Part - II

USING
CONVENTIONAL APPROACH
FOR
DEFORMABLE REGISTRATION

CHAPTER 4

NON-RIGID REGISTRATION OF MULTIMODAL IMAGES (ULTRASOUND AND CT) OF LIVER USING GRADIENT ORIENTATION INFORMATION

Highlights of the Chapter

- *Gradient information from the images is incorporated in the objective function.*
- *Slice selection is performed to find the best matching preoperative CT image.*
- *Quantitative evaluation shows the algorithm is capable enough for clinical applications.*

Abstract:

Image registration is considered as a highly challenging task which is used in various medical applications such as diagnosis and image guided interventions. Registration is performed with medical images captured via different modalities and labeled as moving and fixed images. The transformation of the moving image is achieved by minimizing an objective function through updating the parameters of transformation. The existing techniques have some drawbacks in terms of speed, performance level and accuracy. Considering the limits, a new algorithm for non–rigid registration is proposed in this paper which is executed using the Ultrasound (US) and Computed Tomography (CT) images of Liver. The algorithm includes segmentation of liver surface, selection of best matched slice using similarity measure, calculation of objective function and estimation of transformation. The proposed method is applied to three clinical datasets and quantitative evaluations are conducted. Visual examinations

and experimental results verifies a lower level of registration error and a higher level of accuracy which makes the algorithm acceptable for clinical applications.

4.1. Introduction

Imaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT) etc. are widely used in various clinical diagnosis and research areas as these techniques provide output in form of image with a large amount of detailed data. Since the systems are bulky and expensive, the popularly utilized imaging system is the Ultrasound (US). The process is non-invasive as well as occurs in real time. For the abdomen portion, the US scanning is frequently performed for diagnosis, ethanol injection therapies, biopsies etc. But clinicians often face problems while examining organs or regions, due to the low image quality of the US. To overcome the limit, several researches have been carried out to register a US image with its corresponding CT/MR image to provide detailed and clear information about the anatomy of the organ or lesions. Registration is the process of aligning images (captured by different modalities) geometrically on a single spatial plane. For multimodal images, the estimation of relationship between intensity values of corresponding pixels is very complex. Feature based registration is mostly used for multi sensor image registration methods where edges and points are taken as salient features as they are invariant to intensity changes. These methods can find the transformation parameters for the registration easily, after extracting and minutely obtaining the relevant features and their correspondences from both the images. As the selected features should be spread all over the image for a distinct and reliable registration, gradient information is used as an alternative of salient features. It focuses on the calculation of correlation based similarity measures using gradient information after converting the US image and/or CT/MR image into different type(s). However in most of the cases, gradient magnitude may not be correlated due to difference of contrasts between images.

The relationship of pixels between CT and US images based on which an objective function or any similarity/dissimilarity measure is computed, varies with organs. Generally, the objective function is calculated for a particular organ in which the registration will be applied. Though in [1], an organ independent objective function was tried to develop. An ICP based registration algorithm was proposed in [2] where the liver surface was taken as features and the objective function was the average closest distance between the feature samples. The algorithm was modified in [3, 4] by using additional Power Doppler US image and multilevel B-splines [5] for modelling the transformation. In [6], a registration scheme was developed on the basis of a similarity measure computed using pixel intensity and gradient magnitude and orientation. Research was conducted in [7] by manually selecting corresponding landmark pairs and by minimizing intensity and gradient based similarity measure while configuring the transformation based on a B-spline free form deformation (FFD) model. Some researchers had also used intensity based similarity measures like Mutual Information (MI) [8] rather than features as it represents statistical dependence of intensity values between images [9]. To overcome the problem of local maxima and incorrect global maximum problem in MI based approaches, spatial information was also included with MI [10]. To align same gradient locations and similar gradient orientations between two images, in [11], MI was modified with the local gradient term. But as stated previously, gradient magnitude in multimodal images is not capable of providing sufficient information which is reliable enough for the registration process.

An image based non-rigid registration system for liver image registration between B-mode ultrasound and CT images is proposed in this paper. The developed algorithm focuses on the segmentation of liver surface from the US and CT images, correlates the intervention US image to its best matched CT image based on similarity measure and registers both images with a good registration accuracy.

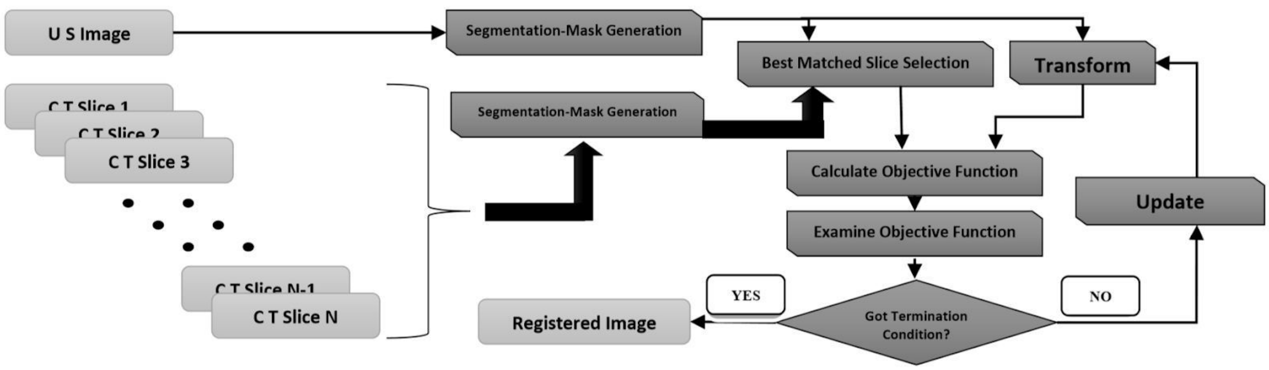

Fig. 4.1. Block diagram of proposed algorithm.

The paper is organized as follows. In Section 4.2, the details of the proposed registration system and algorithms are described. Section 4.3 consists of experiments with clinical datasets and experimental results. Finally, in Section 4.4 and 4.5, conclusions are drawn and acknowledgement is provided.

4.2. Methodology

4.2.1. Overview of the Algorithm

Fig. 4.1 shows the structure of the proposed algorithm. N number of CT slices has been taken as an input image set. An US image is chosen as intervention. The US image and the whole

CT image set have been processed using different processing algorithms for mask generation to extract the liver surface or diaphragm. The masked liver surface images (both US and all CT image sets) are taken in account for best matched slice selection. For the selection process, a similarity measure has been adopted which is calculated using the difference between edge orientations in the surface area of both the images. The maximum measured value of the similarity index corresponds to the best matched slice. After slice selection, features are extracted from two images (1 CT and 1 US image) which helps in the calculation of objective function. The US image is then transformed with predefined parametric values and the value of objective function is checked. Now, the optimization process starts and it continues till the objective function is minimized to a certain value or the number of iterations are completed. For each iteration, transformation parameters are updated. Finally, the transformation is optimized and the transformed US image is registered with the pre-selected CT image.

4.2.2. Liver Surface Features

The surface features of the liver are highly useful for calculating the similarity measure and the objective function to estimate the transformation which is the aim of registration. As the surface is clearly visible for both the CT and US images, it can be tracked and utilized using image processing. The focus is on the intensity and gradient information of the both images. If the acoustic impedance difference is high between inside and outside liver surface, it produces a high reflectivity when scanned using B-mode ultrasound. So, the boundary of the liver surface (or diaphragm) produces high intensity values in US images. However, in CT images, the liver surface region shows almost similar intensity values to its surroundings.

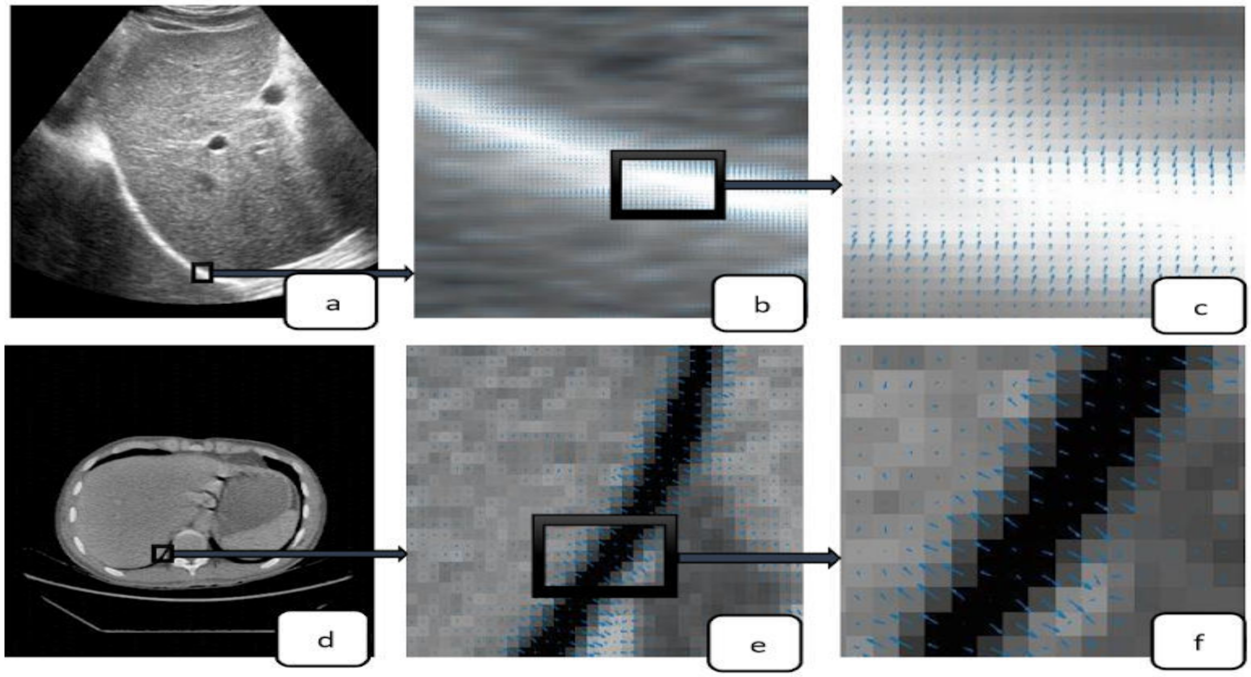

Fig. 4.2. Gradient orientation of liver surface (a), (b), (c) US image,

(d), (e), (f) contrast enhanced CT image

While in the enhanced CT image, the liver surface shows high gradient values which can be related to the surface in the US image. Also the gradient orientation provides useful information as it is present in both CT and US images and can strongly correlate between them. The gradient orientation of the liver surface is demonstrated with arrows in Fig. 4.2.

4.2.3 Segmentation (Mask Generation)

The motive of segmentation in this algorithm is to produce an envelope in both CT and US images, which will track the liver surface and create a mask for further procedures. Two different segmentation algorithms are applied on enhanced CT and US images based on the intensity values of pixels. First contrast enhancement procedure is applied to the CT images.

Next, the enhanced CT images are taken in account for surface selection. A simple technique of isolating the ROI using morphological operations [12] is adopted where the largest connected component present in the image is isolated. After getting the liver segmented from the image, a mask is generated at the surface and the image of the masked liver is merged again with the original enhanced CT image as shown in Fig. 4.3.

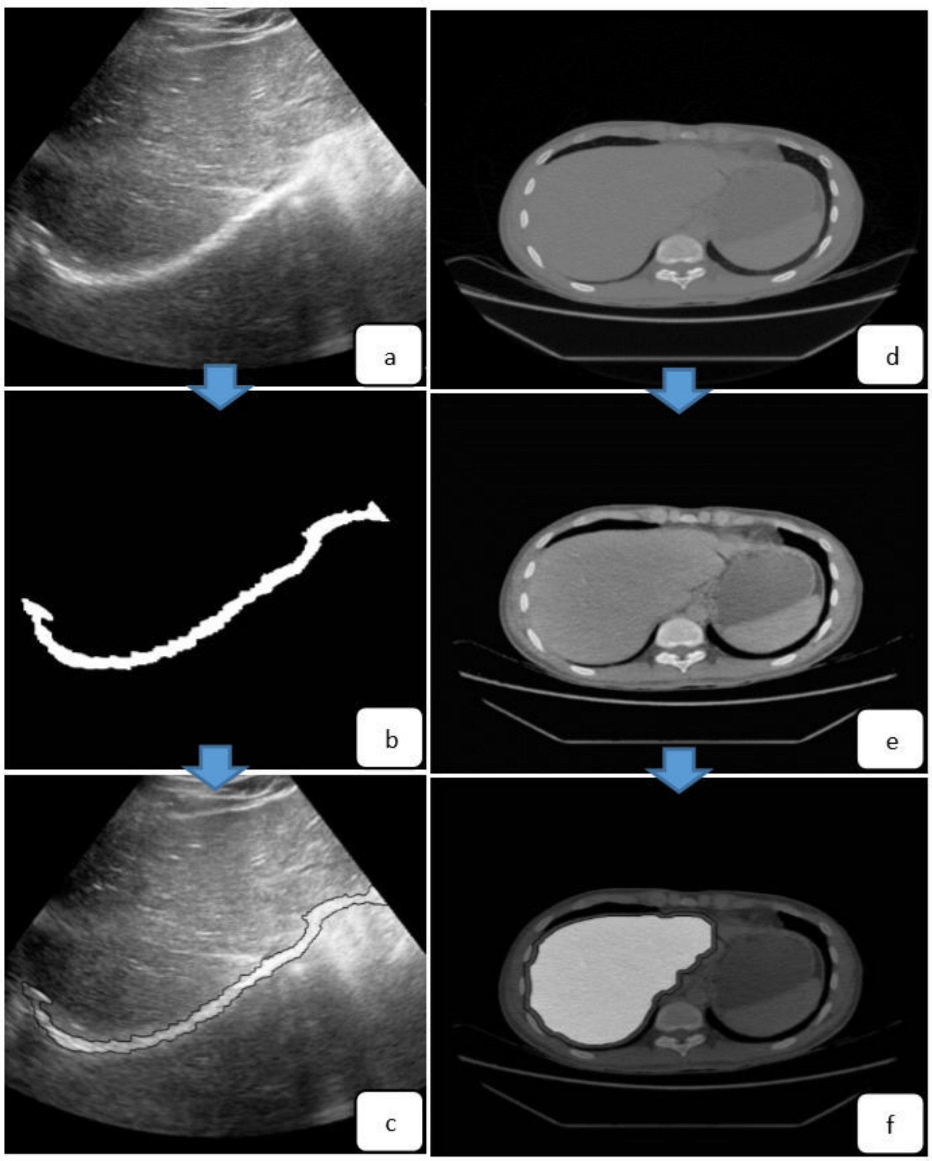

Fig. 4.3. Mask Generation liver surface: (a), (b), (c) US image, (d), (e), (f) CT image.

The frequent intensity variations in US images makes the segmentation process difficult. As mentioned above, the liver surface produces higher reflection which contributes large intensity values in the surface region of the US image. So the connected components with high intensity values are tracked after implementing an adaptive binarization and morphological operations with proper structure elements. Finally a mask has been created along the edges of the liver surface region (shown in Fig. 4.3). The masked US & CT images are then taken in account for further computations.

4.2.4. Calculation of Edge Orientation

The corresponding edges marked in CT and US images has been used to compute information related to its gradient vectors. Though the gradient magnitudes of the edge pixels of the liver surface differ, the gradient orientations are almost similar. To calculate the edge directions, an eigen analysis of structure tensor is adopted.

$$S_T(\nabla I_m) = (\omega_1 \ \omega_2)\begin{pmatrix} \mu_1 & 0 \\ 0 & \mu_2 \end{pmatrix}\begin{pmatrix} {\omega_1}^T \\ {\omega_2}^T \end{pmatrix} \tag{4.1}$$

Here, eigenvalues μ_1 and μ_2 represent magnitudes of ω_1 and ω_2 while those denote the directions of maximum and minimum variation of intensity respectively. The maximum and minimum eigenvalues of pixels located on the edge region must be high. On this basis, ω_1 is taken as edge orientation and (μ_1-μ_2) as gradient magnitude. So, the orientation coincidence can be described as

$$E_{OC}\,(\Delta\varphi) = \tfrac{1}{2}\,(1 + cos\ (2\Delta\varphi)) \tag{4.2}$$

where the difference between the edge orientation angles in CT and US images is defined by $\Delta\varphi$.

4.2.5. Best Matched Slice Selection

The slice selection operation has been performed to find out a best matched CT image from a set of preoperative CT images for achieving higher registration accuracy with the selected US image on the basis of a similarity measure. The similarity measure is gradient based and the calculation for the same can be defined as follows.

$$SM = \left(N_{R_{CT}} + N_{R_{US}}\right)^{-1} . \left(\sum_{p \in (R_{CT} \cap R_{US})} 2.E_{OC}\left(\Delta\varphi_p\right)\right) \tag{4.3}$$

R_{CT} and R_{US} are the liver surface regions of CT and US images respectively, while $N_{R_{CT}}$ and $N_{R_{US}}$ represent the number of pixels in those regions. Also $\Delta\varphi$ denotes the difference of gradient orientation angle on the corresponding points of above mentioned regions. The maximum value of SM indicates the best matched CT slice for an US image.

4.2.6. Calculation of Objective Function

Objective function is based on mutual information (MI) and 3-D joint histogram which includes the axis of edge orientation along with the axes of representing the pixel intensity. While registering, it is necessary to minimize the uncertainty left in an image, considering another. Also the uncertainty of edge orientation coincidence is to be minimized to perform the registration correctly. So, the entropy based objective function can be defined as

$$E\left(I_{m_{CT}}, I_{m_{US}}\right) = H\left(I_{m_{CT}} | I_{m_{US}}\right) + H\left(I_{m_{US}} | I_{m_{CT}}\right) + H\left(E_{OC} | I_{m_{CT}}, I_{m_{US}}\right) \tag{4.4}$$

And it becomes,

$$E\left(I_{m_{CT}}, I_{m_{US}}\right) = H\left(I_{m_{CT}}, I_{m_{US}}, E_{OC}\right) - M\left(I_{m_{CT}}, I_{m_{US}}\right) \tag{4.5}$$

Where MI is stated as, $$M\left(I_{m_{CT}}, I_{m_{US}}\right) = \left[H\left(I_{m_{CT}}\right) + H\left(I_{m_{US}}\right) - H\left(I_{m_{CT}}, I_{m_{US}}\right)\right] \tag{4.6}$$

To overcome the false global minimum problem arose by partial overlapping, the global spatial function is also introduced to the objective function.

$$C\left(I_{m_{CT}}, I_{m_{US}}\right) = (N_{CT} + N_{US})^{-1} . \left(\sum_{p \in (R_{CT} \cap R_{US})} \left(1 + cos\left(\Delta\varphi_p\right)\right)\right) \tag{4.7}$$

Where C is the coincidence measure for global similarity of edge orientations between two images. So, the modified objective function is,

$$F\left(I_{m_{CT}}, I_{m_{US}}\right) = \left(1 - C\left(I_{m_{CT}}, I_{m_{US}}\right)\right) . \left(E\left(I_{m_{CT}}, I_{m_{US}}\right)\right) \tag{4.8}$$

Since the edges provide high gradient magnitude in the CT images, the entropy for CT images is calculated with its gradient magnitude ($|\nabla I_{m_{CT}}|$) rather than its intensity value. The updated objective function can be represented as

$$F\left(I_{m_{CT}}, I_{m_{US}}\right) = \left(1 - C\left(I_{m_{CT}}, I_{m_{US}}\right)\right) . \left(E\left(|\nabla I_{m_{CT}}|, I_{m_{US}}\right)\right)$$

$$= \left(1 - \frac{\sum_{p \in (R_{CT} \cap R_{US})} 2.E_{OC}\left(\Delta\varphi_p\right)}{(N_{CT} + N_{US})}\right) . \left(H\left(|\nabla I_{m_{CT}}|, I_{m_{US}}, E_{OC}\right) - M\left(|\nabla I_{m_{CT}}|, I_{m_{US}}\right)\right) \tag{4.9}$$

The objective function is minimized by an optimization algorithm while updating the parameters.

4.2.7. Transformation Estimation for Registration

For registering the US image and the best matched CT image, a registration algorithm using transformation has been applied. As the suitable values of the parameters are not calculated yet, the registration process will not provide the best output. Hence an optimization algorithm is utilized to compute the best transformation parameter values by constantly minimizing the objective function to a certain value till the maximum iteration reaches.

$$t_p^{\cdot} = arg\ min_{t_p}\ F\left(I_{m_{CT}}, I_{m_{US}}\ ; t_p\right) \tag{4.10}$$

Here, B-spline free form deformation (FFD) algorithm is adopted for pixel based registration. A grid of B-spline control points has been constructed which controls the transformation of the US image. The objective function is used to measure the registration error between the US (moving) and CT (static) image. The gradient descent optimization scheme is utilized to move the control points to achieve the optimal registration between both images with minimal registration error.

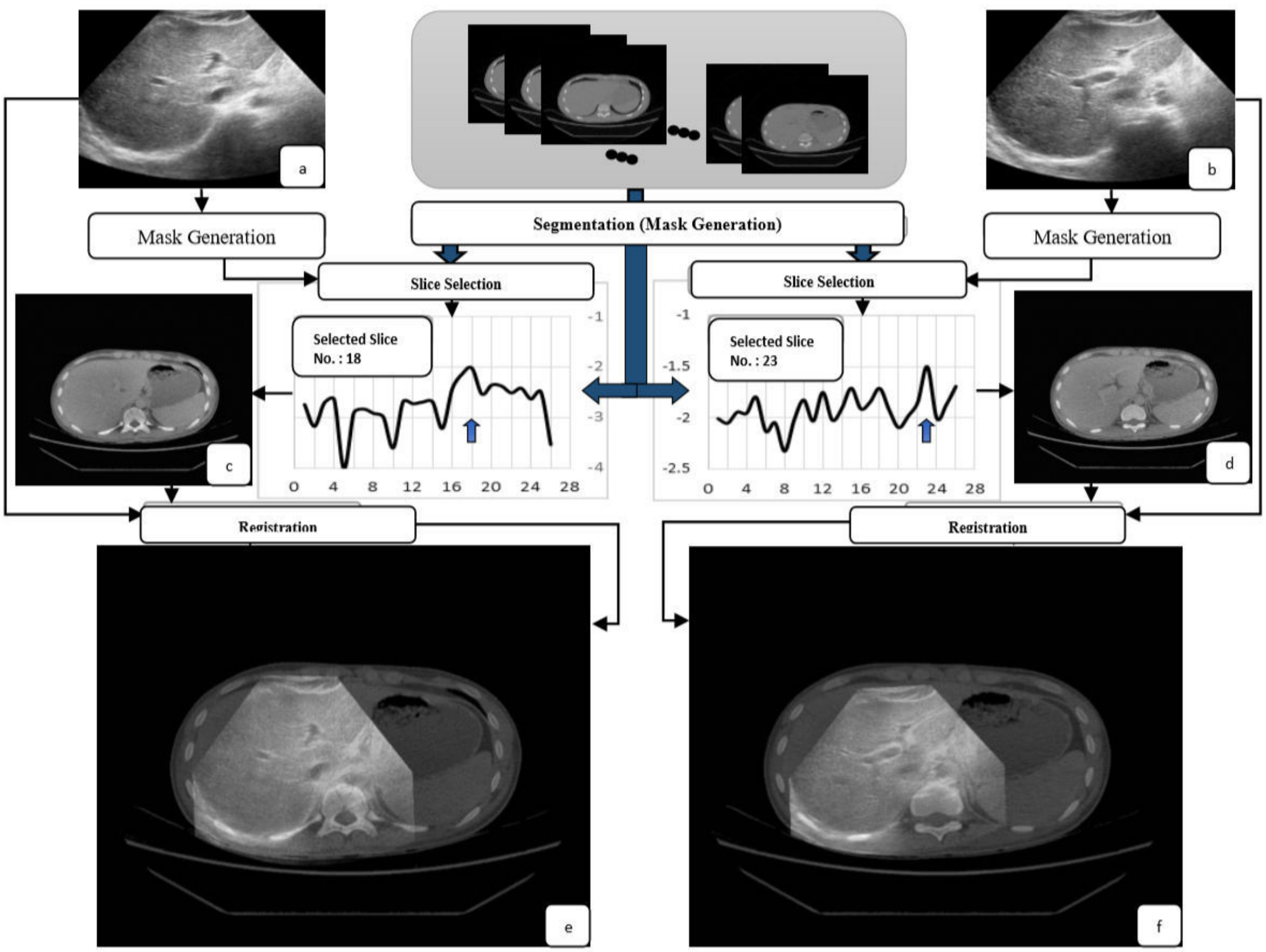

Fig. 4.4. Registration: (a),(b) US image, (c),(d), selected CT image, (e),(f) US-CT registered

4.3. Experimentation

4.3.1. Data Acquisition

Three CT-US datasets (consist of 26 CT and 6 US images of the same volunteer) have been used for testing and quantitative evaluation. A 64 slice CT scanner machine (multi-detector row scanner, 64 rows of detectors) of GE Medical Health Systems was used to acquire the CT images (dimension 512×512; pixel size 0.65×0.65). The B-mode US images were acquired with a 3.5-MHz transabdominal electronic array transducer of Ultrasonography machine of Philips Medical System. For the experiment, the CT and US images were acquired with breath-hold.

4.3.2. Experimental Results

Fig. 4.4 shows the registration outcome of two US images selected as input. The algorithm clearly fetches two CT images for the input respectively based on the similarity measure and correctly registers them with a low level of error. For quantitative evaluation, a distance based measurement is adopted which performs the measurement on the basis of the anatomical features of the liver surface. The distance measure is defined below.

$$D_{CT\_US\_LS} = 2.(N_A + N_B)^{-1} \sum_{p_{US} \in B} min_{p_{CT} \in A} \{d(p_{CT}, T_{LS}(p_{US}))\} \tag{4.10}$$

T_{LS} denotes the transformation of the US image, while *d(.)* represents the distance function. N_A and N_B are the number of sample points taken in Set A and B respectively which consist of the features points extracted from CT and US images. The performance evaluation of proposed non-rigid registration is shown in Table I in terms of distance measurement ($D_{CT\_US\_LS}$).

Table 4.1. Performance Evaluation of Proposed Algorithm

Parameter	Value: mean (± standard deviation) (mm)		
	DATASET 1	**DATASET 2**	**DATASET 3**
$D_{CT\_US\_LS}$	1.59 (± 0.56)	1.47 (± 0.38)	1.91 (± 0.28)

The performance evaluation clearly indicates that the proposed algorithm has a lower registration error as the overall measured distance is almost 2 mm. For clinical applications, a registration algorithm with distance value below 5 mm is considered as acceptable [2]. This parameter defines the accuracy of the algorithm which is showcased in Table 4.1 and is comparable to existing techniques performed in [1, 3, 4, 6, 7].

4.4. Conclusion

A non-rigid multimodal image registration algorithm is presented in this paper. The anatomical features of the liver surface is taken into account for calculating gradient orientation information to correlate the CT and US images. The algorithm sequentially performs the segmentation followed by best matched slice selection, and estimation of transformation parameters by minimizing the objective function. Quantitative evaluation shows that it is capable of performing registration with a high level of accuracy which is useful for clinical applications.

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