Hybrid Ant Colony Optimization, Genetic Algorithm, and Simulated Annealing for Image Contrast Enhancement

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***Abstract*—In this paper, we propose a hybrid algorithm including Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Simulated Annealing (SA) metaheuristics for increasing the contrast of images. In this way, the contrast enhancement is obtained by globally transformation of the input intensities. ACO is used to generate the transfer functions which map the input intensities to the output intensities. SA as a local search method is utilized to modify the transfer functions generated by ACO. GA has the responsibility of evolutionary process of ants' characteristics. The results indicate that the new method performs better than the previously presented methods from the subjective and objective viewpoints.**

Index Terms*—Image Processing, Image Contrast Enhancement, Ant Colony Optimization, Genetic Algorithm, Simulated Annealing, Hybrid Metaheuristics.

I. Introduction

CONTRAST enhancement is one of the key steps in image enhancement. It is used for expanding the range of intensities in a gray scale image, revealing parts of image which are seen difficult, or changing the histogram of images so that they can be interpreted more easily by human. In addition to improve visual perception of an image, contrast increasing is a common preprocessing stage of many image processing applications.

On the other hand, metaheuristics like genetic algorithm (GA), simulated annealing (SA), and ant colony optimization (ACO) are guided random searches to find an optimum solution usually in large search spaces (because of difficulties that the classic methods may have in large search spaces). Genetic algorithm is a global search method which is inspired from the natural evolution. It has advantage of fast convergence, but as a drawback it cannot use system's feedback and hence it has low efficiency in finding accurate best solution [1]. Ant colony optimization is based on the natural pheromone trail deposition and attraction of ants when they seek for food. It uses positive feedback for quick discovery of good solutions. Simulated annealing is originated from heating and then slow cooling in metallurgy annealing process. Although SA searches locally, but in high temperatures it can select worse solutions so that it can escape local optimum. SA has the property of a global metaheuristic.

Recently, hybridization of metaheuristics has been received great interest. Simulated annealing is often used as a local search in combination with other methods. Various combinations of ant colony optimization and genetic algorithm have been proposed. In [2], GA sets the controlling parameters of ACO. In [3], ACO is used as a local search for GA. In [4], GA and ACO run in parallel and the best solution of them is selected.

One of the interesting applications of metaheuristics is in image processing. In [5], [6], and [7] ACO is applied for edge detection, threshold, and segmentation of images, respectively. In [8] and [9], GA is used for global transformation of intensities. In [10] and [11], local image enhancement is performed by GA and particle swarm optimization.

In this paper, we use global contrast enhancement in the sense of intensity transformation of gray scale images. Transfer function, which maps the input intensities to the output intensities, can have enormous number of forms. Hence, metaheuristics are good candidates to perform the optimization in this large search space. We propose a hybrid method which is a combination of GA, ACO, and SA. In the new method, ACO generates transfer functions by moving ants. The characteristics and moving directions of ants are set by GA automatically. This causes GA generally affects the searching process since it is able to quickly find the correct global optimum. Also, SA as a local search modifies and enhances the transfer functions and pheromone traces generated by ACO. The proposed fitness criterion does not need subjective evaluation of users [8], [12] and it has no external parameters, i.e. it is not case dependent and not determined by user [9]. We compare the results with the previously presented researches. The experimental results show that the new method outperforms the other ones.

The rest of the paper is organized as follows. In Section II, the proposed hybrid method is explained. In Section III, we present experimental results and compare with several common methods. Finally, Section IV concludes the paper.

II. Proposed Contrast Enhancement Mechanism

In the proposed method, by mapping the input intensities to the new output intensities according to a transfer function, low contrast images are converted to high contrast ones. The range of intensities in a gray scale image is between 0 and

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255. Hence, the transfer functions generated by ACO and SA map the input intensity range to interval 0 to 255. Fig. 1 shows a typical transfer function.

A. Hybrid Plan

The flowchart of the hybridization plan is illustrated in Fig. 2. As shown, each individual in GA sets the parameters of two ants in ACO. Then, ants generate transfer functions. In the SA phase, a predefined number of ACO's last run transfer functions are selected randomly and some random points in each transfer function are chosen. Finally, SA optimizes each selected point and its neighbors for a predefined number of cycles. Hybridization is performed by using GA and SA alternately between ACO iterations. GA controls the parameters of ACO and ants' moving directions, so it needs to be run several times at the first stages of algorithm in order to reach the near optimum solution. SA as a local search is run frequently at the last stages of algorithm to yield better solutions and to optimize pheromone trails. In addition, in SA, the number of transfer functions, points of each transfer function to be optimized, and the number of optimization process cycles increase in the later stages. Fig. 3 shows the execution process of GA and SA in a complete run of the hybrid algorithm. In order to have a uniform processing time in different runs of algorithm for an image, the stopping condition is a predefined number of ACO iterations (we assumed 100). Different stages of the proposed hybrid algorithm are illustrated in Fig. 4.

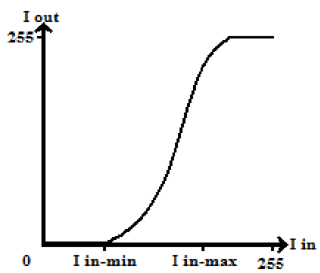

Fig. 1. A typical intensity transfer function.

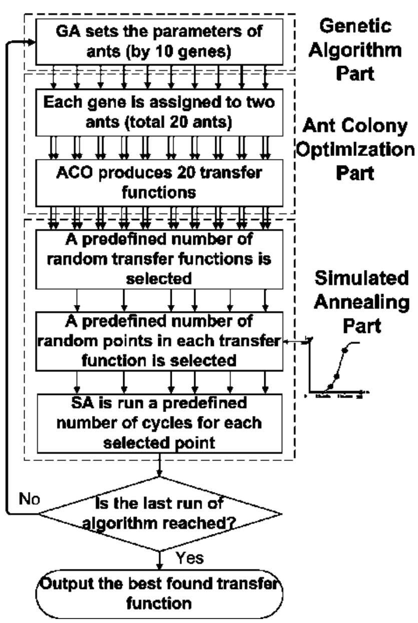

Fig. 2. Flowchart of the proposed algorithm.

Fig. 3. GA and SA schedule in hybrid plan.

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0-All reserving variables⇨0
1-Generate initial population of GA
2-Set initial temperature
3-While (iteration<max_iteration_number)
{4-ACO (ants generate transfer functions)
5-Fitness estimation of generated transfer functions
6-If (any_of_new_fitnesses>best_fitness) then take new fitness as
  best found and save its pheromone trail and transfer function
7-If it is SA's turn, then
  7.1-For (some_of_ACO's_last_run_transfer_functions)
       For (some_points_of_selected_transfer_function)
        For (a predefined number of cycles)
         7.1.1-Edit selected transfer function
         7.1.2-Fitness calculation of new transfer function
         7.1.3-Based on P(old_fitness,new_fitness,temperature)
               decide to replace previous transfer function and
               related pheromone trail and fitness with new ones
  7.2- If (any_of_new_fitnesses>best_fitness) then take new fitness
     as best found and save its pheromone trail and transfer function
  7.3-Decrease temperature
8-If it is GA's turn, then
  8.1-Evaluate fitness of each individual
  8.2-If (fitness_of_each_individual>GA_best_fitness) then take
      new GA fitness as best found and save its related chromosome
  8.3-Selection→Reproduction→Replacement
  8.4-If it is last turn of GA assign best chromosome to parameters
      of all ants
9-Pheromone update}
10-Return best found transfer function as output
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Fig. 4. Pseudo code of hybrid algorithm.

B. Ant Colony Optimization Part

The basic component of ACO is a dynamic evaluation value (pheromone) which has effect on ant's decision for moving. Solution construction and pheromone update are two common stages in ACO iterations. In addition to pheromone, the static evaluation value (heuristic value) is another effective parameter in ant's decision.

Generation of mapping functions is performed by ants' movement from point $I_{in}=I_{in\text{-}min}$, $I_{out}=0$ to the point $I_{in}=I_{in\text{-}max}$, $I_{out}=255$, as shown in Fig. 1. Note that points with $I_{in}<I_{in\text{-}min}$ are mapped to $I_{out}=0$ and points with $I_{in}>I_{in\text{-}max}$ are set to $I_{out}=255$. Selection of the next point to move is based on the roulette wheel technique. The selection probability (P) for each neighbor point of ant is presented as:

$$P = \frac{(1+\tau_i)^{\alpha}\times((1+(\frac{k_i}{\gamma})^{10})\times\eta_i)^{\beta}}{\sum_{i\in G(i)}(1+\tau_i)^{\alpha}\times((1+(\frac{k_i}{\gamma})^{10})\times\eta_i)^{\beta}} \qquad (1)$$

where the parameters α and β control the relative importance of pheromone trail against heuristic value. $G(i)$ is the set of neighborhood points around ant. τ_i is the pheromone amount exists in a neighbor point. In order to avoid the zero probability in areas with no pheromone, the value 1 is added to τ_i . η_i is a heuristic value that for the neighbors of ant is set according to Fig. 5.

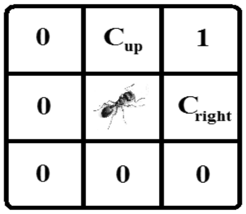


Fig. 5. Heuristic value of ant's neighborhood.

Neighborhood's heuristic values are set aiming to have monotonically increasing transfer function. Also in (1), for up and right directions, k_i is set to I_{in}–$I_{in\text{-}min}$ (horizontal axis) and I_{out} (vertical axis) for the current position of ant and for the other neighbors it is set to zero. The parameter γ helps ants move to target, considering:

$$if\ \frac{k_i}{\gamma} < 1 \rightarrow \left(\frac{k_i}{\gamma}\right)^{10} < \frac{k_i}{\gamma},\ if\ \frac{k_i}{\gamma} > 1 \rightarrow \left(\frac{k_i}{\gamma}\right)^{10} > \frac{k_i}{\gamma} \qquad (2)$$

The power exponent 10 gives enough strength to the technique explained in (2). Considering the ratio of $\frac{k_i}{\gamma}$ and the values of k_i, we can conclude that if an ant excessively moves up (i.e. increasing I_{out}), then the probability of moving to right (with k_i=I_{out}) increases, as follows:

$$if\ (I_{out}\uparrow)\ \&\ (I_{out} < \gamma) \rightarrow P_{right}\uparrow \qquad (3\text{-a})$$

$$if\ (I_{out}\uparrow)\ \&\ (I_{out} > \gamma) \rightarrow P_{right}\uparrow\uparrow \qquad (3\text{-b})$$

The above is true for the probability of up direction if ant moves to the right. Thus, this technique exponentially reminds the ants to go to the last point (i.e. I_{in}=$I_{in\text{-}max}$, I_{out}=255). However, if ants continue their way and reach the border of map (that is, I_{in}=$I_{in\text{-}max}$ or I_{out}=255), they will be guided toward the last point automatically.

The parameters α, β, γ, C_{up}, and C_{right} are set by genetic algorithm. Also, note that the value of γ which comes from GA, is assumed for vertical direction (upside movement of ants) with the range of 255 and it needs to be adjusted automatically for horizontal direction (right side movement of ants) with the range of $I_{in\text{-}max}$-$I_{in\text{-}min}$.

We found that a population of 20 ants has good behavior. After all ants move from the start point to the last point, SA modifies the recent pheromone trail and transfer functions of ants. Then the global pheromone update is performed as:

$$\tau_{ij}(t+1) = (1-\rho)\times\tau_{ij}(t) + \sum_{l=1}^{20}\Delta\tau_{ij}^{l}(t) \qquad (4)$$

where ρ is the evaporation rate equal to 0.4. $\Delta\tau_{ij}^{l}$ is the amount of pheromone deposited between points i and j by the *l-th* ant (which can be changed by SA) and it is equal to $\frac{F}{30\times BF}$. F is the fitness function value of the *l-th* ant (transfer function can be changed by SA). BF is the best found fitness value. It makes pheromone deposition be normalized, since fitness values may have various amounts for different image sizes. Also, 30 in the denominator is to normalize the value of τ_i in contrast to other parameters in (1).

The proposed ACO also has elitism attribute. Deposited pheromone by the best found solution is equal to $\frac{\rho}{4}\times\Delta\tau_{ij}^{BF} = \frac{\rho}{4}\times\frac{BF}{30\times BF} = \frac{\rho}{4}\times\frac{1}{30}$.

C. Genetic Algorithm Part

Genetic algorithm is used in the hybrid algorithm for facilitating faster convergence of ACO. The fundamental parts of GA are encoding, selection, and reproduction. The five parameters of the ACO part (α, β, γ, C_{up}, and C_{right}) are encoded as a real coded chromosome with five genes. We consider 20 ants and total 10 chromosomes, where each chromosome is responsible for adjusting the parameters of the two ants. At the end of each generation, the individuals in the population copy their values to the parameters of the corresponding two ants. The ranges of α and β are from 0 to 5. γ varies between 100 and 250. The ranges of C_{up} and C_{right} are set from 0 to 3.

Parent selection is based on the roulette wheel technique. After all individuals were evaluated by the GA fitness function, two of them are selected to breed two offspring. Replacement of the worst individual and weaker parent by two new offspring produces the next generation. If the worst individual and the weaker parent are identical, then the two worst individuals will be replaced by the two new children. The procedure guaranties survival of the fittest so this genetic algorithm is elitist.

The fitness function for GA is defined as:

$$F^{GA} = F_{mean}^{ant1} + F_{mean}^{ant2} + F_{best\,found}^{ant1,2} \qquad (5)$$

where F^{GA} is the estimated fitness for each individual, F_{mean}^{ant1} and F_{mean}^{ant2} are the average fitness of transfer functions created by the two corresponding ants in ACO's iterations run between the two GA generations. $F_{best\,found}^{ant1,2}$ is the best found fitness value in the mentioned procedure.

Reproduction stage is carried out by crossover and mutation operators. Uniform crossover is used with the probability of 0.85. Each offspring has mutation probability equal to 0.05. Utilized mutation operator just changes one gene of chromosomes with the restriction of -10% to 10% of the original value of that gene.

D. Simulated Annealing Part

The essential components of SA method are neighborhood definition, probability function, initial temperature, and cooling schedule. In our work, SA optimizes the best found transfer function and some other transfer functions created by the last run of ACO. We use random points as the starting points in the selected transfer functions. Also ant's pheromone trail relative to its optimized transfer function is adjusted according to changes made in the transfer function.

Fig. 6 depicts the neighborhood of each point in the transfer function and the resulting action of choosing one of the neighbors. Hollow circle shows the active point (point to be optimized in next cycle) and the filled circle demonstrates the modified location of current selected point or its adjacent points. Note that, in the neighborhood of SA, only the neighbors are allowed in which monotonically increasing form of transfer functions is preserved. Further, if at last none of the neighbors of the current point are selected (regarding the probability function), then the optimization of

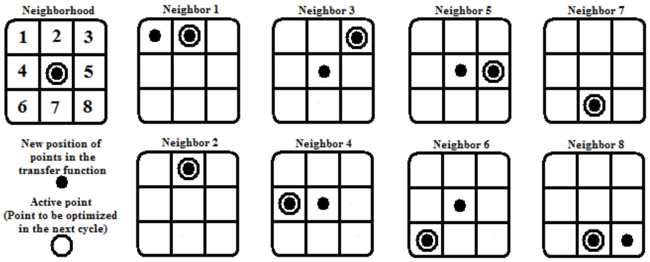


Fig. 6. Neighborhood of each point in SA and resulting action of choosing each of them.

that point will be terminated (i.e. that point is a local optimum).

The probability function for selecting a neighbor based on the analogy with physical systems is defined as:

$$\begin{cases} P = e^{\frac{F^{new}-F^{old}}{0.05\times F^{old}\times T}} & if\ F^{new} < F^{old} \\ P = 1 & if\ F^{new} > F^{old} \end{cases} \tag{6}$$

where F^{new} is the resulted fitness value, F^{old} is the current fitness value, and T is the temperature. The Initial temperature was set to 200. The cooling schedule for the proposed hybrid model is defined as:

$$T(t+1) = T(t) \times 0.5 \tag{7}$$

A. Fitness Criterion

Fitness function is the bottleneck of the work from the point views of quality of the obtained images and computational cost. Automatic image enhancement needs a fitness function independent from any parameter which should be set by human (such as the parameters used in [9]). On the other hand, only multiplication of operands (as used in [10], [11]) is not enough. The reason is that if a processed image has lower values in all operands in contrast to the original image, then multiplication of operands in the fitness function shows extra low value for weaker image. In order to overcome the mentioned problems, we define the fitness function as the geometric mean of the operands as follows:

$$F = \sqrt[3]{STD \times ENTROPY \times SOBEL} \tag{8}$$

where *STD* is the standard deviation of intensities (contrast measure), *ENTROPY* is the entropy (randomness measure) of gray levels in image, and *SOBEL* is defined as:

$$SOBEL = mean(|sobel_{vertical}| + |sobel_{horizontal}|) \tag{9}$$

where $sobel_{vertical}$ and $sobel_{horizontal}$ are the images obtained by applying the vertical and horizontal sobel operators, and *mean*(.) operator denotes the averaging. Sobel as a gradient operator is used for edge detection of images.

Equations (8) and (9) show that the proposed algorithm searches for large global standard deviation (in the sense of high global contrast) and large entropy image forms. Entropy factor guaranties that images seem more natural, since it prevents image binarization. This method also attempts to increase the edges of images (as high contrast images have more edges). Note that the other complicated measures could be used for fitness function, but due to their high computational cost we did not use them.

III. Experimental Results

In order to evaluate the efficiency of the proposed algorithm, we apply it to the several test images used in the literature. The iteration number is set to 100. We also apply several other enhancement methods to compare them with the proposed method. Fig. 7 illustrates the result of applying the new method, linear contrast stretching, histogram equalization, and fuzzy technique (with the rules described in [13]) to three test images. We observe that the proposed method has better performance.

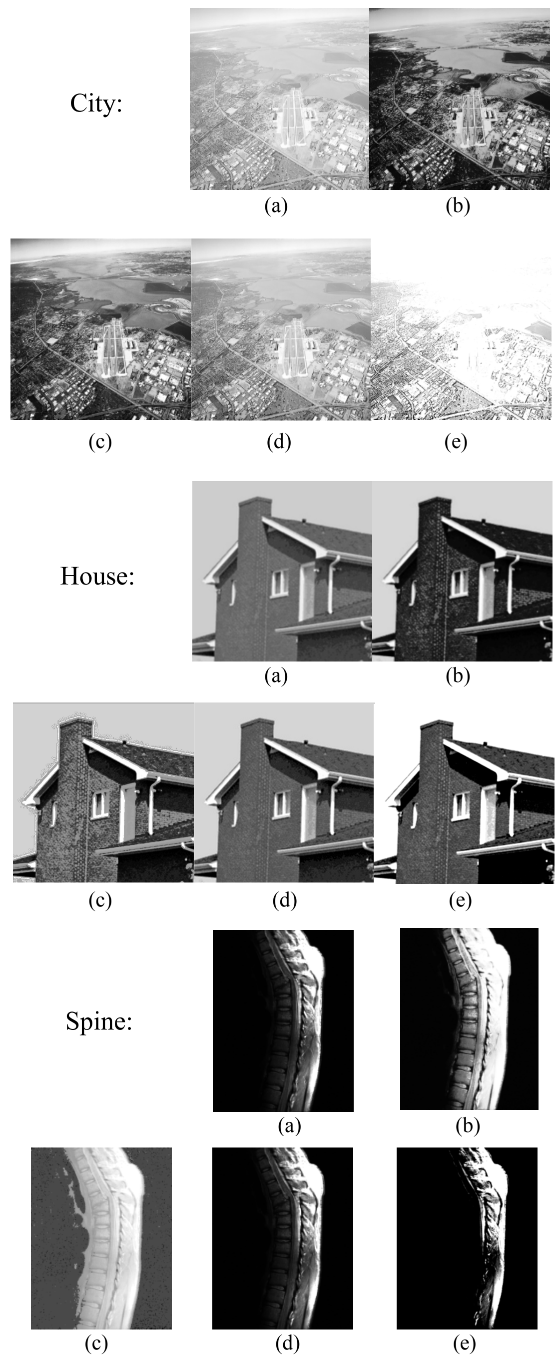


Fig. 7. Results of the proposed and classical enhancement techniques: a) original b) proposed method c) histogram equalization d) linear contrast stretching e) fuzzy method.

Furthermore, Fig. 8 shows the efficiency of our technique compared to the above mentioned methods and the methods of [10] and [11]. Fig. 9 depicts the transfer functions obtained by applying of the proposed method to the test images. Also, Fig. 10 demonstrates the final pheromone trail of ants in search panel. It is observed that ACO converges in all cases.

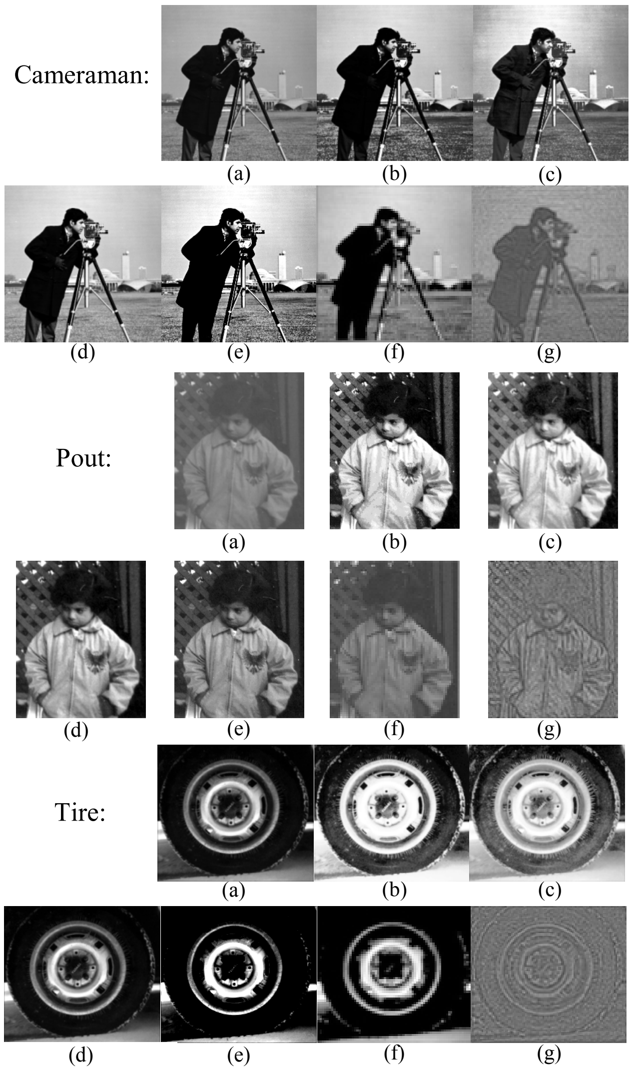


Fig. 8. Results of different enhancement methods: a) original b) proposed method c) histogram equalization d) linear contrast stretching e) fuzzy method f) method of [10] g) method of [11].

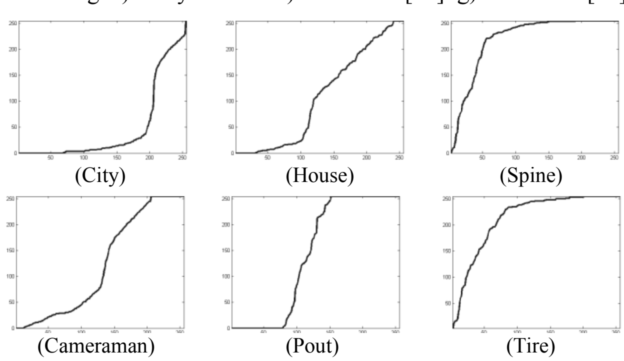


Fig. 9. Transfer functions obtained by the proposed method for test images (horizontal axis and vertical axis are the input intensity and output intensity, respectively).

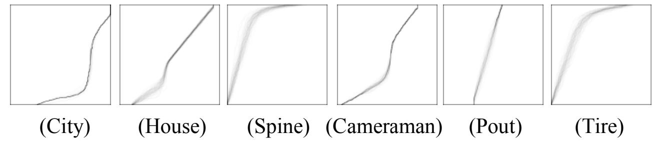


Fig. 10. Final pheromone trail of ants in search space (lower bound is input intensity axis and left bound is output intensity axis).

In order to verify the proposed technique, Tables I and II present the values obtained by the two statistical criteria for different methods. Uniformity and contrast are two descriptors of co-occurrence matrix [13]. High values of contrast and low values of uniformity are desirable. It is observed that the proposed method satisfies the above two criteria better than the other techniques. Table III shows the fitness function values defined in (8) for different methods. As expected, the proposed algorithm has higher fitness values. Detail variance (DV) and background variance (BV) are the other objective measurements [14]. It is desirable that the enhancement methods result in image with higher DV compared to the original image while the BV does not change. Table IV shows the DV and BV of all test images for different methods. We again observe that the new method satisfies the above criteria better in comparison with the other methods.

Table I. Uniformity descriptor for experimental images.

Image	Original	Proposed Method	Histogram Equalization	Linear Contrast Stretching	Fuzzy
City	0.20	0.10	0.05	0.13	0.53
House	0.26	0.21	0.13	0.18	0.23
Spine	0.50	0.40	0.34	0.50	0.73
Cameraman	0.16	0.13	0.07	0.14	0.13
Pout	0.28	0.08	0.07	0.10	0.16
Tire	0.23	0.09	0.06	0.22	0.50

Table II. Contrast descriptor for experimental images.

Image	Original	Proposed Method	Histogram Equalization	Linear Contrast Stretching	Fuzzy
City	0.55	1.55	1.18	0.86	1.41
House	0.05	0.12	0.18	0.10	0.12
Spine	0.08	0.16	0.10	0.15	0.08
Cameraman	0.50	1.04	0.73	0.74	1.16
Pout	0.08	0.33	0.29	0.26	0.19
Tire	0.23	0.58	0.47	0.23	0.34

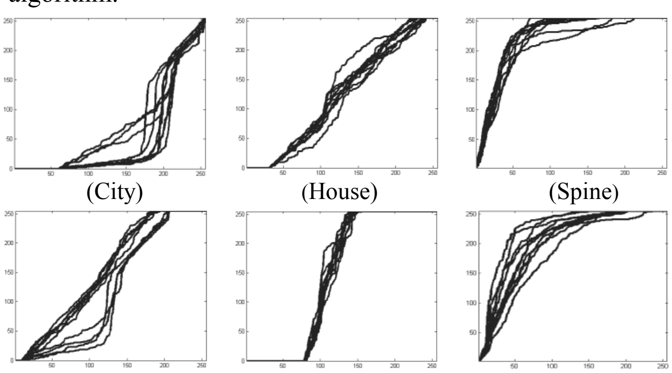
Table III. Fitness values of experimental images.

Image	Original	Proposed Method	Histogram Equalization	Linear Contrast Stretching	Fuzzy
City	25.40	34.38	33.50	29.11	18.84
House	19.17	24.57	24.11	21.45	23.31
Spine	14.50	17.32	14.84	14.50	9.65
Cameraman	24.95	29.77	27.69	28.49	29.32
Pout	13.39	28.89	27.72	26.19	22.39
Tire	25.89	31.63	28.89	26.12	18.81

Table IV. Detail and background variances of the experimental images (using a 3×3 local STD mask. Threshold limit of DV and BV is 30).

Image		City	House	Spine	Cameraman	Pout	Tire
Original	DV	47.30	34.95	44.84	53.42	34.00	41.45
	BV	8.47	3.48	2.05	5.61	3.18	7.44
Proposed Method	DV	63.31	41.81	46.81	56.80	42.38	48.26
	BV	8.19	4.95	2.92	5.32	9.47	8.93
Histogram Equalization	DV	56.28	40.64	35.63	60.38	41.18	43.27
	BV	11.57	6.59	1.73	8.77	9.77	10.86
Linear Contrast Stretching	DV	54.22	36.65	44.84	61.35	44.59	41.60
	BV	9.12	3.90	2.05	6.60	8.25	7.50
Fuzzy	DV	72.39	45.95	53.58	60.30	43.68	53.53
	BV	3.56	4.07	1.11	5.87	6.60	3.25

Repeatability of the proposed algorithm can be proved by Fig. 11 which shows the obtained transfer functions for each of ten times run of algorithm for each test image. As illustrated, the resulted transfer functions almost have the same shape in different runs. However, in some cases it is observed that more than one optimum exist on the transfer function pane as in the case of *cameraman* image. Thus, another measure is needed to evaluate the robustness of the new method. Table V illustrates the average and standard deviation of DV, BV, and fitness values of ten times run of the algorithm. It is observed that the STD values are low compared to the corresponding average values which it means different runs achieve almost the same response. However, it should be noted that the proposed method takes rather more time compared to the classical methods. Global transformation has advantage of being faster than the local processing of images [10], [11]. On the other hand, simulated annealing is used in our method to emphasis the quality, although it increases computational cost of the algorithm.



(City) (House) (Spine)

(Cameraman) (Pout) (Tire)

Fig. 11. Transfer functions obtained from each of ten times run of the proposed algorithm for test images (horizontal axis and vertical axis are input intensity and output intensity, respectively).

Table V. Average and standard deviation of DV, BV, and fitness of ten times run of the proposed algorithm.

Image	Fitness		DV		BV	
	Average	STD	Average	STD	Average	STD
City	33.91	1.15	62.64	7.32	8.79	1.63
House	16.66	0.21	38.83	1.65	2.47	0.28
Spine	17.03	0.27	43.59	1.29	2.54	0.07
Cameraman	29.90	0.29	59.47	1.72	5.90	1.26
Pout	29.34	0.27	43.14	1.90	9.24	0.48
Tire	31.64	0.32	50.61	2.73	8.26	0.58

IV. Conclusions

In this paper, a new hybrid approach was presented to enhance the contrast of images. The proposed SA and ACO are novel approaches used in the global transformation of images. The proposed GA helps in the automation of method. The fitness function used in this work is an improved criterion which results in good performance. It makes the processed images seem natural. We compared the new method with several commonly used techniques such as linear contrast stretching, histogram equalization, fuzzy, and the methods of [10] and [11]. The results indicate that the new method outperforms the above mentioned techniques from the subjective and objective viewpoints. We also found that the proposed method satisfies the desirable uniformity, contrast, DV, and BV values better than the other methods. The new method can be used to improve images from point view of human observer or as a preprocessing task for other image processing applications. Future works can be applying SA and ACO separately.

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