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Dual Channel Pulse Coupled Neural Network Algorithm for Fusion of Multimodality Brain Images with Quality Analysis

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Abstract
Background: In the review of medical imaging techniques, an important fact that emerged is that radiologists and physicians still are in a need of high-resolution medical images with complementary information from different modalities to ensure efficient analysis. This requirement should have been sorted out using fusion techniques with the fused image being used in image-guided surgery, image-guided radiotherapy and non-invasive diagnosis. *Aim:* This paper focuses on Dual Channel Pulse Coupled Neural Network (PCNN) Algorithm for fusion of multimodality brain images and the fused image is further analyzed using subjective (human perception) and objective (statistical) measures for the quality analysis. *Material and Methods:* The modalities used in fusion are CT, MRI with subtypes T1/T2/PD/GAD, PET and SPECT, since the information from each modality is complementary to one another. The objective measures selected for evaluation of fused image were: Information Entropy (IE) - image quality, Mutual Information (MI) – deviation in fused to the source images and Signal to Noise Ratio (SNR) – noise level, for analysis. Eight sets of brain images with different modalities (T2 with T1, T2 with CT, PD with T2, PD with GAD, T2 with GAD, T2 with SPECT-Tc, T2 with SPECT-Ti, T2 with PET) are chosen for experimental purpose and the proposed technique is compared with existing fusion methods such as the Average method, the Contrast pyramid, the Shift Invariant Discrete Wavelet Transform (SIDWT) with Harr and the Morphological pyramid, using the selected measures to ascertain relative performance. *Results:* The IE value and SNR value of the fused image derived from dual channel PCNN is higher than other fusion methods, shows that the quality is better with less noise. *Conclusion:* The fused image resulting from the proposed method retains the contrast, shape and texture as in source images without false information or information loss.

Keywords: Multimodality Brain Images; Dual Channel Pulse Coupled Neural Network (DCPCNN); Subjective Measures; Objective Measures.

Introduction

Image fusion refers to techniques that integrate complementary information from multiple image sensors such that the fused images are made suitable for better human/machine perception. A basic requirement of image fusion is to improve the reliability and capability of the fused image. As the clinical use of various medical imaging systems extends, multi-modality imaging starts playing an increasingly important role. Here, multi-modality imaging refers to image acquisition from more than one modality(sensor) for a patient during the same time period. Different medical imaging techniques provide scans with complementary and occasionally redundant information. The combination of medical images can often lead to additional clinical information not apparent in single modality images. However, it is difficult to simulate the surgical ability of image fusion when algorithms of image processing are merely piled up. Hence many solutions to medical diagnostic image fusion exist, which are widely used by radiologists and physicians. In the recent era of medical imaging, radiologists demand images with high resolution and better information content in context with bones, tissues and boundary visualization for disease diagnosis and computer assisted surgery. In reality, these requirements can not be resolved by a single modality medical image because:

- X-ray Computed Tomography (CT) is more popular with recognizing bone structure;
- Soft tissue information is better visible through a Magnetic Resonance Image (MRI);
- Positron Emission Tomography (PET) provides clear information in blood flow;
- Single-Photon Emission Computed Tomography (SPECT) is used for information about localized function in internal organs, such as functional cardiac or brain imaging and so on.

Since each modality provides access to a specific piece of the picture, complementary information from multiple modalities are required for radiologist to do their diagnosis efficiently. It is for this salient angle that Fusion techniques have attracted a lot of researchers in this domain. In reality, the medical images of different modalities CT/MRI/PET/SPECT can be fused into a single image using different fusion techniques. Generally CT and MRI are classified as anatomical images where as PET and SPECT are classified into pathological images.

In the domain of fusion research, many approaches to fusion techniques have been already proposed and implemented [1]. Fusion techniques can be broadly classified as spatial-domain and transform-domain methods. The methods under the spatial domain are Averaging, Principle Component Analysis, High Pass filtering based technique, Fuzzy logic, etc., but the fused image remains with spatial and spectral distortion. This distortion in turn affects the visualization of tumor region during diagnosis. Spatial techniques with decision rules in fusion, and the uncertainty of the fusion rules [2, 3] is later resolved with fuzzy logic. The problems of spatial-domain are resolved in transform-domain techniques such as Discrete Wavelet Transform (DWT), Laplacian pyramid and Curvelet transform, etc. Nevertheless, the fact remains that each method has its own limitation in the fusion process. As far as pyramid based techniques are concerned, the Ratio pyramid method produces a lot of false information that does not exist in the source images; the Contrast pyramid method loses too much of information from the source; and the Morphological pyramid method creates many false edges. The majority of fusion techniques are based on wavelet transformation [4]. However, the DWT in medical image fusion results with shift variant and additive noise in the fused image. The modification of DWT i.e. Redundant DWT overcomes the problem of shift variant and preserves the exact edge and spectral information without much of spatial distortion [5, 6]. Another widely used transformation is the region-based Contourlet transform, which brings localization, directionality and anisotropy, etc., on the fused image. It has been implemented with two stages such as transformation and decomposition, leading to more complexity in computation [7-9]. To sum up, we could say that, all methods discussed above have some limitation in preserving the texture information, background, contour and edge of the image at the time of performing the fusion task [10].

Pulse Coupled Neural Network (PCNN) is a prominent research topic in the artificial intelligence field for various applications [11] like denoising, segmentation, enhancement, fusion, feature extraction, edge detection, pattern recognition, decoding etc., in image processing techniques. The basic PCNN algorithm was proposed by Johnson in 1995 [12] and further modifications are evolved from 1999 onwards [13].

According to literature review, the multi channel PCNN model has been given in [14, 15] for multispectral images. This model is build with set of PCNN's in parallel with separate channel of input for inter and intra channel linking. This parallel task leads to more computational complexity. Therefore single PCNN fusion technique (spatial/pixel based) is proposed and popularly used, but in reality one PCNN is not sufficient to complete the fusion process [13]. Therefore, a group of more than two PCNNs is used to fuse multi-source images, but it leads to inefficient and impractical real-time image analysis. In need of that, PCNN has evolved into the MPCNN where M refers to the number of channels in PCNN. Each channel is the equivalent of an image, and the fusion technique is carried out with M channels single PCNN [16]. This method results in an accurate outcome than other fusion methods, but it takes approximately twice the computational time (in minutes). The fused image is more informative with better quality and less noise. .

In the proposed fusion model [11, 17] herein, Dual channel PCNN algorithm is explained and implemented to fuse two source images from different modality/subtype of brain images such as CT, MRI with all subtypes, PET and SPECT. The main objective of this paper is to evaluate the Dual channel PCNN with different image sets (Anatomical vs Anatomical, Anatomical vs Pathological) using the following objective measures: Information Entropy (IE), Mutual Information (MI) and Signal to Noise Ratio (SNR) to identify the better-fused image.

Material and Methods

The fusion model chooses the brain images from different modalities and subjects to fusion techniques: dual channel PCNN, Average method, Contrast pyramid, SIDWT with Harr, Morphological pyramid and evaluated using subjective and objective measures.

Multiple-Pulse Coupled Neural Network (M-PCNN)

The M-PCNN algorithm is executed in three stages in sequence namely; dendritic tree, information fusion and pulse generator [17]. The dendritic tree works as a receptive field and captures inputs from the external stimulus and surrounding neurons for feeding and linking functions. The output generated from the functions are fused in the second stage and passed to the pulse generator to generate output pulses. In the M-PCNN algorithm, M represents the channels i.e. number of input images. The following algorithm mathematically illustrates the model of dual channel PCNN for the fusion of two input images.

Algorithm (Dual Channel PCNN)

Step 1: The dual-channel PCNN, as the name implies, has two input images as external input channels i.e. M=2.

Step 2: For the two symmetrical input channels (images), the value of the current neuron is calculated (H^1 and H^2) as given in Equations (1) and (2).

$$H^1_{i,j}[n] = M(Y[n-1]) + S^1_{i,j} \tag{1}$$

$$H^2_{i,j}[n] = W(Y[n-1]) + S^2_{i,j} \tag{2}$$

where S^1, S^2 are input images and $M(.)$, $W(.)$ are the feed functions indicating the influence of surrounding neurons on current neuron and n represents the current iteration from 1 to N (total iterations) and $Y[n-1]$ is the output of neuron from previous iteration.

Step 2.1: The $M(.)$ and $W(.)$ are calculated using convolution operation, shown in Equation (3).

$$M(.) = W(.) = Y(n-1) \oplus K \tag{3}$$

where K is the array of convolution core values.

Step 3: The received signals are mixed together(fusion) and the internal activity of the neuron (state) is calculated. i.e. $U_{i,j}[n]$ as given in Equation (4).

$$U_{i,j}[n] = \left(1+\beta^1 H^1_{i,j}[n]\right)\left(1+\beta^2 H^2_{i,j}[n]\right) + \sigma \tag{4}$$

where β^1 and β^2 are weight coefficients of H^1 and H^2 respectively and σ is a level factor.

Step 4: The pulse generator ($Y_{i,j}[n]$) determines the firing events according to the current iteration (C_n) by comparing the internal state of the neuron $U_{i,j}[n]$ with dynamic threshold of the neuron $T_{i,j}[n]$ as given in Equation (5) and $T_{i,j}[n]$ is defined in Equation (6).

$$Y_{i,j}[n]=\begin{cases}1 & U_{i,j}[n] > T_{i,j}[n]\\ 0 & \text{otherwise}\end{cases} \tag{5}$$

$$T_{i,j}[n] = \exp(-\alpha_T)T_{i,j}[n-1]+V_T Y_{i,j}[n] \tag{6}$$

where V_T and a_T are normalized constant and time constant respectively.
Step 5: Then the new summation is calculated for the current iteration

$$\text{Sum} = \text{Sum}' + C_n \tag{7}$$

Step 6: If *Sum* < *Num,* repeat from step 2; else continue. Here *Num* indicates the total number of neurons in the network.
Step 7: Apply normalization or linear transformation to derive the fused image *U* (i.e) internal state. Here, the linear transformation is applied to derive the fused image from the two input images.

Objective Measures

Evaluation of the fused image in the perspective of visual effects is not a sufficient measure. It also has to be analyzed using the objective measures in terms of texture, information, noise, etc. We have chosen three measures for analysis: Information Entropy for image information, Mutual Information to reflect the difference in fused to the source image and Signal to Noise Ratio to derive the noise level of the fused image.

Information Entropy (IE)

Information Entropy is a measure of the image quality(information that is gained from an image), as defined in [3]. The information entropy obtained is directly proportional to the fused image and it is mathematically given in Equation (8).

$$IE = -\sum_{i=0}^{m} p_i \ln p_i \tag{8}$$

where p_i is the probability of gray level (i), and the range of i is [0,….. 255].

Signal to Noise Ratio (SNR)

SNR of an image is defined as the ratio of the mean pixel value to the standard deviation pixel values [18], and its formula is presented in Equation (9).

$$\text{SNR} = \text{Mean/Standard Deviation} \tag{9}$$

Mutual Information (MI)

MI measures the similarity between two images. If A and B, are the registered images then the MI is defined by Equation 10, as in [17]:

$$\text{MI (A, B)} = \text{EN(A)} + \text{EN(B)} - \text{JE (A, B)} \tag{10}$$

where EN(A) and EN(B), denotes the information entropy of image A image B and JE(A,B) is the joint information entropy of two images A and B. A larger value of MI (A, B) is the superior fusion algorithm from other algorithms.

Parameter Setting

In the Dual-channel PCNN, parameters are set as follows: $\beta^1 = \beta^2 = 0.6$; convolution core K = [0.1091, 0.1409, 0.1091; 0.1409, 0, 0.1409; 0.1091, 0.1409, 0.1091]; level factor $\sigma = 1.3$; time constant $\alpha T = 0.015$; and normalized offset parameter $V_T = 2000$. The parameter for Contrast pyramid, SIDWT with Harr and Morphological pyramid are same in selection rules; that is high pass = salience/match mismatch, low pass= average method and the decomposition level is 2, 4 and 1 respectively. In average method, the value of fused image is calculated from the two source images directly.

Dataset

The brain images of different modalities used in the experiments are taken from Harvard Medical School website [19]. For analysis, the images of three patients with multiple modalities are considered as group1, group2 and group3. All images are registered with the size of 256 * 256 pixels and 256-level gray scale. The modalities of each group of input images are:

- Group1: It has 5 types of images for Sarcoma disease i.e. MRI-PD/T2/T1/GAD and CT
- Group2: It has 4 types of images for Astrocytoma disease i.e. MRI-T2/GAD and SPECT-Tc/Ti.
- Group3: It has 2 types of images for Astrocytoma disease i.e. MRI-T2 and PET-FDG

To illustrate the importance of the proposed fusion technique, the images of three groups (patients) are divided into 8 set of images. In group1 the set of images are T2 with T1, T2 with CT, PD with T2, PD with GAD and in group2 the pairs are T2 with GAD, T2 with SPECT-Tc, T2 with SPECT-Ti and in group3 the pair is T2 with PET- FDG, totally derives to 8 pair of images.

Results and Discussion

In this section, the results obtained for the datasets described above using the proposed and chosen existing fusion algorithms such as Dual channel PCNN(A1), Contrast pyramid(A2), Average method(A3), SIDWT with Harr(A4), Morphological pyramid(A5) are tabulated and discussed. For ease on explanation, the algorithms are named from A1 to A5.

The information entropy value of source image for each of the group is shown in Table 1. It is required for the comparison of image quality of the source to the fused image.

Table 1. Information entropy of all the source images with group detail

Group1	T2/4.6605	PD/4.2842	T1/4.5084	GAD/4.5368	CT/4.5807
Group2	T2/4.8342	SPECT-Tc/4.3599	SPECT-Ti/1.0066	-	-
Group3	T2/4.5921	PET-FDG/4.4553	-	-	-

The source and fused images of two sample sets from group1 (set2) and group2 (set7) is shown below for all algorithms for visualization i.e. the analysis of subjective measure for fusion validation. Set2 comprises of anatomical CT and MRI images; set7 comprises anatomical MRI image and pathological PET image.

In Figure 1, the input images are MRI-T2 and CT (both are anatomical), the visualization of the output from A2 has more contrast than A3, with less information. In Figure 2, the input images are MRI-T2 and SPECT-Ti (anatomical with pathological), the fused image of A2 resulted with more contrast (information loss) and the output from A3 has all the information with observable contrast. But the output of A4 and A5 are same in visualization for both combinations i.e. anatomical with anatomical and anatomical with pathological. The fused image of A4 has some dark spots and A5 has false edges, which does not exist in the input images, indicates the false information in visualization (subjective measure). The fused image from A1 retains all the information of source images with low or high contrast depends on the modality in a better way. From these observations, it is inferred that the proposed approach A1, retains the information of contrast, texture, shape etc in the fused image.

In addition to the subjective evaluation of two different combinations, the 8 set of input images are fused using 5 different fusion algorithms and the fused image is validated with objective measures. The observed results are tabulated in Table 2 and Table 3.

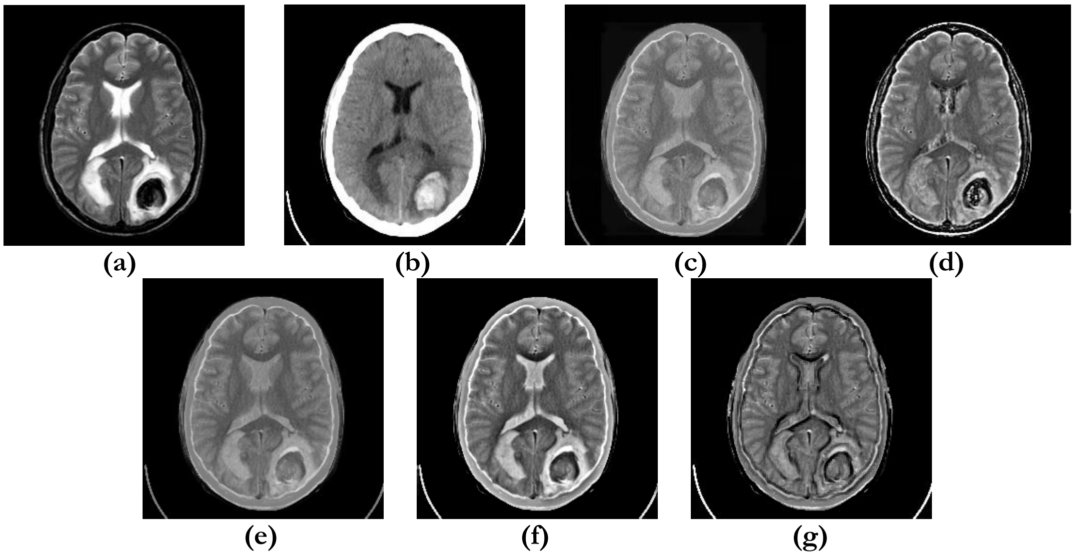

Figure 1. Input and fused images of Set2 - **(a)** MRI- T2 **(b)** CT **(c)** A1- Dual channel PCNN **(d)** A2- Contrast pyramid **(e)** A3- Average method **(f)** A4- SIDWT with Harr **(g)** A5- Morphological pyramid

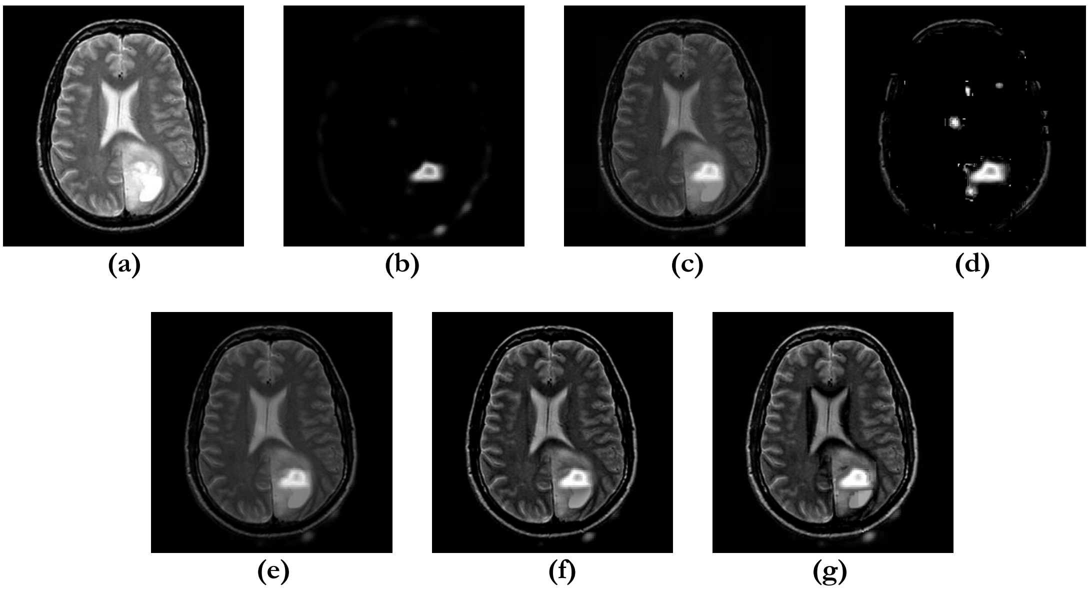

Figure 2. Input and fused images of Set7 - **(a)** MRI- T2 **(b)** SPECT - Ti **(c)** A1- Dual channel PCNN **(d)** A2- Contrast Pyramid **(e)** A3- Average method **(f)** A4- SIDWT with Harr **(g)** A5- Morphological pyramid

From the experimental results, it has been observed that the dual channel algorithm is more suitable for all modality/subtype of brain images than the other methods. The fused image from A1 has resulted with higher information entropy value without information loss or false information. When comparing the IE values of Table 1 with Table 2/Table3 (source images vs fused image), it has been observed that it is increased considerably for A1 algorithm, concludes that the fused image has more information than the source images. MI_AB denotes the cumulative mutual information from MI_AF and MI_BF, where MI_AF and MI_BF is the mutual information between image A with Fused image and image B with Fused image respectively. Here, the fused image from A3 has resulted with higher cumulative mutual information, since in A3 the intensity values of two source images are added and averaged directly. As SNR is concerned, the fused image from A1 has higher value (less noise) than other fusion methods. From the performance evaluation, we identified that the fused image of the proposed method are resulted with more information, less noise and a better visualization than the source images.

Table 2. Objective measures of the fused image using different algorithms for Group1

Objective measure	Algorithm	Set 1	Set 2	Set 3	Set 4
IE	***A1***	***5.6489***	***5.8634***	***5.8394***	***5.6715***
	A2	4.4548	4.5307	4.4553	4.2687
	A3	4.4813	4.6775	4.6851	4.5117
	A4	4.2849	4.6282	4.9898	4.3562
	A5	4.4877	4.5403	4.5629	4.2763
MI_AB= MI_AF+MI_BF	A1	3.2652	3.2261	3.7743	3.2316
	A2	3.3378	3.3742	3.7237	3.2631
	A3	***3.5814***	***3.7419***	***4.1040***	***3.5611***
	A4	3.2250	3.2499	3.6377	3.1730
	A5	3.1824	2.8805	3.5619	3.1391
SNR	***A1***	***0.8956***	***0.9939***	***0.8600***	***0.9244***
	A2	0.7992	0.7930	0.7672	0.8005
	A3	0.8324	0.9371	0.7940	0.8590
	A4	0.7722	0.8462	0.7530	0.8369
	A5	0.7749	0.8513	0.7654	0.8264

Table 3. Objective measures of the fused image using different algorithms for Group2 and Group3

Objective measure	Algorithm	Set 5	Set 6	Set 7	Set 8
IE	***A1***	***6.0431***	***6.0193***	***5.2440***	***5.6610***
	A2	4.7743	4.4264	1.0116	4.2370
	A3	4.8995	4.9089	4.5426	4.7223
	A4	4.6325	4.5765	4.1827	4.4118
	A5	4.7169	4.7058	4.4308	4.5069
MI_AB= MI_AF+MI_BF	A1	3.3783	3.2181	2.5029	3.1085
	A2	3.4554	3.1044	0.8861	2.9299
	A3	***3.7244***	***3.6472***	***4.2536***	***3.4914***
	A4	3.2976	2.9938	2.1715	2.8643
	A5	3.1898	2.9707	2.1941	2.8878
SNR	***A1***	***0.9625***	***0.9139***	***0.7792***	***0.9012***
	A2	0.8243	0.7647	0.1887	0.7765
	A3	0.8943	0.8389	0.7587	0.8325
	A4	0.8452	0.7804	0.6842	0.7904
	A5	0.8403	0.7946	0.7058	0.7905

The Dual Channel PCNN fusion technique also has the following advantages:

- Reduced storage space and cost and efficient Retrieval, since fewer images (fused) are stored in the knowledge- base.
- Data replication is avoided, i.e. storing the same patient data for each modality.

In future, the system for fusion process can be built using hybrid intelligence (e.g. algorithm for edge preserving and fusion) using machine learning techniques. From which, the suitable fusion technique can be identified based on the image types such as satellite, medical, space, visible, infrared etc. However PCNN is concerned, the relation between the input parameters to the output parameter, depends on the application is still an open issue. Therefore, optimization algorithms can be combined along with PCNN for effective analysis.

Conclusion

The Dual channel PCNN was implemented and the results are analysed with four existing fusion algorithms using subjective and objective measures. The experiments were performed on 8 sets of brain images with different modalities/subtypes. When measured with Mutual Information, the Average Method shows up best in terms of reflecting the difference in source to the fused image, while the fused image of dual channel PCNN technique has resulted in better information with minimum noise, when using Information Entropy and Signal to Noise Ratio as the measures. In addition to that, the fused image retains the contrast, shape and texture as in source images without false information or information loss.

List of abbreviations

CT - Computed Tomography
DWT - Discrete Wavelet Transform
IE - Information Entropy
MI - Mutual Information
MRI - Magnetic Resonance Imaging
PCNN - Pulse Coupled Neural Network
PD - Proton Density
PET - Positron Emission Tomography
SIDWT - Shift Invariant Discrete Wavelet Transform
SNR - Signal to Noise Ratio
SPECT- Single Photon Emission Computed Tomography

Conflict of Interest

The authors declare that they have no conflict of interest.

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