Robust Object Detection in Military Infrared Image

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ABSTRACT

The innovation of this paper is that we put forward a new algorithm of object detection form military infrared images with texture background according to the Mean-shift smooth and segmentation method combined with eight directions difference clustering. According to the texture characteristics of background, smoothing and clustering is carried out to extract the characteristics of object. The experimental results show that the algorithm is able to extract the object information form complex infrared texture background with better self-adapting and robustness. Future research particularly lies in raising the accuracy of object extracted.

Keywords: Infrared Image, Mean-Shift, Object Detection, Texture Background, Texture Features

1. INTRODUCTION

The texture feature is one of the important factors in the infrared image data, and texture image processing is an important content which is extensively applied in geology study, remote sensing image processing and etc (Yang & Liu, 2001; Zhang, Tuo, & Liu, 2004; Efros & Leung, 1999; Liang, Liu, Xu, Guo, & Shum, 2001). The texture image shows anomaly in the local district, but expresses a certain regulation in whole. Some methods are used in the texture image processing, like Hust Coefficient, gray degree symbiosis matrix or texture energy analytical method (Deng & Manjunathm 2001; Amiaz, Fazekas, Chetverikov, & Kiryati, 2007; Fazekas, Amiaz, Chetverikov, & Kiryati, 2009). Currently, texture features detection is almost based on statistics and filter, but in actual, the background image also has some characters of texture features. For the texture background object detection from infrared images, a method based on Mean-shift and eight directions difference clustering is presented. By experimental tests, it has a better accuracy and robustness.

2. MEAN-SHIFT METHOD

Given the \( n \) samples \( x_i, \ i = 1, \cdots, n \), in the \( d \)-dimensional space \( \mathbb{R}^d \), then the Mean-shift vector at the \( x \) is defined that:

\[
M_h(x) = \frac{1}{k} \sum_{x_i \in S_h} (x_i - x)
\]  

(1)

\( S_h \) is a district of high-dimensional spheroid with radius \( h \), and satisfies the following relation of \( y \) in order of gather:
\[ S_h(x) = \{ y : (y - x)^T(y - x) \leq h^2 \} \]  \hfill (2)

\( k \) is the number of points in the \( n \) samples \( x_i \), which falls into the \( S_h(x) \) district. \((x_i - x)\) is the deviation vector of the sample \( x_i \). The Mean Shift vector \( M_h(x) \) which is defined in Equation (1) is the average value of the deviation vectors of the \( k \) samples which fall into the \( S_h \) district opposite the \( x \) point. If the sample \( x_i \) is got from the sample of the probability density function \( f(x) \), non-zero probability density gradient points to the direction at which the probability density increases most. On average, the samples in the \( S_h \) district mostly fall at along the direction of probability density gradient, therefore the corresponding Mean-shift vector \( M_h(x) \) points to the direction of the probability density gradient (Comaniciu & Meer, 2002). From Equation (1), as long as it is the sample which falls into \( S_h \) district, the contribution to \( M_h(x) \) calculation is all similar no matter its distance from \( x \), however, the sample which is near the \( x \) is more effective to the statistics characteristic that estimates \( x \) surroundings, therefore the concept of kernel function is introduced. As important values of all samples \( x_i \) are different, therefore a weighted coefficient is used for each sample. So the expand basic form of Mean-shift is:

\[
M(x) = \sum_{i=1}^{n} \frac{G_H(x_i - x)w(x_i)(x_i - x)}{\sum_{i=1}^{n} G_H(x_i - x)w(x_i)}
\]  \hfill (3)

where:

\[ G_H(x_i - x) = |H|^{-1/2} G(H^{-1/2}(x_i - x)) \]

The \( G(x) \) is a unit kernel function and \( H \) is the positive definite symmetric \( d \times d \) matrix; generally it is a bandwidth matrix. \( W(x_i) \geq 0 \) is the weight given to the sample \( x_i \). In the physically applied process, the bandwidth of matrix \( H \) is an opposite angles matrix which:

\[ H = \text{diag}[h_1^2, \cdots, h_d^2] \]

is taken from the direct proportion at the unit matrix in brief. The latter formula is only used to obtain a coefficient \( h \); therefore Equation (3) can be rewritten again as:

\[
M_h(x) = \frac{\sum_{i=1}^{n} G(\frac{x_i - x}{h})w(x_i)(x_i - x)}{\sum_{i=1}^{n} G(\frac{x_i - x}{h})w(x_i)}
\]  \hfill (4)

Background modeling is at the heart of any background subtraction algorithm. Several models have been put forward for background maintenance and subtraction described in introduction. In this paper, we focus only on the two most commonly used techniques, and exclude those which require significant resource for initialization or are too complex.

### 3. MEAN-SHIFT ITERATION ALGORITHM

By passing the \( x \) outside the bracket, we can rewrite Equation (4) as:

\[
M_h(x) = \frac{\sum_{i=1}^{n} G(\frac{x_i - x}{h})w(x_i)x_i}{\sum_{i=1}^{n} G(\frac{x_i - x}{h})w(x_i)} - x
\]  \hfill (5)

The right part of above equation for \( m_h(x) \):

\[
m_h(x) = \frac{\sum_{i=1}^{n} G(\frac{x_i - x}{h})w(x_i)x_i}{\sum_{i=1}^{n} G(\frac{x_i - x}{h})w(x_i)}
\]  \hfill (6)
UML based Model of a Context Aware System
www.igi-global.com/article/uml-based-model-of-a-context-aware-system/131455?camid=4v1a