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Algorithm for Selecting Local Frame Fragments for the Reprint Model of Objects in the Image

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Abstract

For the reprint model of objects (MRO) in the image [1], an algorithm for selecting local fragments of frames (OMFC) has been developed, which highlights the distinctive features of fragments of a local nature in the online video stream. Distinctive features are distinguished by a high information capacity in terms of the identification task. To evaluate the extracted sequence of image fragments from the online video stream using an important requirement, namely the informational significance of the extracted sequence of image fragments from the video stream, the concept of "visibility" is introduced. It is necessary to reflect the degree of difference between a single image frame and neighboring (adjacent) frames from the video stream. The estimation of the visibility takes place using: the extremum of the scalable representation and the calculation of the Shannon entropy. The information and technical entropy are estimated. The algorithm is implemented in the form of a developed PC program. Clustering of the visibility space is proposed to select local fragments from the video stream using 5 steps. To find a unique part of the image, the search for the extremes of the scalable representation is used.

Disciplinary: Digital Image Processing

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1 Introduction

1.1 Algorithm for Selecting Local Fragments of Frames

To train the model of local detectors (LD) [2], a special sample is needed, obtained from the online video stream as a result of the operation of the algorithm for selecting local fragments of frames.

Image quality affects its usefulness, and image quality assessment has been the subject of many case studies for many years. One of the widely used measures for assessing image quality is the Shannon entropy, which has a well-established information-theoretic basis. The value of this entropy is interpreted as the amount of information. However, Shannon entropy is poorly adapted to decoding information in images, since it captures only the compositional information of the image and ignores the configuration aspect.

Therefore, it is also necessary to apply the second algorithm here - the Method of finding the extremes of the scalable representation.

The study is based on the quite natural assumption that the Shannon entropy improved by adding the extremum method [3-5] is a variant of the algorithm based on the average distance between the same/different pixel values.

The result of the algorithm for selecting local fragments of frames is the "crossing" of a sequence of frames, after selecting frames, both components of the ensemble are analyzed in turn and the function of their union is found.

2 Results and Discussion

2.1 Evaluation of Information Technology Entropy

The Shannon entropy formula (denoted as Sh48, which is a short name formed from the letters of the author's surname and the digits of the year of publication) is

$$H(X) = -\sum_{i=1}^{n} P(x_i) log_2 P(x_i) \quad (1),$$

where X is a discrete random variable with possible values {x1, x2, ..., xi, ..., xn}, and $P(x_i)$ is the probability that X will take the value x_i. When Sh48 is used for an image, X denotes the pixel of the image, and $P(x_i)$ represents the proportion of pixels with a gray value of x_i.

To make the Shannon entropy capable of quantifying the configuration information of an image, you should first characterize the pixel configuration of the image using a specific tool, and then reflect the characteristic when calculating the Shannon entropy. Six tools were used in the literature, which led to the following six categories of improved Shannon entropies:

1. Entropy based on the grayscale image matching matrix;
2. Entropies based on the variance of the gray level of the pixel neighborhood;
3. Entropy based on the pixel Sobel [6] gradient;
4. Entropy based on the local binary pattern of the image;
5. Entropy based on the Laplacian pyramid of the image; and
6. Entropy based on the distance between pixels of the same/different values.

Our research is based on points 2 and 3.

2.2 Entropies Based on the Grayscale Image Match Matrix

The Gray Level Matching Matrix (GLCM) was first proposed by Haralick et al. [7] and is still widely used in image processing, e.g. [4,5]. The main idea is the simultaneous appearance of two levels of gray in the image.

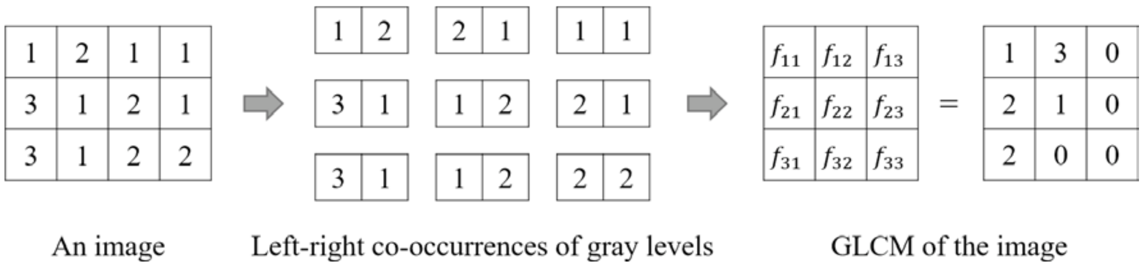

Figure 1: The process of obtaining a gray level matching matrix (GLCM) image.

For example, there are nine gray level matches when scanning the image in Figure 1 from left to right and pixel by pixel. The GLCM of the image, also shown in Figure 1, is a matrix that records the frequency of such a coincidence of every two gray levels. In this example, the aij element of the matrix indicates that the j-th gray level occurs four times (c) directly to the right of the i-th gray level.

Formally, a GLCM with M x N image with L gray level gives us an L x L matrix, $\{f_{ij}$ |l ⩽ I ⩽ L, 1 ⩽ j ⩽ L}, whose element is calculated by equation (2):

$$f_{ij} = \sum_{m=1}^{M} \sum_{n=1}^{N} \begin{cases} 1 & I(m,n) = G(i) \text{ и } I(m+\Delta x, n+\Delta y) = G(j) \\ 0 & else \end{cases} \quad (2),$$

where $G(x)$ is the value of the xth gray level in the image, I(m, n) is the value of the gray pixel located at the point (m, n), and $(\Delta x, \Delta y)$ is a pair of specified parameters called the offset operator (denoted as d). Kharalik et al. [3] provided a total of eight displacement operators (Figure 2), which can be used to create GLCM in eight different directions, i.e. right (R), right-down (RD), down (D), left-down (LD), left (L), left-up (LU), up (U) and top right (RU).

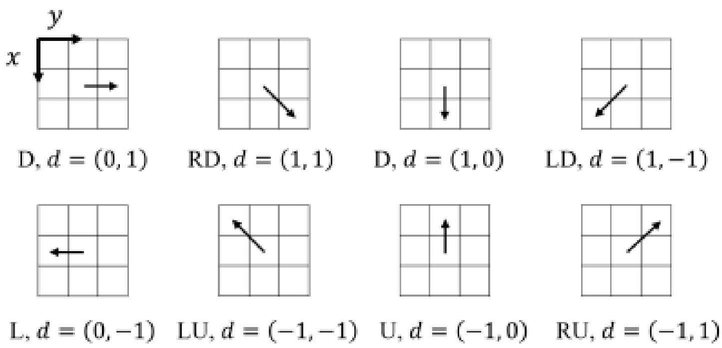

Figure 2: Displacement operators that can be used to generate GLCM in eight directions, i.e. right (R), right-down (RD), down (D), left-down (LD), left (L), left-up (LU).), up (U) and right up (RU).

Based on the GLCM image, Haralik et al. [7] developed a new method for calculating the Shannon entropy (denoted as Ha73), as shown in Equation (3).

Note that according to this equation, it is possible to obtain a total of eight improved Shannon entropies based on GLCM, since there are eight directions (R, RD, D, LD, L, LU, U and RU; see Fig.3) along which GLCM can be generated.

In this study, these eight improved Shannon entropies are denoted as At 73K, Ha73-KV, Ha73-B, Ha73-Db Ha73-L, Ha73-LU, Ha73-U and Ha73-RU respectively:

$$Ha73 = -\sum_i \sum_j \left(\frac{f_{ij}}{\Sigma_i \Sigma_j f_{ij}}\right) \cdot \log\left(\frac{f_{ij}}{\Sigma_i \Sigma_j f_{ij}}\right) \quad (3).$$

It should be noted that all eight improved Shannon entropies by Haralik et al. [7] are calculated based on GLCM generated in only one direction.

It may be objected that the configuration information quantified by such Shannon entropy is incomplete. For this reason, the following GLCM generation method has been proposed to calculate the improved Shannon entropy based on GLCM using Figure 3.

GLCM is generated in two directions. When calculating the improved Shannon entropy based on GLCM Pal and Pal proposed to generate GLCM with displacement operators in two directions, namely "R" and "D". In other words, the element (f_{ij}) of such a GLCM is obtained using Equations (4)-(6). The resulting improved Shannon entropy in this study is designated as PP89:

$$f_{ij} = \sum_{m=1}^{M} \sum_{n=1}^{N} (\delta_1(m,n) + \delta_2(m,n)) \quad (4),$$

$$\delta_1(m,n) = \begin{cases} 1 & I(m,n) + \delta_2(m,n) \\ 0 & else \end{cases} \quad (5),$$

$$\delta_2(m,n) = \begin{cases} 1 & I(m,n) = G(i) \text{ и } I(m+1,n) = G(j) \\ 0 & else \end{cases} \quad (6).$$

2.3 Entropy Based on the Sobel Gradient of a Pixel

Different pixel configurations can lead to different results, which can be detected by calculating the gradient of each pixel [6,8]. One of the frequently used tools for determining the pixel gradient is the Sobel operator [6], which consists of two 3 × 3 cores (Figures 3 and 4), used for image convolution (let's denote the collapsed images as G_x and G_y, respectively).

The first core is designed to detect the edges of the image in the horizontal direction, while the second core works in the vertical direction. Based on G_x and G_y, the gradient (Sobel) of the pixel (i,j) is calculated as

$$G(i,j) = \sqrt{(G_x(i,j)^2 + (G_y(i,j)^2} \quad (7).$$

Quader proposed the Shannon entropy based on the Sable gradient [9], called Qu12-G. But the employment of ml in Equation (7) is redefined as the average pixel gradient of all pixels with a gray l value, as shown in Equation (8).

$$m_i = \frac{1}{|\Omega_l|} \cdot \sum_{(i,j)\in\Omega_l} G(i,j) \quad (8),$$

where Ω_l denotes a set of pixel coordinates with a gray value l; $|\Omega_l|$ is the number of elements in Ω_l; and $G(i,j)$ is the Sobel gradient calculated according to Equation (19).

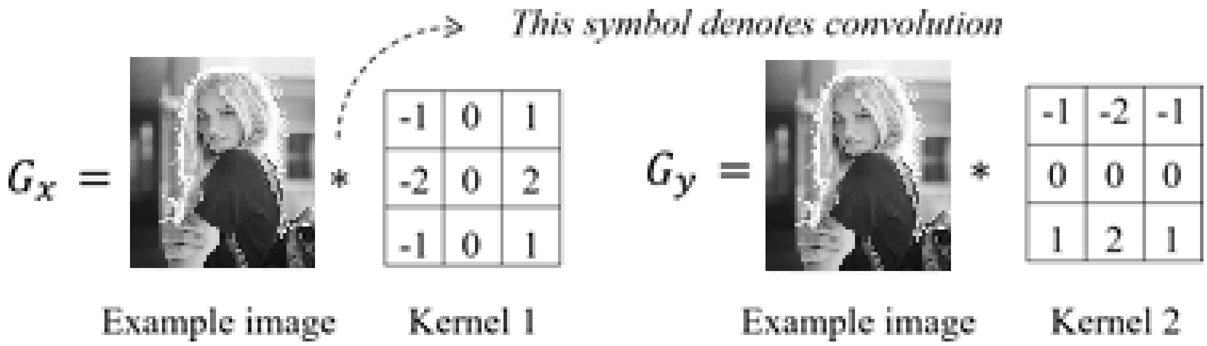

Figure 3: Two kernels defined by the Sobel operator. These kernels are used for image convolution and convolution results (i.e. G_x and G_y) are useful in calculating Sobel gradients.

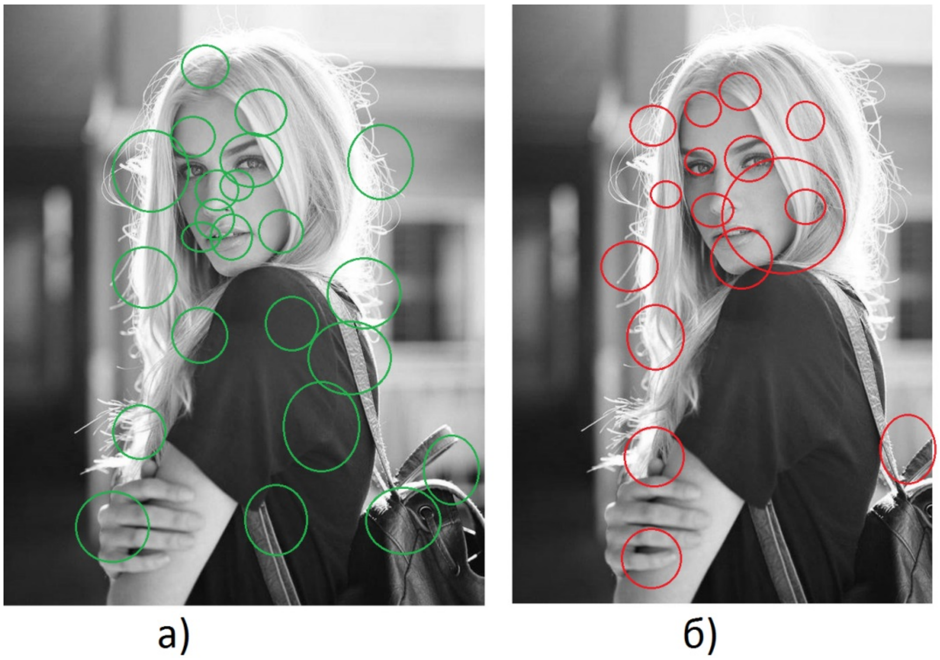

Figure 4: The parts of the image that were detected by the algorithm for selecting local fragments of the frame. a) Parts of the image that have the character of local entropy. b) Parts of the image that are characterized by excellent indicators of structural complexity and intensity.

The significance of this study can be viewed from two points of view. Theoretically, for the first time, it presents a comprehensive assessment framework (including test data, criteria and measures) for the convenience of using various entropies.

This evaluation structure will play a guiding role in further increasing the applicability of information-theoretic indicators for spatial sciences.

3 Conclusion

In practice, the findings of this study are useful for various image processing applications when choosing an entropy measure. For example, a number of range selection algorithms [10-12] for hyperspectral remote sensing images rely on entropy measures to characterize the information content of each band. In this case, the improved Shannon entropies, which are valid and reliable in this study, can be used as effective alternatives to the original Shannon entropy.

4 Availability of Data and Material

Information can be made available by contacting the corresponding author.

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