Enhanced Mutual Information-based Multimodal Brain MR Image Registration Using Phase Congruency

Smita Pradhan, Ajay Singh and Dipti Patra

Abstract In intensity-based image registration methods, similarity measure plays a vital role. Recently, mutual information and the variations of MI have gained popularity for the registration of multimodal images. As multimodal images have contrast changes, it is difficult to map them properly. To overcome this issue, phase congruency of the images that gives the significant features of illumination changed images. Also, the soft tissues present in the brain images have same intensity value in different regions. Hence, another assumption is that different pixels have unique distribution present in different regions for their proper characterization. For this challenge, utility measure is incorporated into enhanced mutual information as a weighted information to the joint histogram of the images. In this paper, spatial information along with features of phase congruency is combined to enhance the registration accuracy with less computational complexity. The proposed technique is validated with 6 sets of simulated brain images with different sets of transformed parameters. Evaluation parameters show the improvement of the proposed technique as compared to the other existing state of the arts.

Keywords Phase congruency · Enhanced mutual information · Target registration error

S. Pradhan (✉) · A. Singh · D. Patra
IPCV Lab, Department of Electrical Engineering, National Institute of Technology, Rourkela, Odisha, India
e-mail: ssmita.pradhan@gmail.com

A. Singh
e-mail: ajayniya.singh@gmail.com

D. Patra
e-mail: dpatra@nitrkl.ac.in

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1 Introduction

Nowadays, in medical imaging applications, high spatial and spectral information from a single image is required to monitor and diagnose during treatment process. These information can be achieved by multimodal image registration. Different modalities of imaging techniques give several information about the tissues and organ of human body. According to their application range, the imaging techniques are CT, MRI, fMRI, SPECT and PET. A computed tomography (CT) image detects the bone injuries, whereas MRI defines the soft tissues of an organ such as brain and lungs. CT and MRI provide high-resolution image with biological information. The functional imaging techniques such as PET, SPECT and fMRI give low spatial resolution with basic information. To get the complete and detailed information from single modality is challenging task, which necessitates the registration task to combine multimodal images. The registered or fused image is more suitable for radiologist for further image analysis task.

Image registration has numerous applications such as remote sensing and machine vision. Several researchers discussed and proposed different image registration techniques in the literature [1, 2]. Image registration technique can be divided into intensity-based technique and feature-based technique [3]. Feature-based techniques consider different features such as line, point and textures whereas intensity-based techniques calculate the similarity metric between the images according to pixel correspondences of the spatial information from neighbouring pixels. Different similarity metrics generally used are maximum likelihood, cross-correlation and mutual information. Recently, mutual information (MI) gains more interest, which matches the data points based on mutual dependence among the images. MI is a powerful approach for multimodal medical image registration. A tremendous survey of this approach and their variations is discussed in [4, 5].

Several variations of MI have been proposed. Regional MI (RMI) technique has been adopted with spline-based interpolation for nonrigid registration in [6]. Another variation of MI, quantitative-qualitative mutual information (QMI), is proposed by Zhang et. al. They experimented for deformed multimodal medical image registration combining phase congruency and QMI [7]. Ye et al. used minimum moment of phase congruency for the selection of feature points of the floating images, and determined the correspondences in the reference image using normalized cross-correlation. They achieved the final set of correspondences of the images by projective transformation [8]. For phase congruency representations of multimodal images, Xia et al. used scale-invariant feature transform. Afterwards, they obtain the putative nearest neighbour matching on the SIFT descriptor space [9]. Also, SIFT has been used as feature extraction for score-level fusion in [10].

In this paper, we proposed a novel registration technique for multimodal brain MR image by incorporating the phase congruency into a new similarity measure-enhanced mutual information. The detailed phase congruency and enhanced mutual information are depicted in Sect. 2. In Sect. 3, proposed method is described. Performance evaluation with experimental results is discussed in Sect. 4 with a conclusion in Sect. 5.

2 Materials and Methods

Let I_r and I_f be the input images such as reference and floating images, where the floating image is transformed with affine transformation. For the alignment of the transformed floating image I_f^* relating to reference image I_r, the objective is to get the transformation parameter p that optimizes the cost function $SM(I_r, I_f)$.

$$P^* = \arg\max_p SM(p; I_r, I_f) \tag{1}$$

2.1 Phase Congruency

According to physiological evidences, human visual system takes strong responses towards the important points for feature detection with high phase congruency. According to Peter, phase congruency (PC) is based on local energy model [11]. PC is a dimensionless quantity that acquires the vital aspects of texture, i.e. contrast, scale and orientation, and has advantages over gradient-based techniques. It is normalised by dividing the sum over all orientations and scales of the amplitudes of the individual wavelet responses at the location α in the image, it can be characterized as

$$PC(\alpha) = \frac{\sum_\theta \sum_s \omega_\theta(\alpha)[\Lambda_{\theta s}(\alpha)\Delta\Phi_{\theta s}(\alpha) - \eta_\theta]}{\sum_\theta \sum_s \Lambda_{\theta s}(\alpha) + \kappa} \tag{2}$$

where ω defines the frequency spread weighting parameter, $\Lambda_{\theta s}$ is the amplitude at θ orientation and sth scale, η is the noise compensation parameter achieved independently in each orientation. κ is a constant factor.

$$\Delta\Phi_{\theta s}(\alpha, \theta) = \cos(\phi_s(\alpha, \theta)) - \overline{\phi(\alpha, \theta)} - \left|\sin(\phi_s(\alpha, \theta) - \overline{\phi(\alpha, \theta)})\right| \tag{3}$$

2.2 Enhanced Mutual Information

In an image, salient regions are visually pre-attentive distinct portions. Saliency can be measured by entropy of local segments within an image. Some of salient key points are detected and represented using speeded up robust feature (SURF) descriptor [12]. Luan et al. measured the saliency or utility by entropy of the image and proposed a new similarity measure, known as quantitative-qualitative mutual information (QMI). QMI is calculated as

$$QMI(I_r, I_f) = \sum_{r\epsilon I_r} \sum_{f\epsilon I_f} W(I_r, I_f)P(I_r, I_f)log\frac{P(I_r, I_f)}{P(I_r)P(I_f)} \tag{4}$$

Similarly, Pradhan et al. have adopted the weighted information as the utility to mutual information measure and proposed enhanced mutual information (EMI) [13]. EMI can be defined as

$$EMI(I_r, I_f) = \sum_{r\epsilon I_r} \sum_{f\epsilon I_f} P(I_r, I_f)log\frac{P(I_r, I_f)}{P(I_r)P(I_f)} + W(I_r, I_f)P(I_r, I_f) \tag{5}$$

where $W(I_r, I_f)$ is joint weighted information of I_r and I_f, which can be calculated by saliency measure of both reference and floating images. Here, the self-similarity measure, i.e. maximum entropy, is considered and multiplied with a dissimilarity measure to get the saliency of each pixel. Then, the joint utility of each intensity pair is calculated as

$$W_n(r,f) = \sum_{j,k\epsilon\Omega} \delta_{I_r}(j).\delta_{I_f}(k) \tag{6}$$

where Ω is the overlap area of both images and $\delta_{I_r}(j)$ and $\delta_{I_f}(k)$ are the weighted information of I_r and I_f, respectively. In the registration procedure, the joint utility is upgraded progressively. The utility varies with the transformation step l with a condition

$$W_n(r,f) + \alpha(l).(1 - W_n(r,f)) \tag{7}$$

where $\alpha(l)0 : 1$.

3 Proposed Methodology

To incorporate the feature information into spatial information through higher saliency value, a hybrid technique known as PC-EMI has been proposed. Figure 1 shows the block diagram of proposed algorithm.

In the first step, phase congruency features of both the reference image and transformed floating image are extracted. Then, the marginal and joint entropies are calculated with the extracted phase congruency of the images. Those entropies are used for the calculation of enhanced mutual information. Saliency or utility measure is another important factor for the calculation of enhanced mutual information. The utility or saliency of the images is evaluated from original images instead of phase congruency mappings. Simultaneously, the joint utility is defined for every intensity pair of the images. Then, it is utilized as the weight to the joint histogram from PC features of the corresponding intensity pair. Then, for a set of transformation parameters, the cost function is evaluated and optimized to get the higher value. For optimal geometric transformation, quantum-behaved particle swarm optimization (QPSO)

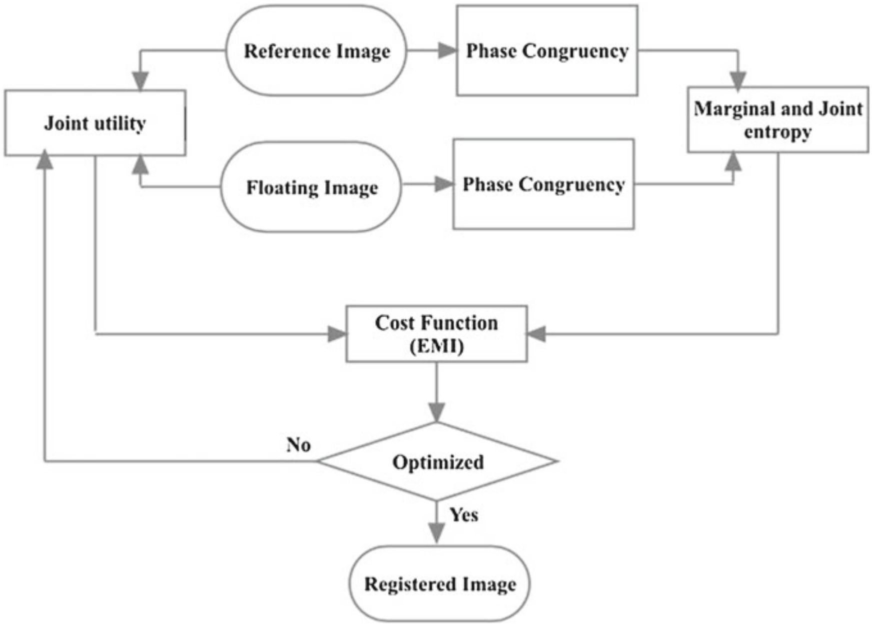

Fig. 1 Block diagram of proposed technique

technique is adopted for maximization of the similarity measure, i.e. enhanced mutual information. The registration approach is summarized in Algorithm 1.

Algorithm 1: PC-EMI Algorithm

Input: I_r, $T(I_f)$
Output: P^* *with high costfunction*
Initialize geometric transformations
for *each transformation* $-$ *step* $= 1$ **to** n **do**
    Calculate the cost function as given by Eq. 5
    repeat
        Use QPSO technique to solve the optimization problem as in Eq. 1
        Update the joint utility using Eq. 6
        Recalculate the cost function
    until ;
    The difference of cost function in three consecutive transformation steps is ≤ 0.01
end

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4 Simulation and Results

To know the performance, the proposed PC-EMI algorithm is tested on 6 set of multimodal brain image data sets. Here, only MR T1 and T2 weighted with transformed images are shown for simulation and analysis. The images are translated, rotated and scaled manually and validated with proposed technique. The proposed algorithm is validated with each data set and compared using different performance measure indices to proof the robustness and accuracy. The performance indices calculated are normalized cross-correlation (NCC), peak signal-to-noise ratio (PSNR), mean squared error (MSE) and normalized absolute error (NAE). The simulation is done in MATLAB R 2013a with a system specification Intel (R) Core(TM) i5−2400 CPU @ 3.10GHz. The simulated brain MR images were taken from the database (http://brainweb.bic.mni.mcgill.ca/brainweb/).

The images must be aligned with a particular transformation parameters that have higher cost function. This is the only condition taken for the registration procedure with minimization of MSE. The input images shown in Fig. 2a, b show MR T2 weighted and T1 weighted, respectively. The size of images is 182×182 with slice thickness of 3 mm. The cost function, i.e. similarity measure value, for EMI is calculated and compared with existing similarity measures, i.e. qualitative-quantitative mutual information (QMI) and mutual information (MI).

MR T2-T2 translated along y-axis image: The registration procedure is done with a set of brain MR T2 weighted and translated T2 weighted along y-axis. The cost function, i.e. the similarity measure value, for PC-EMI is 0.76, which is higher than PC-QMI and PC-MI. To verify the performance of proposed algorithm visually, checker board image (CBI) of registered image and the reference image is shown in Fig. 2c. Figure 1d and e shows the CBI of PC-QMI and PC-MI, respectively. The different performance measures are organized in Table 1. The computational time is additionally arranged in Table 1.

MR T1-T2 translated along x-axis image: In this test, the T2 image is transformed along x-axis manually. Then, the translated T2 image is registered with respect to T1 image using PC-EMI algorithm. The final EMI value is higher whereas the MSE value is lower than the other two methods. The checker board image of reference image and registered image is shown in Fig. 2f–h for PC-EMI, PC-QMI and PC-MI, respectively. Also, the NCC value of proposed technique is higher than that of other methods. All other parameters are presented in Table 1.

MR T1-T2 rotated image: Finally, one set of rotated T2 image and T1 image are registered. The alignment of rotated T2 image is tested within a range [−20, 20]. The fourth row of Fig. 2i–k shows the CBI using PC-EMI, PC-QMI and PC-MI, respectively. The convergence plot for the three techniques is presented in Fig. 3. From the plot, it is observed that EMI has higher value than that of QMI and MI. The computational time with other performance measures is tabulated in Table 1. It is also observed that the computational time for proposed technique is lower as compared to PC-QMI technique. The lower MSE proves the efficiency of PC-EMI algorithm.

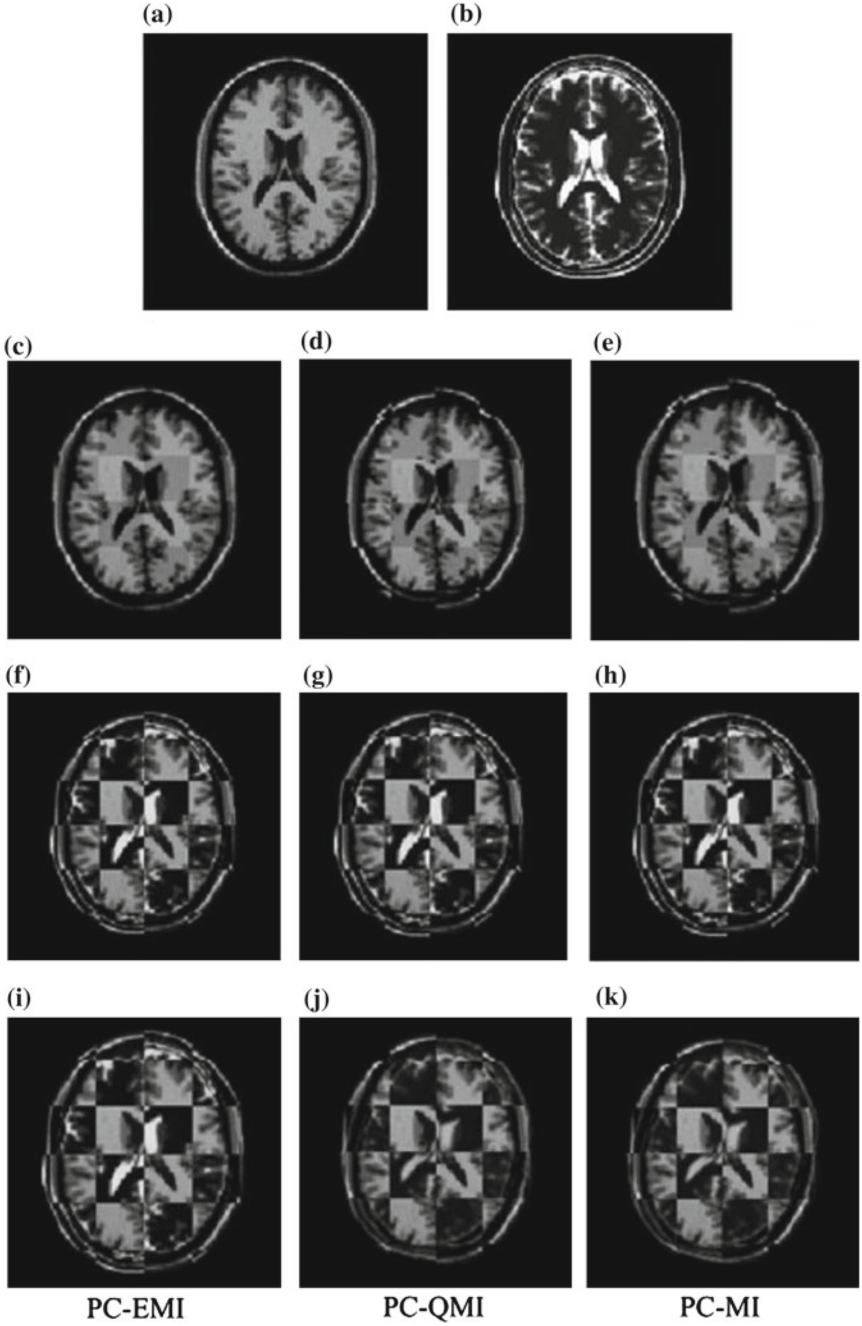

Fig. 2 Checker board image for all techniques

Table 1 Calculated cost value with different performance measures

Data Set	Methods	SM value	MSE	PSNR	NCC	NAE	Time (s)
T2-T2 translated along y-axis Brain MR image	PC-EMI	0.88	1.42×10^3	16.58	0.83	0.34	644.18
	PC-QMI	0.73	3.63×10^3	12.59	0.58	0.73	766.63
	PC-MI	0.62	3.89×10^3	12.09	0.54	0.78	28.83
T1-T2 translated along x-axis Brain MR image	PC- EMI	1.67	3.54×10^3	12.63	0.58	0.84	636.38
	PC-QMI	1.55	4.34×10^3	11.75	0.50	0.93	780.86
	PC-MI	0.51	4.61×10^3	11.49	0.47	0.96	29.53
T1-T2 rotated Brain MR image	PC-EMI	0.92	3.15×10^3	14.97	0.36	0.77	436.38
	PC-QMI	0.60	3.26×10^3	12.95	0.34	0.79	519.33
	PC-MI	0.15	3.30×10^3	12.84	0.33	0.81	19.53

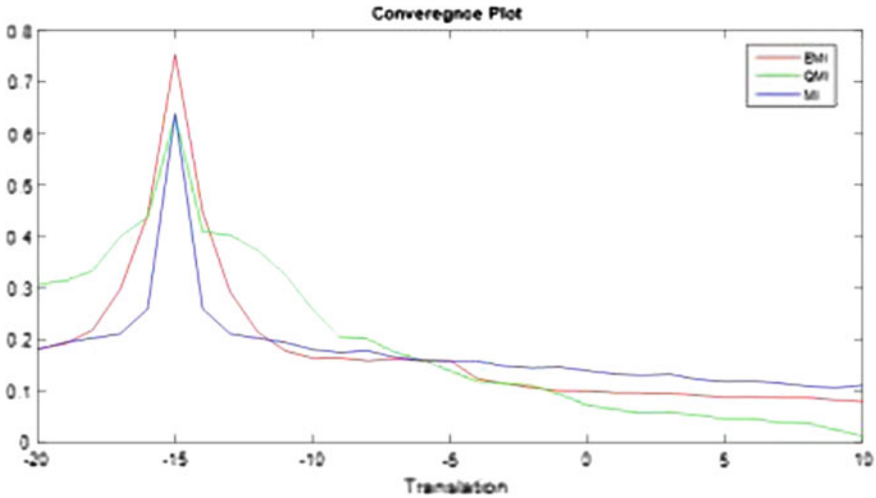

Fig. 3 Convergence plot for T1-T2 rotated image data set

5 Conclusion

The paper proposed a new registration technique, based on phase congruency into enhanced mutual information with the ability of taking feature and structural information. The proposed method is robust towards contrast and scale changes. The method is also rotation invariant. The utility factor gives the weighted information, and phase congruency gives feature information that gives an improvement in the calculation of EMI-based similarity measure for higher registration accuracy than that of other state of the arts. This work can be extended towards nonrigid registration.

References

1. J.B.A. Maintz, M.A. Viergever, A survey of medical image registration, Med. Image Anal, 2 (1), pp. 1–36, (1998).
2. Mani, V.R.S and Rivazhagan, S. Survey of Medical Image Registration, Journal of Biomedical Engineering and Technology, 1 (2), 8–25 (2013).
3. Oliveira, F. P., Tavares, J.M.R. Medical image registration: a review, Computer methods in biomechanics and biomedical engineering, 17 (2), 73–93 (2014).
4. A. Studholme, D.L.G. Hill, D.L. Hawkes, An overlap invariant entropy measure of 3D medical image alignment, Pattern Recogn, 32, pp. 71–86 (1999).
5. J.P.W. Pluim, A. Maintz, M.A. Viergever, Mutual information based registration of medical images: a survey, IEEE Trans. Med. Imaging, 22(8), pp. 986–1004 (2003).
6. Pradhan, S., Patra, D. RMI based nonrigid image registration using BF-QPSO optimization and P-spline, AEU-International Journal of Electronics and Communications, 69 (3), 609–621 (2015).
7. Zhang, Juan, Zhentai Lu, Qianjin Feng, and Wufan Chen.: Medical image registration based on phase congruency and RMI. IEEE International Conference on Medical Image Analysis and Clinical Applications (MIACA), pp. 103–105, (2010).
8. Ye, Yuanxin, Lian Xiong and Jie Shan.: Automated Multi-Source Remote Sensing Image Registration Based on Phase Congruency. ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 1, pp. 189–194, (2012).
9. Xia, R., Zhao, J. and Liu, Y., 2013, October. A robust feature-based registration method of multimodal image using phase congruency and coherent point drift. In Eighth International Symposium on Multispectral Image Processing and Pattern Recognition, International Society for Optics and Photonics, (2013).
10. Bakshi, S., Das, S., Mehrotra, H., Sa, P. K. Score level fusion of SIFT and SURF for iris. IEEE International Conference on In Devices, Circuits and Systems (ICDCS), pp. 527–531, (2012).
11. Kovesi, Peter.: Image features from phase congruency. Videre: Journal of computer vision research, 1.3, pp. 1–26, (1999)
12. Sahu, B., Sa, P. K., Majhi, B. Salient Keypoint Detection using Entropy Map for Iris Biometric. In Proceedings of 2nd International Conference on Perception and Machine Intelligence, pp. 104–109, (2015).
13. Pradhan, S., Patra, D. Enhanced mutual information based medical image registration, IET Image Process., 10 (5) , pp. 418–427, (2015).