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Phase Congruency Image and its Application in Target Tracking*

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Abstract: To deal with the problem that traditional real-time correlation tracking methods are sensitive to the light variation, a Phase Congruency (PC) image based on tracking method is proposed which utilizes the properties of PC function falling in [0, 1] interval, being normalized and invariant to changes of image brightness and constrast. PC detection is performed on the original image, and PC image is obtained. Subsequently, target tracking with correlation tracking methods, such as Minimum Absolute Difference (MAD) is conducted on the PC image. Experiment results show that the proposed method can achieve a satisfactory tracking performance on visible light images and infrared images even though the image brightness and constrast vary abruptly. The phase congruency image based on tracking method can be used to solve the common problems of tracking point drifting, even failed tracking due to image light variation in traditional real-time correlation tracking methods.

Key words: Real-time target tracking; Correlation tracking; Phase congruency detection; Phase congruency image; Brightness variation; contrast variation

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0 Introduction

The correlation tracking method is an efficient image processing method that has been adopted in video tracking systems for high-precision tracking of the targets in complex scenes, which can be widely used in many fields, such as electro-optical fire control and imaging guidance[1]. However, it also has some obvious limitations in practical applications, especially in the field of weapon systems. Such limitations can be mainly summarized in the following aspects. 1) Being sensitive to the brightness variation of the target which always results in tracking point drifting as well as target loss. 2) Being sensitive to the variation of the target contrast.

The purpose of our method is to solve the mentioned two limitations. Phase congruency is a newly emerging image processing method. The key feature of the phase congruency model is to manifest image feature changes that are unobvious and always hidden in an original image. The values of the phase congruency function fall in the interval of [0, 1], so they are normalized results and invariant to changes in image brightness and contrast[2]. This paper detects phase congruency and forms a phase congruency image. Subsequently, correlation tracking is carried on the phase congruency image. Compared with correlation tracking directly performed on the original image, the phase congruency image-based method shows competitive performance.

1 Phase congruency detection

1.1 Phase congruency model

Morrone et al[3] analyzed the phase characteristic of the Fourier series of all kinds of signal at all points and proposed the phase congruency model in terms of the Fourier series expansion of a signal. Phase congruency is a rather new feature detection method, which uses the Fourier components of the signal with the maximum phase congruency as the feature point instead of using local brightness gradient-based methods to detect features. For example, when the square wave is expanded as the Fourier series, all the Fourier components are cosine waves, as illustrated in Fig. 1(a). At the point of the step in the square wave, the phase change of each cosine component is at an angle of 90° or 270°. (depending on whether the step is upward or downward), and meanwhile the phase congruency is maximal. However, the single phase value at other points is changing, thus the phase congruency is low. Similarly, one finds that phase

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congruency is a maximum at the peaks of a triangular wave (at an angle of 0 or 180°.), as illustrated in Fig. 1(b). The key feature of the phase congruency model is searching the feature point only in the domain of Fourier transform without making any hypothesis of the waveform[4-5].

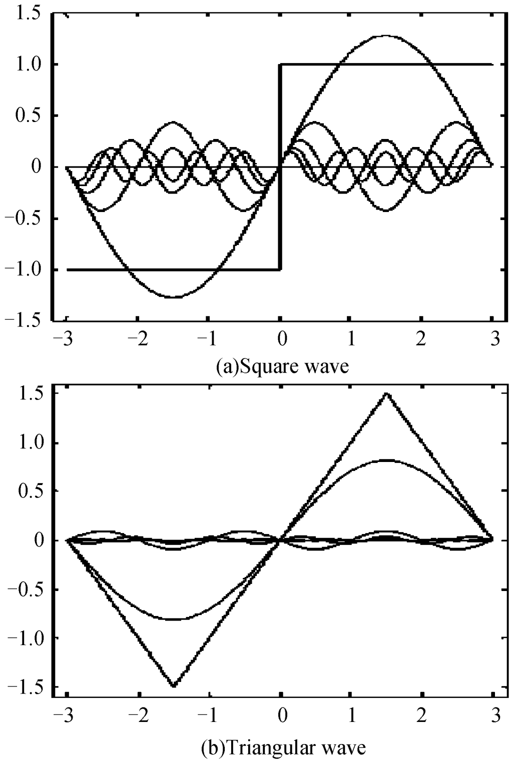


Fig. 1 Fourier series expansion

The phase congruency function in terms of the Fourier series expansion of a signal at location x can be defined as

$$\mathrm{PC}(x)=\max_{\bar{\varphi}(x)\in[0,2\pi]}\{\textstyle\sum_n A_n\cos[\varphi_n(x)-\bar{\varphi}(x)]/\sum_n A_n\} \tag{1}$$

where A_n represents the amplitude of the nth Fourier component, and $\varphi_n(x)$ represents the local phase of the Fourier component at position x. The value of $\bar{\varphi}(x)$ that maximizes this equation is the amplitude weighted mean local phase angle of all the Fourier terms at the point being considered.

According to equation (1), phase congruency is a rather awkward quantity to calculate. Therefore, Venkatesh et al[6] calculated the phase congruency by the local energy model that is defined as follows

$$\mathrm{PC}(x)=\frac{E(x)}{\sum_n A_n(x)+\varepsilon} \tag{2}$$

where ε is a very small constant. This constant is adopted to prevent the instability of the equation when $\sum_n A_n(x)$ is quite small. The local energy can be computed by the equations (3) and (4).

$$E(x)=\sqrt{\sum_n(I(x)*M_n^e)^2+\sum_n(I(x)*M_n^o)^2} \tag{3}$$

$$\textstyle\sum_n A(x)=\sum_n\sqrt{(I(x)*M_n^e)^2+(I(x)*M_n^o)^2} \tag{4}$$

where M_n^o and M_n^e are odd and even symmetry filters respectively with the frequency band number n.

1.2 Log Garbor wavelets

In the above model, we can calculate the phase congruency by the local energy. But before calculating the local energy, the signal should be filtered by the band-pass filter, and then the local frequency feature of the signal can be acquired. Therefore, this paper adopts log Garbor wavelets to filter the signal. The merits of using log Garbor wavelets are shown as follows. First, the log Garbor function has good directional selectivity and the uncertain lower limit in time-frequency measure as the Garbor function. Second, there is always no DC component in the log Garbor function. Fewer filters are used to get more reasonable and uniform covering spectrum through the log Garbor function and the frequency of the natural image is reflected more truly. Additionally, the log Gabor function accords with the characteristic that the cell response of the human visual system is symmetric under the logarithm frequency scale . On the linear frequency scale, the log Garbor function has a transfer function of the form[7].

$$g(\omega)=\mathrm{e}^{\frac{-[\log(\omega/\omega_0)]^2}{2[\log(\beta/\omega_0)]^2}} \tag{5}$$

where ω_0 is the central frequency. To obtain the constant-shape ratio filters, the term β/ω_0 must also be held constant for varying ω_0. For example, a β/ω_0 value of 0.75 will result in a filter bandwidth of approximately one octave and value of 0.55 will result in a two-octave bandwidth.

1.3 Revision of phase congruency function by Log Garbor wavelets

The measure of phase congruency given by the equation (2) is the cosine function of the phase deviation, thus the location accuracy is low. Kovesi[4-5] proposed a new measure of phase congruency with the following form.

$$\mathrm{PC}_2(x)=\frac{\sum_n W(x)\,|A_n(x)\Delta\Phi_n(x)-T|}{\sum_n A_n(x)+\varepsilon} \tag{6}$$

In this formula, the local energy function $E_n(x)=A_n(x)\Delta\Phi_n(x)$ is achieved by the convolution of the signal $I(x)$ and the log Gabor wavelet. The phase deviation function on which to base the calculation of phase congruency is

$$\Delta\Phi_n(x)=\cos[\varphi_n(x)-\bar{\varphi}(x)]-|\sin[\varphi_n(x)-$$

$$\bar{\varphi}(x)]| \quad (7)$$

The weighting function of the filter frequency band is defined as

$$W(x)=\frac{1}{1+e^{h(c-s(x))}} \quad (8)$$

where $s(x)=\frac{1}{N}\left(\frac{\sum_n A_n(x)}{A_{\max}(x)+\varepsilon}\right)$, and $A_{\max}(x)$ is the maximal amplitude value of the filter groups at the location x, c is the threshold value of the filter frequency band, h is used to control the flatness of the transfer function. Generally, c is initialized to 0.4 and h is initialized to 10. The estimated noise energy T is computed by

$$T=kA'_0\sum_n\frac{1}{\sqrt{m^n}} \quad (9)$$

where m is the response amplitude of the neighboring filters, k is the proportional factor adopted in estimating the maximal amplitude of the noise response. Usually, k is initialized to 2.0.

2 Phase congruency image

So far our discussion has been limited to signals in one dimension. However, when we analyze the 2-D image by phase congruency, we should spread 1-D phase congruency to 2-D. In this process, three issues must be resolved: 1) the shape of the filters in two dimensions; 2) the number of the orientations to analyze; 3) the way in which the results from each orientation are combined. Peter Kovesi[5] has researched these issues.

To summarize, the principle of spreading 1-D phase congruency to 2-D can be described as follows.

1) The 1-D filters described previously can be extended into 2-D by simply applying some spreading function across the filter perpendicular to its orientation. Such a 2-D filter is separable; image convolution can be accomplished by a 1-D convolution with the spreading function, followed by a 1-D convolution in the orthogonal direction with the wavelet function. The spreading function to use should be Gaussian.

2) The cross-section of the transfer function in the angular direction should be

$$G(\theta)=e^{-\frac{(\theta-\theta_0)^2}{2\sigma_\theta^2}} \quad (10)$$

where θ_0 is the orientation angle of the filter, and σ_θ is the standard deviation of the Gaussian spreading function in the angular direction.

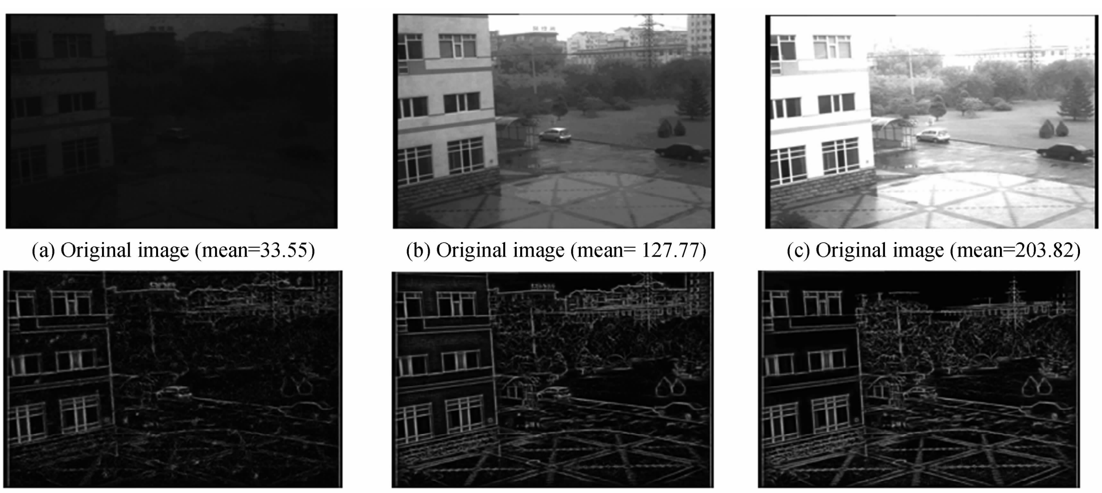
3) A filter orientation spacing of 30 deg. provides a good compromise between the need to achieve an even spectral coverage while minimizing the number of orientations.

4) 2-D phase congruency can be computed by the following equation

$$\mathrm{PC}_2(x)=\frac{\sum_o\sum_n W_o(x)\left|A_{no}(x)\Delta\Phi_{no}(x)-T_o\right|}{\sum_o\sum_n A_{no}(x)+\varepsilon} \quad (11)$$

where o denotes the index over orientations.

Here, we can calculate the phase congruency of an image by equation (11), and the result can be called phase congruency images. For a clear illustration, three images with different brightness of the same scene and their corresponding phase congruency images are given in Fig. 2. Obviously, though the brightness and contrast of the images have changed seriously, the phase congruency images are almost invariant. In other words, the phase image is robust to the image brightness and contrast variation.



(a) Original image (mean=33.55)　(b) Original image (mean= 127.77)　(c) Original image (mean=203.82)

(d) PC image of (a)　(e) PC image of (b)　(f) PC image of (c)

Fig. 2　Original images with different brightness of a same scene and their corresponding PC images

3 Experimental results and analysis

First, we define a criterion "tracking error" to assess the performance of a target tracking method. Here we describe the coordinates of target and tracking result as (x_0, y_0) and (x, y) respectively. Thus the tracking error is defined as

$$e=\sqrt{(x-x_0)^2+(y-y_0)^2} \quad (12)$$

We conduct original image-based MAD, original image-based Zero mean Minimum Absolute Difference (ZMAD), phase congruency image-based MAD, and phase congruency image-based ZMAD on a series of images with brightness variation, respectively. The brightness variation curve of the image sequence is given in Fig. 3, and the corresponding tracking error curves are shown in Fig. 4. The tracking results are shown in Fig. 5. Obviously, tracking drifts occur on the 19th frame for the original image-based MAD and on the 23rd frame for the original image-based ZMAD. However, phase congruency image-based MAD and ZMAD achieve stable and accurate performance during the whole tracking procedure even though the serious brightness variation. In Fig. 4, we can see that the curves of phase congruency image-based MAD and ZMAD are almost the same ; they are equal to zeros , except for a small variation from the 68th frame to the 98th frame. Such observation proves the robustness of phase congruency image to brightness and contrast variation. However, there

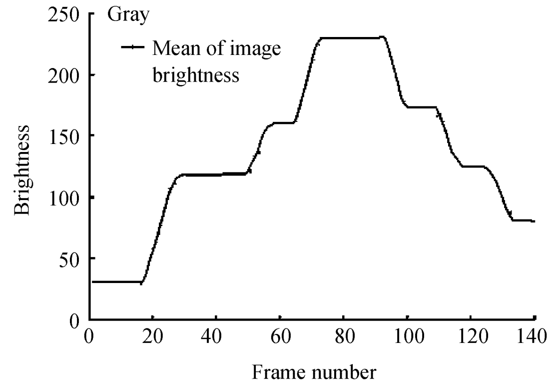


Fig. 3 Brightness curve of the image sequence

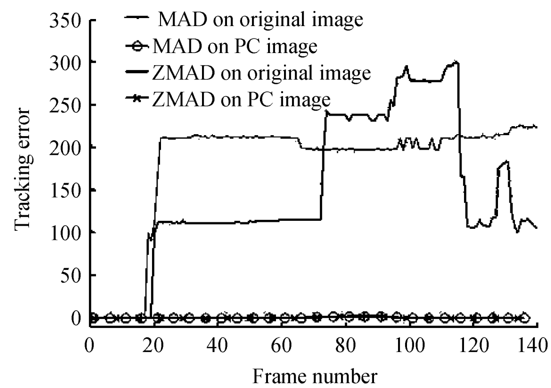
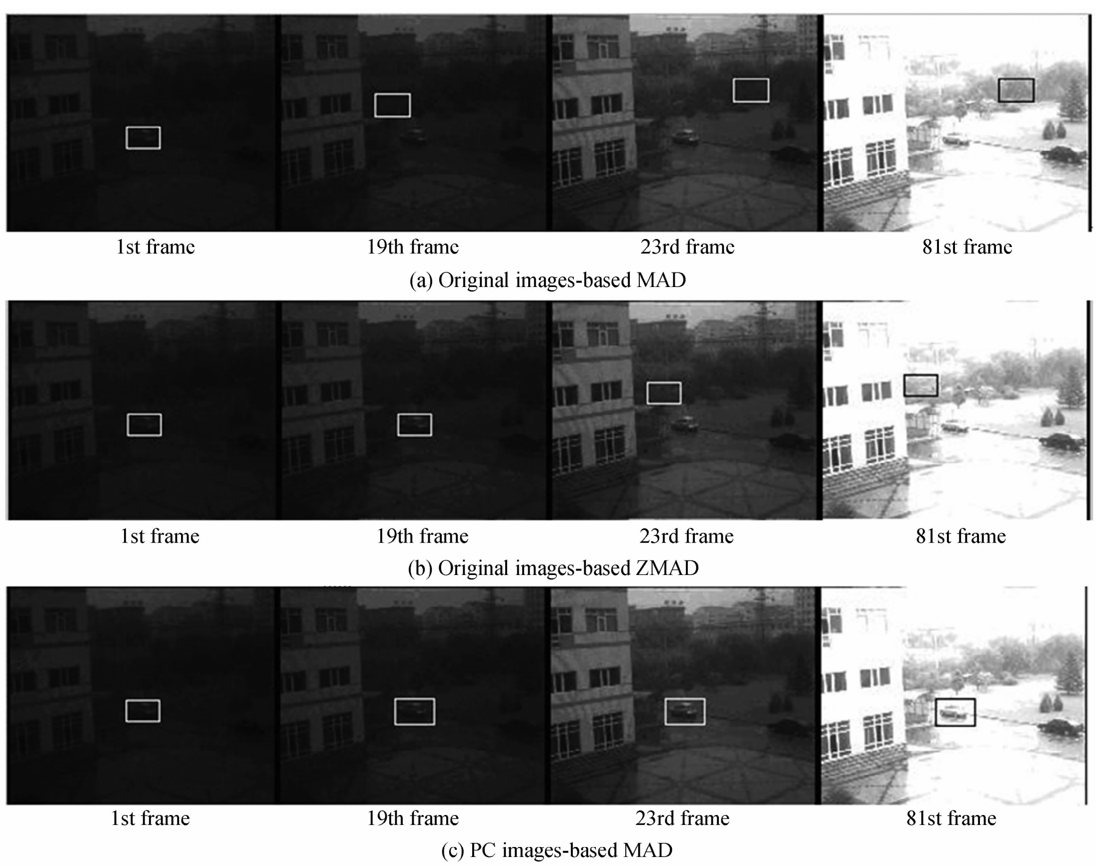
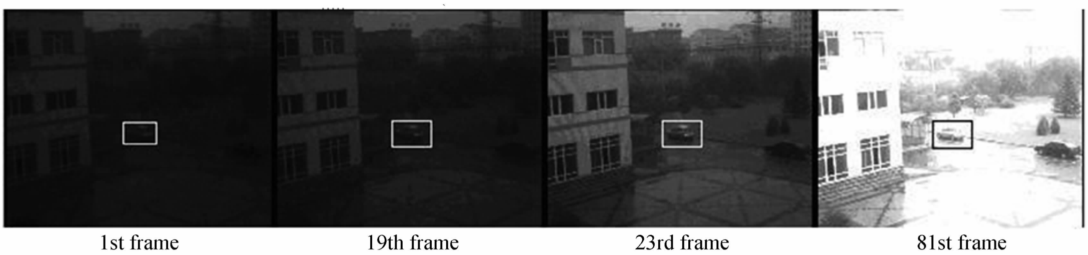


Fig. 4 Tracking error curves





(d) PC image-based ZMAD

Fig. 5 Comparisons between the original and PC image-based correlation tracking

is a significant error around 19th frame to the original image-based MAD, and another significant error around 20th frames to original image-based ZMAD. The experimental result coincides with that involved in Fig. 5.

Phase congruency image-based MAD tracking experiment is also conducted on an infrared image sequence with 3 000 frames in which the camera approached the target gradually. There are scale and brightness variation among such frames. Tracking starts on the first frame, and stable tracking performance is achieved for all of the 3 000 frames. The tracking results are given in Fig. 6.

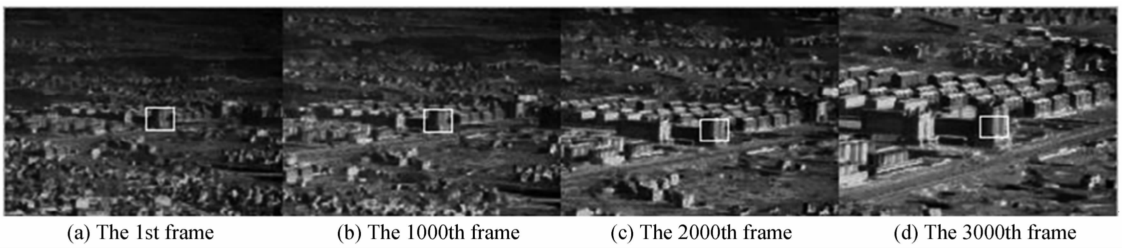


Fig. 6 Tracking results of the PC image-based MAD in infrared image sequence

4 Conclusions

In essence, phase congruency detection is an image preprocessing step. This paper proposes a correlation tracking approach based on phase congruency detection. Experimental results show that this algorithm is insensitive to the brightness and contrast variation of image. We conducted traditional tracking method MAD, and ZMAD on the phase congruency image rather than the original image, and have achieved a stable tracking performance even though there are serious brightness variations in the image sequence. Because the phase congruency detection and the MAD, ZMAD can be realized with Field Programmable Gate Array (FPGA), the process of the phase congruency-based tracking method proposed in this paper can be fulfilled within 3.2 ms at a 40 MHz clock rate. Therefore, correlation based on phase congruency image is quite suitable to the application of real-time image processing systems and real-time target tracking systems.

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相位一致性图像及其在目标跟踪中的应用

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摘　要:针对传统实时相关跟踪方法对照度变化敏感的问题,提出了一种基于相位一致性图像的相关跟踪方法.利用相位一致性函数值在[0,1]区间内且无量纲、对图像的亮度和对比度具有不变性等特点,首先对原始图像进行相位一致性检测,得到相位一致性图像,再利用 MAD(Minimum Absolute Difference)等相关跟踪算法在相位一致性图像中对目标进行跟踪运算.对可见光和红外图像的实验表明,在图像的亮度和对比度发生剧烈变化的情况下,算法仍能保持对目标的稳定跟踪.该方法可用于解决传统实时相关跟踪方法普遍存在的因照度变化导致跟踪点漂移甚至跟踪失败的问题.

关键词:实时目标跟踪;相关跟踪;相位一致性检测;相位一致性图像;亮度变化;对比度变化

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