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Local Linear Reconstruction Based Medical Image Registration in DWT Domain

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Abstract

Non rigid image registration assumes a paramount part over medical imaging framework. In the complicated conditions, it is quiet a testing errand. Sometimes the dataset is perverted by spatially varying intensity contortion. To resolve this, issue many techniques based on LLR have been designed. In this paper, the core idea behind the proposed technique is to reduce the reconstruction time by considering the LLR in transform domain. The proposed technique uses DWT to split the dataset image into sub bands. Low frequency sub band image is reconstructed by reference image, followed by combining all subband images to generate an enhanced image by using inverse DWT. The quantitative (peak signal-to-noise ratio, root mean square error, mean square error and normalized cross correlation) and visual results show the superiority of the proposed technique over the conventional LLR technique and the execution time is reduced by 19%.

Keywords*: Locally Linear Reconstruction, Discrete Wavelet Transform, Image Registration, Medical Images*

1. Introduction

Non-rigid image registration is a key segment in different medicinal imaging frameworks. Many methodologies have been proposed to handle this issue. [6, 8, 9, 11]. With register a picture is itself an enormous assignment. Different issues would here over image registration. Anyway there is also a superior result for issues. In [15] M. A. Audette et al. gave the overview of all surface registration techniques. In [5] F. Maes et al. presented the multimodal image registration. In restorative field, with the assistance of registration, two pictures are register and they help to discover their edge of pivot, scaling and change. Image registration is the methodology of changing over the unique arrangement of purposes of one picture to another picture of comparing focuses is alluded to as image registration. The new divergence measure for the medical images is proposed in [22]. Two images are considered during registration process. One is referred image and another is reference image. The referred and reference picture both are distinctive. The reference image is placed over the refereed image for transforming the points. The reference and refereed both the images could be dissimilar because they are taken during different times and also from distinctive viewpoints. The normalized cross correlation (NCC) and the mutual information (MI) [10, 26] are regularly used to address the multi-modular issue.

Certain derivative techniques of anatomical modalities are MRA (magnetic resonance angiography), CTA (computed tomography angiography), and DSA (digital subtraction angiography). In [2], A. Myronenko recommended the implicit residual complexity measurement (RC), which may be determined starting with the analytically result of intensity correction field. Similar trials accounted for in [2] need illustrated that those RC

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based registration algorithm could process exact effects on the intensity distorted pictures. However, similarly as indicated over [2], those RC is hard will a chance to be connected of the multi-modal pictures. Functional modalities which are depicting information on the metabolism of the underlying anatomy, includes scintigraphy, PET (positron emission tomography), SPECT (single-photon emission computed tomography). These functional modalities combined make up nuclear medical imaging modalities and fMRI (functional MRI). In [2] author addressed the problem of vertebral bones. This work proposes to tackle the problem of image registration by using special class of quasi formal maps called T map (Teichmullar). Registration of Non rigid medical images is proposed by L. Wangn by the method of local linear reconstruction (LLR) [13]. F. Yang, et al, [6] proposed the Non rigid image registration which requires global optimization methods because the functions which are defines by similarity metrics are communally non rigid. The hybrid (HLCSO) is used to capture the interdependency of variables. It achieves the faster convergence and higher accuracy.

For evaluating the degree of similarity or dissimilarity between two images normalized cross correlation is used. The normalized cross correlation ranges between -1 and 1. Normalised cross correlation method is proposed by Y. Raghavender Rao[26]. A Toolbox for Intensity-Based Medical Image Registration known as elastix which is desined by S. Klein. It consist only one method which is work for entire algorithm [20]. M. V. Wyawahare[17] had overviewed the all registration techniques. But Michel A. Audette had surveyed the surface registration techniques for medical imaging [15]. D. Rueckert proposed [4] a new method for the non rigid registration of contrast enhanced breast MRI. There are two types of motion one is global and another is local. Both are modeled differently i.e. global motion is modeled by affine transformation while the local motion is modeled by FFD (free from deformation). The combination of affine and spline based FFD are proposed in this paper. The main advantage of method is high flexibility. For the Comparison of Similarity Measures for Use in 2-D–3-D Medical Image Registration proposed by G. P. Penney [8]. To register a computed tomography (CT) scan of a spine phantom to a fluoroscopy image of the phantom the similarity measures are used. In this paper the author proposes digitally reconstructed radiographs (DRR's) for the comparison of similitude measures for utilization in 2-D 3-D medicinal image registration. When introduce the soft tissue it improves the performance of the algorithm.

The rest of the paper is categorized are as follows. Section 2 presents the methodology and material used. In Section 3 evaluation of parameters are there. Some Results and discussions are describing in Section 4. Section 5 consist the conclusion part.

2. Material and Methods

In the following section we describe the dataset which is used in this for getting the results are used and also mention the working of technique on which this dataset is working. The propose technique is worked in transform domain and gives the better results as compared with the spatial domain.

2.1. Database Used

The different medical images are collected from a number of websites. The images are artificially rotated at different angles before the image processing begins. The angles on which the images are rotated are 5^0, 10^0, 15^0, 20^0, 25^0, 30°.

2.2. Proposed Technique

In this paper the Local linear reconstruction (LLR) method [18, 14, and 13] is proposed in transform domain. In transform domain, Discrete Wavelet Transform (DWT) is used [9]. Wavelets are the mathematical functions which are used in digital signal processing. Wavelets are able to recoup the weak signals from noise. With the help of wavelet based

methods, the image which is compressed that can be as little as around 25% the span of comparable quality picture utilizing the more well known JPEG strategy. Wavelets can take only 10-15 seconds for compressed the image of size 200 KB into 50 KB [11]. So, from all this wavelets methods also reduces the execution time. In Discrete Wavelet Transform, signal energy concentrates to specific wavelet coefficients.

If there is comparison between wavelets based methods and fourier transforms the wavelet based methods are best methods in transform domain. The fourier transforms does not provide any information in time domain. But the wavelets provide the information in both time and frequency domain. Wavelet functions are enlargd, translated and scaled versions of a common function φ, known as the mother wavelet. The DWT, in fact, it indicates a set of transforms not a single transform, each wavelet having different set of wavelet basis functions. Two of the most common are the Haar wavelets and the Daubechies set of wavelets [9]. Wavelet functions have following properties:

- Wavelet functions are localized.
- Wavelet functions are translated, enlarged, scaled version of common mother wavelet.
- Each set of wavelet function forms set of basis function.

DWT have existed in two dimension. One is 1D and second is in 2D but in this paper 2D dimension DWT is used.

2.3. DWT in 2D

For applying DWT on images separable DWT is used. Separable DWT means firstly apply 1D filter bank to the rows of the image. After that same transform will applied on columns of each channel. After doing all this process an image is appeared which is corresponding to vertical, horizontal, and diagonal one approximation image [11]. the following figure shows the working of DWT in 2 dimensional. Floating image is passed and then it is decomposing into low pass filters after down sampling of both rows and columns and it also keeps the even indexed columns and even indexed rows. After down sampling the dataset image is then passed to low pass and high pass filter. Again there is down sampling and finally at last the dataset image is coming with the different bands horizontal, vertical, diagonal, and axial band. All the bands are useful but we use lower band because of the reason is that it has more information as compared with the other the other bands. The down sampling is to ensure that the transformed image subspace resolution after DWT is still same as the original image in spatial resolution. Down sampling is the process of reducing the sampling rate of transformed signal.

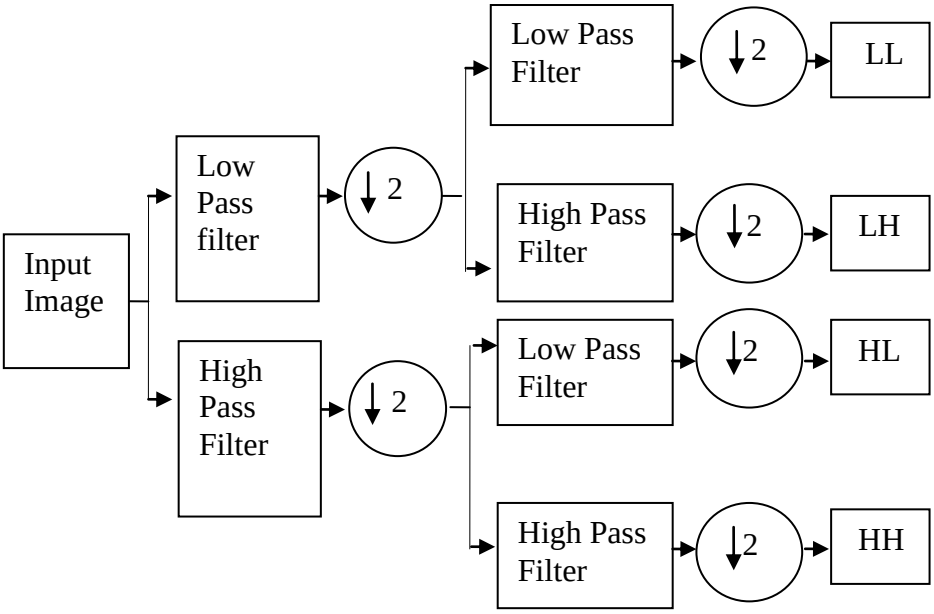

Figure 1. Block Diagram of DWT

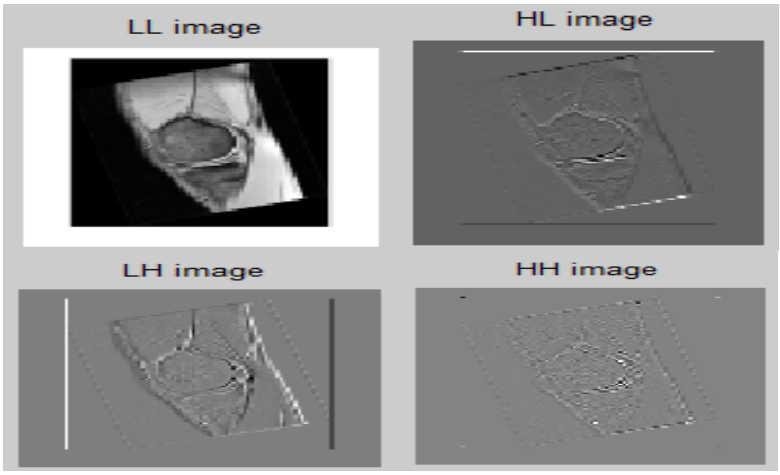

Figure 2. LL, HL, LH, HH Band of Medical Image Obtained by DWT

DWT has higher compression ratio. There is transformation of whole image. DWT allows good localization both in time and spatial domain. DWT has higher flexibility. Wavelets can compress the image in very less time as compared with the other techniques. As shown in the figure LL band of image has highest frequency.

After applying DWT in 2D the floating image is divided into four bands or four corresponding layers i.e. LL, HL, LH, and HH. [2]. The LL band corresponds roughly to a down-sampled (by a factor of two) version of the original image. The LH band tends to preserve localized horizontal features, while the HL band tends to preserve localized vertical features in the original image. Finally, the HH band tends to isolate localized high-frequency point features in the image. Lower Layer of DWT has more information as compared to other layers. So, the lower layer is mostly used among other layers. As mentioned above LL band preserve highest frequencies so the LLR is also work on LL layer.

2.4. Locally Linear Reconstruction (LLR)

When the distorted input image (floating) is placed over the reference image then it will reconstruct linearly within its local region. We assume that the data lie on a low-dimensional manifold which can be approximated linearly in a local area of the high-dimensional space. Therefore, we require that a data point can only be linearly reconstructed from its neighbors [14]. When reconstructing an image, we consider some neighbors only, not all reference points. Thus, we are able to take local, not global, topology into account. Since not only does LLR consider the similarity between points, but also takes the local topology into account, predicted class labels or estimated target values can be more accurate than those determined by its neighbors, which consider the similarity only. LLR can be more robust.

Algorithm 1: DWT_based_LLR
Input: Floating Image (F), Reference Image(R)
Output: Reconstructed Image
Begin
1. Apply 2D DWT on F to convert it into sub bands (LL, HL, LH, and HH) by using equation (1).

$$X_k = \sum_{n=0}^{N-1} x_n \,.\, (\cos(-2\Pi k\tfrac{n}{N}) + j\sin(-2\Pi k\tfrac{n}{N})),\ \ n \in Z \qquad (1)$$

2. Using R, apply LLR on LL sub band.
3. Join modified LL sub band with other three sub bands using inverse DWT.
4. Obtain the final image.

End

Algorithm 2: LLR

1. Initial the transformation U=0(0 is the matrix where all values are zero)
2. Build the N-level image pyramid.
3. **for** level = 1 **to** N **do**
4. **for** iter = 1 **to** MaxIterNum **do**
5. Updating transformation **U** based on Eq.(2);

$$\boldsymbol{U^{t+\tau}} = \left(\tau\lambda\sum^{-1} + \boldsymbol{Id}\right)^{-1}\left(\boldsymbol{U^t} - \boldsymbol{\nabla_U E(R, F[U^t])}\right), \qquad (2)$$

6. **end**
7. Boost up the resolution of floating and reference image.
8. Up sampling the transformation U.

End

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t+τ is the current time, $\sum^{-1}\boldsymbol{U^t}$ is presented by previous time t, Id is the identity matrix. $\left(\tau\lambda\sum^{-1} + \boldsymbol{Id}\right)^{-1}$ is finding out by performing forward and inverse multidimensional DCT [23].

3. Evaluation of Parameters

Following are some parameters on which the existing and proposed techniques are compared;

1. PSNR(peak to signal noise ratio): Peak signal-to-noise ratio [9] is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR block computes the peak signal-to-noise ratio between two images. This ratio is often used as a quality measurement between the original and a resultant image. The higher the PSNR shows the better the quality of the reconstructed image. Larger PSNR indicate a smaller difference between the original (without noise) and reconstructed image. The main advantage of this measure is ease of computation. An important property of PSNR is that a slight spatial shift of an image can cause a large numerical distortion but no visual distortion and conversely a small average distortion can result in damaging visual artifacts, if all the error is concentrated in a small important region. To compute the PSNR following formula is used:

$$\text{PSNR}=10\log_{10}\frac{R^2}{MSE} \tag{3}$$

Where R is the greatest fluctuation in the floating image (255 in here as the images are represented by 8 bit, i.e., 8-bit grayscale representation have been used) [2].

2. MSE(mean square error): For find out the mean square error of input and original image following expression is given:

$$\text{MSE}=\frac{\sum i,j(Iin(i,j)-Iorg(i,j))}{M\ X\ N} \tag{4}$$

Where M and N are size of image

3. RMSE(root mean square error): It is the square root of mean square error.

$$\text{RMSE}=\sqrt{\frac{\sum i,j(Iin(i,j)-Iorg(i,j))}{M\ X\ N}} \tag{5}$$

4. NK(normalised cross correlation): For matching the two image patches the correlation coefficient is valid and also to find the classical solution.

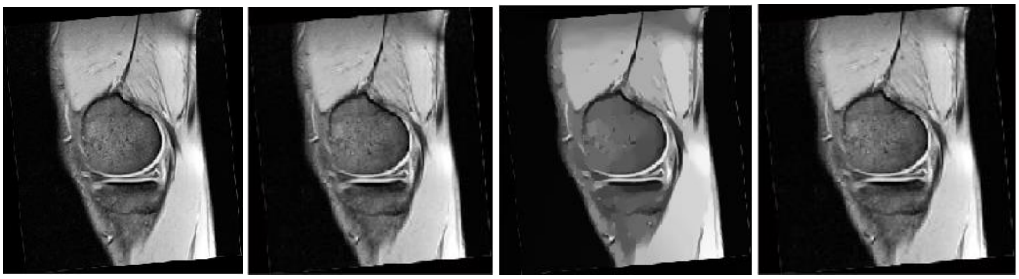
$$\text{NK}=\varphi'_{xy}(t)=\frac{\varphi_{xy(t)}}{\sqrt{\varphi_{xx(0)}\varphi_{yy(0)}}} \tag{6}$$

The quantity of normalised φ xy(t) vary between -1 to 1. The positioning of't' is shown by the value of φ xy(t) =1. The value of φ xy(t) =-1 shows that they have the similar pattern but they differ from opposite signs. The value of φxy(t)=0 indicates that they are not correlated.

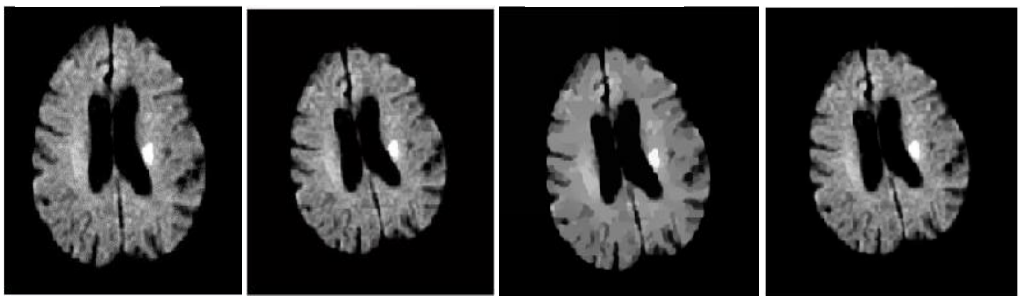
5. Execution Time : The time taken to execute the code is referred to as elapsed time.

4. Results and Discussion

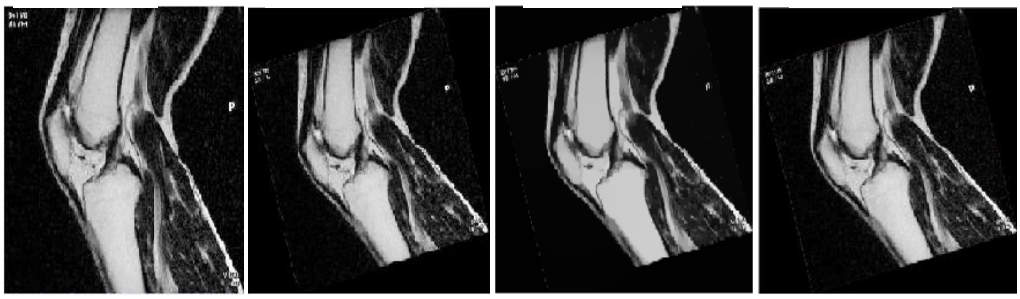
In the first experiment, we compare the proposed technique in transform domain with the existing technique in spatial domain with the different parameters. The comparison of different parameters is shown in table 1. As from the table it is clearly seen that that the proposed method (LLR) in transform domain has more value than that of existing (LLR) in transform domain. Following figures shows the inverse DWT image and final registered image.



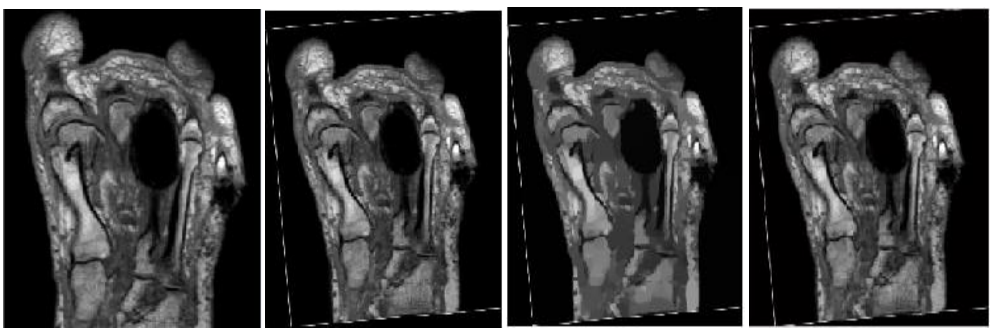
(1) (2) (3) (4)



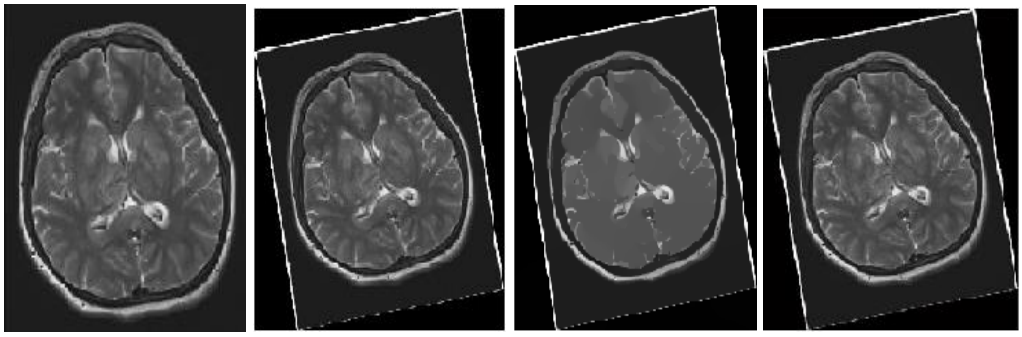
(5) (6) (7) (8)



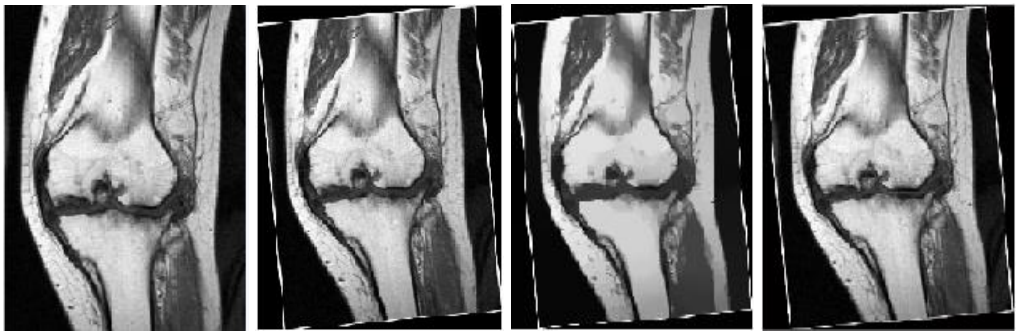
(9) (10) (11) (12)



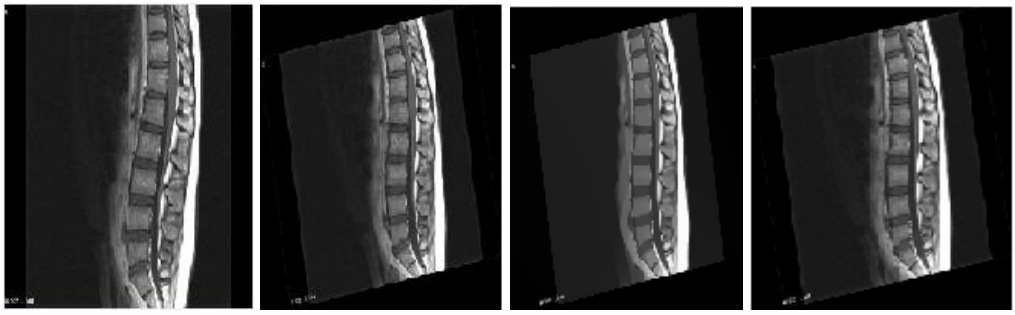
(13) (14) (15) (16)



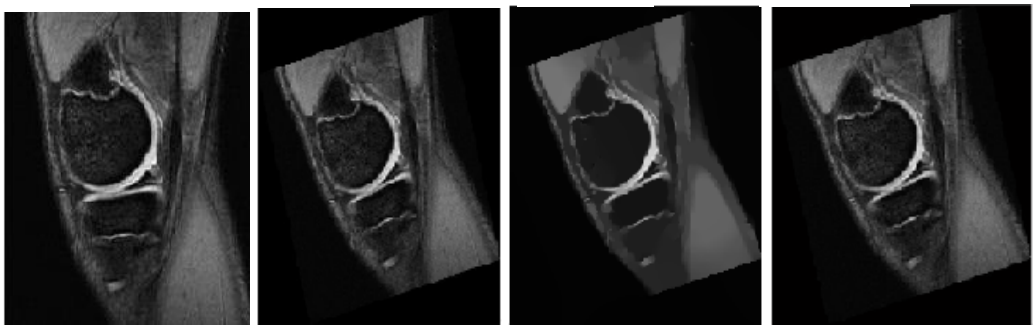
(17) (18) (19) (20)



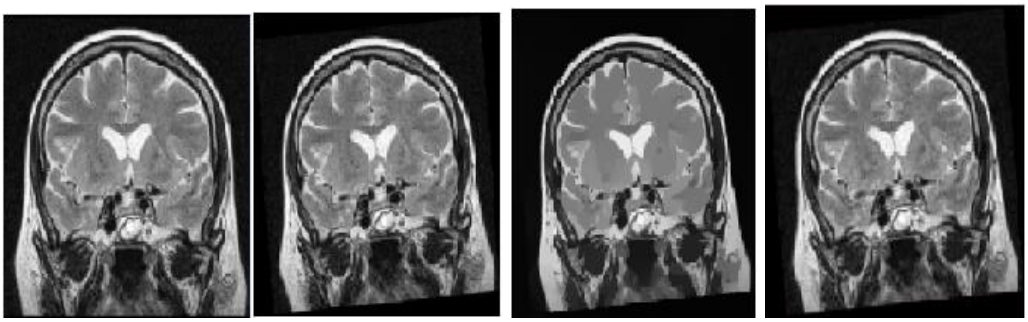
(21) (22) (23) (24)



(25) (26) (27) (28)



(29) (30) (31) (32)



(33) (34) (35) (36)

Figure 4.1. Reference Image (1), (5),(9),(13),(17),(21),(25),(29) and (33) Floating Image(2),(6),(10),(14),(18),(22),(26),(30) and (34) Difference of LLR(3),(7),(11),(15),(19),(23),(27),(31) and (35) and Difference of DWT(4),(8),(12),(16),(20),(24),(28),(32) and (36)

Table 1. Comparison of Values

Images	PSNR		MSE		RMSE		NK	
	Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed
Mri021	42.35	49.92	0.7747	0.1029	0.8798	0.3208	0.391	0.874
Mri022	48.66	58.072	0.8866	0.2498	0.9409	0.3183	0.155	0.869
Mri024	47.73	58.234	0.7204	0.0977	0.847	0.3125	0.396	0.873
Mri025	50.78	57.287	0.5466	0.1214	0.7378	0.3485	0.508	0.826
Mri026	50.45	57.721	0.5878	0.111	0.7658	0.3315	0.408	0.847
Mri027	48.85	57.206	0.8404	0.1239	0.9164	0.3519	0.534	0.87
Mri028	48.96	57.642	0.8264	0.1119	0.9085	0.3345	0.446	0.875
Mri029	49.38	57.705	0.7503	0.1103	0.8656	0.3321	0.448	0.868
Mri030	49.58	57.828	0.7176	0.1069	0.8464	0.3268	0.236	0.853
Mri031	50.83	58.038	0.5382	0.1022	0.7328	0.3196	0.312	0.848
Mri032	49.25	56.71	0.7739	0.1387	0.8789	0.3724	0.417	0.842
Mri033	50.48	58.872	0.5849	0.0844	0.7636	0.2904	0.059	0.87
Mri034	49.93	58.443	0.6652	0.2291	0.8141	0.3052	0.506	0.87
Mri036	49.12	57.558	0.7984	0.1141	0.8926	0.3378	0.471	0.862
Mri037	50.5	58.067	0.6319	0.1018	0.7329	0.3187	0.35	0.854

Table 2. Execution Time of Proposed Technique

Images	021	022	023	025	026	027	028	029	030	031	032	033	034	035	036
Existing	25.27	24.15	22.34	23.72	23.08	23.42	24.09	22.52	26.82	25.44	24.46	23.83	20.68	24.27	22.78
Proposed	4.06	4.71	4.61	4.39	4.09	3.87	4.17	4.05	4.39	5.02	4.07	4.70	4.54	4.08	4.78

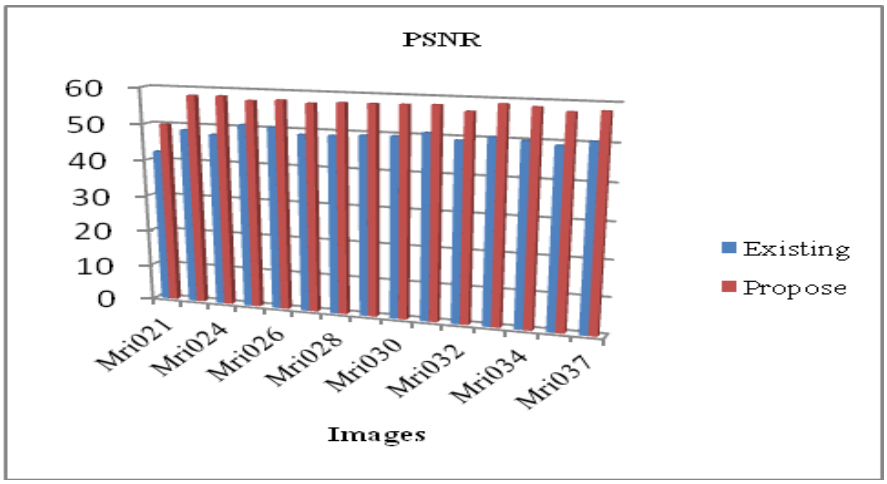


Figure 4. PSNR Values

As shown in the above graph the value of PSNR is high when compared with LLR technique in spatial domain.

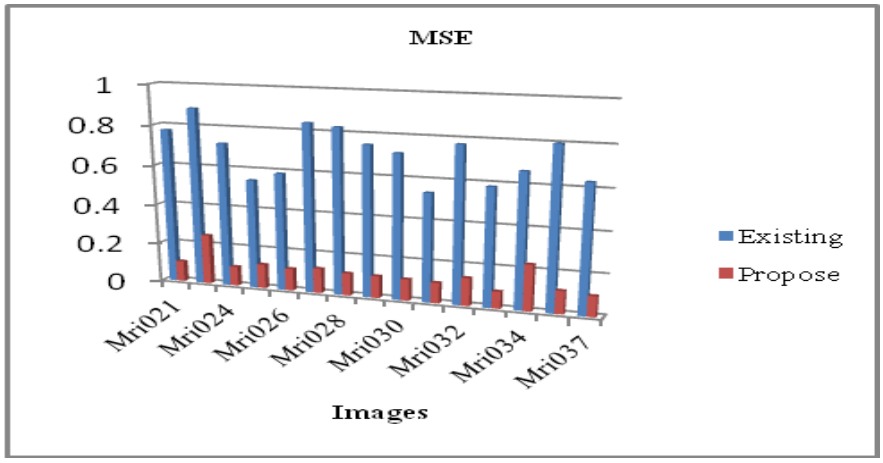


Figure 5. MSE Values

Compute the mean square error of existing and propose. From the graph it is clearly shown that the values of propose technique has less values as compared with base.

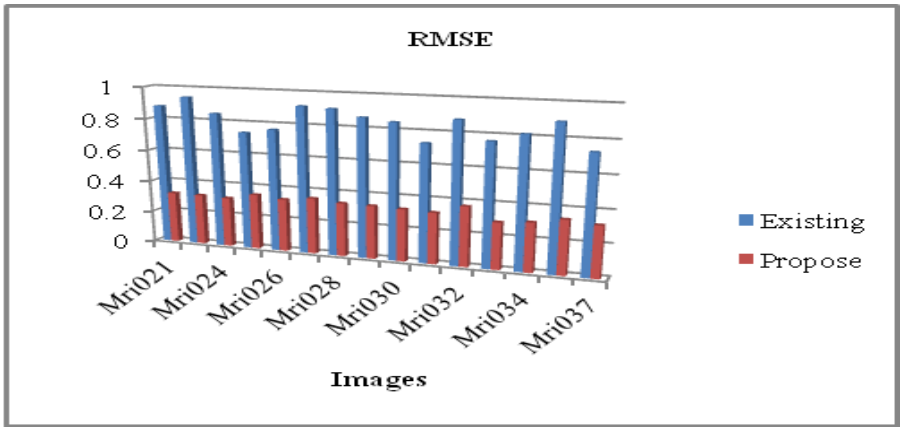


Figure 6. RMSE Values

Compute the RMSE value of existing and propose technique. After that the normalized cross correlation is calculated to find out the correlation between two images. If correlation value is maximum, then pictures will correlate much better.

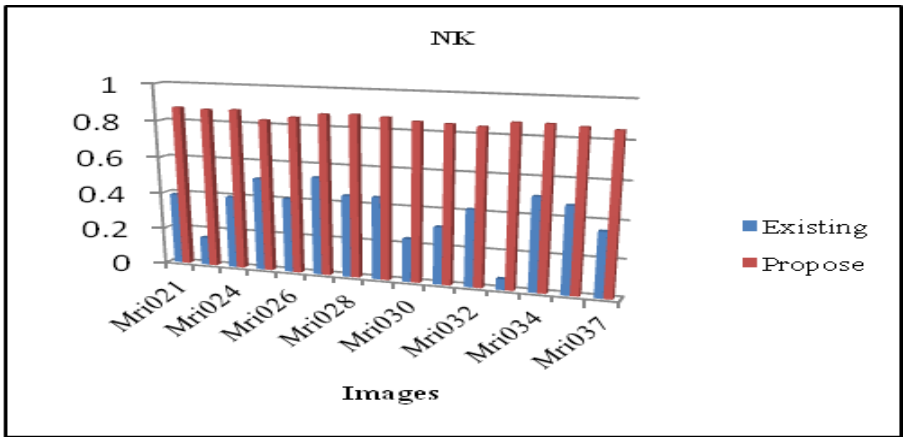


Figure 7. NK Values

The values of normalized cross correlation of existing are lower than the values of propose method.

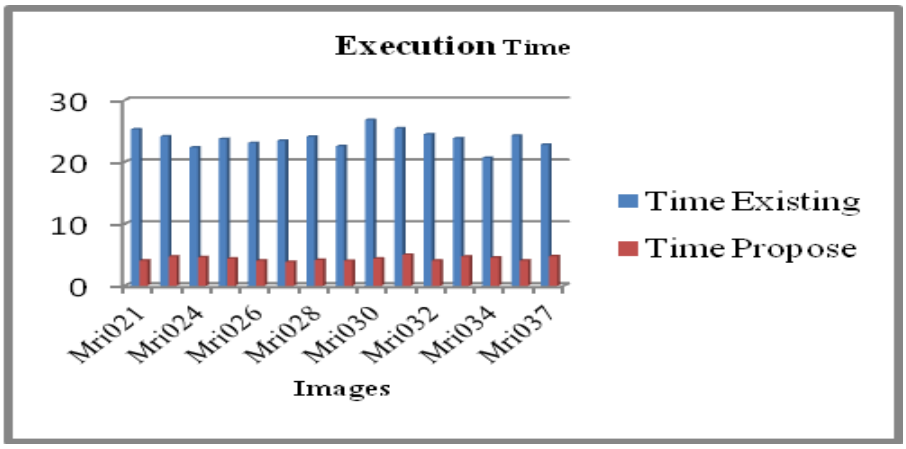


Figure 8. Execution Time

The execution time of existing technique is much higher than the propose technique. Our main target is to reduce the time. We do not change the technique but we change its domain from spatial domain to transform domain. With changing the domain, it improves the all quality matrices.

5. Conclusions

In this paper, we propose a LLR in DWT domain. The extensive experiments are performed on 90 medical images and performance is evaluated using various parameters such as peak signal to noise ratio (PSNR) the PSNR is used to measure the quality of the final registered image, root mean square error (RMSE), mean square error (MSE) and normalized cross correlation (NK). The PSNR is increased by 8%, RMSE is reduced by 53%, MSE is reduced by 53%, NK is increased by 40% and Execution Time is reduced by 19%. The results indicate that the proposed technique outperforms the existing related techniques.

6. Future Scope

The related work is only restricted to medical images. In future, we focus on every type of images. That would be satellite images and other type of images and also focus on large dataset. We also focus on enhancement of DWT. May be in future there is 3D DWT and it works better than existing techniques of DWT. In future we also focus on enhanced LLR which may be helpful in any other field.

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