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Gray-scale Edge Detection and Image Segmentation Algorithm Based on Mean Shift

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Abstract

To solve the problem of the inaccurate segmentation for the gray image, a modified algorithm based on the mean shift is introduced. The modified algorithm constructs a novel kernel function histogram by combing the position information and the gray-scale information of a pixel, and then makes use of the mean shift algorithm with this new kernel function histogram to automatically detect the modes in the gray-scale image, which could be constructed fully by the kernel function defined above, filter and segment the gray image. Experiments based on a gray image with ground background are carried out by Canny, Sobel and the proposed mean shift method, and the results show that the mean shift algorithm could effectively extract not only bright object but also weak object, and the result of the introduced algorithm is more fit factual scene than that of the usual segmentation algorithm such as Canny and Sobel algorithm.

Keywords: *image segmentation, mean shift, kernel probability density function, gray-scale image*

1. Introduction

Image segmentation or object extraction in nature scene is the substantial foundation of such tasks as feature extraction, pattern recognition and target tracking, and it has been widely applied in many fields.

The image segmentation essentially is the feature clustering in some one space. The aim of the image segmentation is to separate an image into some independent, connective and meaningful parts, which are corresponding to these real objects and background. For the objects are complicated themselves and are also affected by nature scene, illumination and shadow, image segmentation is still an elementary problem at present. One serious problem of image segmentation is how to determine the amount of objects under the unsupervised clustering scheme. Based on the fact that objects are uniform generally and there are obvious common boundaries among different clusters, the edge detection is one of the primary clustering methods. Although many classical edge detection algorithms, such as Canny and Sobel algorithm, could effectively suppress noise and locate object's edge, they couldn't yet achieve gratifying result and performance of eliminating nature scene, and over-segmentation or lack-segmentation might happen if image information and prior knowledge could not be fully utilized. Simultaneously, the boundaries between object and background are blurry and even discontinuous for the illumination's uniformity. This will result in that some segmentation algorithms based upon the edge's continuity couldn't get satisfying result [1]. At the same time, some segmentation algorithms, which are based upon the histogram of the gray image, such as the maximum entropy method, lack necessary robustness in application when the objects have multi-gray level usually [2, 3].

The mean shift [4] is a nonparametric statistical method for seeking the nearest mode of a point sample distribution by estimating the density gradient, and has been widely utilized recently in pattern analysis, especially in the color image segmentation [5, 6] and target tracking [7, 8]. The gray image only has space information and intensity information, and it is lack of the color information. This would induce that the original mean shift method, which maybe has been applied successfully to segment the color image, couldn't effectively extract the objects in the gray-scale image [9].

In this paper, an effective algorithm based on mean shift with a novel kernel function histogram, which is constructed by combining the space information and intensity information, is

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introduced. It could automatically seek the modes, suppress scene and extract object from gray-scale image. Finally, the experimental results of Canny, Sobel and the proposed mean shift for the actual image with the complex background show that the latter could effectively extract not only bright objects but also weak objects.

2. Mean Shift-Based Image Segmentation

The mean shift is a simple and nonparametric technique for seeking the modes by estimating the gradient of the probability density function (PDF). The image segmentation algorithm based on mean shift is a mathematic mapping, by which the gray-scale image is classed as some definite modes, and it could be divided into four successive steps, i.e. kernel probability density function estimation, mode detection, image segmentation and region merging. Now, let's introduce the first part, the kernel probability density function estimation.

2.1. Kernel Probability Density Function Estimation

The kernel probability density function estimation makes use of the pixels in the local area to estimate the probability density function. Given n pixels $\mathbf{x}_i$, $i=1,\cdots,n$ in the d -dimensional space R^d , the multivariate kernel probability density function estimator with kernel function $K_{\mathbf{H}}$ and a symmetric positive definite $d \times d$ dimensional bandwidth matrix $\mathbf{H}$ is given by[4]

$$\hat{f}(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} K_{\mathbf{H}}(\mathbf{x} - \mathbf{x}_i) \tag{1}$$

The kernel function $K_{\mathbf{H}}$ is a nonnegative function with zero as center and integral be one in its definitional region. Usually, the kernel function has such a form as

$$K_{\mathbf{H}}(\mathbf{x}) = |\mathbf{H}|^{-1/2} K\left(\mathbf{H}^{-1/2}\mathbf{x}\right) \tag{2}$$

Where K is a bounded function with compact support. The choosing of the kernel function would directly affect the result of image segmentation. According to the theorem of the pattern clustering, the further the data is from the center of the pattern, the litter the probability of being this pattern would be[8]. So the function K is commonly symmetrical and regressive such as the following equation.

$$K(\mathbf{x}) = c_{k,d}\, k\left(\|\mathbf{x}\|^2\right) \tag{3}$$

Where $c_{k,d}$ is the normalization constant, and $k(\mathbf{x})$, the profile of the kernel, is consecutive and differential within the definition region.

To reduce the calculation complexity, the bandwidth matrix $\mathbf{H}$ is usually either diagonal matrix $\mathbf{H} = diag\left[h_1^2,\cdots,h_d^2\right]$ or proportion to the identity matrix $\mathbf{H} = h^2\mathbf{I}$, where $\mathbf{I}$ is the identity matrix. The superiority of the later equation is that there is only one bandwidth parameter h should be provided.

When the bandwidth matrix $\mathbf{H}$ is the proportion to the identity matrix $\mathbf{H} = h^2\mathbf{I}$, the kernel probability density function is estimated as the following expression.

$$\hat{f}(\mathbf{x}) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{\mathbf{x} - \mathbf{x}_i}{h}\right) = \frac{c_{k,d}}{nh^d}\sum_{i=1}^{n} k\left(\left\|\frac{\mathbf{x} - \mathbf{x}_i}{h}\right\|^2\right) \tag{4}$$

The gray-scale image only has the position information (x, y) and the intensity information u, and these two features constructs a feature vector $(\mathbf{x}, u(\mathbf{x})) = ((x, y), u(x, y))$. Usually, the pixel, which belongs to same one pattern, is congregative in space, and the further the pixel is from the center of the pattern, the litter the probability of being the pattern would be. According to the fact just mentioned above, the profile about position $\mathbf{x}$ could be expressed as

$$k_1(\mathbf{x}) = \begin{cases} \frac{2}{p}\left(1 - \|\mathbf{x}\|^2\right) & \|\mathbf{x}\| \le 1 \\ 0 & otherwise \end{cases} \tag{5}$$

Dorin[6] adopts the kronecker delta function δ to describe the profile function about intensity feature.

$$k_2(u(\mathbf{x})) = d(u(\mathbf{x})) \tag{6}$$

In fact, the probability of the pixel, which intensity is equal to that of the central pixel, is very little within the spatial bandwidth h, and that the data abides by the Gaussion function with the intensity of the central pixel as center is more like. So, the profile function $k_2(u(\mathbf{x}))$ about the intensity could be denoted as

$$k_2(u(\mathbf{x})) = \begin{cases} (2p)^{-\frac{1}{2}} \exp\left(-\frac{1}{2}u^2(\mathbf{x})\right) & |u(\mathbf{x})| \le 1 \\ 0 & otherwise \end{cases} \tag{7}$$

By combing the formulas (5) and (7), i.e. the intensity and the position, the kernel probability density function estimator for gray-scale image could be denoted as

$$\hat{f}(\mathbf{x}) = \frac{c_{k,d}}{nh^d} \sum_{i=1}^{n} k_1\left(\left\|\frac{\mathbf{x} - \mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left|\frac{u(\mathbf{x}) - u(\mathbf{x}_i)}{s}\right|^2\right) \tag{8}$$

Where σ is the intensity bandwidth.

Once the kernel probability density function $\hat{f}(\mathbf{x})$ is estimated by the formula (8), the following step is to find the modes in the gray image.

2.2. Mode Detection

The modes locate at the position, where the value of kernel probability density function estimator is maximum or minimum. Therefore the procedure of the modes detection is searching the zero point of the gradient of the probability density function estimator, namely $\nabla f(\mathbf{x}_c) = 0$, where $\mathbf{x}_c$ is the position of the mode.

As we known, the gradient estimation of the probability density function is the gradient of the kernel density estimator, i.e.

$$\begin{aligned}\hat{\nabla} f(\mathbf{x}) &= \nabla \hat{f}(\mathbf{x}) \\ &= \frac{2c_{k,d}}{ns\,h^{d+2}} \sum_{i=1}^{n} (\mathbf{x}-\mathbf{x}_i)\, k_1'\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left\|\frac{u(\mathbf{x}_i)-u(\mathbf{x})}{s}\right\|^2\right) \\ &= \frac{2c_{k,d}}{ns\,h^{d+2}} \sum_{i=1}^{n} k_1'\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left\|\frac{u(\mathbf{x}_i)-u(\mathbf{x})}{s}\right\|^2\right) \left[\frac{\sum_{i=1}^{n} \mathbf{x}_i k_1'\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left\|\frac{u(\mathbf{x}_i)-u(\mathbf{x})}{s}\right\|^2\right)}{\sum_{i=1}^{n} k_1'\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left\|\frac{u(\mathbf{x}_i)-u(\mathbf{x})}{s}\right\|^2\right)} - \mathbf{x}\right]\end{aligned} \tag{9}$$

The later term of the formula (9) is the mean shift vector [4], and it could be expressed as

$$MG(\mathbf{x}) = \frac{\sum_{i=1}^{n} \mathbf{x}_i k_1'\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left\|\frac{u(\mathbf{x}_i)-u(\mathbf{x})}{s}\right\|^2\right)}{\sum_{i=1}^{n} k_1'\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{\mathbf{h}}\right\|^2\right) k_2\left(\left\|\frac{u(\mathbf{x}_i)-u(\mathbf{x})}{s}\right\|^2\right)} - \mathbf{x} \tag{10}$$

Let define $\{\mathbf{y}_j\}$, $j = 1, 2, \cdots$, be the center sequence of the kernel probability density function estimator. If $\mathbf{x}$ is equal to $\mathbf{y}_j$, the next center $\mathbf{y}_{j+1}$ will be equal to $\mathbf{y}_j$ plus the mean shift vector $MG(\mathbf{x})$ expressed as

$$\mathbf{y}_{j+1} = \mathbf{y}_j + MG(\mathbf{x}) \tag{11}$$

The mean shifts always points toward the direction of maximum increase in the probability density function at the steepest velocity. In the low density areas such as the boundary of an object, the velocity is greater than that in the high density area such as the interior of the object. When the velocity is very slow or close to zero at the location $\mathbf{x}_{cj}$, the mean shift procedure could stop and a new mode $\{\mathbf{x}_{cj}, u(\mathbf{x}_{cj})\}$, $j = 1, 2, \cdots$ of the image would be detected.

After these modes in the gray-scale image have been detected, the subsequent procedures are to segment image and to merge the small mode into the similar and great mode respectively.

2.3. Image Segmentation

Let define $\mathbf{z}_i$, $i = 1, 2, \cdots$,be the image pixel segmented by the mean shift procedures. If a pixel $\mathbf{x}_i$ belongs to the mode $\{\mathbf{x}_{cj}, u(\mathbf{x}_{cj})\}$, the gray value of $\mathbf{z}_i$ is equal to the gray value of the j th mode ,i.e.

$$\mathbf{z}_i = (\mathbf{x}_i, u(\mathbf{x}_{cj})) \tag{12}$$

2.4. Region Merging

After the course of image segmentation, every pixel of the gray-scale image has been belonged to one corresponding mode, and has been set one corresponding gray value. Actually, there are many similarities among some modes, and so it is necessary to merge these special modes, namely to incorporate the pixels of these similar modes into one much bigger region, in order to perfectly describe these objects.

If the differences between two modes $\left(\mathbf{x}_{cj}, u\left(\mathbf{x}_{cj}\right)\right)$ and $\left(\mathbf{x}_{ck}, u\left(\mathbf{x}_{ck}\right)\right)$ are littler than not only the space bandwidth $\mathbf{h}$ but also the gray-scale bandwidth σ, the two modes could be incorporated into a new pattern. Usually, these modes with many pixels could be reserved, but the other modes with little pixels, such as noise, are filtered out with the space bandwidth $\mathbf{h}$ and the gray-scale bandwidth σ increasing.

Moreover, if a mode contains less than M pixels, it could be merged into the nearest pattern in space.

3. Experiment Result and Analysis

One gray-scale image with ground background is adopted to evaluate the performance of edge detection and image segmentation between two classical segmentation algorithms, Canny and Sobel, and the mean shift algorithm introduced in this paper.

Figure 1 is the original gray-scale image, and there are sky, mountain, grass land, bottomland (some little section in the grass land), a tree and an airplane, which is in the common boundary between the mountain and the tree.

Figure 1. The original gray-scale image

Figure 2 is the edge image extracted by the function edge ('canny'), Canny algorithm, with the automatic parameter in MATLAB environment. This result shows that the Canny algorithm could effectively suppress the stationary sky and mountain, but is very sensitive to the non-stationary and textured grass land, where there are many unorderly edges. The edges of the airplane are submerged in these unorderly edges, and this would induce the successive target recognition and tracking based on the region feature analysis very difficult.

Figure 3 is the edge image extracted by the function edge ('sobel'), Sobel algorithm, with the automatic parameter in MATLAB environment. From this Figure, it is shown that Sobel algorithm could also effectively suppressed the stationary sky and mountain, but isn't sensitive enough to and couldn't extract these low contrast common boundaries between the sky and the mountain, the bottomland and the tree.

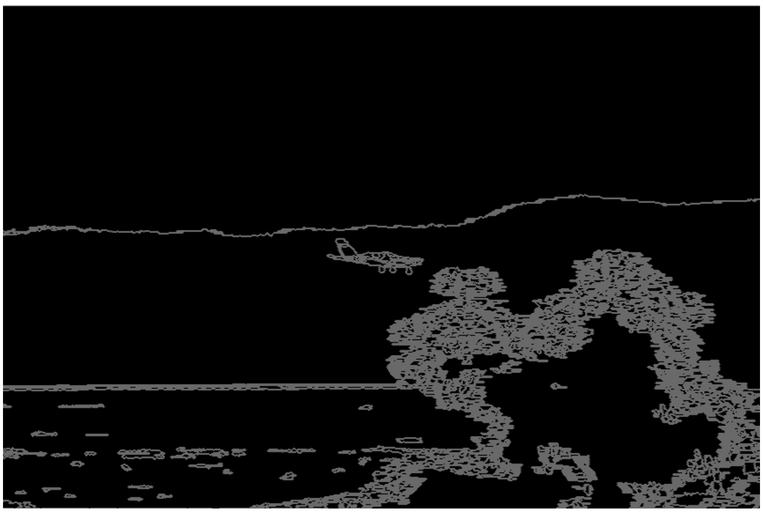
Figure 2. The edge image extracted by Canny algorithm

Figure 3.The edge image extracted by Sobel algorithm

Figure 4 is the segmented result by the mean shift algorithm introduced in this paper, and the main parameters are spatial bandwidth be five, gray bandwidth be seven, and M be ten. Figure (a) is the filtered image, Figure (b) is the segmented image, and Figure (c) is the edge image. The Figure (a) shows that the non-stationary and texture grass land are effectively smoothed as connective regions. From the Figure (b), it is known that the sky and the mountain are also effectively suppressed, and the low contrast common boundaries between the sky and the mountain, the bottomland and the tree, could be extracted well and truly. The Figure (c) shows that the edges of these objects, such as the sky, the mountain, the tree, the airplane, the grass land and the bottomland, are effectively extracted, and all boundaries are close and full.

(a)The filtered image

(b) The segmented image



(c) The edge image

Figure 4.The edge image extracted by mean shift

As we known, there are mainly three parameters adopted to evaluate the performance of image segmentation algorithm, and they are the region consistency, the region contrast and the region shape [9-12]. For the region shape need a reference segmentation image, the region consistency and the region contrast are adopted here. From the segmented image described above, the region consistency extracted by the introduced mean shift is more consistent, and the region contrast is lower than that of the Canny and the Sobel. So the objects extracted by the introduced mean shift fit actual scene than that extracted by the usual segmentation algorithm such as Canny and Sobel algorithm. So the introduced mean shift algorithm is more fit factual scene than the usual segmentation algorithm such as Canny and Sobel algorithm.

4. Discussion and Conclusion

The usual segmentation algorithms usually have the fault of over-segmentation and/or lack-segmentation, and couldn’t entirely and accurately extract the objects in the gray-scale image for it is lack of the color information. The introduced mean shift constructs a novel kernel probability density function by combing the position information and the intensity information of the pixels, and then makes use of mean shift to automatically detect the models, filter and segment the gray-scale image. Experiments based on one gray image with ground background is carried out by the Canny, Sobel and the introduced mean shift, and the results show that the proposed algorithm not only suppress the strong and textured object, but also extract the weak object effectively. The introduced mean shift algorithm is more fit factual scene than the usual segmentation algorithm such as Canny and Sobel algorithm.

Otherwise, the mean shift based segmentation algorithm is sensitive to the spatial bandwidth, and that the spatial bandwidth is adaptively chosen according to the statistical character is one of the research emphases.

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