Detection of Multiple Overlapping String-Shaped Objects Using Spectral Clustering

Clare Maeda*, Shigeyuki Oba*, Naoto Yukinawa** and Shin Ishii**

* *Nara Instutute of Science and Technology, 8916-5 Takayama, Ikoma, Nara 630-0192, Japan*
** *Kyoto University, Gokasho, Uji, Kyoto 611-0011, Japan*
(Tel : +81-743-72-5986; Fax : +81-743-72-5989)
(kurea-m@is.naist.jp)

Abstract: This study presents an image segmentation method for string-shaped objects which may overlap each other in a single image. String-shaped objects, such as electric codes and neurons, are difficult to segment from the others in the presence of crossing parts of two or more objects, and also when they are curvy string-shaped. Crossing parts could mislead extensions of each object, and arbitrary curves often include pixels and/or image patches that have similar features but are difficult to distinguish from different objects. To overcome these difficulties, we propose a spectral clustering-based segmentation method with a new measure to evaluate similarities between pixels on a face of a single picture. In the calculation of the similarity, we combine two different criteria: the similarity of directional features and the corresponding distance between pixel positions on the image. Using a photo image of three electric cables on a white table, we show that our new method effectively segments the string-shaped objects from each other.

Keywords: spectral clustering, multiple object detection, feature vector, similarity matrix, image segmentation

1. INTRODUCTION

Image segmentation is an important problem in various fields of image processing applications such as biological imaging and diagnostic imaging. A number of image segmentation methods have been proposed, and most of them try to incorporate characteristic features of pixels or image patches around pixels. The easiest task of image segmentation is foreground-background detection of a given image, which classifies pixels based on their characteristic features such as color, brightness and texture, because these feature values of a foreground tend to differ substantially from those of a background [1]. On the other hand, segmentation of one foreground into two or more objects, i.e., multiple object detection, is much more difficult because we should consider not only basic features of each pixel but also configurations of the objects including sizes, shapes and positional relationships. In this work, we consider a situation where there are multiple string-shaped objects which overlap each other in an image. In this situation, appropriate segmentation is difficult due to crossing parts of two or more objects and possibly curvy string-shaped objects. Crossing parts could mislead the extensions of each object, and arbitrary curves often include pixels and/or image patches with similar and indistinguishable features from different objects.

In order to cope with these difficulties, we propose a spectral clustering-based segmentation method which incorporates a new measure of similarity between pixels on a face of a single picture. To calculate the similarity, we combine two different criteria: similarity of directional features and the distance between pixel positions on an image.

We apply the proposed method to a photo image of three electric cables on a white table and show that these cables are correctly segmented from each other. The results suggest that the combination of the two criteria is effective for multiple object segmentations, while only poor segmentation is obtained when using similarity based either on directional feature or on distance between pixel positions.

2. SPECTRAL CLUSTERING

Spectral clustering is one of the clustering techniques based on the similarity matrix [4] [5]. It has been used for partitioning points into disjoint clusters so that the points in the same cluster should have high similarities and those in different clusters, low similarities. Image segmentation based on color and

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textural features is a typical application of spectral clustering.

Consider a similarity matrix W whose (i,j) element W_{ij} determines the similarity between the ith and jth pixel features. When we segment a graph, the similarity should take binary values, namely, if $W_{ij}=1$ ($W_{ij}=0$), the ith and jth pixels are similar (not similar). Spectral clustering can be also applied to more general situations of real valued similarities $W_{ij} \in R$.

Spectral clustering, tries to obtain a good clustering result which minimizes "normalized cuts", a cost function to evaluate the quality of the clustering result. Suppose we have a complete graph with vertices $V=\{1,\ldots,P\}$ and a similarity matrix with weight values $W_{pp'}$ for $p, p' \in V$. When we wish to find R disjoint clusters $A = (A_r)_{r\in\{1,\ldots,R\}}$, where $\bigcup_r A_r = V$, so that a certain cost function is minimized. An example of such a function is the R-way normalized cut defined by

$$C(A,W) = \sum_{r=1}^{R}\left(\sum_{i\in A_r, j\in V\setminus A_r} W_{ij}\right) \Big/ \left(\sum_{i\in A_r, j\in V} W_{ij}\right). \tag{1}$$

This is the sum of "cuts", i.e., similarities between pairs of points, one inside and one outside, of a cluster divided by sum of similarities of all pairs of points inside the cluster.

Point of the spectral clustering is its simple and computationally-light algorithm based on k-means, which can minimize the normalized cuts shown above. The algorithm is as follows:

1. Rearrange W into L as

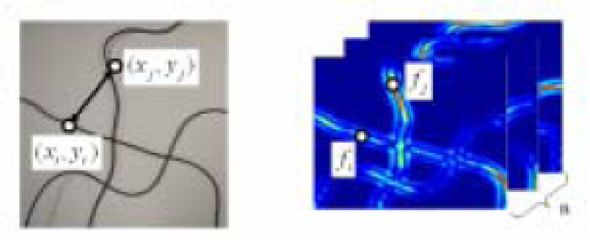
$$L = DWD, \quad D = \mathrm{diag}\left(\left(\sqrt{\mathrm{sum}(W)}\right)^{-1/2}\right), \tag{2}$$

where $\mathrm{sum}(W)$ denotes a vector where each component is the sum of a row of W and $\mathrm{diag}(x)$ denotes a diagonal matrix whose diagonal elements correspond to a vector x.

2. Decompose L into $L = UU^T$.
3. Apply k-means clustering to the resultant eigenvector matrix L. Each resultant cluster is consequently regarded as a single object.

3. SIMILARITY MATRIX

Appropriate definition of a similarity matrix is the most important point in the segmentation of pixels within a single image. In our study, we define the similarity between pixels i and j based on a combination of the distance between pixel positions r_{ij} and the directional feature d_{ij}.



(a) (b)

Figure 1. Two different criteria of similarities.
(a) Similarity of pixel positions. (b) Similarity of directional features.

First, we explain the distance of pixel positions and that of directional features (Figure 1). The distance between positions of two pixels i and j is simply given by an Euclidian distance:

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{3}$$

On the other hand, the distance between directional features is defined as

$$d_{ij} = \sum_{l=1}^{m}(f_{il} - f_{jl})^2, \tag{4}$$

where f_i. is a feature vector whose components are obtained by applying filter banks to the neighboring pixels to the ith pixel (see below).

3.1. EXTRACTING DIRECTION FACTORS

Let the original grayscale image be $I(x, y) \in R$, where (x, y) is a coordinate of the picture.

To extract the directional features of each foreground patch, we applied a set of Gabor filters defined as

$$g(x, y; \sigma, \lambda, \gamma, \theta) = \exp\left(-\sqrt{\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}}\right)\cos\left(\frac{2\pi x'}{\lambda}\right), \quad (5)$$

where θ, σ, γ and λ are parameters that control the angle, variance, ratio of height and width, and wavelength of the filter, respectively. x' and y' are rotated coordinates whose rotation angle is θ:

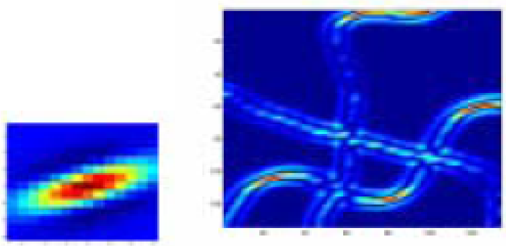
$$x' = x\cos\theta + y\sin\theta, \quad y' = -x\sin\theta + y\cos\theta. \quad (6)$$

In a previous study [2], this Gabor filter was used in computing-aided diagnosis system for pulmonary modules. We prepared multiple Gabor filters with various values of $\theta = \theta_l$, l=1,2,…,m, whereas the variance, ratio and wavelength were set at constants. We obtained filtered images by making convolution of the Gabor filters with making a picture. The information of a direction at the ith pixel is calculated as the following folding-up integral calculus.

$$f_{il} = \sum_{a=-s}^{s} \sum_{b=-t}^{t} I(x_i + a, y_j + b) \times g(a, b; \cdots, \theta_l), \quad (7)$$

where s and t are the widths of convolution and can be set arbitrarily.

Figure 2 shows an example of the Gabor filter with $\theta = 20°$ and the filterd image.



(a) gabor filter (b) filterd image

Figure 2. An example of Gabor filter (a) and its application to an image (b).

3.2.COMBINATION OF TWO DISTANCES

We combined the above-defined two criteria d_{ij} and r_{ij} into a single similarity measure:

$$W_{ij} = \exp(-a * d_{ij}) I(r_{ij} < r), \quad (8)$$

where a and r are parameters which are determined appropriately by hand, and $I(A)$ is an index function which takes 1 if condition A is true, or 0 otherwise.

4. RESULTS

We prepared a photo image taken by a digital camera (Figure 3(a)), in which electric cables are overlapped with each other on a white table, as a demonstration target. We separated the image pixels into foreground and background by applying a threshold to their grayscale intensity. To reduce the computational cost, we selected every third pixel for subsequent analyses.

We prepared 18 Gabor filters with 18 different angles, at 10-degree intervals (0-170 degrees) and the other filter parameters were fixed at $\sigma = 2$, $\lambda = 10$ and $\gamma = 0.5$. The number of clusters was set at 3 in the spectral clustering.

Figure 3 show the results by using the distance vector alone (b), using the directional features alone (c) and using both the distance and the directional features (d).

In Figure 3(b), the electronic cables are not well separated due to the existence of crossing part. This is because we measured the similarity of the object only by the distance of pixel positions. In Figure 3(c), a single cable is separated into several segments; in this case, similarly-directed parts of different cables are clustered to be a single cluster. In Figure 3(d), the cables are correctly segmented from each other.

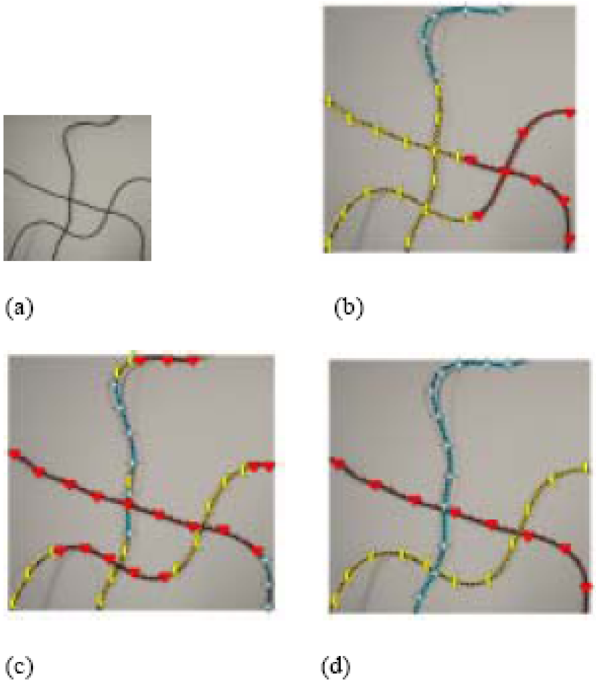


Figure 3. Segmentation results achieved by three definitions of similarities.

(a) Original image of three cables on a white table. (b) A segmentation result based on a distance-based similarity measure. (c) A result based on a directional feature-based similarity measure. (d) A result based on both the features used in (b) and (c).

5. DISCUSSION

As seen in the result, it was impossible to detect correctly the cables in the picture when we used either of the directional features or the distances between pixel positions. However, the proposed method which combines these two similarity criteria showed to be was effective in detecting string-shaped objects in a picture.

In the experiment, it was difficult to determine the parameters in equation (6), and exploration of a determination method will be our future study.

The next step of our study would be to apply the proposed method to other images that are composed of neurons [8] and other biological structures [7]. Preliminary studies have already succeeded in extracting nipples of the retina but not yet vessels. To do these tasks, one possible idea is to use histograms of the similarity [1] for the distance calculation; such a technique will give us more information of similarities among objects in an image.

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