Neiroevolutionary approach for color image enhancement

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Abstract

The paper present a neuroevolutionary method of monochrome and color images enhancement. The proposed method is based on local-adaptive approach to processing color components of image. Neural network is tuned to perform enhancement of particular image using genetic algorithm with use of the generalized image evaluation criterion that relies on the contrast degree of the processed image.

Keywords: *Evolutive neural network, genetic algorithm, adaptive image processing, image enhancement.*

1. INTRODUCTION

Image enhancement techniques are used to emphasize and sharpen image features for display and analysis. *Image enhancement* is the process of applying these techniques to facilitate the development of a solution to a computer imaging problem. Consequently, the enhancement methods usually are application specific and are often developed empirically [1]. Actuality of image enhancement problem conditioned by necessity of it's solving in medical diagnostics, mine searching, patterns recognition, defectoscopy, enhancement amateur photography and etc. As a result of complexity of image self-descriptiveness analysis, in many cases adaptation of image processing algorithm or it's parameters to particular image is required to obtain satisfactory result. Artificial neural networks (ANN) have shown good adaptive capability [2].

From the very beginning ANN are closely related to image processing task [2]. One of the first tasks for ANN was pattern recognition. In nowadays active researches in field of image processing using neuronetworks are performed[3]. Among them the following investigation leads can be emphasized image filtering, pattern recognition, image segmentation, image compression.

One of the advantages of using ANN is ability of ANN to adopt, which appear in form of internal characteristics changing of ANN to perform particular task. Major role in process of training plays the way of quality estimating of training network. Root-mean-square error evaluation is used in classical case, which is proportional to square of deviation between current output values of ANN from required values. For realization of such evaluation a set of training examples must be given. Usually training set is represented as a set of pairs of vectors (**X**, **Y**), where **X** is vector of input signals, **Y** is vector of required outputs of ANN. For the described approach to ANN training the fact of network evaluation value using directly to adopting weights of connections appear sufficient. [2]. In realization of this approach several difficulties can appear:

1. Necessity to redefine of initial problem. Weakly related to initial problem additional subgoal as a consequence can appear, this makes solution very complex. For example, one of the variants of neuronetwork control problem solution consist in approximation of control object with neuronetwork followed by step of control signals optimization to reach required state of control object.
2. Complexity of ***Y*** vector's components determination from training set. This complexity appear in solution of ill-posted problems and in case it's required to analyse sequence of output signals for ANN evaluation. Such complexity can be referred to adaptive behavior problem, chousing game strategy problem, image processing problem and etc.

One of possible solution of listed problems can be in use of *inexact* evaluations of ANN, which reflect qualitative, external properties of it's functioning. For example time of stable state maintaining of control object for neurocontrol task [3], percent of game victories for task of optimal game strategies search [4], image quality for image enhancement task [5] and etc. Such evaluations are more natural and intuitively significant, but as a consequence they can't be used by gradient learning algorithms for connections weights tuning. Therefore appropriate learning algorithm should perform neurinetwork tuning, without information about exact value of error for the each output of that ANN.

When inexact evaluation is used it is very difficult to create (if it's ever possible) to create formalized method of ANN learning, consequently problem of connections weights tuning becomes linear search problem. Even for simple structure ANN space of solution search theoretically infinitely large number of points and cover set of real numbers. Though, in practice, number of points is limited by precision of computer's floating point number representation, resulting quantity of points makes it difficult to solve the problem with simple methods: linear search or random search.

Evolutionary algorithms have made a good showing for solving such optimization problems. Characterizing feature of these algorithms is capability to find suboptimal domains in the search space in a short time. Approach to tuning and learning of ANN using evolutionary algorithms is known as neuroevolutionary approach. [3]. It's necessary to point out that neuroevolutionary algorithms can be allied to ANN learning problems with exact evaluation as well as to learning with inexact evaluation [6].

In this paper it's proposed use of genetic algorithm [7] for tuning and learning of ANN for solving a task of monochrome and color images enhancement. Using evolutionary approach to ANN learning lets us evaluate quality of ANN functioning entirely, by means of processed image evaluation without subsequent error of output determination for ANN. The use of developed neuroevolutionary algorithm NEvA [8] underlies at the heart of proposed method for realization local-adaptive approach to pixels' color component processing. Neural networks, one for each color component, are tuned to perform enhancement of particular image color component using genetic algorithm with use of the generalized image evaluation criterion that relies on the contrast degree of the processed image. In this work we used R, G, B color components of RGB color representation.

2. IMAGE ENHANCEMENT METHOD

The main idea of proposed method is changing of pixels' color components values of a given image to increase it's contrast. At that transformation is applied to each pixel's color component separately. Proposed method is a modification of method proposed in [9], but in this paper we observe approach with separate processing of color components instead of brightness processing while maintain full adaptation of ANN to processed image.

Assume that exists some function *T*, which performs transformation of characteristics of each pixel in the way that obtained image is optimal with respect to some chosen criteria. In this case neuronetwork image enhancement problem can be defined as problem of approximation of unknown function *T*. Problem become complicated because of the fact that view and behavior of function *T* are unknown and because of absence conventional criteria of image quality evaluation.

For distinctness consider that changing of pixel's color component value is performed on the base of information about statistical properties of component distribution in pixel's surroundings with radius *r* and on the base of average component value of whole picture. Similar approaches has shown their efficiency for evolutionary [8] and heuristically-theoretic methods [10] of image enhancement.

Consequently, changing of pixel's n-th component can be represented with the following transformation:

$$Cn^{*}(x,y) = T\left(Cn(x,y),\ Cn_{avg}, R_{Cn}^{n,(x,y)}\right), \tag{1}$$

where $Cn^*(x,y)$ is new n-th component value of pixel with coordinates (x,y), $Cn(x,y)$ is current value of pixel's n-th component, Cn_{avg} is average value of n-th component of the input image, $R_{Cn}^{(x,y)}$ defined as:

$$R_{Cn}^{(x,y)} = \log\left(\frac{Cn(x,y)}{Cn(x,y)\otimes F(x,y,c)}\right), \tag{2}$$

where $\otimes$ denotes convolution operator, F is function of filter that provides particular spatial information about processed pixel's surroundings. In this paper Gaussian function was chosen to be a filter function. It' defined as:

$$F(x,y,c) = Ke^{-\frac{x^2+y^2}{c^2}}, \tag{3}$$

were K is constant that selected so that $\iint F(x,y,c)dxdy = 1$ [11], c is standard deviation of Gaussian filter that is in charge for amount of spatial information that R would contain.

During the color image processing each color component processed separately with its respective neural network. Main idea of observed color transformation is in fact that color components processed separately. This gives us ability to remove global or local color component shift that appeared due to bad weather conditions (smog, haze), poor light, or in pictures taken underwater. ANN that approximate transformation (1) has 3 input and 1 output.

Evaluation of image is performed with respect to two factors:

1. Pixels number on the borders between domains with different color components values.
2. Number of component values gradation of resulting image.

The more pixels are on the borders between domains with different component values the more contrast would have processed image. To avoid degeneration of image to binary during an attempt to increase contrast factor considering number of color component gradation in resulting image was introduced.

Consequently processed image quality is evaluated in the following way:

$$fn = \frac{a\cdot b - \mu n}{a\cdot b} + \frac{256-\exp(Hn)}{192}, \tag{4}$$

$$Hn = -\sum_{i=1}^{256} kn_i \log(kn_i) \tag{5}$$

where a and b are width and height of image in pixels, correspondingly, kn_i is part of pixels on the processed image with i-th level of n-th component value. First item in (4) is responsible for maximizing of Pixels number on the borders between domains with different component values, second item is responsible for increasing a number of component value gradation. The objective of evolutionary learning is minimization of function fn, value of which for i-th organism is considered as error of the ANN corresponding to that organism.

Consequently, evaluation of ANN is performed according to sequence containing $a*b$ output signals. Using the proposed method of image enhancement it's possible to use several images for ANN learning. In this case ANN evaluation is calculated as average evaluation of the processed images for n-th color component. It's needed to point out that trained ANN can pe applied for enhancement of images that were not used in training.

In previous works [9,11] it was shown that for brightness processing approach ANN that was trained on some training images presented better enhancing for one type of images, but showed poor performance enhancing other pictures, while outer pictures were very well enhanced by ANN trained on some other training images. Though we have managed to selected a few training images and algorithm parameters with which method performed satisfactory enhancement results for broad class of input images, ANN that was learned to enhance a narrow class if images performed netter. Stronger dependence of resulting image on training images was noticed for color component processing approach. Consequently adaptation of algorithm to current image was also required.

Further experiment has shown, that in case ANN was trained on an image that I needs to enhance results of processing were very good. Also in this case it was possible to use c=80, that decreased "aura" effect, thought we didn't got rid of it completely. But this approach was quite processor-time consuming: full cycle of learning+processing of 500x500 pixels image took about 40 minutes on Athlon 2000+ based computer, mostly because of time consuming ANN training process.

To overcome training time factor in this work we used the same approach as in [9] to ANN adaptation to processing image. To speed up training step this approach implies a few simplifications:

1. Learning is performed on scaled input image. For 500x500 image we used 20% scaling so that ANN was learned in 100x100 image. It's advisable to use scaled images not less then 50x50 to maintain correspondence of ANN to input image. Also it's better to use scaling factors like 1/2, 1/3, 1/4, 1/5. 1/6 and etc.
2. R_L for scales image in calculated with c scaled with the same factor (c=13 for 20% scaling)
3. Rn_L calculated in surrounding of less radius (r=10 for 20% scaling).

After applying changes listed above image enhancement method was still demonstrating good results and had satisfactory processor-time consumption: learning + processing cycle time for 500x500 pixels image was about 70 seconds on Athlon 2000+ based computer.

Image processing schedule of proposed neuroevolutionary image enhancement method is illustrated on fig. 1.

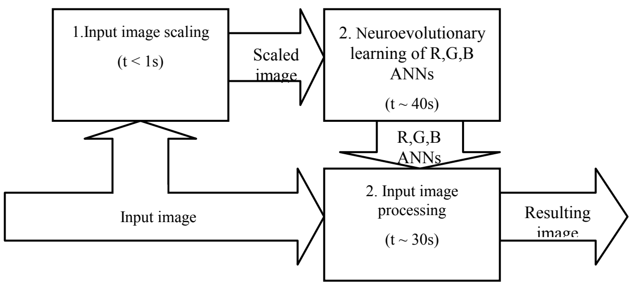


Figure. 1. Image processing schedule of neuroevolutionary image enhancement method. Time of computing t is given for processing of 500x500 input image using Athlon 2000+ based computer.

3. RESULTS

For experimental testing of proposed method the following parameters was used:

- edge detector: Sobel edge detector[1];

- maximum time of evolution: 25 generations

- learning stop criteria: f<1,5

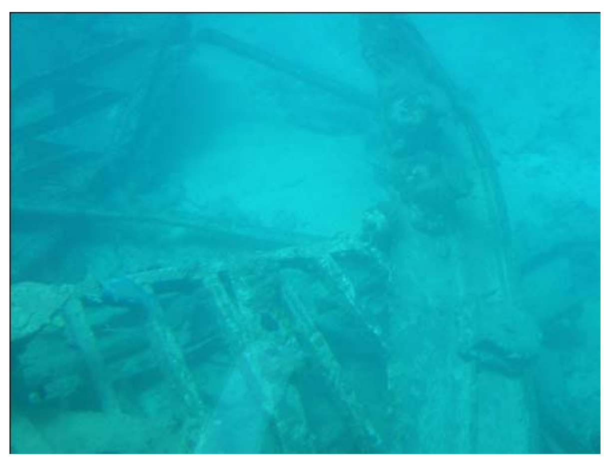
Since for image evaluation inexact evaluation is used there's no reason to train ANN to reach the minimum of f function. Experimentally was discovered that best enhancement is performed for f lie in [1.4; 1.6]. If f is less than 1.4 image becomes too contrast and increased probability of undesired color shifts, with loosing a general brightness and large objects fidelity, in case f is more then 1.6, low contrast images are usually produced.

Proposed method has shown it's applicability for enhancement of images with undesired constant color component. For color images, especially images with heavy smoke or haze (Figure 2), underwater images (Figure 3), it produced better results in comparison with [9] removing constant color component and uncovering colors of objects that were otherwise hidden behind it.

a.

b.

Figure. 2. Example of method application for enhancement images obscured with heavy smoke (a), (b).



a.

b.

Figure. 3. Example of method application for enhancement underwater images (a), (b)

For monochrome images enhancement this algorithm has shown relatively poor results: while producing results close to those received in [9] processing time was about 3 times more then in [9].

ANN obtained as a result of neiroevolutionary learning were rather simple: had 0 - 3 hidden neurons and 3-10 connections. Also it's need to point out that though network was adopted to perform image enhancement of a particular picture it can be successfully applied to other pictures with close brightness/details distribution.

4. CONCLUSION

We present a new method of image enhancement using evolving neural networks with adaptation to processed image. Several simplifications have been made to increase adaptation speed. Even if network is adopted to perform image enhancement of a particular picture it can be successfully applied to other pictures with close color distribution level of details. Experiments have shown applicability of proposed method for enhancement of images with undesired constant color component.

5. ACKNOWLEDGEMENTS

This work was supported by grant № 06-08-00840 of the Russian Foundation for Basic Research.

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