International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-1, October, 2019

Evaluation Method for the Optimization of 3D Rigid Image Registration on Multimodal Image Datasets

Bhumika Handa, Gaganpreet Singh, Rose Kamal, Arun S Oinam, Vivek Kumar

Abstract: Optimization based three dimensional (3D) rigid image registration (RIR) is one of the most commonly used methods of image registration in radiotherapy. Interpolator and similarity metric plays a crucial role in optimization image registration process. In this paper, the efficiency of image registration algorithm is analyzed by using various combinations of interpolators and similarity metric in terms of quantitative measures and is compared with commercially available image registration algorithm in radiotherapy. Computed Tomography (CT) and Cone Beam Computed Tomography (CBCT) image datasets were registered by image registration algorithm written in python language using simple image tool kit (SITK). Different combinations of similarity metric and interpolator such as mean square difference (MSD), mutual information (MI), demons and nearest neighbor (NN), linear, B- spline respectively were used in this study. The efficiency of the algorithm was quantified in terms of mean square error (MSE), structural similarity index (SSI), normalized cross correlation (NCC) and mutual information (MI). The image registration algorithm with most efficient combination of similarity metric and interpolator was selected for comparison with the commercially available image registration algorithm. The algorithm for multimodal (CT-CBCT) 3D image registration with NN interpolator and MI similarity metric showed the highest values of SSI, NCC and MI as 0.865, 0.933, 1.223 respectively among other combination of interpolator and similarity metric. Further this algorithm when compared and statistically analyzed with commercially available image registration algorithm of Treatment Planning System (TPS. most commonly used for radiotherapy treatment) resulted in no significant difference (F value NCC-3.18, MI-4.010, SSI-2.776) in their quantitative measures. The present study is limited to 3D RIR and can be extended for deformable image registration.

Keywords: Rigid Image Registration, Computed Tomography, Cone Beam Computed Tomography, Mutual Information, Nearest Neighbor, Treatment Planning System

I. INTRODUCTION

Development of different imaging modalities and acquisition techniques has increased the utility of digital images in medicine/clinics.

Revised Manuscript Received on October 30, 2019.
* Correspondence Author
Bhumika Handa, Centre for Medical Physics, Panjab University, Chandigarh, India. Email: bhumika1051@gmail.com
Gaganpreest Singh, Centre for Medical Physics, Panjab University, Chandigarh, India. Email: gaganpreetsingh@live.com
Rose Kamal, Centre for Medical Physics, Panjab University, Chandigarh, India.Email: rose.kamal22@gmail.com
Arun S Oinam*, Department of Radiotherapy, P.G.I.M.E.R, Chandigarh, India. Email: asoinam@gmail.com
Vivek Kumar*, Centre for Medical Physics, Panjab University, Chandigarh, India. Email: vivek@pu.ac.in

Image registration techniques has vital role in various medical applications of radio diagnosis, radiotherapy, nuclear medicine, surgical procedures and motion tracking. Medical image registration is a process in which two or more images are geometrically aligned which are acquired from different ports (multi-view registration),
at different times (multi temporal registration) or by different image acquisition devices (multimodal registration) [1-8]. Various imaging modalities provide disparate imaging information, to epitomize, a magnetic resonance imaging (MRI), computed tomographic (CT), positron emission tomography (PET) images provides better visualization of soft tissues, hard tissues (bone) and information of biological processes within the body (functional image), respectively[9-14]. Registration of numerous images provides better visualization for delineation of tumor and organs volumes. Accurate delineation plays an important role in radiotherapy as the tumor doses has been increased whereas the margins of the planning target volume has been decreased. Besides this image registration also plays a vital role to reproduce treatment setup during radiotherapy treatment with the help of integrated cone beam computed tomography (CBCT) and six dimensional (6D) couch which provides three translational and three rotational-degree of freedom.

In rigid image registration (RIR), all voxels move and/or rotate uniformly to keep voxel-to-voxel relationship similar before and after transformation [3]. Most common technique used for RIR is based upon optimization. An optimization method estimates the best transformation to minimize the registration errors and maximize the similarity metric values. Numerous registration errors may occur due to under or over sampling of the images [14]. Accuracy of registration method can be improved by wisely selecting the interpolator and similarity metric. Several authors have investigated various image registration methods and effect of interpolation on image registration [15-17]. Pluim et al [15] reported the effect in terms of artifacts and speed introduced by interpolation methods in image registration. Mahmoudzadeh et al [16] evaluated eight standard interpolation techniques and compared the effect of cost functions for optimized automatic image registration (OAIR) on 3D spoiled gradient recalled (SPGR) magnetic resonance images (MRI) and qualitative assessment is made by Magnetic resonance image scans and joint histogram. Along with the interpolator, similarity metric is also an important part of image registration process.

Various similarity metrics are available with different characteristics, which are sensitive to imaging modality, image content, target image, partial image overlap, sampling, histogram binning, and image degradation [18]. Akerl et al [19] has studied numerous similarity metrics on the basis of accuracy and robustness for image processing. The discrete effect of interpolator and similarity metric on image registration is available but both of these produce combine effect on quality of image registration.

In radiotherapy, contouring and treatment planning workstations have inbuilt image registration algorithms which are used for patient treatment planning. Most of the commercial available registration methods requires either external input or region of interest (ROI) which results in image registration variation subject to the user selection. Apart from this, TPS provides few parameters to measure the quality of image registration. However, how accurately the quality of registration is measured it is to be checked by an independent software by using various parameters of quality metrics of image registration. The aim of this paper is to analyze and compare the automatic image registration algorithm with commercially available registration algorithm in radiotherapy using various combinations of interpolator and similarity metrics. Rigid image registration code is written in python language using Simple Insight Segmentation and Registration Toolkit (SITK) in which registration is performed using various combinations of similarity metric and interpolator to analyze their effects on quality of image registration. In this paper, an effort is made to explore the potential of fully automatic 3D RIR algorithm and to evaluate the quality of RIR by various quality measurement metrics of registrations which are not available in the commercial TPS.

II. MATERIAL AND METHODS

A. Preparation of 3D image datasets

Fifteen, 3D image datasets of CT and CBCT of pelvic area were randomly selected retrospectively for this study. All CT scan images were acquired using Philips CT (Brilliance Big Bore) and CBCT scans were acquired using on-board imager (OBI) integrated with (Trilogy 5823) of varian medical systems (Palo, Alto, USA). The CT image datasets were imported in Eclipse TPS version 11.03 (Varian Medical Systems, Palo Alto, CA, USA). CT and CBCT image datasets were exported in digital imaging and communication in medicine DICOM-RT format using export filter of Eclipse TPS. Parameters of exported CT and CBCT datasets are defined in Table I.

Table I: CT and CBCT datasets parameters

Parameters	CT	CBCT
Slice thickness	3.00 mm	2.5mm
Orientation	Axial	Axial
Matrix size	512×512	384×384
No. of slices	variable	variable
Pixel spacing	1.175×1.175	1.171×1.171
Kilo voltage	140	125
Tube current	285	80

B. Optimization method for registration

It is an iterative method in which transformation is performed in iterations until the similarity measure reaches the maximum value [13-14].

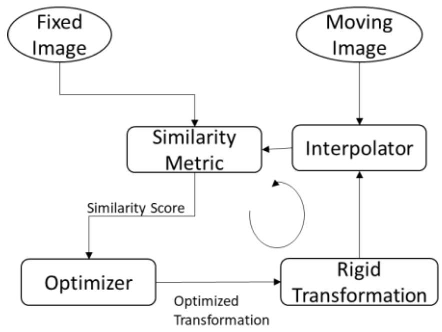

Fig. 1 Diagrammatic representation of optimization based automatic RIR algorithm

The workflow of RIR using optimizer, similarity metric and interpolator is shown in Fig 1. In this approach, two image datasets pass through the interpolator (interpolates voxel values between two image datasets), similarity metric (evaluates accuracy of image dataset registration), optimization and transformation processes. Optimization process in image registration depend on the values obtained from the interpolator and similarity metric modules, which affects the accuracy of image registration.

B.1 Similarity metrics

The similarity metrics used for image registration must have less computational complexity, more robustness, optimum time calculation and should reach global maxima values when accurate transformation is obtained. Mean square difference (MSD), mutual information (MI) and demons are used as similarity metric in this study. MSD is most commonly used similarity metric and is mathematically expressed as:

$$\text{MSD} = \sqrt{\sum_{i,j\in M}(a_i - b_j)^2} \quad (1)$$

Where i, j represents voxels in corresponding image datasets in the domain defined as M [21]. This method is mainly used for two similar image datasets. Now a days, for medical image registration MI is being utilized which is based on Shanon definition of entropy which measures the relation between intensity values of two image datasets [21]. The MI registration states that when two images are perfectly aligned the value of MI is maximum [15]. It shows robustness in both unimodal and multimodal registration as it does not depend upon range of intensity value of images. Demons is a method which uses displacement vectors of each voxel.

Demons move displacement vector according to image gradient. If voxel value in moving image is lower than the target image value, the vector is moved towards gradient direction and vice-versa [20].

B.2 Interpolator

After applying transformation during image registration, interpolator computes the voxel values in the roto-translated image. Interpolation is performed after each iteration, due to this accuracy and non-complexity of interpolator is of great importance [16]. Interpolation function can affect the gray level values that may result in inaccurate measurement of similarity metric [19].

In this study linear, nearest neighborhood and b-spline interpolation methods are utilized. Linear interpolation is a basic method of interpolation which interpolates values between two linear points [16]. In the nearest neighbor algorithm, voxel value is calculated with the use of its nearest neighbor voxel which does not alter the gray level values [19]. B-spline interpolates using weighted voxel values in a wider neighborhood and it considers neighboring points as control points where it combines the intensity values using a set of polynomial [16]. The above mentioned interpolators and similarity metrics are selected to analyze the effect on the quality of 3D RIR.

C. Algorithms for the 3D image registration

C.1 SITK Based Registration method

An automatic 3D RIR code using Simple Insight Segmentation and Registration Toolkit (SITK) is written in Python language (version 3.6.3, 64 bit architecture). The images of the 3D datasets, exported from the TPS, were preprocessed to convert the intensity values to the Hounsfield units (HU) using rescale slope and rescale intercept parameters extracted from the DICOM header of each image of the CT and CBCT datasets. Sorting and stacking algorithms are applied on both the datasets in which images were sorted using Image Patient Position (IPP) and instance number parameters from the DICOM header of each image and stacked to form a 3D matrix of different sizes in the order of increasing z values (number of slices) for the CT and CBCT datasets.

For RIR, out of two 3D image datasets, one is considered as moving and other as fixed. To register different datasets, number of SITK in-build functions are used in this code. In RIR algorithm, centered transform initializer function, euler 3D Transform function, resample function is used for center to center alignment, translational and rotational operations and for sampling of two image datasets respectively. Further, Image Registration Method function is used for initialization of various parameters in registration (table II).

Table II. Parameters used in RIR Method function

Code Parameters	Values
Metric sampling strategy,	random
Metric sampling percentage	1%
Learning rate	1.0
Number of iterations	100
Convergence minimum value	1e-6
Convergence window size	10

C.2 Commercial TPS based registration

Commercially available different image registration algorithms present in mage registration module of the Eclipse TPS are used to register the 3D image datasets. However, due to the lack of availability of different quantitative measures of image registration accuracy, 3D RIR was performed independently outside the TPS environment by writing in-house registration module. Image registration module was written in python language which reproduces the same registration accuracy as that of TPS. Spatial registration file (RE.dcm) exported from TPS that contains the information of translational and rotational shifts applied by commercial registration algorithms was used to apply these shifts outside the TPS. The translation shift was applied by the formulae:

$$X= (X_s - IP_{CBCT\_X}-IP_{CT\_X})/CT_{PS}$$

$$Y= (Y_s-IP_{CBCT\_Y}-IP_{CT\_Y})/CT_{PS}$$

$$Z= (IP_{CBCT\_Y}-IP_{CT\_Y} +Z_s)/CBCT_{ST}$$

Where X_s, Y_s, Z_s are translational shifts in x, y, z directions obtained from translational shift matrix extracted from spatial registration file (RE.dcm). IP_{CBCT_X}, IP_{CBCT_Y}, IP_{CBCT_Z}, IP_{CT_X}, IP_{CT_Y}, IP_{CT_Z} are the coordinates of Image Patient Position (IPP) of CBCT and CT image datasets in x, y, z direction respectively whereas CTPS is pixel size of CT image dataset and CBCTST is slice thickness of CBCT image dataset. Furthermore rotational shift was applied by calculating euler angles from the registration matrix from TPS by formulae in table III:

Table III. Formulas for rotation about x, y, z axis using rotation matrix

Axis	$R_{31} = +1$	$R_{31} = -1$	Otherwise
X (Φ)	0	0	arctan2 $(\frac{R21}{\cos\theta}, \frac{R11}{\cos\theta})$
Y (ψ)	- arctan2(R_{12},R_{13})	arctan2(R_{12},R_{13})	arctan2 $(\frac{R32}{\cos\theta}, \frac{R33}{\cos\theta})$
Z (θ)	$\frac{-\pi}{2}$	$\frac{\pi}{2}$	-arcsinR_{31}

In table III formulae for rotation is given along X, Y and Z axis where R represents the value at (row, column) of transformation matrix.

D. Quantitative measures of 3D RIR

The quality of 3D RIR algorithms are analyzed using parameters viz normalized cross correlation(NCC), structural similarity index(SSI), mean square error (MSE) and MI [22-24].

D.1 Normalized Cross correlation

NCC indicates the linear relationship between two measured quantities [22-24]. NCC value is calculated as:

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\ \sqrt{\sum_i (y_i - y_m)^2}} \quad (2)$$

$$r = \begin{Bmatrix} 0 \text{ no correlation} \\ -1 \text{ negative correlation} \\ +1 \text{ positive correlation} \end{Bmatrix}$$

Where x_i, y_i represents the HU values of ith voxel and x_m, y_m are the mean HU values of the 1st and 2nd 3D image dataset respectively.

D.2 Structure similarity index (SSI)

SSI indicates the value of similarity measure of two 3D image datasets using the combination of luminance, contrast and structure functions [24]. SSI is calculated as:

$$SSI(x, y, z) = f(l(x, y, z), c(x, y, z), s(x, y, z)) \quad (3)$$

Where SSI represents structure similarity index, l(x,y,z) is luminance, c(x,y,z) is contrast and s(x,y,z) is structure function of x and y 3D image datasets.

D.3 Mean square error

MSE indicates the geometric alignment of the two 3D image datasets. MSE is calculated as:

$$MSE = \frac{1}{MNO} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \sum_{k=0}^{O-1} [g(i,j,k) - f(i,j,k)]^2 \quad (4)$$

MSE=0, indicates the perfect alignment and two images whereas MSE>0 indicates Misalignment. Where g(i, j, k) and f(i, j, k) represents the HU value corresponding to i, j, k index of the 3D image datasets.

D.4 Mutual information

MI indicates the value of statistical dependency between two 3D image datasets [21]. MI is calculated as:

$$MI(X,Y) = H(X) + H(Y) - H(X,Y) \quad (5)$$

The maximization of MI represents accurate alignment of image. H(X), H(Y) represents the entropy of X and Y 3D image dataset respectively, whereas H(X, Y) represents the joint entropy of both the 3D image datasets.

The above parameters defining the quantitative measure of 3D RIR based on SITK and TPS registration algorithms are statistically compared using ANOVA method and the results are shown in the next section.

III. RESULTS

A. Visualization of 3D image registration datasets

Figure 2 represents the typical axial slice of moving and fixed image of pelvic area of CT and CBCT image datasets respectively and unregistered fused images are shown in Fig 3.

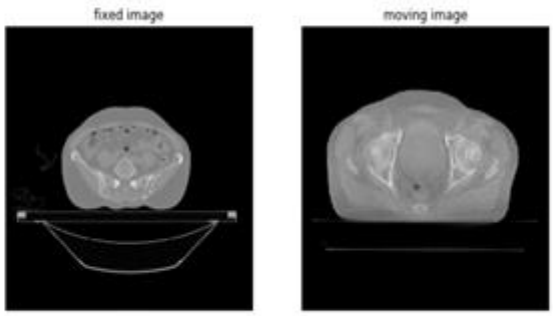

Fig 2 Axial view of an arbitrary slice of fixed CT (left) and moving CBCT (right) image dataset

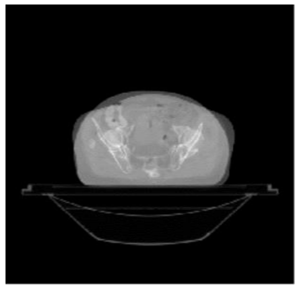

Fig 3 Non-registered CT and CBCT image

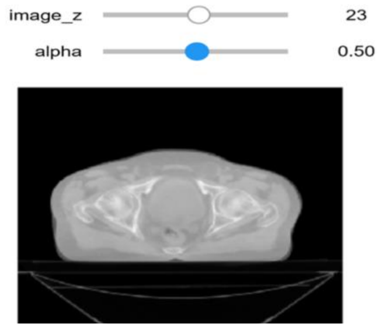

Fig 4 Image registration by code developed in Python

Figure 4 displays the registered image of a dataset in which CT and CBCT images are kept as fixed and moving image datasets respectively. Transparency factor (or alpha) value of 0.5 expresses the partial view of CT images blended with CBCT images whereas image_z represents the z index of the registered dataset.

B. Evaluation of registration accuracy

The registration accuracy of SITK based registration algorithms for fifteen patient datasets was evaluated by performing image registration of same modality image datasets in terms of MSE, SSI, NCC, MI shown in table IV.

Table IV: Effect of various combination of similarity metrics and interpolators on the accuracy of RIR in terms of different parameters of quantitative measures SITK based algorithms

Similarity metric	Interpolator	MSE	SSI	NCC	MI
Mean square	Linear	0.003	0.800	0.868	0.893
Mean square	Nearest neighbor	0.006	0.773	0.853	0.839
Mean square	B-spline	0.007	0.772	0.845	0.809
Mutual information	Linear	0.004	0.813	0.887	1.021
Mutual information	Nearest neighbor	0.006	0.865	0.933	1.223
Mutual information	B-spline	0.003	0.828	0.912	1.065
Demons	Linear	0.004	0.807	0.892	0.986
Demons	Nearest neighbor	0.008	0.782	0.694	0.883
Demons	B-spline	0.003	0.725	0.758	0.580

It is found that the values of MSE, SSI, NCC, and MI were very close to their ideal values when mean square similarity metric with linear interpolator, mutual information similarity metric with nearest neighbor interpolator and demons similarity metric with linear interpolator were used for 3D RIR using SITK based optimization algorithms. ANOVA test were also performed to compare statistical significance of the above mentioned combination of similarity metrics and interpolators. Table 5 represents the results of ANOVA test executed for each quantitative parameter measured for registration algorithms.

Table V. Statistical F and F critical values of quantitative parameters for registration algorithms

Parameters	F value	F critical value
Mean square error	1.036	2.207
Normalized cross correlation	3.318	2.115
Structural similarity index	2.776	2.115
Mutual information	4.01	2.115

As shown in the above table, no significant difference was observed while comparing the mean square error of above mentioned algorithms as f value is less than the f critical value whereas in NCC, SSI, MI appreciable difference is noticed among algorithms as f value is greater than f critical value. Algorithm with similarity metric mutual information and nearest neighbor interpolator is deduced to be the most efficient as it has the maximum value of all the quantitative parameters as represented in table V. Furthermore the NN interpolator and MI similarity RIR algorithm is compared with the TPS registration algorithm.

Table VI. Different parameters of quantitative measures of SITK based RIR algorithm with similarity metric MI and interpolator NN and TPS image registration algorithm.

Algorithm	MSE	SSI	NCC	MI
TPS	0.023	0.764	0.901	0.759
SITK based NN interpolator, MI similarity metric	0.021	0.789	0.894	0.753

ANOVA test was performed to compare the TPS image registration algorithm and SITK based RIR algorithm with similarity metric MI and interpolator NN. It is observed (table IV) that there is no significant difference between the efficiency of image registration in terms of MSE, SSI, NCC, and MI.

IV. DISCUSSION

Image registration has become imperative part of various steps involved in radiotherapy treatments. Over the years, a broad range of image registration techniques have been developed for various types of datasets [1-14]. Datasets of medical images of pelvic region of the body were used in this study in contrast to the brain images dataset because a very few publication governs the fully 3D RIR of the pelvis region of the body, however some of the publications reported the semi-automatic RIR of 3D image datasets [12-14]. Intensity values to HU conversion is the main step especially in medical image registration because in most of the clinical scenarios HU values based window levels are set to visualize and differentiate the different anatomical structures of the body more clearly. Most of the literature reported the effect of interpolation on medical image registration used for MRI and CT images in terms of noise, time consumption [15-17]. In this study, (i) apart from interpolation, similarity metric were also used to explore the possibility of increased accuracy for fully automatic 3D RIR; (ii) CT and CBCT image datasets were used instead of MRI and CT image datasets because in radiotherapy, CBCT is the most widely used imaging modality for daily patient positioning and setup reproducibility throughout the course of patient treatment. Efficiency of registration algorithm was analyzed with different combinations of similarity metrics and interpolators in terms of quantitative metrics: MSE, NCC, SSI and MI and is shown in Table 5. It is observed that the efficiency of linear interpolator is less than the NN interpolator in the combinations with all similarity metrics.

This may be due to the fact that linear interpolator interpolate the intensity values of voxels in a linear manner that does not consider the effect of intensity values of the surrounding voxels whereas NN interpolate the intensity values of voxels by considering the intensity values of all the surrounding voxels [21].

Moreover, B-spline interpolator is one of the new methods that is extensively used for deformable image registration however it is found that in this study the results of image registration algorithm with B-spline interpolator was not superior as compared to NN interpolator for optimization based RIR. NN interpolator with MI similarity metric shows maximum efficiency of RIR algorithm among the other combinations of similarity metric and interpolators due to the entropy dependence of MI incorporating the intensity values of all the voxels of 3D image datasets that results in efficient image registration in combination with NN interpolator. Furthermore, it was observed in table 6 using ANOVA test that according to NCC, SSI, MI significant difference exists between RIR algorithm with different similarity metrics and interpolators (alternative hypothesis) whereas according to MSE no significant difference was observed because it does not take into account the intensity values of voxels.

In addition the NN interpolator and MI similarity metric SITK based RIR algorithm was compared with commercially available TPS image registration algorithm. Numerous available commercial image registration techniques available require external input which are more prone to inter-observer errors. Thus, resulting in dramatic reduction of quality and reproducibility of image registration. Image registration in commercial TPS systems require, user defined region of interest and apply inherent preprocessing and thresholding technique to perform semi-automatic 3D RIR [25-27]. Furthermore, they do not provide quantitative value defining the accuracy of image registration and no information of specific method of optimization, interpolation and similarity metric is provided. However, in this study the two fully 3D image datasets of CT and CBCT imaging modality are used for registration and fully automatic 3D RIR is improvised and provides the comparable and slightly better results as compared to semi-automatic registration performed by an expert in the TPS.

The image registration algorithm with MI similarity metric and NN is the best among others for RIR. This method is applicable only in pelvic region and CT-CBCT RIR. In future this research will be extended in other areas of the body and for multimodality such as PET-CT, MRI-CT.

V. CONCLUSION

The present study recommends (i) the use of NN interpolator and MI similarity metric for optimization based 3D RIR algorithm which showed better image registration efficiency when compared with other combination of interpolator and similarity metric (ii) the use of quantitative measures viz. MSE, SSI, NCC and MI for making accurate decisions of 3D image registration in routine clinical practice which are not available in most of the commercial TPS. Apart from this the recommended method, shows an equivalent result as that of the automatic registration method of TPS.

REFERENCES

1. Zhao, Wenyi, Rama Chellappa, P. Jonathon Phillips, and Azriel Rosenfeld. "Face recognition: A literature survey." ACM computing surveys (CSUR) 35, no. 4 (2003), pp. 399-458.
2. Wang, XiaoShen, LongGen Li, ChaoSu Hu, JianJian Qiu, ZhiYong Xu, and Yan Feng. "A comparative study of three CT and MRI registration algorithms in nasopharyngeal carcinoma." Journal of applied clinical medical physics 10, no. 2 (2009), pp. 3-10.
3. A. Vyas, S. Yu, and J. Paik, “Fundamentals of digital image processing in Signals and Communication Technology”, 2018.
4. Petrou MM, Petrou C. Image processing: the fundamentals. John Wiley & Sons; (2010 May 17).
5. Brown, Lisa Gottesfeld. "A survey of image registration techniques." ACM computing surveys (CSUR) 24, no. 4 (1992), pp. 325-376.
6. Wein, Wolfgang, Barbara Roeper, and Nassir Navab. "2D/3D registration based on volume gradients." In Medical Imaging, Image Processing, vol. 5747, (2005), pp. 144-150
7. R. K. Sharma and M. Pavel, “Multisensor image registration,” in Sid International Symposium Digest of technical papers, 1997. 951-954
8. Zitova, Barbara, and Jan Flusser. "Image registration methods: a survey." Image and vision computing 21, no. 11 (2003): pp.977-1000.
9. J. V Hajnal, D. Hawkes, and Hill, Medical Image Registration (Biomedical Engineering). 2019(R1–45).
10. Sotiras, Aristeidis, Christos Davatzikos, and Nikos Paragios. "Deformable medical image registration: A survey." IEEE transactions on medical imaging 32, no. 7 (2013), p1153.
11. Maintz, JB Antoine, and Max A. Viergever. "A survey of medical image registration." Medical image analysis 2, no. 1 (1998), pp. 1-36.
12. Oh, S. and Kim, S.”Deformable image registration in radiation therapy”, Radiation oncology journal, 35(2), (2017) p.101.
13. Wyawahare, Medha V., Pradeep M. Patil, and Hemant K. Abhyankar. "Image registration techniques: an overview." International Journal of Signal Processing, Image Processing and Pattern Recognition 2, no. 3 (2009), pp.11-28.
14. Bhagalia, Roshni, Jeffrey A. Fessler, and Boklye Kim. "Gradient based image registration using importance sampling." In 3rd IEEE International Symposium on Biomedical Imaging: Nano to Macro, 2006., pp. 446-449
15. Pluim, Josien PW, JB Antoine Maintz, and Max A. Viergever. "Interpolation artefacts in mutual information-based image registration." Computer vision and image understanding 77, no. 2 (2000), pp. 211-232.
16. Mahmoudzadeh, Amir Pasha, and Nasser H. Kashou. "Evaluation of interpolation effects on upsampling and accuracy of cost functions-based optimized automatic image registration." Journal of Biomedical Imaging (2013), p.16.
17. Leng, Juelin, Guoliang Xu, and Yongjie Zhang. "Medical image interpolation based on multi-resolution registration." Computers & Mathematics with Applications 66, no. 1 (2013), pp.1-18.
18. Škerl, Darko, Boštjan Likar, J. Michael Fitzpatrick, and Franjo Pernuš. "Comparative evaluation of similarity measures for the rigid registration of multi-modal head images." Physics in Medicine & Biology 52, no. 18 (2007), p.5587.
19. Skerl, Darko, Bostjan Likar, and Franjo Pernus. "A protocol for evaluation of similarity measures for rigid registration." IEEE transactions on medical imaging 25, no. 6 (2006) , pp.779-791.
20. Pennec, Xavier, Pascal Cachier, and Nicholas Ayache. "Understanding the “demon’s algorithm”: 3D non-rigid registration by gradient descent." In International Conference on Medical Image Computing and Computer-Assisted Intervention,. Springer, Berlin, Heidelberg, (1999), pp. 597-605.
21. Neri, Emanuele, Davide Caramella, and Carlo Bartolozzi. "Image processing in radiology." Medical Radiology. Diagnostic Imaging. Springer, Berlin (2008).
22. J. P. Industrial L. & M. Lewis, “Fast Normalized Cross-Correlation Template Matching by Cross-,” Vis. Interface, (1995).pp.120-123
23. Rao, Y. Raghavender, Nikhil Prathapani, and E. Nagabhooshanam. "Application of normalized cross correlation to image registration." International Journal of Research in Engineering and Technology 3, no. 5 (2014), pp.12-16.
24. Kaur, Avneet, Lakhwinder Kaur, and Savita Gupta. "Image recognition using coefficient of correlation and structural similarity index in uncontrolled environment." International Journal of Computer Applications 59, no. 5 (2012).
25. Sahoo, Prasanna K., S. A. K. C. Soltani, and Andrew KC Wong. "A survey of thresholding techniques." Computer vision, graphics, and image processing 41, no. 2 (1988): 233-260

26. Sezgin, Mehmet, and Bülent Sankur. "Survey over image thresholding techniques and quantitative performance evaluation." Journal of Electronic imaging 13, no. 1 (2004): 146-166.
27. Liu, Dongju, and Jian Yu. "Otsu method and K-means." In 2009 Ninth International Conference on Hybrid Intelligent Systems, vol. 1, IEEE (2009) pp. 344-349.
28. Thévenaz, Philippe, and Michael Unser. "An efficient mutual information optimizer for multiresolution image registration." In Proceedings 1998 International Conference on Image Processing. ICIP98 (Cat. No. 98CB36269), vol. 1, IEEE (1998), pp. 833-837.

AUTHORS PROFILE

Bhumika Handa M.Sc. (Medical Physics), RSO
Mrs Bhumika Handa, got her Post MSc. In Medical Physics from Panjab University, Chandigarh, India. She is qualified Radiation Safety Officer (RSO) from Baba Atomic Research Centre, Mumbai, India. She is gold medalist in Masters of Medical Physics. She has worked as RSO in Metro Hospital and Cancer Institute, New Delhi, India. She is currently working as Research Scholar in department of Medical Physics, Panjab University. She is well versed with all advanced treatment techniques like IMRT/SRS/SBRT/IGRT. Her research interests include development of image registration algorithms, radiobiology and monte carlo simulation. She has published one research article and presented various posters in national and international conferences.

Gaganpreet Singh, M.Sc. (Medical Physics) ,RSO, and FCMPI
I am working as a Clinical Medical Physicist in the radiotherapy department. He is well versed with all advanced treatment techniques like IMRT/SRS/SBRT/IGRT. He is actively involved in R&D.
No. of Publications: 01
Membership: Life Membership of Association of Medical Physics of India, Life Membership of Association of Radiation Oncologist of India, Life Membership of College of Medical Physics of India
Achievement: Gold Medalist in M.Sc. (Medical Physics), Award Mohan Dai Oswal Award for Best Paper Presentation in AMPI-NC 2015 and AMPINC 2017, Award Mohan Dai Oswal Award for Best Poster Presentation in AMPI-NC 2019
Research Area: Radiotherapy
Research interest: Algorithm development, Radiobiology, Monte Carlo Simulation. I am actively doing research from the last five years in the area of designing and implementation of new method for the radiotherapy plan evaluation and also I am involved in many collaboration studies which is closely related with the area of IMRT/VMAT delivery algorithm, 4D Delivery and evaluation techniques of SBRT.

Rose Kamal, M.Sc.(Medical Physics)
He has completed Masters in Medical Physics from Panjab University, Chandigarh. Currently, working as research scholar in Centre for Medical Physics, Panjab University, Chandigarh. His research interests include development of leaf sequencing, dose calculation, image registration algorithms and radiobiology of hypo-fractionated treatments.
He has published one research article and presented various papers in national and international conferences. He is lifetime member of Association of Medical Physicists of India.

Dr. Arun S. Oinam (Assistant Professor (Med Phys), PGIMER, Chandigarh)
Dr. Arun S. Oinam, got my Post MSc. Diploma in Radiological Physics from Bhabha Atomic Research Centre (BARC), Mumbai University, India after getting MSc degree in Physics from Manipur University. He joined as a Medical Physicist in the Department of Radiotherapy, PGIMER, Chandigarh in 2000 and completed my Ph.D degree from GNDU, Amritsar, on the thesis entitled as "Dosimetric and Radiobiological Evaluation of Radiotherapy Treatment Plans". He was also a fellow of VSRP of Tata Institute of Fundamental Research Centre (TIFR), Mumbai. He is presently working as a faculty of Medical Physics in Radiotherapy Department, PGIMER, Chandigarh as an Assistant Professor.

He got the best paper awards of oral presentation in Medical Physics Conference-AMPICON-2008 and North Zone AROI Conference-NZAROICON-2007. He is also serving as reviewer of several Research Journals like Clinical Oncology of ELSEVIER publication, Computational and Mathematical Methods in Medicine of Hindawi Publishing Corporation, International Journal of Cancer Therapy and Oncology of EJournal Publication, Medical Devices: Evidence and Research of Dove Medical Press Ltd. He has published more than 35 index Research papers (Full Text) in National and International Journals.
Now, he is associating with the different RESEARCH PROJECT like

1. EMBRACE protocol GEC-ESTRO for MR Image base Intracavitary Brachytherapy of Uterine Cervix treatments using CT and MR image fusion.
2. Fractionation Treatment in Gamma Knife.
3. Radiotherapy Treatment of periampullary carcinoma.
4. Self Control Deep Inspiration Breath-hold Radiotherapy

Dr. Vivek Kumar, Chairperson, Dept of Medical Physics, Panjab University
Dr. Vivek Kumar, got his Ph.D. in Experimental Physics from Panjab University in 2007 and done Post doctorate from Weizmann Institute of Science, Israel. He is presently working as chairperson of Centre of Medical Physics, Panjab University.
Professional Background: Assistant Professor, Centre for Medical Physics, P.U., Chandigarh (2010 –till date) Chairperson, Centre for Medical Physics, PU, Chandigarh (July, 2018 - onwards) Member Faculty of Science, PU, Chandigarh (2018 - onwards) Co-coordinator, CET(UG) Admissions, PU, Chandigarh (2018 & 2019) . He has visited various International Research Laboratories experiments such as in France, Switzerland, Belgium, Germany, and Israel. He has chaired scientific sessions in conferences/workshops: 07, Academic Association Memberships: 07, Scientific Conference/Workshop Organized:12, Publications in International Journals:25, Book Authored: 01, Book chapters:01 ,Inter-University Accelerator Centre Technical Reports:02, Papers in Symposium/Workshop/Conferences: 72.