International Journal of Advances in Image Processing Techniques– IJIPT
Volume 1 : Issue 3 [ISSN 2372 – 3998]
Publication Date : 30 September, 2014

Image Vectorization and Significant Point Detection

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ABSTRACT
In this paper we present a novel method for compact representation of images as a list of lines and splines. The method uses vectorization of images based on significance measure. The image could be represented as a list of dominant points (spline control points) instead of the m × n array of pixels. This is a compact representation of images and experiments have shown that the compression achieved in vector images is 99% and for curved images also we could represent the image as a list of spline curves. These dominant points are called the significant points using which the original image could be reconstructed without any significant loss of information. The method is affine transformation invariant. This method has many advantages such as compression, faster processing, transmission and less storage. The compact representation of image could be used for pattern matching such as character recognition. The paper also discusses piece-wise linear reconstruction of image from these significant points. Low reconstruction error is a measure of goodness of proposed technique.

Keywords
image vectorization, reconstruction, segmentation.

1. INTRODUCTION
Image vectorization plays an important role in digital image processing. Vectorization is based on the use of geometrical primitives such as points, lines, curves etc., to represent images. With the increasing use of images the need for its storage and transmission has also increased, which can be achieved by the use of vectorization techniques. Representing line images in vector forms has a number of advantages over representing them in raster forms. Firstly, vector forms require less storage data. Secondly, editing and transforming vectorized images is much easier than editing their raster counterparts. For these reasons, vectorization techniques are widely used in analyzing line images.

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The method consist of extracting and thinning the boundary of input binary image as per [1], finding the contour and then calculating the significance of every pixel in the image. Then we extract the dominant points according to the relevance of the significance measure of pixels of the boundary image. A number of techniques have been proposed to solve the problems of vectorization but the methods are not suitable for noisy and large size data. The main motivation of our work was to compute the minimal list of most significant pixels which determine the shape of the image. The basic idea of generating dominant points is that first calculate the significance of each pixel and then ignore all the pixels with significance measure less then a threshold.

2. LITERATURE REVIEW
Tanaka and Kamimura [2] presents a vectorization method based on energy minimization principle. In [3] the skeleton of digital pattern can be extracted from the distance transform of the pattern, computed according to quasi-euclidean distance function according to [4]. The main advantage of this method is that the pattern can be reconstructed starting from the skeleton. In [5], contour vectorization is applied to convert binary image of drawings from raster to vector form. In [6] presents a practically automatic method in order to extract the skeleton and the basis topology of the binary image using the Kmeans technique and Delaunay triangulation degeneration [5]. In [7] author presents a novel technique for medial axis noise removal. In [8], the author presents the vectorization method based on discrete contour evolution.

In [8] vectorization is done according to the vertical distance from any pixel to the chord line and mathematical morphology is used to achieve better results. Four structural templates are used to remove noise. Then in the skeleton abstraction method, the morphological sequential homotypic abstraction method based on the eight structural elements templates are used to retain the endpoints and the isolated points of the thin lines. Its main advantages are rapid processing rate, accuracy and smaller storage. But this method is only suitable to multi-arc connected at the node and self-closed arc cannot be vectorized because two endpoints are at same position.

3. PROPOSED WORK
In digital images contours can be distorted due to noise and errors, it is therefore necessary to remove the distortions and preserve the appearance at the level sufficient for object

recognition. Since any digital curve can be regarded as a polygon without loss of information (with possibly a large number of vertices), it is sufficient to study evolutions of polygonal shapes. The basic idea is that in every evolution step, a pair of consecutive line segments are replaced with single line joining their end points. The key property of evolution is the order of substitution. The substitution is done according to the relevance measure. The higher the value of relevance measure, the larger is the contribution to the shape of the curve. The proposed method eliminates noise influence without changing the shape of the object, where in each successive step we get the simplified curve shape.
The basic idea of the proposed method is to vectorize the image in an efficient way and to remove noise as well. Contours of an object in digital images are distorted by digitization noise and segmentation errors. Initially we find the contour of the image by first extracting and thinning the boundary by morphological boundary extractor as in [1].

3.1Contour Extraction

The boundary extraction as explained in Section 3.1 is fol- lowed by finding the position of edges using 8-neighbour scan [1]. A digital image is a group of pixels each having a certain value. If the image is binary that value is 0 or 1. The boundary (β) of any given pattern (ρ), is the set of border pixels of ρ. We need an ordered sequence of the boundary pixels from which we can extract the general shape of the pattern ρ. Contour tracing is a preprocessing technique that is applied to digital image β in order to extract their general shape. Once the contour of a given ρ is extracted, it is used for vectorization. Therefore, correct extraction of the con- tour will produce more accurate results which will increase the chances of correctly classifying a given ρ.

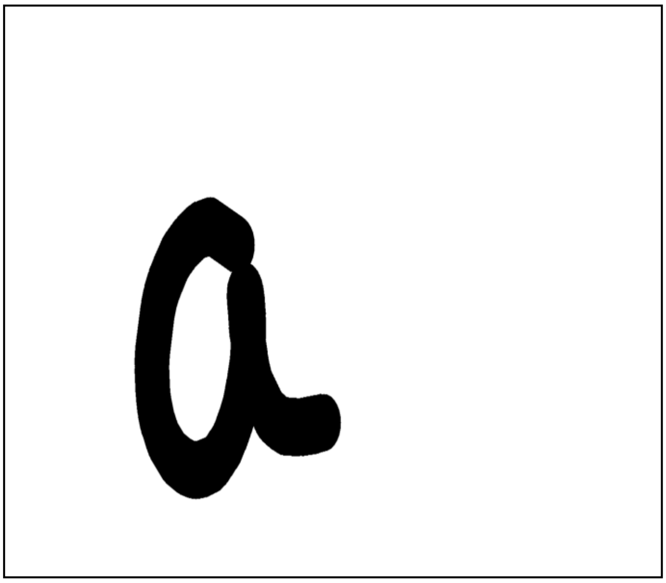
The complete contour tracing method is summarized in Algorithm 1.

Algorithm 1 Pseudo Code for Contour Tracing

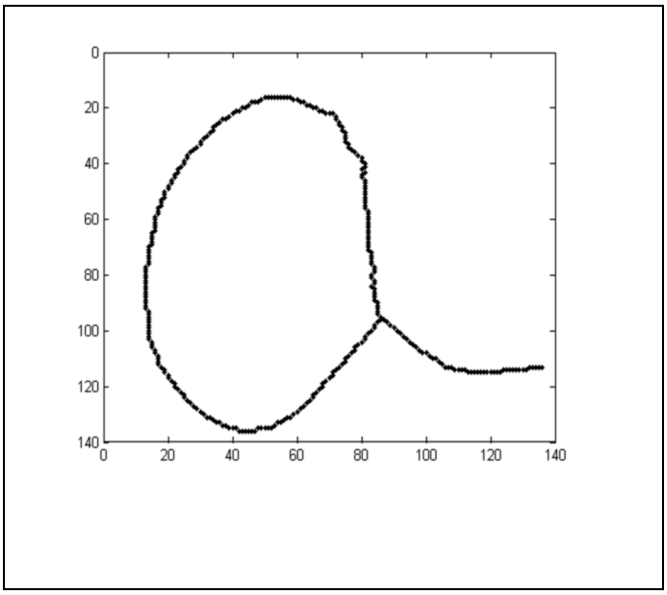
Require: $\beta(x, y)$. {Simple boundary β image.}

```
ζk = k^th connected component of (β).
for all (ζ) do
    s(i, j) = left most foreground pixel of ζk.
     p(i, j) = s(i, j).
       repeat
          if (p(i, j) == 1) then
             ζk,row = i
             ζk,column = j
          end if
          proceed to the next 8-connected neighbor of ζk.
       until (p(i, j) == s(i, j))
       k = k + +
end for
  {Return the contour.}(ζ)
```

Next step is to calculate the significance measure SM of each contour (ζ) pixel. Any digital curve ζ can be interpreted as a polygonal curve with a possibly large number of vertices. For example all points in the digital curve can be the vertices or the vertices can be chosen to be the endpoints of the maximal digital line segments contained in ζ. Thus, we assume that the digital curve ζ is a polygonal curve with vertices $v_0, v_1 \dots, v_{m-1}$. Hence ζ is composed of the digital line segments $s_0, s_1 \dots, s_{m-1}$, where s_i is the continuous line segments joining v_i to v_{i+1}, for $i = 0, \dots, m-1$.



1. Original Image



2. Image after applying contour tracing algorithm.

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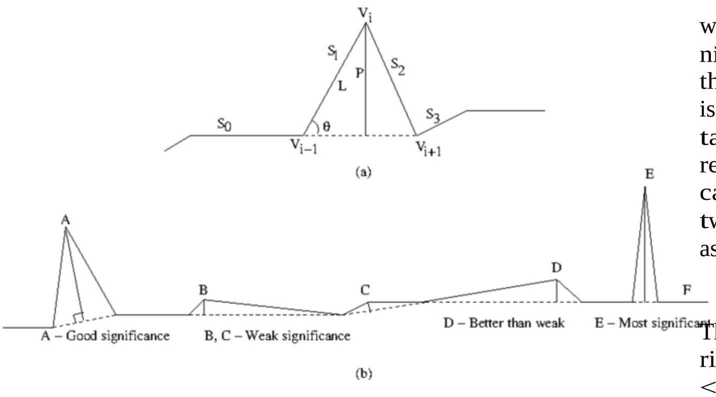

Figure 1: (a) Significance measure SM calculation. (b) Various cases implying the use of SM, of points on the shape of the curve ζ.

Let ζ be a digital curve and i be the i^{th} pixel in the curve ζ. We assign a value to the i^{th} pixel which measures the significance of the contribution of that pixel to the curve ζ. The SM of the i^{th} pixel depends on the perpendicular distance (P) of the pixel from the horizontal (between the previous $(i - 1^{th})$ and next $(i + 1^{th})$ pixel). The larger the value of the P greater is its contribution to the shape of the curve.

Consider Figure 1. For each two adjacent line segments S_1 and S_2 in the decomposition of a digital line segment ζ, we determine the $SM(V_i)$ which represent significance of the contribution of i^{th} pixel to the shape of ζ. The exact value of the SM is calculated as shown in Equation 7.

$$SM(V_i) = P = L \sin\theta \quad (7)$$

Since

$$\sin\theta = \frac{P}{L}$$

. Where L is the length of the line segment S_1 between two consecutive points (V_{i-1}, V_i), θ is the angle between the line segment S_1 and horizontal (base); and P is the perpendicular from V_i to horizontal. The horizontal or base is the straight line shown dashed in Figure 1(b), drawn between the previous V_{i-1} and the next V_{i+1} point to the curve's i^{th} point, that is V_i.

3.3 Non-Maxima Suppression

After we calculate the SM of the pixels we threshold (τ) the result which is done in two stages. In the first stage we remove all the pixels whose SM≈0, which happens when consecutive points are collinear. So in first stage all the pixels which forms a straight line with respect to its neighbouring pixels are removed. And in the next stage τ value is different for every image. It is done based on the factor that how many points the user needs as output. The mathematical significance of the SM is

$$SM_i = \begin{cases} 0 & \text{straight line} \\ < \tau & \text{weak significance} \\ L & \text{maximum significance point} \\ > \tau & \text{good significance point.} \end{cases}$$

where, θ as $\pm 5^0 \leq \theta \leq \pm 90^0$ gives good result. Good significant points GSP are identified only when the length of the line segment between two prospective significant points is greater than τ_L, where by experimental verification τ_L taken as the fifth root of the contour length gives the best results. Figure 1(b) shows a contour where point A is significant, B, C has weak significance, because the length between two collinear point $L < \tau_L$ while significance of D is good as length between two consecutive collinear point is $L \approx \tau_L$.

$$GSP = \max[SM(V_{i-1}, V_i, V_{i+1})] \&\& L \approx \tau_L \quad (8)$$

The $\pm\tau_L$ neighborhood smoothing at point i makes the algorithm scale adaptive. Smoothing neighborhood length taken $< \tau_L$ generates redundant significant points and a greater value misses some significant points as shown in Figure 2.

4. TEST RESULTS AND EVALUATION OF SIGNIFICANT POINTS

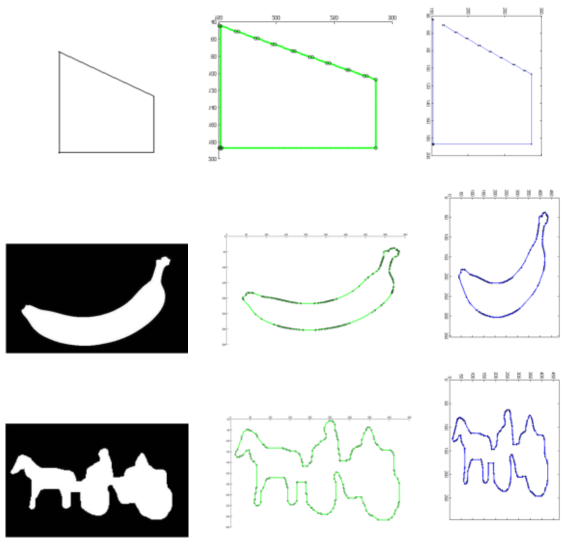

Figure 3: Result of the proposed technique on (1) polygonal, (2) curved and (3) combination image: (a) original image, (b) vectorized image, (c) reconstructed image.

The algorithm is tested on various set of images as shown in Figure 3 and have been successful in determining the correctness of our approach. It captures all good significant points which are better approximation of the change in curve shape as shown by the reconstructed images from the extracted significant points of the respective images.

1. Simple polygonal image with straight lines as shown in Figure 3(1).
2. Highly curved image: Figure 3(2) shows the results of our algorithm on a highly curved image. This image has many diffused diagonal edges also, such cases are encountered in real test images. All significant points are detected and are very well localized.
3. Combination of straight lines and curves: Similarly Figure 3(3) shows the results on an image which is a combination of straight lines and curves here also all significant points are detected.

Using vectorization any image can be expressed as a curve defined with a list of control points. The degree of the curve is one less than the number of control points. Using this vectorized image representation we could achieve a high degree of compression as shown in Equation 9.

$$\frac{\text{Number of vectorized points}}{\text{Number of original points}} \tag{9}$$

Experimental results conducted on 200 images(in every category) shows that the compression achieved in polygonal figures is ≈ 0.0053%. For curved figures it is ≈ 0.33% and for a combination figure it is ≈ 0.28% usually. he technique is affine transformation invariant as shown by Moment analysis on Figure 3. The results are enumerated in Table 1.

Table 1: Moment Analysis

Case	Original	Rotate (180^0)	Scale (1.3)
Polygon	$3.6736e^{003}$	$3.6736e^{003}$	$4.8653e^{003}$
Banana	$3.6083e^{003}$	$3.6083e^{003}$	$4.9236e^{003}$
Carriage	55.3929	55.3929	90.8130

Thus this technique always give localized and consistent significant points irrespective of translation, scaling and rotation of the input image.

We further use the parameters proposed in [9] to check the accuracy and consistency of our method. The Consistency(CCN) is computed as:

$$CCN = 100 * 1.1^{-|N_w - N_o|}$$

where n_w is the number of significant points in the wrapped image and n_o is the number of significant points in the original image. The accuracy(ACU) is defined as:

$$ACU = 100 * \frac{\frac{n_m}{n_o} + \frac{n_m}{n_g}}{2}$$

where n_g are the number of 'ground truth' significant points marked by humans and n_m is the number of matched significant points compared to ground truth. The algorithm has a mean CCN of 90% and ACU of 95% irrespective of rotations and scaling.

Our proposed detector has been able to match a 95% accuracy as our method identifies all the good significant points (high N_a/N_o) and also detects some other significant points (high N_a/N_g).

5. COMPARISON WITH EXISTING

The motivation of our work was to reduce the computational complexity of SM, without compromising with the performance and results. As in [8], vectorization is using Equation 10.

$$P_d = \frac{|ax_i + by_i + c|}{\sqrt{(a^2 + b^2}} \tag{10}$$

where P_d is the deflection of each pixel from the chord $|ax_i + by_i + c|$ drawn between pixel P to P + T, where T is the minimum threshold. If deflection is greater than a particular value than new chord is constructed starting from P + T else if deflection is less than T it is incremented. And in [7], the relevance measure is given by Equation 11.

$$K(s1, s2) = \frac{b(s1, s2) \times l(s1) \times l(s2)}{l(s1) + l(s2)} \tag{11}$$

where s_i and s_{i+1} are the two consecutive segments and $l(s_i)$ is the length of the segment s_i and $b(s_i, s_i)$ is the turn angle between the two segments; in each iteration the pixels with less relevance measure are ignored till we get the required number of pixels. Compared to our method where SM is computed using only one multiplication operation as shown in Equation 7, and thus is computationally efficient.

6. CONCLUSIONS

This paper succeeds to vectorize the images based on the proposed significance measure. Reconstruction of the image from the dominant significant points is also done in order to determine the accuracy of the method, which gives the satisfactory results. Examples have proved that this method has the characteristics of faster processing and smaller storage. In this paper a boundary based curve vectorization algorithm is analysed for transformation invariance and compression achieved. Tests are performed on a wide variety of bi-level and gray-scale images. The comparison between the proposed approach and other vectorization methods show that our approach being computationally less expensive is very competitive with respect to the most widely used curvature scale spaced: CSS [9] under similarity and affine transforms. Also the proposed technique is both highly consistent and accurate in determining the significant points of the image. The detector has on average a 95% ACU and a mean CCN of around 90%. The novelty of the approach lies in its simplicity and efficiency.

Furthermore, it uses only one parameter τL, which can be assigned a constant value as per personal preference of neighborhood, and it is also adaptive to the length of the boundary curve. Experimental results show that τ_L taken as fifth root of boundary length is sufficient for extracting good significant points.

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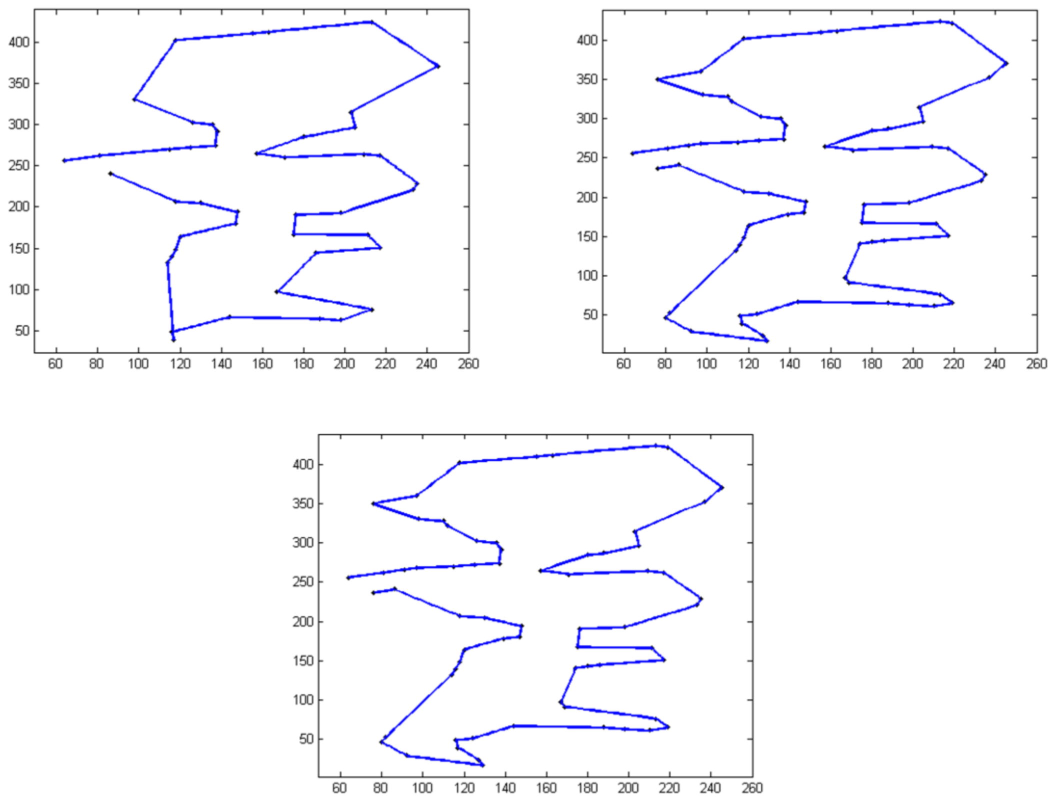

Figure 2: Effect of smoothing neighborhood length. (a) For L < τ_L many false significant points are detected; (b) all good significant points are detected and for (c) l > τ_L many good significant points are missed.