Recent Advances in Medical Image Registration: A Review

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Abstract Medical imaging is a fundamental task in clinical diagnosis for planning and evaluation of therapy. Different imaging modalities like MRI (Magnetic Resonance Imaging), CT (Computerized Tomography), SPECT (Single Photon Emission Compounded Tomography), PET (Positron Emission Tomography).., are widely used to depict aspects of anatomy and functional information. Image registration (IR); interchangeably refer to as matching, aligning and fusing, spatially aligns two or more images that gives detailed information about a scene. In medical imaging it is widely used to study the anatomical properties of an organ, nature of tissues and progress of the disease. As so much literature is being available on medical image registration (MIR), in this paper we covet to give an overview of diverse works published, putting efforts on the most recent advances in the area. Registration methods are classified based on modality of the images, basis function, geometrical transfer functions, regularization/optimization procedures, subjects (intra- or inter-) and objects (head, abdomen...) to be registered. Each work is independently studied and major components of each work are identified to present them in a systematic fashion. This paper is contributed to provide comprehensive details of existing MIR methods hence, handy for future scholars. Also, quantification of several existing MIR techniques is discussed.

Key words: *Image registration, medical image analysis, review*

1. Introduction

Image registration (IR) in clinical therapy has been one of the key processes for image-guided neurosurgery, radiation therapy, drug dosage and target prediction, and critical laser treatments. The process establishes spatial relationship between two or more images of different dimensionality and acquired from different sensors. In this paper, we restricted our analysis to methods that involve two images with the first image being referred to as the *reference/fixed/target (T) image* and the second image is referred to as the *sensed/ moving/source (S) image*. Image registration is interchangeably termed as *matching, aligning*, and *fusing* throughout the article. IR has become one of the most successful areas of image processing, with automated algorithms available in a number of applications in many fields; the one that is addressed here is *medical imaging*. Medical imaging is about establishing shape, structure, size, and spatial relationships of anatomical structures within the patient (intra-patient) acquired at different time points, e.g., to follow disease progression and/or response to treatment, or from different sources/ modalities to fuse complementary information, or from different patients (inter-patient) to analyze a population [1].

The term registration is first used in the year 1900 in a US patent by Becker [2]. Later this is observed in various fields like film industry [3], printing [4] and emerged as we know it today as an electronic device for combining and comparing two images. This idea was later extended to an image correlator, a tube that is possible to move the sensed image with respect to the reference image and align the images [5]. The first example of digital image registration is traced back to the work of Roberts at MIT in 1963 and methods for registering full digital images first appeared in remote sensing applications. Registration activities during 1970s focused on alignment of satellite images. Further, in 1980s methods that could spatially align images with local geometric differences were invented. Due to the increased use of medical images during 1990s and the need for spatially aligning multimodality images, considerable advances were made in formulation of information theoretic similarity/dissimilarity measures that could compare and register multimodality images [6]. A wider survey of image registration fields was published by Brown [7] in 1992. A broad range of techniques have been independently studied by establishing the relationship between the variations in the images and type of registration techniques which can most appropriately be applied. A classification review with the emphasis on medical image matching was presented in 1993 [8]. Maintz and Viergever [9] classified medical image registration methods based on nine salient criteria: dimensionality, nature of registration basis, nature of transformation, domain of transformation, interaction, optimization procedure, modalities involved, subject and object. Zitova and Flusser [10] used area-based and feature-based approaches as basis for their review published in 2003. Evolutionary computation based registration techniques found in [11]. A comprehensive study of automated image registration methodologies that have been used in the medical field has presented in [12] by Oliviera and Tavares. Recently, Sotiras *et al.* [13] provided an extensive survey on deformable techniques in medical imaging. A qualitative review of 3D coarse registration methods is recently published in 2015 [14]. For more information about image registration and its role in the medicine one may refer to [15] [16] [17] [18] [19] [20] [21] [22].

2. Classification:

Elsen *et al*., [8] formulated the classification of registration methods. Dimensionality: matching can be performed in any dimension. A 1-D method may perform a temporal match on a time series of spatially consistent images. In 2-D methods, projection images or tomographic slices of different recordings are aligned, assuming that the images are made exactly in the same plane relative to the patient. Three dimensional methods consider a tomographic image not as a set of individual slices but as a volumetric data set that can be registered with another (2-D or 3-D) image. Some methods may include time as extra dimension. In extrinsic registration, artificial objects are attached to the patient and they must be clearly visible and accurately detectable in all the modalities. These are computationally efficient and can be automated easily. In intrinsic methods salient visible Landmarks, segmented binary structures or voxel intensities are used as reference. Imaging coordinates of the two devices are matched in non-image based approaches.

Majority of the registration techniques are classified based on the mode of transformations used for modeling the images. Translations and rotations suffice to register images of rigid objects. These are applied to approximately align images that show small changes in objective shapes and intensities. The affine transformation preserves the parallelism of lines, but not their lengths or their angles. It extends the degrees of freedom of the rigid methods with a scaling factor for each image dimension. Projective transformation is used when the scene appears tilted. Straight lines remain straight, but parallel lines converge toward vanishing points. The projective transformation requires that straight lines in the reference image remain straight in the sensed image. Planar-to-curved-surface image alignment is possible using curved transformations. It allows inter-modality matching of sectional data with volumetric image of homologous objects. Most of the cases an image does not confirm to a rigid, an affine approximation or any of the forms mentioned above. In such scenarios a nonrigid/deformable registration significantly works for applications ranging from modeling, tissue deformations to variability in anatomical structures. Diffeomorphism, an invertible and differentiable process, deals with estimating deformations that map between images and an application of this mechanism is published in [23]. This kind of registration remains a challenging research problem due to its smoothness requirement and higher degree of freedoms in the deformation process. The images can be aligned using either global or local features in all the above methods and these can be interactive, semi-automatic, or automatic. The best elements can be computed and searched from the set of alternatives using optimization procedures. Two images to be registered may be taken from the same source or different sources. A mono-modal method registers two images of same source and contrarily, images from distinct sensors aligned using a multimodal technique. Establishing spatial relationships within an object acquired at different time points is intra-subject, or from different sources/ modalities to fuse complementary information is inter -subject registration. An atlas is the collection of intra-subject or inter-subject data to a single frame. Registration process also varies with the type of targeting object like brain, lever, and heart.

The general steps involved in image registration and the relation between them are shown in Figure:1. An image registration system can be considered as a black box that receives a reference image and a sensed image and resamples the sensed image to spatially align with the reference image. This operation assigns the same coordinates to corresponding points in the images, defining both images in the same coordinate system. Depending on the severity of the intensity and geometric differences between the reference and sensed images, different steps may be needed to register the images. If the images can be treated as rigid bodies, they will have only translational and rotational differences. By translating and rotating the sensed image with respect to the reference image, the images can be registered. Early methods achieved image registration in this manner. The process is simple but it is not efficient. It is also limited to images that have only translational and rotational differences. Moreover, the presence of outliers in one or both images can break down the registration process.

A more robust approach will select a number of control points in the reference image and will try to locate them in the sensed image. This is achieved by selecting small windows centered at the points in the reference image and searching for the windows in the sensed image. If the images have only translation and rotational differences, each correct match will produce the same rotational parameter. By matching multiple windows in the images, the rotation parameter shared by two or more matches can be used to register the images even in the presence of outliers. If the geometries of the images are not related by a rigid transformation, a sequence of steps as shown in Figure:1 is needed to register the images. This registration is termed as non-rigid [24] and a hierarchical non-rigid model for 3D images introduced in [25]. First, a number of control points are selected in each image. Then, features describing the neighborhoods of the points are calculated and the most informative features are selected. Initial correspondence is established between the points using the features of the points. Additional information about the images is then used in the form of constraints to distinguish the correct correspondences from the incorrect ones. Once a set of corresponding points in the images is found, the parameters of a nonlinear function to transform the space of the sensed image to that of the reference image are determined.

The aim of this paper is to provide an overview of thoroughly referred advances in medical image registration since 2012 with the emphasis on competent, robust and application specific image registration methods. Nonetheless, the scope is extended to cover certain methods which are not mentioned in [[2] [3] [4] [5] [7] [9] [10] [11] [12] [13] [14] [26]]. Moreover, all the methods follow the order shown in Figure:1.

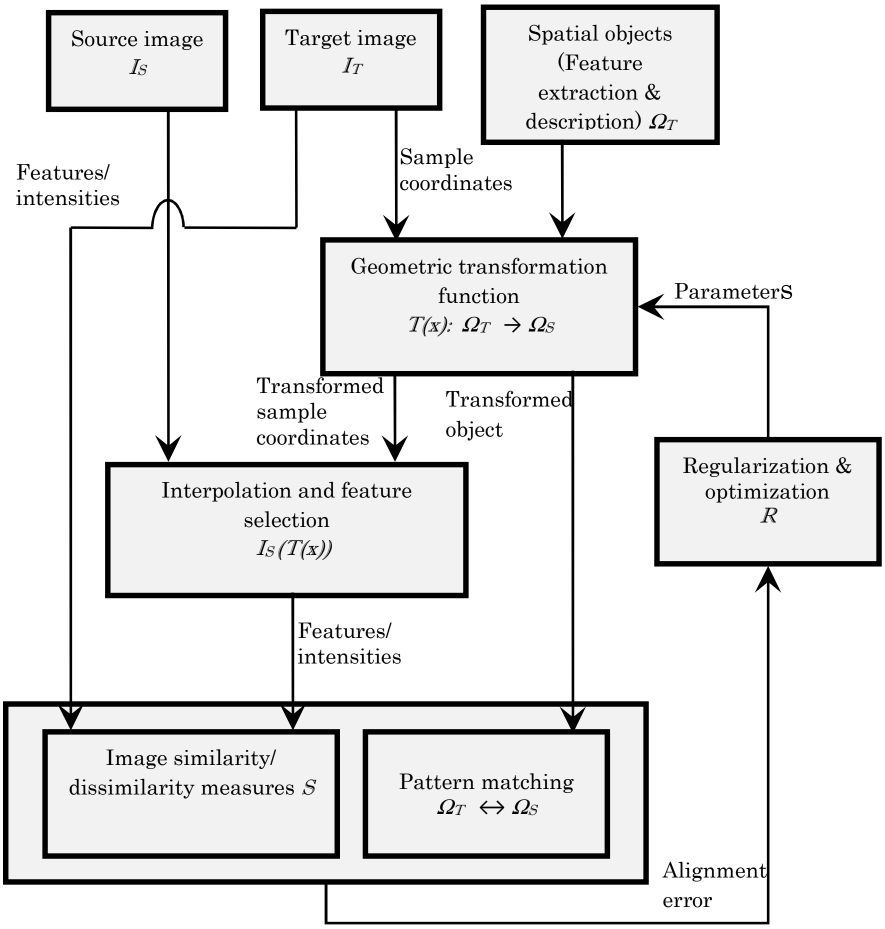

Fig. 1. Image registration framework.

3. Similarity/Dissimilarity Methods:

The similarity/dissimilarity is used as a metric to measure the dependency between corresponding values of two images and point descriptors used to describe the intensity and geometric differences between them. Sarvaiya *et al.,* [27] matched two templates using a simple normalized cross correlation (NCC) between them. An improved cross correlation using spatial signature method significantly increases the discrimination of the correlation coefficient, registration reliability, robustness and accuracy for a given template window size [28]. A fast NCC algorithm for InSAR image registration developed using the coherent cross correlation as the objective function to avoid the oversampling rate and computational burden [29] and a heterogeneous method is proposed [30] using a directional Frost filtering on SAR image to reduce coherent speckle and retain the edges and texture details. The 2D multi-scale and multi-direction Gabor filters are used to extract the image characteristics. Gabor features and morphological processing are together used to evaluate the treatment response of facial wrinkles [31]. Sub-pixel precision of NCC is evaluated in [32] when measuring surface displacements. In this work bi-cubic interpolation is used for image registration and to implicitly optimize the subset sizes a new sub-pixel registration algorithm is implemented. Scatter search [33] and hybrid biomechanical algorithms are the other two approaches for intensity-based methods [34]. Correlation-coefficient maximization is used for rigid intensity based registration for medical images suffer from slow convergence and sensitivity [35]. The shape of Gaussian windows adjusted in a self-adaptive fashion with aid of weighted zero-normalized sum-of-squared difference correlation criterion [36] and a Gauss-Newton approach is used to joint image registration and intensity correlation [37]. A new mechanism for non-rigid image fusion is explored in [38], called stochastic quasi-Newton method, achieved 500 times faster results compared to existing methods.

Gaidhane *et al.,* [39] proposed a covariance matrix based template matching with normalized energy for detecting and locating the disease in complicated medical images. Mutual information (MI) is used as registration metric to align PET/CT cardiac images with genetic algorithm [40] as optimization method in [41]. A regional MI method which is invariant to the overlapped regions is proposed to register brain MR images using P-spline interpolation [42]. The problem of spatial dependency between adjacent voxels in images is resolved using a spatial MI similarity measure applied to 3D brain image registration [43]. A dissimilarity measure is explored depending on the overall image content encapsulated in its local MI and its invariance to information preserving transforms is shown by Gueguen *et al.* [44]. A new similarity measure 3-EMI estimates MI for low number of samples and strong additive Gaussian noise [45]. Registration of nonrigid medical images is performed based on Gerschgorin circle theorem and covariance matrix properties and optimized using Levenberg-Marquardt back propagation (LMBP) algorithm [46]. A novel multimodal nonrigid registration method [47] that offers a superior performance in estimating the nonrigid deformation field is introduced based on a parametric registration technique, local variability measures (LVM) and an optical flow method [48] and joint structure tensor and local entropy approaches [49]. A new scheme consists of a preregistration process (coarse registration) and a fine-tuning process (fine registration)-implemented by the maximization of MI using a Marquardt-Levenberg search, is presented in [50]. Legg *et al.,* [51] proposed a method for improving accuracy and efficiency of mutual information for multimodal retinal image registration using adaptive probability density estimation. Various new schemes using MI found in [52], [53], & [54]. In the latest paper, [55] an excellent attempt is made to explain the role and scope of MI in image registration. Hallack *et al.,* [56] estimated relaxation time (T_{10}) using variable flip angle sequences for pharmacokinetic (PK) analysis of tumorsbin DCE-MRI exams.

Zimmer and Piella proposed an adaptive multiscale similarity measure, neglecting spatial relationships and local image properties [57]. Registration using Robust point matching [58] for retinal images and Huber similarity measure [59] give satisfactory results for images having spatially-varying intensity distortion. A grid matching using Hausdorff distance and near set resulted in more accurate alignment of two or more images having an identical view [60]. Recently, skeleton similarity as anatomical prior used for free form registration of human cochlear micro CT data [61]. Free form deformation is combined with edge preserving scale space for efficient multiscale deformable registration of medical images [62].

The displacement and strain measurement accuracy in large deformations has improved significantly by self-adaptively tuning the Gaussian window shapes with weighted sum-of-squared difference correlation criterion [63]. This parameter tuning improves the quality of registration process by evaluating parameter configuration [64]. Philip *et al.,* [65] estimated an accurate probability distribution by means of optimal histogram bin size selection that impacts fundus image registration accuracy and runtime. An edge extraction algorithm based on bilateral filter is used to extract infrared and optical image characteristics and Cross Cumulative Residual Entropy (CCRE) measures the similarity between them [66]. The speed and accuracy of image registration improved using a method called Optimized Hierarchical Block Matching of scene color images [67], but its performance to be verified with medical images. A self-similarity context is employed for multi-modal scans to densely extract the discriminative descriptors [68]. Recently, geometric and spatial context are incorporated in multimodal registration to overcome the limitations in MI with local intensity variations and the ignorance of the spatial and geometric information [69]. More recently, new low-level static and dynamic context features are proposed and integrated into a discriminative voxel-level classifier to improve the detection of mild traumatic brain injury [70].

A generalized approximate nearest neighborhood field (ANNF) is schemed to estimate ANNF maps between any image pairs, not necessarily related. Applications are illustrated in optic disk detection and super resolution images, but not applied to medical images [71]. A novel 3D vorticity based approach is explained in [72] for registering low resolution range images . In a recent work by Panagiotis *et al.,* [73] the problem of swift and systematic extraction of points that correspond to the same location (called tie-points) from pairs of large-sized images is addressed. In the manuscript [74], the registration is performed with the deconvolution of the joint statistics with an adaptive Weiner filter that has shown improved comparative accuracy and analytical efficiency. Fuzzy theory plays significant role in MIR [75]. Lindblad *et al.,* [76] presented four novel point-to-set distances defined for fuzzy or gray-level data based on integration over α cuts and the fuzzy distance transform. These set distances perform excellently on the Mixed National Institute of Standards and Technology database (MNIST) digit classification task and this performance is restricted only to rigid bodies. This is extended to non-rigid case using interval-valued intuitionistic fuzzy sets [77].

In a method proposed by Nigris *et al.,* [78] , the gradient oriented alignment evaluation is restricted to locations of low gradient magnitude, where the uncertainty of fixed image gradient orientations is minimal but this approach is asymmetric. This asymmetry is due to resampling artifacts that affect the registration accuracy by producing local optima, altering the gradient, and shifting the global optimum. A novel mathematical framework for representing uncertainty in the large deformation diffeomorphic IR based on the Bayesian posterior distribution over the deformations aligning a moving and a fixed image is presented in [79]. Aganj *et al.,* [80] show the sum-of-squared-differences cost function formulated as an integral to be more accurate compared with its traditional sum form. Super-resolution images are aligned based on least square adjustment phenomenon by combining the advantages of Vandewalle and Keren algorithms [81]. A new prealignment algorithm [82] in medical image registration based on orientation histogram matching accumulated from local orientation of each pixel without any feature extraction has shown promising results in the registration of monomodality and multimodality images. Since no feature extraction involved, it is faster and yet provides quality matching. Complex shapes containing various numbers of sub-shapes in the presence of excessive noise are registered using their characteristics (scaling, rotation and translation) by minimizing the dissimilarity term between the two shapes [83]. In the treatment of Osteoarthritis (OA) Xue and Ning [84] employed a new semantic registration scheme that makes use of anatomic information regarding the knee joint and aligns the multimodal MR image data by simulating the actual movement of the knee joint. Some clinical assumptions in the work not allow physicians for the early detection of OA. However, some specific methods such as sub-region analysis, texture analysis can be investigated in the future studies. The article [A9] described a cartilage matching to ensure longitudinal focal and local changes of cartilage morphology due to OA. In orthodontics, three-dimensional maxillodental cone beam CT and photogrammetry are registered to observe variations over time [85]. Similar approach is applied for cone beam CT-planning CT in head and neck [86], to estimate the intensity-modulated radiotherapy dose and cone beam CT-blue-ray model [87], for dental implant surgery.

Anatomical tree structures [88] are also part of medical image registration that generates landmarks automatically for image matching. A combination of image-based and landmark- based 3D registration is used in ex-vivo MRI from patients undergoing epilepsy surgery for which, target registration error (TRE) is used to assess accuracy and the added benefit of deformable registration [89]. For motion correction in quantitative MRI (qMRI) a non-rigid group wise IR is used. In a work published in [90], the deformable field is decomposed into two components *viz.* a piecewise constant component and a smooth component for which the total variation filter and a fourth-order filter are used, respectively, for registering images. A graphics processing unit (GPU) enables parallel processing of mutual information to achieve more than 50 fold improvements in the standard method [91] and the similar approach implemented in multicore environment [92]. In the volume sweeping approach [93], one volume is swept through the other, the overlapping volumes are coarsely aligned in the x and y directions, and a similarity measure is calculated at each sweeping position that gives best similarity measure is chosen as the prealignment. A robust approach called convex hull matching technique is proposed for registration of medical images that have different Euclidean transformations [94]. A fast registration is achieved using implicit polynomial models for the real-time pose estimation [95]. An optical flow algorithm is used for displacement between two images using approximation order [96]. When the images are corrupted by the spatially-varying intensity distortion, it is still a challenging task to perform non-rigid registration. To address this difficulty a novel locally linear reconstruction based dissimilarity measurement is proposed [97]. More image matching and similarity measures and applications in clinical surgery are given in [98], [99], [100], [101], [102] & [54].

4. Segmentation, interpolation and feature description:

Despite its long track record, segmentation in medical image computing still remains an active field of research, largely due to complexities of anatomical structures, cross-subject and cross-modality variations. Clinically, it has many benefits for effective patient management, both in terms of pre-operative planning and post-operative assessment of the efficacy of the therapeutic procedures [103]. In a recent work of Menze *et al.,* [104] twenty state-of-the-art tumour segmentation algorithms are applied to a set of 65 multi-contrast MR scans of low- and high-grade glioma patients-manually annotated by up to four raters-and to 65 comparable scans generated using tumour image simulation software. Karasev *et al.* [105] proposed a new approach for segmentation of injured or unusual anatomic structures in medical imagery using partial differential equation control of active contours. In the article [106], a localized fuzzy c-means based algorithm is used with spatial information for image segmentation and bias field estimation of medical images. Hierarchical Markov random field (MRF) is used for 3D medical image segmentation based on local priors who model local variations of shape and appearance and provide consistency [107]. A study proposed a novel region-based level set method utilizing both global and local image information complimentarily for automated medical image segmentation [108]. Another idea of segmentation is based on high level knowledge of training sets [109]. A standard affine registration method combined with a small non-diffeomorphic deformation, non-linear registration method which optimizes mutual information, with a cascading of regularization parameters in the segmentation of structures within the brain [110]. This approach is simple, fast and accurate.

Spin image is a good point descriptor of the 3D surface. A new spin-image-based registration algorithm is proposed on the basis of a new-constructed 3D feature space, which composed of the curvature, the Tsallis entropy, and reflection intensity of the sensor. This improves computational efficiency and robustness [111]. In [112], multimodal IR is carried out by maximizing a Tsallis entropy-based divergence using a modified simultaneous perturbation stochastic approximation algorithm, which is further extended to correlative microscopy using image analogies [113]. Another work to register anatomical and functional brain images of the same patient in the 3D terrain, described in [I73]. Andrews and Hamarneh [F32] employed the generalized log-ratio transformation for thigh muscle segmentation. This method generates a probabilistic segmentation that can be used to produce uncertainty information.

Chen *et al.* [F19] presented a new retinal image segmentation approach using topological vascular tree. This approach is fairly robust to be against translation, rotation, scaling and even modest distortion. Automated blood vessel detection is becoming of crucial interest for better management of vascular disease. A new infinite active contour model for automated vessel segmentation is been proposed using hybrid region information of the image [114]. Miri *et al.,* [115]proposed a multimodal segmentation using a machine-learning graph-based approach for optic disc and cup from fundus images and spectral domain optical coherence tomography.

Khalvati *et al.,* [116] presented a robust atlas-based segmentation algorithm for the breast boundary in 3D MR images. This combines probabilistic atlas and atlas selection approaches into a single frame work where two configurations are realized. Dynamic contrast-enhanced (DCE) images of colorectal tumours are automatically segmented using region-of-interest segmentation. Tissue segmentation is performed using a combination of thresholding and morphological operations, and further refined using shape information from consecutive images [117]. Iglesias *et al.,* [118] proposed a method to segment four brainstem structures (midbrain, pons, medulla oblongata and superior cerebellar peduncle) from 3D brain images. This segmentation relies on a probabilistic atlas of the brainstem and its neighboring brain structures.

An approach, for integrated volume segmentation through multi-atlas registration using a graphical model where registration and segmentation nodes are coupled, is presented in [119] and a Kalman filtering scheme is proposed in [120] provides better multi atlas segmentation for better registration and segmentation accuracy. To handle the large deformations Ozere and Guyader [121] used a theoretically well-motivated joint segmentation-registration method. In this, the shapes to be matched are implicitly modeled by level set functions and are evolved in order to minimize a functional containing both a nonlinear-elasticity-based regularizer and a criterion that forces the evolving shape to match intermediate topology-preserving segmentation results. A study [122] used structural MRI-based multivariate pattern classification to identify and cross-validate a differential diagnostic structure of schizophrenia patients and to quantify the impact of major clinical variables, including disease stage, age of disease onset and accelerated brain ageing on the signature's classification performance. Clark *et al.,* [123] used symmetric normalization for the segmentation of murine 4D cardiac micro-CT data.

Interpolation constructs new data points within the range of a discrete set of known data points. The features obtained by segmentation or other feature extraction processes are to be approximated/interpolated to reduce the computational complexity and to increase the pre-processed feature quality. Though an interpolator reduces artifacts in match metric and improves the registration speed in medical image registration, the impact of the interpolation error on image registration has not been quantified to date. Cheng *et al.,* [124] employed a method to cancel bias induced by correlation coefficient interpolation for sub-pixel image registration. A comparison of local interpolation schemes for landmark-based image registration in given in [125]. Hu and Shao [126] used three different types of interpolators to achieve curve smoothness and anti-micro-fluctuation in registering medical images. Aganj *et al.* [127] introduced a new quasi-volume-preserving constraint that allows volume change only in areas with well-matching image intensities, and show that such constraint puts a bound on the error arising from spatial non-uniformity. Landmark constrained registration based on quasi-conformal theories is proposed and tested on 27 vestibular system surfaces [128] and this is improvised using analytic regularization [129]. The inclusion of the manual segmentations into registration may degrade registration accuracy. This is been addressed by introducing the weighted assimilated constraint that eliminates a new surface from the manual segmentation [130]. In [131], a block-to-pixel interpolation is applied to achieve real-time single image dehazing for faster image recovery. Zhang *et al.,* [132] used a gamma regularization based reconstruction for low dose CT. An efficient second-order accurate and continuous interpolation is explained in [133] for block-adaptive grids. A nonlinear image interpolation algorithm based on exponential polynomials is used to magnify an image while persevering edge features [134]. For fetal brain MRI an adaptive regularization is used to achieve super-resolution [135].

Statistical shape analysis plays a key role in various medical imaging problems. Such methods provide tools for registering, deforming, comparing, averaging, and modeling anatomical shapes. One of applications in simulation of deformable elastic endometrial tissue shape is given in [136]. Detailed segmentation of the vertebrae is an important pre-requisite in various applications of image-based spine assessment, surgery and biomechanical modeling. In particular accurate segmentation of the processes is required for image-guided interventions [137]. A new method is proposed based on statistical shape decomposition and conditional models [138]. The aim is to handle the complex geometry of the processes and the large variability between individuals. Another method, regression segmentation, is introduced to analyze spinal images of multiple anatomical structures in multiple anatomic planes from multiple imaging modalities [139]. Recently, Mateos *et al.,* [140] tackled the problem of large training datasets with statistical shape models by introducing a new statistical interspace model by modeling each individual shape independently. This completely eliminated the inter-process overlap while improving the segmentation accuracy. The theory of stationary velocity fields to facilitate interactive nonlinear image interpolation and plausible extrapolation for high quality rendering of large deformations and devise an efficient image warping method on the GPU [141]. For accurate quantitative bone morphometry various interpolator schemes are studied and analysed in [142]. A fast multidimensional B-spline interpolation using template metaprogramming is presented in [143].

5. Rigid, non-rigid/deformable image registration techniques:

Image registration can be of any type like rigid, non-rigid/deformable, affine etc. nonrigid image registration is a prerequisite for various medical image process and analysis applications. Image pair is often aligned initially based on a rigid or affine transformation before a nonrigid/deformable registration method is applied in medical image registration. Inappropriate initial registration may compromise the registration speed or impede the convergence of the optimization algorithm. A novel technique is proposed for prealignment in both monomodality and multimodality image registration based on statistical correlation of gradient information [82]. An orientation histogram matching accumulated from local orientation of each pixel is used to determine the rotational differences without any feature extraction.

Zhang *et al.,* [144] proposed a nonrigid image registration method for lung CT images using a hybrid feature detector which can detect tissue features of lungs effectively based on Harris and SIFT. Another registration and fusion technique is proposed based on deformation models in [145], mesh deformation constraints in [146] and a frequency domain iterative image registration algorithm based on local region extraction [147]. Zhao and Jin [148] proposed a new framework for capturing large and complex deformation in image registration. In a recent work, Onofrey *et al.,* [149] discussed the role of statistical deformation models in low-dimensional nonrigid registration.

The usefulness of preoperative images is limited in laparoscopic liver surgery, as the liver shifts due to respiration, induction of pneumoperitoneum and surgical manipulation. To evaluate this shift Viyajan *et al.,* [150] proposed a new method by extracting the centerlines of the segmented vessels from the images taken at different respiration and pressure settings. Dakua [151] presented a novel algorithm for efficient segmentation based on Chaotic theory. Ferreira *et al.,* [152] detailed segmentation algorithms for ear image data.

The introduction of 'spline' paved the way for the introduction of better and smooth features in image registration problems. Lobachevsky splines are proposed for landmark based image registration and their performance is compared with Gaussian and thin plate splines [153]. Sun *et al.,* [154] presented a new non-rigid registration method by using nonlinear complex diffusion corner detection and thin-plate spline model. A new affine transformation termed as B-spline affine transformation (BSAT) is defined at each point of two elastically aligned images [155]. A bidirectional objective/cost function is used to improve the performance of the iterative closest point (ICP) method [156]. Multilevel B-Spline is used in digital subtraction [157].

An elastic registration using hierarchical spatially based mean shift is resented in [158] that eliminates the outliers by analyzing statistical information on the displacements of the candidate register points. In a new approach for spline-based elastic registration Stefan and Rohr [159] introduced point landmarks and intensity information, with a regularization based on Navier equation, are directly integrated to a single energy minimizing functional based on matrix-valued non-radial basis functions. This technique is applied to 3D synthetic images, 2D MR brain images, and 3D CT lung images. Another work based on Navier-Stokes partial differential equation that varies in both temporal and spatial domains, is published in [160] and to chest radiography in [161]. Acquisition-to-acquisition signal intensity variations are inherent in MR images. The lack of a standard image intensity scale in MRI leads to many difficulties in tissue characterization, image display and analysis including segmentation. Bagci *et al.,* [162] investigated the role of intensity standardization in registration tasks with systematic and analytic evaluations involving clinical MR images. A statistical biomechanical surface registration is proposed to MR-TRUS fusion for prostate interventions [163]. This method counters the difficulties in some regions of the images due to poor contrast, low slice resolution, or tissue ambiguities. Another landmark constrained approach is explained for surface registration between genus-one surfaces. This minimizes the local geometrical distortion and is stable under geometric noises and landmark selection errors [164].

Prostate MR Images and corresponding whole-mount histology sections from postoperative radical prostatectomy specimens are elastically registered for accurate estimation of the spatial extent of prostate cancer [165]. A similar MR-CT registration [166] and CBCT/CT deformable registration [167] are developed for prostate cancer therapy. Recently, elastic registration of 3T multimodality MR images based on the modality independent neighborhood descriptors (MIND) distance metric is proposed by Marami *et al.* [168] in this, elastic registration of prostate MR images based on deformation states, shown promising accuracy for localizing prostate tumours in MRI-guided targeted biopsy. Lu *et al.,* [169] proposed a new non-rigid method based on linear elastic model based on global registration and extracting features of global registration. This method ensures better accuracy and enhanced robustness..

An adaptive mesh refinement strategy for the finite element method (FEM) based elastic registration model is given in [170] and compared its performance with the existing FEMs. This scheme has been extended to surface registration incorporating curvature, volume preservation, and statistical information [171]. Wen *et al.,* [172] introduced a Navpass model in the detection of CT images using a Dynamic Region Growing (DRG) algorithm. Registration is carried between image space coordinates and patient space coordinates with a high accuracy. Organ motion and deformations are not included as part of this work. A GPU based high speed affine transformation using a normalized gradient fields distance measure is implemented on CUDA [173]. In an image-guided neurosurgery the similarity measure Linear Correlation of Linear Combination (LC^2) is used to align either freehand ultrasound (US) slices or US volumes with MR images [174]. Similar approach for multi-scale registration of real-time and stored MR images is published for image-guided cardiac interventions. A new approach called Geodesic information flows used for better extraction of features and their fusion [175]. Anatomical statistical model and their role in feature extraction detailed in [176].

Dynamic movement of the heart during scan compromises image quality for shorter image acquisitions. So they combine the live feedback from real-time images and accurate visualization of anatomical structures from preoperative images [177]. The target registration error achieved as 1.51mm. Further, in volumetric imaging of prostate that can be used to optimize imaging for cancer detection, Nir *et al.,* [178] proposed a particle filtering framework to contend with high dimensionality of the search space and multimodal nature of the optimization. This process is used in the registration of histological slices to volumetric imaging of prostate. Furthermore, to record the motion of the kidneys by dynamic contrast enhanced MR imaging, Hodneland *et al*., [179] introduced a segmentation-driven image registration based on normalized gradients and a Mahalanobis distance for supervised segmentation. Merrem *et al.,* [180] developed an algorithm that uses a variational calculation scheme to align the moving kidney images. Wavelet based image stitching using L1 and L2 norms is presented in [181]and recently, a Gaussian curvature based image registration is explained in [182]. A mathematical model for improving robustness for inter-subject medical image registration is given in [183]. The performance of these methods is to be thoroughly studied in medical imaging. The sparse representation of a certain object point reveals several similar candidate points in the intermediate images [184] & [185]. MIR based on sparse representation with KSVD is published in [186] and with polynomial expansion in [187]. Sparse temporal-variation can be used for accurate registration of dynamic contrast-enhanced breast MR images [188] and simultaneous fusion and denoising of medical images [189]. A biomechanical model is practiced for the fusion of ultrasound CT volumes with x-ray mammograms. Benerjee *et al.,* [190] presented an approach for rigid fusion of 4D ultrasound images.

Weistrand and Svensson [191], combined image information (intensities) with anatomical information-provided by contoured image sets, to form an ANAtomically CONstrained Deformation Algorithm (ANACONDA). Its ability to handle different modalities, large deformations and air pockets are verified in the published work. A novel, robust and efficient framework, Streamline-based Linear Registration, is used to successfully align bundles as well as whole brain streamlines for analyzing specific white-matter fascicles [192]. Sundarapandian *et al.,* [193] used a non-uniform MRF model and pivotal control points in the registration of digital subtraction angiography (DSA) images. This reduces the motion artifacts in DSA. A novel 3D-2D rigid registration is proposed in [194] based on evaluation of similarity between corresponding 3D and 2D gradient covariances, which are mapped into the same space using back projection. The existence of high inter-individual variability makes shape interpretation in biological images complex. Nasreddine *et al.,* [195] developed a robust variational method which benefits from the geometrical information present in the images. In this method, the successive shapes are represented by a level-set representation, which is used to carry out registration.

6. Feature selection and geometric Transformations:

Several feature and intensity based nonrigid/deformation models have mentioned above but in the below references more emphasis is put on models involved geometric transformations in nonrigid image registration. Comparative studies of geometric transformations for nonrigid registration are reported in [196] & [197]. In 2008, Bay *et al.,* [198] presented a novel method termed as Speeded-Up Robust Features (SURF). SURF is a scale- and rotation-invariant detector and descriptor that outperforms previous schemes with respect to repeatability, distinctiveness, and robustness, yet faster. Many variants of SURF are published in the literature. Its application in multi-atlas segmentation is recently published in [199]. Principal component analysis (PCA) is another widely used feature extractor in image processing; its advances and applications are also noted in [2]- [14]. L2-based PCA imparts robustness in the presence of outliers and noise. Noisy images can be registered using a technique called maximum a-posteriori estimation [200]. To provide globally optimum solution in polynomial time, Brooks *et al.,* [201] modeled L1-norm PCA procedure and [202] proposed an L1-based IR by coupling parametric and non-parametric transformations. High dimensional medical image registration using statistical deformation model is built based on generalized n-dimensional PCA and tested with human brain images [203]. Recently, Leng *et al.,* [204] proposed a novel robust adaptive PCA based on Intergraph matrix for image registration to improve robustness and real-time performance.

An intensity based free-form registration [205] regularized by a statistical shape model is applied to cervical MR images [206]. The risk of dose with limited toxicity in nearby organs is reduced by using a real-time direct PCA technique-a robust approach for motion estimation [207] and strain estimation [208] of abdominal organs. An extension to [201] is published recently, which takes local data points into account. This approach is more robust to outliers and yet to be verified with medical images [209]. Moreover, the issue of cumulative dose estimation from cone beam computed tomography (CBCT) is resolved by registering the images using surface-constrained parameters [210]. In a work published in [211] PCA and Wavelets are together used for fusion quality and in [212] wavelet-based fusion used for diffusion tensor imaging and tactography of the human heart. PCA-Demons algorithm based image registration is used to study anatomical morphology [213] and a chain-diffeomorphic demons algorithm combined global and local information for MIR [214]. Large deformation diffeomorphic registration of diffusion-weighted imaging data is presented in [215]. In the recent work of Du *et al.,* [216] an accurate non-rigid registration method is proposed based on heuristic tree for registering point sets with large deformations. An Intergraph matrix is created based on robust adaptive PCA [204] and conformal geometric invariant [217] are used for 3-D MIR. The registration-by-regression method proved inaccurate with 3D-2D registration [218]. To improve the registration accuracy in surgical navigation [219] proposed a hybrid method that incorporates anatomical landmarks near the target.

Toews and Wells [220] present 3D scale invariant features to model-image alignment problem in human brain CT and MR images. A medical image registration approach using a segmentation step based on fuzzy C-Means (FCM) clustering and Scale Invariant Feature Transform (SIFT) is given in [221]. A new method of registration for tumour tracking in 2D liver US images, by describing each voxel by three image features: intensity, local phase and phase congruency, is modeled in [222]. This method is diffeomorphic in nature, which ensures the invertibility of deformations. The number of deformations can be reduced to improve the speed without affecting the nature of registration. One of such methods is reduction by lie group symmetries, described in [223], recently. 3D volumetric inter-modality MR-US image registration is performed using robust patch-based correlation ratio (RaPTOR), which computes local correlation ratio values on small patches and adds them to form a global cost function [224]. This method is applied in image-guided neurosurgery. In 2014, robust-initialization for single-plane 3D CT to 2D fluoroscopy IR is proposed [225]. A fast diffeomorphic IR is given in [226]. In a more recent work [227], a new and efficient features descriptor based on the local diagonal extrema pattern (LDEP) is proposed for CT images. This is not implemented in image registration problem. In the article by Wang and Vemuri in 2007 [228], a tri-cubic B-spline based representation of the deformation function is used along with cross-cumulative residual entropy as similarity measure, for efficient and robust computation of nonrigid registration problem. To reduce the target registration error (TRE) in lung CT image registrations, a novice mass preserving scheme is developed. A tissue appearance model based on the principle of preservation of total lung mass is proposed to account for the local change in lung tissue intensity during the breathing cycle [229]. A new geometrical function, called fast adaptive bidimensional empirical mode decomposition (FABEMD) based on mutual information, is employed to register the bidimensional intrinsic mode functions (BIMFs) instead of registering two images. This leads to a significance decrease in computation time while maintaining good accuracy of the registration [230]. Another approach with the same motto based on surface preserving regularization function is disclosed in [231]. Ezys- a novel GPU based registration program is used as part of the said work. A new method, local affine transformations guided by internal structures (LATIS) successfully registered MRI and whole-mount histology for treating prostate cancer [232], [233] & [234]. A correlation- and Hough transform- based automatic image registration (CHAIR) is proposed to align images with sub-pixel accuracy [235]. Reducindo *et al.,* [236] combined rigid registration with local optical flow technique based on the conditional statistics of the joint intensity distribution (CS-JID) to register multimodal images. Non-rigid application of optical flow model is given in [237]. Multimodal MRI knee data registration is detailed in [84] and robust inverse-consistent linear registration in [238]. Local optimal problem in MI is solved using Firefly algorithm with Powell optimization [239].

Gaussian-Hermite moments have been analyzed with respect to the fluctuation of moment invariants on image geometric transformations [240]. Source and target images are jointly segmented into a smaller number of classes and registered iteratively in a report given by Jan Kybic and Borovec [241]. Both [240] & [241] have not applied to human medical images till date. A pulse couple neural network (PCNN) used in contourlet transform domain for multimodal images [242]. In [243] Fourier based reconstruction is developed for radiation dose reduction in medical x-ray CT and fractional Fourier transform domain used to register medical images [244]. Local invariant features and global deformable geometry are blended to overcome the problem of initialization and accuracy of inter-subject anatomical variability matching of cardiac images [245]. A boosting algorithm is introduced inspired by the theory on hypothesis boosting to improve existing deformable image registration (DIR) methods. This is been validated on three DIR methods: ANTSgSyn, NiftyReg, and DROP [246]. The accurate alignment of two images in which a certain structure is present in only one of the two is problematic for conventional methods. In [247], a geometrical penalty term is incorporated in a conventional free-form registration framework. This method is demonstrated on cervical MR images for brachytherapy. The local phase image is hardly affected by unwanted signal fluctuations due to a space-variant background and a space-variant contrast. The registration based on the structure tensor of the local phase effectively deals with intra-image signal fluctuations [248]. Self-similarity weighted graph based implementation of α-MI for non-rigid registration is proposed in [249] and a multi-frame registration of cell nuclei in live cell fluorescence microscopy image data in [250]. To register functional fluorescence (IF) and structural histology (HE) images in a pyramidal fashion, HE image is synthesized from the multichannel IF image using a supervised machine learning technique [251]. A self-similarity measure uses local structural information and is invariant to rotation and to local affine intensity distortions. Ziad H Saleh *et al*., [252], explained a distance discordance metric (DDM), which is based on the variability in the distance between corresponding voxels from different images, which are co-registered to the same voxel location in a reference image. The DDM at that location represents the mean dispersion between voxels. A limitation of DDM is that it requires multiple samples of the images to be registered. In a recent article by Ruppert *et al*., [253] a novice registration of medical images based on watershed transform with multi-scale-parameter search optimization is employed that is more accurate and noise insensitive compared to other optimizers such as particle swarm, simulated annealing and differential evolution.

In a method for multi-modal image fusion [254] the two-state Hidden Markov Tree model is extended into the shift-invariant shearlet transform [255] that improves the fusion quality and a MRF [256] & [257] used for group-wise registration [258]. Better results achieved using cross-scale coefficient selection for the fusion of volumetric medical images [259]. Intensity- and feature- based similarity methods are combined for automatic registration of very high resolution images using a quadtree structure in [260]. Different physical brain images are fused using multi-grid transformation [261]. Metz *et al.,* [262] proposed a registration method for motion estimation in dynamic medical imaging data, avoiding a bias towards a specifically chosen reference time point hence reduces computational cost. The deformation model is characterized as the integration of a time-constant velocity field in a method SymBA [263]. Deformable MR-Ultrasound images [264] and 1D-3D intra-operative nuclear images [265] are registered for image/radio-guided surgeries. Euler integration obtained the displacement from a stationary velocity field for diffeomorphic image registration [266].

Pre-clinical populations can be subjected to controlled interventions, which significantly change the appearance of the brain obtained by imaging. Existing systems for registration, which assume image similarity to a reference scan, may fail when applied to these images. An affine registration solution that uses a graphical model of a population is presented to decompose difficult pair wise registrations into a composition of steps using other numbers of the population [267]. An extendable frame work that focused on rapid clinical application deployment introduced in [268]. A combination of image-based and landmark-based 3D registration is used to register in-vivo MRI and the ex-vivo MRI from patients undergoing epilepsy surgery. This method results in dense and accurate spatial correspondence between in-vivo MRI and histology and allows for the spatially local and quantitative assessment of pathological correlates in MRI [89].

7. Regularization and optimization:

Automated quantitative analysis systems for medical images often lack the capability to successfully process images from multiple sources. Optimization gives the best solution from all feasible solutions whereas, regularization introduces additional information for solving ill-posed problems, usually occur in deformable transformations. Most of the above mentioned works have used these processes as part of the registration but not much attention is paid. The following discussion is targeted recent optimization and regularization methods. The problem of merging parameters into local extrema is solved by including the idea of chaos optimization and hybridization in genetic algorithm [269], [270] & [271]. Only infrared and visible images are registered using this technique. Dame and Marchand [272] computed Hessian matrix for optimization that gives robust and accurate results for real-time image registration. For the cortical registration to intensify sub-regions of the brain, Robinson *et al.,* [273] adapted a Fast Primal Dual (Fast-PD) approach for discrete MRF optimization to spherical registration. The deformation labels are framed as a discrete set of rotations and a novel regularization term is derived from the geodesic distance between rotation matrices. An extension to this technique is an iterative optimization routine that determine the discretely or structurally changing objects. This knowledge is incorporated in an algebraic reconstruction method to reconstruct CT image objects, iteratively [274]. Furthermore, Zhou and Xie's work in [275] focused on how to revise registration results interactively for deformable methods.

The uncertainty in the registration problem is estimated by using Gaussian process interpolation to enable seamless integration of image features and accuracy [276]. Demirovic *et al.,* [277] replaced the Gaussian filter with a bilateral filter for better handling of the discontinuities. This technique is applied to lung motion estimation by integrating bilateral filters [278]. The inverted contrast relationship between T1- and T2-weighted brain images is exploited by INVERSION (Inverse contrast Normalization for VERy Simple registratION). This results in simple and robust similarity measure also used for rigid alignment of diffusion images [279]. Various regularization methods like locally adaptive regularization [280], Bayesian estimated regularization [281], spatially varying [282] and totally varying regularizations [283] place significant role in solving the ill-posed problems in numerous medical imaging techniques. Two new reconstruction methods, NEGML and AML, are introduced for the reconstruction of the PET data to overcome positive-bias due to non-negativity constraint [284] and a Spline Initialized FADS Algorithm (SIFADS) is used for the 4-D dynamic SPECT reconstruction [285]. An automatic point correspondence is calculated using an artificial immune system optimization technique for medical image registration in [286].

Leibfarth *et al.,* [287], implemented three different optimization metrics, global mutual information (GMI), GMI combined with a bending energy penalty (BEP) for regularization (GMI+BEP) and localized mutual information with BEP (LMI+BEP to integrate PET/MR into radiotherapy treatment planning. Suspicious locations are always challenging during a 3D ultrasound guided prostate therapy. Sun *et al.,* [288] employed the multi-channel modality independent neighbourhood descriptor (MIND) as the local similarity feature and an efficient convex optimization approach to register MR and TRUS (transrectal ultrasound). Several optimization techniques are used in [289] to study on neurodegeneration at different stages using MR images of Alzheimer's patients. The same has applied to non-parametric discrete registration to achieve less computation time [290].

In the article [291], the limited memory Broyden-Fletcher-Goldfarb-Shanno with boundaries (L-BFGS-B) is combined with cat swarm optimization for nonrigid multimodal image registration using the normalised mutual information measure and the free form deformation models. Wang *et al.,* [292] studied the mutual information multimodality medical registration based on modified simplex optimization method and achieved the accurate registration of multimodal image with different resolutions. In the paper [293], an ensemble registration using a Gaussian mixture model is extended from gray images to color medical images. The color component regularization term is incorporated to decrease the transformations differences. This results in an easy and stable color component transformation. A new computationally efficient method (fast automatic step size estimation for gradient descent optimization) in [294], determined the step size for gradient descent methods. Further, a fast rotation-free feature based image registration is proposed in [295] that uses improved N-SIFT and GMM based parallel optimization.

8. Applications:

MIR plays vital role in the modern medical imaging. It has changed the way of understanding an image acquired from different modalities and techniques. Few have already mentioned above and a detailed cataloguing is done in this section. Myocardial T2 quantification is achieved using non-rigid registration (NRR) to follow-up a heart transplant patient [296]. A NRR is used to compare intraplaque neovascularization and plaque elasticity [297] and assessed the treated region with locoregional therapy to provide valuable information for predicting hepatocellular carcinoma recurrence [298]. Registration improves voxel-wise reproducibility and decreases uncertainty that enables to analyze blurred (due to organ motion) and unprocessed (due to low speed imaging) images [299].

Longitudinal tumour changes in chemotherapy can be evaluated using attribute-matching and mutual-saliency procedures to mark the response to the treatment in a deformation model [300]. Applications of rigid and non-rigid registration in correction of motion artefacts in microscopy image sequences collected from living animals has discussed in [301]. Real-time 2D/3D registration is used for tumour motion tracking in image guided radiotherapy [302]. Moreover, a 3D treatment margin is defined for image guided focal therapy for MR imaging visible prostate cancer [303].

The value of T1/T2-weighted imaging registration is evaluated to reduce the postbiopsy hemorrhage effect for prostate cancer localization [304]. This is extended to evaluate the clinical impact of a high definition micro-multileaf collimator and a linac-integrated cone-beam computed tomography in patients treated with conformal radiotherapy for localized prostate cancer [305]. High intensity focused ultrasound (HIFU) that employed a 3D multimodal image non-rigid registration is effective at restraining local extrema and improves the accuracy of tumour therapy [306] also, MR-HIFU ablation treatment of painful bone metastases [307].

Localized emphysema is clinically assessed using pulmonary kinematic analysis with non rigid image registration [308]. Further, a noninvasive method for deforming malignant pulmonary nodule elasticity is developed using DIR [309]. A semi-automated algorithm for 3D atlas-based registration is presented for quantifying misalignment in complex femoral shaft fractures from a single intraoperative cone-beam CT image of the fractured limb [310]. A DIR method is used to define the postimplant seroma in permanent breast implant brachytherapy by adapting preimplant semorams to postimplant images [311] and cardiac dosimetric of deep inspiration breath-hold level variances is evaluated in CT scans [312]. Further, airflow limitation in smokers is evaluated using paired inspiratory/expiratory volumetric CT and DIR [313]. This is enhanced by applying symmetric regularized correspondence fields [314]. Echo planar imaging distortions are corrected using DR-BUDDI [315]. The applications of DIR are also found in small artery visualization in contrast-enhanced whole body MR angiography [316], sparsity reconstruction of dynamic MRI [317], validation of non-invasive imaging techniques [318], dose distribution for carbon-ion beam lung treatment [319], evaluation of tumour response to therapy [320], discriminating between Alzheimer’s disease and healthy controls [321], cone-beam CT guided transoral robotic base of tongue surgery [322], quantitative analysis of regional lung ventilation by registering CT and hyperpolarized gas/1H MRI [323], 4D radiation therapy of lung cancer by estimating tumour motion [324].

A nonlinear registration method is applied in the enhancement of retinal images at very high spatial resolution for better medical diagnosis [325]. A study investigates whether metal artifacts influence the precision of image-to-patient registration, either with or without intermediate user intervention during the registration procedure, in an application for corrective osteotomy of the distal radius in [326]. Another 3D-2D image registration is applied to spine interventions and vertebral labeling to evaluate precision and robustness in them [327]. Similar approach is used in C-Arm image-assisted navigation system for spinal surgery [328]. Kinematic analysis of healthy hips is studied using 3D-2D model-to-image registration technique during weight-bearing activities [329]. A deformable slice-to-volume registration method is proposed to map a 2D transvaginal ultrasound to 3D pelvic MR images, mapping and characterizing endometrial implants [330].

9. Evaluation of Registration Methods:

Quantifying of each component or the entire registration process existing in the literature is also a challenging attempt. Since no ‘golden estimation’ criterion is existed, evaluation of medical image registration is still a problem. Misregistration impacts power/cost of registration-based imaging validation studies [331]. Accurate registration over multiple scans is necessary to assess treatment response of bone diseases (e.g. metastatic bone lesions) [332]. A satisfactory gold standard database for the evaluation of rigid registration is provided in [333], [334], & [335] and the Nonrigid Image registration Evaluation Program (NIREP) is made available in a software package. Part of this work with their accuracy and consistency evaluation has published in [336], [337] & [338] which shows no registration method is universally addressed all medical related issues. In the article published in 2012, a qualitative meta analysis method is applied to analyze medical image registration performance evaluation [339]. Validation of non-rigid medical image registration techniques is published in [340]. Four CT-MRI co-registration techniques for radiotherapy treatment are evaluated and published advantages and drawbacks of them in prone rectal cancer patients [341]. Chandler *etc al.,* [342] compared the performance of manual, rigid and non-rigid registration techniques to correct anatomical misalignment in acquired liver CTp data sets. The DIR accuracy is evaluated for the rectum and bladder based on dose/volume [343], intensity-based DIR evaluation [344], dose monitoring in head and neck radiotherapy [345], [346], & [347], thoracic CT-CT DIR using auto-segmented 3D anatomical landmarks [348] and Fiducial landmarks are used for spatial evaluation of MIR [349]. A robustness based evaluation of similarity measures for brain image registration is discussed in [350].

In lung cancer radiation treatment precision of imaging plays vital role. A study aiming to evaluate Elekta 4D cone beam CT-based automatic dual-image registrations is published in [351]. Six different scenarios for correcting breathing motion in abdominal dual-energy CT perfusion measurements are compared with respect to rigid and deformable motion algorithms [352]. In free-breathing breast cancer patients inter- and intra-fraction geometric errors are very common in daily image-guided radiotherapy [353]. Diffusion-weighted imaging techniques for prostate cancer localization are quantitatively evaluated in [354]. Anatomical detection methods for cephalometric x-ray images are evaluated and compared in [355]. Ryan *et* *al.,* [356] validated a NRR error detection algorithm using clinical MRI brain data. Rohlfing [357] proved image similarity and tissue overlaps as unreliable surrogates for image registration accuracy. Accuracy of spin-image-based registration of partial capitates bones in 4DCT of the wrist is calculated in [358]. Korhonen *et al.,* [359] studied the feasibility of MRI-based reference images and Wikstrom *et al.,* [360] compared patient position displacements from body surface laser scanning and cone beam CT bone registrations for image-guided radiotherapy of the pelvis. An automatic quality assessment of intra-patient CT lung registration is presented in [361]. Mohagheghi *et al.,* [362] proposed the accuracy assessment of marker-free registration methods using an image-guided dental system.

10. Conclusion:

A gigantic survey is conducted with more emphasis on recent works since 2012. It is observed that existing similarity measures are sensitive to noise and raw image signals (intensities) and there is a need to observe more robust features to counter them. Though, rigid models are very fast and simple to implement, majority of them do not suitable for medical images where higher level of nonlinear analysis is required. Nonetheless, appropriate choice of rigid models and similarity/dissimilarity metrics that are independent of noise may give fruitful results and hope for the future work. Contrarily, deformable models offer accurate and reliable registration of anatomical structures but, the proposed nonlinear/ nonrigid methods require solutions for large system of equations or a large number of iterations. Hence, they are computationally ineffective and consistency is still ambiguous. Deformation methods based on group-wise segmentation and other local approximations have tackled this problem but, no effort is made to allow rigidity assignment to certain local features to deform some image regions more than others. Very few geometric transformations are defined that can detect the outliers and can preserve certain geometric properties so that high resolution images with sharp edges and corners can be registered. Various combinations of distance metrics, transformation models, and regularization and interpolation models can be verified based on the problem chosen.

12. References

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