Table 2: Accuracy and iterative number comparison among intensity ECC, gradient ECC, and ACMI.

Pair mode	Pairs	Accuracy (median/maximum mm) Intensity ECC	Gradient ECC	ACMI	Number of iterations (Mean ± SD) Intensity ECC	Gradient ECC	ACMI
Original images							
T1-PET	7	2.78/4.96	2.73/4.31	2.38/4.22	269.5 ± 84.8	111.3 ± 29.9	172.2 ± 44.0
T2-PET	7	1.91/6.37	1.52/5.84	1.39/5.51	288.0 ± 145.1	87.5 ± 45.8	161.7 ± 43.9
PD-PET	7	2.46/6.19	1.97/4.72	1.62/3.41	222.2 ± 108.7	93.2 ± 36.9	159.9 ± 58.6
T1 rec-PET	4	3.19/8.37	2.88/6.12	2.63/5.43	240.5 ± 92.2	102.4 ± 33.1	145.5 ± 49.7
T2 rec-PET	5	3.15/9.15	3.04/7.13	2.72/6.08	220.3 ± 97.8	93.6 ± 42.8	174.9 ± 37.3
PD rec-PET	5	3.07/8.13	2.65/7.41	2.37/6.74	224.7 ± 89.5	99.3 ± 41.9	183.1 ± 63.0
Subsampled version							
T1-PET	7	4.13/8.25	3.70/7.37	3.40/7.48	169.0 ± 65.0	93.7 ± 31.4	127.5 ± 36.4
T2-PET	7	4.14/9.18	3.52/6.18	3.06/5.10	189.0 ± 63.4	79.1 ± 35.9	138.8 ± 40.6
PD-PET	7	3.07/12.94	2.74/7.06	2.59/5.36	151.5 ± 63.3	82.1 ± 39.0	135.7 ± 32.8
T1 rec-PET	4	4.62/10.37	3.95/9.22	3.51/8.83	150.2 ± 59.3	88.6 ± 28.9	118.5 ± 26.3
T2 rec-PET	5	5.25/16.15	4.92/10.88	4.83/7.07	176.5 ± 59.1	89.7 ± 34.2	136.7 ± 35.6
PD rec-PET	5	4.17/11.82	3.39/8.17	3.03/6.33	144.5 ± 52.2	90.7 ± 40.6	113.7 ± 29.4
Small-overlapped version							
T1-PET	7	4.15/5.78	3.71/6.65	3.33/7.17	146.2 ± 93.2	94.9 ± 35.7	112.3 ± 29.9
T2-PET	7	3.34/8.37	2.44/6.07	2.20/4.94	207.5 ± 88.2	120.5 ± 61.3	153.0 ± 48.2
PD-PET	7	3.98/8.18	3.11/6.21	2.84/5.11	213.7 ± 83.1	106.8 ± 47.9	134.2 ± 51.4
T1 rec-PET	4	3.33/10.85	2.96/8.13	2.61/6.72	139.5 ± 64.1	68.6 ± 40.7	96.5 ± 43.6
T2 rec-PET	5	4.17/12.05	3.89/9.27	3.21/7.38	170.0 ± 79.3	63.9 ± 37.0	99.1 ± 46.5
PD rec-PET	5	3.39/9.10	3.30/7.58	3.16/6.91	193.0 ± 114.8	103.4 ± 58.0	133.1 ± 52.8

4. DISCUSSION AND CONCLUSION

Though MI method is a well-known effective criterion for Multimodal image registration, it still has some disadvantages which often make the alignment less than optimal.

First, MI is unreliable to measure the degree of alignment between two images. MI function includes only intensity information but little spatial information of images, so it usually either produces several global maxima or presents a global maximum which does not correspond to the correct alignment. Some research introduced spatial information such as gradient-based information [6–8] or feature-based information [19–21] to improve the quality of image registration. These methods were effective but they did not took full advantage of the phase information of gradient field or the relationship between intensity images and their gradient fields.

Second, MI function is easily influenced by the intensity interpolation and presents many local maxima to trap the optimization [4, 5], leading to the failure of registration. Various high-order interpolation methods [22, 23] and global optimization algorithms [6] were introduced to reduce the influence of local maxima. But these methods are computationally expensive [24, 25]. Moreover, these methods are meaningless if the similarity measurement is unreliable [26, 27].

Third, MI is sensitive to the reduction of resolution or overlapped area of images. MI is a similarity measurement method and its reliability depends on the statistical stability of samples. The reduction of resolution or the overlapped area decreases the sample size, then deteriorates the statistical stability of samples. As a result, MI presents a poor performance for the registration of images with low resolution or small overlapped area. NMI [11] and ECC [10] were introduced to solve this problem, but no significant improvement was observed [25, 28]. They are also sensitive to the reduction of resolution or overlapped area of images.

To overcome these disadvantages of MI, we propose a technique for Multimodal image registration, namely ACMI, based on adaptive combination of intensity and gradient field mutual information. We constructed GCM from which the gradient field mutual information of original intensity images is calculated. The GCM is obtained from corresponding original images by a spherical gradient coder and includes both magnitude and phase information of gradient field of original images. The gradient field mutual information provides sufficient spatial information for the similarity measurement of images, besides it is smoother due to the relatively higher intensity uniformity of GCMs. ACMI combines the advantages of intensity ECC and gradient ECC, and adopts a coarse-to-fine and gradient-to-intensity registration strategy, so it overcomes the nonsmoothness and unreliability of traditional MI function. Results of simulated data experiments and actual registration both demonstrate that ACMI function performs better than traditional MI and it is much less sensitive to the reduction of resolution or overlapped area of two images.

According to its advantages, ACMI function is suitable for the registration of low-resolution images or impaired images. One example is the registration with multiresolution