A Review of 3D-2D Registration Methods and Applications based on Medical Images

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Abstract. The registration of preoperative three-dimensional (3D) medical images with intraoperative two-dimensional (2D) data is a key technology for image-guided radiotherapy, minimally invasive surgery, and interventional procedures. In this paper, we review 3D-2D registration methods using computed tomography (CT) and magnetic resonance imaging (MRI) as preoperative 3D images and ultrasound, X-ray, and visible light images as intraoperative 2D images. The 3D-2D registration techniques are classified into intensity-based, structure-based, and gradient-based according to the different registration features. In addition, we investigated the different application scenarios of this registration technology in medical clinical treatment, which can be divided into disease diagnosis, surgical guidance and postoperative evaluation, and also investigated the evaluation method of 3D-2D registration effect.

Keywords: 3D-2D Registration; Intensity-based; Structure-based; Gradient-based; Medical Clinical Treatment.

1. Introduction

Multimodal medical image registration techniques first emerged in the 1990s. In the process of clinical treatment, in order to obtain more comprehensive information about patients to improve clinical diagnosis and treatment, medical images of the same patient taken at different times and by different devices need to be aligned and fused. Multimodal medical image registration technology refers to the spatial pose transformation of one modal medical image to achieve the optimal spatial match with another modal medical image.

Medical image registration techniques can be divided into three-dimensional (3D)-two-dimensional (2D) registration, 3D-3D registration, and 2D-2D registration according to the image dimension. The 3D-2D matching-based method projects the 3D object to the 2D reference image plane and geometrically aligns the projected image with the reference image. Such methods find a geometric transformation by optimal registration so that the projection of the 3D object corresponds as much as possible to the 2D reference image in space [1]. The 3D-3D matching-based method achieves the fusion of 3D-3D images by finding the corresponding 3D key information of the two images, and then aligning the key information of both by a spatial registration algorithm [2]. The 2D-2D registration method achieves accurate matching of 2D images by extracting the corresponding feature points, feature contours or grayscale information [3].

Cross-dimensional medical image registration technology based on 3D-2D matching can often achieve information enhancement of 2D reference images, spatially complement the 3D topological structure information of patient organs, and assist doctors to better identify key tissues before or during surgery, thus enhancing surgical safety and accuracy. However, the low resolution and high noise of 2D reference images have led to a large challenge in 3D-2D medical image registration technology. This paper focuses on 3D-2D medical image registration technology and its application in clinical surgery. 3D-2D medical image registration technology can assist in preoperative diagnosis, surgical navigation, and postoperative evaluation. Among them, 3D-2D medical image registration technology can be used in preoperative diagnosis by combining the patient's electronic computed tomography (CT) [4], magnetic resonance imaging (MRI) [5], cone beam computed tomography (CBCT) [6] and other 3D images are matched to X-ray, ultrasound, and visible light images to establish an accurate identification model of the anatomical structure of the lesion, thus assisting the surgeon to more accurately understand the relative position of the lesion and its adjacent tissues, and improving the accuracy and precision of surgical planning. In surgery, 3D-2D registration technology can align the 3D model of the patient's organ before surgery to the 2D image acquired in real time during surgery, providing the surgeon with real-time precise positioning information of the lesion, which can assist the surgeon in accurately avoiding dangerous tissues.

3D-2D medical image registration techniques can be divided into three categories: intensity-based, feature-based, and gradient-based. In this paper, we investigate and analyze these three 3D-2D medical image registration methods in depth. Intensity-based 3D-2D registration relies on the pixel information in 3D and 2D images, and the registration is achieved using the complete image information. The projection of 3D image to 2D image is first calculated, and then the similarity between the projected 2D image and the reference 2D image is compared, and the transformation that makes the highest similarity is found by an optimization strategy. The intensity-based registration method uses all the grayscale information of the image, and this method can improve the accuracy and stability of the registration. However, this method computes all the grayscale information of the image, which leads to low registration efficiency [7]. To solve the problem of mismatching grayscale information of different modal images, the feature-based method achieves registration by the feature information in the image, firstly extracting the feature points in the image, then matching according to the extracted features, and finding the transformation model parameters of the image by the optimal matching points. The feature-based registration method extracts the important features of the image and avoids incorporating all the information in the image into the operation to reduce the registration time. However, the limitation of matching some of the image features causes this method to be extremely sensitive to the selection of features [8]. The gradient-based registration method uses the gradient information in the image as a similarity metric to achieve registration. Since the gradient direction of the corresponding feature points on the tissue-organ boundaries does not change significantly depending on the imaging mode, making full use of the gradient information can improve the registration efficiency and reduce the local extremes in the registration process thus improving the registration accuracy [9].

The purpose of this paper is to investigate the registration techniques and clinical application scenarios of preoperative 3D medical images (CBCT, CT, MRI) with intraoperative 2D images (X-ray, ultrasound, visible images). Positron Emission Computed Tomography (PET) images [10] are obtained by imaging with nuclides injected into the body, and 3D-2D registration involving this image is beyond the scope of this review. This paper investigates 120 papers between 1975 and 2022, classifies 3D-2D registration techniques into intensity-based, structure-based, and gradient-based types for detailed analysis, and describes evaluation methods of 3D-2D registration. In addition, for the clinical application scenarios of this technology, this paper summarizes the application scenarios into disease diagnosis, surgical guidance and postoperative evaluation according to the surgical procedure.

2. Methods

In recent years, 3D-2D medical image registration technology has gained widespread attention and has become a hot spot for research at home and abroad. Such technology can effectively assist doctors in accurately identifying the tissue structure of patients' vital organs intraoperatively, and safely and precisely performing surgical procedures such as lesion removal and surgical repair. Thus, this paper first elaborates different methods of 3D-2D medical image registration, then investigates in detail the effectiveness of the technique in different application scenarios, and finally describes the evaluation methods of registration effectiveness in a categorical manner.

2.1 Current Status of 3D-2D Registration Methods

3D-2D registration methods can achieve information enhancement of intraoperative 2D medical images, thus assisting physicians to quickly and accurately identify tissue structure information of patient lesions. Currently, 3D-2D registration methods can be classified into intensity-based, structure-based and gradient-based according to the image information.

2.1.1. Intensity-based 3D-2D Registration Method

Intensity-based 3D-2D registration starts by comparing the similarity between the 2D projection image of the 3D image and the reference 2D image, and then uses an optimization strategy to find the transformation that makes the highest similarity. Currently, the interference of interventional instruments and soft tissues with images is a major challenge in image registration. Demirci et al. [11] proposed a framework for 3D-2D image registration based on de-occlusion, which effectively removes the occlusion of surgical instruments using a spline interpolation algorithm [12] and a stent editing model, and then uses Huber and Tukey gradient [13] based on the correlation of similarity metric to quantify the matching performance of 3D-2D medical images, thus limiting the anomalous matching introduced by the noise of the intervening images, and the registration effect of this method is shown in Figure 1. In order to improve the speed of de-occlusion registration, Zheng et al. [14] proposed a 3D-2D image registration method based on Markov Random Field (MRF) [15]. The new point similarity metric is reasonably inferred by solving the maximum a posteriori estimate of the MRF model composed of the image to be aligned and the digitally reconstructed radiograph (DRR), and then the similarity metric is optimized by an a priori constrained model of the neighborhood structure to achieve the optimal registration. For the interference of soft tissue and interventional instruments, the method can achieve higher registration accuracy with faster convergence speed.

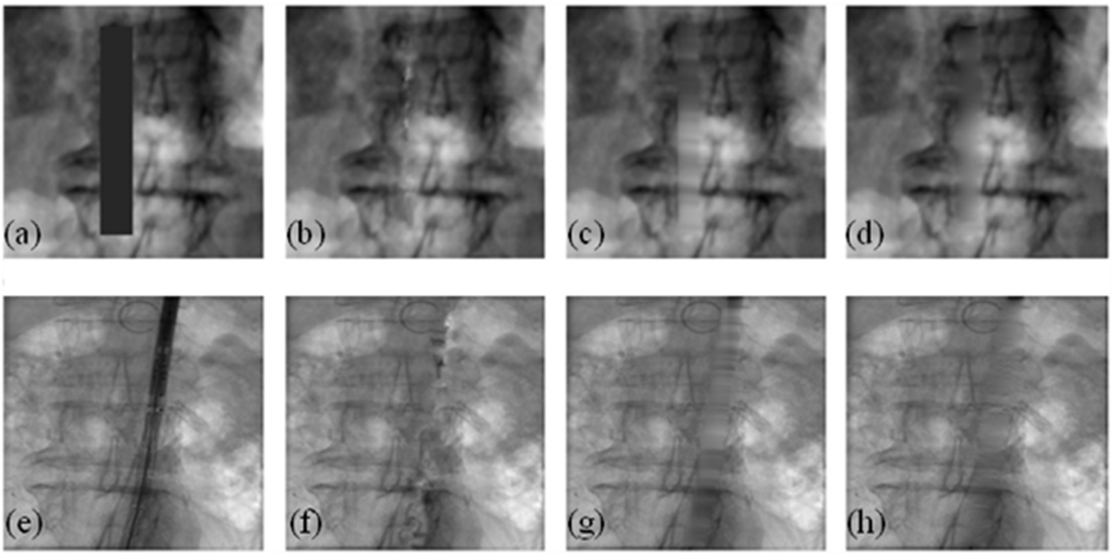

Figure 1. De-masking processing [11]: (a-d) real patient scans using synthetic projection and artificial masking, (a) original, (b) patch, (c) spline interpolation, (d) bracket editing. (e-h) real experiments, (e) original, (f) patch, (g) spline interpolation, (h) bracket editing.

To improve the matching accuracy, the projection-based registration method projects the voxel information of the 3D image onto the 2D imaging plane to achieve an accurate match with the 2D image. Birkfellner et al. [16] proposed a 3D-2D fluoroscopic medical image registration method based on fast DRR projection. The method was computed by Gaussian footprint to suppress discretization artifacts and proposed a splat rendering [17] variant model to project single voxels directly to the 2D imaging plane. The main advantage of using splat is that the number of voxels used for DRR generation is greatly reduced and rendering complexity is reduced. In order to ensure the accuracy of matching DRR projections with 2D X-ray digital subtraction angiography (DSA), Hipwell et al. [18] proposed an registration method based on 3D magnetic resonance angiography (MRA) projections. The method first converts the MRA image into an image of the vascular system in order to generate projection information, and then performs a matching search in a custom circular region of interest, and finally compares the registration performance of six similarity measures: correlation, gradient correlation, difference entropy, mutual information, pattern intensity, and gradient difference, in order to select the most suitable registration scheme, and the registration effect of this method is shown in Figure 2. The accuracy of MRA and DSA registration can be improved by this method, and the robustness of the registration can be enhanced when combined with binary segmentation of the vessels. Kerrien et al. [19] proposed a fully automated 3D-2D subtraction angiography registration method. This method compares the 2D angiographic image with the Maximum Intensity Projection (MIP) of the 3D angiographic volume [20] in two ways, firstly, by maximizing the intercorrelation information of the two images for a wide range of registration, and then by recovering the rigid body motion of the remaining part using an improved optical flow technique [21], and the registration effect of this method is shown in Figure 3. This method can effectively solve the problem of translation and rotation errors arising from matching the 3D vascular skeleton projection with the 2D skeleton extracted by DSA.

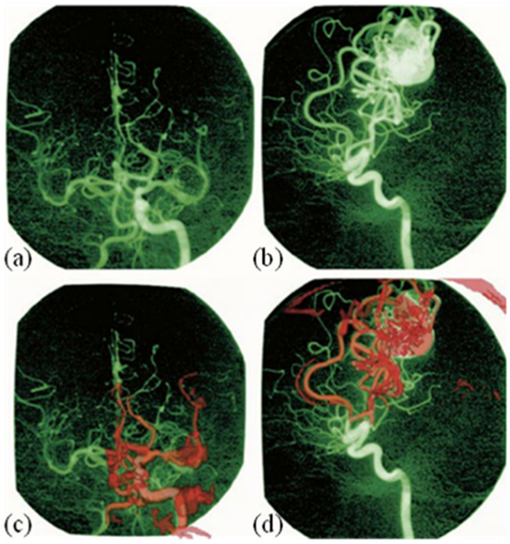

Figure 2. Example of registration [18]. the DSA image is shown in green and the aligned 3D model is shown in red. (a), (c) are images aligned using the gradient difference method and (b), (d) are images aligned using the mode intensity method.

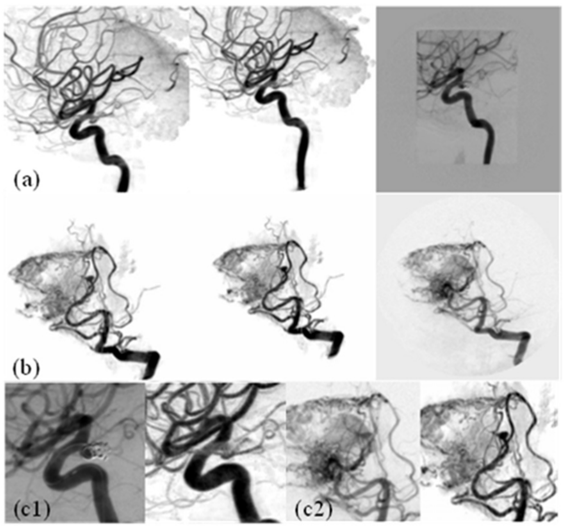

Figure 3. (a), (b) shows an example of the registration results [19], where the three images in each row are the initial MIP image, the aligned MIP image, and the DSA image, respectively. The third row shows a zoomed-in view of the above results:(c1) left: DSA image, right: MIP image, and (c2) corresponds to (b).

To optimize the quality of similarity measures for the evaluation of matching effects, Chung et al. [22] proposed a 3D-2D image registration algorithm based on Kullback-Leibler Divergence (KLD) [23]. The method first estimates the expected joint intensity distribution between the pre-aligned images, and then minimizes the KLD difference between the expected and actual intensity distributions to find the optimal transformation for the registration of the two images. Compared with the maximum log-likelihood-based method [24], this method has less range dependence on the sampled region and is more efficient for registration. To achieve fast and accurate 3D-2D registration, modal transformation-based methods have been proposed by researchers. Aubert et al. [25] proposed a 3D-2D spine image registration algorithm based on GAN [26] for cross-modal image conversion. The method converts the X-ray image into a DRR projection before matching the conventional X-ray image with the DRR projection, which transforms the multimodal registration problem into a unimodal registration problem, and the effect of this projection is shown in Figure 4. The method can achieve similarity matching in the same image domain, and the separation of adjacent and superimposed structures can avoid interference to the matching. In addition, the insensitivity of the method to the similarity measure and the larger capture range improve the registration stability and accuracy, and the registration effect of the method is shown in Figure 5.

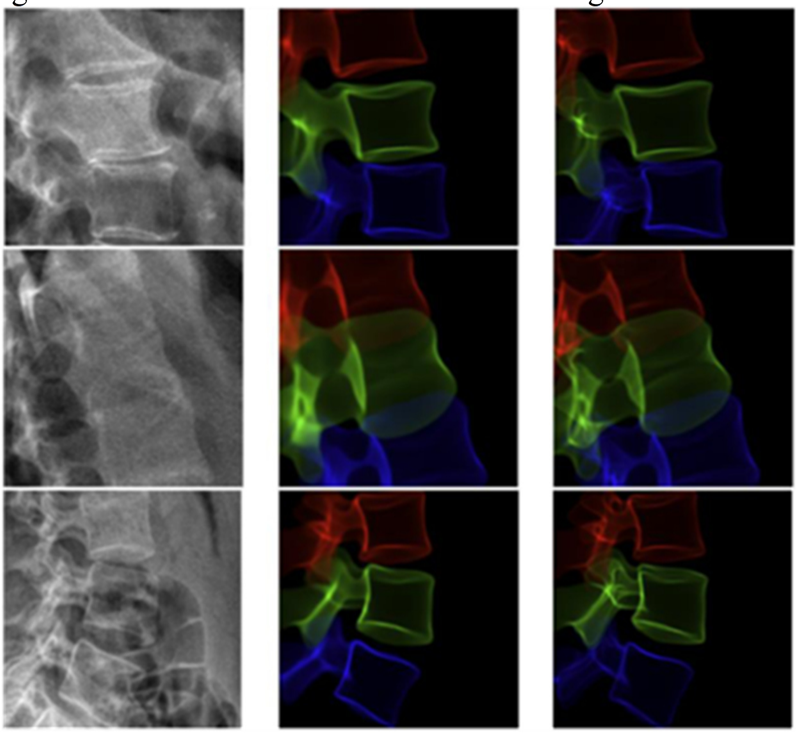

Figure 4. Example of DRR prediction of L2-L3-L4 lumbar spine in lateral view [25], the first column is the original X-ray image, the second column is the DRR image based on GAN transformation, and the third column is the original DRR image.

The above intensity-based 3D-2D registration method finds the optimal transformed pose of 3D data by matching the intensity information of 3D data with that of 2D data. Interpolation-based de-obscuring 3D-2D registration techniques can minimize surgical background interference, but algorithms such as interpolation and filter optimization require high accuracy in identifying a priori structural features of the registration data, and lack registration stability in complex surgical environments. The projection-based 3D-2D registration technique uses the intensity information of 3D image voxels as the registration data. This method utilizes most of the voxel information, thus ensuring 3D-2D registration accuracy, but the registration time is long and not suitable for applications that require real-time registration. The 3D-2D registration method based on similarity optimization achieves fast and accurate matching of 3D-2D images by improving the similarity measure to assess the quality of registration.

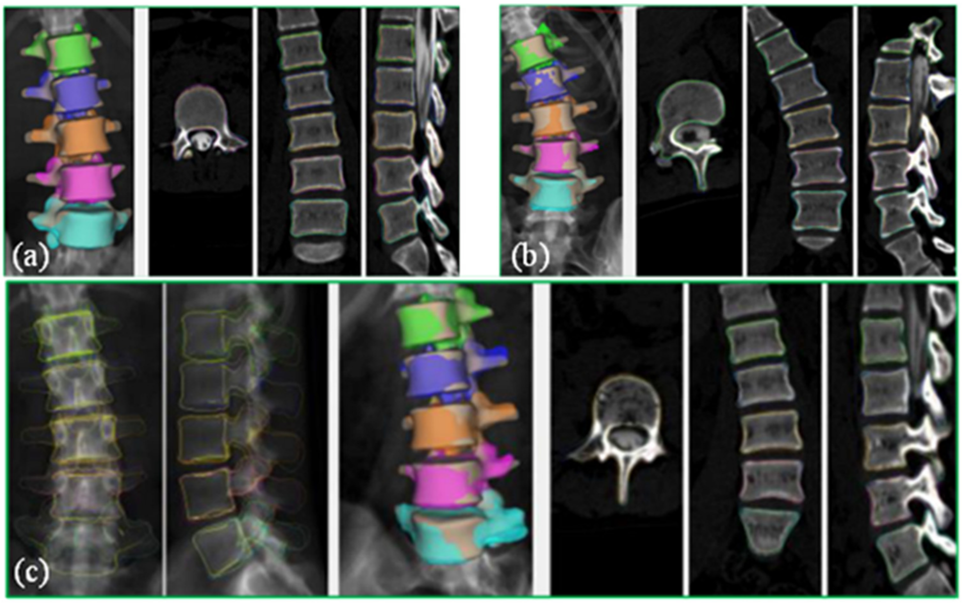

Figure 5. (a), (b), (c) Superimposition of 3D reconstruction of biplane X-ray images and 3D segmentation of CT scans for three patients (L1-L5 colored in green, blue, orange, pink, and cyan, respectively). The projection contours of three patients are shown in axial, coronal and lateral views, and an additional third patient model is shown in the posterior anterior and lateral projection views of the CT-generated DRR [25].

2.1.2. Feature-based 3D-2D Registration Method

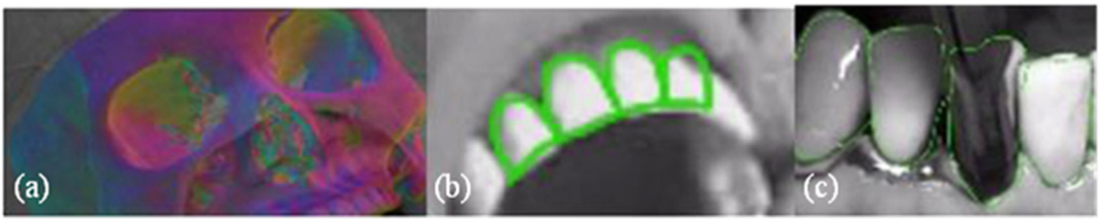

Figure 6. (a) Image registration, (b) image overlay, and (c) registration during masking [27].

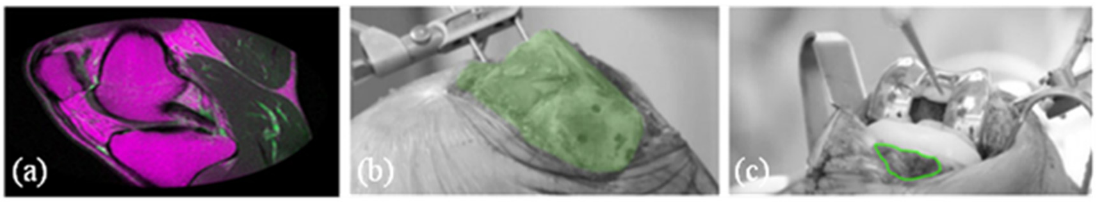

Figure 7. (a) Image registration, (b) volume subtraction, and (c) image superimposition [30].

The feature-based 3D-2D registration method first extracts the customized feature information, and then finds the relative spatial transformation pose between 3D-2D images by an optimization algorithm, so as to achieve the optimal matching between them. Currently, the more mature and widely used feature-based registration methods include the Iterative Closest Point (ICP) algorithm. Murugesan et al. [27] proposed a 3D-2D oral and maxillofacial image registration method based on rotation matrix and translation vector [28] iterative optimization. The method utilizes two stereo cameras and a translucent mirror to reduce the spatial matching geometric error to improve the accuracy and speed of registration between the preoperative 3D image and the intraoperative video stream, which is shown in Figure 6, and includes the 3D image overlay and stereo tracking model based on Wang et al. [29] to improve depth perception. The above methods can minimize the geometric errors introduced by ICP algorithms. To minimize the error metric in ICP, Pokhrel et al.

[30] proposed an improved ICP registration method for 3D-2D image registration of the knee joint. The method utilizes a "point-to-point" error measurement model to reduce the number of matching iterations. In addition, the use of volume subtraction technique [31] and color transfer function [32] can reduce the knee cutting error and ensure the cutting accuracy, and the registration effect of the method is shown in Figure 7.

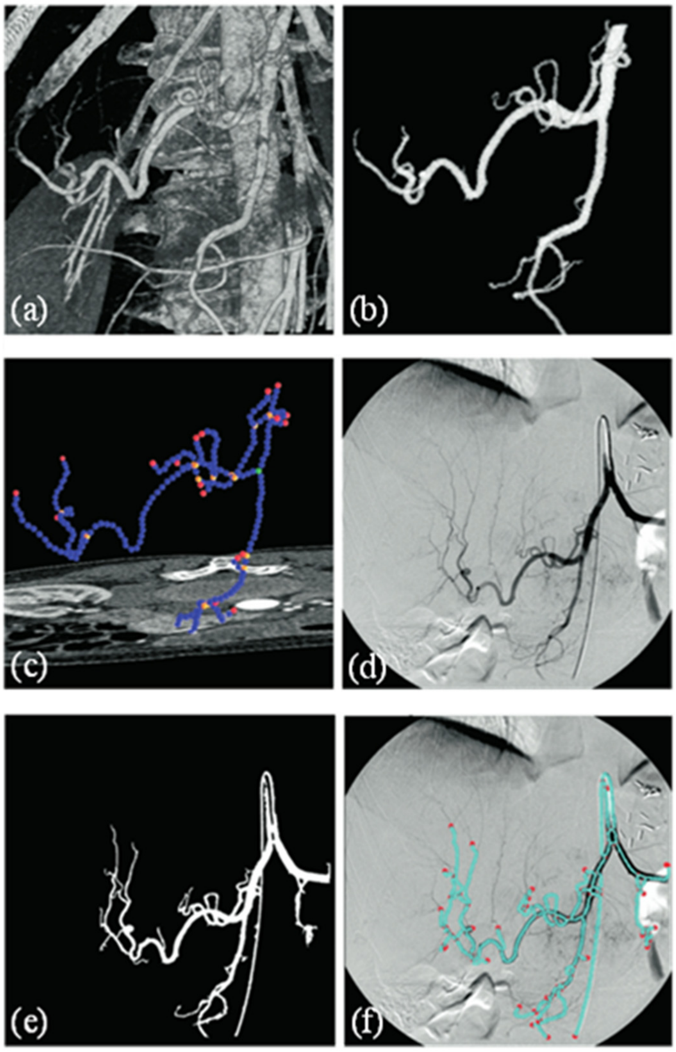

Figure 8. (a) Body rendering of computed tomographic angiography, (b) segmented vessels, and (c) extraction map, where green points are root nodes, orange points are internal, red points are external bifurcation points, and blue points are vessel segment sampling points. (d) and (e) show the original DSA and its segmented vessels. (f) shows a 2D plot (blue-green is the sampling point and red is the bifurcation point) [33].

Since the ICP algorithm depends on the initial pose of the target, to solve this problem, Groher et al. [33] proposed a 3D-2D registration method based on an improved feature space computed tomography angiography image with DSA images. The method first combines smoothing, background removal and vessel enhancement filter models to achieve accurate segmentation of 3D and 2D vessels, and extracts key feature information based on the wave propagation algorithm [34], and then creates a projected centerline cyclic map as the feature space, and finally iteratively solves the rotation and translation parameters of the pose transformation matrix to achieve the optimal matching of 3D and 2D vessels, and solves the matching accuracy degradation problem caused by the initial pose misregistration of 3D and 2D vessels. The registration effect of the method is shown in Figure 8. However, the method does not deal with the deformation of organ tissues due to the natural activities of the body, which results in incomplete matching of vascular structures. To solve the registration problem of deformation-prone tissues and organs, Zikic et al. [35] proposed a method for elastic registration of 3D vascular structures to 2D projection images. The method is divided into the optimization of two parts: the differential measurement [36] and the regularization term. The distance between the projected feature points of the 3D vascular structure and the corresponding points of the 2D projection image is reduced using the differential term, and the deformation simulation of the vascular structure can be performed using the regularization term, and the registration effect of the method is shown in Figure 9. The above strategies improve the depth perception of 3D space with accurate registration performance. Wang et al. [37] proposed a real-time markerless 3D-2D registration method based on feature matching combined with a tracking framework. The method reduces the search range of preoperative dental model and intraoperative image online matching by tracking the frame, and reduces the probability of mis-matching with other targets outside the frame. In addition, the online matching framework achieves the initial registration of the target, which in turn solves the problem that ICP registration methods rely heavily on the initial rotational pose. Lee et al. [38] developed an improved ICP registration method based on a weighting and perturbation strategy. The method uses a stereo vision algorithm [39] to extract a sparse point cloud of the patient's face, which is later aligned by an improved ICP method to deal with local minima and outliers.

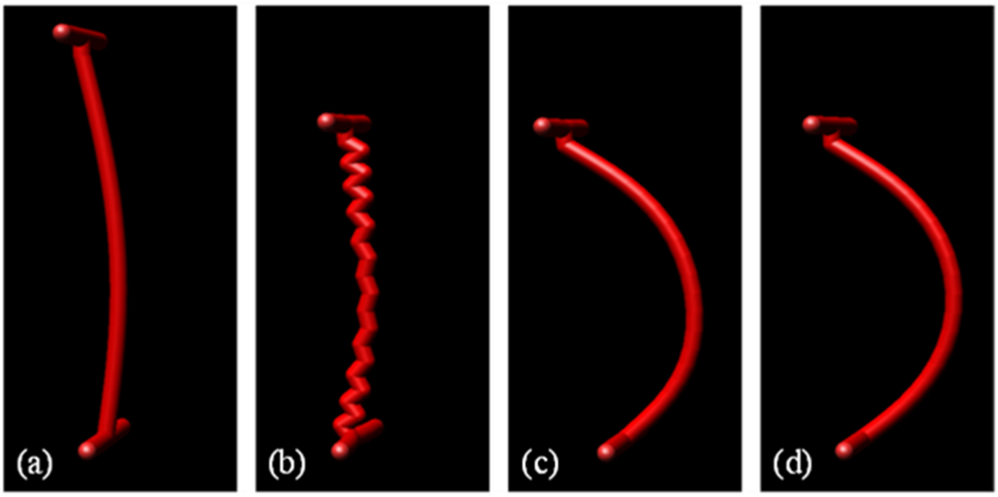

Figure 9. Demonstration of the effect of the joint use of the length-preserving and diffusion regularization terms [35]. (a) input 3D image, (b) length-preserving results, (c) length-preserving and diffusion regularization results clearly produce more natural results, (d) real image.

Since the similarity measure of the ICP registration method is based only on the Euclidean distance [40], in order to find the optimal registration measure, Tsai et al. [41] proposed a 3D-2D registration method based on the volume model. This method uses the weighted edge matching score [42] as a similarity measure to determine the registration error, and this registration accuracy is better than both the pattern intensity-based and gradient difference-based matching methods. Yamazaki et al. [43] developed a 3D-2D knee implant registration technique based on single-plane fluoroscopy [44]. This technique quantifies the error behavior of six free variables into evaluation curves and analyzes the obtained evaluation curves, which can effectively improve the accuracy of implant positioning. However, the registration accuracy of this model depends on the initial pose, which leads to the stability of the results to be improved. To ensure the robustness of image registration, Deguchi et al. [45] proposed an image similarity metric for bronchoscopic tracking. This method focuses only on the image sub-blocks with characteristic shapes, and then determines the key sub-blocks based on the sub-block feature values to calculate the similarity, which can improve the safety and stability of bronchoscopic tracking, and the sub-block selection of this method is shown in Figure 10. In addition, Luo et al. [46] proposed a method that uses degradation of structural information to characterize image differences. This Discriminative Structural Similarity Measure (DSSM) can successfully adapt to image variations in endoscopic videos due to nonlinear illumination, specular or internal reflections or collisions with the body cavity wall, and thus the registration is more accurate and stable. The tracking results of different methods are shown in Figure 11.

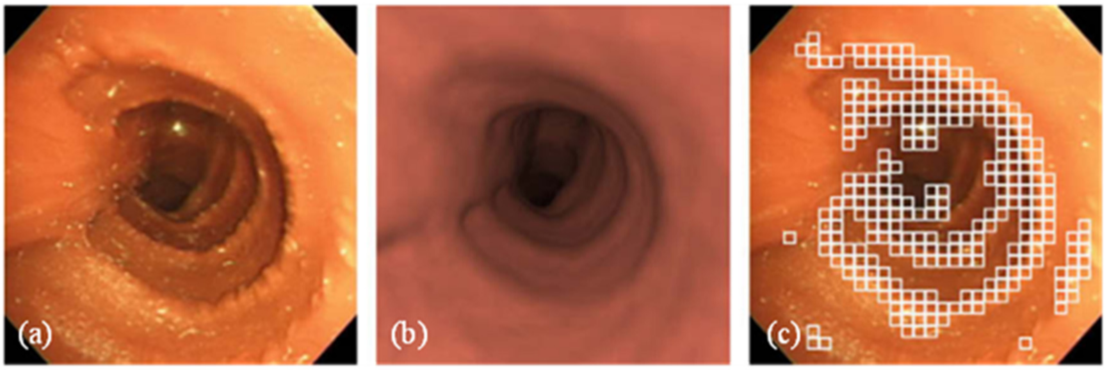

Figure 10. (a) Virtual bronchoscopy image (b) Real bronchoscopy image (c) Selected sub-blocks [45].

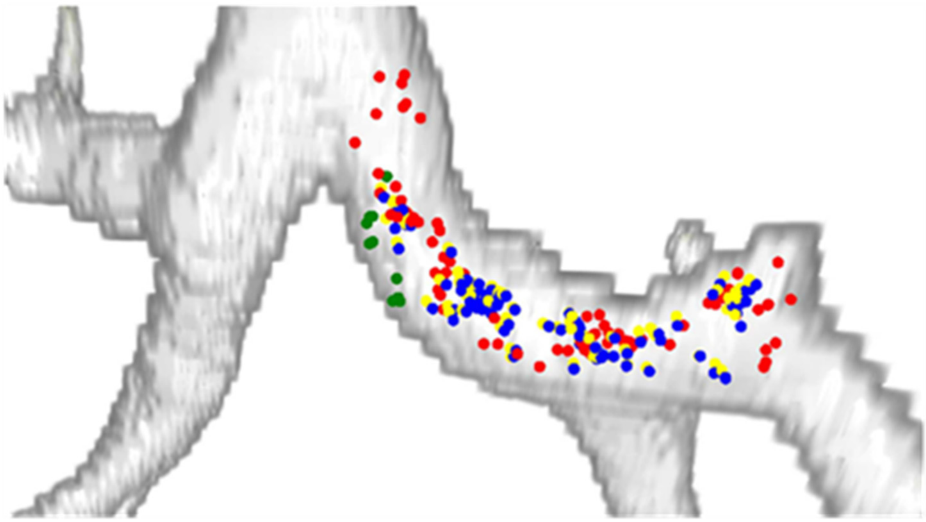

Figure 11. Endoscopic tracking effect using different methods. Correction of mean square error (red dots), normalized and squared differences (green dots) and DSSM (blue dots) with reference facts (yellow dots).DSSM gives a better indication of the tracking position [46].

The above feature-based 3D-2D registration method first extracts the feature information of interest (including feature points, centerlines, contours, etc.) using the feature detection method, and then aligns the corresponding feature points of the image to be aligned to find the optimal matching parameters for the pose transformation. Improved ICP-based algorithms using rotation matrix and volume subtraction techniques can achieve improved registration speed and accuracy, but such algorithms are more sensitive to feature detection and lack registration robustness. The algorithm based on the combination of feature matching and tracking framework can quickly and robustly achieve optimal registration, enhance depth perception, and improve the image registration accuracy of dynamic tissue organs. However, the occlusion caused by surgical instruments or interventional instruments can affect the registration effect. However, the construction of similarity metric depends on the distribution pattern of feature information to a certain extent. A similarity metric that effectively describes the quality of feature matching can significantly improve the accuracy and speed of 3D-2D medical image registration. Therefore, it is a hot research topic in the field of 3D-2D matching to improve the similarity metric of feature matching.

2.1.3. Gradient-based 3D-2D Registration Method

The gradient-based 3D-2D registration method uses the gradient information of the corresponding features to solve for the similarity between 3D and 2D images to achieve a highly accurate and robust registration. Tomaževič et al. [47] performed registration by finding the best match between the 2D projection image of the 3D MRI gradient image and the X-ray gradient image. However, the occlusion of soft tissues and surgical instruments led to a decrease in their registration accuracy. In order to improve the registration accuracy, Mitrović et al. [48] proposed a 3D-2D registration algorithm based on robust gradient reconstruction. However, the method did not consider the errors caused by simulated deformation, background artifacts, and joint motion. To ensure the stability of the registration performance, Markelj et al. [49] developed an registration method based on the gradient of the 3D image with the coarse reconstruction of the 2D image with the 3D gradient, and their gradient reconstruction results are shown in Figure 12. The method uses the random sample consensus algorithm [50] and the gradient matching criterion function to establish the gradient correspondence during the bit-pose search, and the experimental results show that the registration accuracy and robustness of the method are effectively improved.

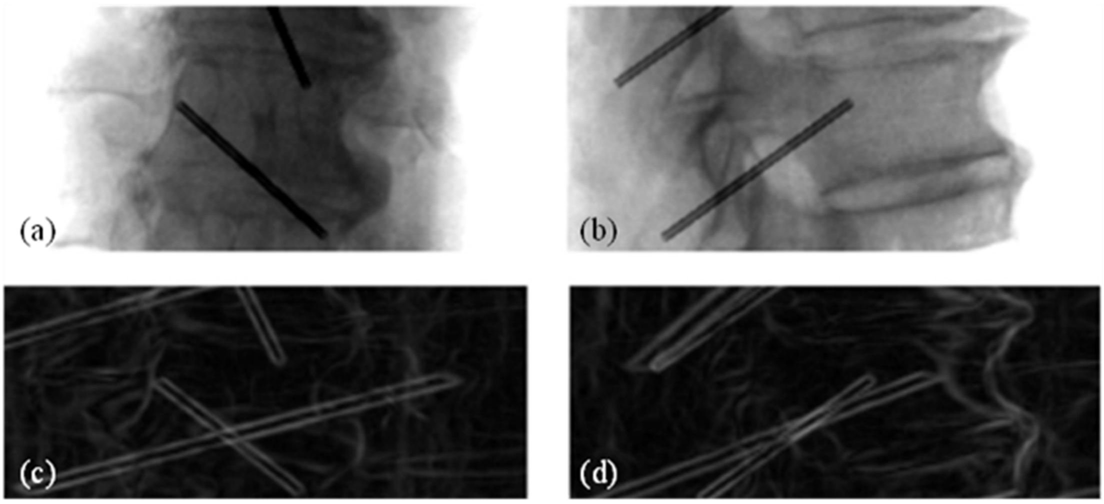

Figure 12. anteroposterior (a) and lateral (b) X-ray images of a single vertebral body using a simulated medical tool and corresponding coarse reconstructed 3D gradient images of anteroposterior (c) and lateral (d) cross-sections [49].

Mitrović et al. [51] proposed a method based on matching 3D vascular models with 2D image intensity gradients. The method achieves accurate registration by matching the geometric elements of the 3D vascular tree structure with the 2D intensity gradient direction based on the neighborhood-based similarity metric, and is particularly robust to significant changes in the contrast of cerebral vascular images. Tomaževič et al. [52] proposed a 3D-2D registration method based on the inverse projection gradient [53]. The method uses the bone surface normal lines defined preoperatively in the 3D images and the inverse projection gradient of the intraoperative X-ray images to find rigid transformations between the images. The method combines intensity and gradient information, which can simultaneously improve the registration accuracy and efficiency of the algorithm. To solve the problem of reduced registration accuracy due to occlusion in surgery, Livyatan et al. [54] proposed an improved gradient projection 3D-2D registration method. The method first estimates the initial pose of the 3D image, and then combines coarse registration of bone contours and fine gradient registration of edge pixels to achieve high-precision 3D-2D matching of bone tissue.This method can overcome the problem of instrumentation occlusion in X-ray images.

The above gradient-based 3D-2D registration method uses the gradient information of features as a similarity metric to find the best match between images, and since the gradient-based method is accurate, the gradient data set can be reduced to make the registration faster. The registration method can improve the accuracy and robustness of the registration by removing occlusions in the image and eliminating background artifacts through the gradient correlation techniques. However, the registration results usually lead to poor registration convergence if the initial registration error is large [49]. Future research can explore deep learning-based gradient registration methods to achieve subpixel-level image correspondence for more accurate image registration.

2.2 Current Status of 3D-2D Registration Application Scenarios

3D-2D registration methods can be used in clinical practice for different functions to assist physicians in making more accurate decisions. Currently, 3D-2D registration methods can be divided into preoperative disease diagnosis, intraoperative navigation, and postoperative evaluation depending on the application scenarios.

2.2.1. Disease Diagnosis

The 3D-2D registration methods applied to disease diagnosis allows rapid and accurate localization of the lesion, planning of the scope, and helps to personalize and implement surgical treatment plans. Lalys et al. [55] proposed a hybrid image guidance system for the diagnosis and treatment of peripheral arterial disease. To avoid repeated contrast injections, the system reduces the burden on the physician by fusing real-time images from the interventional phase with a 2D panoramic view of the peripheral arterial system from the diagnostic phase [56]. Zhang et al. [57] developed a multiscale, deformable 3D-2D registration method applicable to spinal deformities. The method first transforms the vertebral labels and planning information in the preoperative CT images using a multiscale mask [58], and then evaluates the registration of the spine using a spline curve [59] matched with the registration labels, and the registration results are shown in Figure 13. This method can maintain a high registration accuracy within the real spine curvature variation. Gillies et al. [60] developed an automatic motion correction registration method applied to prostate biopsies. The method first uses normalized intercorrelation and Powell optimization methods [61] for registration, and subsamples and crops the images to avoid the optimization process from falling into local optima, and then evaluates the real-time registration performance using motion compensation methods. This method allows for accurate localization of cancerous tissue as well as improved detection of prostate cancer in biopsies.

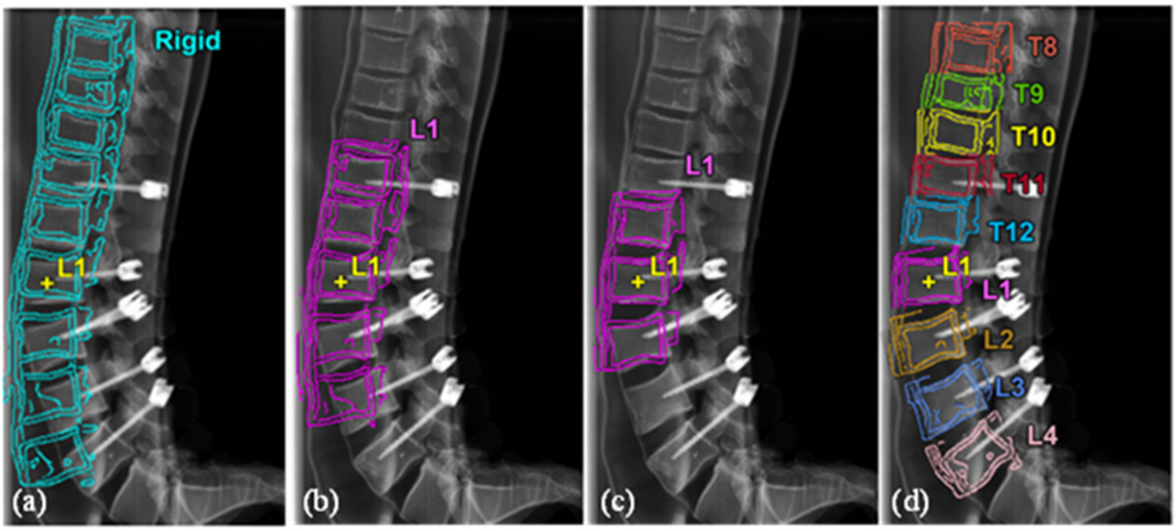

Figure 13. Representative results for cases of anterior spinal convexity obtained using (a) rigid and (b-d) multiscale frames. The resulting L1 registration is shown in magenta in (d), while the registration results for the other vertebrae (T8-L4) are shown in various colors [57].

Registration techniques are widely used in cardiac segmentation and real-time tracking. Lu et al. [62] implemented a non-rigid registration-based propagation framework for cardiac segmentation. This method uses the n-dimensional scale-invariant feature transformation method [63] to extract feature point pairs from fixed and motion images, and then achieves automatic segmentation of heart images based on image registration, which effectively reduces the effects of heart motion and boundary blur on segmentation, and the registration effect of this method is shown in Figure 14. Li et al. [64] developed a real-time nonrigid image registration technique for myocardial strain analysis. This technique improves the matching accuracy by minimizing the sum of squared pixel intensity differences of a finite element model of the heart [65] to eliminate artifacts caused by the motion of the adjacent structures. However, the stability of the method is more related to the image quality and signal-to-noise ratio. To improve the stability of the registration process, Lorenzo-Valdés et al. [66] proposed an registration method for fully automated segmentation of the myocardium and ventricles. The method aligns the cardiac mapping model to MRI images of the heart using a freeform-based registration algorithm, which helps to mark and track specific regions of the heart.

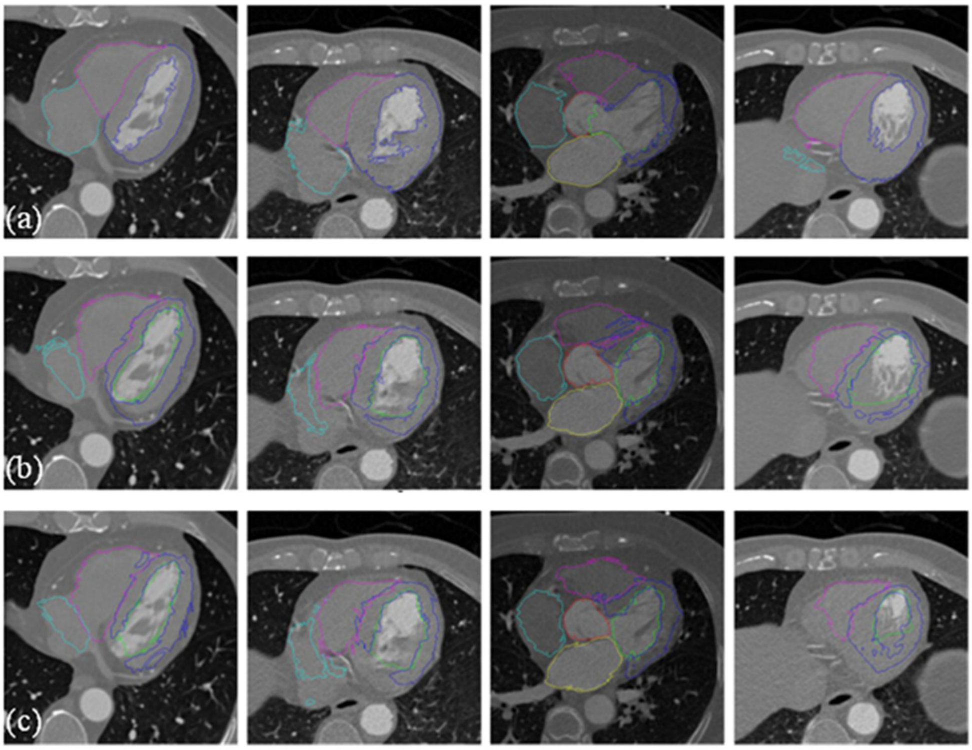

Figure 14. Display of heart segmentation results for four patients using (a) the gold standard segmentation method, (b) the mutual information method, and (c) the hybrid method of mutual information and Euclidean distance [62].

In the diagnosis of complex cardiac diseases, Leung et al. [67] developed a rigid registration method for the diagnosis of cardiac insufficiency. The method first extracted 2D four-chamber, two-chamber, and short-axis planes from 3D images of echocardiograms, while later improved the automatic analysis of 3D loading echocardiograms by finding the optimal registration with a simplex optimization algorithm [68]. Khalil et al. [69] proposed an image registration technique for the diagnosis of mitral valve disease [70]. This technique includes temporal and spatial registration. Among them, temporal registration interpolates and reduces noise of echocardiographic frames based on electrocardiogram signals, and spatial registration is performed using mutual information methods and pattern search optimization algorithms [71]. Even without the optical tracking technique, the results of this method are still highly accurate, but the registration process is highly complex and takes a long time to compute.

The 3D-2D registration method described above for preoperative disease diagnosis helps physicians identify the type of disease, develop treatment plans, and improve the quality of the procedure. The registration technique can reduce the use of contrast agents when assisting in the diagnosis of vascular diseases, thus reducing the radiation hazard to patients. In addition, 3D-2D registration techniques can track specified regions of the heart in real time to ensure the accuracy of disease diagnosis. 3D-2D registration methods can improve the accuracy of complex heart disease diagnosis. However, the computational complexity of such methods is generally high. Therefore, reducing the time spent on 3D-2D registration techniques for complex disease diagnosis is a current research priority.

2.2.2. Intraoperative Navigation

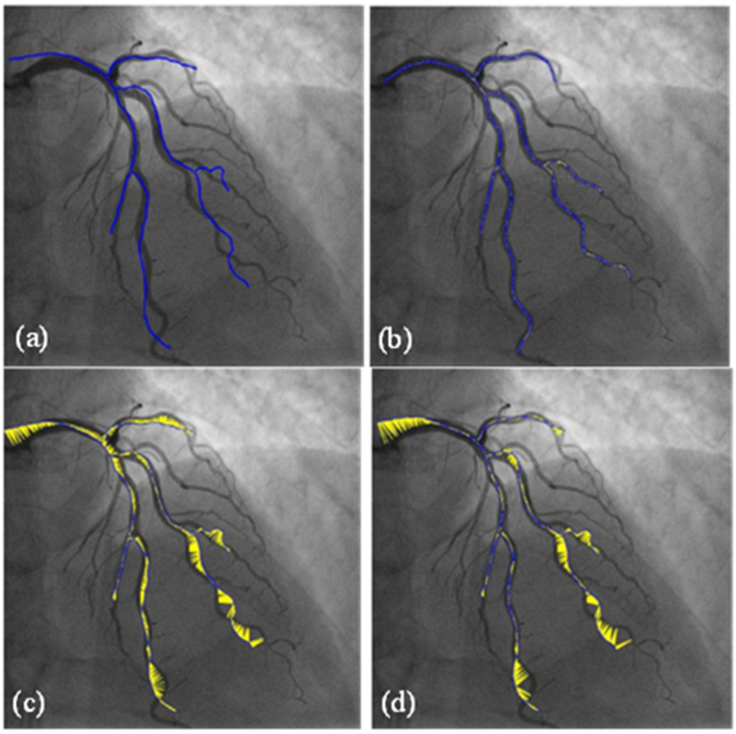

Figure 15. Registration results for the left coronary artery [72]. (a) Initial pose projection of the 3D model estimated by projection registration (blue), (b) registration position (blue) and projection difference (yellow) using the method proposed in this paper, (c) registration position (blue) and projection difference (yellow) using ICP, and (d) registration position (blue) and projection difference (yellow) using the coherent point drift algorithm.

A 3D-2D registration method applied to intraoperative navigation allows the surgeon to know the relative position of the instrument to the organ tissue in real time, thus ensuring the effectiveness of the surgical treatment as well as reducing the risk of the procedure. Liu et al. [72] proposed a 3D-2D registration method for percutaneous coronary interventions. The method first extracts the vascular centerline as the topological feature, and then uses the axonometric projection transformation [73] to find the optimal registration state of the two modes, and finally realizes the tree node registration according to the morphological structure of the vascular tree to ensure the edge matching, and the registration results are shown in Figure 15. This method reduces the amount of registration calculations, but is prone to mis-matching in the event of complete blockage of the main vessel. To reduce the dependence on the initial image, Toth et al. [74] proposed an adjacent anatomical structure registration method for simultaneous cardiac treatment. The method achieves optimal matching of the MRI left ventricle to the X-ray coronary vein by using a dynamic outlier rejection method [75], which allows abnormal values to be detected at the vascular reconstruction stage and prevents the registration process from falling into local optima. Ma et al. [76] proposed a movable Augmented

Reality (AR) surgical navigation system applied to minimally invasive surgery. Without external tracking markers, the surgeon can obtain a wide and flexible viewing area by moving the 3D overlay device and eliminate the mismatch effect caused by device motion via using the motion tolerance of the autostereoscopic overlay image [77].

In addition, registration techniques can support the smooth execution of spine surgery. Uneri et al. [78] proposed a 3D-2D image registration method applied to the placement of surgical instruments in spine surgery. This method uses deformable registration to calibrate deformed instruments (kerf pins and spinal fixation rods) in spine surgery and calculates intraoperative imaging device pose and deformation parameters to obtain the precise position of surgical instruments. Otake et al. [79] developed a 3D-2D registration framework for application to spinal interventions. The framework uses normalized gradient information as a similarity metric and refines the registration states using a covariance matrix adaptive evolution strategy [80], which improves the robustness and efficiency of the registration, but is not stable to deformation and content mismatch. To enhance the registration stability, Naik et al. [81] proposed a 3D-2D registration framework applied to pedicle screw placement. The framework used ICP algorithm and DRR generation technique to align the pedicle screw trajectory between X-ray images and CT images, and then the validity of the registration trajectory was evaluated by displacement and orientation errors. The registration results are shown in Figure 16.

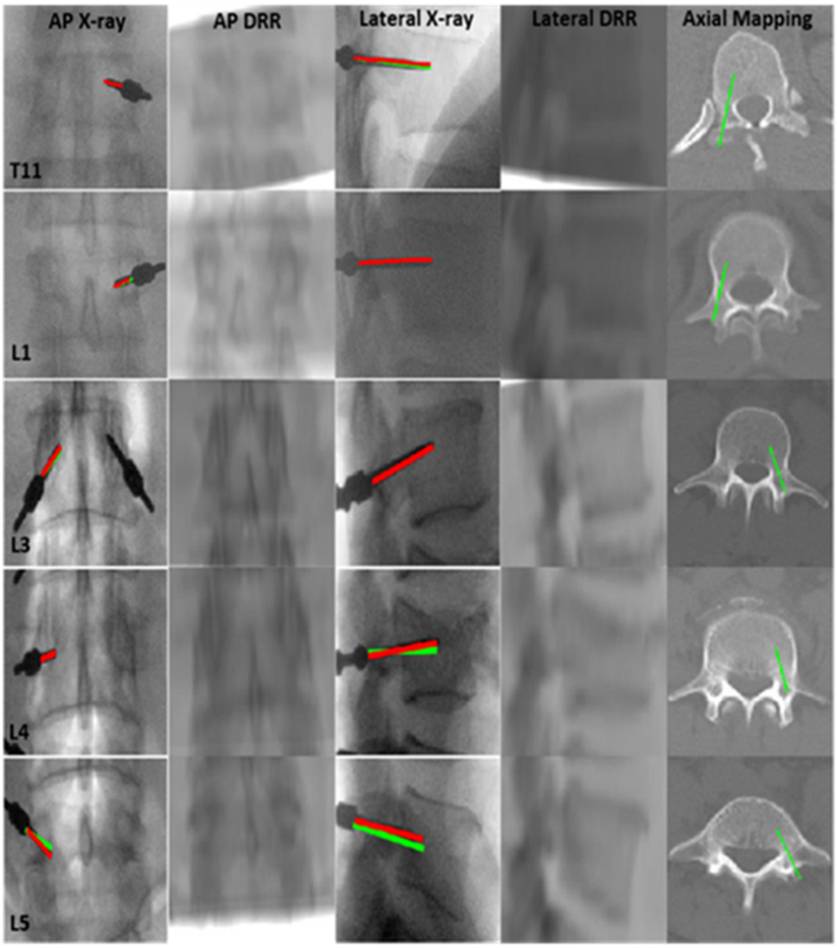

Figure 16. Clinical validation of pedicle screw trajectory registration [81]: the red and green lines in columns 1 and 3 are the central axes of the true and reprojected trajectories shown on anterior-posterior and lateral slices, respectively. Columns 2 and 4 show the DRR images generated at the best anatomical marker registration points in the anterior-posterior and lateral planes, respectively. Column 5 shows the axial trajectory maps on preoperative CT at the best registration points of different vertebral segments.

Wang et al. [82] proposed a dental AR surgical navigation system based on 3D image overlay. The system proposed an integration photography [83] registration strategy with virtual spatial markers, which enabled the registration process without reference markers. However, this method led to a decrease in registration accuracy due to inconsistent virtual and real gingival morphology. To overcome this problem, Wang et al. [84] developed an registration method for oral and maxillofacial surgery. This method first used a scanner to perform 3D optical reconstruction of the teeth, while later extracting the exposed tooth portion based on curvature analysis [85], and finally using an ICP algorithm to match with preoperative CT data. Since the registration process does not rely on external reference markers, it reduces the invasiveness of the procedure. Zhang et al. [86] proposed a markerless automatic registration framework applied to laparoscopic partial nephrectomy. The framework used a stereo reconstruction algorithm [87] and a point cloud stitching algorithm [88] to obtain intraoperative reconstructed point clouds, and then used the ICP algorithm and the coherent point drift algorithm [89] for registration and optimization. The results of clinical experiments are shown in Figure 17. The frame can automatically and accurately match soft organs without the use of external tracking devices, but the dynamic deformation of the target organ is prone to loss of accuracy.

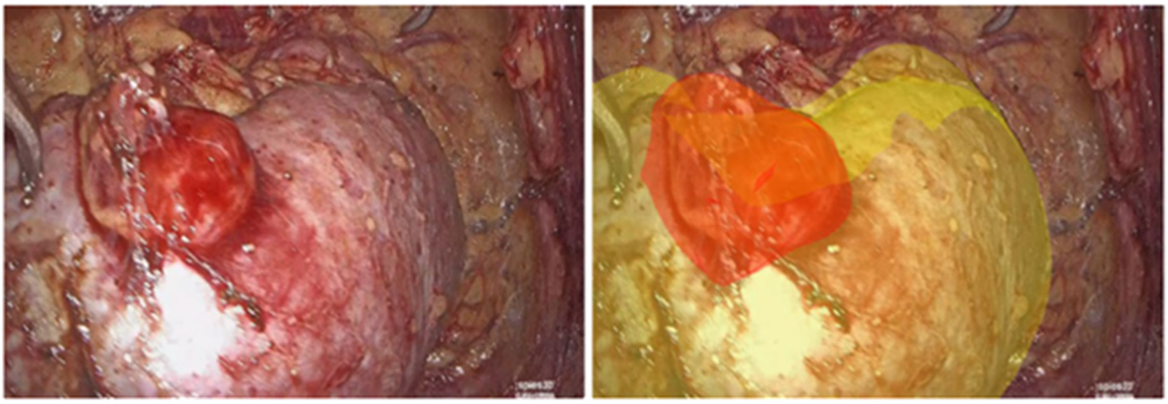

Figure 17. Results of human kidney in vivo data navigation [86]. Accurate laparoscopic display of the location of the kidney (yellow) and the tumor (red).

Intraoperative navigation is one of the most widely used areas of registration technology, and real-time registration can help surgeons improve surgical precision and reduce surgical risk. Currently, registration methods applied to cardiac surgery are gradually maturing, using the characteristic structures of organ tissues and denoising methods to achieve precise and stable 3D-2D matching, freeing the surgery from external tracking systems. For orthopedic surgery, different similarity measures and optimization algorithms are often used to tune the registration process to achieve precise positioning of deformable surgical instruments and trajectories. In addition, in oral and maxillofacial surgery and minimally invasive abdominal surgery, accurate registration of organs and tissues can be achieved without the need for external reference marks, which improves the efficiency of surgery. However, due to the presence of intraoperative occlusion and environmental interference, further improvement of registration accuracy and speed is still an urgent need for intraoperative navigation applications.

2.2.3. Postoperative Evaluation

The purpose of postoperative evaluation is to evaluate the surgical outcome, understand the patient's prognosis, and develop a follow-up treatment plan. Zheng et al. [90] proposed a 3D-2D registration framework for evaluating hip arthroplasty, which instead of using mutual information maximization for registration, merges spatial information into a Kullback-Leibler derived variational approximation via the MRF model [91]. The similarity metric incorporating spatial information can effectively deal with the problem of being obscured by gonads in X-rays, and the registration effect is shown in Figure 18. Jaramaz et al. [92] proposed an registration method for measuring the position of the acetabular cup after total hip arthroplasty. This method uses the mutual information method and pixel masking method [93] to eliminate bony structures that block the line of sight, thus avoiding misregistration. However, patients must undergo a pelvic CT scan during the consultation, and to reduce the complexity of postoperative evaluation, Zheng et al. [94] developed a 3D-2D deformable registration method for evaluating postoperative acetabular cup orientation. This method uses a single anteroposterior X-ray image to instantiate a model of the patient's pelvic surface, thus allowing the assessment of postoperative acetabular cup orientation without the need for a CT examination.

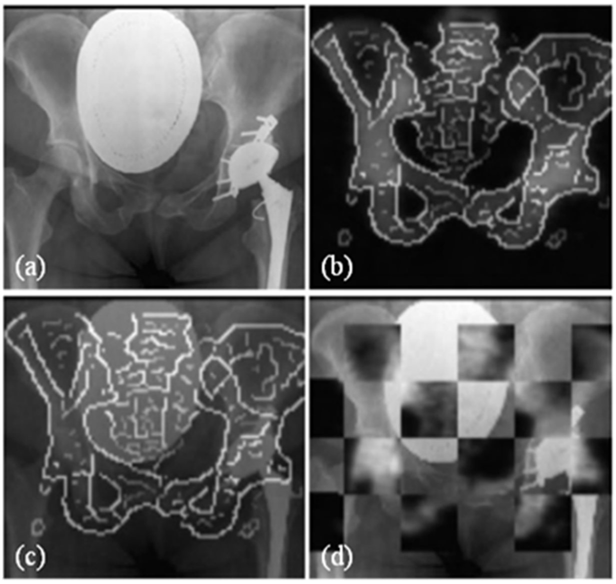

Figure 18. (a) Original X-ray image, (b) DRR created from subsampled CT data with its Canny edge detector extracted edges, (c) overlay of extracted edges on the X-ray image, (d) check board display of DRR and X-ray images [90].

Because of the complex and variable status of knee implants, registration techniques contribute to a better postoperative evaluation. Saadat et al [95] proposed a 3D-2D registration method for assessing the status of knee implants, which eliminates the need for postoperative CT scans and enables postoperative 3D analysis based on a single knee implant radiograph by using the edge position difference as a similarity metric and combining it with a gradient descent algorithm [96] to optimize the parameters, improving the speed and robustness of the registration. Kim et al. [97] developed an registration method for postoperative 3D analysis of total knee arthroplasty. This method makes the assessment of implant status, lower extremity registration, and gap balance easier by calculating the relative angle of the implant to the lower extremity bone, and the effect of this registration is shown in Figure 19. At the same time, only two orthogonal orientations of the X-ray images are required for the evaluation and analysis at any moment, which facilitates the physician's examination of the patient's knee condition. Morita et al. [98] proposed an registration method for assessing the in vivo motion of the implanted knee, which uses particle filters [99] to estimate the postural position of the femoral and tibial implants on the DRR, and taking full account of the continuous knee motion reduces the time required for registration.

3D-2D registration techniques can also address other clinical challenges. Xie et al. [100] proposed a deformable registration method for postoperative target area outlining in breast cancer. The introduction of point metric and masking techniques into the intensity-based B-spline [101] registration method can effectively eliminate the effects caused by tumor resection and jacket insertion. CT delineation of the breast contour is important for postoperative radiotherapy as well as for the evaluation of patients undergoing breast-conserving surgery [102]. Otake et al. [103] developed and evaluated a 3D-2D registration method for application in orthopedic or neurosurgery.

The method is groundbreaking in modeling the projection geometry using nine degrees of freedom while finding the optimal model parameters using gradient-dependent similarity measures and derivative-free optimization methods [104]. This method ensures registration despite certain perturbations in degrees of freedom and solves the problem of restricted location of the detection instrument. Due to the variability of individual knee posture, Kang et al. [105] proposed an registration method applied to assess the tunnel position after anterior cruciate ligament reconstruction. This method uses the image contour as feature information and then estimates the image registration using the probability density of the von Mises-Fisher-Gaussian mixture distribution [106], which is optimized by an expectation maximization algorithm [107]. The physician can also determine the tunnel location without using CT images.

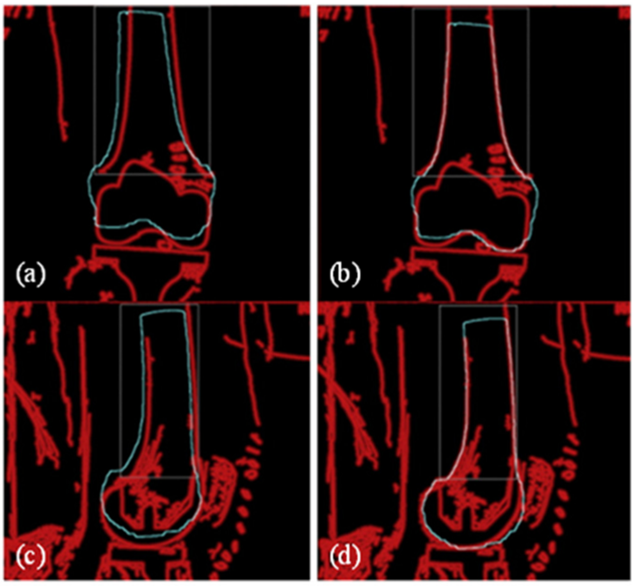

Figure 19. Femoral model registration results (left column: before registration, right column: after registration) [97]. As can be seen from the figure, the contours of the femoral model from the virtual projection image are perfectly aligned with the contours of the actual X-ray image

3D-2D registration methods play an important role in assessing the quality of surgery and in developing follow-up treatment plans. Specifically, areas such as monitoring the status of the implant and outlining the radiotherapy target area postoperatively require registration techniques for stereoscopic analysis. Due to the complex structures within the pelvis, hip arthroplasty is susceptible to interference from physiological structures such as the gonads. Registration techniques can not only eliminate the obscuration of radiographs, but also simplify the process of assessing the acetabular cup orientation. In addition, the stability status of the knee implant is key to postoperative evaluation, and improved registration methods improve accuracy and speed, and enable 3D motion analysis using only X-ray images. The registration technique also helps to evaluate the treatment outcome of breast-conserving surgery, neurosurgery, and ligament surgery. Reducing the complexity of post-operative evaluation and allowing physicians to accurately and easily determine patient prognosis are the focus of future research in 3D-2D registration methods.

2.3 Evaluation of 3D-2D Registration Methods

A necessary step before any registration method can be widely used in clinical practice is the evaluation and validation of the method. Currently, one way to evaluate registration techniques is based on highly accurate "gold standard" datasets. Tomaževič et al. [108] proposed a 3D-2D registration evaluation method based on the generation of reliable "gold standard" data. The method designs a lumbar spine model with benchmark markers, and then establishes a precise correspondence between 3D and X-ray images to assess the accuracy of registration by determining the target registration error. To overcome the impact of the above methods that cannot assess the variable contrast and mobility of soft tissues, Pawiro et al. [109] developed a pig head dataset with additional benchmark markers to obtain realistic data with bones and various soft tissues for accurate validation of 3D-2D registration algorithms. In addition, D'Isidoro et al. [110] proposed a standardized evaluation method for 3D-2D registration of the hip that introduces a gold standard validation dataset consisting of a CT scan of a female hip and 19 2D fluoroscopic images in different views, while using a multiple projection point criterion to reduce the effect of noise. To enhance the generalizability of gold datasets, Madan et al. [111] proposed a framework for automatic generation of gold standard registration datasets.

In addition, the use of standardized evaluation methods helps to elaborate the potential clinical applications of registration methods. The standardized evaluation method process consists of generating an evaluation image dataset, selecting evaluation criteria, designing evaluation metrics, and determining the final evaluation protocol to evaluate the effectiveness of the registration method in a generalized manner [112]. Jannin et al. [113] proposed a framework for evaluating medical image processing. The reference standard for this framework is the exact or approximate solution from scientific experiments, or the combined results of multiple independent registration methods, or expert solutions, thus increasing the acceptance of registration methods for many clinical applications and accelerating the formal introduction of the technology into use. Kraats et al. [114] introduced a standard evaluation method to obtain accurate registration of 2D images with 3D images by rotating the geometry of the X-ray imaging system in 3D, while identifying registration failure criteria in order to facilitate the evaluation of the registration method. In addition to assessment methods, Jannin et al [115] argued that assessment metrics need to be defined and selected according to the role of the registration method in the clinic and systematically consider the impact of model uncertainty caused by propagation during image-guided therapy.

Standardized evaluations can determine the performance and limitations of 3D-2D registration for objective comparisons between methods. Currently, the generation of gold standard datasets and the design of sound evaluation criteria and metrics can optimize the evaluation process of 3D-2D registration. Most of the "gold standard" datasets are only applicable to the evaluation of registration methods in a particular domain, so the development of automatic gold standard dataset generation methods can enhance the universality of the evaluation methods. In addition, standardized evaluation schemes provide accurate evaluation metrics for hypothesis testing and statistical analysis of registration results. Although the evaluation methods are publicly available, some 3D-2D registration methods are validated in non-public or simulated datasets, making comparisons with other methods impossible [116]. In the future, extending the publicly available gold standard dataset and enhancing the broad applicability of validation techniques are important research areas for evaluating registration methods.

3. Discussion

This paper reviews various mainstream methods of 3D-2D medical image registration, application scenarios and their evaluation methods. The main registration methods investigated in this paper include intensity-based, feature-based, and gradient-based. Intensity-based registration methods rely on the information contained in voxels and pixels in 3D and 2D images to find the correspondence between images, which can be improved by various similarity measures and optimization algorithms to improve registration accuracy and remove surgical background interference. However, intensity-based registration methods have some disadvantages, the first one being the loss of valuable 3D information due to 3D to 2D projection [116], and the second one being that their registration speed is reduced by the fact that the method uses all the information of the image. Feature-based registration methods use the structural features of interest to find the registration parameters that allow the image to be optimally matched, among which the ICP algorithm is widely used and its registration speed is high. However, its accuracy depends on the initial rotational pose of the registration data. Gradient-based registration methods combine intensity information and gradient features to achieve optimal matching between images, and gradient correlation techniques can be used to reduce motion errors, thus further improving registration accuracy and speed. Today, the more widely used clinical methods are those based on structural features and gradient information, because both of these methods can provide physicians with fast registration of target organ tissues.

In addition, the 3D-2D registration investigated in this paper is mainly used for preoperative disease diagnosis, intraoperative navigation tracking, and postoperative evaluation. The registration method for preoperative diagnosis can assist the surgeon in planning the extent of the lesion and treatment planning, thus ensuring the quality of the surgery. At the same time, such methods not only broaden the doctor's vision and senses to diagnose complex diseases, but also reduce the patient's physical damage caused by diagnostic tests. In addition, registration methods applied to intraoperative navigation are the most widely used in clinical applications and can help improve surgical precision and reduce surgical risks. Such methods enable precise intraoperative registration, providing the surgeon with a visual 3D image of the tissue and organs in the focal area, thus enabling more precise operations, while eliminating the need for external tracking systems or reference markers during the procedure, reducing surgical complexity and patient discomfort. However, improving the accuracy and speed to ensure precise intraoperative image registration in real time remains a challenge in this field. In addition, assessment of the quality of the surgery and modification of the subsequent treatment plan are also areas of application of registration methods. Such methods are useful for postoperative stereoscopic analysis of large and complex surgeries such as hip and knee, and also have an important role in removing occlusions and delineating postoperative radiotherapy target areas [100]. Ultimately, standardized data sets and assessment frameworks are key to evaluate the effectiveness of registration methods.

Human factors will hinder the acceptance and acceptance of 3D-2D registration methods [117]. Most registration methods require manual marking of feature information to achieve accurate registration, however, this method makes the registration process human-involved, which can lead to increased time spent and subjective errors. In addition, even though the gold standard dataset and evaluation framework for assessing registration methods can enhance the comparability of different registration methods, the so-called "gold standard" is mixed with subjective factors of experimenters, which makes the evaluation of method effectiveness unstable and cannot determine method merit.

In the future, registration methods will further broaden the scope of applications, including new directions in the medical field, unmanned vehicles, aerospace, and other fields. The prevalence of malignant tumors is increasing year by year, and early detection and treatment is the key to cure cancer. The registration method can use medical images to identify the location, size and pathological type of tumors for early screening. In addition, neurological diseases such as epilepsy, Parkinson's disease, and Alzheimer's disease are incurable, making early prevention particularly important. Future registration techniques could enable subpixel-level matching of the basal nuclei of the brain to determine the morphological location of important brain structures more precisely to prevent the occurrence of these diseases [118]. With the development of unmanned driving technology, registration techniques contribute to assisted localization of unmanned vehicles [119], combining deep neural networks to achieve registration of source and target point clouds to ensure safe driving. Remote sensing technology is an important way to provide earth observation data, but it has a wide range of imaging models. Therefore, it requires registration techniques to produce accurate and complete image information [120].

4. Conclusion

In this paper, we provide an overview of 3D-2D registration methods for preoperative 3D CT/MRI images and intraoperative X-ray and ultrasound images. We investigated the characteristics of the registration methods, the application scenarios and the evaluation methods. Each registration method has its unique advantages, but there is also room for further improvement. The intensity-based registration method uses all the pixel information of the image for registration, and achieves high accuracy matching at the cost of reduced registration speed. The feature-based registration method achieves registration by extracting structural features of interest, reducing the amount of data involved in the operation and the registration time. The gradient-based registration method incorporates gradient features and intensity information, and achieves a better balance in maintaining matching speed and accuracy. In fact, 3D-2D registration has been gradually applied to clinical applications as a mature image processing technique. With the advancement of technology, registration can perform functions such as planning the extent of lesions, segmenting vital organs, tracking navigation in real time, and evaluating patient prognosis. In addition, assessing the quality of matches for registration methods is critical for clinical application, and the process is based primarily on standardized data sets and an evaluation framework to ensure comparability between methods. Currently, 3D-2D registration methods are facing new challenges that focus on reducing physician complexity and improving patient discomfort while further improving accuracy and speed.

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