Use of Wavelet-Fuzzy Features with PCA for Image Registration

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Abstract- In this paper, we discuss an Image Registration system based on neural network, which uses Wavelet-fuzzy features of an image. In this system, Wavelet-fuzzy features are extracted from an image and then reduced using Principal Component Analysis (PCA). The reduced feature set is then used for training the neural network for image registration. The geometric transformation between the reference and sensed image sets are evaluated using affine transformation parameters. The trained neural network produces registration parameters (translation, rotation and scaling) with respect to reference and sensed image. Two parameters namely Mean Absolute Registration Error and Mutual Information are used as evaluation parameters. Experimentally, we show that the proposed technique for image registration is accurate and robust for distorted and noisy inputs.

Index Terms – Fuzzy Logic, Gaussian Noise, Image Registration, Neural Network, Principal Component Analysis (PCA), Wavelet Transform,

1.0 INTRODUCTION

Image Registration is required as a pre-processing step in many image processing tasks [1]. Image registration is required for comparing two or more images of the same scene taken at different time or from different viewpoints or from different sensors [2]. It plays an important role in disease diagnosis from medical images. The goal of image registration is to determine the geometric transformation that aligns the reference and sensed image. The alignment and integration of images, obtained from different sources and environment, helps to gain complementary information, which is not available from independent images. Registration of distorted and noisy images is a difficult task. Different techniques have been proposed for registration of noisy and distorted images. I. Elhanany et al. [3] proposed feed forward neural network using DCT (Discrete Cosine Transformation) for feature extraction. They extracted DCT coefficients from the lowest frequency band and fed them as input feature vectors to neural network. Feed forward neural network has also been used for image registration using Fourier transform for medical image registration in [4].

Wavelet transform has been commonly used in image processing. P. Ramprasad et al. [5] proposed wavelet technique for matching noisy and poor contrast dental x-rays based on optimization of correlation coefficient of wavelet coefficients. In this, single level wavelet decomposition is performed and then correlation coefficients are calculated. The optimization is performed by maximizing the correlation coefficients. There technique performs better when compared to conventional and manual technique. It registers the images that differ only by rotation and translation but not scaling. Wavelet techniques has been used for registering multi-resolution [6] and multi-modal images [7].

Neural network based systems are reported to perform well when the feature sets are reduced using Principal Component Analysis (PCA) [8].

Fuzzy logic has been used in process control, management and decision making, operation research, economies, pattern recognition and classification. Lu et al. [9] used fuzzy set in multi-modal image registration. In this, Generalized Fuzzy Operator (GFO) is utilized to detect edge. Edges are detected using distance transform (DT). A distance transform of a binary image measures the distance of non-edge pixels to the nearest edge pixel while the edge pixels get the value zero. Fuzzy similarity measure is used to compute similarity measure between the reference and the target images.

In [10], Li et al. proposed fuzzy-wavelet feature extraction approach for pattern recognition. In [11], the authors presented a neural network based image registration technique that used wavelet-fuzzy features. In this paper, we present a neural network based image registration technique that used wavelet-fuzzy features along with PCA. The proposed technique is well suited for noisy and distorted images. Here, the wavelet-fuzzy features are extracted using wavelet transform and fuzzy set. The extracted features are then reduced using PCA. The reduced feature vectors are fed as input vectors to feed forward neural network (NN) and neural network is trained for image registration.

This paper is organized as follows. In Section 2.0, we discuss the proposed registration technique. In Section 3.0, we present our experimental results for noiseless and noisy images. Finally, we conclude in section 4.0.

2.0 PROPOSED REGISTRATION TECHNIQUE

The proposed technique for image registration works in two stages. In the first stage, affine transformation is applied and some noise is appended to the reference image. Additive White

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Gaussian Noise (awgn) is added to improve the performance for distorted inputs. Wavelet transform and fuzzy set is then used to extract the features. In [10], wavelet-fuzzy has been used for feature extraction. These extracted features are then fed to feed forward neural network (NN) as an input. The feed forward NN with one hidden layer and four output layer nodes is then trained by considering the four affine transformation parameters as the four target outputs. We then save the layer weights of the trained network. This stage is called as training phase. The second stage is test phase. In this phase, we extract the features and feed them to the trained NN, and we get the estimated parameter values as output. The overall process is illustrated in Figure1.
The wavelet-fuzzy feature extraction process involves two steps namely (i) Pre-processing step and (ii) Wavelet-fuzzy feature extraction step.

Pre-processing step: To extract the features using the proposed feature extraction method, some preprocessing of images is done. Suppose that an image has $M \times N$ pixels. The image matrix can be reshaped to 1 x ($M.N$) vector, given as-

$(a_{1,1},a_{1,2},\ldots,a_{1,N},a_{2,1},a_{2,2}\ldots a_{2,N},\ldots\ldots,a_{M,1},a_{M,2},\ldots a_{M,N})_{1\times(M.N)}$

where $a_{i,j}$, i =1,2,3,…M and j=1,2,3,….N. This reshaped vector is to be used for feature extraction.

Fuzzy logic → PCA
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Wavelet-Fuzzy Feature Extracti decomposed to a single level approximation signal and detail signal using 'haar' wavelet transform as shown in figure 2.

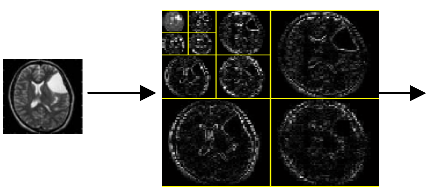


Figure 2

The data size of both the approximation and detail signals at the resolution 2^j are $N_0 \times 2^j$ after the j[th] decomposition. The approximation-detail pairs ($h_{A_{2^j}}(k), h_{D_{2^j}}(k)$), k=1, 2,.$N_0 \times 2^j$ is used in wavelet-fuzzy feature extraction.

The linguistic value sets for x_A , x_D – the approximation and detail signals respectively, are given as-

$$T_A = \begin{pmatrix} v_{A,1} \\ v_{A,2} \\ \vdots \\ v_{A,c_A} \end{pmatrix}, \quad T_D = \begin{pmatrix} v_{D,1} \\ v_{D,2} \\ \vdots \\ v_{D,c_D} \end{pmatrix} \qquad (1)$$

where T_A and T_D are the term sets for the approximation and detail signal respectively; $v_{A,k}$ and $v_{D,l}$, k = 1,2,…….c_A and l=1,2,……c_D are the linguistic values for x_A,x_D , respectively; c_A and c_D are cardinalities for T_A and T_D, respectively. The corresponding membership function is denoted as follows:

$$\mu_A(h_A(k)) = \begin{pmatrix} \mu_{A,1}(h_A(k)) \\ \mu_{A,2}(h_A(k)) \\ \vdots \\ \mu_{A,c_A}(h_A(k)) \end{pmatrix}, \quad \mu_D(h_D(k)) = \begin{pmatrix} \mu_{D,1}(h_D(k)) \\ \mu_{D,2}(h_D(k)) \\ \vdots \\ \mu_{D,c_D}(h_D(k)) \end{pmatrix} \qquad (2)$$

With the two parameters K_A and K_D for tuning sensitivity and robustness, here we have taken K_A = K_D =1, the feature vector of a signal can be expressed as follows:

$$F = \begin{bmatrix} \sum_{k=1}^{N_0 2^j} \Lambda\left(\mu_A^1\left(\frac{h_{A_{2^j}}(k)}{K_A}\right), \mu_D^1\left(\frac{h_{D_{2^j}}(k)}{K_D}\right)\right) \\ \sum_{k=1}^{N_0 2^j} \Lambda\left(\mu_A^1\left(\frac{h_{A_{2^j}}(k)}{K_A}\right), \mu_D^2\left(\frac{h_{D_{2^j}}(k)}{K_D}\right)\right) \\ \vdots \\ \sum_{k=1}^{N_0 2^j} \Lambda\left(\mu_A^{c_A}\left(\frac{h_{A_{2^j}}(k)}{K_A}\right), \mu_D^{c_D}\left(\frac{h_{D_{2^j}}(k)}{K_D}\right)\right) \end{bmatrix} \qquad (3)$$

After extracting features from image using wavelet-fuzzy, the next step is to reduce the features using Principal Component Analysis (PCA). PCA helps to reduce redundant data and transforms correlated variables into smaller number of uncorrelated variables using largest eigenvectors of the correlation matrix. Following algorithm is used to reduce the feature vectors. The reduced feature vectors are used as an input to feed forward NN.

PCA Algorithm:

Let X be a data set of dimension M x N [12]

Step 1: Calculate the empirical mean:

$$u[m] = \frac{1}{N}\sum_{n=1}^{N} X[m,n]$$

Step 2: Calculate the deviations from the mean:

$$B=X-uh$$

where h is a 1xN row vector of all 1's:

h[n]=1 for n=1……N

Step 3: Find the covariance matrix C:

$$C = \frac{1}{N} B.B*$$

Step 4: Find the eigenvectors and eigenvalues of the covariance matrix C:

$$[D,V]=V^{-1}CV$$

where, D is the diagonal matrix of eigenvalues of C and V is the eigenvector matrix. Matrix D will take the form of an MxM diagonal matrix, where

$D[p,q]=\lambda_m$ for $p=q=m$

Step 5: Rearrange the eigenvectors and eigenvalues: Sort the columns of the eigenvector matrix V and eigen value matrix D in order of decreasing value.

Step 6: Select a subset of the eigenvectors as basis vectors: Save the first L columns of V as the M x L matrix W:
W[p,q]=V[p,q] for p=1………..L where $1 \leq L \leq M$

3.0 EXPERIMENTAL RESULTS

A single MRI image of brain is used to produce the training data set using different parameter values for rotation, scaling, vertical translation and horizontal translation. The transformation parameter values for training images are given in Table I. A total of 256 images are generated, each of size 128 by 128 pixels. Features are extracted using wavelet-fuzzy feature extraction steps. These feature vectors are used to train the neural network. The test data set contains 81 images. Features are extracted from the test images and fed to the trained NN.

The transformation parameter values for test images are given in Table II. The transformation values for training and test sets are same that has been used by H. Sarnel et al. [13]. Figure 3 shows the original image and transformed images after applying rotation, scaling and translations and also a noisy image.

The designed neural network has 7 neurons in one hidden layer and 4 neurons in the output layer. Hidden layer has a tangent sigmoid transfer function and linear function for the output layer neurons, and Levenberg Marquardt method was used for training.

Mean Absolute Registration Error (MAE) and Mutual Information (MI) is calculated for 81 images in test set for image registration with PCA and without PCA. Table III shows MAE values and Table IV shows MI values for without noise images, 5db noise images and 20db noise images. From these results, it can be concluded that using wavelet-fuzzy features after feature reduction with PCA improves the performance for noisy and distorted images when compared to using the wavelet-fuzzy features directly without PCA.

Values used for training set	Transform parameter
0.9,0.965,1.035,1.1	Scale
-5,-2,2,5	Rotation (degrees)
-5,-2,2,5	Vertical translation (pixels)
-5,-2,2,5	Horizontal translation (pixels)

Table 1: Affine transformation parameter values for training set

Values used for test set	Transform parameter
0.93,1,1.07	Scale
-3,1,4	Rotation (degrees)
-4,0,3	Vertical translation (pixels)
-3,1,4	Horizontal translation (pixels)

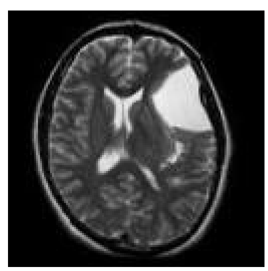
Table 2: Affine transformation parameter values for test set

Feature Extraction Technique	Without Noise	5db Noise	20db Noise
Wavelet+fuzzy	1.28416	1.318225	1.308850
Wavelet+Fuzzy+PCA	1.26834	1.264930	1.2553912

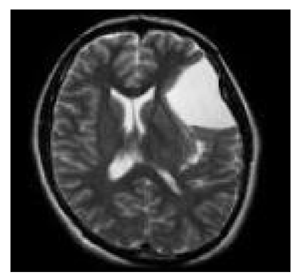
Table 3: Mean Absolute Registration Error

Feature Extraction Technique	Without Noise	5db Noise	20db Noise
Wavelet+fuzzy	0.874757	0.936966	0.930331
Wavelet+Fuzzy+PCA	1.012543	1.008405	1.010163

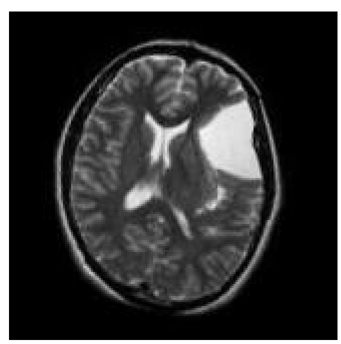
Table 4: MI values for Image Registration



(a)



(b)



(c)

(d) **(e)**

Figure 3: (a) Original Image (b), Transformed, rotated and scaled Image (c) Transformed, rotated and scaled Image (d) Translated, rotated, scaled images with 5db noise (e) Translated, rotated, scaled images with 20db noise

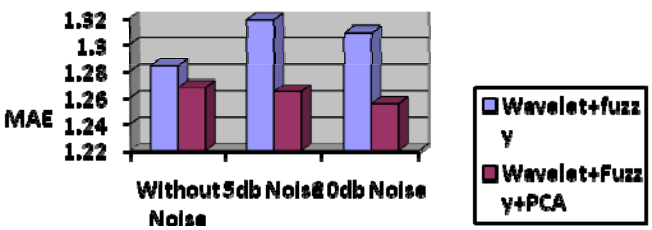


Figure 4: Mean Absolute Registration Errors

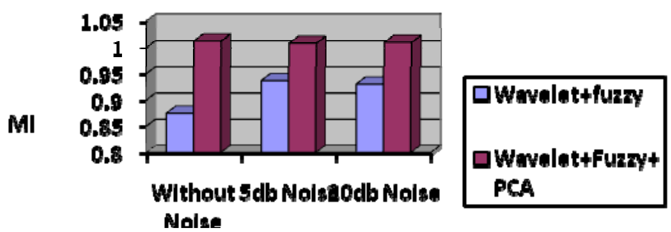


Figure 5: MI values for Image Registration

4.0 CONCLUSION

In this paper, we have discussed the use of wavelet transform and fuzzy set for feature extraction for image registration. The extracted features are reduced using PCA. The reduced feature vectors are then used to train the NN. According to the experimental results, the proposed method is more efficient and robust to noise and distorted inputs. We compare the results of the proposed NN based image registration system with the results of the system where PCA is not used to reduce the extracted wavelet-fuzzy features. Experimentally, we find that reducing the extracted wavelet-fuzzy features using PCA as in the proposed system improves the performance of the neural network based image registration with smaller mean absolute registration error and larger mutual information values.

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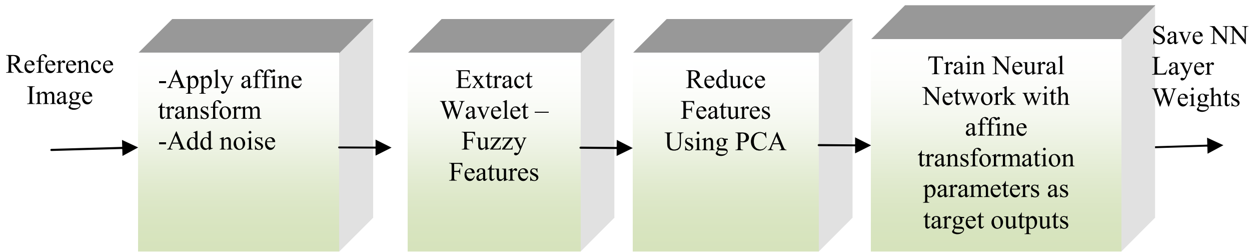

Figure 1(a): Training Phase

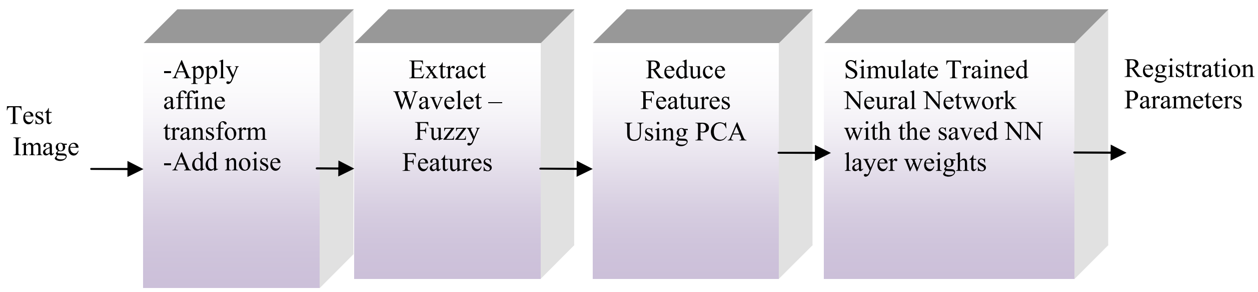

Figure 1(b): Test Phase

Figure 1: Proposed Image Registration