Neural Network Technology for Image Downscaling

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Abstract – in this paper described for the first time neural network technology developed to zoom out images scale. The developed method uses a neural structure model geometric transformations to establish the connections between frames pairs of images of high and low resolution. Adjusted so in the learning process synaptic scales allow to change the scale of images of one class without substantial loss of quality.

Key words – frame processing, resolution, reduce the image, machine learning, neural-like structure, model of geometric transformations.

I. Introduction

Scaling of images is an important task of technical vision. With the development of modern technologies, the resolution mobile displays increased to a satisfactory level, which leads to the possibility of high-quality image display. But same resolution pictures is much larger than the screen resolution of mobile devices. In this regard, there is need to develop an effective method decimation of image quality performance. The paper describes a new method reduce the resolution of images based on machine learning.

II. The task of reducing the resolution of images based on machine learning

Technological progress, particularly in mobile devices is not standing still. Resolution of cameras of these devices is growing, but the screen resolution, for obvious reasons, can not be as great. That is why there is an actual problem decimation of images while preserving their informative quality pictures to display on your mobile device. Known methods decimation characterized by low computational complexity and efficient implementation [3]. But they do not provide clarity of borders in images.

Moreover, the re-discretized images with specified reduction coefficient as a rule contain unwanted artifacts, foremost, Gibbs phenomenon, pixelisation, oversmoothing, different kinds of smudges, etc. In the research, we propose a new method for image resolution reduction, which is based on machine learning. The realisation of this learning algorithm is conducted with the help of neural structures with geometrical transformations. The reason why we chose this method is due to its multiple advantages over the existing neural networks [1].

The input data of method is a pair of images with low (image 1) and high (image 2) resolution. To implement technologies training these pictures are divided into the same number of frames (square areas of the function of the image intensity).

Obtained frames will be different in dimension (for image 1 and image 2 respectively) but their number - the same, for example ***n***. It is worth mentioning that when reducing an image with coefficient k, the variable that defines the size of the frame from image 2 needs to be k times smaller than the variable that defines the size of the frame from image 1.

Then, every frame is represented in a vector form. Let's say the vector of the frame in Fig.1 is $A_n^{(k)}$, and the vector of the frame in Fig. 2 is A_n. Next, we form a training matrix from the corresponding pairs of training images.

$$N = \begin{pmatrix} A_1^{(k)} & A_1 \\ \dots & \dots \\ A_n^{(k)} & A_n \end{pmatrix} \qquad (1)$$

Next step is training our model using neural structure of geometric transformations model (GTM NLS).

Topology GTM NLS for this occasion is shown in figure 1.

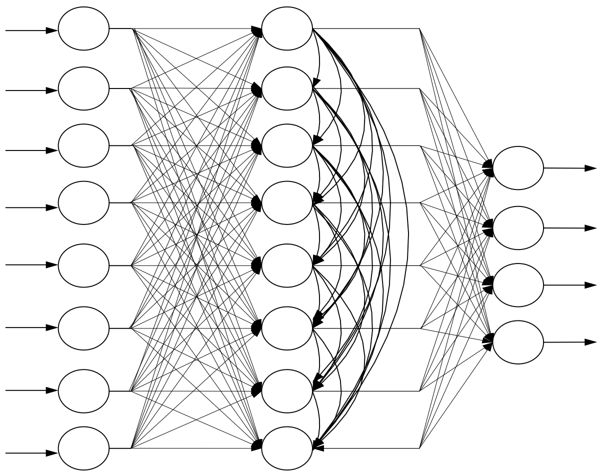

Fig. 1. NLS GTM topology for solving the problems of decreasing of images resoltion

The number of inputs of NLS GTM is defined by dimension of frame $\dim A_n^{(k)}$ and number of outputs - by dimension of frame $\dim A_n$. Study algorithm is described in detail in [2, 4].

In the use of NLS GTM input high-resolution image is given which is presented in the matrix:

$$T = \begin{pmatrix} A_1^{(k)} \\ \dots \\ A_n^{(k)} \end{pmatrix} \qquad (2)$$

It should be noted that in the use mode other pairs of images different from training pairs can be used, but of the same resolution.

III. The modeling of the method

For the modeling of the method a couple of images with resolutions 504×504 and 252×252 pixels respectively have been used.

Low resolution image is presented on the figure 2.a). Figure 2.b) presents a test image of low resolution. High resolution images for both cases are not given. Coefficient of decreasing of resolution was k = 2.

a) training b) test

Fig. 2. Samples image

The purpose of the modeling was to establish the optimal parameters in adapting NLS GTM to solution of the problem.

The first experiment was to establish the optimum size of the frame for the best quality of the output sample based on PSNR rate. Parameters NLS GTM were described above, but here the number of neurons in the hidden layer was equal to the dimension of the input image frame. 5 experiments for different images were conducted. The dimensions of frames that were used in the experiments presented in Table 1.

TABLE 1

PSNR DEPENDENCE FROM CHANGES OF FRAME DIMENSIONS OF RELATED IMAGES

Dimension of the input image frames	Dimension of the output image frames	PSNR
2×2	1×1	33,0314
4×4	2×2	25,9687
6×6	3×3	22,1276
8×8	4×4	20,5778
12×12	6×6	19,2504

The results of experiments found that the best indicators of the quality of output images according to PSNR were received for the first case.This conclusion is confirmed for other images used in the experiment. Visibility of research results is shown in figure 3.

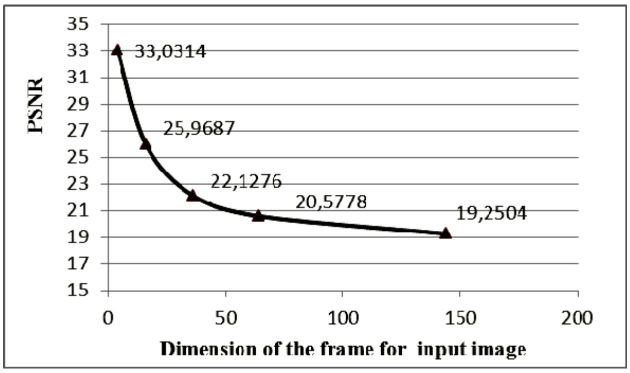

Fig. 3. PSNR dependence from changes of frane dimensions of input images

NLS GTM provides filtering noises of various nature by reducing the number of neurons in the hidden layer. Given this, in the next experiment we made reducing the image resolution by changing the number of neurons in the hidden layer. In the practical implementation of the method, given the results in Table 1, a pair of images were devided to the frames with dimension 2×2 and 1×1. So, number of inputs of NLS GTM equals to 4, and outputs - 1. Number of neurons in the hidden layer ranged from 1 to 4. Figure 4 presents the results of the experiment.

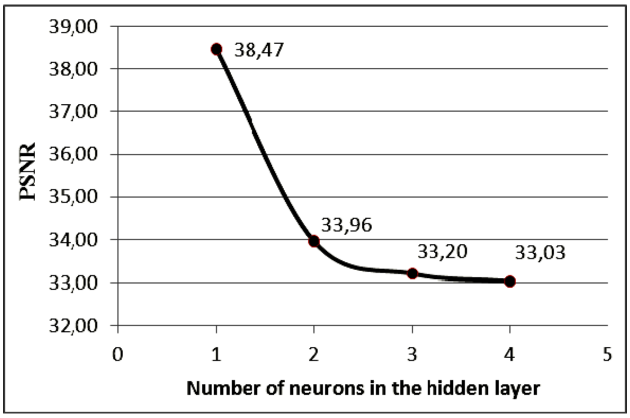

Fig. 4. PSNR dependence from changes of the number of neurons in the hidden layer.

Conclusion

The paper describes a new technology to reduce the resolution of images based on machine learning. Study is implemented by adapting of NLS GTM to solution of this problem. A number of practical experiments were conducted based on which optimal values of NLS were established. The peculiarity of the developed technology is that neural structure of geometric transformation model applied to one pair of images can be applied to other samples. However, it shows good results when using the images of one class.

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