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Target extraction from blurred trace infrared images with a superstring galaxy template algorithm

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HIGHLIGHTS

- A superstring galaxy template algorithm for extracting target of blurred infrared image is proposed.
- We use a superstring sphere mapping to change the feature space of pixel samples.
- The targets are extracted by galaxy covering algorithm based on their region characteristics.

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ABSTRACT

Accurate and efficient targets extraction from blurred trace infrared images has very important meaning for latent trace evidence collection in crime scene. Based on the superstring theory, a superstring galaxy template extraction algorithm for infrared trace target is presented. First, all of the pixels are divided into three classes: target pixels, background pixels and blurred pixels. Next, the superstring template characteristics for every pixel in a blurred infrared image are calculated as the features of each pixel. Finally, a galaxy covering algorithm is proposed, target pixels and background pixels are used for training the galaxy covering domain of every galaxy classifiers, and these classifiers will divide each blurred pixel into two classes: a target pixel or a background pixel. Experimental results indicate that the superstring galaxy template algorithm can improve the target extraction rate and reduce the extraction error rate.

1. Introduction

Current latent handprint and trace evidence collection technologies are usually invasive and can be destructive to the original deposits in crime scene [1]. Infrared images have been applied to many military or civil fields [2]; if they are used to collect hand print traces of the criminal, the original deposits will not be destroyed [3]. However, in crime scenes, infrared images of the traces are generally shot after the criminal has been gone for more than a second. In these circumstances, the infrared image will always be blurry because the gray level of its pixels will not accurately reflect the contour of the hand trace. Extracting the hand trace contour from this type of blurred infrared image is a challenging task [4].

Template extraction methods have been widely applied to extract targets from images in recent years. These existing template image extraction algorithms proposed in the literature can be classified into two categories: gradient-based approaches and statistics-based approaches.

Gradient-based approaches extract pixel gradient features from images based on abrupt changes in pixel intensity. Such as the Robert cross-gradient template [5], the Prewitt operators [6], the Sobel operators [7], the Marr–Hildreth edge detector [8], the Canny edge detector [9], and the deformable templates [10].

As the pixel gradient features extracted by the gradient-based approaches are more sensitive to blurring, statistics-based template algorithms have used templates to extract region statistical characteristics, including Feature template method [11], Functional template method [12], Spatial matrix template method [13], Artificial immune-activated neural network method [14] and Immune kernel clustering network method [15]. However, the regional features extracted by these statistics-based template algorithms cannot describe the differences between targets and background of a blurred infrared image. What is more, the classifier trained by these template algorithms cannot divide blurred pixels into a target pixel or a background pixel effectively.

To overcome these problems and extract hand trace contour from a blurred infrared image, a superstring galaxy template algorithm (SGTA) is proposed in this paper. Theoretical physicists were troubled by the existence of five separate string theories, these theories believed that our physical space have only three

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large dimensions, however, superstring theory provides that there is an extra dimension [16]. According to this idea, superstring theory explains all of the particles and fundamental forces of nature in one theory by modelling them as vibrations of tiny super symmetric strings. So we can draw lessons from the ideology of superstring galaxy to do sphere mapping and galaxy covering for the pixel feature space of blurred infrared images.

Considering the blurring nature of blurred infrared images, we design templates to extract neighborhood characteristics of three kinds of pixels, target pixel, background pixel and blurred pixel. Then, inspired by superstring theory, we present a superstring sphere mapping to change the feature space of pixels. Finally, a galaxy covering algorithm is proposed to train galaxy classifiers, which divide blurred pixels into target one and background one accurately and efficiently.

The remainder of the paper is organised as follows: the next section presents our proposed variable region template algorithm. Section 3 presents the simulation experiments, and Section 4 presents the conclusions of this paper.

2. Superstring galaxy template algorithm

2.1. Preliminary classification

Considering the temperature of human hand is always higher than the temperature of its surroundings, the gray level of target pixels is always larger than the gray level of background pixels.

First, we divide the image pixels into three pixel sets. For a blurred infrared image that has R rows and C columns, $f(u,v)$ is the gray level at pixel sample point (u,v), $u = 1, 2, \ldots, R$, $v = 1, 2, \ldots, C$. We classify blurred infrared image pixels by using maximal between-class variance method [17] to get a gray threshold k_1^* and two pixel sets, C_1' (with gray range $[0, k_1^*]$) and C_2' (with gray range $[k_1^*+1, L-1]$). Then, classify pixel set C_1' by using maximal between-class variance method to get a gray threshold k_2^* and two pixel sets, background pixel set C_4 (with gray range $[0, k_2^*]$) and blurred pixel set C_3 (with gray range $[k_2^*+1, k_1^*]$); and classify pixel set C_2' by using maximal between-class variance method to get a gray threshold k_3^* and two pixel sets, blurred pixel set C_2 (with gray range $[k_1^*+1, k_3^*]$) and target pixel set C_1 (with gray range $[k_3^*+1, 255]$). Finally, set the pixel category label. The class label of target pixels is 1, whose gray value ranges are $[k_3^*+1, 255]$. The class label of background pixels is -1, whose gray value ranges are $[0, k_2^*]$. The class label of blurred pixels is 0, whose gray value ranges are $[k_2^*+1, k_1^*]$ and $[k_1^*+1, k_3^*]$.

2.2. Superstring features extraction

Suppose each pixel point (u, v) is a sample x_i. Then, there are $R \times C$ pixel samples in the blurred infrared image. We use tow kinds of templates to extract region features $T^2_{(u,v)}$ and $T^3_{(u,v)}$ of each pixel from a blurred infrared image.

A template g_i^2 ($i = 1, 2, \ldots, R \times C$) of the size 5×5 is used to obtain the neighborhood characteristics $T^2_{(u,v)}$ of every pixel sample. Where $f(s, t)$ is the gray value at pixel (s, t).

$$T^2_{(u,v)} = \frac{1}{25} \sum_{(s,t) \in g_i^2} f(s,t) \tag{1}$$

A template g_i^3 ($i = 1, 2, \ldots, R \times C$) of the size 7×7 is used to obtain the neighborhood characteristics $T^3_{(u,v)}$.

$$T^3_{(u,v)} = \frac{1}{49} \sum_{(s,t) \in g_i^3} f(s,t) \tag{2}$$

Then, the region features are converted by superstring sphere mapping using the following formula

$$T^4_{(u,v)} = \sqrt{d^2 - \left(T^2_{(u,v)}\right)^2 - \left(T^3_{(u,v)}\right)^2} \tag{3}$$

where $d \geqslant \max\left\{\left|T^2_{(u,v)}\right|, \left|T^3_{(u,v)}\right|\right\}$. The feature space of pixel samples is a half-hypersphere in three dimension space, as shown in Fig. 1. Each pixel is a three-dimensional vector $x_i^{j_i} = \left\{x_{i1}^{j_i}, x_{i2}^{j_i}, x_{i3}^{j_i}\right\}$, where i is a sequential value, $i = 1, 2, \ldots, R \times C$, j_i is the class label of $x_i^{j_i}$. $x_{i1}^{j_i} = T^2_{(u,v)}$, $x_{i2}^{j_i} = T^3_{(u,v)}$, $x_{i3}^{j} = T^4_{(u,v)}$.

The distance between two pixel samples depends on the spherical angle between the two samples, the larger the angle, the further the distance is.

Seen by the definition of inner product, where $\langle , \rangle$ is the inner product operator.

$$\begin{aligned} \langle x_1^1, x_2^1 \rangle &= |x_1^1| \cdot |x_2^1| \cdot \cos\theta_1 \\ \langle x_1^1, x_3^2 \rangle &= |x_1^1| \cdot |x_3^2| \cdot \cos\theta_2 \end{aligned} \tag{4}$$

As the pixel samples in superstring template space are all on the surface of a half-hypersphere, so

$$\left|x_i^j\right| = d \quad (i = 1, 2, \cdots R \times C) \tag{5}$$

Then,

$$\begin{aligned} \langle x_1^1, x_2^1 \rangle &= d \cdot d \cdot \cos\theta_1 = d^2 \cdot \cos\theta_1 \\ \langle x_1^1, x_3^2 \rangle &= d \cdot d \cdot \cos\theta_2 = d^2 \cdot \cos\theta_2 \end{aligned} \tag{6}$$

Seen from the nature of trigonometric functions

$$\begin{aligned} &\theta_1 \propto \cos\theta_1 \quad \theta_1 \in [0, \pi] \\ &\theta_2 \propto \cos\theta_2 \quad \theta_2 \in [0, \pi] \end{aligned} \tag{7}$$

The relationship between the inner product and the angle is shown as the following formula

$$\begin{aligned} &\theta_1 \propto d^2 \cdot \cos\theta_1 = \langle x_1^1, x_2^1 \rangle \quad \theta_1 \in [0, \pi] \\ &\theta_2 \propto d^2 \cdot \cos\theta_2 = \langle x_1^1, x_3^2 \rangle \quad \theta_2 \in [0, \pi] \end{aligned} \tag{8}$$

Formula (8) means that we can determine the magnitude of distance by calculating the inner product in superstring template feature space.

2.3. Galaxy covering algorithm

Details of the training algorithm, the galaxy covering algorithm, are described as follows.

Step 1. Use samples in target set and background set as the training sample set $M = [\cdots, x_i^{j_i}, \cdots]$, $x_i^{j_i}$ is the pixel sample point, $i \in [1, R \times C]$ is the sequential value, $j = 1, 0$ is the class label. N is the number of samples in M.

Step 2. Randomly choose α pixel samples $x_i^{j_i}$ as the center point w_m of a galaxy covering region. For each galaxy covering region, calculate the values of $\left\langle w_m, x_i^{j_i} \right\rangle$ for every training sample in M,

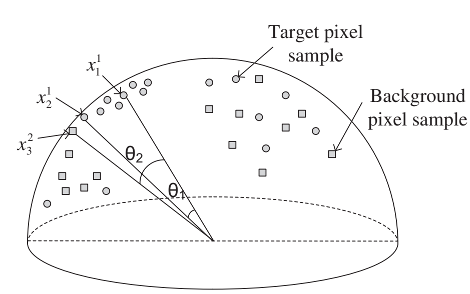

Fig. 1. Superstring template feature space of pixel samples.