[15] A preprocessing method for correlation-extremal systems

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Abstract

In this paper we discuss an image preprocessing method for different shooting conditions. The method can be applied in machine vision systems using a correlation-extremal mapping method. An information-theoretic method for image preprocessing based on entropy analysis is offered. The investigation of the method has shown that, when preprocessed, same-scene images obtained under different conditions have a more stable correlation coefficient than the original images

Keywords: technical vision, entropy analysis, correlation, image preprocessing.

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Introduction

Correlation-extreme systems are used in various fields of technology. The correlation analysis has many advantages: technique is proven, there are fast algorithms for computing the correlation and there are hardware implemented solutions. To date, of great interest are simple and cheap correlation visual systems, implemented in the form of special processors.

In this article, we set out to use the correlation image matching method, but in difficult circumstances: namely, when comparing dissimilar images registered by different sensors. To solve the problem of comparison of multiple images of the scene, obtained under different conditions or even differing by the type of representation, the work suggests information-theoretic preliminary image encoding method. In various examples its effectiveness is demonstrated when used in conjunction with the extreme-correlation algorithm.

1. Correlation image analysis. Formulation of the problem

One typical problem of technical vision is element by element comparison of two images of the same object registered by different sensors, or two images of the same object obtained by one sensor, but at different conditions. To make such a comparison, it is necessary to perform the mutual binding of these images and thus to adjust the relative spatial shifts, differences in enforcement, offset caused by turning, as well as geometric distortion and distortion of the brightness of each image [1-3].

Image comparison methods can be divided into two groups: the extreme methods and techniques that compare characteristic features [4].

When comparing the same type of images (most often it is a series of images), the application of methods of isolation and analysis of characteristic features are preferable because of their lower computational complexity. To compare dissimilar images, on the contrary, the use of this methods is inappropriate, since different characteristic features are highlighted in the images of the same scene.

Extreme way of mutual binding (combining) of a pair of functions is that the value is generated which measures correlation between these functions, and position of the maximum of correlation function is found.

The normalized cross-correlation function (NCCF) R_{XY} of two random fields X and Y is defined as:

$$R(i, j; m, n) = \frac{E[X_{i,j} - EX_{i,j}]\cdot[Y_{m,n} - EY_{m,n}]}{\sqrt{DX_{i,j} \cdot DY_{m,n}}}, \qquad (1)$$

where E is mathematical expectation, D is dispersion.

Let us consider the case when two images I and I' are shifted against each other vertically and horizontally (see Figure 1).

Fig.1. Example of shifted images

The normalized cross-correlation function R(I, I') is shown in Fig.2. NCCF maximum offset relative to the center determines images offset to each other.

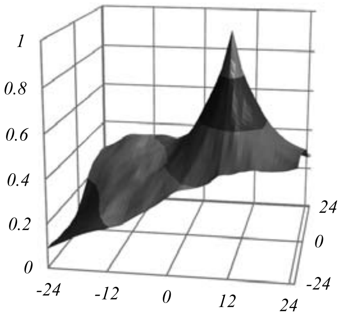


Fig.2 . NCCF of images with offset

In this case, I and I' are parts of a single image, while in practice problems arise when it is necessary either to compare different images from the same source but at different conditions or from different image sources.

Here is an example. Suppose we need to compare aerial photograph to topographic map of the same area (Figure 3, a source of "Yandex. Maps").

a)

b)

Fig.3. Images: a) map, b) photo

Figure 4 shows the cross-correlation function of the images.

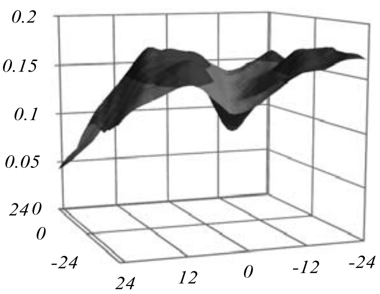


Fig.4. NCCF of images, shown at Fig.3

The figure shows that the function has no maximum, indicating the image shift (in this case the offset is zero). This example shows that the correlation-extreme method has limitations on the types of the compared images.

Therefore the task of adapting the correlation-extreme method for use when comparing the disparate images is of considerable practical interest. In this study we propose to solve this problem by the image preprocessing method based on entropy coding, in particular by replacement of image with the map of its local entropy, which, as we will show, is much more resistant to the influence of factors that we study, than the source image.

2. Method of preprocessing of images based on the entropy coding

The solution is achieved by using the method of pre-processing the images based on the accounting of the internal statistical relationships between the elements that are present in images . This solution is based on the assumption that statistically interrelated elements in changing conditions of obtaining images remain statistically related. The image is considered as a realization of a random process [7, 8].

In order to identify internal statistical relationships information-theoretic methods are used in processing the data of any nature. When applied to solution of the problem it is proposed to implement entropy coding of images, namely to calculate map of local entropy for each of the original images.

Local entropy (H_n) represents the degree of unexpectedness of an n-th event occurence, the smaller its a priori probability, the higher is its local entropy.

Let us define what will be understood in this case as an "event" and how to calculate local entropy:

– for each image counting its neighborhood is considered, a fragment with $m \times n$ dimensions;

– each fragment entropy is calculated [9]:

$$H(z) = -\sum_{i=1}^{m}\sum_{j=1}^{n} p(e_{i,j})\log(p(e_{i,j})). \qquad (2)$$

– an event $(e_{i,j})$ is considered to be a pixel brightness value, its probability $(p(e_{i,j}))$ is estimated by counting the number of entrances of this value all across the fragment of $m \times n$ size and dividing it by the number of pixels in a fragment.

The output image is formed by replacing each sample with a value, calculated by the formula of local entropy (i.e. local entropy map is constructed).

Figure 5 shows the local entropy maps of images shown in Figure 3.

a)

b)

Fig. 5. Local entropy maps: a) of the map (the image shown in the negative at the request of the printing house); b) of the image

View of the correlation function of maps of local entropy is shown in Figure 6. The figure shows that the correlation function has a pronounced maximum corresponding to zero shift.

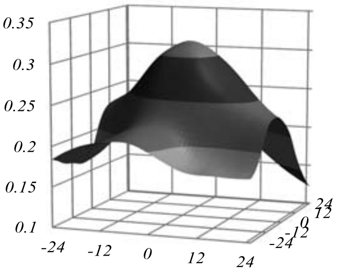


Fig 6. NCCF of the maps of local entropy of images

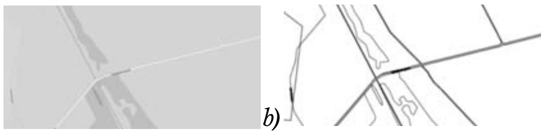
3. Testing the method

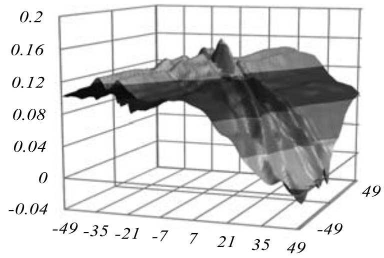
Similar results were obtained using other test images (maps and aerial photos, photos in winter and summer, conventional and infrared images).

In the first example, as in the previous, a topographical map and an aerial photograph of the same area were used as the test images (Fig. 7a and 7b, the source is "Yandex. Maps").

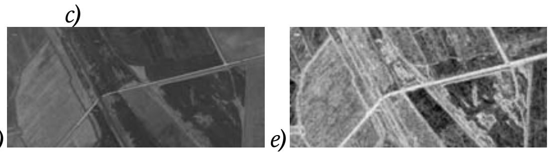
Cross-correlation of the two original images was calculated, NCCF view is shown in Fig.7c. The figure shows that the correlation function has many local maxima. Search of the global maximum of such "non-smooth" function is availilable by the method of exhaustive search, or by methods of successive approximation with a small step, which leads to high computational cost.

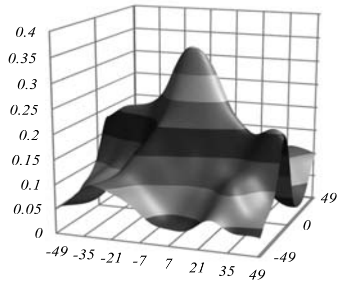
At Figures 7d, 7e there are maps of local entropy of images, and on Fig. 7f there are their NCCF.


a) b)



c)

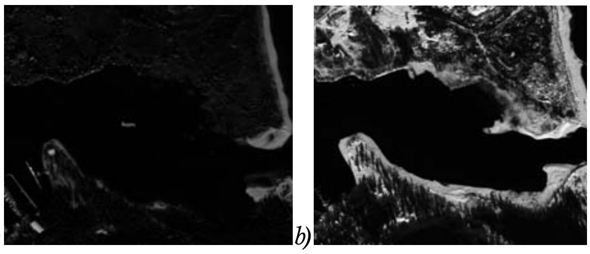

d) e)

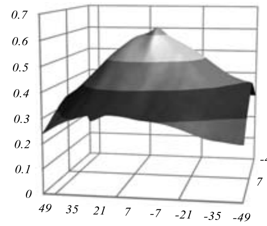


f)

Fig. 7. Example 1: a) map, b) photo, c) NCCF (a) and (b), d) map of the local entropy of topographic map (image shown in the negative at the request of the printing house), e) map of the local entropy of the image, f) NCCF (d) and (e)

In this example, let us consider the image of the same area taken at different times of the year (Fig. 8, the source of images are "Yandex. Maps" and «Google Maps»).


a) b)



c)

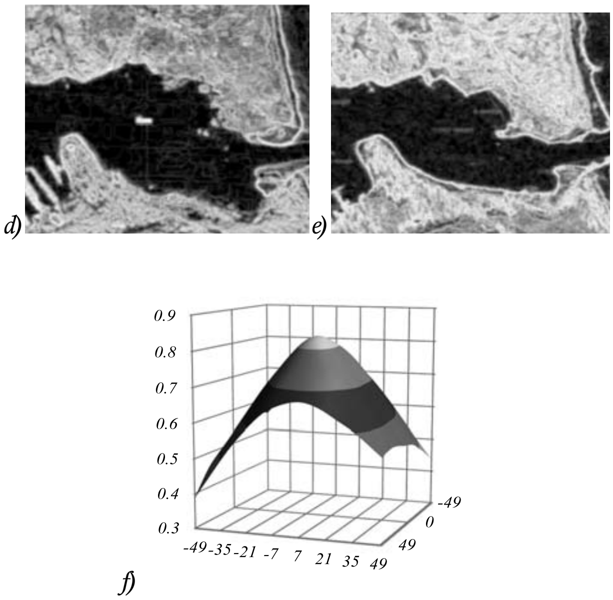
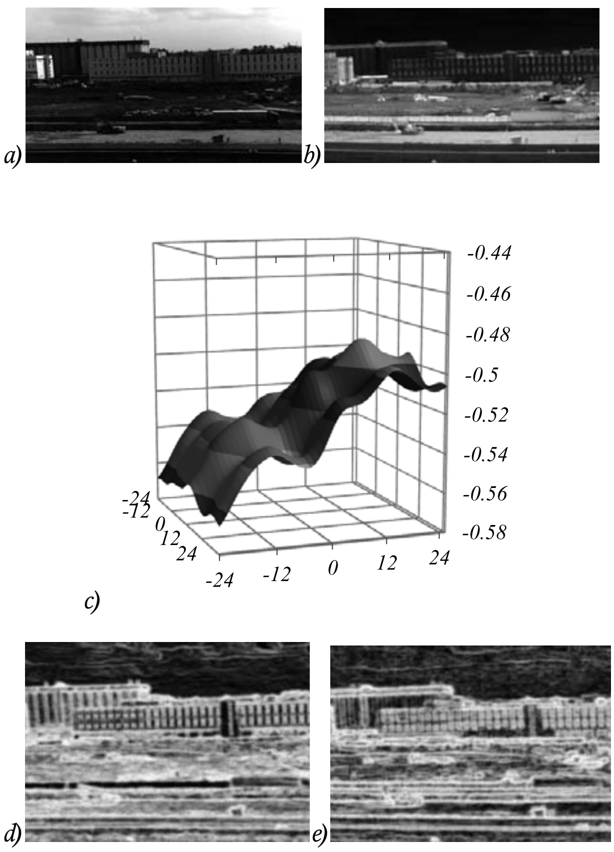


Fig. 8. Example 2: a) summer photo, b) winter photo, c) NCCF (a) and (b), d) map of local entropy of the summer photo, e) map of local entropy of the winter photo, f) NCCF (d) and (e)

In the third example we compared images of the same scene, filmed by conventional and infrared imaging cameras (Fig.9).



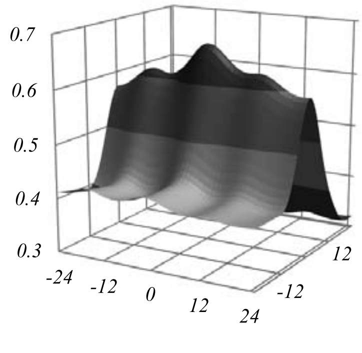


Fig. 9. Example 3: a) a shot from a conventional camera, b) a shot from an infrared imager, c) NCCF (a) and (b), d) map of local entropy of the shot from a conventional camera, e) map of local entropy of the shot from an infrared imager, f) NCCF (e) and (f)

Discussing the results

In these examples we have seen that the images after preprocessing exhibit a higher correlation coefficient (see. Table) and smoother NCCF, than the original images. Example 3 also shows that preprocessing method based on local entropy is invariant to inversion of brightness of images (in this example – image fragments).

Tab. Values of maximums NCCF

	Images without preliminary processing	Maps of local entropy of images
Example 1	0.18	0.35
Example 2	0.63	0.83
Example 3	-0.51	0.67

Thus, the entropy image preprocessing can be recommended for use in comparing the images by correlation-extreme method for two reasons:
– it increases the correlation between dissimilar images;
– correlation function of the local entropy maps is smoother than the correlation function of the original images, which can significantly reduce the amount of computation to find the extreme.
It can be assumed that these properties are related to the fact that local entropy map contains no fine details available in the image, and we can try to achieve the same effect by first removing small

details in the source images by using the low-pass filter (generally, it is this type of preprocessing that is used for comparison of images by correlation method). For comparison let us take a section of NCCF along the OX and OY axes for three examples discussed above (Fig.10-12). The gray solid line denotes the NCCF of source images, the black dotted line – the NCCF of smoothed images, the black solid line – the NCCF of maps of local entropy of images.

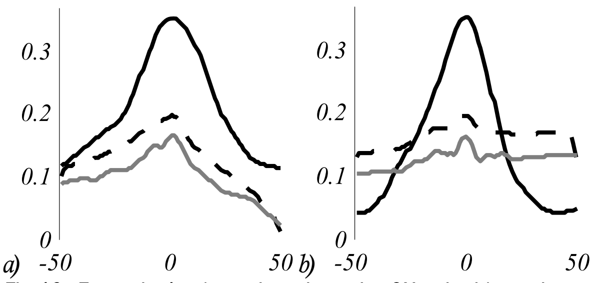


Fig.10. Example 1: a) section along the OX axis, b) section along the OY axis (gray solid – source images, black dotted line – smoothed images, black solid line – image local entropy maps)

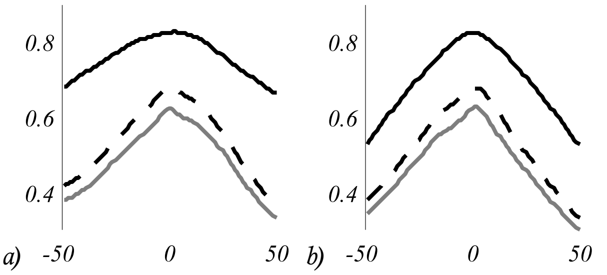
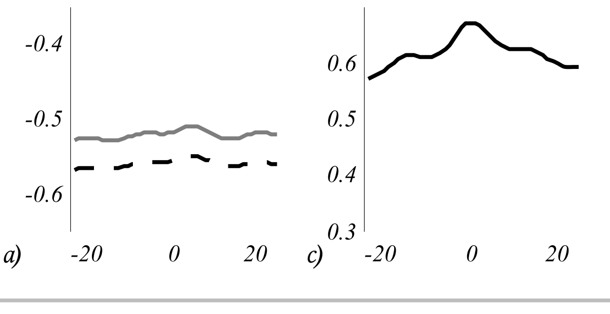


Fig. 11. Example 2: a section by the OX axis, b) a section by the OY axis (gray solid line – source images, black dotted line – smoothed images, black solid line – entropy of images)

As it is seen from Fig. 9*c* and 9*f* (example 3), at a given range of displacement along x and y, NCCF of source images is negative, and NCCF of maps of local entropy is positive. Therefore, for a clearer display, correlation functions in Figure 12 are shown in separate schedules.



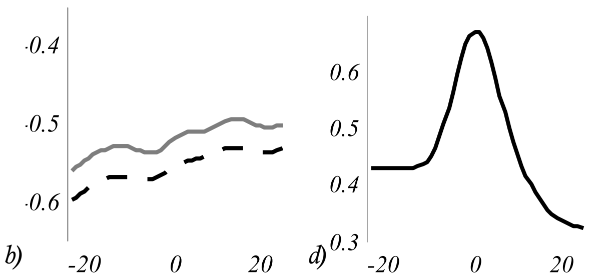


Fig. 12. Example 3: a) a section on the OX axis (the source and smoothed images), b) a section on the OX axis (entropy), c) a section on the OX axis (the source and smoothed images), d) a section on the OY axis (entropy)(gray solid – source images, black dotted line – smoothed images, black solid line – image entropy)

Having smoothed the original images, it is possible to somehow increase the module of the correlation coefficient, as well as to “smooth” the CF, but not to the same extent as the entropy preprocessing do. The above figures show that without pre-coding the solution of overlapping of images was not correct (example 3, Fig. 12), or solution accuracy has not changed after coding, but the correlation coefficient has increased (examples 1 and 2, Fig. 10 and 11).

Conclusion

In this article we set out to use the correlation image comparison method when comparing the dissimilar images. Carried out researches of the preprocessing method based on local entropy showed that the images of the same scene obtained under different conditions, demonstrate after pretreatment a higher and more stable correlation coefficient than the original ones. Designed preprocessing method allows to solve effectively the problems of automatic combination of images of the following types:

- aerial photos taken in different time;
- aerial photos and topographical maps;
- conventional and infrared images.

Thus, the use of this method will allow to significantly widen the application field of the correlation-extreme image matching method.

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