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Two-Frames Image Superresolution based on the Aggregate Divergence Matrix

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Abstract— **The paper describes the method image superresolution from two frames on the basis of aggregate divergence matrix elements of the theory and genetic algorithms. Shows different ways for building oversampling images algorithms based on the proposed method. Experimentally established the effectiveness of the procedures oversampling images at high zoom resolution by the developed method. Comparative performance evaluation method with existing ones.**

Keywords — superresolution; similarity measure; crossover operations; aggregate divergence matrix

I. Introduction

One of the major problems of intellectual vision is to improve the quality of digital images. Among the main methods of image quality is a resolution control, including its increase. A physical restriction of image capture devices does not always allow obtaining the image resolution which required for a particular vision system. In addition, the image registration device is characterized by exposure to different nature noise, which necessitates the use of procedures sharpening, filtering etc.

The importance of oversampling image confirmed by a vast number of modern scientific works. The same applies to the problem of superresolution [11], [12], [13], [14], [15]. However, the growing volume of processed information requires new, more efficient methods of solving problems providing superresolution (SR) images for specific areas. Particularly acute is the problem in such application areas as monitoring (including space), video surveillance, criminalistics, video convert, medical visualization [5], [6], [16], video communication [10] etc.

The need to preserve (and in some cases – improvement [4]) content and texture, especially in case of further intelligent image analysis [7] in machine vision systems, is an important objective method of SR [8], [9]. The complexity of this problem become deep throughout needed to preserve image edges sharpening with the intensity fluctuation function and reduce artifacts and distortions that occur in the input image processing.

Therefore, the urgent task is to develop methods and the development of image superresolution that would ensure qualitative results oversampling at high zoom for images that define the fluctuating intensity function.

II. Analysis of Previous Studies

In [1] a method that using symmetric matrix distances for image resolution changing was developed. Algebraic features selections that are the characteristics of each line and pile proceeded according to Moore-Penrose pseudoinverse techniques. A similar approach is used in the oversampling and in the case of two input images [2]. The latter method provides a matrix divergences application and crossover operations to obtain characteristics of each vector row or column.

The aim of this paper is to develop a method image superresolution with using aggregate matrix divergence to ensure effective oversampling results for large rate increase.

III. Preliminary Processing of Images

Input data of the developed method are two same resolution image:

$$I_1 = \left[c_{1\,i,j} \right]_{i=1..h}^{j=1..l} \quad \text{and} \quad I_2 = \left[c_{2\,i,j} \right]_{i=1..h}^{j=1..l}, \qquad (1)$$

where $c_{i,j}$ - the function of pixel intensity with coordinates (i, j).

The work proposed method requires preliminary processing on pairs of images, which determined execution following procedures.

1. Normalization of images I_1 and I_2 according to the expressions:

$$c_{i,j} = c_{i,j} + \frac{1}{2}\left(\max_{\substack{i\in[1;h];\\ j\in[1;l]}} c_{i,j} + \min_{\substack{i\in[1;h];\\ j\in[1;l]}} c_{i,j} \right), \qquad (2)$$

$$c_{i,j} = Kc_{i,j}\,, \qquad (3)$$

where $K = \left(\max\limits_{i\in[1;h];\; j\in[1;l]} c_{i,j} \right)^{-1}$. As a result, we get: $\forall i \in [1;h], j \in [1;l] : c_{i,j} > 0$.

2. Construction of the new vector $\tilde{c}_i$ normalized input images from the corresponding lines (columns) using single-point crossover operation:

$$\tilde{c}_i = kc_{1i} + (1-k)c_{2i}, \tag{4}$$

where k - crossover operations coefficient; c_{1i}, c_{2i} – dimension vectors l, elements of which are matrix rows I_1 and I_2 respectively.

As a result, we obtain a new matrix:

$$\tilde{I} = \left[\tilde{c}_i \right]_{i=1..h} = \left[\tilde{c}_{i,j} \right]_{i=1..h}^{j=1..l} \tag{5}$$

If the horizontal direction increase, matrix $\tilde{I}$ will look like:

$$\tilde{I} = \left[\tilde{c}_j \right]_{j=1..l} \tag{6}$$

where $\tilde{c}_j$ vectors constructed according to (4) for the corresponding columns normalized input images I_1 and I_2 respectively.

IV. AGGREGATE DIVERGENCE MATRIX CONSTRUCTION

Aggregate divergence matrix ∇_i, that is the basis of the superresolution method, in the case of two input images, is constructed as follows:

$$\forall i \in [1;h] : \nabla_i = A_i - \left[\underbrace{\left(\tilde{c}_i \quad \dots \quad \tilde{c}_i \right)}_{l} \right]^T, \tag{7}$$

$$A_i = \frac{1}{\max\limits_{\substack{i\in[1,h] \\ j\in[1,h]}} \left(\tilde{c}_{i,j} \right)} \begin{pmatrix} \dot{c}_{i,1} & \dots & \dot{c}_{i,1} \\ \dots & \dots & \dots \\ \dot{c}_{i,l} & \dots & \dot{c}_{i,l} \end{pmatrix}; \quad \dot{c}_{i,j} = \frac{1}{j} \left(\sum_{x=1}^{j} \tilde{c}_{i,x} \right) \tag{8}$$

In applying the procedures for changing the resolution on rows of images $\tilde{I}$ aggregate divergence matrix defined by (7) - (8) will look like:

$$\forall j \in [1;l] : \nabla_j = \left[\underbrace{\tilde{c}_j \quad \dots \quad \tilde{c}_j}_{h} \right]^T - A_j, \tag{9}$$

$$A_j = \frac{1}{\max\limits_{\substack{i\in[1,h] \\ j\in[1,h]}} \left(\tilde{c}_{i,j} \right)} \begin{pmatrix} \ddot{c}_{j,1} & \dots & \ddot{c}_{j,1} \\ \dots & \dots & \dots \\ \ddot{c}_{j,h} & \dots & \ddot{c}_{j,h} \end{pmatrix}; \quad \ddot{c}_{j,i} = \frac{1}{i} \left(\sum_{x=1}^{i} \tilde{c}_{x,j} \right) \tag{10}$$

V. DEFINING VECTORS-FEATURES BASED ON MOORE-PENROSE MATRIX AGGREGATE DIVERGENCE PSEUDOINVERSE

The next step of the proposed method is to search vectors-features, which act as the image I characteristics of each line (column).

Let us consider the construction a characteristic vector (vectors-features) in the direction i. To solve the problem of constructing feature vectors y_i consider the equation [1]:

$$\nabla_i y_i = c_i, \tag{11}$$

where $y_i = (y_{i,1}, \dots, y_{i,l})$ – l- dimensional vector image characteristic values I for i-th row. This means that feature vector y_i built for each line i. By oversampling toward j for each j-th column will built vector y_j.

Equation (11) establishes a linear algebraic system l equations and formal vector finding y_i is: $y_i = \nabla_i^{-1} c_i$, where ∇_i^{-1} – square $l \times l$ matrix that is inverse to matrix ∇_i. Since matrix ∇_i is degenerate ($\det(\nabla_i) = 0$), then inverse matrix ∇_i^{-1} does not exist and formal solution y_i can be found only in approximate form.

One of the easiest and effective ways of finding feature vector y_i i-th line is approaching its residual $\|c_i - \nabla_i y_i\|^2$ in the solution scheme of Moore-Penrose linear system [3].Under this scheme the feature vector y_i is defined as the sum of the approximate (partial) solution nondegenerate system and homogeneous system solution $\nabla_i y_i = 0$:

$$y_i = \nabla_i^+ c_i + \left(1 - \nabla_i^+ \nabla_i\right) \| c_i - \nabla_i y_i' \|_l^2, \tag{12}$$

where ∇_i^+ – pseudoreverse to ∇_i Moore-Penrose matrix [2]; $\left(1 - \nabla_i^+ \nabla_i\right)$ – nuclear projective operator; discrepancy $\|c_i - \nabla_i y_i\|^2$ r_i is a vector of dimension l, which determines the approach of the solution y_i; $\|\cdot\|_l$ – l- norm.

According to [1] matrix $\nabla_i^+ \nabla_i$ is nondegenerate, ensuring the existence and uniqueness of linear systems solutions $\nabla_i y_i = 0$. According to [3] using singular value decomposition (SVD) of the matrix operator ∇_i, pseudoinverse matrix ∇_i^+ defined as: $\nabla_i^+ = V_i \Sigma_i^+ U_i^T$. Here U_i, V_i – square $l \times l$ matrix SVD-decomposition operator ∇_i ; Σ_i^+ – square $l \times l$ matrix which is diagonal matrix for pseudoinverse matrix to diagonal matrix Σ_i matrix SVD-decomposition ∇_i and received by follows:

$$\Sigma_i^+ = \mathrm{diag}\left\{\frac{1}{\sigma_{i,1}},\dots,\frac{1}{\sigma_{i,l}}\right\}, \quad (13)$$

where $\sigma_{i,q}$ ($\sigma_{i,1} \geq \sigma_{i,2} \geq \dots \geq \sigma_{i,l} \geq 0$) – singular nonzero numbers of matrix Σ_i.

Finding a solution for (13) is an iterative process of solving the problem of minimizing the discrepancy:

$$\min_j \left(\| c_i - \nabla_i y_i^j \|_i^2 \right), \quad (14)$$

where j – index, which defines the iterative step process for solving (13).

In homogeneous areas operator (9) is degenerate. Therefore, the solution of the problem (12) looking on (13).

VI. ALGORITHMIC IMPLEMENTATION OF THE IMAGE SUPERRESOLUTION METHOD

Solution of (12) with the operator of (7) or (10) is used to solve the problem of two-frame image superresolution in the case of crossover transactions. Since the input in this case there are two images I_1 and I_2, there are at least three solutions of the problem oversampling. The first two are similar to [1] consists in the building enhanced images added to the original matrix and I_1 or I_2 vector $c_i + y_i$ position in line (or column). Here c_i – the function of intensity of the input image (i.e. the original, not normalized by (2) and (3) of significance). A third solution is the synthesis of matrix rows and columns, enhanced by the expression:

$$c_{3\,i} = \frac{c_{1\,i} + c_{2\,i}}{2} + y_{1\,i}, \quad i = 1..l \quad (15)$$

SR increase procedure similar to the procedure described in [1, 2], consists of two consecutive parts, which oversampling image carried in the vertical and horizontal directions, respectively. Ordering action of each part of the algorithm can be arbitrary.

The algorithm for the image superresolution problem solving involves the following steps:

1) construction mutated input vector from vectors corresponding two input images based on (4).

2) construction aggregate divergence matrix (7) and (9).

3) calculation of characteristic vectors y_i square matrices built on relationships (7 or 9), on the iterative procedure (12).

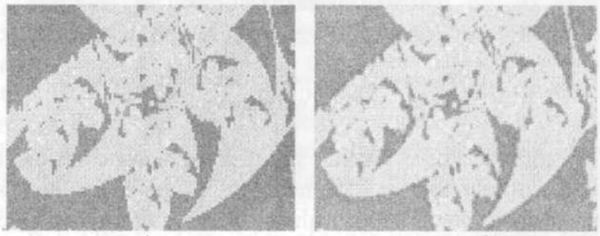
4) building enhanced image by adding to the original matrix I_1 or I_2 characteristic vectors like [1], or synthesis increased images according to (15).

The first three parts consistently applied to all the rows of I to increase the size of a given image height. Only then enlarged image matrix $I_1^{(m)}$, $I_2^{(m)}$ or $I^{(m)}$ built by (15) or like according to [1].

Further procedure of increase implemented on larger image $I_1^{(2)}$, $I_2^{(2)}$ or $I^{(2)}$ until the variable m reaches targeted coefficient increase.

VII. RESULTS OF PRACTICAL EXPERIMENTS

In order to assess the effectiveness of oversampling image by the developed method was conducted a series of practical experiments. A couple of input different qualities images, which used for simulation of the method shown in Fig.1.



a) b)

Figure 1. A pair of input 2-byte, grayscale image, resolution, dimension – 231×199 pixels: a) I_1; b) I_2

The crossover coefficient: k = 0.7. This value obtained by solving the optimization task [2] used in the work to automatically determine k.

Fig. 2 shows PSNR depends, resulting oversampling of images I_1, I_2 and the synthesis of image $I^{(m)}$ according to (15).

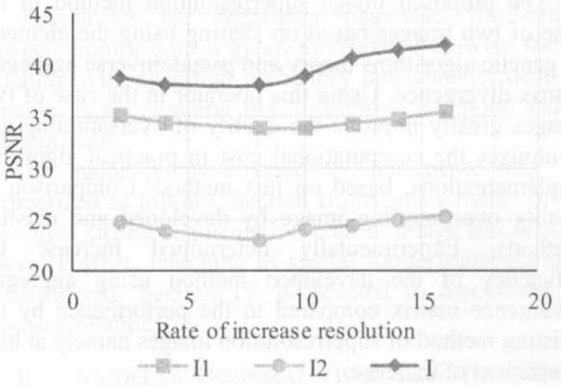


Figure 2. Dependence PSNR from coefficient of increase for images $I_1^{(m)}$, $I_2^{(m)}$ and $I^{(m)}$ obtained by method

As shown in Fig. 2 oversampling best results obtained at the synthesized image $I^{(m)}$. It is worth noting about PSNR behavior change. Three areas PSNR determine the intervals drop, growth and satiation values of PSNR (i.e.

the growth with smaller gradient). A significant increase PSNR in cases coefficient resolution change grater may be the main argument for practical using oversampling procedures, based on the proposed method.

Comparing the results of the proposed method and existing (in the case of one input image [1]) shows the following results (Fig.3).

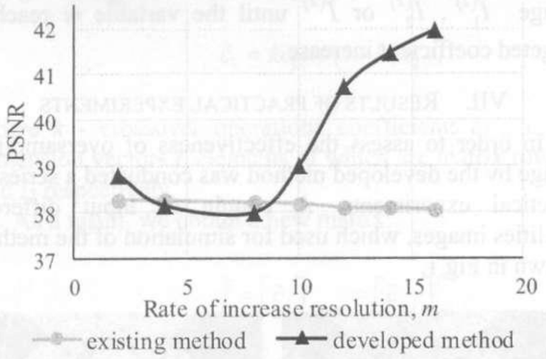


Figure 3. Comparison of the work developed and existing methods based on PSNR when changing *m*

From the Fig. 3 we can say that for small coefficient values of increase ($m < 10$) using the proposed method is not justified since PSNR values for existing methods are considerably higher. The value of PSNR developed method starting to exceed the value of PSNR for existing only when $m > 10$. Obviously, the exact value of the inflection point $m = 10$ in the comparison of the effectiveness of the methods obtained for a given image I_1 and I_2. However, experiments with other images in general, confirmed that for other images this point will be close to exactly value of 10.

VIII. Conclusions

The proposed image superresolution method in the case of two images based on sharing using the elements of genetic algorithms theory and pseudoinverse aggregate matrix divergence. Using this operator in the case of two images greatly improve the quality of oversampling and minimizes the computational cost in practical algorithm implementations, based on this method. Comparison of quality oversampling image by developed and existing methods. Experimentally determined increase the efficiency of the developed method using aggregate divergence matrix compared to the performance by the existing method of superresolution images namely at high coefficient of increase.

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