ANALYSIS OF RELIABILITY AND IMPACT FACTORS OF MUTUAL INFORMATION SIMILARITY CRITERION FOR REMOTE SENSING IMAGERY TEMPLATE MATCHING

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ABSTRACT:

Reliability of similarity measure is a key factor for successful image matching. In this paper, mutual information is introduced to template image matching as a similarity measure. Its ability of adapting to different scene, overcoming the grey reversal, and factors which influence on the successful matching of mutual information method are discussed. These factors include signal-noise ratio, information content and self-similarity. The test data are remote sensing images captured by different sensors, with different spatial resolution and at different seasons. Some typical scenes such as city, town, village, river, stream, and field land are used to test its ability of adapting to different scenes and the ability to overcome the grey reversal. The experiments manifest that there is no strong relationship between success rate and the amount of signal-noise ratio or information content for the mutual information matching method. The successful matching based on mutual information is mainly affected by whether there are similar pattern areas in the reference image or not. The experiments also indicate that when the scene has large non-linear change of grey, the success rate of mutual information matching method is much greater than that of cross-correlation method.

1. INTRODUCTION

Template matching is essential in many image analysis and computer vision tasks. Reliability of similarity measure is a key factor for successful template matching. In conventional template matching methods, cross-correlation methods are often used because of their strong suitability to different scene, simple arithmetic and easily parallel calculation. However, when a big grey aberrance (such as grey reversal), geometrical deformation (such as rotation) and random noise exist in images to be matched, the success rate of matching is low and matching usually fails. Therefore, it is necessary to study more reliable similarity measure to boost up the ability to overcome intensity aberration and random noise in order to improve the success rate of matching (Brown, 1992; Zitova et al., 2003;Su et al., 2000).

In this paper, mutual information is introduced to template image matching as a similarity measure. Its ability of adapting to different scene, overcoming the grey reversal, and factors which influence on the successful matching of mutual information method are discussed. Mutual information is a fundamental concept in the information theory, and it is the measure of the statistic relativity for two stochastic variables. When images with the same structure matched best, the mutual information of corresponding pixels is the biggest in principle (Maes, et al., 1997; Studholme, et al., 1999; Arlene, et al., 2003). Because mutual information similarity criterion doesn't need any assumption of pixel value relationship between the images to be matched, and any segmentation and pre-processing are not required before matching too, it has been widely applied in the matching of various kinds of images such as medicine images (Josien, et al., 2003). Whereas, in template matching, there are few articles discussed about it so far as I know, so it is a valuable topic to be discussed farther.

The factors, which affect the successful matching of mutual information method, are also analysed. These factors include signal-noise ratio, information content and self-similarity. The relationship between these factors and success rate of matching are presented. The success rate of mutual information and cross-correlation based methods are compared. Some beneficial conclusions are drawn.

The rest of the paper is organized as follows. The basic principle of mutual information is described in Section II. The test data and matching method are described in Section III. Reliability and impact factors of mutual information similarity criterion are discussed in detail in section IV. Finally, some conclusions are drawn in Section V.

2. MUTUAL INFORMATION SIMILARITY METRIC

Mutual information (MI) is a concept developed from information theory. It indicates how much information one random variable tells about another. The MI registration criterion can be thought of as a measure of how well one image explains the other. It is applied to measure the statistical dependence between image intensities of corresponding pixels in both images, which is assumed to be maximal if the images are geometrically aligned; therefore, it can be regarded as the similarity measure in image matching (Maes, et al. 1997; Viola, et al.1997; Arlene, et al. 2003; Josien, et al. 2003). It has been widely applied in the matching of various kinds of images such as medicine images that obtained with different mode, and also has been used in remote sensing imagery registration recently (Chen,et al. 2003).
The mutual information is denoted by information entropy as follows:

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$$
\begin{aligned}
MI(U,V) &= H(U) - H(U|V) \\
&= H(V) - H(V|U) \\
&= H(U) + H(V) - H(U,V)
\end{aligned} \qquad (1)
$$

Where U and V are two images to be matched. $H(U)$ and $H(V)$ are the margin entropy of U and V ,respectively, and they describe the uncertainty of stochastic variable. The $H(U,V)$ is the joint entropy of images U and V . The $H(U|V)$ is the conditional entropy, which describes the total amount of uncertainty of U when V is known. The relationship between mutual information

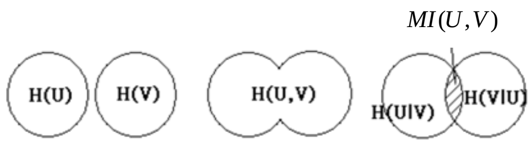

Figure 1. The relationship between mutual information and $H(U), H(V), H(U,V)$ and $H(U|V)$

and $H(u), H(V), H(U,V)$ and $H(U|V)$ is shown in Figure 1.

In Figure 1, the circle denotes the margin entropy of image, the united area of two circles denotes joint entropy, and the overlap part of two circles is mutual information. It is shown that mutual information integrates margin entropy and joint entropy, and it is the difference of the both. Entropy is often expressed by probability density of variable, as follows:

$$H(U) = -\sum_{u} p_U(u) \log p_U(u) \qquad (2)$$

$$H(U,V) = -\sum_{u,v} p_{UV}(u,v) \log p_{UV}(u,v) \qquad (3)$$

$$H(U\,|\,V) = -\sum_{u,v} p_{UV}(u,v) \log p_{U|V}(u\,|\,v) \qquad (4)$$

Where $P(u)$ and $P(v)$ are the marginal probability distribution of variables U and V , $P(u,v)$ is their joint probability. For grey image, $P(u)$ and $P(v)$ can be estimated by their grey histograms, respectively, and $P(u,v)$ can be estimated by their joint histogram.

An alternative $NMI(U,V)$ was proposed by Studholme et al (1999):

$$NMI(U,V) = \frac{H(U) + H(V)}{H(U,V)} \qquad (5)$$

This alternative is designed to compensate for the sensitivity of MI to changes in image overlap. The results of their experiments indicate that the $NMI(U,V)$ measure provides significantly improved behaviour over a range of imaging fields of view.

3. EXPERIMENT DATA AND MATCHING METHOD

The test images are the remote sensing images captured by different sensors, in different season and time with different spatial resolution (Some are shown in Figure 2). SPOT (pan) acquired on December 21, 1999 with 10-meter spatial resolution are regarded as reference images. They all have 256×256 pixels. Corresponding IRS-C (pan) images acquired in July 1996 are used as the source images for generating input image samples for template matching. The spatial resolution of IRS-C (pan) image is 5.8 meter. Several of the input image samples with 65×65 size are obtained by

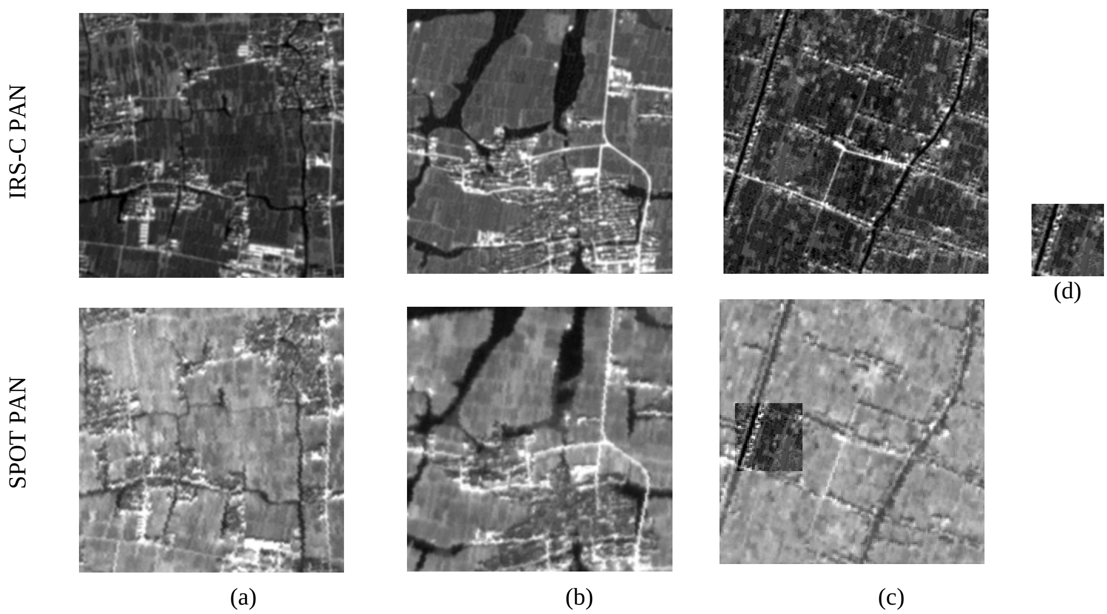

Figure 2. Some scene images used to experiment: (a), (b) and (c) are the IRS-C source input images and corresponding SPOT reference images, respectively, and named by Village, Stream and Farmland. (d) is an input image cropped from IRS-C(pan) Farmland, and its size is 65×65 pixels.

cropping the source IRS-C image with an interval of 20 pixels apart. Images to be matched cover different landscape, such as city, village, river, farmland, etc. and they have different characters of signal -noise ratio, information content, and self-similarity pattern.

MI is estimated by grey histogram, and NMI is used to eliminate the influence of the image overlap. Since the size of reference and input images are small, when the number of grey levels in each image is high (e.g., 256 grey levels), the statistical power of the probability distribution estimation by mutual information will be reduced (Knops et al. 2006). Therefore, image grey-level reduction is needed. In the paper's test, image grey-level is set as 16. The implementing process of MI matching is as fellows:

(1) Searching input image pixel by pixel and probability of every grey-level is estimated.

(2) Moving the input image on the reference image pixel by pixel, and corresponding sub-image with the same size of the input image is cropped from the reference image. The probability of every grey-level is estimated for every sub-image.

(3) Calculating the probability of the grey pairs presented in corresponding position of the images to be matched. The value of normalized mutual information is obtained in terms of information entropy formula (5).

The position, on which the NMI is the greatest, is regarded as the correct matching position for the input image in the reference image.

4. IMPACT FACTORS OF MUTUAL INFORMATION SIMILARITY CRITERION AND ITS VALIDITY

Whether image matching is successful or not depends to some degree on the characteristic of images except for the matching method. Factors of image quality, which influence on the performance of the area-based matching, mainly include signal-noise ratio, self-similar pattern, the number of independent pixels, square difference. The signal-noise ratio often used to forecast whether the matching is successful or not by area-based matching methods (Su, et al., 2000). The information content is the main factor, which impacts the success of matching by feature – based methods (An, et al., 2005). All methods may be failure if some self-similar pattern areas present in the reference images. This paper pays mainly attention to how the signal-noise ratio, information content and self-similar pattern influence on the matching validity based on mutual information method.

4.1 The Signal-Noise Ratio

The signal-noise ratio is an important parameter for matching performance, which is mainly determined by weather status when the image is captured, the noise degree of sensor and the equipment used for digitising image. The greater the signal-noise ratio is, the more favorable it is for matching. Thus, the signal-noise ratio is an important factor to estimate image quality, especially in real time image matching for navigation and position estimation (Ma, et al., 2001). It is applied to describe various errors of input image and reference image, and it is a more important rule for forecasting performance of matching (Du, et al., 2003). In scene matching, it implies the grey difference between corresponding pixel for input image and reference image. The definition of signal-noise ratio is as follows:

$$SNR = \frac{S}{N} = \frac{VAR(\overline{ref})}{VAR\left[\overline{ref} - \overline{rel} * \frac{VAR(\overline{ref})}{VAR(\overline{rel})}\right]} \qquad (6)$$

Where $VAR(*)$ denotes the calculation of variance of image (see equation (7)); $\overline{ref}$ is the reference image processed, and its each pixel grey value is obtained by subtracting average grey value of ref image from corresponding pixel grey value in ref image; $\overline{rel}$ is the corresponding input image, which is also processed by the same method as $\overline{ref}$ image. Suppose the size of image I is $R \times C$, I' is the average grey value image of I, then,

$$VAR(I) = \left[\frac{1}{R \times C} \sum_{I=0}^{R-1} \sum_{j=0}^{C-1} (I(i,j) - I')^2\right]^{1/2} \qquad (7)$$

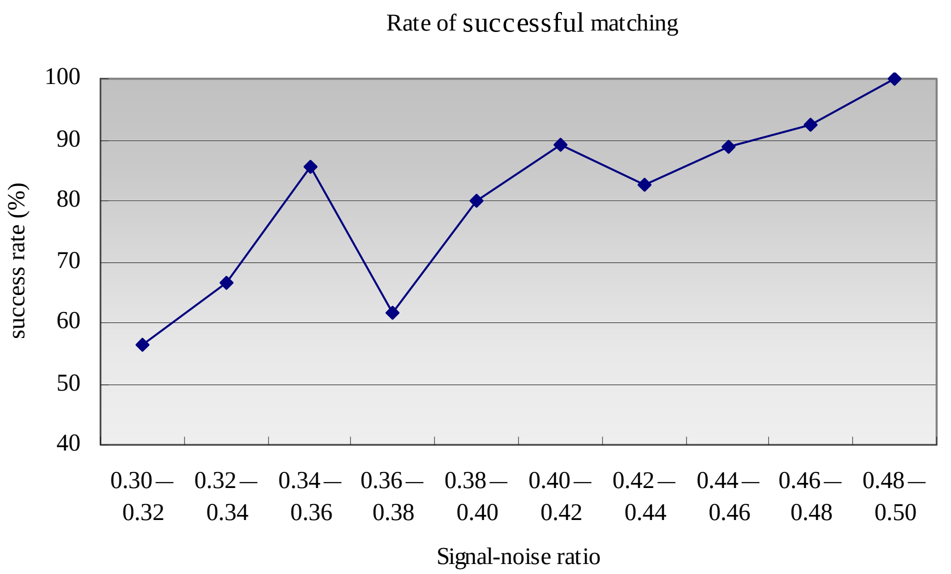

Figure 3. Successful matching rate of images whose signal-noise ratio is between 0.3-0.5

269 input images with 65×65 pixels cropped from IRS-C source images are used for test. Their signal-noise ratio is between 0.3—0.5, and different scene area is covered. Signal-noise ratio between input image and its corresponding SPOT image is calculated, shown in Table 1 and Figure 3.

Table 1. The relationship between signal-noise ratio from 0.3 to 0.5 and rate of successful matching

Signal-noise ratio	Number of input images	Number of correct matching	Rate of successful matching (%)
0.30—0.32	16	9	56.25
0.32—0.34	18	12	66.67
0.34—0.36	21	18	85.71
0.36—0.38	34	21	61.76
0.38—0.40	45	36	80.00
0.40—0.42	28	25	89.28
0.42—0.44	29	24	82.76
0.44—0.46	27	24	88.89
0.46—0.48	27	25	92.59
0.48—0.50	24	24	100.0

From curve's trend in Figure 3, we can see that the greater the signal-noise ratio is, the greater the success-matching rate is in the whole. But, there is some exception, for example, success-matching rate for images, whose signal-noise ratio is from 0.32 to 0.36, is greater than that of images whose signal-noise ratio is from 0.36 to 0.38. It is shown that images' signal-noise ratio has no strong relation to the success-matching rate for mutual information based method. It is obvious that mutual information expresses statistical characteristic of image's grey value, good matching result can still be obtained when non-linear change of image's grey value is taking place and images to be matched have lower signal-noise ratio value.

4.2 Summation of Image Gradient

Image gradient reflects image's information content and the amount of features the image contained, and it is the key factor for feature-based matching. The value of gradient is great when image contains rich prominent features. However, the value of gradient is small for flat area, and it is zero for the area, whose grey-level is invariable. Gradient calculator in common use is Robert, Prewitt, Krisch arithmetic, etc. Following is an example for calculating gradient located at (x, y) for image $I(x, y)$ using Sobel arithmetic, viz.:

$$\begin{aligned} G_x &= (I(x-1, y+1) + 2I(x, y+1) + I(x+1, y+1) \\ &\quad - (I(x-1, y-1) + 2I(x, y-1) + I(x+1, y-1)) \\ G_y &= (I(x-1, y-1) + 2I(x-1, y) + I(x-1, y+1) \\ &\quad - (I(x+1, y-1) + 2I(x+1, y) + I(x+1, y+1)) \end{aligned} \qquad (8)$$

Gradient at (x, y) for image $I(x, y)$ is a vector, as follows:

$$\nabla I = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{bmatrix} \qquad (9)$$

Magnitude of gradient is $mag(\nabla I) = \left[G_x^2 + G_y^2\right]^{1/2}$.

The value of magnitude of gradient at very pixel is added together, and then the summation of image gradient for whole image is derived. It shows edges contained in the image and the change of image's grey-level. Therefore, summation of image gradient can represent image's information content. In this paper, experiment is carried out for the relationship between the summations of image gradient and success rate based on mutual information matching method. It is also found out that there is no strong relation between image gradient and matching success rate using mutual information method. 267 input images, whose image gradient is from 4.0 e+005 to 6.0e+005, are used to test and detail statistic is obtained, shown in Table 2 and Figure 4.

The curve in Figure 4 shows that image's gradient magnitude has

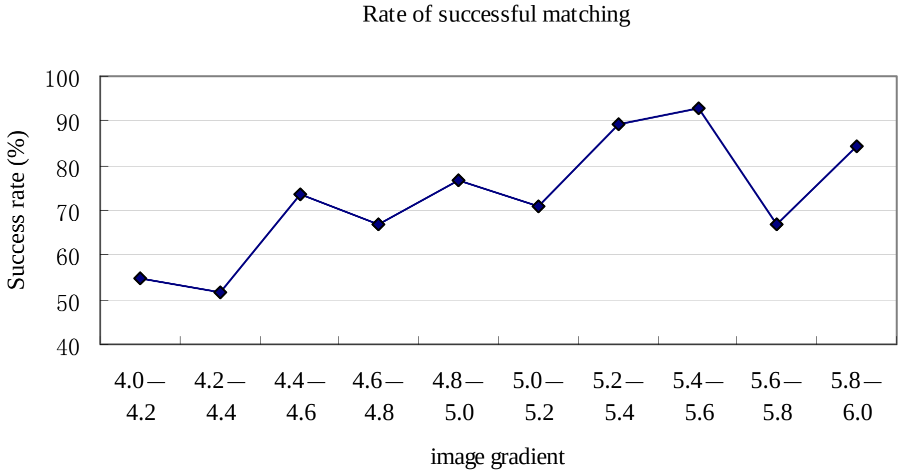

Figure 4. Success rate of matching for images whose summation of gradient magnitude is from 4.0e+005 to 6.0 e+005

no strong relation to the success-matching rate for mutual information based method. Even if there are much less features in the image, good matching result can also be obtained using mutual information matching approach.

Table 2. The relationship between image gradient and matching success rate

Image gradient	Number of input images	Number of correct matching	Success rate (%)
4.0—4.2	20	11	55.00
4.2—4.4	27	14	51.85
4.4—4.6	34	25	73.53
4.6—4.8	33	22	66.67
4.8—5.0	30	23	76.67
5.0—5.2	31	22	70.97
5.2—5.4	19	17	89.47
5.4—5.6	28	26	92.86
5.6—5.8	26	24	66.67
5.8—6.0	19	16	84.21

4.3 Self-Similar Pattern

In image matching, self-similar pattern in reference image seriously affects success rate of matching. Self-similar pattern often indicates some sub-area, which grey or some features appear in the reference image repeatedly. Different method has different definition about self-similar pattern. For area-based method, the definition of self-similar pattern is the number of sub-areas, which have similar grey level distribution. Whereas, for feature-based methods, the definition of self-similar pattern is the number of sub-areas, which have similar feature distribution (Xie, et al., 1997). Suppose a sub-image i is selected from reference image, its self-similar pattern is defined as follows:

$$cf_i = \frac{p_i}{s} \tag{10}$$

Where s is the number of all sub-images, which are used for matching when sub-image i is searching on the reference image pixel by pixel. Suppose the size of a reference image is $M \times N$ pixels, and the size of a sub-image is $m \times n$ pixels, then, $s = (M - m + 1) \times (N - n + 1)$, where p_i is the number of sub-images in s, whose grey correlation coefficient obtained by matching them to sub-image i is greater than the threshold TH.

It is known that cf_i denotes two dimensions relativity about a sub-area to the whole area. If a number of sub-images are cropped equably from reference image, then, the mean self-similar pattern value of these sub-images can be used to inspect two dimensions relativity of reference image. Therefore, self-similar pattern value of a reference image is defined as the following equation:

$$cf = \frac{1}{l}\sum_{i=1}^{n} cf_i \tag{11}$$

Where l is the number of sub-images cropped from the reference image. And these sub-images must satisfy some requirements.

The bigger the self-similar pattern value is, the stronger two dimensions relativity of image self is, and the higher the error of matching is. In the calculating of self-similar pattern value, TH and n are two important parameters. Selection of TH is a key problem. Only when a reasonable TH is selected, characteristics of image's self-matching can behave fully. The Selection of n affects the calculation time and reliability of self-similar pattern value. Sampling interval determines how much n is. Setting $TH = 0.96$ and $n = 20$ are made after experiments in the paper. The relationship between self-similar pattern and success rate of matching based on mutual information is shown in Table 3 and Figure 5.

Table 3. The relationship between self-similar pattern value for different scene and success rate of matching

Different scene image	Self-similar pattern value	Success rate of matching (%)
Farmland	0.989	69
Village	0.519	78
River	0.336	81
Town	0.117	93
Stream	0.010	100

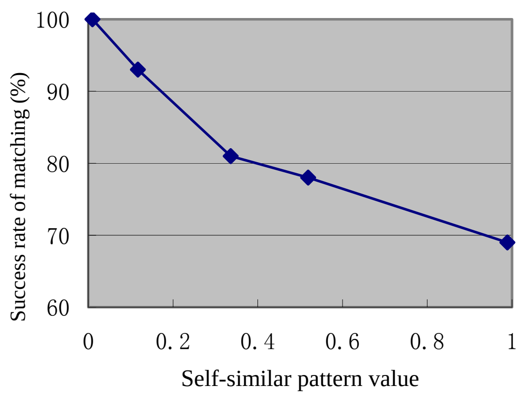

Figure 5. Self-similar pattern and success rate of image matching

From Figure 5 we can see that the bigger the value of self-similar pattern is, the lower the success rate of matching is, since there are many self-similar areas in the reference image, which leads to many mistakes in matching and reduce the validity of matching based on MI. Self-similar pattern means how many self-similar areas are in one image, the more the self-similar areas there are, the more the peaks of MI value there are, and local maximum of MI will cause matching error. There is a strong relativity between matching success rate and self-similar pattern.

4.4 The Validity of Mutual Information Similarity Metric

The validity of mutual information similarity metric applied in template matching for dissimilar image can be validated by success rate of matching. The success rate of matching shows the ability of matching method adapted to images with various grey aberrations and random noise. Experiments for matching validity are implemented by various landscapes images, including farmland, road, town, river, stream and city. Some images have abundance features, higher S/N ratio and smaller non-linear variation of pixel intensity. Some images have bigger variation of pixel intensity and even grey reversals because of these images were captured in different season. Also, there are some images with many self-similar areas. Table 4 gives success rate for different scene images using MI and cross-correlation methods.

Table 4. Comparison of success rates by 16 grey level normalized mutual information and cross-correlation approaches for different scene images

Various Scene images	Cross-correlation (%)	16 grey levels normalized mutual information (%)
Village1	61	78
Town	85	93
Farmland	28	69
River	63	81
City	65	88
Village	10	57
Stream	82	100
Average	56.3	80.9

Experiments manifest that the success rate of MI is much greater than that of cross-correlation method when the scene images have great grey aberration and even reversal. It shows that the performance of MI is far excelled than that of cross-correlation in dissimilar scene matching.

5. CONCLUSION

The performance of MI has no strong relationship to S/N ratio and information content of images to be matched, but has a strong relationship to self-similar pattern in the reference image that also validates the theoretical essence of MI definition and accounts for MI has strong ability to overcome grey distortion. It is also showed that good matching performance can be derived even images to be matched have much lower S/N ratio and grey reversion. Various scene images are used to test the matching performance based on MI, and success rates are all higher. It is manifested that MI is a universal similarity measure and no need feature detection, pre-processing, user initialization and tune of parameter before matching. It is especially suitable for dissimilar images matching and it outperforms greatly than cross-correlation method.

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