Clustering based Multi-modality Medical Image Fusion

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Abstract. The unwanted data obtained through the medical image fusion is the main problem in biomedical applications, guided-image surgical and radiology. The Stationary Wavelet Transform (SWT) denoted the various advantages over conventional representation of imaging approach. In this research article we introduced innovative multi-modality fusion technique for medical image fusion based upon the SWT. In our approach it disintegrates of source images into approximation layers (coarse layer) and detail layers through the Stationary Wavelet Transform scheme, then applying of the Fuzzy Local Information C-means Clustering (FLICM) and Local contrast fusion approach to overcome the blurring effect, sensitiveness and conserve the quality evaluation in the distinguish layers. The demonstration shows that it preserves more detailed information in the source images and it enhances the more quality features and edge preserved of the final fused image obtained through the reconstruction procedure by recursive initial steps. The different methodologies with other techniques to evaluate performance such as mutual information, edge based similarity and blind image quality. This shows that in both the objective and subjective analysis our methodology results attained more supercilious performance.

Keywords. Multi-modality medical images, stationary wavelet transform, fuzzy local information C-means clustering, image Quality evaluation.

1. Introduction

Multi-modality image fusion based approach has been prominent research year in the coming years. The combination of information in decision–level fusion provide the more abstraction level, joining output through various set of rules to produce the ultimate fused based decision [1]. The acquired information is then joined by related decision rules to strengthen the usual elucidation. Amidst the thousand's dissimilarity among the various fusion based approach, broadly applied techniques inclusion never bounded to, hue-saturation [2], PCA [3,4], distinguished combination of arithmetic example is Hermitian transformation [3], Artificial neural networks (ANN’s) all examples pyramid algorithm (PA), wavelet (WT), curvelet (CVT) and contourlet transformation(CT) for multi-resolution analysis.

The hue saturation transformation accomplished to latest intensity level, collaborate to hue saturation evolved in an image fusion in intensity hue saturation. The comparatively simple fusion algorithm affects the large area used for the pixel-level medical image fusion. Intensity hue saturation joined to the principal component analysis to better the quality fusion image. Although, various shortcomings of method should be contemplate : (i) Fusion level for the pixel is the techniques most delicate to registration of the precision ; (ii) In hue-saturation transform color space input is less than equal to 3. (iii) The lack of the fidelity in the original color features it is based on the HIS. In the recent time, employed in the latest methods Wang et al. [6], example is the ST, to decrease the disturbance
issue in the color of the image, and the combined the variable-weight notion discussed in Li and Wang [5] and the inadequacy is away from the non-subsampled shearlet transform conventional transparency method fused image of the multi-resolution and contourlet transform.

Resolution for the multiple analysis depends on the fusion on transformation pyramid, applied on the past 30 years. Image fusion pyramid techniques, Gaussian pyramid transform through this whole system are designed, the larger portion has been altered and broadly applied. These more established multiple analysis approaches considered different structure like FSD structure [8], morphological structure [7], ratio-structure [12], gradient structure [9], Laplacian pyramid [10], contrasting structure [11]. Although, the contrasting structure fused image based on technique lost more source information to acquired the understandable subjective image; the ratio produce by the structured technique gives the large amount of the investigation procedure in the morphological structured technique, never there in the actual input images [14].

Predominantly, depend on the wavelet fusion perceptible reduced the color, distortion and noise. Nevertheless, the issues and constraint related with this approach include: (i) The comparative to high calculation complication in wavelet-based fusion in comparison the ordinary approach; (ii) The spectral loss of content from insignificant substance in the fused images; (iii) The user that determine the essential constant values. The enlighten the evolution of depend on the fusion technique (for example curvelet (CVT) and contourlet (CT) may enhance fulfillment of the outcomes, but these new techniques leads to the better performance for the evaluation of the complexity and parameterization [15], [21].

The various ANN structures introduced image based fusion, for example SOFM and PCNNs [16]. Through the competitive studying to consider a cluster input for the self organizing feature maps (SOFM) taking for the analysis which choose the goal is to part of ultimate fusion, yet considered the final neurons number to be fixed before the manual work for every fusion [17], [22]. Few issue on constraint analogous neural network fusion: (i) lengthy repetition of the process of neural network and they require to before manual checked every process of fusion; (ii) The infrequently done negligence coincide, for example pulse-coupled neural network depend on the approach the unspecified amount of_neurons did not throw during the whole process of repetition [18], [23].

According to particular sequence to prevail over the computational complexity and parameterization set through the hands in multiple resolution analysis image fusion as lengthy process repetition on multiple-organized neural network-based on the fusion, we set the rules for the novel pixel-based fusion for multi-modality based images depend maxima method [19]. The disintegrate converted the image to many-layers of the identical size as the previous image. Identical wavelet approach, image disintegration to rough and comprehensive level of layers [20], [24]. As introduced methodology deploy comprehensive level of layers, give consideration to the size of region, information about the edges, indicated in the process of the fusion [25] – [27].

The paper is organized as: section 2 is a brief description of SWT. Section 3 is description of FLICM. Section 4 represents proposed method. Section 5 shows result analysis. Section 6 shows conclusion.

2. Stationary Wavelet Transform

In comparison with conventional Wavelet transform (WT), Stationary wavelet transform (SWT) characteristic of shift-invariant and shows redundant information [28]. It uses up-sampling technique alternative to down-sampling technique, consequently the size and shape of counter-images in domain transform technique not vanish. Stationary wavelet transform (SWT) take the little details in exquisite scales and the massive details in fine grained scales by its multiple scale disintegration [29]. Thus, disintegrated counter-images can take crucial information of input images, on this basis stationary wavelet transform (SWT) known as trous algorithm. Wavelet transform (WT) mostly used multiple-scale transform techniques in digital processing of image, besides it is drawbacks of property shift-invariant, and therefore it is also algorithm for non-redundant decomposition [30]. Consequently, Stationary wavelet transform (SWT) is good to retain vast information about input image through properties of redundant every scale. It is more suitable Stationary wavelet transform (SWT) to disintegrate the crucial selection of details from input images converted to distinguished parts through the property of multiple resolutions analyzing quality [31].
3. Fuzzy Local Information C-Means Clustering Algorithm (FLICM)

Generally, a novel factor fuzzy $G(h_i)$ is presentation to objective fuzzy local information C-Means function to increase the execution of clustering. Factor for Fuzzy membership is mathematically evaluated shown:

$$G(h_i) = \sum_{j \in X} \frac{1}{d_{ij} + 1} (1 + \mu_{h_i})^m \|x_j - v_h\|^2$$  \hspace{1cm} (1)

Through the definition of $G(h_i)$, of the fuzzy local information C-Means objective function is described as:

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \{\mu_{h_i}^m \|x_i - v_h\|^2 + G_{h_i}\}$$  \hspace{1cm} (2)

Additionally, computation partition matrix for membership function, cluster center is calculated follow:

$$\mu_{h_i} = \frac{1}{\sum_{j=1}^{N} \left( \frac{\|x_i - v_h\|}{\|x_j - v_h\|} \right)^{-\frac{1}{m-1}}}$$  \hspace{1cm} (3)

$$v_h = \frac{\sum_{i=1}^{N} \mu_{h_i}^m x_i}{\sum_{i=1}^{N} \mu_{h_i}^m}$$  \hspace{1cm} (4)

In this first membership partition matrix evaluated randomly. The final fuzzy local information C-Means algorithm represented:

Step i) First fixed $c$ cluster prototypes, $m$ fuzzification parameter and the finish condition.

Step ii) Set random matrix partition for fuzzy.

Step iii) Evaluate cluster prototype using the equation 4

Step iv) Calculate the matrix partition for fuzzy applying the (iii)

Step v) If max $\{U^k - U^{k+1}\} < \varepsilon$ then conclude, else fixed $\sigma = \sigma + 1$ & go to step iv.
4. Proposed Methodology

Step I: First take images A and B are disintegrated into by applying Stationary wavelet transform (SWT) coarse(c) and detail layer (d) are obtained.

Step II: FLICM of both coarse layer \( G_1 \) and \( G_2 \) are calculated using following

\[
g(\mathbf{h}_i) = \sum_{i \in \mathcal{N}_i} \frac{1}{z(i)} (1 + \mathbf{w}_{\mathbf{h}_i})^{m} \left\| x_j - \varphi_{\mathbf{h}_i}\right\|^2 \tag{5}
\]

\[
J_m = \sum_{i=1}^{N_i} \sum_{h=1}^{c_i} [\mathbf{w}_{\mathbf{h}_i}^{m} \left\| x_i - \varphi_{\mathbf{h}_i}\right\|^2 + G_{\mathbf{h}_i}] \tag{6}
\]

\[
\mathbf{w}_{\mathbf{h}_i} = \frac{1}{\sum_{j=1}^{N_j} \left( \left\| x_i - \varphi_{\mathbf{h}_i}\right\|^2 + \mathbf{w}_{\mathbf{h}_i} \right)^{m} + \mathbf{w}_{\mathbf{h}_i}} \tag{7}
\]

\[
\varphi_{\mathbf{h}_i} = \frac{\sum_{i=1}^{N_i} \mathbf{w}_{\mathbf{h}_i}^{m} x_i}{\sum_{i=1}^{N_i} \mathbf{w}_{\mathbf{h}_i}} \tag{8}
\]
Step III: Determine contrast detail layers and approximation layers are calculated.

\[
S_L(x,y) = \frac{\sum_p \sum_q [d_L(x+p,y+q)w_y(p,q)]}{\sum_p \sum_q [M(x+p,y+q)w_y(p,q)]}
\]  
(9)

Step IV: Both FLICM of coarse layer are fused following:

\[
C_F = \begin{cases} 
M_A + R_1 & FLICM_A > FLICM_B \\
M_A + M_B + R_1 + R_2 & FLICM_A = FLICM_B \\
M_B + R_2 & FLICM_A < FLICM_B 
\end{cases}
\]  
(10)

Step V: Both local contrasts of detailed layers are fused using following:

\[
d_{LF} = \begin{cases} 
d_{LA} + R_1 & S_{LA} > S_{LB} \\
\frac{(d_{LA} + d_{LB} + R_1 + R_2)}{4} & S_{LA} = S_{LB} \\
d_{LB} + R_2 & S_{LA} < S_{LB} 
\end{cases}
\]  
(11)

Step VI The acquired fused image through the reconstruction procedure over outcome of step (iii) and step (iv) by following.

\[
f = C_F + \frac{1}{N} \sum_{L=1}^{N} d_{LF}
\]  
(12)

5. Results and Discussion

The results of existing methods and proposed methods are tested which are shown in figures 2 and 3. In the proposed fused method, there is more sharpness in the edges as well as in the features gives more fined contrast for detection any medical deformalities through the medical practitioner this shows the introduced fusion approach acceptable at greater extend as compare to the above previous method because it gives more information about contrast, textures, sharp features and edges. This suggests that the DWT method and maxima method are not feasible as compare to the proposed fused method is clearer and visually effective. It is shown that objective performance evaluation means transferring most of the edge information of the input images to the fused images. This fusion method is designed and implemented for clinically diagnosis of distinguish modality medical images the medical images acquired in the proposed research methodology to extracting the performance distinguish fusion metrics is applied such as mutual information how much information contained in the fused image give information about the source image. Edge based similarity measures gives information about the edges transferring moving from the source images to the fused image gives information about edge and orientation conserved values at that location (i,j) of every source image. Image decomposition strategy main focused and interest in the addressing in the medical image in the direction to construct algorithms that try to extract features at the distinguish scales and orientation within images. The advanced information about human should be sensitive to the better contrast (high), intensity in the pixel, edge information and depend on the fusion approach are directive to contrast, show dependencies between distinguish scales or orientations, edge and texture detection. In doctor’s point of view difficult to assessing the quality of image objective approach assessment approach is used to detect error between a fused image and two actual images. Different types of errors in this loss of noise and the increase of information presented in the fused image how much information is extracted from the original image for the measurement. Furthermore, it is based on the impressionistic analysis; we can manage the intent analysis on the experimental outcome given by distinguished fusion based rules. The computation of mutual information A image and F fusion image (mI_{AF}), mutual information B image and F image fusion
(mI_{BF}), the accumulative mutual information (mI_{AB,F}), (q_{AB,F}) and BSSIM. The results of performance metrics are shown in table 1. From table 1, it can be analyzed that proposed method gives better outcomes.

![Image](image1.png)

**Figure 2.** (a) Input CT image (b) Input MR Image, (c) Outcomes of [20], (d) Outcomes of [12], (e) Outcomes of [16], (f) Outcomes of Proposed Method

![Image](image2.png)

**Figure 3.** (a) Input MR-T1 image (b) Input MR-T2 Image, (c) Outcomes of [20], (d) Outcomes of [12], (e) Outcomes of [16], (f) Outcomes of Proposed Method

| Approach | M_{AB,F} | Q_{AB,F} | SSIM |
|----------|----------|----------|------|
| [20]     | 3.8604   | 0.7437   | 0.9886 |
| [12]     | 3.8359   | 0.7363   | 0.9876 |
| [16]     | 3.8420   | 0.7428   | 0.9865 |
| PROPOSED | 3.9538   | 0.7939   | 0.9907 |

**Table 1.** Objective computation of outcomes applying group images ($N=1$).

6. Conclusion
Multi-modality image fusion perform crucial role in clinical diagnosis, but recent methodology unable to fulfill the whole range of necessary condition. Thus, introduction of stationary wavelet transform (SWT) consideration of medical image fusion. The two medical images to analyze the quality of the image oppose to another approach. To evaluate the image quality of varied approach, apply a quality computation measures such as $MI$. The experimental consequences shows that our proposed methodology better performance than the other approach. In our approach is also more productive, analysis shows satisfactory outcome for fusion based medical applications. In this methodology exempted there is less noise more sharpness around the edges. The later research article, input images noise will influence the detail layers, then perform analysis find and reduction of the noise in the detail layers, and construct vigorous medical image fusion approach.

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