However, the open-loop state responses may converge to two different steady states.

IV. Conclusion

The approaches for guaranteeing the stabilizing and robustness of the fuzzy time-delay systems have been derived by using the parallel distributed fuzzy control. Moreover, the criterion for the system with the same input matrix $\mathbf{B}_i = \mathbf{B}_j$, $i \neq j$, have been also proposed. These design methodologies are independent of size of the time delays. The suitable control gains $\mathbf{F}_i$ and perturbation bounds $b_i$can be obtained easily by using LMI's tool. Furthermore, the design algorithm shows that we can obtain the larger perturbation bounds b_i by choosing a suitable q_i. Finally, a practical example has been illustrated to show the effectiveness of the proposed control design method.

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Gray-Scale Image Enhancement as an Automatic Process Driven by Evolution

Cristian Munteanu and Agostinho Rosa

***Abstract*—Image enhancement is the task of applying certain transformations to an input image such as to obtain a visually more pleasant, more detailed, or less noisy output image. The transformation usually requires interpretation and feedback from a human evaluator of the output result image. Therefore, image enhancement is considered a difficult task when attempting to automate the analysis process and eliminate the human intervention. This paper introduces a new automatic image enhancement technique driven by an evolutionary optimization process. We propose a novel objective criterion for enhancement, and attempt finding the best image according to the respective criterion. Due to the high complexity of the enhancement criterion proposed, we employ an evolutionary algorithm (EA) as a global search strategy for the best enhancement. We compared our method with other automatic enhancement techniques, like contrast stretching and histogram equalization. Results obtained, both in terms of subjective and objective evaluation, show the superiority of our method.**

***Index Terms*—Evolutionary algorithms, image enhancement, local enhancement method, objective enhancement criterion.**

I. Introduction

Producing digital images with good brightness/contrast and detail is a strong requirement in several areas like vision, remote sensing, biomedical image analysis, fault detection. Producing visually natural images or transforming the image such as to enhance the visual information within, is a primary requirement for almost all vision and image processing tasks. Methods that implement such transformations are called image enhancement techniques. The task of image enhancement is a difficult one considering the fact that there is no general unifying theory of image enhancement at present, because there is no general standard of image quality that can serve as a design criterion for an image enhancement processor [1]. Most of the enhancement techniques in existence to date are empirical or heuristic methods, dependent on the particular type of image [2]. More important, most of these techniques require interactive procedures to obtain satisfactory results, and therefore are not suitable for routine application [3]. Besides requiring the user interaction, many such methods require specification of external parameters, which sometimes are difficult to fine-tune [1]. Finally, the enhancement methods most widely employed treat the spatial information in the image in a global fashion, while in many cases it is necessary to adapt the transformation to the local features within different regions of the image [2]. Automatic enhancement, that is a method to yield enhanced images without human (subjective) intervention is a notoriously difficult task in image processing [4]. This is because automatic enhancement requires specifying an objective criterion for enhancement, while evaluating the quality of an image is done finally by the human interpreter. In what follows we propose an evolutionary method for automatic image enhancement having the following advantages.

1) It uses a local enhancement technique based on a variation of the statistical scaling method [1], [4].
2) It doesn't employ any kind of interaction with the user, during running stages of the algorithm.
3) It uses an objective evaluation criterion with no additional external parameters, that produces an objective quality score.

Manuscript received February 25, 2003; revised July 29, 2003. This paper was recommended by Associate Editor V. Govindaraju.

The authors are with the LaSEEB, Instituto de Sistemas e Robótica, Instituto Superior Técnico, 1049-001 Lisbon Portugal (e-mail: cmunteanu@omni.isr.ist.utl.pt; cristi@laseeb.org; acrosa@laseeb.isr.ist.utl.pt).

Digital Object Identifier 10.1109/TSMCB.2003.818533

II. Evolutionary Enhancement Algorithm—Relation to Classical and Evolutionary Approaches. Objectives and Motivations

First, we will briefly review the basic strategies for image enhancement. According to [4] image enhancement techniques fall into four main categories: point operations, spatial operations, transform operations, and pseudocoloring methods. Point operations include contrast stretching, window slicing, and histogram modeling. They are zero-memory operations that remap a given input gray-level into an output gray-level, according to a global transformation [1], [4]. These methods have the disadvantage of treating the image globally, not being able to differentiate between several areas of the image that might require different levels of contrast enhancement. One advantage is that some of the point operations, such as histogram equalization and linear contrast stretching, are automatic methods. Linear contrast stretching employs a linear transformation that remaps the gray-levels in a given image to fill the full range of values. Histogram equalization applies a transformation that yields a close-to-uniform histogram for the relative frequency of the gray-levels in the image. Other classes of methods are spatial operations that might suffer from excessively enhancing the noise in the image or conversely by smoothing the image in areas that need sharp details [3]. Next, we have transform operations that perform enhancements only in particular spatial frequency domains [4], and pseudocoloring that artificially "color" the gray-scale image based on a color mapping, with the disadvantage that extensive interactive trials are required to determine an acceptable mapping [1].

Evolutionary algorithms (EAs) have been previously applied to image enhancement [5]–[8]. In [5], the authors apply a global contrast enhancement technique using genetic programming (GP) [9] to adapt the color map in the image as to fit the demands of the human interpreter. Results reported with this method were unsuccessful [5]. In [6], we applied a real-coded genetic algorithm (GA) with a subjective evaluation criterion to globally adapt the gray-level intensity transformation in the image. A similar global technique was adopted in [7], where the evaluation score was given by an objective criterion proportional to the number of edges in the image and to a clumping factor of the intensity transformation curve. In [8] we have attempted a partial automatization of the evaluation process by employing a multiple regression technique to yield evaluations to novel enhancements of a given image, based on previous subjective evaluations done by the human interpreter. Evolutionary image enhancement techniques used so far, have several drawbacks (some common to the classical methods, as well).

1) The use of a global enhancement method that is incapable of adapting to the local spatial content in the image [6]–[8], and that in many cases yields poor results [2].
2) Requirement for time-consuming user interaction sessions [10], [11], as each enhancement result treated as an individual in the population of the EA, should be rated subjectively by a human interpreter [7], [8].
3) Inclusion of additional external parameters in the objective evaluation criterion that makes the automatic image enhancement strongly parameter dependent [7].

Our approach to image enhancement takes into account several factors:

1) locality and adaptability of the method to the given image, as opposed to global enhancement methods;
2) automation of the image enhancement process;
3) robustness, that is producing good enhancement results on a large category of images.

Following the recommendations in [12], the problem, as we have defined it, is amenable to application of a suitable heuristics. The first factor imposes the use of a local enhancement technique as the enhancement processor. The second and third factors impose the use of suitable heuristics, capable of searching for the best configuration of the enhancement processor, according to a predefined objective enhancement criterion. The complexity of the respective criterion implies using a global search heuristics that finds good solutions of the best enhancement processor configuration in relatively small time. Genetic algorithms (GAs) are well known global search heuristics [13] proven efficient in many image processing and computer vision applications [14]. Therefore, the use of GAs is fully justified by the nature of the task to be solved.

III. Structure of the Algorithm: Image Processing Tasks

A. Enhancement Kernel

Local enhancement methods apply transformation functions that are based on the gray-level distribution in the neighborhood of every pixel in a given image [2]. One such example of a local enhancement method is the adaptive histogram equalization (AHE), which has shown good results in medical imaging [15]. However, AHE uses an enhancement kernel that is quite computationally expensive. Our method employs a less time consuming enhancement kernel that is similar to statistical scaling presented in [2]. Moreover, AHE might yield unsatisfactory outputs: images with noise artifacts, false or over-enhanced shadows [1]. These shortcomings are often due to a bad choice of the method's parameters values for a given image, turning AHE into a technique that is difficult to automate.

The enhancement kernel we propose applies to each pixel at location (x, y) a transformation T that takes the gray-level intensity of the pixel in the input image $f(x, y)$ and changes it to the value $g(x, y)$—the gray-level intensity in the output image. Letting H_{size} and V_{size} denote the horizontal, and vertical size of the image, respectively, the transformation T is defined as

$$\begin{aligned} g(x,y) &= T\left(f(x,y)\right) \\ &\equiv \left(\kappa \frac{M}{\sigma(x,y)+b}\right) \cdot [f(x,y) - c \cdot m(x,y)] \\ &\quad + m(x,y)^a \\ &\text{for } x = \overline{0 \ldots H_{\text{size}}-1} \text{ and } y = \overline{0 \ldots V_{\text{size}}-1}. \end{aligned} \tag{1}$$

In (1), $m(x, y)$ and $\sigma(x, y)$ are the gray-level mean and standard deviation computed for the pixels inside a neighborhood (window) centered at (x, y) and having $n \times n$ pixels (see Fig. 1). The global mean of the image is $M = \sum_{x=0}^{H_{\text{size}}-1} \sum_{y=0}^{V_{\text{size}}-1} f(x, y)$. a, b, c, and κ are parameters of the enhancement kernel, taken as: $0.5 < \kappa < 1.5$; $a \in \Psi_1$, $b \in \Psi_2$, $c \in \Psi_3$, with $\Psi_1, \Psi_2, \Psi_3 \subset \mathbb{R}_+$ the parameters' domains. The original method in [2] allowed only for a reduced range of possible output enhancements, as constants in (1) where taken as $b = 0$, and $c = 1$, while the last additive term of the expression in (1) was not present.

We have broadened the spectrum of the transformation output range by modifying the original method as shown in (1). In our modified method, a nonzero value for b allows for zero standard deviation in the neighborhood, while c allows for only a fraction of the mean $m(x, y)$ to be subtracted from the original pixel's gray-level intensity $f(x, y)$. The last term $m(x, y)^a$ may have a brightening and smoothing effect on the image. Quantities $m(x, y)$ and $\sigma(x, y)$ depend on the neighborhood of the pixel, therefore they are dependent on the local information, meaning that the enhancement kernel itself is a local transformation. The parameters of the method a, b, c, and κ are the same for all pixels in the image. The task for the EA is to find the best combination of the

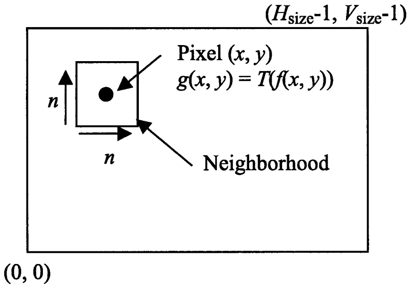

Fig. 1. Enhancement kernel—applying to each pixel in the image the operation $T(\bullet)$ in the neighborhood.

four parameters according to an objective criterion that describes the quality of the enhancement.

B. Enhancement Evaluation Criterion

In order to apply an automatic image enhancement technique, which does not require human intervention and no additional external parameters, an objective criterion for the quality of the enhancement method should be chosen. Let us proceed by noting that a good contrast and enhanced image has a high number of edgels (that are pixels belonging to an edge [1]). Compared to the original image, the enhanced version should have a higher intensity of the edges [7]. The number and intensity of edgels are not enough to describe a valid enhancement criterion for a more *naturally* enhanced image. The problem is that an image can have an *extreme contrast* with sharp transitions from white to black (or conversely, from black to white), and a relatively small number of gray-levels (an extreme contrast image is a binary image containing only black and white pixels). In this case the image will have a relatively high number of edges and a very high intensity of edges. What is additionally needed is a quantification of the number of gray-levels present in the image. Without any prior information this number should be evenly distributed across the image, which translates to having the histogram of the image approach the uniform distribution, as in the case of histogram equalization techniques. We first compute the histogram of the image: for images with 256 gray-levels the histogram has 256 bins. The bounds of a bin indexed i, are written as A_i and B_i, for $i \in \{1, \ldots, 256\}$. Based on the histogram, we introduce an "entropic measure" of the enhanced image I, as

$$H(I) = \begin{cases} -\sum_i \upsilon_i \log_2(\upsilon_i), & \text{for } \upsilon_i \neq 0 \\ 0, & \text{for } \upsilon_i = 0 \end{cases} \tag{2}$$

with υ_i the frequency of pixels having gray-levels between bounds A_i and B_i. Note that the measure in (2) is not an actual entropy, as υ_i are frequencies, rather than probabilities.

The number of edgels and intensity of edges are deducted using a simple and efficient edge detector algorithm, namely the Sobel's edge detector [1]. The Sobel detector is used as an automatic threshold detector [16]. We are interested in computing the sum of intensities of edges in I, that according to the Sobel's transformation is $E(I)$[14], [17]:

$$E(I) = \sum_x \sum_y \sqrt{\delta h_I(x,y)^2 + \delta v_I(x,y)^2} \tag{3}$$

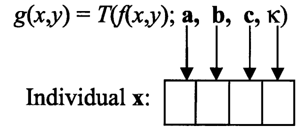

Fig. 2. EA's individual representation.

where for each pixel (x, y)

$$\begin{aligned}
\delta h_I(x,y) &= g(x-1,y+1) + 2g(x,y+1) \\
&\quad + g(x+1,y+1) - g(x-1,y-1) \\
&\quad - 2g(x,y-1) - g(x+1,y-1) \\
\delta v_I(x,y) &= g(x+1,y+1) + 2g(x+1,y) \\
&\quad + g(x+1,y-1) - g(x-1,y+1) \\
&\quad - 2g(x-1,y) - g(x-1,y-1).
\end{aligned}$$

In (3) $g(x, y)$ denotes the gray-level intensity of the pixel at location (x, y) in the enhanced image I.

Finally, on the output of the Sobel detector, that is an image with pixels $\delta h_1(x,y)^2 + \delta v_I(x,y)^2$, we count how many pixels have bigger intensity than the threshold. Thus, we get the number of edgels in I, that is $\eta(I)$. The threshold is generated automatically using an estimation of the signal-to-noise ratio in the image; more details can be found in [16] and [1].

Our enhancement evaluation criterion $\mathrm{Eval(I)}$ for a given image I, will be proportional to

$$\mathrm{Eval(I)} \sim \begin{cases} H(I) \\ \eta(I) \\ E(I) \end{cases}. \tag{4}$$

The best enhancement is the one that maximizes the criterion in (4). According to the proportionalities in (4), a maximal $Eval(I)$ will correspond to an image with maximal number of edgels $\eta(I)$, having sharp edges (e.g. $E(I)$ maximal), and a uniform histogram equivalent to a maximal entropic measure: $H(I)$. It means that when maximizing $H(I)$ we indirectly perform a histogram equalization [1], [4].

IV. Structure of the Algorithm: Evolutionary Components

A. Representation of the Individual Within the Evolutionary Algorithm

EAs are search and optimization methods that use a fixed size population of individuals representing potentials solutions to the optimization problem. The population undergoes successive iterations called generations, in which according to a predefined evaluation criterion called fitness, better individuals are selected to survive into the next generation, in a process similar to natural selection. Subsequent to selection, in each generation the information contained in the individuals is modified using the so-called variation operators: crossover and mutation [9].

Our choice for the specific implementation of EA, should take into account the features of the enhancement problem. A real-coded GA [9] with several operator modifications was the preferred choice, the reasons being made clear in the following. The EA has to find the best combination of parameters a, b, c, and κ, that gives the best enhancement for a given image. The parameters have real values, therefore the simplest coding of the EA individual is a direct one to one coding: the EA individual is as a string of four real numbers denoting the four parameters. The representation is described in Fig. 2, where $T(\cdot)$ designates the operation in (1).

B. Fitness Function

$Eval(I)$ given in (4) is directly related to the fitness function of the EA, that allocates to each individual $\mathbf{x} = (a, b, c, \kappa)$ an utility or quality value called fitness. The fitness of each individual $\mathbf{x}$ in the EA's population at each generation t, is calculated according to a fitness function $F(\mathbf{x})$, that should obey all proportionalities of $Eval(I)$ in (4). The calculation of the fitness starts by applying the enhancement procedure in (1) to the input image with the parameters of the enhancement kernel given by the individual $\mathbf{x}$. Next, the resulted image (enhancement), will be evaluated using $F(\mathbf{x})$. We take $F(\mathbf{x})$ to be

$$F(\mathbf{x}) = \ln\left(\ln\left(E\left(I(\mathbf{x})\right) + e\right)\right) \cdot \frac{\eta\left(I(\mathbf{x})\right)}{H_{\text{size}} \times \mathrm{V}_{\text{size}}} \cdot e^{H(I(\mathbf{x}))} \quad (5)$$

where notations are clear from (1)–(4). By writing $I(\mathbf{x})$ instead of I, we stress that the enhanced image was obtained using the parameters in $\mathbf{x}$; e is the Euler constant that avoids undefined points when the edge intensity is 0. We used a log-log measure of the edge intensity not to over-emphasize this parameter when compared to the others in the fitness function. Empirical evidence shows that $E(I(\mathbf{x}))$ typically varies within three orders of magnitude. Large values for edge intensity might produce extreme contrast and un-natural images, as discussed in Section III-B. From empirical evidence we have noticed that $H(I(\mathbf{x}))$ for different enhancements and different images, varies slowly in a run of the EA. This variation is within one order of magnitude smaller than the variation of the other fitness function components. To balance the contribution of $H(I(\mathbf{x}))$ with respect to the rest of the fitness function components, we have chosen to take the exponential of the entropic measure in (5).

C. Selection

Both the selection and crossover for the EA have been used to insure a steady convergent behavior of the algorithm. The trade-off we had to make is the well-known trade-off between exploration and exploitation present in any search method including EA. The convergent exploitation assured by selection and crossover should well-balance the wide exploration effect achieved by our mutation operator. The selection method was chosen as a combination between binary tournament, which has a constant, and relatively high selection pressure [18], with a K-elitist scheme [19] that assures the preservation of the K best individuals in the population.

D. Crossover and Mutation

The crossover operation has been taken to strengthen the correlation between parents and children, again to assure an exploitative behavior of the search algorithm. We chose arithmetic crossover (AX) [20], between several choices of real-coded GA crossover operators like α-BLX [21], SBX [22], and UNDX [23], because in the case of AX, offspring genes are close to the parents' genes as they are produced inside the line connecting both parental genes [20]. Therefore, AX assures the required "focused" and exploitative search behavior. The population of the GA is paired at random, and for each pair of individuals (parents) $x^p_{\{1,2\}}$ we apply a linear combination and get the offspring $x^o_{\{1,2\}}$

$$x^o_1 = \varphi x^p_1 + (1-\varphi)x^p_2, \quad x^o_2 = (1-\varphi)x^p_1 + \varphi x^p_2 \quad (6)$$

where φ is a sample drawn from an uniform distribution: $U([0,1])$.

Mutation operator has to insure high levels of diversity in the population. We introduced PCA-mutation in [24], and shown that it has very good capabilities in maintaining high levels of diversity in the population. At each generation t, the population of the EA $P(t)$ can be viewed as a cloud of N points in an l-dimensional space, where N is the size of the population and l is the length of the individuals in the population. It can be shown (see a detailed analysis in [24]) that when an EA converges the number of principal components (PCs) decreases. PCs are calculated with the principal components analysis (PCA) method [25], [26] on the data cloud $P(t)$. This reduction in the number of PCs comes as a result of the loss of diversity in the population as the EA moves on. Our PCA-mutation works directly on the components of the data cloud $P(t)$ to combat this loss of diversity by increasing the components that tend to become small. As shown both theoretically and empirically in [24], PCA-mutation can attain very high levels of population diversity, and when counterbalanced with an exploitative selection and a focused crossover scheme, the strategy can be quite effective in preventing genetic drift and premature convergence. One potential disadvantage of PCA-mutation is the fact that it is computationally expensive when chromosomes are large. However, in our application this is hardly the case, as l is quite small ($l = 4$).

```
EVOLEHA (InputImage)
 {
  -t:= 0.
  -Randomly initialize P(t) within specific bounds.
  while (Termination criterion ≠ true) do
   -Compute fitness for all individuals x in P(t):
    {
     -OutputImage=T(InputImage;x), with T
       given in Eq. (1).
     -Calculate F(x), for I=OutputImage, with
       Eq. (5).
    }
   -Perform binary tournament selection (see [9])
    on P(t) ⇒ P′(t).
   -Perform AX crossover (Eq. 6) on P′(t) with
    rate Pc ⇒ P″(t).
   -Perform PCA-mutation (see [24]) on P″(t) with
    rate Pm ⇒ P‴(t).
   -Form P(t+1) by applying a k-elitist scheme
     (see [19]) to P‴(t)∪P(t).
   -t:=t+1.
  od
 }
 BestOutputImage=T( InputImage; argmax{F(x;t)} )
                                 x,t
```

Fig. 3. EVOLEHA: pseudocode. $P(t)$, $P'(t)$, $P''(t)$, $P'''(t)$, and $P(t+1)$ are populations with the same size N.

E. Summary

The proposed EVOLutionary EnHancement Algorithm (EVOLEHA) is summarized in Fig. 3.

V. Experimental Results

In order to evaluate EVOLEHA, we compared our method to two automatic enhancement methods: linear contrast stretching and histogram equalization [1], on 12 images. Results for EVOLEHA were given for typical runs of the GA. We found that suitable intervals in (1) are $\Psi_1 = [0, 1.5]$, $\Psi_2 = [0, 0.5]$, $\Psi_3 = [0, 1]$. Therefore, the chromosomes will be initialized within these bounds. The GA has population size $N = 40$, chromosome length $l = 4$, K-elitism with $K = 5$, generational type replacement [9], AX with $P_c = 0.8$, PCA-mutation with $P_m = 0.3$ and $c_{\max} = 1$ (see [24]). Table I lists the images and the parameters specific to each image. The GA's termination criterion (see Fig. 3) is triggered whenever the maximum number of generations (third column in Table I) is attained. Some images (see Table I) require a higher maximum number of generations to assure a good convergence

TABLE I
IMAGE SIZE AND NUMBER OF MAXIMUM GENERATIONS FOR THE GA RUN IN EVOLEHA

Image	**Size (pixels)**	**GA max no. of generations**
a) abdomen	256×256	40
b) airplane	512×512	50
c) cameraman	256×256	40
d) eight	242×308	40
e) head	256×256	40
f) house	256×256	40
g) pout	291×240	50
h) tire	205×232	40
i) autumn	160×273	50
j) boat	168×291	50
k) galaxy	282×257	50
l) afmsurf	199×291	50

TABLE II
RESULTS IN TERMS OF FITNESS SCORE

Image / fitness	**Linear stretching**	**Histogram Equalization**	**EVOLEHA**
a) abdomen	1.5391	0.801	11.296
b) airplane	69.797	29.991	257.364
c) cameraman	33.070	8.917	100.975
d) eight	26.210	7.007	159.947
e) head	25.578	10.666	140.837
f) house	47.037	19.271	230.031
g) pout	13.525	13.566	124.001
h) tire	0.899	0.380	2.394
i) autumn	53.085	37.953	229.409
j) boat	97.178	31.285	224.729
k) galaxy	1.281	1.885	17.416
l) afmsurf	27.475	19.153	121.543

of the GA. For a large category of images, experiments performed show that a maximum number of generations equal to 50 suffice for the GA to find good solutions. Moreover, a different termination criterion can be employed, that is: stop the GA evolution when no substantial improvement of the best solution is registered. Experimentally, we checked that this event occurs around 40–50 generations, therefore we are assured that 50 generations is a good estimation of the time required to discover good solutions.

In Table II the fitness [see (5)] is given for each image and each method employed. From this table it is clear that EVOLEHA scores much better then the other methods. Histogram equalization scored better than contrast stretching only on the *pout* and *galaxy* images.

A. Subjective Evaluation

To evaluate the performances of the image enhancement techniques 6 human interpreters (two of which were image processing experts) evaluated subjectively the images produced by the three methods. Each image had to be ranked by giving a score ranging 1-3, the best score being 1, with no ties allowed. The subjective criterion was natural brightness/contrast for the enhanced images. Results are given in Table III. EVOLEHA ranks best when globally ranked (see the "total rank" row in Table III), and ranks best for each image, but the *airplane* and *tire* images. Even if the brightness/contrast appears good for these images (see Fig. 4 and 5), the fact that our method adds an averaging effect on the image seems to have biased the human evaluators into not favoring EVOLEHA. The subjective fitness evaluation gives credit to EVOLEHA in favor of the other methods. However, an objective criterion should also be employed to rank the methods. The objective evaluation results are given in the next section.

TABLE III
SUBJECTIVE EVALUATION RESULTS (LOWER RANK VALUE IS BETTER)

Method	**Linear Stretching**				**Histogram equalization**				**EVOLEHA**			
Rank	1	2	3	**Av**	1	2	3	**Avg**	1	2	3	**Av**
a)	1	2	3	2.3	0	3	3	2.5	5	1	0	1.1
b)	3	3	0	1.5	3	1	2	1.8	0	2	4	2.6
c)	2	3	1	1.8	0	2	4	2.6	4	1	1	1.5
d)	1	4	1	2.0	0	1	5	2.8	5	1	0	1.1
e)	1	3	2	2.1	0	2	4	2.6	5	1	0	1.1
f)	1	3	2	2.1	1	1	4	2.5	4	2	0	1.3
g)	3	1	2	1.8	1	2	3	2.3	2	3	1	1.8
h)	4	2	0	1.3	0	1	5	2.8	2	3	1	1.8
i)	1	2	3	2.3	0	4	2	2.5	5	0	1	1.3
j)	1	3	2	2.3	0	2	4	2.6	5	1	0	1.1
k)	1	5	0	1.8	0	0	6	3	5	1	0	1.1
l)	2	2	2	2	0	2	4	2.6	4	2	0	1.3
Total	2	3	1	**1.9**	5	1	3	**2.5**	3	1	8	**1.5**

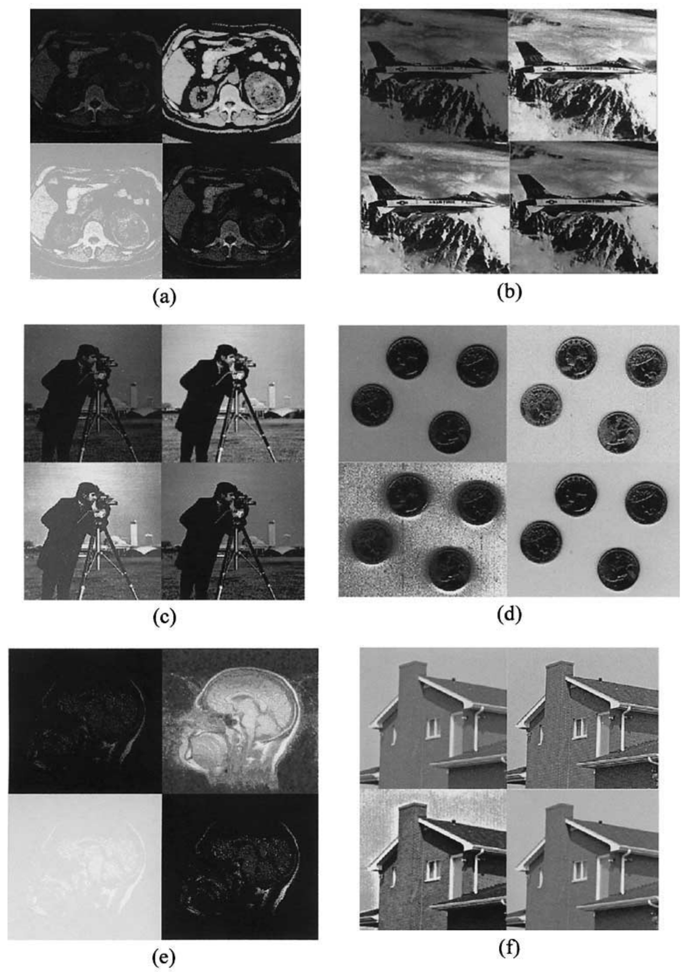

Fig. 4. Enhancement results, part I. Result sets (a)–(f) correspond to test images (a)-(f) listed in the first column of Table I. Result set comprises: upper left—original image; upper right—EVOLEHA; lower left—histogram equalization; lower right—linear contrast stretch.

B. Objective Evaluation

The objective evaluation criterion was taken to be the Detail Variance (DV) and Background Variance (BV) from [27]. DV and BV values are obtained firstly by computing the variance of the gray-levels in the neighboring pixels of each pixel in the image. Next, the pixel is classified to the foreground when the variance is more than a threshold; otherwise it is classified to the background. The averaged variance of

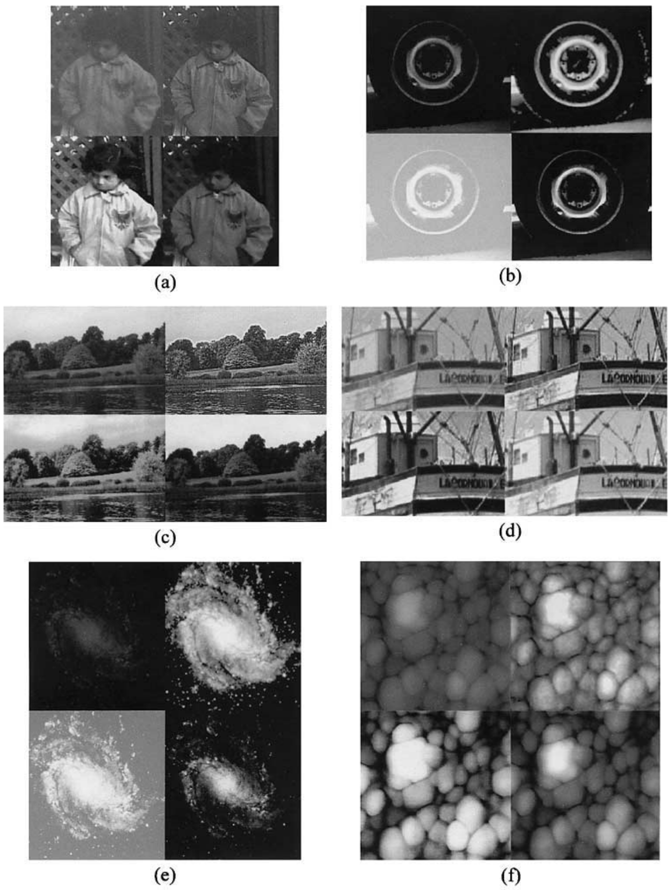

Fig. 5. Enhancement results, part II. Result sets (a)–(f) correspond to test images g)-l) listed in the first column of Table I. Result set comprises: upper left—original image; upper right—EVOLEHA; lower left—histogram equalization; lower right—linear contrast stretch.

all pixels included in the foreground class is DV, and the averaged variance of all pixels included in the background class is BV. One achieves efficient contrast enhancement, when the DV value of the resulted image increases while BV is not changed much compared to the original image [27]. The DV-BV criterion is far from being perfect, it merely gives an indication of how to evaluate the images in a more systematic way [27]. Results are given in Table IV, where the threshold was chosen to be 0.01 and the $n \times n$ neighborhood has $n = 3$. From Table IV, the results indicate a good behavior of EVOLEHA, better than the other methods for most images. However, for the *airplane* and *pout* images results might indicate otherwise, though from Figs. 4 and 5 the same images appear to have more detail in the case of EVOLEHA. A more objective explanation can be found by calculating the number of edgels as detected with the Sobel automatic edge detector. The image having the highest number of edgels will be rated as having higher detail content. From Table V it is clear that EVOLEHA achieves the best detail content for the *airplane* and *pout* images when compared to the other methods.

C. Robustness

Robustness of EVOLEHA is related to the repeatability of the results. To evaluate the robustness ten independent runs of EVOLEHA were performed for each image. Fig. 6 gives the equivalent gray-level transformation between the input image and the output (enhanced) image for each run. Only the graphs for four images have been given, however conclusions hold for all tested images. To evaluate the repeatability of the experiments we should see that for each image

TABLE IV
DV AND BV VALUES FOR ENHANCEMENT METHODS

Image	Original		Linear stretch		Histogram equalized		EVOLEHA	
	DV	BV	DV	BV	DV	BV	DV	BV
a)	0.12	0.02	0.13	0.02	0.20	0.02	0.22	0.01
b)	0.13	0.02	0.18	0.02	0.21	0.03	0.18	0.04
c)	0.15	0.02	0.18	0.02	0.21	0.03	0.17	0.02
d)	0.17	0.01	0.19	0.02	0.16	0.04	0.20	0.04
e)	0.13	0.03	0.12	0.03	0.13	0.06	0.13	0.04
f)	0.17	0.02	0.18	0.02	0.18	0.04	0.19	0.04
g)	0.18	0.01	0.15	0.02	0.15	0.04	0.14	0.01
h)	0.14	0.01	0.16	0.01	0.38	0.00	0.17	0.01
i)	0.05	< 0.01	0.06	<0.01	0.08	<0.01	0.14	<0.01
j)	0.04	< 0.01	0.06	0.01	0.06	0.01	0.07	0.01
k)	0.02	< 0.01	0.07	<0.01	0.06	<0.01	0.07	<0.01
l)	0.02	< 0.01	0.03	<0.01	0.05	<0.01	0.12	<0.01

TABLE V
THE NUMBER OF EDGELS IN *AIRPLANE* AND *POUT* IMAGES

Image	Original	Linear stretch	Histogram equalized	EVOLEHA
b) *airplane*	3067	3067	3008	3261
g) *pout*	1492	1492	1937	2039

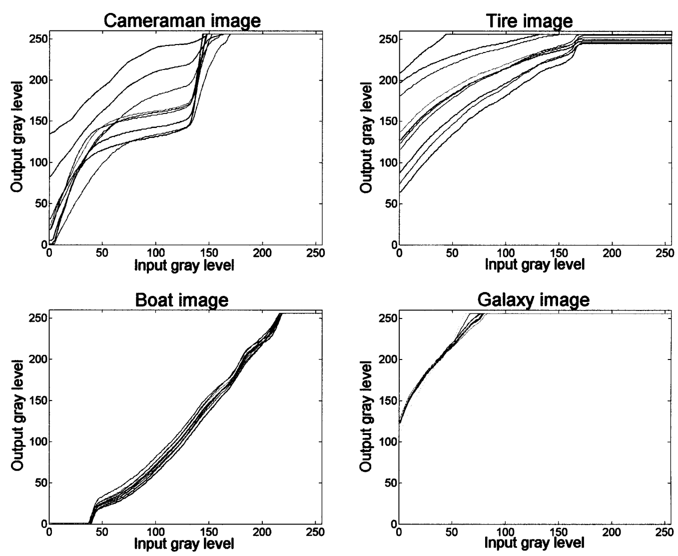

Fig. 6. Input-output gray-level transformation for EVOLEHA.

all the curves have the same shape and are clustered together (i.e., they are similar). Improvement of robustness may be achieved by increasing the maximum number of generations the GA is let to run.

D. Discussion of Results

Summarizing the results obtained, our GA-based method proved to be efficient in image enhancement. Both human subjective evaluation and objective criterions like DV-BV and "number of edgels," point out that our method produces better images than the classical linear contrast stretching and histogram equalization techniques, for a diverse set of images. On several images like *abdomen*, *head*, *eight*, *tire*, *autumn*, and *galaxy*, our EVOLEHA method achieved spectacular results. In terms of robustness EVOLEHA obtains similar results on different independent runs for one given image. Thus, we conclude that besides being efficient EVOLEHA is also robust. In terms of computational complexity, for the moment, EVOLEHA is a heavy algorithm. This is mainly because the GA requires making a series of trial enhancements until producing the final good result. Typically, EVOLEHA runs between 10–15 min on a computer with a 600 MHz processor and 512 MB RAM, while the other two methods run bellow one minute on the same computer. A substantial gain in speed can be attained by distributing the individuals of the GA (enhancements/evaluations) on several processors working in parallel. This is in agreement with the modern view that fast GAs can be implemented as parallel algorithms [9].

VI. Conclusions

In this paper we propose a new approach to automatic image enhancement using real-coded GAs. Results obtained indicate that EVOLEHA outperforms the classical point operations (linear contrast stretching and histogram equalization), which are also automatic methods, in terms of high effectiveness on a large category of images. The method applies a real-coded GA with significant modifications like PCA-mutation, in order to attain better explorative behavior. The search is well-balanced and robust due to a more exploitative crossover and selection scheme. Automatic behavior was achieved by specifying a suitable objective evaluation function proportional to the number and intensity of edgels and to the entropic measure of the image. The GA evolves the parameters of a local enhancement method (i.e., enhancement kernel) that better adapts to the local features in the image, in comparison to linear contrast stretching and histogram equalization that treat the image globally.

EVOLEHA achieves a combined goal (e.g. efficiency, robustness, wide applicability) that is not attained by other known enhancement methods. EVOLEHA can be viewed as the best choice for a first-step preprocessor on virtually any kind of gray-scale images.

The proposed algorithm may be extended in several ways, such as: fine-tuning the GA parameters in order to reduce the population size and the maximum number of generations required. A more substantial extension is to be researched, in which the chromosome will code local parameters of the method that applies to each neighborhood. Another possible extension of EVOLEHA would be introducing specialized criteria into the evaluation function in order to better enhance specific categories of images, such as: biomedical images, satellite images, images that appear in print. The tradeoff between efficiency and computational cost will be further investigated, and a parallel version of EVOLEHA will be tested.

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