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Interesting Target Detection and Matching Algorithm Based on Phase Information

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Abstract. Interesting target detection and matching algorithm in complex natural backgrounds images is studied in this paper. Firstly, logGabor filter bank is analyzed, which is consistent with human visual system characteristics. Several kinds of local features from the filter bank can form the integrated feature. Integrated feature congruency (IFC) model is established. And upon compensating noise for IFC, an improved integrated feature congruency (IIFC) model is obtained, in which, target detecting is translated to find the interest points that are significant across scales and orientations. This model is applied to complex natural backgrounds images for target detection and matching. Experimental results show that this method's performance.

Keywords: interesting target detection, image matching, phase information, integrated feature congrurency

1. Introduction

Target detection and recognition has been widely used in many fields. And interesting target detection is the key part, in which the main problem is how to select relevant information into a limited attention bottleneck. The target image shows a complex scene—it contains a mixture of various types of relevant features, unwanted details, and noise—and any useful representation must remove such noise and unwanted details.

The existing target detection methods can be categorized into three kinds. The first one is the CFAR detection algorithm [1]. The second one is using the fractal feature for target detection. In the detection of given size target, extended fractal feature method is put forward [2, 3]. The third one is the morphologic technique for given shape target. With the development of wavelet wavelet-based multiscale methods for target detection have appeared, such as method based on wavelet multiscale extended fractal feature [4] and energy feature based on wavelet [5].

In interesting target detection, it seems that processing is just for the target existing in the image. The reason may be simple, because the important problem is how to select useful information from very limited information. And there exists another reason that different visual tasks may involve the analysis of very distinct spatial locations on the image. Object feature detection can be implemented by local phase congruency, i.e., local energy model [6, 7]. But the prediction of interesting target can not simply be based on the spatial locations of more relevant objects in the scene, because the object to be detected (target) may be altered by some kind of camouflage, for example. A camouflaged target may remain undetected by means of the local energy model using nonmaximal suppression via the threshold of 10% or 20% of the global maximum value (since it is altered by camouflage). However, it is obvious that the target might still be perceived in the scene in case it would be judged unlikely to be accidental in origin, and therefore, it should

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have some degree of alignment in its statistical structure across a number of scales and orientations. Consequently, it may be detected via a feature perception model, in which interest points are locations of locally maximal congruence in certain combinations of separable features [8]. In this paper, several separable features are analyzed and the integrated feature congruency (IFC) model is established firstly. Then, by noise compensation for IFC, we get the improved integrated feature congruency (IIFC) model. And it's used in target detection and matching.

2. Phase filter bank

Multi-scale analysis is an effective method in the field of target detection and recognition of natural images. Filter bank used in the decomposition of image consists of logGabor filters of different spatial frequencies and orientations [9]. By definition, logGabor filter has no DC component and its transfer function has extended tail at the high frequency end. So, it should be able to encode natural images more efficiently than ordinary Gabor functions, which would over-represent the low frequency components and under-represent the high frequency components in any encoding process. Another point in support of the logGabor function is that it is consistent with measurements on human visual systems which indicate we have cell response that are symmetric on the log frequency scale.

A logGabor filter is a Gaussian function in the spatial frequency domain around some central frequency (r0,θ0). In the frequency domain, it can be represented as a complex. The real part is called the even-symmetric logGabor filter, and the imaginary part is called the odd-symmetric logGabor filter as follows,

$$\begin{aligned} G_{(r_0,\theta_0)} &= G_{(r_0)}G_{(\theta_0)} \\ &= \exp\left\{-\frac{[\log(r/r_0)]^2}{2[\log(\sigma_r/r_0)]^2}\right\}\exp\left\{-\frac{(\theta-\theta_0)^2}{2\sigma_\theta}\right\}, \end{aligned}$$

where θ0 is the orientation angle of the filter, r0 is the central radial frequency, and σ_θ and σ_r are the angular and radial sigma of the Gaussian, respectively.

The convolution of a logGabor function (whose real and imaginary parts are in quadrature) with a real image results in a complex image. Its norm is called energy and its argument is called phase. Let $O_{even}^{(r,\theta)}(x,y)$ be the image convolved with the even-symmetric logGabor filter and $O_{odd}^{(r,\theta)}(x,y)$ be the image convolved with the odd-symmetric logGabor filter.

In this paper, four different resolutions and six different angles for each resolution are chosen. To ensure that the filter bank covers the 2-D frequency planar smoothly, its distribution structure shape likes 'rose'.

3. Feature computing

Local information of complex natural image can be represented by a collection of separable features extracting several individual characteristics of the scene. For complex natural image, interesting target can be defined as the area where several features are most consistent. Before defining the integrated feature congruency function, we first define separable features and integrated features.

3.1. Separable features computing

Using each logGabor filter, $G(r,\theta)$, we can get the separable features capturing characteristics of the respective filter output, $O_{even}^{(r,\theta)}(x,y)$ and $O_{odd}^{(r,\theta)}(x,y)$ [8, 10].

(1) Normalized even-symmetric filter output

$$F_1^{(r,\theta)}(x,y) = \frac{O_{\text{even}}^{(r,\theta)}(x,y)}{\max_{(x,y)}\max_r O_{\text{even}}^{(r,\theta)}(x,y)} \tag{1}$$

(2) Normalized odd-symmetric filter output

$$F_2^{(r,\theta)}(x,y) = \frac{O_{odd}^{(r,\theta)}(x,y)}{\max_{(x,y)}\max_r O_{odd}^{(r,\theta)}(x,y)} \tag{2}$$

(3) Measure of symmetry

$$F_3^{(r,\theta)}(x,y)=\frac{|O_{even}^{(r,\theta)}(x,y)|-|O_{odd}^{(r,\theta)}(x,y)|}{\max_{(x,y)}\max_r(|O_{even}^{(r,\theta)}(x,y)|-|O_{odd}^{(r,\theta)}(x,y)|)} \tag{3}$$

(4) Measure of asymmetry

$$F_4^{(r,\theta)}(x,y)=\frac{|O_{odd}^{(r,\theta)}(x,y)|-|O_{even}^{(r,\theta)}(x,y)|}{\max_{(x,y)}\max_r(|O_{odd}^{(r,\theta)}(x,y)|-|O_{even}^{(r,\theta)}(x,y)|)} \tag{4}$$

(5) Local contrast of even-symmetric filter output

$$F_5^{(r,\theta)}(x,y)=\frac{1}{Z}\frac{1}{Card[W(x,y)]}\sum_{(p,q)\in W(x,y)}\left[O_{even}^{(r,\theta)}(p,q)-\overline{O_{even}^{(r,\theta)}(p,q)}\right]^2 \tag{5}$$

where

$$\overline{O_{even}^{(r,\theta)}(p,q)}=\frac{1}{Card[W(x,y)]}\sum_{(p,q)\in W(x,y)}O_{even}^{(r,\theta)}(p,q)$$

$$Z=\max_{(x,y)}\max_r\frac{1}{Card[W(x,y)]}\sum_{(p,q)\in W(x,y)}\left[O_{even}^{(r,\theta)}(p,q)-\overline{O_{even}^{(r,\theta)}(p,q)}\right]^2$$

(6) Local contrast of odd-symmetric filter output

$$F_6^{(r,\theta)}(x,y)=\frac{1}{Z}\frac{1}{Card[W(x,y)]}\sum_{(p,q)\in W(x,y)}\left[O_{odd}^{(r,\theta)}(p,q)-\overline{O_{odd}^{(r,\theta)}(p,q)}\right]^2 \tag{6}$$

where

$$\overline{O_{odd}^{(r,\theta)}(p,q)}=\frac{1}{Card[W(x,y)]}\sum_{(p,q)\in W(x,y)}O_{odd}^{(r,\theta)}(p,q)$$

$$Z=\max_{(x,y)}\max_r\frac{1}{Card[W(x,y)]}\sum_{(p,q)\in W(x,y)}\left[O_{odd}^{(r,\theta)}(p,q)-\overline{O_{odd}^{(r,\theta)}(p,q)}\right]^2$$

3.2. Definition of integrated feature

In research on theory of human attention feature, integrated feature is defined as a particular subset of separable features at a fixation point [11]. For any logGabor function in the filter bank, the integrated feature at (x,y) can be defined as an L-D feature vector,

$$F^{(r,\theta)}(x,y)=[F_1^{(r,\theta)}(x,y),F_2^{(r,\theta)}(x,y),\ldots,F_L^{(r,\theta)}(x,y)] \tag{7}$$

where $F_i^{(r,\theta)}(x,y)$ is the separable feature of filter output, $1\le i\le L$. Different combination of these separable features can get different integrated feature which leads to different detection results.

4. Integrated feature congruency model

To measure the congruency of integrated feature across scales and orientations, integrated feature congruency function (IFC) is given. Fundamental to this definition of the integrated feature congruency function is the selection of a proximity measure between integrated features at each scale and orientation. This proximity measure should be given in a numerical form to indicate the degree of resemblance of integrated features, over all logGabor filters at each scale and orientation (*x*,*y*). And integrated features at each scale and orientation are expressed as vectors and, consequently, the most obvious choice for measuring congruency among integrated features is the normalized correlation defined as the cosine of the angle between normalized vectors. This definition is fast to compute and usually suffice.

Definition: The congruency function in certain integrated feature F at location (x,y) is defined as

$$IFC_F(x,y)=\frac{1}{z}\sum_\theta\sum_r\rho\left[F^{(r,\theta)}(x,y),\overline{F^\theta(x,y)}\right] \tag{8}$$

where

$$\overline{F^\theta(x,y)}=\sum_r F^{(r,\theta)}(x,y),$$

and the correlation ρ is defined as

$$\rho(F^1,F^2)=\left|F^1\right|\left|F^2\right|\cos(F^1,F^2),$$

with $\cos(F^1, F^2)$ being the cosine of the angle between vectors F^1 and F^2. The normalization Z is

$$Z = \sum_{\theta}\sum_{r}\left|F^{(r,\theta)}(x,y)\right|\left|\overline{F^{\theta}(x,y)}\right| + \varepsilon$$

where ε is a small positive constant to avoid division by zero.

Given a particular definition of integrated feature F and the integrated feature congruency function $IFC_F(x,y)$, interest points are simply detected as locations (x,y) of local maxima of the function $IFC_F(x,y)$.

5. Improved integrated feature congruency model (IIFC)

In target detection from complex background, noise processing is a key part. Generally, the following assumption about noise is true: (1) noise is additive, (2) noise is everywhere in an image and its level is generally constant, and (3) features occur sparsely in an image. Then noise compensation method can be used [7]. We use noise compensation in integrated feature congruency function (IFC) and get the improved integrated feature congruency function (IIFC).

5.1. Noise compensation

Kovesi studied the noise and its relationship with filter responses in phase congruency research [6]. He thought that the response of the smallest scale (highest center frequency) filter pair in the filter bank will be almost entirely due to noise. Using Kovesi noise compensiation method, we can get new integrated feature congruency function

$$IIFC_F(x,y) = \frac{1}{Z}\sum_{\theta}\left\{\sum_{r}\rho\left[F^{(r,\theta)}(x,y), \overline{F^{\theta}(x,y)}\right] - T\right\} \tag{9}$$

Note that the noise compensation is performed in each orientation independently. This is because the image noise content is anisotropic, that is, the noise varies with different orientation. And in practice this has been found to give significantly better results.

5.2. Computational complexity of IIFC

From the definition of IIFC, we know that the computational load of IIFC is fairly high. It needs FFT, IFFT, and matrix multiplication during its implementation. If the image size involved is N×N, it will need about $25N^2\log_2 N$ complex multiplications, $50N^2\log_2 N$ complex addition, and N2 real multiplications. Here the radix-2 FFT and IFFT are assumed.

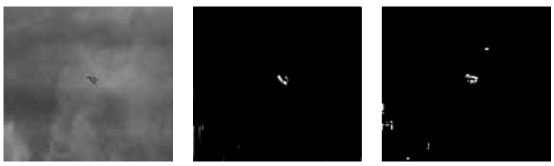
6. Experimental results

To demonstrate the performance of IIFC, we compare IIFC with IFC, phase congruency model (PC) [6], and target detection algorithm based on wavelet and energy [12], respectively.

Here, the number of scales used in logGabor filter bank is 4, the number of orientations is 6, and the scaling of center frequency is 2. The image size is 128×128. And the feature combination is $\{F_1,F_2,F_3,F_4\}$.

6.1. Comparisons between IIFC and detection algorithm based on wavelet and energy

This comparison mainly tests the detection ability to weak-small target. The result is shown in Fig.1. The contrast in Fig.1(a) between the target and the background is lower than 3%. The IIFC detection result is consistent with human visual characteristics and shows that IIFC has good effect for weak-small target detection. In the detecting result based on wavelet and energy, there is still some noise.



(a)Original (b)Result of IIFC (c)Result of Ref.[14]

Fig.1: Comparison for weak-small

6.2. Target matching based on IIFC and POC

Combining IIFC and Phase Only Correlation algorithm (POC), we get a new kind of phase-based image matching method (PIM).

Subsequently, by mathematical morphology and region labeling, we eliminate complex background disturbance and locate the matching targets exactly with processing results of the algorithm of Phase Only Correlation. And the matching tests are shown in Fig.2.

7. Conclusion

Some existing target detection algorithms are discussed. LogGabor filter bank used in this paper is introduced. Six separable features are analyzed and defined and integrated feature congruency model (IFC) is established. Then by noise compensating for IFC, we get the improved integrated feature congruency model (IIFC). And its computational complexity is analyzed briefly. The test results show that IIFC can detect targets from complex natural backgrounds scene effectively. Not only can it be used in single target image, but also in multi-targets image. Not only is it suitable to big target, but also to weak-small target. And it is general and has good anti-noise ability. Experimental results show that the PIM algorithm is effective in detecting interesting targets and locating the matching targets exactly. This algorithm is invariant to image illumination, contrast, rotation and scaling. And this model is robust, general and accords with the human vision system (HVS) characteristics.

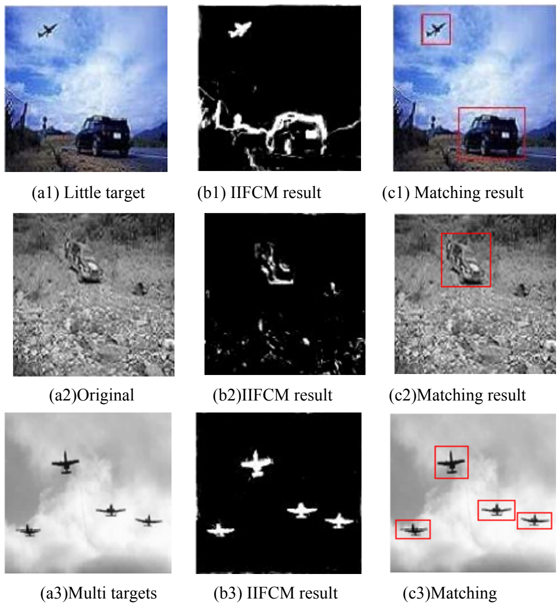


Fig.2: Matching results

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