Multi-modal Brain MR Image Registration using A Novel Local Binary Descriptor based on Statistical Approach

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***Abstract*—Medical image registration (MIR) has played an important role in medical image processing during the last decade. Its main objective is to integrate information inherent in two images, from different scanning sources, of the same object for guiding medical treatments such as diagnostic, surgery and therapy. A challenging task of MIR arises from the complex relationships of image intensities between the two images. Its performance is primarily depending on a chosen similarity measure technique. In this work, a statistical local binary descriptor (SLBD) is proposed as novel local descriptor of similarity measure, which is simple for computation and can handle Multi-modal registration more effectively. The proposed SLBD employs two statistical values, i.e., the mean and the standard deviation, of all intensities within the image patch for its computation. Finally, these experimental results have shown that SLBD outperforms other descriptors in terms of registration accuracy. In addition, SLBD has demonstrated that SLBD is robust to different modalities.**

Keywords—Local binary descriptor; multi-modal image registration; statistical approach; medical image registration; similarity measure

I. Introduction

Nowadays, medical imaging techniques (MIT) have been continuously improved, and this leads to the advancement in computer-aided surgery and radiotherapy (CAS). In general, in the procedure of CAS, medical practitioners need to utilize medical images produced from different scanning protocols [1] to perform their works. The medical images from different sources can provide different kinds of information for them. For instance, an MRI image provides functional information whereas anatomical information is from an X-Ray image. Multi-modal image registration (MIR) is the process of finding an optimal amalgamation of both corresponding anatomical and/ or functional structures of the two images [2]. Therefore, MIR can help medical practitioners to perform more effective diagnosis of a disease. Basically, MIR has three main components: 1) the similarity measure used to evaluate the similarity between images that are to be registered, 2) the transformation model deforming the moving image to the fixed image, 3) the optimization method determining the optimal parameter for the transformation to achieve the best similarity [3]. Applications of MIR in medical image processing have faces more challenges due to the complex relationships of intensities between multi-modal images. One major challenge task is how to improve the similarity measure between the two multi-modal medical images in order to achieve more accurate and efficient registration [4, 5].

In the last decade, Mutual information (MI) is an important concept relevant to several theorems of information theory and most widely studied as similarity measures. Particularly, it has been extensively and successfully used to measure the intensity relationships in image processing [6] [7]. During the last decade, many researchers have enhanced the accuracy of image registration based on MI, such as Tsallis and Renyi's entropies [8], Jensen- Renyi's entropy [9], hybrid EMPCA-Scott approach [10], and self-similarity α-MI (SeSaMI) [11]. However, the notion of MI alone still has a well-known drawback, i.e., it ignores spatial information [12]. For medical image registration, spatial information is important because it provides the medical information. Therefore, many researchers have enhanced MI to handle spatial information, such as second-order MI (SMI) [13], Regional MI (RMI) [14], PCA Regional MI (PRMI) [15], Conditional MI (CMI) [16]. However, Heinrich et al. [17] have noticed that these approaches are still difficult to find an accurate correspondence between different modality images. Therefore, they proposed a method, called MIND, based on neighbourhood information. MIND uses the sum of squared differences (SSD) to estimate the similarity of two images. It has higher accuracy than several methods. However, MIND is highly subject to the central patch. This limitation affects the noise robustness [18]. Hence, they introduced a so-called self-similarity context (SSC) to improve the noise robustness of MIND. SSC avoids the central patch and uses pairs of patches within six-neighbourhood [18].

Local binary pattern (LBP) is one of the most effective and well-known approaches used in texture classification [19]. Trichet and Bremond [20] introduced a novel pedestrian detection technique by using a 12-valued filter representation based on LBP. It can improve filtering performance, which leads to a sharper feature. Hong et al. [21] proposed the LBP-Top for facial expression recognition to reduce the demand of loops and the computational cost. Weber Local binary pattern (WLBP) was presented by Liu et al [22]. It is a combination of Weber local descriptor and LBP and is robust to many challenges. The non-local mean local binary descriptor (NLM-LBD) was presented in [23]. By taking advantage of structural information, he NLM-LBD can improve the NLM method in terms of both computation time and quality for real-time denoising applications. DRLBP [24] was an enhancement of LBP for rotation robustness. These approaches have high computation speeds for registration, but some structural information may be lost.

Recently, Jiang et al. [25] proposed miLBP descriptor that can improve robustness to noise, intensity and non-uniformity of medical image processing. Its performance is better than recent methods such as SeSaMI [11], CoCoMI [26], and SSC [18]. In addition, Lu et al. [27] introduced a registration technique by combining local features and geometric invariants. Shen et al. [28] enhanced MI with a hybrid optimization technique based on Powell's method and cuckoo search. Yonghong et al. [29] applied an improved particle swarm optimization (PSO) to an image registration algorithm based on MI. The value of MI of the registered image is calculated and is used in the fitness function of PSO. Bai et al. [30] presented Multi-modal CT rigid MIR with regional weighted mutual information (RWMI), which is robust to large rotation and translation. However, RWMI is sensitive to registration with very small overlap and small intensity variance. Furthermore, Borvornvitchotikarn and Kurutach [31] have improved miLBP, which combines miLBP and DRLBP. This method achieves the best results for registration with rotational transformations. The other work of authors also enhanced the miLBP, which adopts the mean and standard deviation of the image patch for adaptive threshold and uses the sorting operation for sorting the pixels within image patch. Therefore, it could provide terms of robustness in modality-independent and rotation-invariant descriptor (miRID) [32]. Yang et al. [33] have proposed MIR based on image segmentation and symmetric self-similarity. This method uses BCFCM to segment multi-modal medical images and extracts target regions in medical images.

However, due to limitations of existing approaches, the spatial information may be lost from the computation of those descriptors. Hence, the key reason for the proposed SLBD approach is that it makes the multi-modal image similarity measure remain the spatial information of the regions of interest.

The contributions of this work are summarized as follows:

- This work points out and proposes a novel approach to measure the similarity or dissimilarity between the intensities of pixels in the regions of interest on multi-modal medical images. The proposed similarity measure is suitable to handle the complexity of intensity relationships between two modalities of images more effectively. In addition, it can avoid the weakness of the traditional LBD, where image artefacts within the central patch directly affect its performance. Moreover, this method still retains the structural information potentially, which can estimate a direct patch-to-patch mapping between image multi-modality. This proposed approach will be called SLBD (for statistical local binary descriptor) and will be described in detail in Section III.
- The proposed similarity measure is a complementary method to previous LBD-based methods such as miLBP and miRID.

This paper is organized as follows. Section II presents the background. Section III describes the proposed method. The experimentations and results present in Section IV. The discussions and conclusion will be discussed in Sections V and VI, respectively.

II. Background Concepts

A. Image Registration

MIR is a process of transforming a moving image to optimally align with a fixed or target image. Its goal is to maximize the similarity or minimize the dissimilarity between the two registered images. To accomplish the task, MIR needs to have three main components: a similarity metric, a transformation model, and an optimization model. The similarity metric is a measure of how well the two images match. The transformation model is used to transform the moving image to match the fixed image. The optimization model is to find a variation of parameters in the transformation model to maximize the matching criteria [34]. To formally formulate the notion, registration T′of a moving image I_m and a fixed image I_f is defined by (1),

$$T' = \arg\min_T D\left(I_f, T(I_m)\right) \tag{1}$$

where $D\left(I_f, T(I_m)\right)$ is a dissimilarity measure which determines the degree of alignment between I_f and $T(I_m)$ and T denotes a deformable transformation. In (1), T′ is to find the optimal transformation T that provides the minimum value of D [12].

B. Similarity Measure based on Local Binary Pattern

The standard LBP was introduced by Ojala et al. [35]. It is a simple principle of the texture classification. For the patch size of 3 x 3, the binary result gives 8-bit integer codes. The LBP operator can be defined as follows:

$$LBP = \sum_{n=1}^{N} s(g_n - g_c).\,2^{n-1}, with \tag{2}$$

$$s(x) = \begin{cases} 1, x \geq Th \\ 0, x < Th \end{cases} \tag{3}$$

where n is the position of a neighbouring pixel, N denotes the number of the neighbouring pixels, g_n is the intensity of the neighbouring pixel at the position n, g_c is the intensity of the central pixel, and Th is the threshold value. In the area of medical image analysis, LBP-based similarity metrics, such as miLBP [25] and Hybrid LBP (HLBP) [36], could provide higher accuracy in registration results. HLBP can cope well with the variation of the local intensity on the 4D CT lung registration, which includes a median binary pattern and a generalised central-symmetric LBP. The miLBP is another LBP-based method which can provide the highest accuracy on the registration of CT-MR images with different modalities from Brainweb [37] and RIRE [38] datasets. Moreover, miLBP adopts the technique of the adaptive threshold using the standard deviation δ of the intensity values of the neighbouring pixels. The miLBP is defined by (4), (5) [25]. The concept of miLBP can be illustrated in Fig. 1.

$$miLBP = \sum_{n=1}^{N} s(|g_n - g_c|).2^{n-1}, \text{ with} \quad (4)$$

$$s(|g_n - g_c|) = \begin{cases} 1, |g_n - g_c| > \delta \\ 0, |g_n - g_c| \leq \delta \end{cases} \quad (5)$$

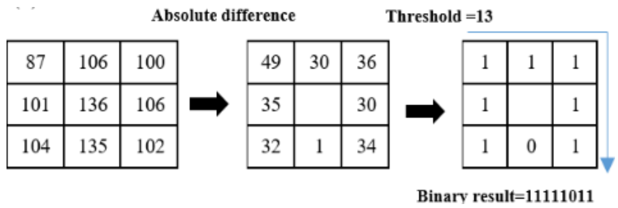


Fig. 1. Illustration of the miLBP Performed on Image Pixels (here: δ =13).

miRID [32] has the potential to increase the stability of medical image registration to rotation variations. Instead of utilizing the intensity of the center pixel, miRID uses the mean of all intensity values inside the patch to achieve this. In addition, the sorting procedure is conducted on intensity values within the patch to make miRID stable against rotational deformations. The miRID is defined by (5), (6).

$$miRID_I^P = \Gamma_{i=1}^{P} s(Sort|g_i - M|), \text{ with} \quad (5)$$

$$s(|g_i - M|) = \begin{cases} 1, |g_i - M| > \delta \\ 0, |g_i - M| \leq \delta \end{cases} \quad (6)$$

where $\Gamma_{i=1}^{P}$ represents the bitcount operation, which counts the number of bits having the value of 1. $|g_i - M|$ denotes the absolute difference of the intensity difference between g_i and M. M represents the mean of intensity of all pixels. $Sort$ operation indicates the descending order operation. P denotes the number of the pixels in the patch and δ represents the standard deviation of all pixels.

III. Proposed Method

This section will present a novel local binary descriptor, which enhances the technique of LBP. This descriptor can prominently handle the complexity of intensity relationships between different modalities. Both LBP and miLBP methods estimate the similarity value based on the use of the central pixel. However, image artifacts within the central patch can affect the performance of the descriptors. Therefore, this method needs to avoid the use of the central pixel in computing the intensity relationships in a descriptor that is to register multi-modal images. To accomplish that, the proposed method adopts the mean m and the standard deviation δ of all intensity values within the patch as the threshold values instead of using the intensity of the central pixel. Evaluating the similarity between two images is formally defined by (7) - (11). The overview of the proposed SLBD is illustrated in Fig. 2.

This work will define the binary pattern $SLBD_I^P$ of the intensities within the region of interest as follows:

$$SLBD_I^P = \complement_{i=1}^{P} s(g_i), \text{ with} \quad (7)$$

$$s(g_i) = \begin{cases} 1, \lambda_{lower} \leq g_i \leq \lambda_{upper} \\ 0, \text{otherwise} \end{cases} \quad (8)$$

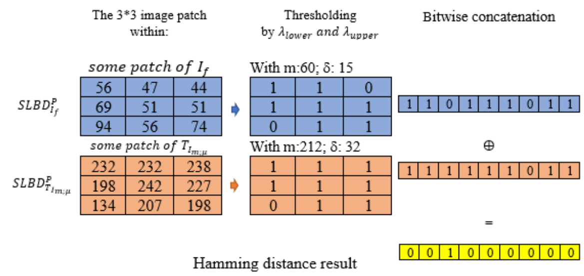


Fig. 2. Overview of the SLBD Concept.

where:

$SLBD_I^P$ is the binary pattern of pixels' intensities within the interesting region of image I.

$\complement_{i=1}^{P}$ is the bitwise concatenation operation, where:

P represents the total number of pixels within the image patch.

$i, 1 \leq i \leq P,$ is a pixel location in the patch ;

$s(g_i)$ is a binary value assigned to the pixel i based upon the intensity value g_i against the boundary values $(m - \delta)$ and $(m + \delta)$;

m denotes the mean value of the intensities of all pixels within the patch, as defined in (9):

$$m = \frac{1}{P}\sum_{i=1}^{P} g_i \quad (9)$$

δ denotes the standard deviation of the intensity values of all pixels within the patch, as defined by (10):

$$\delta = \sqrt{\frac{1}{P-1}\sum_{i}^{P} (g_i - m)^2} \quad (10)$$

λ_{lower} and λ_{upper} are the threshold values defined as follows:

$\lambda_{lower} = (m - \delta);$

$\lambda_{upper} = (m + \delta);$

In this proposed approach, it is assumed that the moving image I_m and the fixed image I_f are of the same size G. Then, the dissimilarity measure $A_{(I_f, T_{I_{m;\mu}})}$ between the two images can be evaluated by (11). The value of $A_{(I_f, T_{I_{m;\mu}})}$ is within a range of [0,1].

$$A_{(I_f, T_{I_{m;\mu}})} = \frac{1}{G} bitC \left\{ \complement_{i=1}^{G} SLBD_{I_f} \oplus \complement_{i=1}^{G} SLBD_{T_{I_{m;\mu}}} \right\} \quad (11)$$

where:

$SLBD_{I_f}$ and $SLBD_{T_{I_{m;\mu}}}$ are the binary patterns of image I_m and image I_f.

$\oplus$ denotes Hamming distance operation.

G is the image size.

$T_{I_{m;\mu}}$ represents a transformation with respect to transformation parameters μ.

The $bitC$ function is bit count operation which counts the number of bits having the value of 1.

For solving (1), this experiment will find the optimal transformation using a gradient descent optimization method. where $\nabla A_{(I_f, T_{I_m};\mu)}$ is derivative of the cost function $A_{(I_f, T_{I_m};\mu)}$ with respect to the non-rigid transformation parameter μ in (12). The optimization of the cost function is shown in (13). where ϕ_{k+1} is the next postion, ϕ_k denotes the current position and s_k represents the step size.

$$\nabla A_{(I_f, T_{I_m};\mu)} = \frac{\partial A_{(I_f, T_{I_m};\mu)}}{\partial \mu} \tag{12}$$

$$\phi_{k+1} = \phi_k - s_k \nabla A_{(I_f, T_{I_m};\mu)} \tag{13}$$

Fig. 3 shows the block diagram illustrating the proposed registration model. Formulas for evaluating the values of some components can be found in (7) - (13). Specifically, the $SLBD$ is used to represent the binary pattern of the original fixed image and the transformed moving images. The dissimilarity value between $SLBD$ of I_f and $SLBD$ of $T_{I_m};\mu$ is calculated by $A_{(I_f, T_{I_m};\mu)}$ as defined by (10). To find the optimal transformations, $SLBD$ minimizes the dissimilarity values with $A_{(I_f, T_{I_m};\mu)}$.

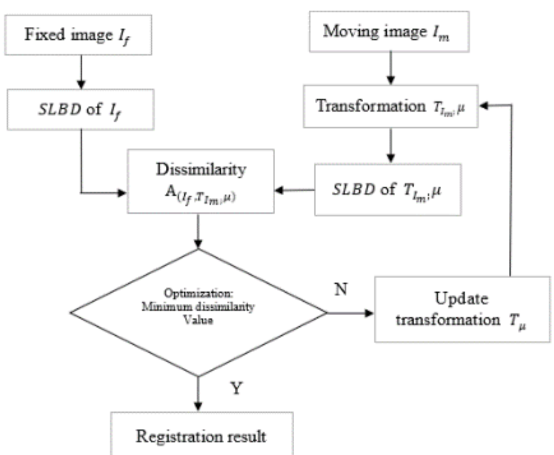


Fig. 3. Block Diagram of the Registration Model.

IV. Experimentation and Results

The previous section has presented SLBD as a local similarity descriptor for measuring the dissimilarity of the image patches in MIR. Its advantages are simplicity of computation and effectiveness in dealing with different modalities. This section will investigate the performance, in terms of registration accuracy, of the proposed algorithm in comparison with other approaches: MI [38], SSC [18], miLBP [25], RWMI [30], and miRID [32]. This experiments were configured the image patch size as follows: for the MI and RWMI methods, the image patch with the size of 7 x 7 pixels and 64 bins was used. For the SSC, miLBP, miRID, and SLBD methods, an image patch with the size of 3 x 3 pixels was chosen. More details for parameter setting on SSC, miLBP methods can be found in their original works [18] and [25], respectively. These methods were quantitatively assessed by the mean target registration error (mTRE) [17] and tested on a computer with an Intel® Core™ i7-7700 CPU 3.60 GHz and RAM memory 16.0 GB. SLBD is implemented as a local similarity descriptor into non-rigid image registration, which uses Free-form deformation (FFD) with three hierarchical levels of B-spline central point [39].

This experiment carries out registrations of T1-T2, T1-PD, and T2-PD modalities from the BrainWeb dataset [37]. The voxel values are defined at a 1mm. and an image size of 181 x 217 x 181 voxels with 3% noise and 40 % intensity non-uniformity. As the moving images, the 2D 15th slice of a T1-weighted image is shown in both Fig. 4(a) and Fig. 5(a) and the 2D 15th slice of T2-weighted image in Fig. 6(a). In the first experiment, they were rotated within the range of -20^{o}. Fig. 4(b) shows the corresponding T2-weighted image and Fig. 5(b) and Fig. 6(b) show the corresponding PD-weighted images, as the fixed images. The checkerboard images of the registered images using SLBD are shown in Fig. 4(c), Fig. 5(c), and Fig. 6(c). The transformations of these registrations are shown in Fig. 4(d), Fig. 5(d), and Fig. 6(d).

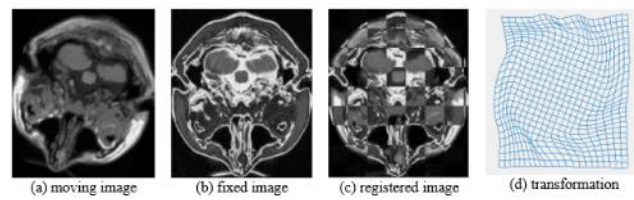


Fig. 4. T1-T2 Registration.

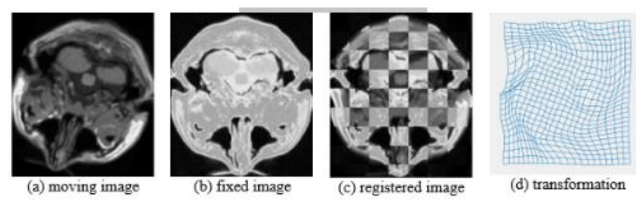


Fig. 5. T1-PD Registration.

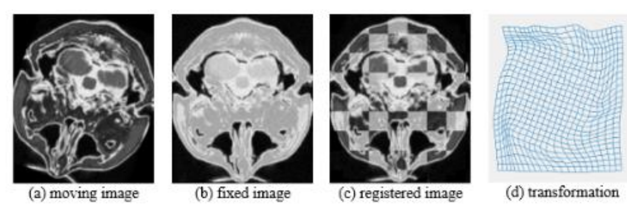
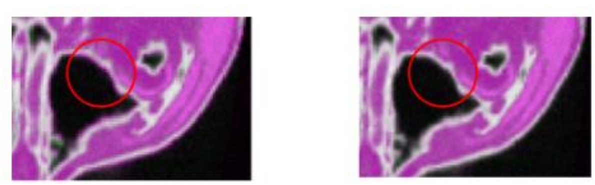


Fig. 6. T2-PD Registration.

Fig. 7(a), (b) show the expansion of the inner contour area indicated by the red circles. The proposed SLBD method performs better compared to the miRID method.



(a) miRID. (b) SLBD.

Fig. 7. (a),(b) The Expansion of the Overlapped Inner Contour Area of the Registration Results for the miRID, and SLBD.

TABLE I. RESULTS OF MULTI-MODAL NON-RIGID IMAGE REGISTRATION WITH BRAINWEB DATASET

Methods	**Modalities**			**mTRE.**
	T1- T2	**T1-PD**	**T2-PD**	
MI [38]	2.63	2.88	3.01	2.84
SSC [18]	2.46	2.27	2.47	2.40
miLBP [25]	2.44	2.45	2.35	2.41
RWMI [30]	2.48	2.49	2.51	2.49
miRID [32]	2.35	2.37	2.43	2.38
SLBD	**2.12**	**2.23**	**2.11**	**2.15**

Table I shows the performance evaluation of T1-T2, T1-PD, and T2-PD registrations in terms of the target registration error (TRE.). It is obvious that the registration errors of SLBD are the lowest, especially in the cases of T1-T2, and T2-PD. SLBD could achieve the best overall registration accuracy (mTRE=2.15). They are a significant improvement compared to miRID (2.38), SSC (2.40), miLBP(2.41), RWMI (2.49), and MI (2.84), respectively. To illustrate the cases, Fig. 4 to 6 show the visual results of the SLBD method experimenting on the T1, T2, and PD-weighted MR images. These resulting images estimated by SLBD are more like the fixed images.

V. DISCUSSIONS

Generally, white matter appears as a bright grey in both T1 and PD and a dark grey in T2. Cerebro-spinal fluid appears as a dark grey in T1, a light grey in T2, and a grey in PD. These are the challenges in the non-rigid image registration with different MR modalities. However, in this experimentation on the registrations of T1-T2, T1-PD, and T2-PD using various approaches, it has been found that the proposed method, SLBD, has the least errors. In comparison, the miLBP [25], RSSD [31], and miRID [32] have the high speeds of MIR and also have the robustness of modality-independent. The miRID [32] could perform the best performance in MIR both rigid and non-rigid registration. However, those descriptors may lose the structural information due to their calculation. For example, miLBP represents the 8-pixels within the image patch to the single value of 0-255 ranked by multiple 2^{n-1} and miRID uses the sorting operation for sorting the pixels in the image patch. The computation of both miLBP and miRID may be possible to lose the spatial information of the regions of interest in the computation of both miLBP and miRID. Unlike, miLBP, RSSD, and miRID, SLBD was easily represented by the pixels within the image patch by an adaptive threshold. Another advantage is that SLBD can maintain the spatial information appropriately. The binary pattern results of SLBD can be estimated by the similarity with the patch-to-patch mapping of the corresponding regions.

VI. CONCLUSION

This paper has presented a novel similarity descriptor, called SLBD, based on a simple statistical concept. It is an enhancement of the local binary descriptor for multi-modal image registration. This experimentation shows that proposed approach outperforms others in terms of accuracy of multi-modal medical image registration. In addition, the proposed method is simpler in its computation. In future work, SLBD will implement as the loss function of deep convolutional neural networks for estimating the similarity between the ground truth and the prediction.

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REFERENCES

[1] Y. Ou, Development and validations of a deformable registration algorithm for medical images: Applications to brain, breast and prostate studies. University of Pennsylvania, 2012.

[2] K. A. Bachman, "Mutual information-based registration of digitally reconstructed radiographs and electronic portal images," Master's thesis, Applied Mathematics, University of Colorado at Denver, 2005.

[3] W. R. Crum, T. Hartkens, and D. Hill, "Non-rigid image registration: theory and practice," The British Journal of Radiology, 2014.

[4] F. Alam, S. U. Rahman, and A. Khalil, "An investigation towards issues and challenges in medical image registration," Journal of Postgraduate Medical Institute (Peshawar-Pakistan), vol. 31, no. 3, 2017.

[5] F. Alam, S. U. Rahman, S. Ullah, and K. Gulati, "Medical image registration in image guided surgery: Issues, challenges and research opportunities," Biocybernetics and Biomedical Engineering, vol. 38, no. 1, pp. 71-89, 2018.

[6] A. Sotiras, C. Davatzikos, and N. Paragios, "Deformable medical image registration: A survey," Medical Imaging, IEEE Transactions on, vol. 32, no. 7, pp. 1153-1190, 2013.

[7] F. Maes, A. Collignon, D. Vandermeulen, G. Marchal, and P. Suetens, "Multimodality image registration by maximization of mutual information," Medical Imaging, IEEE Transactions on, vol. 16, no. 2, pp. 187-198, 1997.

[8] S. Sahoo, P. K. Nanda, and S. Samant, "Tsallis and Renyi's embedded entropy based mutual information for multimodal image registration," in Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 2013 Fourth National Conference on, pp. 1-4: 2013.

[9] Y. He, A. B. Hamza, and H. Krim, "A generalized divergence measure for robust image registration," Signal Processing, IEEE Transactions on, vol. 51, no. 5, pp. 1211-1220, 2003.

[10] T. Borvornvitchotikarn and W. Kurutach, "A hybrid EMPCA-Scott approach for estimating probability distributions in mutual information," in 2016 International Computer Science and Engineering Conference (ICSEC), pp. 1-5, 2016.

[11] H. Rivaz, Z. Karimaghaloo, and D. L. Collins, "Self-similarity weighted mutual information: A new nonrigid image registration metric," Medical image analysis, vol. 18, no. 2, pp. 343-358, 2014.

[12] K. Kasiri, P. Fieguth, and D. A. Clausi, "Self-similarity measure for multi-modal image registration," in Image Processing (ICIP), 2016 IEEE International Conference on, pp. 4498-4502, 2016.

[13] D. Rueckert, M. Clarkson, D. Hill, and D. J. Hawkes, "Non-rigid registration using higher-order mutual information," International Society for Optics and Photonics, pp. 438-447,2000.

[14] D. B. Russakoff, C. Tomasi, T. Rohlfing, and C. R. Maurer Jr, "Image similarity using mutual information of regions," in Computer Vision-ECCV 2004: Springer, pp. 596-607, 2004.

[15] Y.-W. Chen and C.-L. Lin, "PCA based regional mutual information for robust medical image registration," in Advances in Neural Networks–ISNN 2011: Springer, pp. 355-362,2011.

[16] D. Loeckx, P. Slagmolen, F. Maes, D. Vandermeulen, and P. Suetens, "Nonrigid image registration using conditional mutual information," Medical Imaging, IEEE Transactions on, vol. 29, no. 1, pp. 19-29, 2010.

[17] M. P. Heinrich et al., "MIND: Modality independent neighbourhood descriptor for multi-modal deformable registration," Medical Image Analysis, vol. 16, no. 7, pp. 1423-1435, 2012.

[18] M. P. Heinrich, M. Jenkinson, B. W. Papiez, S. M. Brady, and J. A. Schnabel, "Towards realtime multimodal fusion for image-guided interventions using self-similarities," (in eng), Medical image computing and computer-assisted intervention : MICCAI ... International Conference on Medical Image Computing and Computer-Assisted Intervention, vol. 16, no. Pt 1, pp. 187-194, 2013.

[19] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Transactions on pattern analysis and machine intelligence, vol. 24, no. 7, pp. 971-987, 2002.

[20] R. Trichet and F. Bremond, "LBP Channels for Pedestrian Detection," in 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 1066-1074, 2018.

[21] X. Hong, Y. Xu, and G. Zhao, "LBP-TOP: a Tensor Unfolding Revisit," Asian Conference on Computer Vision, Springer, Cham, pp. 513-527, 2016.

[22] F. Liu, Z. Tang, and J. Tang, "WLBP: Weber local binary pattern for local image description," Neurocomputing, vol. 120, pp. 325-335, 2013.

[23] H. Yu and A. Li, "Real-Time Non-Local Means Image Denoising Algorithm Based on Local Binary Descriptor," KSII Transactions on Internet & Information Systems, vol. 10, no. 2, 2016.

[24] R. Mehta and K. Egiazarian, "Dominant Rotated Local Binary Patterns (DRLBP) for texture classification," Pattern Recognition Letters, vol. 71, no. Supplement C, pp. 16-22, 2016.

[25] D. Jiang, Y. Shi, D. Yao, M. Wang, and Z. Song, "miLBP: a robust and fast modality-independent 3D LBP for multimodal deformable registration," International Journal of Computer Assisted Radiology and Surgery, journal article vol. 11, no. 6, pp. 997-1005, 2016.

[26] H. Rivaz, Z. Karimaghaloo, V. S. Fonov, and D. L. Collins, "Nonrigid registration of ultrasound and MRI using contextual conditioned mutual information," IEEE transactions on medical imaging, vol. 33, no. 3, pp. 708-725, 2014.

[27] Y. Lu, K. Gao, T. Zhang, and T. Xu, "A novel image registration approach via combining local features and geometric invariants," PloS one, vol. 13, no. 1, 2018.

[28] L. Shen, X. Huang, C. Fan, and Y. Li, "Enhanced mutual information-based medical image registration using a hybrid optimisation technique," Electronics Letters, vol. 54, no. 15, pp. 926-928, 2018.

[29] Y. Yonghong, L. Jiying, W. Qiang, and Z. Tao, "Improved Particle Swarm Optimization Image Registration Based on Mutual Information," in 2019 11th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), pp. 450-453,2019.

[30] L. Bai, G. Li, C. Zhu, E. Wu, and R. Ma, "Regional Weighted Mutual Information for Multimodal Rigid Registration," in 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), pp. 1-6, 2018.

[31] T. Borvornvitchotikarn and W. Kurutach, "Robust Self-Similarity Descriptor for Multimodal Image Registration," in 2018 25th International Conference on Systems, Signals and Image Processing (IWSSIP), pp. 1-4, 2018.

[32] T. Borvornvitchotikarn and W. J. S. Kurutach, "miRID: Multi-Modal Image Registration Using Modality-Independent and Rotation-Invariant Descriptor," vol. 12, no. 12, p. 2078, 2020.

[33] Z. Yang, N. Kuang, Y. Yang, B. J. K. T. o. I. Kang, and I. Systems, "Brain MR Multimodal Medical Image Registration Based on Image Segmentation and Symmetric Self-similarity," vol. 14, no. 3, 2020.

[34] Y. Ou, A. Sotiras, N. Paragios, and C. Davatzikos, "DRAMMS: Deformable registration via attribute matching and mutual-saliency weighting," presented at the Medical image analysis, 2011.

[35] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," Pattern recognition, vol. 29, no. 1, pp. 51-59, 1996.

[36] Z. Cao, E. Dong, Q. Zheng, W. Sun, and Z. Li, "Accurate inverse-consistent symmetric optical flow for 4D CT lung registration," Biomedical Signal Processing and Control, vol. 24, pp. 25-33, 2016.

[37] B. BrainWeb, "Simulated Brain Database," Online: http://brainweb. bic. mni. mcgill. ca/cgi/brainweb2, 2010.

[38] T. M. Cover and J. A. Thomas, Elements of information theory. John Wiley & Sons, 2012.

[39] D. Rueckert, L. I. Sonoda, C. Hayes, D. L. Hill, M. O. Leach, and D. J. Hawkes, "Nonrigid registration using free-form deformations: application to breast MR images," Medical Imaging, IEEE Transactions on, vol. 18, no. 8, pp. 712-721, 1999.