No-Reference Image Quality Assessment through Interactive Neuroevolution

Yury R. Tsoy, Vladimir G. Spitsyn, Alexander V. Chernyavsky
Computer Engineering Department
Tomsk Polytechnic University, Tomsk, Russia
qai@mail.ru, spitsyn@ce.cctpu.edu.ru, avcher@tpu.ru

Abstract

Image quality assessment is a complex problem due to subjective nature of human visual perception. One of possible ways to take into consideration user's subjectivism is to develop interactive system which could learn the properties of user's visual perception. In this paper we present a novel way to do this via interactive neuroevolution approach. The key feature of this approach is training of artificial neural network to evaluate image quality on the base of interaction with user. Obtained solutions can then be used for image quality assessment for various automated image and video processing techniques.

Keywords: *Image quality assessment, Neuroevolution, Interactive evolution.*

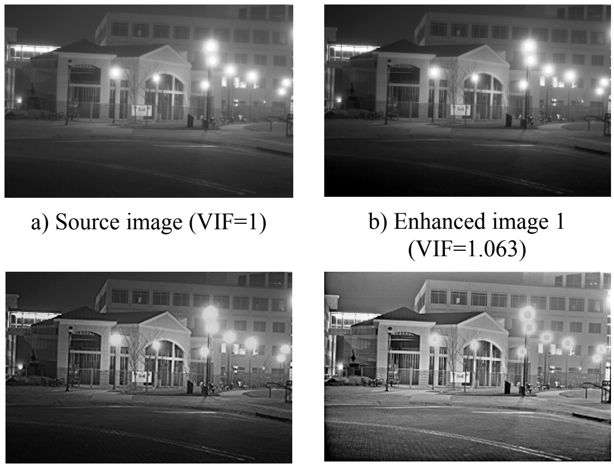
1. INTRODUCTION

Image quality assessment plays significant role in image processing and especially in image enhancement. For now there is no common approach to evaluate the quality of images therefore different authors use different image quality measures. For example, various pixel-wise difference measures are widely spread in analysis of noise removal algorithms such as well-known peak signal-to-noise ratio (PSNR).

There are two types of image quality measures: with reference image and without reference (no-reference) image. Note that many reference measures are non-informative for evaluation of image quality because of calculation of pixel-wise difference only. For example given two images A and B for which is known *a priori* that A is *visually better* then B one can calculate PSNR for two pares of images (A,B) and (B,A) thus considering two cases when reference and distorted images are swapped. The problem is that knowing only PSNR(A,B) and PSNR(B,A) it is impossible to detect whether A is better then B or vice versa. Moreover, with the third image C which is *worse* than B and knowing PSNR(A,B) and PSNR(B,C) it is hard to suggest not looking at the image C the value of PSNR(A,C) without calculation. For example, in general case it is impossible to answer the question "Is it true that PSNR(A,B) > PSNR(A,C)?".

Thus pixel-wise difference between two images is hardly useful for image quality assessment due to contradiction of logical character emerging because difference measure between two images and their quality are not correlated in general. It is also notable that different researches didn't revealed statistically significant advantage of sophisticated quality metrics over simple PSNR measure [1-3].

There are with reference image quality metrics that provide understandable results in the way which is most intuitive for users. For example well-known VIF (Visual Information Fidelity) measure [4] yields 1 if two images are identical, >1 if the distorted image is visually better than the reference one and <1 otherwise. Although authors reported [4] that VIF measure correlates with subjective user opinion for simple kinds of distortions its behavior for images with complex distortions is far from ideal. The example is given in Figure 1. Although images 1c and 1d are better than 1a and 1b their VIF scores are lower. Moreover image 1d received the lowest VIF score while it has the best visual quality.



a) Source image (VIF=1)

b) Enhanced image 1 (VIF=1.063)

c) Enhanced image 2 (VIF=0.8224)

d) Enhanced image 3 (VIF=0.309)

Figure 1. Results for VIF measure. Although images c) and d) are better than image a) their VIF scores are lower

Use of no-reference quality measures is significantly complicated by absence of reference image therefore most no-reference quality measures should adopt properties of human visual perception to assess image quality. Since in common case there is no information about signal and noise characteristics presented in the image the no-reference image quality assessment is related to blind signal separation problem.

Although a lot of information is accumulated about human visual system (HVS) [5] this information is averaged and thus doesn't consider valuable details of subjective perception which could be useful for the concrete user. The adjustment of known averaged HVS properties for each user is possible but it should be done by a specialist and can consume a lot of time. Thus an automated interactive adjustment of HVS properties is of great interest.

In this paper we propose the way to approximate subjective properties of HVS of certain user using interactive neuroevolutionary approach.

The paper is organized as follows. The Section 2 gives brief introduction to evolutionary and neuroevolutionary algorithms. In the Section 3 developed adaptive neuroevolutionary algorithm for design and training of artificial neural networks is described. The Section 4 contains description of proposed interactive method for approximation of user's HVS properties. Some conclusive remarks and future work milestones are given in the Conclusion.

2. EVOLUTIONARY AND NEUROEVOLUTIONARY ALGORITHMS

It's been shown that *interactive evolution* approach [6] can be used to learn human subjectivism for interactive creation of music and art. The interactive evolution is based on *evolutionary computation* [7] algorithms which are probabilistic heuristic search techniques inspired by evolutionary principles of heredity, mutability and natural selection. General scheme of evolutionary search is depicted in Figure 2.

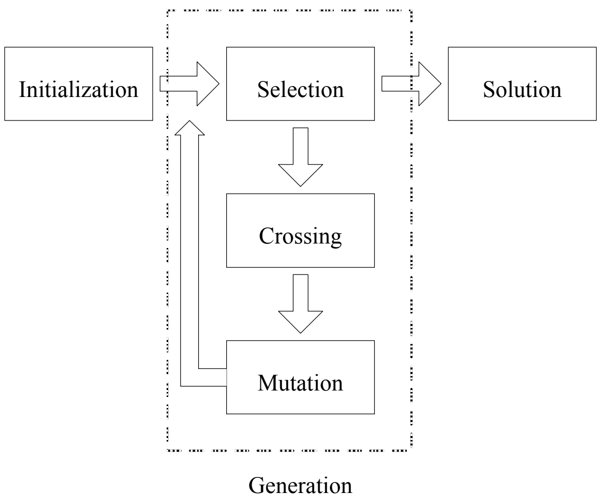


Figure 2. General scheme of evolutionary search.

The evolutionary search is organized in iterations (*generations*). In most cases in each generation a set of candidate-solutions (*population*) is used to generate the new set of presumably better solutions using specific evolutionary operators that act in analogue with selection (breeding), crossing (recombination of solutions) and mutation (variation of solutions). This new set of candidate-solutions replace (partially or wholly) the previous one for the next generation. Selection is performed on the base of *fitness* value for each candidate-solution, which is usually calculated according to some objective function – *fitness function*. Proper use of proper evolutionary operators allows to improve fitness of newer solutions and thus leads the search towards (quasi)optimal solution.

The notion of interactive evolution approach is that fitness function is unknown and selection of candidate-solutions is made by user himself. This allows one to overcome difficulties arising from informal nature of human perception. The general scheme for interactive evolution showing single iteration of evolutionary search is presented in Figure 3.

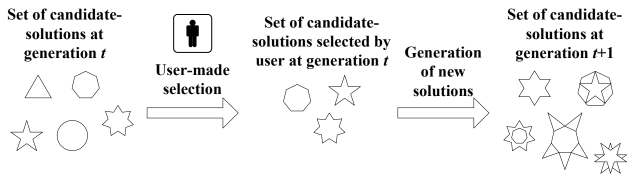


Figure 3. General scheme of interactive evolution iteration. The key feature of interactive evolution is that selection of candidate-solutions is not automated but performed by user.

In most cases solutions obtained by evolutionary algorithms (EA) represent set of (quasi)optimal parameters set under optimization. The EAs that are used to search for artificial neural network's (ANN) [8] weights and structure are called neuroevolutionary (NE) algorithms. Of great interest here are NE algorithms for simultaneous design and training of ANNs since such algorithms has the widest applicability in comparison with NE algorithms for only design or training of ANNs, traditional ANN approach and EAs.

For now NE is widely used in computation intelligence field to solve various problems such as "standard" neural classification and approximation problems as well as problems from adaptive behavior and evolutionary robotics domains [9-11]. Recent advances in NE field demonstrate that NE algorithms can be applied to produce promising generative encodings [10] and for fast image enhancement [11].

The next Section gives introductory description of the developed NE algorithms NEvA which will be used later for interactive neural approximation of HVS properties.

3. BRIEF DESCRIPTION OF NEvA ALGORITHM

Developed neuroevolutionary (NE) algorithm NEvA implements simultaneous design and training of ANNs through evolution of networks' structures along with the connections' weights. In this paper only a brief description is presented but interested reader can refer to [12].

Each ANN is genetically encoded as the list of its connections. The weight of each connection is presented with 19-bit integer mapped over the range [-26,2144; +26,2143] with the step of 0,0001. Truncation selection is used for parental subpopulation formation. Original genetic operators for recombination and mutation, which respect structures of the ANNs undergoing recombination and mutation, are used. Nodes with sigmoid activation function

$$o = \left(1 - \exp(-aS)\right)^{-1},$$

where S is a weighted sum of input signals, a – constant parameter, are considered.

The population size adapts to the properties of evolution during the algorithm run using simple resizing strategy. The strategy arises from the experimental observation [13] that if the average fitness is increasing (the fitness maximization task is considered) than the population size is worth decreasing and vice versa, in case of the average fitness's stabilization or decrease the population should be expanded. This resizing mechanism is also remarkable because it is in a good agreement with biological evidence that genotypic diversity decreases when evolution speed is increasing for population of simple organisms [14].

Most of parameters of developed NE algorithm NEvA are adapted during the algorithm run and in most cases user only needs to set number of iterations and target value of objective function.

4. INTERACTIVE IMAGE QUALITY ASESSMENT

Here the proposed way to learn interactively user's image quality demands is described. We will consider grey-scale images and their characteristics.

First of all note that user's evaluation of visual image quality is of complex nature and combines various criterions such as contrast and lightness. Although the key point here is the main goal for which the user intends to use the image some generic demands for good-looking images are known:

1. High overall contrast.

2. Rather uniform distribution of lightness levels which means that image should not be too dark or too bright.

3. High level of details in dark and bright regions of the image which is provided by high local contrast.

The main difficulty here is that single value that denotes image visual quality should correspond to all of these demands.

To describe image under evaluation the following set of image characteristics may be considered:

1. Mean brightness: M_L.

2. Deviation of brightness: D_L.

3. Entropy of brightness distribution: $H = -\sum_i l_i \log l_i$, where l_i is fraction of the pixels with the i-th level of brightness.

4. Number of pixels on edges: μ .

5. Mean intensity of edge pixels: I_μ .

6. Level of HVS adaptation: $C = 1 - \frac{M_L - L_{\max}/2}{L_{\max}/2}$.

We will approximate dependency between presented 6 image characteristics and image quality measure using ANNs in the following way.

Each ANN is used to approximate some transformation

$$f = f(M_L, D_L, H, \mu, I_\mu, C),$$

so that ANN output is considered as a no-reference image quality measure since ANN evaluates only one image at a time. We assume that the more ANN output value the better is the image under evaluation. ANN training is performed by stages.

During the each t-th stage user is proposed to give ranks to 9 images $\mathbf{P}(t) = \{P_i(t) : i = 1,..,9\}$ that are placed according to the scheme in Figure 4 so that image with the best visual quality receives the lowest rank and image with the worst quality receives the highest rank. Images are presented in such a way that user could choose whether he prefers lighter/darker and more/less contrast images. After images are ranked NE algorithm is assigned a task to evolve ANN that ranks the images in the same way the user does. When such a network is found the next (t+1)-th stage takes place.

$P_1(t)$ brigthness - contrast -	$P_2(t)$ brigthness -	$P_3(t)$ brigthness - contrast +
$P_4(t)$ contrast -	$P_5(t)$ primary image	$P_6(t)$ contrast +
$P_7(t)$ brigthness + contrast -	$P_8(t)$ brigthness +	$P_9(t)$ brigthness + contrast +

Figure 4. Scheme of images placement for ANN training. The image $P_5(t)$ in the center is a primary and all the surrounding images are obtained from the $P_5(t)$ image by applying brightness and contrast increase ("+") or decrease ("-") transformation

At the next stage the image that had received the best rank during the previous stage becomes the primary and placed in the center and the other images are generated from it (illustrative example is given in Figure 5). If there is more than one best ranked image than the primary image for the next stage is chosen at random. This will lead evolution of ANNs towards the images with user-preferable brightness and contrast characteristics.

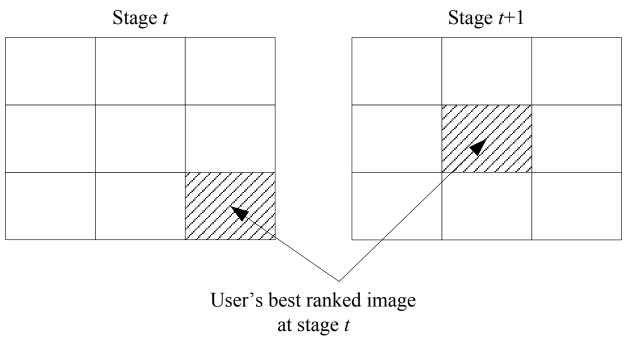


Figure 5. Illustrative example showing that image with the best rank at the stage t becomes primary at the stage (t+1) involving all the surrounding images to be generated from this new primary image using certain brightness and contrast transformation (see Figure 4).

As the stage's number increases the difference between the central image and the surrounding images is decreasing. This provides increasing complexity of the ANN training task and allows to evolve ANNs that are able to distinguish more subtle differences in images quality.

The training is stopped when user is unable to decide how to rank presented images or user makes a decision that image in the center is good enough and can't be improved any more. This gives user control over the ANNs' training.

Note that the primary image at stage 0 can be of any quality and the interesting question here is what kind of primary images ("bad" or "good") is the best for ANN training. It seems that primary image at stage 0 with rather poor initial quality is better for training since change of quality in result of brightness and/or contrast change is easier to detect in this case. And the special question is how do noised primary image influences the training results.

5. CONCLUSION

The novel way for no-reference image quality assessment is proposed in this paper. The key feature is that image quality evaluation is made by neural network which is trained to take into consideration some of user's visual perception preferences using interactive neuroevolution approach.

ANNs obtained in result of training can be used in image and video processing applications where automated image quality assessment is necessary, for example, for neural image enhancement [11]. Also such automated methods for image quality assessment can be used for different image enhancement algorithms comparison together with wide spread mean opinion score calculations.

For now image quality is approximated with use of image brightness characteristics only. This simplifies the research but limits obtained neural solutions from the image quality assessment point of view (only brightness related distortions can be judged). For the further extension of the proposed approach more image properties should be considered such as image blockiness and smoothness.

Proposed approach will be implemented and tested on various images and performance of obtained results will be compared with performance of the other with reference and no-reference quality measures.

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About the author

Yury R. Tsoy is a PhD student at Tomsk Polytechnic University, Computer Engineering Department. His contact email is qai@mail.ru.

Vladimir G. Spitsyn is a professor at Tomsk Polytechnic University, Computer Engineering Department. His contact email is spitsyn@ce.cctpu.edu.ru.

Alexander V. Chernyavsky is a PhD student at Tomsk Polytechnic University, Computer Engineering Department. His contact email is avcher@tpu.ru.