

Multimodal Medical Image Informatics with Lifting wavelet Transform based Fusion Scheme

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Abstract

Image informatics means maintaining and extracting useful and relevant information of an image and especially aiming for medical images. This paper is based on the concept of fusion of digital medical images and further comparative assessment of individual images with fused image. Fusion of images is done using a unique wavelet transform called Lifting. Images are assessed by calculating their individual mean value, standard deviation, average information entropy, average gradient and cross entropy.

Keywords -fusion, digital, medical images, wavelet transform, lifting, mean value, standard deviation, information entropy, gradient, cross entropy.

I. Introduction

Due to image sensor malfunction and physical limitations valuable information in any medical image can be noised [1],[2]. Many de-noising schemes are generally used to improve visual features in an image. Many a times more than one image is taken for a particular scene to enhance the information level and then combined and mingled into a single image so to improve richness of combined image according to featured information's expressed in individual medical images [2]. This process of feature extraction and combined into a single image is called image fusion [3],[7]. Now this fused image has all the information from both images[4]. This type of fusion is called feature level fusion as the features like edges ,boundaries and patches etc can get finally extracted[31]. Note here that feature level fusion emphasizes on the features like any crack, patch and boundary wall etc as an anomaly in any medical image[17],[20]. The increased contrast , entropy (information) and average gradient value in the fused image explains the usefulness of fused image as compared to individual images[5],[6],[8],[11].

II. Overview of wavelet Transform

Continuous wavelet Transform (CWT)

The CWT or continuous-time wavelet transform of $f(t)$ with respect to a wavelet $\psi(t)$ is defined as

$$W(a,b) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

Where a and b are real and $*$ denotes complex conjugation. Thus, the wavelet transform is a function of two variables [9], [10], [28]. The a is called dilation variable while b is called translation variable. The mother wavelet should possess following properties [29], [30].

(a) The function integrates to zero.

$$\int_{-\infty}^{+\infty} \psi(t) dt = 0 \quad (2)$$

(b) It is square integrable or equivalently has finite energy

$$\int_{-\infty}^{+\infty} |\psi(t)|^2 dt < \infty \quad (3)$$

Discrete Wavelet Transform (DWT)

This equation (4) is a type of non redundant wavelet representation [27], [30].

$$\hat{f}(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k, l) 2^{-k/2} \psi(2^{-k}t - l) \quad (4)$$

Equation (4) uses discrete values for dilation and translation parameters. The dilation takes values of the form $a = 2^k$ where k is an integer. At any dilation 2^k , the translation parameter takes values of the form $2^k l$ where l is again an integer [12], [14]. The values $d(k, l)$ are related to values of the wavelet transform

$$W(a,b) = W[\hat{f}(t)] \quad (5)$$

at $a = 2^k$ and $b = 2^k l$. This corresponding to sampling the coordinates (a,b) on a grid. The two-dimensional sequence $d(k, l)$ is referred to as the discrete wavelet transform (DWT) of $\hat{f}(t)$ [13].

III. Lifting Wavelet Transform

Lifting wavelet transform is a multi resolution analysis used for the construction of the second generation wavelets. It is an efficient implementation of the wavelet transform algorithm. The discrete wavelet transform (DWT) can be viewed as a predictor-error decomposition [15], [16]. The scaling coefficients at a given scale (j) are "predictors" for the data at the next higher resolution or scale ($j-1$). The wavelet Coefficients are simply the "prediction errors" between the scaling coefficients and the higher resolution data that they are attempting to predict [18]. This interpretation has led to a new framework for DWT known as the lifting scheme [17]. It lifts the wavelet transform to a more sophisticated level and is implemented by factoring the wavelet transforms into lifting steps. The lifting scheme consists of the iteration of the following three steps [17], [19].

(i) Lazy wavelet transform: This step divides the original data $(x[n]) \in \mathbb{R}, n \in \mathbb{Z}$ into its even and odd polyphase components $x_e[n]$ and $x_o[n]$ respectively where

$$x_e[n] = x[2n] \quad (6)$$

$$x_o[n] = x[2n+1] \quad (7)$$

(ii) Predict: This is also called as dual lifting. In this step the odd poly phase coefficients are predicted from the neighbouring even coefficients using a predictor P and the wavelet coefficients (high pass) or details are generated as the error in predicting the odd samples from the even using prediction operator [19], [21].

$$d = x_o - P(x_e) \quad (8)$$

using these details one can recover the odd components as [20].

$$x_o = P(x_e) + d \quad (9)$$

iii) Update: This is also termed as primal lifting. This step updates the even set using the wavelet coefficients to compute the scaling function coefficients (low pass). It applies an update operator U to detail coefficients obtained in previous step [21], [22], [23].

$$S = x_e + U(d) \quad (10)$$

This step is also invertible and reproduces x_e as

$$X_e = s \cdot U(d) \quad (11)$$

Lifting scheme has the advantage of fast implementation of wavelet transform as it makes use of similarities between high pass and low pass filters[23],[13]. It provide perfect reconstruction of original signal which is not possible by standard implementation even though they are lossless in principle. It helps in saving auxiliary memory as the original signal is gradually replaced by its transform[26]. Lifting scheme has further advantage of simplicity of inverse transform as the inverse transform is obtained by reverting the order of operations and inverting the signs in forward lifting steps[25],[27]. It also reduces the computational complexity by a factor of two as compared to non-lifting wavelet transform. It also provides flexibility as compared to classical wavelets[19][24].

IV. Proposed Scheme

1. Decomposition of input images using lifting wavelet transform.
2. Calculation for Modulus of gradient of lifting wavelet transform.
3. Fusion based on threshold value of gradient of wavelet coefficients.
4. Inverse lifting wavelet transform of fused image is done.
5. Evaluation of image fusion performance.

V. Result Analysis

We performed experiments on two teeth x-ray images using Matlab software R2015a. The images are original tooth X-ray of one of co-author of this paper. We named Image 1 as M1 and image 2 as M2. The fused image F1 is obtained with all improved evaluation parameters. The parameters calculated for discussed images are mean value (shows average intensity), average gradient (detail information), average entropy (information), cross entropy (fidelity) and standard deviation(contrast in image). The high value has been found for all discussed parameters except cross entropy in case of fused image as compare to individual images M1 and M2. Low value of cross entropy for fused image shows its fidelity with individual images.

TABLE I. Assessment Result for Images

Parameters	Image (M1)	Image (M2)	Fused Image (F1)
Mean Value	12.8434	13.7624	16.1981
Average Gradient	0.2794	0.3213	0.3821
Standard Deviation	157.8302	158.8302	163.2141
Information Entropy	2.27	2.37	3.680
Cross Entropy	-	-	0.746

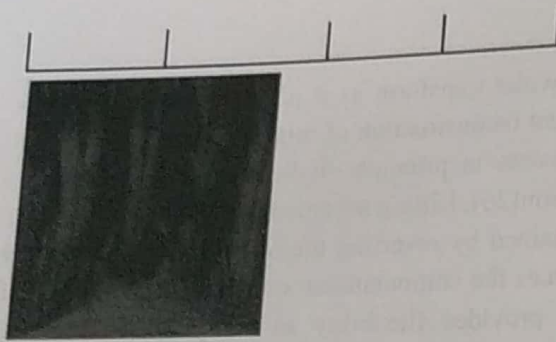


Figure.1. Image 1(M1)



Figure.2. Image 2 (M2)



Figure.3 Fused Image (F1)

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