ROBUST COLOR IMAGE ENHANCEMENT USING FRAMELET DIFFUSION FILTER

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Abstract
Capturing an image with sensors is an important step in many areas. The captured image is used in several applications, which all have their own requests on the quality of the captured image. Acquired images are often degraded with blur, noise, or blur and noise simultaneously. A novel method for color image enhancement using adaptive feature extraction based on particle swarm optimization (PSO) framelet. In framelet extraction blurring component analysis effectively and then apply Partial differential equation based-diffusion–shock-filter coupling model, where noisy and blurred images are denoised and sharpened. The proposed model is based on using the single vectors of the gradient magnitude and the second derivatives as a manner to relate different color components of the image. This model can be viewed as a generalization of the Bettahar–Stambouli filter to multivalued images. The proposed algorithm is more efficient than the mentioned filter and some previous works at color images de-noising and deblurring without creating false colors.
Keywords: Gray image, Adaptive framlet filter, PSO, Adaptive Diffusion filter, Blur cluster image.

I. INTRODUCTION

Digital image processing is the use of computer algorithms to perform image on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of Multidimensional Systems.

An image may be defined as a two-dimensional function, f(x, y) where x and y are spatial coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements and pixels. Pixel is the term used most widely to denote the elements of a digital image.

Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the electromagnetic (EM) spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate also on images generated by sources that humans do not customarily associate with images. These include ultrasound, electron microscopy, and computer-generated images. Thus, digital image processing encompasses a wide and varied field of applications.

II.LITERATURE SURVEY

J. Weickert, B.M.Haar Romeny proposes,"Image Enhancement Based On Statistics Of Visual Representation" This paper introduces a novel algorithm to image enhancement that exploits the multi-scale wavelet and statistical characters of visual representation. Processing includes the global dynamic range (brightness) correction and local contrast adjustment, whose parameters are picked automatically by the information contained in the image itself. Experimental results show that the new algorithm outperforms other many existing image enhancement methods and is highly resilient to the effects of both the image-source variations.

L. Alvarez and L.Mazorra proposes, “The Application Of Multi Wavelet Filter Banks To Image Processing” Multi wavelets are a new addition to the body of wavelet theory. Realizable as matrix-valued filter banks leading to wavelet bases, multi wavelets offer simultaneous orthogonality, symmetry, and short support, which is not possible with scalar two-channel wavelet systems.

After reviewing this theory, we examine the use of multi wavelets in a filter bank setting for discrete-time signal and image processing. Multi wavelets differ from scalar wavelet systems in requiring two or more input streams to the multi wavelet filter bank. Algorithms for symmetric extension of signals at boundaries are then developed, and naturally integrated with approximation-based preprocessing. We describe an additional algorithm for multi wavelet processing of two-dimensional for (2-D) signals, two rows at a time, and develops a new family of multi wavelets (the constrained pairs) that is well-suited to this approach. This suite of novel techniques is then applied to two basic signal processing problems, denoising via wavelet-shrinkage, and data compression. After developing the approach via model problems in one dimension, we apply multi wavelet processing to images, frequently obtaining performance superior to the comparable scalar wavelet transform.

S. Bettahar and A. B. Stambouli proposes,” Image Enhancement And De-Noising By Complex Diffusion Processes” The linear and nonlinear scale spaces, generated by the inherently real-valued diffusion equation, are generalized to complex diffusion processes, by incorporating the free Schrodinger equation. A fundamental solution for the linear case of the complex diffusion equation is developed. Analysis of its behavior shows that the generalized diffusion process combines properties of both forward and inverse diffusion. We prove that the imaginary part is a smoothed second derivative, scaled by time, when the complex diffusion coefficient approaches the real axis. Based on this observation, we develop two examples of nonlinear complex processing: a regularized shock filter for image enhancement and a ramp preserving denoising process.

III. RGB COLOR MODEL

The simplest and most common color model is RGB (red, green, blue) model, which is based on a Cartesian coordinate system (Figure 2.1). In RGB model, each color appears in its primary spectral components of red, green, and blue. We use this for color monitors, scanners, image storage, etc.

RGB COLOR CUBE

RGB model is used in the processing of aerial and satellite multiband image data. Aerial and satellite images are obtained by image sensors operating on the different spectral ranges. Each image plane has physical meaning, So color combination obtained using RGB is convenient for spatial data.

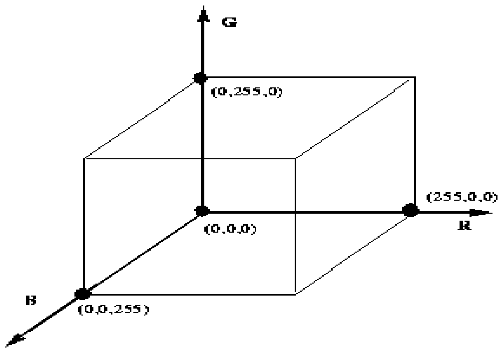


Figure 1: RGB cube

RGB (RED GREEN BLUE)

The RGB colour model relates very closely to the way we perceive colour with the **r**, **g** and **b** receptors in our retinas. RGB uses additive colour mixing and is the basic colour model used in television or any other medium that projects colour with light. It is the basic colour model used in computers and for web graphics, but it cannot be used for print production.

The secondary colours of RGB – cyan, magenta, and yellow – are formed by mixing two of the primary colours (red, green or blue) and excluding the third colour. Red and green combine to make yellow, green and blue to make cyan, and blue and red form magenta. The combination of red, green, and blue in full intensity makes white.

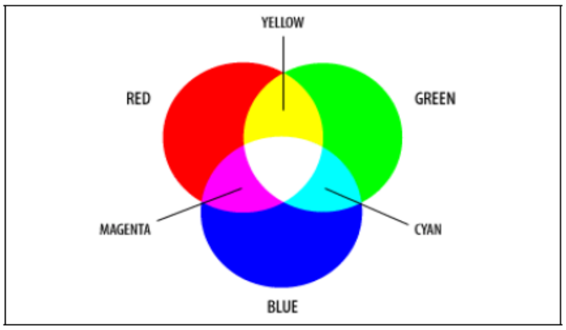


Figure 2: RGB (RED GREEN BLUE)

PARTICLE SWARM OPTIMIZATION

In computer science, particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.PSO is originally attributed to Kennedy, Eberhart and Shi and was first intended for simulating social behaviour, as a stylized representation of the movement of organisms in a bird flock orfish school.

The algorithm was simplified and it was observed to be performing optimization. The book by Kennedy and Eberhart describes many philosophical aspects of PSO and swarm intelligence. An extensive survey of PSO applications is made by Poli. PSO makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. More specifically, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time.

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

Formally, let $f: \mathbb{R}^n \to \mathbb{R}$ be the cost function which must be minimized. The function takes a candidate solution as argument in the form of a vector of real numbers and produces a real number as output which indicates the objective function value of the given candidate solution.

The gradient of f is not known. The goal is to find a solution $\mathbf{a}$ for which $f(\mathbf{a}) \le f(\mathbf{b})$ for all $\mathbf{b}$ in the search-space, which would mean $\mathbf{a}$ is the global minimum. Maximization can be performed by considering the function $h = -f$ instead.

Let S be the number of particles in the swarm, each having a position $\mathbf{x}_i \in \mathbb{R}^n$ in the search-space and a velocity $\mathbf{v}_i \in \mathbb{R}^n$. Let $\mathbf{p}_i$ be the best known position of particle i and let $\mathbf{g}$ be the best known position of the entire swarm. A basic PSO algorithm is then:

For each particle $i = 1, ..., S$ do:

Initialize the particle's position with a uniformly distributed random vector: $\mathbf{x}_i \sim U(\mathbf{b}_{lo}, \mathbf{b}_{up})$, where $\mathbf{b}_{lo}$ and $\mathbf{b}_{up}$ are the lower and upper boundaries of the search-space.

Initialize the particle's best known position to its initial position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$

If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$

Initialize the particle's velocity: $\mathbf{v}_i \sim U(-|\mathbf{b}_{up}-\mathbf{b}_{lo}|, |\mathbf{b}_{up}-\mathbf{b}_{lo}|)$

Until a termination criterion is met (e.g. number of iterations performed, or a solution with adequate objective function value is found), repeat:

For each particle $i = 1, ..., S$ do:

Initialize the particle's position with a uniformly distributed random vector: $\mathbf{x}_i \sim U(\mathbf{b}_{lo}, \mathbf{b}_{up})$, where $\mathbf{b}_{lo}$ and $\mathbf{b}_{up}$ are the lower and upper boundaries of the search-space.

Initialize the particle's velocity: $\mathbf{v}_i \sim U(-|\mathbf{b}_{up}-\mathbf{b}_{lo}|, |\mathbf{b}_{up}-\mathbf{b}_{lo}$

IV.BLOCK DIAGRAM

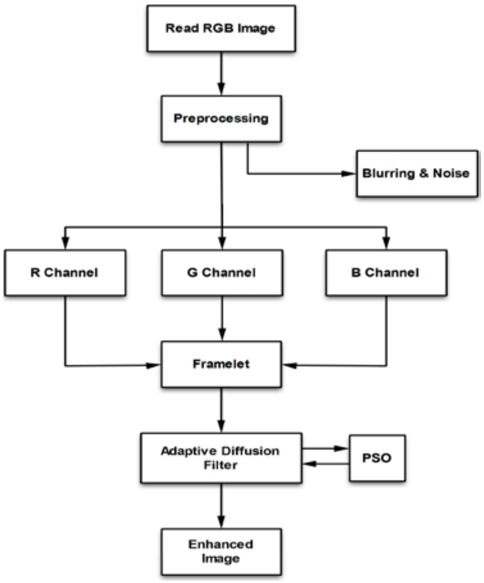


Figure 3: Block diagram of Image Enhancement using Adaptive Framelet Diffusion filter

THE FRAMELET TRANSFORM

As it is well known, except for the Haar filter bank, two-band finite impulse response (FIR) orthogonal filter banks do not allow for symmetry. In addition, imposition of Orthogonality for the two-band FIR filter banks requires relatively long filter support for such properties as a high level of smoothness in the resulting scaling function and wavelets, as well as a high approximation order. Symmetry and orthogonality can both be obtained if the filter banks have more than two bands. Furthermore, due to the critical sampling, orthogonal filters suffer a pronounced lack of shift invariance, though the desirable properties can be achieved through the design of tight frame filter banks, of which orthogonal filters are a special case. In contrast to orthogonal filters, tight frame filters have a level of redundancy that allows for the approximate shift invariance behavior caused by the dense time-scale plane. Besides producing symmetry, the tight frame filter banks are shorter and result in smoother scaling and wavelet functions.

TIGHT FRAMELET FRAME

A set of functions $\{\varphi_1, \varphi_2, \ldots\ldots\varphi_{N-1}\}$ in a square integrable space L2 is called a frame if there exist $A > 0$, $B < \infty$ so that, for any function $f \in L_2$.

Where A and B are known as frame bounds. The special case of A = B is known as tight frame. In a tight frame we have, for all $f \in L_2$

$$\sum_{i=1}^{N-1}\sum_{j}\sum_{k}\left|\langle f, \psi^{i}(2^{j}-k)\rangle\right|^{2} = A\,\|f\|^{2}$$

We can find the fast wavelet frame (or frame let) transform, from multi resolution analysis which is generally used to derive tight wavelet frames from scaling functions. The frame condition can be explained in terms of over sampled filters, given a set of N filters, we define them in terms of their polyphone components:

$$H_i(z) = H_{i,0}(z^2) + z^{-1}H_{i,1}(z^2),$$
$i = 0, 1, 2, \ldots.. N-1$

Where

$$H_{i,l}(z) = \sum h_i(2n-l)z^{-n}, l = 0,1,2\ldots..$$

Now we can define the signal $X(z)$ in terms of poly phase components,

$$X(z) = ((X_0(z)\ X_1(z)))$$

The equation ($X_l(z)$), l =0, 1 *is* defined in terms of the time domain signal, $x(n)$, as follows:

$$X_l(z) = \sum x(2n-1)z^{-n}$$

The given input signal is X (z) and obtained output signal is $\bar{X}(z)$ .these two signals satisfying the perfect reconstruction condition when

$$X(z) = \bar{X}(z)$$

Similarly in terms of filter banks

$$H^T(z)H(z^{-1}) = I$$

On the other hand, in our proposed method we are having a three-band tight frame filter bank and PR conditions can be expressed in terms of the Z -transforms of the filters h_0, h_1, h_2 . Moreover, the perfect reconstruction (PR) conditions can be easily extended to N filters

$$A\|f\|^2 \le \sum_{i=1}^{N-1}\sum_{j}\sum_{k}\left|\langle f, \psi^{i}(2^{j}-k)\rangle\right|^{2} \le B\|f\|^2$$

down sampled by 2:

$X(z) = 1/2[H_0(z)H_0(z^{-1}) + H_1(z^{-1})H_1(z)]X(z) + 1/2[H_0(-z)H_0(z^{-1}) + H_1(z^{-1})H_1(-z)]X(-z)$

From the above equation we can get the perfect reconstruction conditions

$H_0(z)H_0(z^{-1}) + H_1(z^{-1})H_1(z) = 2;$

$H_0(z^{-1})H0(-z) + H_1(z^{-1})H_1(-z) = 0$

The following Figure 1 represents the three band perfect reconstruction filter bank.

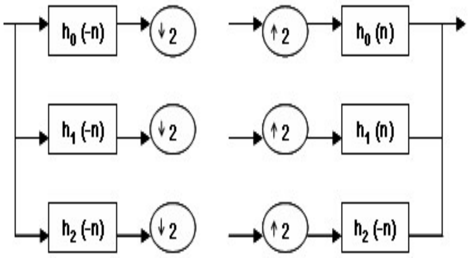


Figure 4: A three-band PR filter bank.

We already know, about the PR conditions for the filter banks. We can write these perfect reconstruction conditions in matrix form as

$$H^T(z)H(z^{-1}) = I$$

$H(z)$ is a matrix [4].

The symmetry condition for $h_0(n)$ is

$$h_0(n) = h_0(N-1-n)$$

Where N is the length of the filter $h_0(n)$.

To show this, suppose that $h_0(n)$, $h_1(n)$ & $h_2(n)$ satisfy the PR conditions and that

$$h_2(n) = h_1(N-1-n)$$

The 2D extension of filter bank is illustrated on this figure

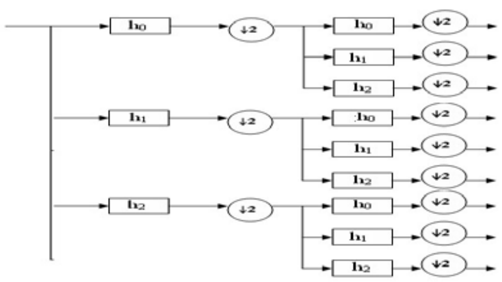
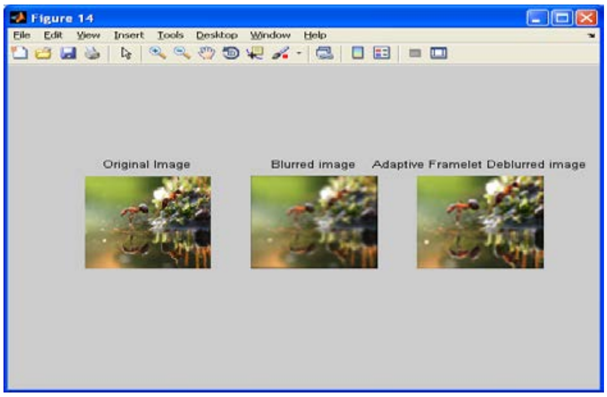


Figure 5: An over sampled filter bank for a 2-D image

V.RESULT:

A novel method for color image enhancement using adaptive feature extraction based on particle swarm optimization (PSO) framelet. In framelet extraction blurring component analysis effectively and then apply Partial differential equation based-diffusion–shock-filter coupling model, where noisy and blurred images are denoised and sharpened. The proposed model is based on using the single vectors of the gradient magnitude and the second derivatives as a manner to relate different color components of the image. This model can be viewed as a generalization of the Bettahar–Stambouli filter to multivalued images.



VI.CONCLUSION

A novel method for color image enhancement using adaptive feature extraction based on particle swarm optimization (PSO) framelet. In framelet extraction blurring component analysis effectively and then apply Partial differential
equation are based on diffusion–shock-filter coupling model, where noisy and blurred images are denoised and sharpened. The proposed model is based on using the single vectors of the gradient magnitude and the second derivatives as a manner to relate different color components of the image. This model can be viewed as a generalization of the Bettahar–Stambouli filter to multivalued images. The proposed algorithm is more efficient than the mentioned filter and some previous works at color images de-noising and deblurring without creating false colors.

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