

Optimal Parameter Tuning Based Multi-Scale Image Enhancement

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Abstract:

Image enhancement is the preprocessing technique of image processing. In this paper propose a Particle Swarm Optimization (PSO) method for tuning the parameters of multi-scale image enhancement is presented. The multi-scale such as Laplacian pyramid, discrete wavelet transform, stationary wavelet transform and dual tree-complex wavelet transform. These algorithms are used for multi-resolution decomposition. The image enhancement using multi-scale scheme heavily depends on the parameter such as Gaussian surround space constants, no of scales, gain, offset etc. Due to the hard selection of these parameters, PSO has been used in order to investigate the optimal parameters for the best image enhancement. The multi-scale image enhancement scheme is based on the luminance and contrast masking characteristic of the human visual system. The advantages of the proposed system are: 1) achieve both global and local enhancement simultaneously, 2) achieve dynamic range compression, 3) adjusting overall brightness, 4) optimal selection of parameters

Keywords: Multi-scale transform, Particle Swarm Optimization, luminance masking, contrast masking

I. INTRODUCTION

Image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing has many advantages over analog image processing. Image enhancement is to improve the visual quality of the image. There are two types of image enhancement. They are spatial domain, Frequency domain. Spatial domain techniques directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. Spatial techniques are particularly useful for directly altering the gray level values of individual pixels and hence the overall contrast of the entire image.

Frequency domain techniques are based on the manipulation of the orthogonal transform of the image rather than the image itself. Frequency domain techniques are suited for processing the image according to the frequency content. The advantages of the image processing are computer vision, face detection, feature detection, medical image processing, microscopic image, remote sensing [5].

The paper arranged as follows. Section II reviews the existing techniques. Section III describes the process and implementation of the proposed algorithm. Section IV is experimental results Section V is conclusion and remarks.

II. EXISTING ALGORITHM

In the last two decades, various image enhancement algorithms have been proposed. Image

enhancement algorithms can be classified into two categories either direct or indirect enhancement algorithms. Indirect enhancement algorithms enhance the image without explicitly defining and measuring image contrast. Such algorithm includes Histogram Equalization (HE).

HE over enhances many of the image details. Many of the indirect enhancement algorithms simply define a global or adaptive one-to-one mapping by which the intensity values of individual pixels are modified [6]. Because these approaches do not directly measure image contrast, they can often times yield inadequate detail preservation or over enhancement.

A direct image-enhancement algorithm is proposed for screening mammograms. The algorithm is based on a multi scale contrast measure defined in the wavelet domain [7]. Frequency domain methods operate on transforms of the image, such as the Fourier, wavelet, and cosine transforms [3]. Single-scale center/surround retinex to a multi-scale version that achieves simultaneous dynamic range compression/color consistency/ lightness rendition [2]. These algorithms doesn't provide the local and global enhancement simultaneously.

Transform based histogram are based on the properties of the logarithmic transform domain histogram and histogram equalization [4]. Unsharp masking algorithm enhance the contrast of specific regions, objects and details too bright [9]. A multi scale contrast measure defined in the wavelet domain which use the multi scale algorithm [7].

Laine's [11] and Tang's [12] algorithms are able to enhance the contrast of some of the image structures, but cannot equalize or provide the necessary brightness. The existing multi-scale image enhancement algorithm measures the contrast at multiple scales. Based on the measurement the image contrast is enhanced. In multi-scale image enhancement algorithm produce approximation coefficients at different scales and the algorithm cannot automate the approximation coefficients [1]. The proposed method is able to visually pleasing brightness and enhances fine detail.

III. PROPOSED ALGORITHM

In above details it was found that the existing algorithms would not be able to handle the parameters optimally [1]. To handle this problem Particle Swarm Optimization algorithm is used for optimal selection of parameters.

Here propose optimal parameter tuning based multi-scale image enhancement. Multi-scale image enhancement is measured by multiple transforms such as Laplacian Pyramid, Discrete Wavelet transform, Stationary Wavelet transform and Dual tree Complex Wavelet transform. The image contrast at many different scales can be measured and subsequently enhanced. Each scale produce the approximation coefficients. Due to the hard selection of these approximation coefficients PSO algorithm is proposed.

PSO has been used in order to investigate the optimal parameters for the best image enhancement. The objective of the proposed PSO is to maximize an objective fitness criterion in order to enhance the contrast and detail in an image by adapting the parameters of a novel extension to a local enhancement technique.

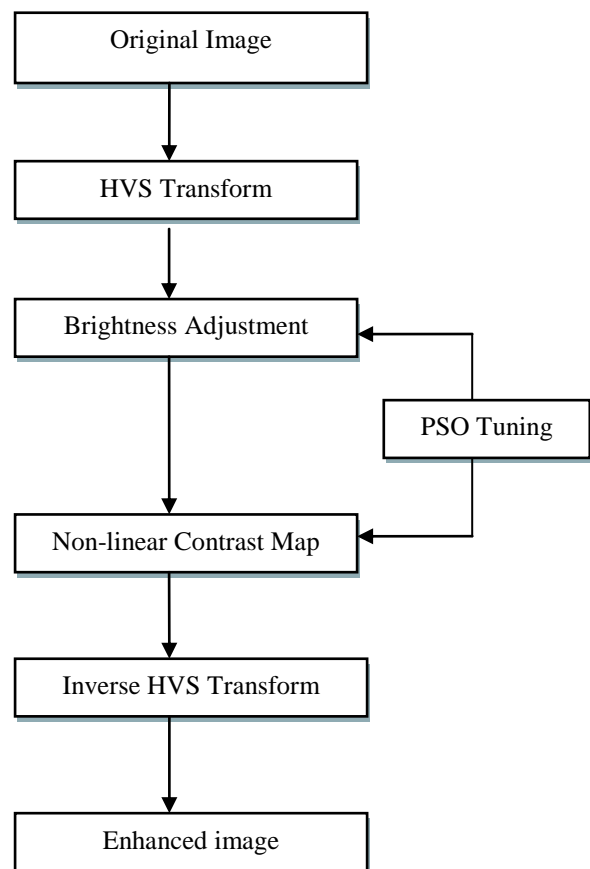


Fig 1: Proposed System Architecture

The proposed system has four modules. They are

1. Multi-Resolution Decomposition
2. Brightness adjustment
3. Non-linear contrast mapping
4. PSO tuning

A. Multi-Resolution Decomposition

The original image is decomposed into subbands by using the pyramidal scheme such as Laplacian pyramid (LP) and wavelet based decomposition scheme such as Dual Tree complex Wavelet Transform (DT-CWT), Stationary Wavelet Transform (SWT) [1]. These multiple transforms measure the luminance and contrast coefficients.

In multi-scale transformation the image is represented as I . Each transform generate the approximation coefficients $y_0^{(n)}$ and detail coefficients $y_1^{(n)}$ at scale n . Initializing $y_0^{(0)} = I$ the approximation coefficients at a scale are generated by using Eq(1) and Eq (2)

$$y_0^{(n)} = REDUCE [y_0^{(n-1)}] \quad (1)$$

Where $REDUCE(x) = [w * x]_{\downarrow 2}$ (2)

w is a Gaussian smoothing filter and $[.]_{\downarrow 2}$ denotes down sampling operation. The detail coefficients at scale n are then calculated by using Eq (3) and Eq (4)

$$y_1^{(n)} = y_0^{(n)} - EXPAND [y_0^{(n+1)}] \quad (3)$$

Where $EXPAND(x) = w * [x]_{\uparrow 2}$ (4)

And $[.]_{\uparrow 2}$ denotes the upsampling operation.

By using the multi-scale transform the contrast and luminance is measured. The contrast measure LM of the image is measured by using Eq(5)

$$C_{LM}^{(n)} = \frac{y_1^{(n)}}{b_1 + |\bar{y}_0^{(n+1)}|^{\alpha_1}} \quad (5)$$

where b_1 is the small non-negative constant α_1 is the parameter control the contrast and \bar{y} is the expansion function which is given in Eq(6)

$$\bar{y} = EXPAND(|y|) \quad (6)$$

The multi-scale LCM (Luminance Contrast Masked) is defined in Eq(7)

$$C_{LCM}^{(n)} = \frac{C_{LM}^{(n)}}{b_2 + |\bar{C}_{LM}^{(n+1)}|^{\alpha_2}} \quad (7)$$

Where b_2 is the small non-negative constant and α_2 is the parameter control the contrast.

The N level HVS-LP decomposition is described as follows:

1. Generate an N+1 level Laplacian pyramid of I using the Eq.(1) and (3)
2. Measure the LM contrast of the original image using Eq.(5)
3. Measure the LCM contrast of the original image using Eq.(7)
4. Initialize $y_0^{(N+1)} = y_0^{(N+1)}$,

$$C_{LM}^{(n)} = C_{LM}^{(n)}$$

The proposed method use multi-resolution decomposition schemes such as HVS-LP, HVS-SWT and HVS-DT-CWT transforms. These transforms decompose the image and measure the contrast and luminance of the image.

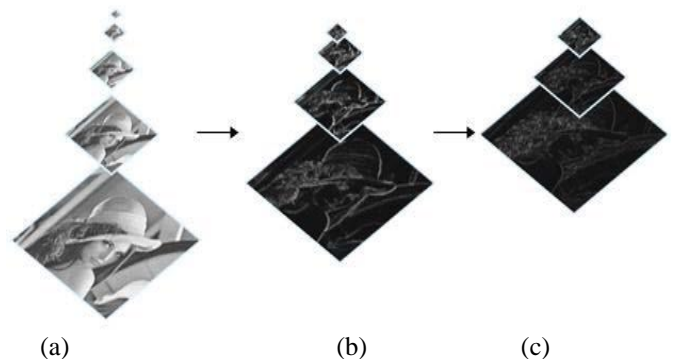


Fig 2: Generation of (a) approximation, (b) detail and (c) contrast coefficient sub bands

The laplacian pyramid and wavelet transforms are restore the fine image details, measure the edge details and measure the contrast coefficients in each sub bands.

TABLE I

COMPARISON OF EXISTING DIRECT IMAGE ENHANCEMENT ALGORITHM WITH PROPOSED METHOD

Direct Enhancement Algorithm	α_1	α_2	Coefficient Mapping	Brightness Adjustment	Dynamic Range Compression
Multi-scale Unsharp Masking	0	0	Linear	No	No
Laine's Algorithm	0	0	Non-Linear	No	No
Tang's Algorithm	1	0	Linear	No	No
Direct Multi-scale	Variable	Variable	Non-Linear	Yes	Yes
Proposed method	Optimum value	Optimum value	Non-Linear	Yes	Yes

B. Brightness Adjustment

The brightness of the image can be sufficiently and accurately adjusted by altering the approximation coefficients. For accurate brightness adjustment select the optimum coefficients. Using the multiple transforms the brightness of the image can be measured by $y_0^{(N)} = y_0^{(N)} + K$

Where K is the brightness parameter. With K=0 the current brightness level of the image is preserved.

C. Non-linear Contrast Mapping

If the contrast at a given scale is enhanced, areas of low contrast should be enhanced more than the areas of high contrast and in this case the non-linear contrast mapping function should not cause smoothing. However if the contrast is to be decreased, for example to remove non-uniform illumination or to avoid signal clipping because caused by the brightness adjustment step areas of low contrast should have their contrast decreased less than areas of high contrast and the non-linear mapping function should not cause contrast enhancement.

Contrast non-linearly mapped is given by

$$C'_{LM} = \text{sgn}(C_{LM}^{(n)}) \lambda_i^{(n)}(|C_{LM}^{(n)}|)$$

Where the non-linear contrast mapping function $\lambda_i^{(n)}(\cdot)$ is defined in Eq(8)

$$\lambda_i^{(n)}(x) = \begin{cases} k_1^{(n)} \cdot x & x \leq T_i^{(n)} \\ k_2^{(n)} \cdot x + (k_1^{(n)} - k_2^{(n)}) T_i^{(n)} & x > T_i^{(n)} \end{cases} \quad (8)$$

Calculate the enhanced LM contrast by

$$C'_{LM} = C'_{LM} \left[b_2 + |\overline{C'_{LM}}^{(n+1)}|^{\alpha_2} \right] \quad (9)$$

Calculate the enhanced detail coefficients by

$$y_1^{(n)} = C'_{LM} \left[b_1 + |\overline{y_1^{(n+1)}}|^{\alpha_1} \right] \quad (10)$$

Calculate the enhanced approximation coefficients by

$$y_0^{(n)} = y_1^{(n)} + \text{EXPAND}[y_0^{(n+1)}] \quad (11)$$

Then the enhanced image is

$$I' = y_0^{(0)} \quad (12)$$

D. PSO Tuning

PSO algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock. In PSO, each single solution is a “particle”. All of the particles have fitness values which are evaluated by the objective

function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the personal and global best particles. The swarm is initialized with a group of random particles and it then searches for optima by updating through iterations. In every iteration, each particle is updated by following two “best” values. The first one is the best solution of each particle achieved so far. This value is known as solution. Another one is that, best solution tracked by any particle among all generations of the swarm. This best value is known as solution. These two best values are responsible to drive the particles to move to new better position.

Fitness value of all the enhanced images generated by all the particles is calculated. From these fitness values pbest&gbest are found. In PSO the most attractive property is that pbest&gbest are found according to their fitness values. With the help of these best values, component wise new velocity of each particle is calculated to get the new solution. In this way new positions of particles are created for generations. When the process is completed the enhanced image is created by the global best (gbest) particle, as it provides the maximum fitness value and the image is displayed as the final result.

Main steps for PSO algorithm is as follows:

- ❖ Initialize number of particles with random position and velocity.
- ❖ Evaluate the fitness value for each particle.
- ❖ Evaluate gbest.
- ❖ Evaluate pbest.
- ❖ Update velocity & position.
- ❖ Evaluate the fitness value for new position
- ❖ If condition is fulfilled gbest is the solution else repeat above steps.

For each particle: Initialize particle

Do: For each particle:

- Calculate fitness value.
- If the fitness value is better than the best fitness value (pbest)in history
- Set current value as the new pbest

End

For each particle:

- Find in the particle neighborhoods, the particle with the best fitness
- Calculate particle velocity according to the velocity equation (13)
- Apply the velocity constriction
- Update particle position according to the position equation(14)
- Apply the position constriction
- End

While maximum iterations

$$v_i = v_i + c_1 * rand() * (pbest_i - present_i) + c_2 * rand() * (gbest_i - present_i) \quad (13)$$

$$present_i = present_i + v_i \quad (14)$$

v_i is the particle velocity, $present_i$ is the current particle, $pbest_i$ and $gbest_i$ are stated before. $rand()$ is a random number between (0,1), c_1, c_2 are learning factors. Usually $c_1 = c_2 = 2$.

IV. EXPERIMENTAL RESULTS

The effectiveness of the image enhancement algorithms is evaluated through computer simulations. The enhancement procedure can effectively enhance the image both locally and globally in each of the transform domain. The

proposed image enhancement algorithm is compared with HE, MSR, Laine's algorithm, Tang's algorithm and direct multi scale algorithm.

The comparisons of the presented approaches with other existing enhancement techniques are shown in fig 3. HE over enhances many of the image details. Laine's and Tang's algorithms are able to enhance the contrast of some of the image structures, but cannot equalize or provide the necessary brightness. The proposed enhancement method achieves both local and global enhancement simultaneously. In order to provide some quantitative assessment, entropy is used to measure visual quality of the image. The visual quality of the image is compared with existing image enhancement algorithms. Table II demonstrate the comparison results.

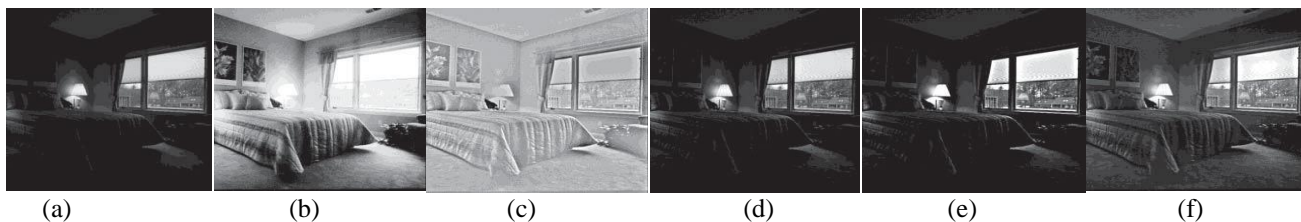


Fig 3: (a) Original image, (b) HE, (c) MSR, (d) Laine's algorithm, (e) Tang's algorithm, (f) proposed

TABLE II

QUANTITATIVE IMAGE ENHANCEMENT ASSESSMENT VIA ENTROPY

Image	Original	HE	MSR	Laine's	Tang's	Proposed
1	6.4462	5.5451	7.2239	6.6086	6.6349	7.7063
2	6.3195	5.5805	6.1654	6.6332	6.7225	6.8276
3	5.6851	4.9162	6.6213	5.8212	5.7015	6.7598
4	6.7464	5.9207	6.8111	7.2053	7.2223	7.5560

V. CONCLUSION

Thus the paper introduces the multi-scale image enhancement algorithm and PSO algorithm for optimal selection of the approximation coefficients of many scales. Multi-scale enhancement algorithm used multi transforms which is capable of adjusting the appropriate level of brightness and using the non-linearly mapping to contrast coefficients at each scale.

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