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A new phase based approach to multimodal image registration

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ABSTRACT

The major challenges in automatic multimodal image registration are the in consistency in intensity (or) contrast patterns and the existence of non overlapping regions between images. Also presence of high non-homogeneous image contrast makes it very difficult to compare the image contents. The proposed method is using a phase representation derived from Dual Tree Complex Wavelet Transform as similarity metric for registering multimodal images. This method uses a transformation that minimizes the residual error between phase representations of two multimodal images. Sub pixel level local optimization techniques are used to improve the stability in handling situations like small initial overlapping between images. This method has been tested on various multimodal images. This technique has better accuracy than existing registration techniques even in the presence of image non-homogeneity and inconsistency in intensity patterns.

1. Introduction

Medical images have been used increasingly for diagnosis, treatment planning, monitoring disease processes, and other medical applications. A large variety of medical imaging modalities exists including Computed Tomography (CT), X-ray, Magnetic Resonance Imaging (MRI), Ultrasound, etc. Frequently a group of images need to be compared to one another and/or combined for research and analysis. In many medical studies, multiple images are acquired from subjects at different times or with different imaging modalities. Misalignment inevitably occurs, causing anatomical and/or functional feature shifts within the images. Computerized Image Registration (alignment) approaches can offer automatic and accurate image alignments without extensive user involvement and provide tools for visualizing combined images.

The main contribution of this paper is a novel phase based similarity metric which identifies structurally significant regions in the image.

1.1 Challenges in Multimodal Image Registration:

Images acquired using different modalities are captured using different imaging devices at different times having different geometric distortion. This distortion makes it difficult to compare the image content from different modalities. The relationship between intensity values of corresponding pixels in different modalities is unknown. Multiple intensity values in one image may map to a single intensity value in another image. Also image non-homogeneities cause same content within single image is represented by different intensity values. The goal of the proposed method is to overcome all these issues to achieve stable registration of multimodal images.

1.2 Existing Methods:

Most widely used multimodal registration methods are based on Mutual Information and its entropy based alternatives []. Mutual Information allows direct intensity based comparison of multimodal images. Works efficiently even same content within a single image is represented by different intensity values. But the intensity relationship between multimodal images is unconstrained by Mutual Information, and this leads to high non-monotonicity. But most of the local optimization schemes are dependent on the monotonicity of the underlying cost function. Direct intensity based cost functions using MI get trapped in the local optima and this causes lot of problem in situations with small initial overlap, where the optimization scheme has to travel a long distance before reaching global convergence. Moreover direct intensity computation of MI involves a lot of computation, which takes a longer time

Next popular Multimodal registration schemes are the Feature based registration schemes. In feature based methods the images are transformed to a common feature space before evaluating the cost function. The main advantage of local phase is, it is largely independent of intensity and also it is highly stable in the presence of signal non-homogeneities. Some of the limitations of using local phase in Multi modal Image Registration are, local phase representation provides no information about structural significance of images. Also local phase representation do not account for noise. The approaches proposed by Liu et al. and Hemmendroff have some major drawbacks, that is these methods do not make use of local frequency information from multiple scales (or) orientations. These methods are sensitive to image non-homogeneity and does not account for image noise.

The proposed method is using a Local Phase based representation for constructing structural significant characteristics within an image. The perceptually significant structural representation based similarity metric used in the proposed method is largely independent of intensity.

2. Proposed Method:

This method first extracts the structurally significant local phase representation for each of the images under evaluation. Then the Local Phase Representation can be used to align the

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images on a pixel level using an efficient registration algorithm. This approach is largely independent of intensity variation between images acquired using different modalities. Two images obtained from same scene using different modalities can have significantly different intensity characteristics but have similar structural characteristics. The main advantage of using local phase representations are, it is largely independent of intensity values and it is highly robust to the presence of signal non-homogeneities.

The approach used in proposed method for constructing a structural representation of images is to use local phase relationship to identity structurally significant characteristics within an image. The proposed method is using a local phase representation that peaks at locations of high perceptual significance.

Points of high perceptual significance coincide with points of high structural significance within an image.

As only the local phase information is used, this similarity metric is largely independent of intensity variations in the Multimodal images.

From the above mentioned points it is clear that the local phase based approach is an efficient technique for creating structural representation of images, which are evaluated in direct fashion.

Two images from different modalities (MRI, CT (or) PET), are taken. The image which is going to be registered is called the Input image and the other image is called as the Reference image Apply Dual Tree Complex Wavelet Transform to both input and reference image. Then obtain the Local phase based similarity metric for both input and reference image for different scales and orientations using the following equations.

$$P(x,\theta) = \frac{\sum_n W(x,\theta)\lfloor A_n(x,\theta)\Delta\Phi(x,\theta) - T\rfloor}{\sum_n A_n(x,\theta) + \varepsilon}$$

$$\Delta\Phi(x,\theta) = \cos(\phi_n(x,\theta) - \bar{\phi}(x,\theta)) - |\sin(\phi_n(x,\theta) - \bar{\phi}(x,\theta))|$$

where W represents the frequency spread weighting factor, An and φn represent the amplitude and phase at wavelet scale n respectively, $\bar{\phi}$ represents the weighted mean phase, T represents the noise threshold and ε is a small constant used to avoid division by zero. The values of T, ε, and n used in the proposed method are 2.0, 0.01, and 4 respectively. If all the complex-valued wavelet components are in phase, the phase deviation terms $(\Delta\Phi)$ go to zero and the phase-coherence goes to approximately one (if the amplitudes of the wavelet components are non-zero)

$$\mu(x) = 1/2 \sum_\theta P(x,\theta)^2 + 1/2 \left[4\left(\sum_\theta (P(x,\theta)\sin\theta)\right)(P(x,\theta)\cos\theta)\right)^2$$

$$+\sum_\theta [(P(x,\theta)\cos(\theta))^2 - (p(x,\theta)\sin\theta))^2])^2]^{(1/2)}$$

μ(x) is the phase based structurally significant similarity metric used in the cost function of the proposed technic. After obtaining the phase coherence of both input and reference image, compute the Root Mean Square Error between input and reference image. Compare the residual error with a threshold value and modify the transformation parameters (translation, rotation) and transform the input image, until the residual error becomes less than or equal to the threshold value. Once the error is minimized below the threshold, the images are aligned accurately.

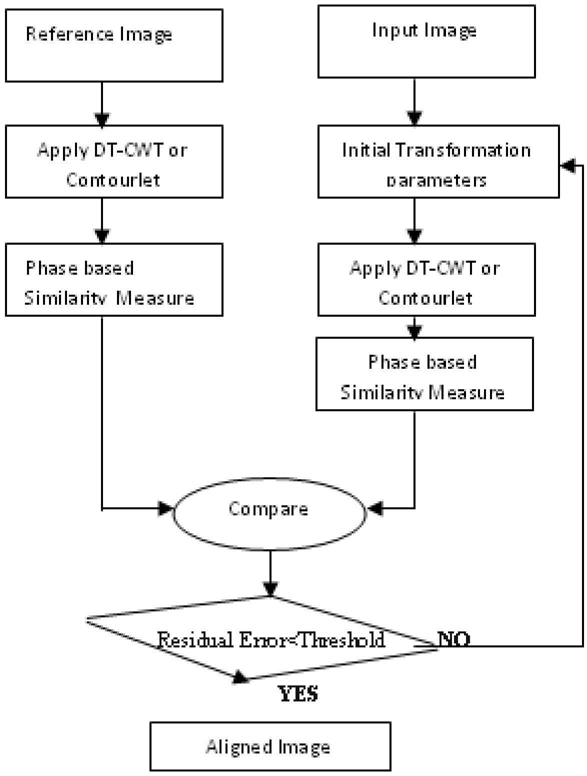
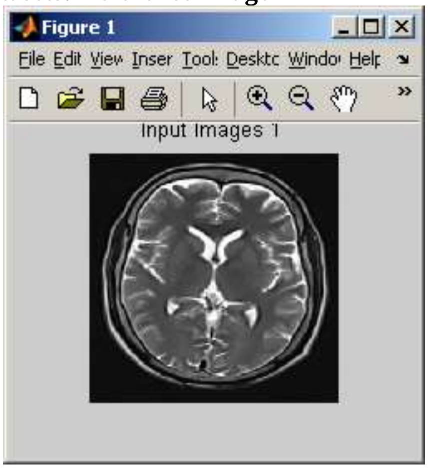


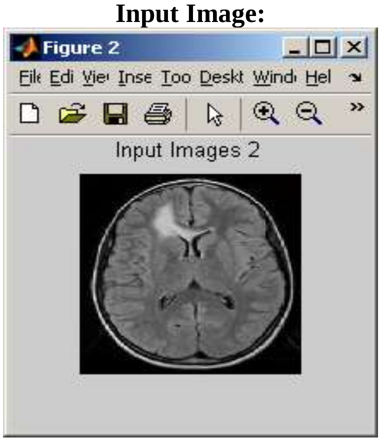
Fig: 1 Flow chart representing the proposed method

Results:

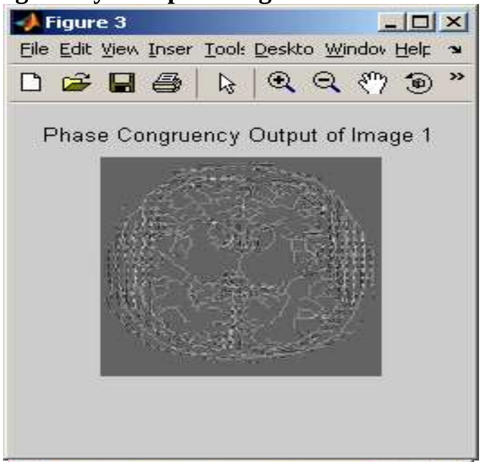
For MR Datasets: Reference Image

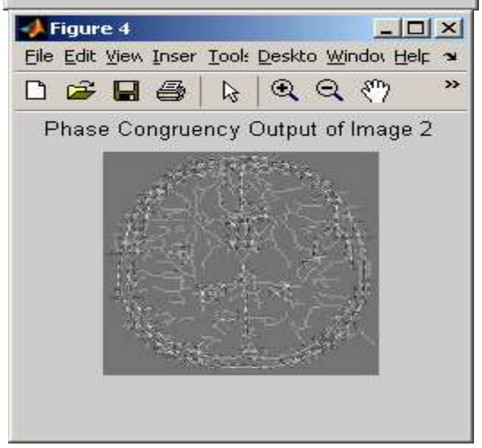


Input Image:



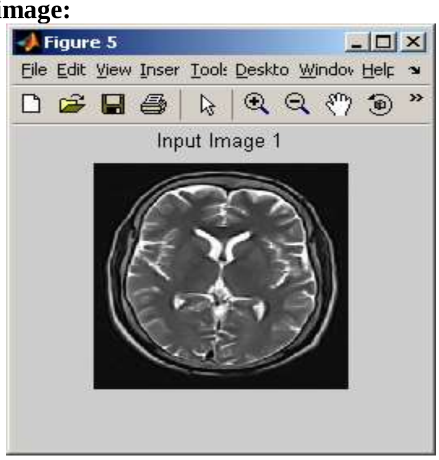
Phase Congruency of Input Images



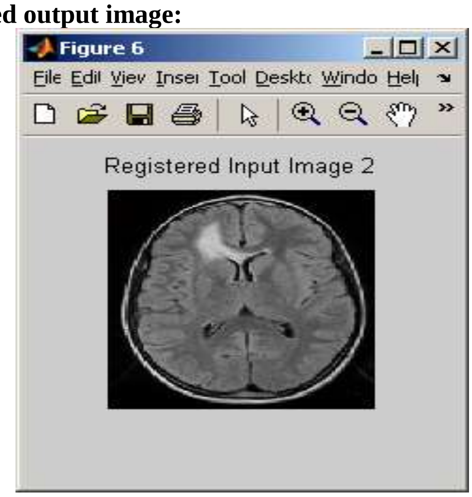


Output:

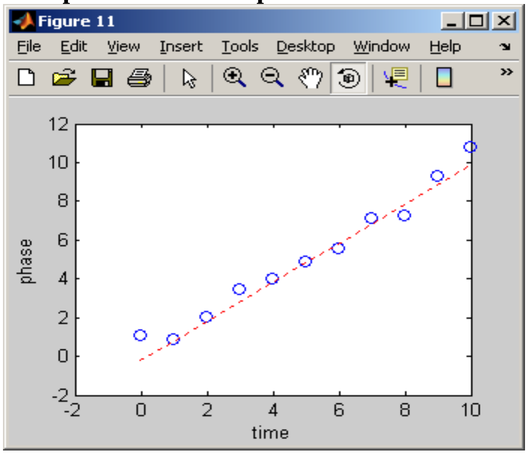
Reference image:



Registered output image:

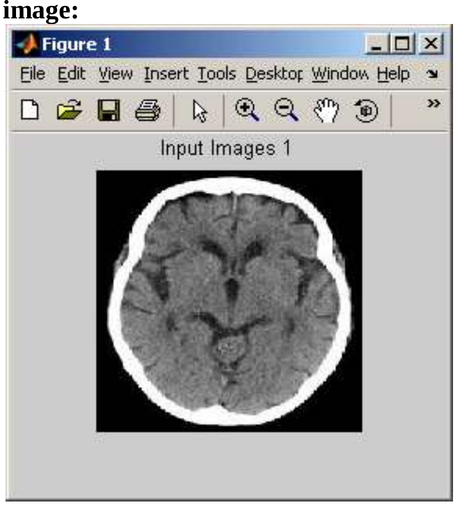


Graphical representation on phase coherence:

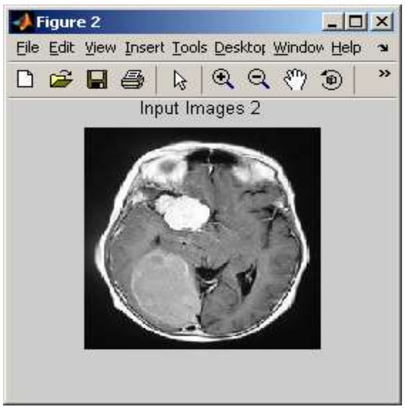


For CT Datasets:

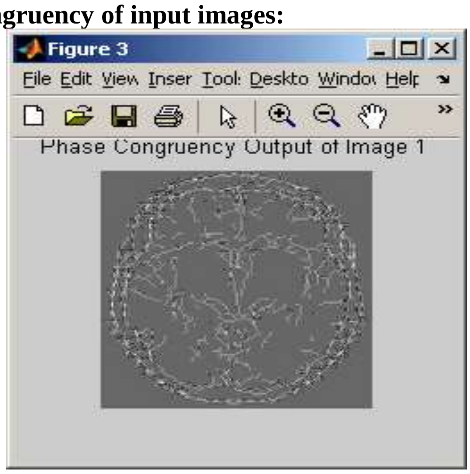
Reference image:

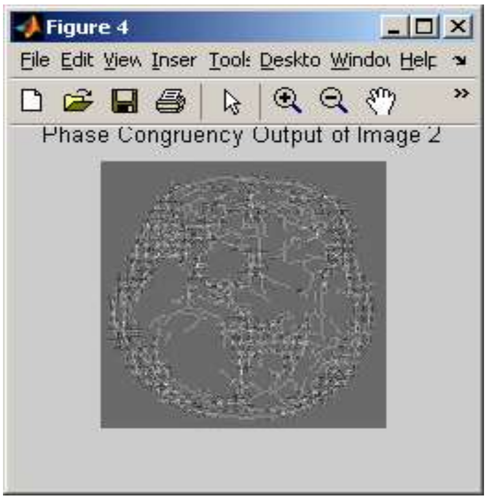


Input Image:



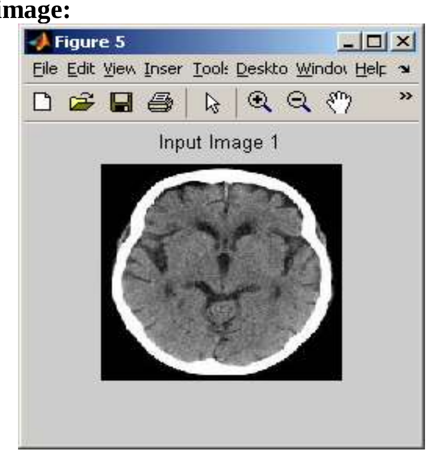
Phase congruency of input images:



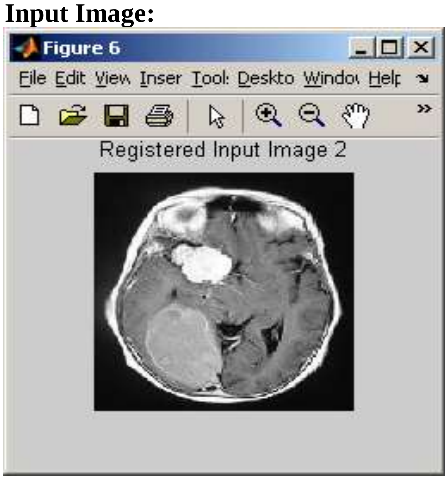


Output:

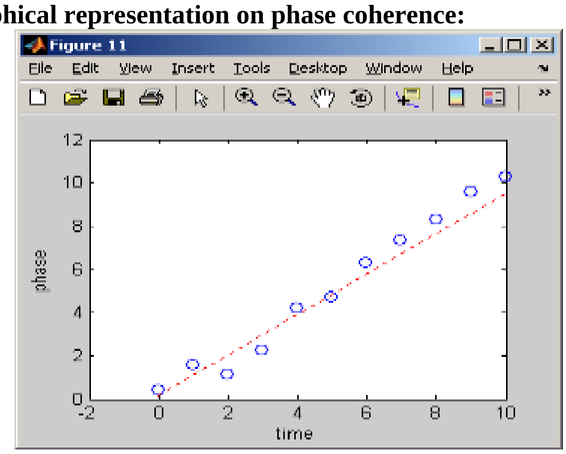
Reference image:



Registered Input Image:



Graphical representation on phase coherence:



For Ct datasets:

Using Contourlet Transform:

Datasets	RMSE	Corr. Coefficient	Elapsed Time	Mutual Information
CT1	0.0039	0.7824	7.2265	1.2622
CT2	0.624	0.8172	7.4242	1.2003
CT3	0.0391	0.7955	7.3257	1.1878

Using Dual Tree-Complex Wavelet Transform:

Datasets	RMSE	Corr. Coefficient	Elapsed Time	Mutual Information
CT1	0.0039	0.7866	12.5419	1.3175
CT2	0.624	0.8213	12.3820	1.1980
CT3	0.0391	0.7938	12.8149	1.1677

For Mri datasets:

Using Contourlet Transform:

Datasets	RMSE	Corr. Coefficient	Elapsed Time	Mutual Information
MR1	0.0586	0.8280	7.4188	1.1276
MR2	0.0508	0.7878	7.3630	1.1703
MR3	0.0624	0.8097	7.0684	1.5041

Using Dual Tree-Complex Wavelet Transform:

Datasets	RMSE	Corr. Coefficient	Elapsed Time	Mutual Information
MR1	0.0586	0.7969	11.8781	1.0438
MR2	0.0508	0.7838	10.7742	1.1302
MR3	0.0624	0.7537	12.7010	1.5458

Conclusion:

From the results it is evident that the proposed local phase based similarity measure is robust and it is suitable for Multimodal Image registration, since it is highly insensitive to luminance (or) intensity variations and also works well in the presence of image noise. The proposed method shows better performance with both MRI and CT images with intensity variations, presence of image noise and existence of image non-homogeneity between images.

In future the proposed method can be tested in a wider range of imaging modalities like ultrasound Positron Emission Tomography etc,. Furthermore, the proposed method has to be tested in the presence of severe noise.

References:

1. A.Collignon, F. Maes, D. Delaere, D.Vandermeulen, P.Suetens and G.Marchal (1995). 'Automated multi-modality image registration based on information theory', Proceedings of information processing in medical imaging (pp. 263–274).

2. P.Viola and W.Wells (1997), 'Alignment by maximization of mutual information', International Journal of Computer Vision, 24(2), 137–154.

3. C.Stenholm, D.Hill, and D.Hawkes (1999), 'An overlap invariant entropy measure of 3D medical image alignment', Pattern Recognition, 32(1), 71–86.

4. W.Crum, D.Hill, and D.Hawkes (2003), 'Information theoretic similarity measures in non-rigid registration', Proceedings of information processing in medical imaging (pp. 378–387).

5. M.Felsberg and G.Sommer (2001), 'The monogenic signal', IEEE Transactions on Signal Processing, 49(12), 3136–3144.

6. A.Wong, W.Bishop and J. Orchard (2006), 'Efficient multi-modal least-squares alignment of medical images using quasi-orientation maps', Proceedings of international conference on image processing, computer vision, and pattern recognition.

7. E. Haber and J.Modersitzki (2006), ‘Intensity gradient based registration and fusion of multi-modal images’, Proceedings of the international conference on medical image computing and computer assisted intervention (pp. 726–733).
8. J.Orchard (2007), ‘Globally optimal multimodal rigid registration: an analytic solution using edge information’, Proceedings of the IEEE international conference on image processing.
9. J.Liu, B.Vemuri and J.Marroquin (2002). ‘Local frequency representations for robust multimodal image registration’, IEEE Transactions on Medical Imaging, 21(5), 462–469.
10. M.Hemmendorff, M.Andersson, T.Kronander, and H.Knutsson(2002), ‘Phase-based multidimensional volume registration’, IEEE Transactions on Medical Imaging, 21(12), 1536–1543.
11. A.Wong and W.Bishop (2008), ‘Efficient least squares fusion of MRI and CT images using a phase congruency model’, Pattern Recognition Letters, 29(3), 173–180.
12. P.Kovesi (2003), ‘Phase congruency detects corners and edges’, Proceedings of Australian pattern recognition society conference (pp. 309–318).
13. I.Selesnick, W.Ivan, R.Baraniuk and N.Kingsbury (2005), ‘The dual-tree complex wavelet transform’, IEEE Signal Processing Magazine, 22(6), 123–151.
14. Alexander Wong (2010), ‘An Adaptive Monte Carlo Approach to Phase-Based Multimodal Image Registration’, IEEE Transactions on Information Technology in Biomedicine, Vol. 14, No. 1