to detect edges within an image (Baxes, 1994). Edges play a very important role in the extraction of features (and their dimensions) for object recognition and identification in image analysis operations (Gonzalez and Wood, 2008). The final method relates to detecting edges so as to separate an image into several different regions by way of grouping pixels that have the same grey levels.

Since edges play an important role in the recognition of objects within an image, contour description methods have been developed that completely describe an object based upon its contour. The most common methods are (a) a method based upon a coding scheme called chain codes, (b) the use of higher order polynomials to fit a smooth curve to an object's contour, and (c) the use of Fourier transform and its coefficients to describe the coordinates of an object's contour (Russ, 2007).

Apart from image analysis operations, edges and contours have been used for image editing (Elder and Goldberg, 2001) and image compression applications. For instance, Elder and Zucker (1998) proposed a novel image compression scheme based on edge detection techniques where only edge and blur data rather than the entire image is sent over a digital link. This compression technique is especially appealing because edge density is linear in image size, so larger images will have higher compression ratios. The argument is that for natural images, most scenes are relatively smooth in areas between edges, while large discontinuities occur at edge locations. Thus, much of the
information between edges may be redundant and subject to increased compression. The work of Elder and Zucker proposes two necessary quantities: the intensity at edge locations in the image and an estimate of the blur at those locations. Using these quantities, it is possible to reconstruct an image perceptually similar to the original.

On the other hand, Vasilyev (1999) proposed a method for compressing astronomical images based on simultaneous edge detection of the image content with subsequent converting of the edges to a compact chained bit-flow. Vasilyev combined this approach with other compression schemes, for example, Huffman coding or arithmetic coding, thus providing for lossless compression schemes comparable to present compression protocols such as JPEG.

The proposed reconstruction process uses image contour detection rather than edge detection. The definition of contour used in this work relates to the term used in cartography and surveying where a contour line joins points of equal elevation (height) above a given reference level (Smith et al. 2009).

In this context, the pixel values stored in an image can be considered as the values of some variable z where each pixel can be assumed as an elevation value z at its x and y coordinates, thus defining a 3D shape (Weeks, 1996). This shape is often a complex 3D surface that can be represented by scattered contours nodes where each node (or vertex) of a given contour also corresponds to a position ( $\mathrm{x}, \mathrm{y}$ ) having a constant colour intensity or elevation z.

For the class of grey-scale images investigated in this work (i.e. human faces, landscapes and relatively small aerial images) this reference level and the contour intervals (or contour increments) are selected based on the dynamic range and/or on the image histograms. Image histograms provide a convenient, easy-toread graph of the concentration of pixels versus the pixel brightness in an image. Using this graph it is possible to discern
how much of the available dynamic range is used by an image (Gonzalez and Woods, 2008).

The dynamic range is represented by how many grey levels in the grey-scale are occupied. For instance, the pixel values of Figure 1-a fall between grey values 0 and 220 (within a range of 0 to 255) with none in the other regions. This indicates a relatively wide dynamic range of brightness (Cunha et al. 2006) thus, in general, requiring a larger contour representation (hence nodes) than an image with a narrow grey-scale distribution (small dynamic range).

## 2. GENERATING 3D DATA POINTS

The process of generating 3D data points from contours comprises the step of assigning coordinate values to pixels in the image. This is followed by interpolating between pixels to find the coordinates of points in the path of a contour having the same colour intensity value.

For instance, Figure 1(a) shows the original image of Peter.tif $\left(400^{2}\right)$ whereas Figure 1(b) is the results of joining corresponding contour nodes using line segments. By way of example, the contour increments in Figure 1(b) is 8, ranging between 0 and 220 grey-scale values or colours. In this instance, bilinear interpolation was used to determine the contour nodes (Watson, 1992).


Figure 1. (a) The original image of Peter.tif $\left(400^{2}\right)$, whereas (b) is a contour representation of (a) for contour increments equal to 8 grey-scale values.

In the interest of reducing to a minimum the number of nodes or contour vertices, and thus minimise data storage and transmission time, it is often possible to represent the contours using fewer line segments. It is important however, to maintain sufficient details so as to portray important features such as minute wavers and concavities. In most real world cases, an image will contain contour portions with little direction changes (i.e. straight regions) and portions with a lot of direction change (i.e. curved regions) as shown in Figure 2(a).

A variation of the basic contouring approach, referred to as variable line segment boundary representation (Baxes, 1994) can be used to better represent small contour segments changes without using small line segments throughout the contour description.

Therefore, this technique can be used to remove nodes from contours as it combines multiple line segments and replaces them with a single longer segment over portions of the contour that have small direction changes. A variable number of contour nodes are covered by a single line segment, depending on how contour direction occurs. The nodes that are eliminated during this process may be recovered if required in the reconstruction process.

This way, the line segments of a given contour will not unduly record multiple short line segments (and thereby nodes) where the contour direction change only a little. The implementation of the line segment approach is carried out by first performing a line segment contouring operation, using line segment lengths that are sufficiently short so as to contain the contour details required to reconstruct an original raster image.

Then, the angles of each pair of adjoining line segments are compared. Where the directional angles are similar or identical, the two lines segments are combined to create a single line segment representing their combined length and overall angle (see Figure 2(b)). The end result is a contour segment representation that can be significantly more concise, while maintaining a high level of accuracy.


Figure 2. (a) A contour often contain regions of little change and regions of great change and (b) The variable line segment description combines adjoining contour segments with similar direction angles (after Baxes, 1994)

Another technique which may assist in removing redundant nodes from the reconstruction process is to compare the area these contours occupy and the shorter and longest distance to their centroids (Bonham-Carter, 2006). These parameters may offer the best statistical constraint for deciding whether a contour (and its nodes) is very similar to another and thereby could be removed.

Also, within any group of at least three close nested contours it may possible to test for redundant nodes by removing the
middle contour and interpolate and/or diffuse between the other two. However, this process may have the disadvantage of smoothing and/or distorting particular high frequency (sudden changes of brightness values within an image) information necessary for a more accurate reconstruction of the original image.

## 3. ENCODING 3D DATA POINTS

For easy extraction, processing and transmission over a digital link, the contours data was encoded and saved in an ASCII file (i.e. txt). This file contains a two-row matrix where each contour line defined in the matrix begins with a column that defines the value of the contour line and the number of ( $\mathrm{x}, \mathrm{y}$ ) vertices in the contour line.

The remaining columns contain the data for the ( $\mathrm{x}, \mathrm{y}$ ) pairs. The $\mathrm{x}, \mathrm{y}$ values are stored to the first decimal place and separated by a point. In the coding shown below 120 is the grey-scale intensity of a selected contour and the contour line is formed by 7 vertices. The x coordinate of the vertices are in the top row (i.e. 18.2 17.2...14.7) whereas the corresponding y coordinates are placed in the bottom row (i.e. 110 109...93.2)
$120 \quad 18.217 .21717 .317 .115 .714 .7$
711010910899.5979593 .2

Additional tests are presently being undertaken to ascertain the use of binary files (as compared to ASCII .txt file) as a way to further reduce memory requirements and speed of transmission of contour data.

## 4. FROM 3D POINTS TO PIXELS

In this gridding process contours nodes are projected or mapped on a uniformly spaced grid. Depending on the final resolution required, this grid may be selected so as to create pixels in $x$ and y corresponding to the original input image. To determine the pixel brightness which would exist at the intersections of a regular grid using randomly spaced 3D node locations, several interpolators may be used depending on the application and accuracy requirements.

There exist several interpolation schemes available for this task. Estimations of nearly all spatial interpolation methods can be represented as weighted averages of sampled data (De Jong and van der Meer, 2004). They all share the same general estimation formula as shown in equation 1 :

$$
\begin{equation*}
\hat{z}\left(x_{0}\right)=\sum_{i=1}^{n} \lambda_{i} z\left(x_{i}\right) \tag{1}
\end{equation*}
$$

Where $\check{z}$ is the estimated value of an attribute at the point of interest $x_{0}, z$ is the observed value at the sampled point $x_{i}, \lambda_{i}$ is the weight assigned to the sampled point, and $n$ represents the number of sampled points used for the estimation (Webster and Oliver, 2001).

In this work the interpolation process is an estimation process which determines the pixel brightness which would exist on the intersections of a regular grid using the randomly spaced nodes of contours. Several local interpolators may be used depending on the application and accuracy requirements. The method used in this work is referred to as cubic splines. A brief explanation follows.

The splines consist of polynomials with each polynomial of degree $n$ being local rather than global. The polynomials describe pieces of a line or surface (i.e. they are fitted to a small number of data points exactly) and are fitted together so that they join smoothly (Burrough and McDonnell, 1998; Webster and Oliver, 2001). The places where the pieces join are called knots. The choice of knots is arbitrary and may have an important impact on the estimation (Burrough and McDonnell, 1998). For degree $n=1,2$, or 3 , a spline is called linear, quadratic or cubic respectively.

In the ensuing tests, cubic splines were selected as they are very useful for modeling arbitrary functions (Venables and Ripley, 2002) and are used extensively in computer graphics for free form curves and surfaces representation (Akima, 1996).

## 5. TESTS AND RESULTS

Table 1 shows the results of a first test aimed at determining the degree of accuracy and memory storage requirements to be expected when reproducing a digital image from scattered contour nodes. The figures are based on the Peter.tif $\left(400^{2}\right)$ in Figure 1(a). The R.M.S. (Spiegel and Stephens, 1999) is random standard error of the differences of grey-scale values between the original Peter.tif and the same image reconstructed using the nodes for contour increments ranging between 2 and 8.

The figures in Table 1 show a linear degradation of the R.M.S. as the contour interval is increased. The table also illustrates the amount of memory required to store the contour nodes needed for the reconstruction of Peter. As expected, as the contour interval increases, the memory requirement decreases at the expense of image quality.

| Contour <br> increments | Accuracy <br> R.M.S. | Memory <br> required | Maximum <br> difference | Minimum <br> difference |
| :---: | :---: | :---: | :---: | :---: |
| 2 | 2.7 | 0.051 Mb | 5 | 7 |
| 4 | 6.3 | 0.042 Mb | 17 | 27 |
| 6 | 9.8 | 0.033 Mb | 33 | 30 |
| 8 | 19.4 | 0.021 Mb | 39 | 42 |

Table 1. Accuracy and memory requirements needed to reconstruct the original image of the Peter using contour increments between 2 and 8 grey-scale intensity values.

By way of comparison, the .txt file needed to store the x and y coordinates of the nodes necessary to reproduce Peter (for contour increment of 6 grey-scale values) used approximately the same amount of memory of a JPEG compressed ( 0.029 Mb ) version of the same image for a compression ratio of $7: 1$, while reproducing a more accurate image with improved visual details (see Figure 3).

In Figure 3, the difference in visual quality between Peter reconstructed with contour data (Figure 3(c)) and the corresponding JPEG image (Figure 3(b)) is evident. Indeed, the blocking effects, typical of a lossy JPEG protocol, were almost completely eliminated.

In addition, the maximum and minimum differences of pixel intensity values resulting from subtracting the JPEG version of Peter from the original Peter.tif were respectively -36 and +44 grey-scale values with an R.M.S. equal to +/-35. By contrast, the contour approach produced maximum and minimum
differences equal to -33 and +30 respectively with an R.M.S. of +/- 9.8 pixel grey-scale intensity values.


Figure 3. (a) A JPEG version (section only) of Peter for a compression ratio of 7:1 and (b) the same image reconstructed using the contour nodes for a contour increment equal to 5 .

The proposed compression process was further tested using the image of the lake $\left(400^{2}\right)$ and the aerial view $\left(400^{2}\right)$ shown in Figure 4 and Figure 5 respectively.

The maximum and minimum differences of pixel intensity values resulting from subtracting the JPEG version of lake.jpeg from the original lake.tif were respectively -39 and +51 greyscale values with an R.M.S. equal to $+/-38$. By contrast, the contour approach produced maximum and minimum differences equal to -35 and +37 respectively with an R.M.S. of $+/-10.3$ pixel grey-scale intensity values.

On the other hand, the maximum and minimum differences of pixel intensity values resulting from subtracting the JPEG version of aerial.jpeg view from the original aerial view.tif were respectively -35 and +47 grey-scale values with an R.M.S. equal to $+/-35$. By contrast, the contour approach produced maximum and minimum differences equal to -31 and +42 respectively with an R.M.S. of $+/-7.8$ pixel grey-scale intensity values.


Figure 5. The original image of lake.tif $\left(400^{2}\right)$.


Figure 5. The original image of aerial view.tif $\left(400^{2}\right)$.

| Contour <br> increments | Accuracy <br> R.M.S. | Memory <br> required | Maximum <br> difference | Minimum <br> difference |
| :---: | :---: | :---: | :---: | :---: |
| 2 | 3.7 | 0.172 Mb | 6 | 8 |
| 4 | 7.3 | 0.076 Mb | 23 | 29 |
| 6 | 10.6 | 0.064 Mb | 35 | 34 |
| 8 | 20.5 | 0.043 Mb | 39 | 46 |

Table 2. Accuracy and memory requirements needed to reconstruct the original image of lake using contour increments between 2 and 8 grey-scale intensity values

| Contour <br> increments | Accuracy <br> R.M.S. | Memory <br> required | Maximum <br> difference | Minimum <br> difference |
| :---: | :---: | :---: | :---: | :---: |
| 2 | 3.1 | 0.151 Mb | 7 | 8 |
| 4 | 6.8 | 0.062 Mb | 21 | 31 |
| 6 | 8.8 | 0.059 Mb | 37 | 33 |
| 8 | 18.4 | 0.041 Mb | 39 | 44 |

Table 3. Accuracy and memory requirements needed to reconstruct the original image of aerial view using contour increments between 2 and 8 grey-scale intensity values.

## 6. COLOUR IMAGES

When processing colour images, the same concepts above hold true. However, instead of a single grey-scale intensity value, colour digital images have pixels that are generally quantised using three components (i.e. Red, Green and Blue). In general, all image processing operations can be extended to process colour images simply by applying them to each colour component (Bovik, 2007).

Each of the three RGB components are processed, encoded and reconstructed separately as if they were three different grey scale images (Duperet, 2002). The results of the three reconstructions are then merged or fused to recreate the original colour image. In terms of image quality (R.M.S.) memory requirements the results from the contouring approach, for the same classes of images (i.e. faces, landscapes and aerial views), were similar to those obtained from the grey-scale imagery described above.

## 7. CONCLUSIONS

- Generating contour nodes from digital images involves assigning coordinates values to pixels in the raster format, and interpolating between the pixels to find the coordinates of points in the path of a contour having the same greyscale intensity value. This enables the contour nodes to be found to sub-pixel accuracy if required.
- The conversion of certain classes of digital images into contour maps may be used to compress and reconstruct images in pixel format that are more accurate and with improved visual details than JPEG compressed versions of the same image, while requiring similar memory space for storage and speed of transmission over digital links.
- For the images investigated in this work, the contour approach to image compression requires contour data to be filtered and discriminated from the reconstruction process.
- Spline interpolation was used to reconstruct digital images from the nodes of their contour representations. The process involves determining the pixel intensity value which would exist at the intersections of a regular grid using the nodes of randomly spaced contours.
- Refinements to the proposed method are being undertaken to increase the accuracy achievable for a variety of scenes and dynamic ranges (including bi-tonal imagery).
- More research is required to assess the accuracy of the compression process in the presence of added random noise, a variety of image scenes with various levels of details and/or video imagery.
- Further tests are required to determine whether a binary coding of the contour data may have an impact on memory requirements.


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