A Wavelet-Based Similarity Measure to register pre-/intra-operative MR images of the brain

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Abstract - *Definition of a proper similarity measure to be adapted to a specific application is a crucial step in registration of medical images. The problem with most commonly used similarity measures in medical applications is that they perform registration in spatial domain based on simplifying assumptions about the interdependencies of the pixel intensity values. Therefore, they are incapable of decorrelating spatially-varying intensity inhomogeneity, occurring in MR imaging. To overcome this problem, Residual Complexity (RC) has been introduced for correcting intensity inhomogeneity in the Discrete Cosine Transform(DCT) domain. In this work, it is proposed to employ Discrete Wavelet Transformation(DWT) instead of DCT which is more efficient in representing the final residual image between the two registered images with minimum compression complexity. Here, the performance of Wavelet based RC (WRC) is compared to RC and some well-known similarity measure. WRC shows more than 30% improvement in the registration result in comparison with RC.*

Keywords: registration similarity measures, Residual Complexity, intensity inhomogeneity, wavelet residual complexity, intra operative MRI.

1 Introduction

Selecting a proper similarity measure for registration of images in a specific application is a critical step towards a successful registration. This is because the similarity measure establishes necessary spatial correspondence between intensities of the images, and is maximized when the images are in correct alignment. Finding a suitable similarity measure becomes even more important in medical image registration applications, since the employed algorithm affects the diagnosis or treatment procedures designed for the patients. One of such applications is registration of pre- to intra-operative MR images of brain, for which several similarity measures such as Normalized Mutual Information (NMI) [1-2] and Sum of Squared Distances (SSD) [3-4] have been commonly used. These similarity measures are defined based on some simplifying assumptions, such as pixel-wise independence and stationarity of the image intensities in the spatial domain [5]. These assumptions become invalid when the images are corrupted by spatially-varying distortions, such as intensity inhomogeneity occurring in MR images. In a recent paper by some of the authors of this paper [6], it was shown that image intensity inhomogeneity occurs in the intra-operative MRI images of the brain, due to utilization of surface coils for image acquisition during surgery [7]. This can severely challenge the algorithms implemented for registration, because the relationship between the pixels of the image and, therefore intensity statistics of the image change. Furthermore, due to the variations in MR parameters the intensity inhomogeneity could change from slice to slice and among different acquisitions [8].

Thus, it is highly desirable to adaptively remove intensity inhomogeneity along with the registration procedure, and in a unified framework. Since intensity inhomogeneity is a low frequency distortion which correlates with the pixels, its elimination can be better performed by decorrelating the pixels' intensities in the transform domain. In a recent publication, Myronenko *et al.* proposed a novel similarity measure called 'Residual Complexity (RC)', which performs well in registration of the images corrupted by intensity inhomogeneity fields [9]. The main idea is to eliminate the intensity inhomogeneity field in Discrete Cosine Transform (DCT) domain. Based on this idea, in [6], we utilized RC to register pre- and intra-operative MR images of the brain more locally and sparsely. Since the registration is able to adapt itself to any new image, it was proved efficient for real-time image guided neurosurgeries [6].

The minimum value of RC similarity measure is achieved at the correct alignment of the two images, where the residual between the two images to be registered has the maximum number of zero coefficients. This implies the importance of compression in reducing the complexity of the residual image. DCT does not in itself contain compression and sparseness. Since most of the DCT coefficients are near zero, in order to achieve compression, the DCT coefficients should be quantized, so that the nearly zero coefficients become zero [10]. Although DCT is a well-known method for image compression, it performs the transformation on blocks of the image, and therefore the blocks usually remain correlated to some extent [10]. In recent years, Discrete Wavelet Transform (DWT) has received great interest as a substitute for DCT in the image compression area [11]. DWT transforms the whole image and can provide multiple image resolutions. It also provides better spatial resolutions at high frequencies and better frequency resolutions at low frequencies, i.e. the spatial-frequency resolution in DWT is adaptive [10]. This is a desirable property in our application, because intensity inhomogeneity is a low frequency artifact, as mentioned earlier. Therefore, as DWT provides better frequency resolution at low frequencies, intensity inhomogeneity can best be decorrelated from other intensities of the images in the DWT domain. Due to interesting properties of DWT and in order to perform registration procedure more locally and sparsely, in this paper we use RC with DWT representation instead of DCT.

2 Residual Complexity

Residual Complexity (RC) is an intensity-based similarity measure, which is suitable for registration of the images distorted by spatially- varying intensity inhomogeneity. RC is defined by eliminating the intensity inhomogeneity from the similarity measure formulation simultaneously with registration problem. This is done by introducing an intensity correction field that enforces the alignment of the images in the intensity domain. An adaptive regularization term is defined for the intensity correction field. The registration problem is then solved for intensity correction field and the regularization term [9]. The registration problem using RC is optimized when the difference (residual) of the images achieves its minimum complexity.

Consider two images I and J, which are aligned using the geometric transformation defined by T. By analytically solving the registration formulation and in the same time eliminating the intensity inhomogeneity from the formulation, the final form of the RC similarity measure can be represented by:

$$E_{RC}(T) = \sum \log\left(\left(q_n^T r\right)^2 / \alpha + 1 \right).$$
$$r = (I - J(T)). \tag{1}$$

where 'q_n's are of a form of basis functions, and α is a trade-off parameter [9].

2.1 DCT representation of Q

In order to specify Q, the discrete cosine transform (DCT) coefficients are selected [9]. Therefore, the matrix multiplication of $Q^T r$ is a DCT of r. The DCT-II form of basis functions, which is commonly used in image processing, is used for defining eigenvalues of $\boldsymbol{Q}$. For 1-D, we have:

$$q_n(k) = \frac{w_n}{\sqrt{N}} \cos\left(\frac{\pi(2k-1)(n-1)}{2N} \right), \tag{2}$$

for k = 1, 2… N, n = 1, 2… N and,

$$w_n = \begin{cases} 1, \ldots n = 1, \\ \sqrt{2}, \ldots n = 2 \ldots N. \end{cases} \tag{3}$$

As it can be seen in the above formulas, smaller DCT coefficients are more penalized with respect to the larger ones due to the existence of the term $log(x^2+1)$. The *log* function decreases rapidly to zero as the number of points is increased, causing the DCT coefficients to become sparse [9, 12]. The value of RC reaches its optimum value more accurately by imposing sparseness on the DCT coefficients of the residual image. For this purpose we set a threshold value, which is obtained by taking the mode of the coefficient matrix. The coefficients below this threshold (mostly occurring in higher frequencies) are set to zero. Although setting a threshold on DCT is expected to enhance the results, the selection of the threshold is a blind process. By taking DWT instead of DCT this problem can be solved.

2.2 Wavelet representation of Q

Instead of applying DCT transform, it is expected that the residual image can be better (by fewer significant intensities) represented by using discrete wavelet transform (DWT). Here, the Haar transformation is selected for representation of the residual image in the transform domain.

$$w_\varphi[j,k] = \frac{1}{\sqrt{M}} \sum_n f[n] \varphi_{j,k}[n]$$
$$\varphi_{j,k}[n] = 2^{j/2} \varphi\left(2^j n - k\right), j = 0,1,\ldots,\log_2^{N-1}, k = 0,1,\ldots,2^{\mathrm{j}} \tag{4}$$
$$\varphi(n) = \begin{cases} 1, \ldots for \ldots 0 < n < 1 \\ 0, \ldots o.w \end{cases}$$

where $f[n]$ represents the discrete function defined in [0,N-1], φ(t) is Haar scaling function, and w_φ denotes the wavelet transform of the given discrete function [13]. The modified similarity measure obtained by replacing DWT instead of DCT in RC formulation is called Wavelet RC (WRC).

In order to improve the results of registration, the coefficients of DWT matrix of the residual image are truncated by thresholding. The threshold value was set on the approximation component and some detail components of DWT matrix. For this purpose, the variance of each compartment of DWT matrix is computed and the compartments with lower variances are set to zero.

2.3 Implementation

Here, the FFD Bspline transformation, which has been applied in registration of pre- and intra-operative MR images, is used for modeling the deformations of brain [1]. The optimization is performed using the gradient descent method.

3 Results

The performance of the registration using the new similarity measure is evaluated on synthetic images and on the pre- and intra- operative MR images of the brain.

3.1 Synthetic image

The reference and source synthetic images used in this experiment are shown in Fig.1 (a) and (b), respectively. The source image is distorted by adding a mixture of K Gaussian functions with standard deviation of *30*, which simulate various degrees of spatially-varying intensity inhomogeneity. This is done as the following formula:

$$I_{after}(x,y) = I_{before}(x,y) + \frac{1}{K}\sum_{k=1}^{K} e^{-\frac{\|[x;y]-\mu_k\|^2}{2(30)^2}} \tag{5}$$

where $I_{before}(x,y)$ and $I_{after}(x,y)$ are the images before and after adding intensity inhomogeneity distortions, respectively, K is the number of Gaussians, x and y are the pixel locations, and μ_k defines the mean locations of the Gaussians, which are generated randomly in each image.

The source image was registered to the reference image over 200 iterations, and the grid size was 7×7 pixels. The optimal number of decomposition levels for DWT was experimentally found to be 4. The registration of the source to reference synthetic images for six distortion levels, each representing the number of Gaussian functions added to the image, using WRC was compared to CC, SSD, NMI, and RC methods.

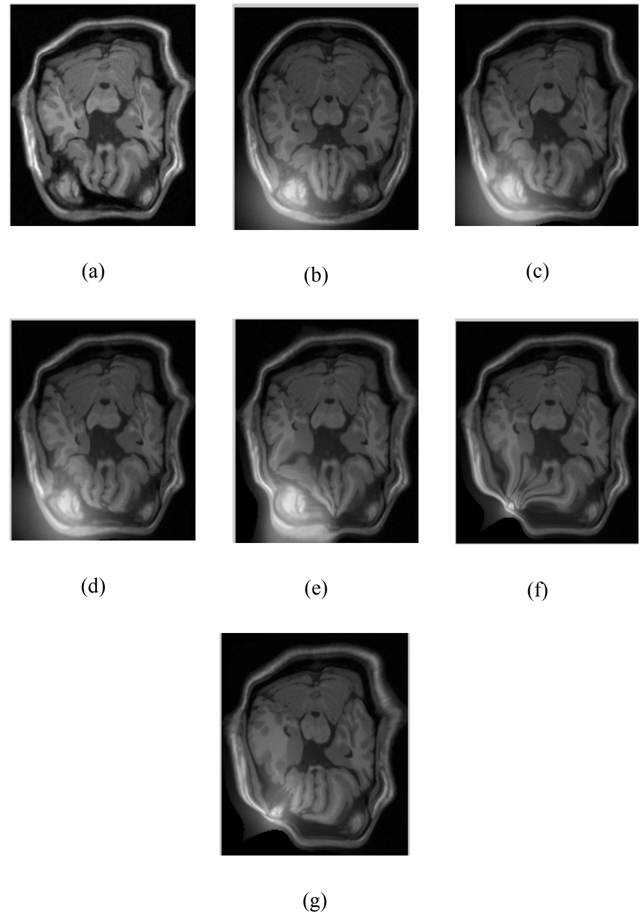

Fig. 1. (a) reference image; (b) source image; and registered images using (c) RC, (d) WRC, (e) NMI, (f) CC, and (g) SSD.

Furthermore, the effect of enforcing further sparseness on the transformed residual image matrix was examined by Thresholded RC (TRC) compared with Thresholded WRC (TWRC). Approximately, 25% of the coefficients of DCT and DWT matrices were set to zero. Fig. 1(c)-(g) illustrates the outcomes of registration using RC, WRC, NMI, CC, and SSD with a mixture of 2 Gaussian functions, i.e. K=2. TRC and TWRC returned visually similar results to RC and WRC registration.

TABLE I. THE RMSE OF REGISTRATION USING CC, SSD, NMI, RC, WRC, TRC, AND TWRC SIMILARITY MEASURES IN VARIOUS DISTORTION LEVELS.

Distortion level	CC RMSE, pixels	SSD RMSE, pixels	NMI RMSE, pixels	RC RMSE, pixels	WRC RMSE, pixels	TRC RMSE, pixels	TWRC RMSE, pixels
1	0.06±0.00012	0.089±0.00087	0.074± 0.00032	0.02± 0.00057	0.019± 0.00052	0.019± 0.000005	0.018± 0.00001
2	0.057± 0.00075	0.077± 0.0013	0.053± 0.00017	0.027± 0.00026	0.018± 0.00022	0.021± 0.00017	0.016± 0.00001
3	0.051±0.00014	0.069±0.00078	0.054± 0.00026	0.022± 0.00043	0.017± 0.00041	0.017± 0.00005	0.015± 0.0000002
4	0.042±0.00008	0.083±0.00094	0.057± 0.00013	0.02± 0.00018	0.016± 0.00003	0.019± 0.00014	0.014± 0.000002
5	0.041±0.00021	0.08±0.0013	0.042± 0.0001	0.015± 0.00015	0.0145± 0.00003	0.0141± 0.000004	0.014± 0.0000005
6	0.043±0.00059	0.064±0.00084	0.043± 0.0002	0.018± 0.00007	0.016± 0.00002	0.018± 0.00007	0.015± 0.000003

The registration performance is evaluated using RMSE measure, which is obtained by applying the resulting transformation to the clean source image (without intensity distortion) and computing the RMS error between the reference and this new image. The intensity inhomogeneity distortion is randomly overlayed on images at the beginning of each registration procedure. The RMSE values over 10 automatic registrations were averaged. The mean and variance of RMSE results are summarized in Table I.

As can be inferred from Table I, both RC and WRC significantly outperform NMI, CC and SSD similarity measures. More interestingly, WRC outperforms RC by 5 to 33%. The performance of WRC with increasing distortion levels remains almost constant. This means that WRC is less sensitive to the variations of intensity inhomogeneity than RC. Also, WRC shows lower variance in consequent implementations of the algorithm in a given distortion level. These outcomes can be expected due to the superiority of DWT in decorrelating the components with respect to DCT.

Moreover, as can be interpreted from Fig. 2 and Table I, TRC performs about 11% better than RC, TWRC registers the images better than WRC by about 8%, and TWRC is less sensitive to the various amounts of intensity inhomogeneity in comparison with RC, TRC, and WRC.

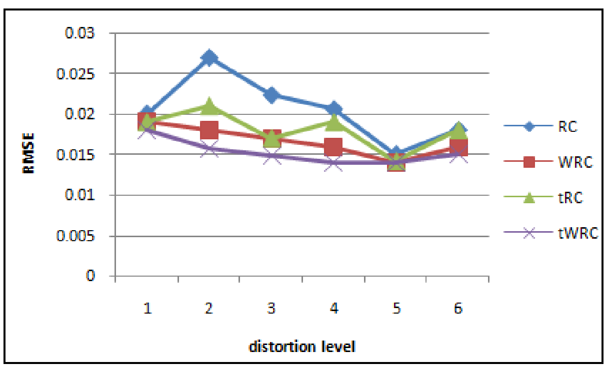

Fig. 2. Comparison of the performance of RC, WRC, TRC, and TWRC.

3.2 Real MR data

The algorithm is then implemented for registration of real pre- and intra-operative T1-weighted MR data, as shown in Fig. 3(a) and (b). The images are acquired from patients undergoing tumor resection surgeries, acquired at a 1.5T pre- and 0.5T intra-operative scanners. The voxel size is 0.9×0.9×2.5 mm^3 (www.spl.harvard.edu).

The grid size was selected to be 10×10 pixels, and the number of iterations was 70. The outcomes of registration using various similarity measures are illustrated in Fig.3. Since NMI has been previously introduced as a better similarity measure for registration of pre- to intra-operative MR images of brain than SSD and CC [1], here, we only compare RC and WRC with NMI. The registration performance is quantified using Cumulative Inverse Consistency Error (CICE) measure as proposed in [14], and the results are summarized in Table II. It can be inferred from Table II that while both RC and WRC outperform NMI in registering pre- to intra-operative MR images of the brain, WRC enhances the result by about 13% as compared to RC.

In Fig.3 (f), the edge map of the resulting image using WRC is obtained and overlayed on the reference image, which shows that the edges of the registered image are perfectly in alignment with the reference image. The performances of TRC and TWRC were almost the same as RC and WRC, respectively; thus, for saving the space, these results are not included in the text.

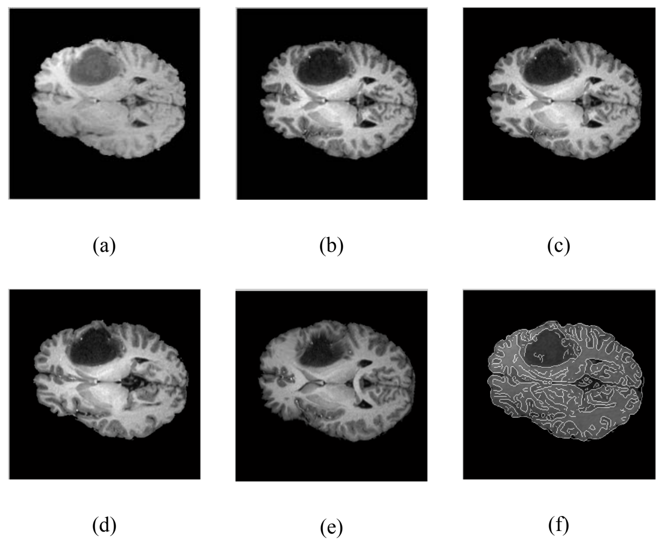

Fig. 3. (a) reference image; (b) source image; and registered images using (c) RC, (d) WRC, and (e) NMI, (f) the overlay of edges in the registration result using WRC on the reference image.

TABLE II. EVALUATION OF REGISTRATION RESULTS USING CC, SSD, NMI, RC AND WRC SIMILARITY MEASURES BY CICE

	NMI	**RC**	**WRC**
CICE (%)	12.55	7.01	6.1

4 Conclusion

Intensity inhomogeneity is a slowly- and spatially-varying artifact occurring in MR images, which can be eliminated from the image intensities in the transform domain. In this work, DWT was used instead of DCT in the RC formulations for representing the residual image between the images to be registered in the transform domain. It is observed that WRC can efficiently and adaptively register MR images of brain due to the property of wavelet functions in more sparse representation of residual images. This similarity measure also outperforms NMI similarity measure, which has been suggested in previous publications for application in registration of pre- to intra-operative MR images [1-2], by about 51%. Also, it enhances the results of registration obtained by RC. WRC was shown to be robust to various degrees of intensity inhomogeneity distortion, which is an advantageous property for unpredicted distortion levels occurring in intra-operative MR images of the brain during neurosurgery. We are currently working on enforcing more sparseness on WRC similarity measure. This seems to further enhance the registration outcome, since the residual image can be represented by fewer coefficients and achieve its minimum value more promptly.

5 References

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