Presentation of Robust Method in Image Contrast Enhancement Using Particle Swarm Optimization

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Abstract- One of the most important processes in digital image processing is image contrast enhancement. Contrast enhancement may be itself a primary objective of the process or is performed as one of the pre-processing stages in order to obtain better quality for operating next major stages such as detection. In this thesis, multiobjective developed Particle Swarm Optimization (PSO) algorithm use to enhance gray digital image contrast so that image information content is maximized and also the mean intensity of the image is preserved as much as possible. The proposed method will be implemented on different images.

Keyword: Image contrast enhancement, Entropy, Mean intensity, Particle Swarm Optimization algorithm, Multiobjective optimization, Gamma Correction.

1. INTRODUCTION

Contrast enhancement for gray-level images which is implemented in form of histogram transformation [5], is considered as one of the basic processes which facilitates the next higher level operations such as detection and recognition. Color images can be enhanced by separating the color and intensity components [6]. Image contrast enhancement can be performed using hardware techniques or software algorithms. Most proposed software methods for enhancing the contrast are based on manipulate in image histogram by some transformation functions to achieve desirable contrast enhancement. As a result, this process will also receive the most information in the image which is available in result of efficient usage of gray-level. In [8], a local histogram transformation has been used to obtain the contrast enhancement in the particular interesting areas of the image. However, in this method overall intensity has been changed and it may be decrease easy viewing. To take into account of the created disturbance in overall intensity, a Bi-histogram transformation approach has been proposed for enhancing contrast [9],

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however the information content may be reduced. Similar methods also have been presented in [10] and [11] in which histogram was divided into linear parts. Modifications on histograms have been created by considering human visual properties for easy viewing [12] and resultant histograms on nonlinear curves [13]. This method is typically used in display device and is known as gamma correction [14-16]. Moreover, desirable visual effects can be imported by appropriate adjustment of gamma factor.

It is desirable that mean intensity should be considered for observation fitness in addition to achieving maximum information for effectiveness of observation. Therefore, a multiobjective solution is naturally required especially arise when the objectives of intensity maintenance and contrast enhancement are in contradiction. This leads to use of evolutionary computational techniques such as genetic algorithms [18] and [19], which their flexibility is considerable in confronting of multiobjective problems. Particle swarm optimization algorithm [20-21] is considered due to their simplicity in implementation. In comparison to genetic algorithm, PSO does not require selection, crossover and mutation operations. Taking advantageous of PSO in contrast enhancement [22] and other issues [23-28] are presented.

In this study, PSO improvement methods are discussed for multiobjective optimization in contrast enhancement. In the following we describe first animal herding algorithm. Then, the gamma correction and the used value function were described and finally we present the results of multi-image contrast enhancement.

2. PSO algorithm

Swarm intelligence is a kind of artificial intelligence which is based on collective behavior in self-organized and decentralized systems. These systems are usually consisted of a population of simple agents which interact locally with each other and their environment. Although usually no centralized control does not impose modality of agent behavior on them, their local interactions lead to the emergence of public behavior. Examples of such systems can be found in nature like ant colonies, bird flocking, bacteria growth and fish schooling.

In fact, PSO algorithm is composed of a curtain number of particles which are randomly initialized. For each particle are defined two values of velocity and position which are modeled with a velocity and position vectors, respectively. These particles fly iteratively around in n-dimensional space to search new possible options by calculating optimality value as a measure criterion. The dimension of problem space equals to the number of parameters in corresponding function for optimization. To each particle were assigned two best memories. The first one is the storage of the best position of each particle achieved in the past and another one is that, the storage of best position arisen among all particles. With this experience from memories, the particles decide how to move in the next step (iteration). In each iteration, all particles move in
n-dimensional space of the problem until the general optimum point is found. A particle updates its velocity and position in terms of the best local and absolute solutions. It means

\[
V_{m,n}^{\text{new}} = V_{m,n}^{\text{old}} + \tau_1 \cdot r_1 \cdot (p_{m,n}^{\text{local best}} - p_{m,n}^{\text{old}}) + \tau_2 \cdot r_2 \cdot (p_{m,n}^{\text{global best}} - p_{m,n}^{\text{old}})
\]

\[
p_{m,n}^{\text{new}} = p_{m,n}^{\text{old}} + v_{m,n}^{\text{new}}
\]

Where
- \( v_{m,n} \), the particle velocity
- \( p_{m,n} \), the particle variables
- \( r_1, r_2 \), the independent random numbers with uniform distribution
- \( \Gamma_1, \Gamma_2 \), training factors
- \( p_{m,n}^{\text{local best}} \), the best local solution, and \( p_{m,n}^{\text{global best}} \), the best absolute solution.

PSO algorithm updates the velocity vector of each particle and then adds the new velocity value to the position or value of particle. Velocity updating affected by both the best local and absolute solution. The best local and absolute solution, are the best solutions which have been obtained by a particle and in whole population, respectively until the current time of algorithm implementation. Constants \( \Gamma_1 \) and \( \Gamma_2 \) called conceptional and social parameters, respectively. The main advantage of PSO is that the implementation of this algorithm is simple and it requires determining quantitative parameters. Also PSO is capable of optimizing a complex cost functions with large number of local minimum.

In the following shape has been shown PSO pseudo code.

**Step 1 (Initialization):** for each particle \( i \) in the population:

Step 1.1: initialize \( X_i \) randomly,
Step 1.2: initialize \( V_i \) randomly,
Step 1.3: evaluate \( f_i \).
Step 1.4: initialize \( P_i \) with the index of the particle with the best function value among the population.
Step 1.5: initialize \( P_i \) with a copy of \( X_i \), \( \forall i \leq N \).

**Step 2:** Repeat until a stopping criterion is satisfied:

Step 2.1: find \( P_i \) such that \( f[P_i] \leq f_i \), \( \forall i \leq N \).
Step 2.2: for each particle \( i \), \( P_i = X_i \) if \( f_i < f_{\text{best}}[i] \), \( \forall i \leq N \).
Step 2.3: for each particle \( i \), update \( V_i \) and \( X_i \) according to equation2 and 3.
Step 2.4: evaluate \( f_i \) for all particles.
3. Gamma Correction
Consider a uniform distribution that its corresponding cumulative distribution defined as:

$$\zeta = \{G_m \in [0, 1], m = 1..Z \}$$

And then using a power rule with factor $\gamma$, has been modified which is required to determine optimally.
As a special case we consider $\gamma = 1$ which displays uniform distribution. The mean intensity will be equal to $\bar{I} = 0.5(L - 1)$. Thus, gamma factor is obtained as follows:
\[ \gamma = \frac{\log\left(\frac{\bar{I}}{L-1}\right)}{\text{LOG}(0.5)} \]

And cumulative distribution generated by this gamma factor will be equal to:

\[ \zeta \leftarrow \zeta^{\gamma} \ast (L-1) \]

4. Contrast enhancement using multiobjective PSO

In PSO algorithm typically exist two absorption points for particles; the global best location \( x_{k}^{g} \) and the best experienced location \( x_{k}^{p} \). In the optimization problem discussed in this study which includes finding gamma factor optimally, there are two inconsistent objectives: 1- maintaining of mean intensity and 2- maximization of the image information content. Conventional PSO algorithm can be applied in a way which include different multiobjective optimization, called multiobjective particle swarm optimization (MPSO). In MPSO the equation of particle velocity updating is considered as:

\[ v_{k+1}^{i} = w^{i} v_{k}^{i} + c_{1}^{i} (\gamma_{k}^{M} - \gamma_{k}^{i}) + c_{2}^{i} (\gamma_{k}^{H} - \gamma_{k}^{i}) \]

Where \( \gamma_{k}^{M} \) and \( \gamma_{k}^{H} \) are the best solutions based on mean intensity and information content. Each particle of \( \gamma_{k}^{i} \) is applied as gamma factor for contrast enhancement and mean intensity and the corresponding information content are calculated as fitness. The best solutions for these two objectives are evaluated as follows:

\[ \begin{align*}
\gamma_{k}^{M} &= \{ \gamma_{k}^{M} (|M^m - M^0| < |M^i - M^0|), \forall m \neq i \} \\
\gamma_{k}^{H} &= \{ \gamma_{h} > H^h > H^i, \forall h \neq i \}
\end{align*} \]

Where the mean intensities \( (M^m, M^i, M^o) \) are calculated from equation * and superscript o represents the original image and entropy \( H^i \).

To consider the visual comfort of observer, the mean intensity maintenance may be prioritized to the information content maximally. But unlike the weighted sum approach, in this approach for MPSO does not require determining the weight for objectives by user. The best gamma factor is stored in each iteration to compare with new obtained values according to objectives in next iterations.
5. Results and Discussion
In figure 1 was shown the results of applying the used method on these images.

Figure 1: the used test images in the right and result of contrast improvement in the left
Table 1 compares the original image and its result in terms of entropy.

Table 1: The result of image improvement on image entropy

<table>
<thead>
<tr>
<th>Image</th>
<th>Entropy before improvement</th>
<th>Entropy after improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lenna image</td>
<td>7.51</td>
<td>7.9609</td>
</tr>
<tr>
<td>Tehran image</td>
<td>7.3245</td>
<td>7.5625</td>
</tr>
<tr>
<td>Gilan image</td>
<td>7.0121</td>
<td>7.6894</td>
</tr>
</tbody>
</table>

Also, average deviation values of mean pixel brightness are presented in below table for images after contrast improvement.

Table 2: The result of image improvement and deviation reduction of mean pixels

<table>
<thead>
<tr>
<th>Image</th>
<th>Mean deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lenna image</td>
<td>0.013641</td>
</tr>
<tr>
<td>Tehran city image</td>
<td>0.081017</td>
</tr>
<tr>
<td>Gilan image</td>
<td>0.0013533</td>
</tr>
</tbody>
</table>

6. Conclusions

In this paper, a method based on multiobjective particle swarm optimization has been studied for enhancing of digital image contrast and simulation and extraction results have been done. The objectives in corresponding optimization include the image entropy maximization as a criterion for image information content, and also lack of change in mean intensity of image (minimization of mean intensity deviation). In order to applying changes in images for enhancing contrast has been used of gamma correction method. To apply PSO algorithm for multiobjective optimization in this problem is considered each of the objectives optimization using an absorptive point for particle in search space. The solutions which are the best for each of the optimization objectives are considered as an absorptive point for other particles. The results of applying this technique on different images showed that this technique can enhance simultaneously the contrast image with increasing entropy and histogram change and also mean intensity image and as a result, can preserve visual comfort for observer.
REFERENCES


