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# Multi-Spectral Stereo Image Matching Based On Adaptive Window

Bin Yan[1], Xiangshan Kong[1,*],Fuyou Jiang [2], Peng Xu[2],Hui Yuan[2]
[1]University of Electronic Science and Technology of China, Chengdu, China
[2]State Grid Sichuan Electric Power Company, Chengdu, China

***Abstract*— In the multi-spectral image registration, because of the different imaging mechanism, the distribution of image's pixel gray value is non-linear. So the traditional matching algorithm based on gray correlation and image feature cannot be used simply. Since the mutual information measure does not need to assume the relation between the gray of image with different imaging principle, so it is very good in the field of multi-spectral image registration. But because the mutual information only utilizes the statistic characteristic of the gray, the spatial position relation between pixels in the image is neglected. Meanwhile, because of the influence of matching window size, the matching method based on mutual information measure is easy to form false matching. In this paper, we add spatial information by combining phase consistency and mutual information. Besides, the Adaptive window algorithm is used to solve the effect of matching window shape and size on the matching result. Experimental results show that the proposed algorithm has a better matching effect.**

***Keywords*— *multi-spectral; image registration; mutual information; phase consistency; adaptive window***

## I. INTRODUCTION

In recent years, Binocular stereo vision based on visible and infrared images has developed rapidly. Visible images are rich in contrast, color and shape information. In comparison, infrared images show its advantages in such special conditions as darkness and fog. Images captured by various image sensors can reduce dependence of the system on the natural environment. Therefore, the application of multiple morphological image sensors to stereo vision can enlarge the application field of binocular vision, and the key technology of image fusion is image registration.

The research on stereo vision based on multi-spectral images began in 2000, Egnal used MI as a stereo matching similarity measure [1]. Compared with traditional matching algorithm in images with different spectral characteristics, the experiments of Egnal proved that MI had a better matching effect. But using MI measure alone does not get enough depth information.

Fernando Barrera combined MI with gradient information [2], although they finally got a sparse 3D depth map, but it proved that stereo-vision is available in images with distinct spectral characteristics.

Axel Beauvisage adopted phase consistency algorithm as feature detector [3], and combined it with MI as matching measure to achieve multi-spectral stereo odometry. However, in the matching process, the 80*80px fixed size window can not guarantee the same disparity value in the same matching window[4], so the matching error increased.

In this paper, infrared image is used as reference image, visible image as the image to be matched, and the phase consistency feature of infrared image is extracted. A window centered on the feature point is established and another window centered on the pixel to test is established too. In the process of searching corresponding point of feature in the visible image, the gray information of the infrared image is referenced to classify the image. The matching window adaptively changes along the polar line according to the segmentation information. Also, phase consistency and mutual information are combined as matching measure. Calculating the matching measure value in two windows, the corresponding point with maximum matching measure as the best matching point. The method obtained in this paper has a good matching effect.

## II. SIMILARITY MEASURE OF IMAGE REGISTRATION

Because of the different imaging principle of multi-spectral image, the distribution of image's pixel gray value is non-linear. Mutual information can be used as the measure of statistical correlation between images. It is widely used in multi-spectral images without assuming the relationship between gray levels. But the mutual information only utilizes the statistical characteristic of the gray level and neglects the spatial position relation between the pixels in the image. While phase consistency can detect the edge features of multi-spectral images and make up for the lack of mutual information, so it is an effective way to combine the two methods.

### A. Mutual Information

Mutual information originates from information theory, which is used to describe the statistical correlation between two systems, or how much information is contained in another system. It can be described by entropy, which expresses the complexity of a system or uncertainty. The entropy of system A is defined as:

$$\mathrm{H(A)} = -\sum_{a} p_A(a) log p_A(a) \tag{1}$$

The joint entropy of two systems is:

$$\mathrm{H(A,B)} = -\sum_{a\epsilon A, \mathrm{b}\epsilon \mathrm{B}} p_{AB}(a,b) log p_{AB}(a,b) \tag{2}$$

H(A|B) represents the entropy of system A in the condition of known system B. H(A)-H(A|B) represents the component in system B that contains system A. that is, mutual information. It can be expressed as follows:

$$I(A,B) = H(A) - H(A|B) = H(A) + H(B) - H(AB) \quad (3)$$

H(A) represents the entropy of system A and H(B) represents the entropy of system B. I(A,B) which describes overlapped parts of two systems represents mutual information.

Mutual information can be described as follows:

$$\mathrm{MI}(X,Y) = \sum_{x\epsilon X}\sum_{y\epsilon Y} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right) \quad (4)$$

where P (x) is the edge probability density of infrared images, p (y) is the edge probability density of visible images and p (x,y) is the joint probability density of two images.

### B. Phase Congruency

Phase consistency is a frequency analysis technique used to detect image edges and corners. It chooses a point with the most consistent phase of Fourier component in an image as a feature point. It is binary, which means 1 represents salient features, and 0 represents no features. Phase consistency originated from the local energy model proposed by Morrone [5].The expression is as follows:

$$\mathrm{PC}(x) = \frac{|E(x)|}{\sum_n A_n(x)} \quad (5)$$

$A_n(x)$ represents the amplitude of the Fourier component at position x, , |E(x)| represents local energy. As can be seen from the expression, phase congruency is the ratio of local energy to the sum of the amplitude of all Fourier components, and its essence is to measure the phase similarity of each frequency component in the image. In the subsequent study, Kovesi proposed phase consistency with noise compensation [6].The phase consistency at x is:

$$\mathrm{PC}(x) = \frac{\sum_n W(x)\lfloor A_n(x)\Delta\Phi_n(x) - T\rfloor}{\sum_n A_n(x) + \varepsilon} \quad (6)$$

Where $\Delta\Phi_n(x) = \cos\left(\phi_n(x) - \bar{\phi}(x)\right) - |\sin(\phi_n(x) - \bar{\phi}(x))|$. $A_n(x)$ represents the amplitude at position x, $\Phi_n(x)$ represents phase of the $n^{th}$ component at position x, W(x) represents the frequency weighting function, $\Delta\Phi_n(x)$ is the phase deviation function, T is the threshold for noise compensation, $\varepsilon$ is a small constant that avoids being divisible by zero, and $\lfloor\ \rfloor$ represents that if a positive number is in the symbol, it returns itself, and if it is a negative number, returns 0.

In visible and infrared images, edge information is the only effective component, and edge detection based on phase consistency can effectively extract the common features of two kinds of images. The feature of phase consistency has geometrical invariance, robust to noise, and edge feature can be detected in the condition of weak contrast.so it is very suitable for feature point matching of multispectral images.

## III. ADAPTIVE MATCHING WINDOW

In the process of stereo matching, pixels in the same matching window should satisfy the same disparity value[4]. However, in the traditional local matching method, a fixed size window doesn't meet this requirement. The matching window must be large enough to contain enough intensity changes, as well as small enough to avoid the effect of projection distortion. If the matching window is too small to contain enough intensity changes, a poor parallax estimation will be obtained because the signal-to-noise ratio is too low. Conversely, if the matching window is too large which causes the problem of containing the scene points with different depths, the different projection distortions of the left and right images will result in mismatch problem. So the size of the matching window must be properly selected depending on local variations of intensity and disparity.

Visible and infrared image registration has its unique advantage, because the infrared image can reflect the thermal radiation information of different objects. The different gray values can reflect the regional feature to some extent, so the gray information of the infrared image can be used as the reference of the region segmentation. This way can achieve the similar results with the segmentation algorithm. The adjacent pixels that have the same gray scale also have a similar disparity value[7], So we can use the difference of pixel gray value to achieve the adaptive change of the matching window. FIGURE I shows the adaptive window change process .

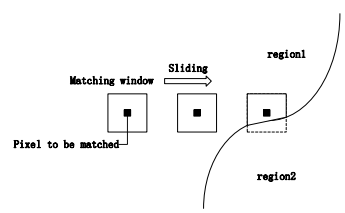



FIGURE I. ADAPTIVE WINDOW CHANGE PROCESS

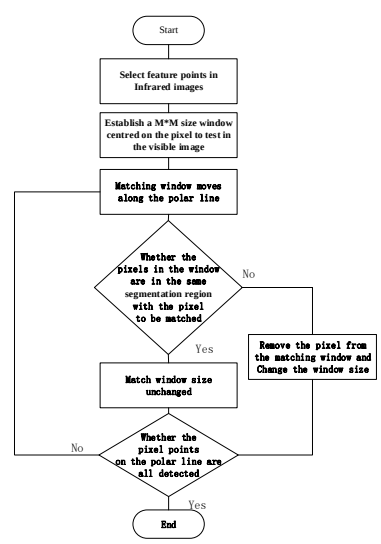



FIGURE II. WORK FLOW OF ADAPTIVE MATCHING WINDOW ALGORITHM

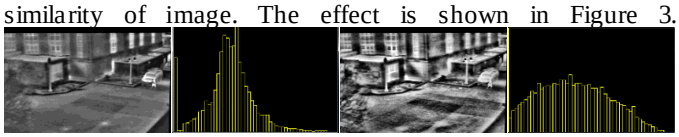
As shown in FIGURE II, at the beginning of the match process, a regular rectangular matching window of size M*M with the feature point of infrared image as the center is established. In the visible image, a matching window of the same size(M*M) which centres on the point to be matched is established too, and the point is on the polar line corresponding to the feature point. When the matching window in the visible image searches for a matching point along the polar line, the pixels in the matching window will be compared to the point to be matched. The pixels with different segmentation regions will be removed from the window. So the window will be adjusted adaptively.

## IV. MATCHING BASED ON ADAPTIVE MATCHING WINDOW

In this paper, the method of phase consistency and mutual information is used as the similarity detection measure, and the Adaptive matching window is added to improve the low matching accuracy caused by the uncertainty of matching window size.

### A. Image Equalization Processing

In order to solve the problem of fuzzy and low contrast of infrared image, this paper utilizes the Contrast Limited Adaptive Histogram Equalization algorithm to improve the similarity of image. The effect is shown in Figure 3.

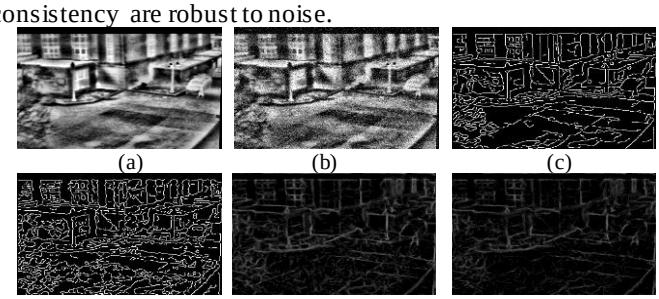


(a) (b) (c) (d)

FIGURE III. (A)ORIGINAL INFRARED IMAGE (B)ORIGINAL INFRARED IMAGE HISTOGRAM(C)IMAGE BY CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION ALGORITHM(D) HISTOGRAM BY CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION ALGORITHM

### B. Feature Detection

Because edge information is the only effective component in visible and infrared images, Edge detection based on phase consistency can effectively extract the common features of two kinds of images. At the same time, because the features of phase consistency has geometrical invariance, insensitive to illumination change and robust to noise, this paper uses phase consistency as the algorithm to extract features. As shown in Fig.4, the influence of noise on the Canny operator can be found in the figure, but image features extracted by phase consistency are robust to noise.



(a) (b) (c)

(d) (e) (f)

FIGURE IV. (A) ORIGINAL INFRARED IMAGE(B) INFRARED IMAGE WITH GAUSSIAN NOISE(C) ORIGINAL INFRARED IMAGE AFTER CANNY DETECTION(D) INFRARED IMAGE WITH GAUSSIAN NOISE AFTER CANNY DETECTION(E) PHASE CONSISTENCY DETECTION OF ORIGINAL INFRARED IMAGE(F) PHASE CONSISTENCY DETECTION IN INFRARED IMAGE WITH GAUSSIAN NOISE

### C. Feature Point Matching

Because the visible image is rich in texture information, the characteristic in visible image does not necessarily exist in infrared image. So we use the infrared image as the reference image and the visible image as the image to be matched. In this paper, mutual information and phase consistency are used as similarity measure. After adding the Adaptive matching window, the mutual information in the matching window is as follows:

$$\mathrm{I}(\omega_l;\omega_r) = \sum_{a_i\epsilon\omega_l}\sum_{b_j\epsilon\omega_r} p_{\omega_l\omega_r}(a_i,b_j)\log\left(\frac{p_{\omega_l\omega_r}(a_i,b_j)}{p_{\omega_l}(a_i)p_{\omega_r}(b_j)}\right) \quad (7)$$

Where $\omega_l$ represents a matching window centered on a feature point of the infrared image, $\omega_r$ represents a matching window centered on a pre-matching point in a visible image, $p_{\omega_l}(a_i), p_{\omega_r}(b_j)$ are respectively marginal probability density of the visible image and the infrared image in the matching window, and $p_{\omega_l\omega_r}(a_i,b_j)$ represents joint probability density for two matching windows.

$$p_{\omega_l\omega_r}(a_i,b_j) = \frac{1}{N}H(a_i,b_j) \qquad a_i\epsilon\omega_l, b_j\epsilon\omega_r \quad (8)$$

Where N is the number of pixels in the matching window and $H(a_i,b_j)$ represents joint probability histogram in two matching windows.

Because the mutual information directly calculates the similarity of two images, but the phase consistency provides contrast information only in one image, in order to compare the phase consistency similarity of two images, the following cos () similarity function is used.

$$\mathrm{PC}(\omega_l,\omega_r(i)) = \frac{\mathrm{PC}(\omega_l)*\mathrm{PC}(\omega_r(i))}{\|\mathrm{PC}(\omega_l)\|*\|\mathrm{PC}(\omega_r(i))\|} \quad (9)$$

$\mathrm{PC}(\omega_l)$ represents the phase consistency value of all pixels in the matching window centered on a feature point in an infrared image. $\mathrm{PC}(\omega_r(i))$ represents the phase consistency value of all pixels in the matching window centered on a point i to test in an visible image. $\|\mathrm{PC}(\omega_l)\|, \|\mathrm{PC}(\omega_r(i))\|$ represent their Euclidean norm.

Combined with phase consistency, pixel spatial information are added to mutual information. The combination of the two algorithms is as follows:

$$Z_i = \frac{MI(\omega_l,\omega_r(i))}{\overline{MI}} + \frac{PC(\omega_l,\omega_r(i))}{\overline{PC}} \qquad i\epsilon\Omega \quad (10)$$

Where $\omega_l$ represents a matching window centered on the feature point of infrared image, $\omega_r(i)$ represents a matching window centered on point i in the visible image. $\overline{MI}$ and $\overline{PC}$ represent the average value of MI and PC respectively.

After the image is corrected, each line is a polar line, and the pre-matching point of the visible image must be on the same line of the infrared image's features. As shown in Figure 5, The 80*80 matching window centered on the infrared image feature point is established. A matching window with the same size centered on the point which locates the same line with the feature point is established in the visible image.

When the matching window in the visible image is moving along the polar line, the adaptive window algorithm is utilized, and the window in the infrared image changes along the matching window. The next step is that calculates $Z_i$ of two matching windows, and the matching point with the maximum $Z_i$ is the best match point. In general, if $Z_i$ is very low, it respects match effect is poor and the pre-matching point should be discarded. But phase consistency is closely related to image contrast, and $Z_i$ in low contrast regions tend to be lower than $Z_i$ in high contrast region. We use adaptive threshold based on matching window entropy information to solve this problem. The formula is as follows:

$$\max_{i\epsilon\Omega}(Z_i) > \alpha E(\omega_1) \tag{11}$$

Where E represents entropy function and $\alpha$ is a scaling constant set to 0.5. If the above formula is satisfied, the match is successful. Otherwise, the point to be tested is discarded. The similarity measure is calculated until the pixel points on the polar line are all detected

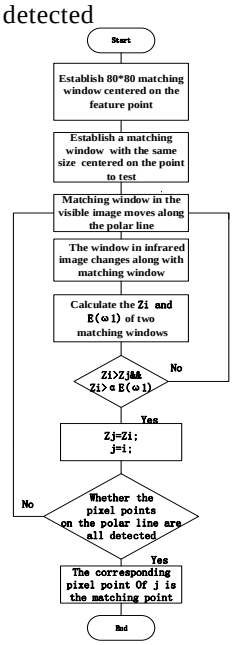



FIGURE V. FEATURE POINT MATCHING WORK FLOW

## V. EXPERIMENTAL VALIDATION

This paper uses the data set named OSU Color-Thermal Dataset provided by Fernando. The image pairs of the dataset have been rectified, which greatly simplifies the matching process. In order to verify the effectiveness of the algorithm, we will compare it with the mutual information algorithm, besides Mutual information combined with phase consistency algorithm. The comparison effect is as follows:

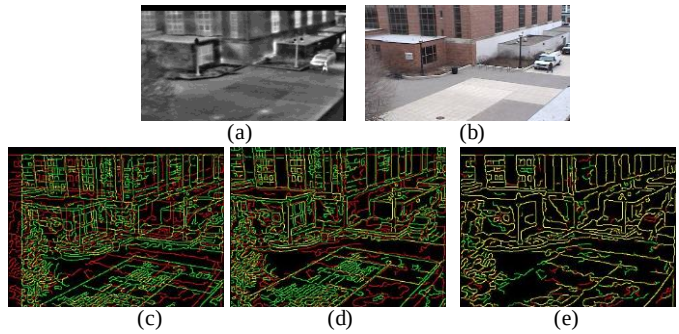



FIGURE VI (A) ORIGINAL INFRARED IMAGE(B)ORIGINAL VISIBLE IMAGE(C) MUTUAL INFORMATION ALGORITHM (D) MUTUAL INFORMATION COMBINED WITH PHASE CONSISTENCY ALGORITHM (E) THE ALGORITHM OF THIS PAPER

From the experimental results, it can be seen that the matching accuracy based on mutual information is not very high ,because of the lack of spatial information between pixels. The algorithm of Mutual information combined with phase consistency has added edge information and improved the matching accuracy, but the matching effect is not perfect. By using the proposed algorithm of this paper, the Adaptive matching window is added to the algorithm of Mutual information combined with phase consistency, which improves the matching accuracy effectively, and proves that the adaptive change of the matching window can improve the matching effect between the infrared image and the visible image. In order to evaluate superiority of the algorithm, RMS error is used as the indicator. As shown in table 5-1, compared with the previous two algorithms, the proposed algorithm in this paper effectively reduces the RMS error.

Table 5-1 RMS error of three matching algorithms

| **algorithm** | ***Mutual Information*** | ***Mutual information combined with phase consistency algorithm*** | **The algorithm of this paper** |
|---|---|---|---|
| RMS error | 0.52 | 0.37 | 0.17 |

The final experimental results are as follows:

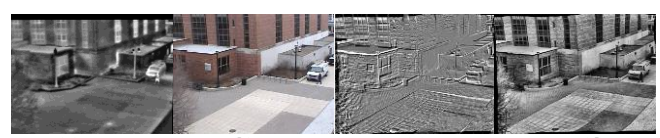



FIGURE VII. (A) ORIGINAL INFRARED IMAGE (B) ORIGINAL VISIBLE IMAGE (C)THE DIFFERENCE BETWEEN THE MATCHED IMAGE AND THE ORIGINAL IMAGE(D) THE MATCHING IMAGE PROCESSED BY THE ALGORITHM IN THIS PAPER

## ACKNOWLEDGMENT

In this paper, we combine phase consistency with mutual information, improving the lack of spatial information in mutual information. The Adaptive window is added to solve the problem of projection distortion and low SNR caused by unreasonable window size, and matching accuracy is improved effectively. However, there are still some drawbacks in our algorithm, the algorithm does not behave as expected when matching the low texture area. In all, this paper we proposes a new idea based on visible light and infrared image matching,

and our algorithm have an elegant performance on the matching process.

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