Abstract: Content-based image retrieval (CBIR) approach permits the user to extract a picture from an enormous database based mostly upon a question. An efficient and effective retrieval performance is achieved by selecting the simplest transform and classification techniques. However, the current transform techniques like Fourier Transform, cosine transform, wavelet transform suffer from discontinuities like edges in pictures. To overcome this disadvantage use Ripplet Transform (RT) has been implemented along with the neural network based mostly classifier referred to as Multilayered perceptron (MLP) for locating a good retrieval of image. Medical image fusion using PCNN and modified spatial frequency based on the ripplet transform type I, the source medical picture are divide by discrete RT(DRT), the low frequency sub bands (LFSs) are fused using the max selection rule. For the fusion of high frequency sub bands (HFSs) a PCNN model is utilized. In the proposed medical diagnosis system use different technique like Mutual Information (MI), Spatial Frequency (SF) and Entropy (EN).

Keywords: content-based image retrieval(CBIR), Image Fusion, Ripplet Transform, PCNN.

1. Introduction

Advances in data storage and image acquisition technologies have large databases. So as to deal with these data and to with efficiency manage these collections, it's necessary to develop an economical image retrieval system. In Content based Image Retrieval (CBIR) system the pictures may be retrieved from outsized information supported the visual content information. The visual content of a picture is analyzed in terms of low-level features extracted from the image. These low level features embrace color, shape and texture fea. There are many transform techniques implemented for the feature extraction process. However the transforms techniques like Fourier Transform (FT) and wavelet Transform (WT) suffer from discontinuities like edges and contours in images. In order to remove that conventional transforms an efficient technique known as Ripplet transform(RT) has been implemented for feature extraction. It is the next dimensional of the curvelet transform, create to show pictures at different scales and different directions partitioning 2 dimensional (2D) singularities on at random shaped curves. Inorder to enhance the retrieval performance and to decrease the procedure complexities a neural network based mostly classification tool known as Multilayer perceptron (MLP) has been applied.

There are several MGA tools were proposed like Ridgelet, Curvelet and Contoulet etc. These MGA tools do not suffer from the problems of wavelet, for improve the fusion result used MGA tools [3], [4]. For proposed technique used RT in the proposed method, because RT is capable of resolving two dimensional (2D) singularities and representing picture edges more efficiently. To handle this problem, Jun XU et al. Proposed a new MGA-tool called RT. RT is a higher dimensional generalization of the Curvelet Transform (CVT), is used to represent picture or 2D signals at different scales and different directions. Ripple Transform used to create a new tight frame with sparse representation for picture with discontinuities along Cd curves [12].

2. Ripplet Transform (RT)

The conventional transforms like Fourier Transform(FT), Cosine Transform, Wavelet Transform(WT) suffer from discontinuities like edges and contours in pictures. To handle this problem, Jun XU et al. Proposed a new MGA-tool called RT. RT is a higher dimensional generalization of the Curvelet Transform (CVT), is used to represent picture or 2D signals at different scales and different directions. Ripple Transform used to create a new tight frame with sparse representation for picture with discontinuities along Cd curves [12].

A. Continuous Ripplet Transform (CRT)

For a two Dimensional integrable \( f(x) \), the CRT is defined because the real number of \( f(\tilde{x}) \) and ripples as \( \rho_{\tilde{a}\tilde{b}\tilde{\theta}}(\tilde{x}) \) given in

\[
R(a,\tilde{b},\theta) = (f,\rho_{\tilde{a}\tilde{b}\tilde{\theta}}) = \int f(\tilde{x})\rho_{\tilde{a}\tilde{b}\tilde{\theta}}(\tilde{x})d\tilde{x}
\] (1)
Where \( R(a, b, \theta) \) are the coefficients as ripplet and \( \tilde{a} \) denote operator as conjugate. The ripplet function of the equivalent. 1 is defined as
\[
\rho_{a\theta}(\tilde{x}) = \rho_{a\theta}(R_\theta(x - \tilde{b}))
\]
(2)

Where \( \rho_{a\theta} \) is that the ripplet part perform given by the shape
\[
R_\theta = \begin{bmatrix}
\cos \theta & \sin \theta \\
-\sin \theta & \cos \theta
\end{bmatrix}
\]
(3)

The equation (3) shows the rotation matrix, where \( \tilde{x} \) and \( \tilde{b} \) are 2D vectors; \( b \& \theta \) denotes the position parameter and rotation parameter severally. The ripplet part perform is defined in frequency domain as 1
\[
\rho_a(r, \omega) = \frac{1}{\sqrt{c}} a^\frac{1+\delta}{2d} W(a r) V(a^\frac{1}{\alpha}, \omega)
\]
(4)

Where \( \rho_a(r, \omega) \) is that the Fourier remodel of \( \rho_{a\theta} \) in coordinate system, and \( a \) is that the scale parameter. \( W(r) \) is that the "radial-window" and \( V(\omega) \) is the "angular window". There are 2 side have supports at point \([1/2, .2] \) and \([-1, 1] \) severally. They satisfy the subsequent acceptableness conditions:
\[
\int_{-\frac{1}{2}}^{\frac{1}{2}} W^2(r) dr = 1
\]
(5)
\[
\int_{-1}^{1} V^2(\omega) d\omega = 1
\]
(6)

Figure. The application of polar frequency domain. (The shaded 'wedge' corresponds to the frequency remodel of the part function).

The ripplet functions decay in no time outside the elliptical effective region, that has the subsequent property for its length and width: width \( \approx \) length \( \delta^4 \). Length and dimension is that the major and axis of the conic section severally. The region tuned by \( c \& d \) as a support and \( d \) as degree be speaks the foremost distinctive property of ripplets (i.e) the final scaling.

The CRT will capture solely the characteristics of high frequency elements of \( j \) the size parameter 'a' cannot take the worth of infinity. So the 'full' CRT consists of fine scale RT and coarse scale isotropic WT[6]. The input perform may be reconstructed supported its ripplet coefficients.

**B. Discrete Ripplet Transform (DRT)**

As digital image process wants distinct transform rather than continuous remodel, here we describe the discretization of RT [6]. The discretization of CRT(Continuous ripplet remodel) is based on the discretization of the parameters of ripplet functions \( a, \tilde{b} \) and \( \theta \) substitute \( a, \tilde{b}, \theta \) respectively , and satisfy that \( a_j = \frac{2^j}{c}, \tilde{b}_k = [c\cdot 2^{-j}\cdot k_1, c\cdot 2^{-j}\cdot d, k_2]^T \) and \( \theta_l = \frac{2\pi}{c}\cdot 2^{\frac{2(j-l)}{d}}, \) where \( \tilde{k} = [k_1, k_2]^T \) and \( j, k_1, k_2, l \in \mathbb{Z} \). \( (\cdot)^T \) denotes the transpose of a vector \( d \in \mathbb{Z} \), since any real number may be approximated by rational numbers so we will represent \( d \) with \( d=n/m \) and \( n, m \neq 0 \in \mathbb{Z} \). Usually, we prefer \( n, m \leftarrow N \) and \( n, m \) are measure each primes, within the frequency domain, the corresponding frequency response of ripplet perform is within the type
\[
\rho_j(r, \omega, a, d) = \frac{1}{\sqrt{c}} a^\frac{n_m}{2d} W(2^{-j} r) V(2^{-j}\frac{n_m}{2d}, \omega - l)
\]
(7)

where \( W \) and \( V \) satisfy the subsequent acceptableness conditions:
\[
\sum_{j=-\infty}^{\infty} |W(2^{-j} r)|^2 = 1
\]
(8)
\[
\sum_{j=-\infty}^{\infty} |V(2^{-j}\frac{n_m}{2d}, \omega - l)|^2 = 1
\]
(9)

given \( c, d \) and \( j \). The 'wedge' comparable to the ripplet perform within the frequency domain is
\[
H_{j, \delta}(r, \omega) = \begin{cases}
1 & |r| \leq 2^j, |\omega - \frac{2^j\pi}{2d}| \leq \frac{\pi}{2d} \\
\frac{1}{2} & |r| > 2^j, |\omega - \frac{2^j\pi}{2d}| \leq \frac{\pi}{2d} \\
0 & \text{else}
\end{cases}
\]
(10)
The DRT of an \( M \times N \) image \( f(n_1, n_2) \) are within the form of
\[
R_{j,k,l} = \sum_{n_1=0}^{M-1} \sum_{n_2=0}^{N-1} f(n_1, n_2) \rho_j, \theta_l(n_1, n_2)
\]
(11)

Where \( R_{j,k,l} \) square measure the ripplet co-efficients. The image may be reconstructed through Inverse Discrete Ripplet Transform (IDRT)
\[
\hat{f}(n_1, n_2) = \sum_{j=0}^{J-1} \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} R_{j,k,l} \rho_j, \theta_l(n_1, n_2)
\]
(12)

As a generalized version of the present curvelet transform, RT is not only capable of resolution second Dimensional singularities, but it additionally has few smart properties [7]:

1. It forms a brand new tight enclose a perform house. And is capable of localizing in spatial and frequency domain providing a additional economical and effective representation for images or 2D signals.
2. It has general scaling with impulsive degree and support that will capture second singularities on different curves in any directions. Jun XU et al. have showed that RT will give a more practical representation for pictures with singularities on smooth curves [6].
3. Pulse Coupled Neural Network

PCNN may be a single stratified, two-dimensional, and laterally connected neural network of pulse coupled neurons. The PCNN neurons structure is shown in Fig. 2. The nerve cell consists of Associate in Nursing input half (dendritic tree), linking half and a generator. The nerve cell receives the input signals from feeding and linking inputs. Feeding input is that the primary input from the neurons receptive space., the quality PCNN model is delineate as iteration by the subsequent equations [10], [16]:

\[
F_{i,j}[n] = e^{-\alpha_F} F_{i,j}[n-1] + \sum_{k,l} w_{i,j,k,l} V_{k,l}[n-1] + S_{i,j}
\]

\[
L_{i,j}[n] = e^{-\alpha_L} L_{i,j}[n-1] + \sum_{m,n} m_{i,j,m,n} Y_{m,n}[n-1]
\]

\[
U_{i,j}[n] = F_{i,j}[n](1 + \beta L_{i,j}[n])
\]

\[
Y_{i,j}[n] = \begin{cases} 1, & U_{i,j}[n] > T_{i,j}[n] \\ 0, & \text{otherwise} \end{cases}
\]

\[
T_{i,j}[n] = e^{-\alpha_T} T_{i,j}[n-1] + V_f Y_{i,j}[n]
\]

In the Eq.(12) to Eq.(16), the indexes i and j seek advice from the pixel location within the image, k and l seek advice from the dislocation in an exceedingly symmetric neighborhood around one pixel, and n denotes the current iteration (discrete time step). Here n varies from one to N (total variety of iterations). The dendritic tree is given by Eqs.(12)-(13).The 2 main elements F and L area unit known as feeding and linking, severally. \(w_{i,j,k,l}\) and \(m_{i,j,m,n}\) area unit the synaptic weight coefficients and \(S\) is that the external input. \(V_f\) And \(V_y\) area unit normalizing constants. \(\alpha_F\) And \(\alpha_L\) area unit the time constants; usually, \(\alpha_F < \alpha_L\). The linking modulation is given in equivalent weight.(16), wherever \(U_{i,j}[n]\) is that the internal state of the neuron and \(\beta\) is that the linking parameter. The heart beat generator determines the firing events within the model in equivalent weight.Eq.(15). \(Y_{i,j}[n]\) Depends on the inner state and threshold. The dynamic threshold of the nerve cell is equivalent Eq.(16), where \(V_f\) and \(\alpha_F\) area unit normalized constant and time constant, severally.

4. Proposed Method

The notations used in this section as follows: A, B, R represents the 2 source pictures and therefore the resultant image, severally. \(C = (A,B,R)\). \(L_{i,j}^C\) Indicates the LFS of the image \(C\) at the coarsest scale \(G\). \(D_{i,j}^{gh}\) represents the HFS of the image \(C\) at scale \(g\), (g = 1,…,G) and direction h. \((i, j)\) denotes the spatial location of every coefficient . The method is simply extended to more than two pictures.

A. Fusing Low Frequency Subbands

The LFSs coefficients area fused using ‘max selection’ rule. According to this fusion rule, choose the frequency coefficients from \(L_{i,j}^g\) or \(L_{i,j}^h\) with larger definite quantity because the fused coefficients:

\[
L_{i,j}^{\text{new}}(i, j) = \begin{cases} L_{i,j}^g(i, j), & L_{i,j}^g(i, j) \geq L_{i,j}^h(i, j) \\ L_{i,j}^h(i, j), & \text{otherwise} \end{cases}
\]

(17)

B. Fusing High Frequency Sub Bands

The HFSs of the supply pictures are fused PCNN. As humans area unit sensitive to options like edges, contours etc., so rather than PCNN in DRT domain directly (i.e., using individual coefficients), changed spatial frequency (MSF) in DRT domain is taken into account because the image feature to inspire the PCNN.

1) MODIFIED SPATIAL FREQUENCY (MSF): spatial frequency (SF) projected by Eskicioglu et al. is calculated by row and column frequency [17]. It reflects the entire activity level of an image, which implies the larger the SF, the upper the image resolution. We have used a changed version of SF within the proposed MIF technique. The MSF consists of row (RF), column (CF) and diagonal frequency (DF). For a M×N pixels image f the MSF is outlined as

\[
MSF = \sqrt{RF^2 + CF^2 + DF^2}
\]

Where,

\[
RF = \frac{1}{M(N-1)} \sum_{m=1}^{M} \sum_{n=2}^{N} \left[f_{m,n} - f_{m,n-1}\right]^2
\]

(19)

\[
CF = \frac{1}{(N-1)M} \sum_{m=2}^{M} \sum_{n=1}^{N-1} \left[f_{m,n} - f_{m-1,n}\right]^2
\]

(20)

And,

\[
DF = P + Q
\]

Where,

\[
P = \frac{1}{(M-1)(N-1)} \sum_{m=2}^{M} \sum_{n=2}^{N} \left[f_{m,n} - f_{m-1,n-1}\right]^2
\]

(22)

\[
Q = \frac{1}{(M-1)(N-1)} \sum_{m=1}^{M-1} \sum_{n=1}^{N-1} \left[f_{m-1,n} - f_{m,n-1}\right]^2
\]

(23)

2) FUSION USING DRT-MSF-PCNN:

Let, \(MSF_{i,j}^{r,h,c}\) be the changed spatial frequency similar to a coefficient \(D_{i,j}^{r,h,c}\), measured by using overlapping window around the involved coefficient where \(C = (A,B)\). so as to reduce the machine complexity, we tend to use a simplified PCNN:

\[
F_{i,j}^{g,\text{new}}[n] = MSF_{i,j}^{g,h,c}[n]
\]

(24)
The linking input is up to the total of neurons firing times in linking range. \( W_{i,j,k,l} \) is that the conjunction gain strength and subscripts k and l are unit the dimensions of linking range the PCNN. \( \alpha \) is the decay constants. \( \beta \) is that the linking strength. \( V_L \) and \( V_\theta \) area unit the amplitude gains. \( U_{i,j}^{g,h,c} \) is that the total internal activity and \( \theta_{i,j}^{g,h,c} \) is that the threshold. If \( U_{i,j}^{g,h,c} \) is larger than \( \theta_{i,j}^{g,h,c} \), then the nerve cell can generate a pulse \( Y_{i,j}^{g,h,c} = 1 \), is known as one firing time.

\[
L_{i,j}^{g,h,c}[n] = e^{-\alpha_t} L_{i,j}^{g,h,c}[n-1] + V_L \sum_{k,l} W_{i,j,k,l} Y_{i,j,k,l}^{g,h,c}[n-1]
\]

\[
U_{i,j}^{g,h,c}[n] = F_{i,j}^{g,h,c}[n] * (1 + \beta L_{i,j}^{g,h,c}[n])
\]

\[
\theta_{i,j}^{g,h,c}[n] = e^{-\alpha_t} \theta_{i,j}^{g,h,c}[n-1] + V_\theta Y_{i,j}^{g,h,c}[n-1]
\]

\[
Y_{i,j}^{g,h,c}[n] = \begin{cases} 1, & \text{if } U_{i,j}^{g,h,c}[n] > \theta_{i,j}^{g,h,c}[n] \\ 0, & \text{otherwise} \end{cases}
\]

\[
T_{i,j}^{g,h,c}[n] = T_{i,j}^{g,h,c}[n-1] + T_{i,j}^{g,h,c}[n]
\]

Where, the feeding input \( F_{i,j}^{g,h,c}[n] \) up to the normalized modified spatial frequency \( MSF_{i,j}^{g,h,c} \). The linking input \( L_{i,j}^{g,h,c} \) is up to the total of neurons firing times in linking range. \( W_{i,j,k,l} \) is that the conjunction gain strength and subscripts k and l are unit the dimensions of linking range the PCNN. \( \alpha \) is the decay constants. \( \beta \) is that the linking strength. \( V_L \) and \( V_\theta \) area unit the amplitude gains. \( U_{i,j}^{g,h,c} \) is that the total internal activity and \( \theta_{i,j}^{g,h,c} \) is that the threshold. If \( U_{i,j}^{g,h,c} \) is larger than \( \theta_{i,j}^{g,h,c} \), then the nerve cell can generate a pulse \( Y_{i,j}^{g,h,c} = 1 \), is known as one firing time.

The total of \( Y_{i,j}^{g,h,c} = 1 \) in n iteration (namely the firing times), is employed to represent the image info. Here, instead of \( Y_{i,j}^{g,h,c} [n] \), we've analyzed \( T_{i,j}^{g,h,c} [n] \), since neighboring coefficients with similar options represent similar firing times in an exceedingly given iteration times.

C. ALGORITHM

The medical pictures to be coalesced at pixels area unit aligned. Here we tend to outlines the salient steps of the projected MIF method:

1. Decompose the registered supply medical pictures A and B by DRT to get the LFSs and HFSs.
2. Fused the coefficients of LFSs using the ‘max selection’ rule delineate in Section IV-A, to get the fused LFS.
3. Compute the MSF as delineate in Section IV-B1, using overlapping window on the coefficients in HFSs.
4. Input MSF of every HFSs to inspire the PCNN and generate pulse of neurons with Eqs.(24)–(29). and cypher the firing times \( T_{i,j}^{g,h,c} [n] \) by equivalent weight.(31).
5. If \( n = N \), then iteration stops. Then fuse the coefficients in the HFSs by the subsequent fusion rule:
6. Apply inverse ripplet remodel (IDRT) on the fused LFS and HFSs to get the ultimate fused medical image.

The diagram of the projected MIF theme is shown in Fig. 3.

![Diagram of the projected MIF technique.](image)

5. Results and Other Technique Comparison

The projected MIF technique, extensive experiments were carried out on numerous modalities of medical pictures. Fig. 4(a)-(b) and Fig. 4(c)-(d) shows 2 different sets of supply pictures used in the analysis , and are show by IS1 and IS2, severally. The CT image in Fig. 4(a) shows the bones and therefore the MRI image in Fig. 4(b) displays the soft tissues info. The T1- weighted man image in Fig. 4(c) of IS2 contains the soft tissues however no illness info, and therefore the MRA image in Fig. 4(d) shows the illness info

shown by the marked ellipse) however no soft tissues info. The decomposition parameter of DRT was levels = [1, 2, 4, 4]. Parameters of PCNN was set as \( k \times l = 3 \times 3 \)

\[
\alpha = 0.2, \beta = 0.2, V_L = 1.0, V_\theta = 20,
\]

\[
W = \begin{bmatrix} 0.707 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707 \end{bmatrix}
\]

and \( N=200 \).
Where RF is that the row frequency and CF is that the column frequency:

\[
RF = \sqrt{\frac{1}{M(N-1)} \sum_{m=1}^{M} \sum_{n=2}^{N} [f_{m,n} - f_{m-1,n}]^2}
\]

(34)

\[
CF = \sqrt{\frac{1}{(N-1)M} \sum_{m=2}^{M} \sum_{n=1}^{N} [f_{m,n} - f_{m-1,n}]^2}
\]

(35)

where \(M \times N\) denotes the dimensions of image and the grayscale value of the picture element of image \(F\) at position \((m, n)\) as indicates \(F(m, n)\).

D. MI

A larger measure implies higher quality. Given 2 pictures \(X_F\) and \(X_R\), MI is outlined as [18]:

\[
MI = I(x_A ; x_F) + I(x_R ; x_F) + I(x_F ; x_R)
\]

(36)

Where 

\[
I(x; y) = \sum_{uv} h_{x,y}(u,v) \log \frac{h_{x,y}(u,v)}{h_x(u)h_y(v)}
\]

(37)

where \(h_x, h_y\) area unit the normalized grey level histograms of \(X_F\) and \(X_R\), severally. \(h_{x,y}\) is that the joint grey level bar graph of \(X_F\) and \(X_R\), and \(L\) is that the variety of bins. \(X_F\) and \(X_R\) correspond to the reference and fused pictures, severally. \(I(x_F ; x_R)\) indicates what proportion info the fused image \(X_F\) conveys regarding the reference \(X_R\). Thus, the upper the mutual info between \(X_F\) and \(X_R\), the a lot of possible \(X_F\) resembles the best \(X_R\). An professional practician was asked to subjectively judge the effectiveness of the projected MIF technique. When careful manual inspection, the practician conformed to the effectiveness of

Table II: Performance Comparisons Using IS1

<table>
<thead>
<tr>
<th>Scheme</th>
<th>MI</th>
<th>SF</th>
<th>EN</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheme[7]</td>
<td>-</td>
<td>6.56</td>
<td>6.39</td>
<td>53.82</td>
</tr>
<tr>
<td>Scheme[5]</td>
<td>2.71</td>
<td>-</td>
<td>6.73</td>
<td>57.98</td>
</tr>
<tr>
<td>Scheme[6]</td>
<td>2.06</td>
<td>-</td>
<td>4.98</td>
<td>-</td>
</tr>
<tr>
<td>Our theme</td>
<td>3.35</td>
<td>7.82</td>
<td>7.04</td>
<td>70.42</td>
</tr>
</tbody>
</table>

The projected theme. He found that the coalesced pictures obtained by the projected MIF theme, were a lot of clear, informative and have higher distinction that is useful in image as well as interpretation.

Figure 5: Results of the projected MIF theme (a) fused image of IS1; (b) fused image of IS2
6. Conclusion

Propose a Medical diagnosis system based on ripplet transform using modified spatial frequency motivated PCNN. The DRT is capable of resolving two dimensional singularities and representing image edges more efficiently, which makes the fused images clearer and more informative. To integrate as much information as possible into the fused images the low frequency source subbands are fused using ‘max selection’ rule, and PCNN is used to select the ‘better’ coefficients from the decomposed source high frequency subbands. To improve the result, instead of using single coefficient to motivate the PCNN, modified spatial frequency is used as the image feature to motivate the PCNN. The proposed MIF method is analyzed both visually and quantitatively, and is compared with several existing IF techniques, and the superiority of the proposed scheme is established.

7. Acknowledgment

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References


