Adaptive visualization for needle guidance in RF Liver Ablation: taking organ deformation into account

Ruxandra Lasowski\textsuperscript{a,b} and Selim Benhimane\textsuperscript{a} and Jakob Vogel\textsuperscript{a} and Tobias F. Jakobs\textsuperscript{c} and Christoph J. Zech\textsuperscript{c} and Christoph Trumm\textsuperscript{c} and Christian Clason\textsuperscript{d} and Nassir Navab\textsuperscript{a}

\textsuperscript{a} Technical University Munich, Chair for Computer Aided Medical Procedures (CAMP), Boltzmannstr. 3, 85748 Garching, Germany;
\textsuperscript{b} Siemens Medical Solutions, Computed Tomography, Siemensstr. 1, 91301 Forchheim, Germany;
\textsuperscript{c} Institute for Clinical Radiology, University of Munich, Grosshadern Hospital, Marchioninistr. 15, 81377 Munich, Germany;
\textsuperscript{d} Technical University Munich, Center of Mathematics, Research Unit M6, TU Munich, Boltzmannstr. 3, 85748 Garching, Germany

ABSTRACT

Interventional procedures on deformable organs pose difficulties for the radiologists when inserting the probe towards a lesion. The deformation due to the breathing makes a reliable and automated alignment of the interventional 2D CT-Fluoro to the pre-interventional 3D CT-Volume very challenging. Such alignment is highly desirable since, during the intervention, the CT-Volume brings more information as it is enhanced with contrast agent and has a higher resolution than the CT-Fluoro slice. A reasonable solution for the alignment is obtained by employing a robust optimization technique. However, since we would like to help the needle guidance towards the lesion, due to the involved deformation, a single slice of the 3D CT-Volume is not satisfactory.

The main contribution of this paper consists in visualizing slices of the 3D CT-Volume that are resulting from the out-of-plane motion parameters along weighted isosurfaces in the convergence basin of the similarity function used during the alignment. This visualization copes with the uncertainty in estimating the deformation and brings much more information than a single registered slice. Three experienced interventional radiologists were consulted and their evaluation clearly highlighted that such visualization unfolding the neighborhood with the belonging structures, like vessels and lesion spread, will help the needle guidance.

1. INTRODUCTION

Patients with unresectable primary liver tumors and metastases can be interventionaly treated with Radiofrequency Ablation (RFA). The percutaneous needle insertion toward the lesion can be performed under the guidance of different imaging modalities like CT, CT-Fluoro, Ultrasound, iMRI. Our clinical partners perform the RFA under CT-Fluoro guidance. The registration of the interventional CT-Fluoro images to the contrast-enhanced 3D CT-Volume would allow to display the target lesion and the corresponding structures in the intervention room with the high quality of the pre-interventional CT-Volume. However, to perform a deformable registration and present one deformed slice as a solution in the intervention room, is for this application not feasible. The reasons for this ill-posedness are listed below. RFA is performed while the patient is breathing continuously, whereas the pre-interventional CT-Volume is usually acquired during full inspiration to assess the pleural cavity in its full extension. Breathing instructions during the intervention are common, but the conditions are not the same due to moderate pain and stress. Furthermore, the CT-Fluoro slice is noisy due to the lower radiation dose applied (e.g. 59mA in Fluoro mode, 260mA for diagnostic scan) and thicker (4mm or 6mm) than the pre-interventional scan (1mm or 3mm). Without proper contrast in the intrahepatic vessels and the liver

Further author information:
Ruxandra Lasowski: E-mail: micu@cs.tum.edu,
Nassir Navab: E-mail: navab@cs.tum.edu
parenchyma, metastases and vessels can poorly be appreciated using CT-Fluoro slices. For primary liver tumors (HCC) visualization with the CT-Fluoro image is easier, in case of previous transarterial chemoembolization treatment with lipiodol oil. Attempts for a non-rigid 2D/3D registration employing the DEMONS algorithm [1] did not really succeed even for very small deformations. In this paper, instead of targeting a unique solution for the registration process, we are proposing a set of solutions defined in the neighborhood of the registration result. In this neighborhood, out-of-plane motion parameters samples on the isosurfaces of the minimized cost function are found using a line search strategy. This is based on the assumption that the optimization path of the similarity measure during minimization encounters uncertainty along flat hypersurfaces. The visualization of a subvolume in the pre-interventional volume brings much more intuitive information to the interventional radiologist than one single slice. This information includes for instance the vessels and also lesion spread and distribution. Therefore, the needle guidance toward the lesion is improved. In addition, this could result in less radiation dose for the patient and examiner.

1.1. Related Work
In [2], the authors report that they observed a weak perspective for the out-of-plane rotations similar to the DRR-based registration, where the uncertainty arrives at the translation along the direction of the normal beam. The authors suggest a second slice as solution to this problem since the new generation of multislice CT-scanner already provide this functionality. In contrast to that solution, we would like to visualize the volume along axes in the parameter space, where the cost function is flat and the uncertainty is high. Rigid slice-to-volume registration for similar applications has been reported in [2], [3]. In [3], slice-to-volume registration is used to align iMRI interventional slices to pre-interventional MRI volume for radiofrequency ablation of prostate cancer. Different cost functions were used at different resolutions. Sufficiently accurate results were achieved for transversal slice acquisitions in order to aid image-guided therapy. In [2], the authors report that the success of the employed cost functions and optimization algorithms highly depended on the breathing motions artefacts. This is also our experience. In order to overcome the breathing motion artefacts, the noise and also the needle artefacts in the CT-Fluoro slice, we are employing a slice-to-volume rigid least-squares minimization. To this end, an Iteratively Reweighted Least-Squares (IRLS) technique is used. Equivalent approaches have been already employed for robust feature-based registration for vascular image registration in [4] and retinal mosaicing in [5]. Similar work regarding visualizing a subvolume, has been proposed in [6], [7]. In contrast to that approach, where the volume is defined by piecewise registration, this paper aims to first obtain a solution to the global registration and then visualize a specific volume that encompasses its neighborhood. This volume takes into account in which projection parameters the registration is most sensitive, and is obtained from the definition of slices defined by motion parameters on weighted isosurfaces.

In the remainder of the paper, we will first describe the method we use to solve the registration problem. Then, we will explain the sampling on weighted isosurfaces, the trajectory computation and the visualization path definition. The validation using ground truth simulations with synthetic data and real world experiments are presented in the fourth section. This is followed by a qualitative evaluation of the adaptive visualization done by three experienced interventional radiologists. Finally, we will conclude by summarizing the presented work.

2. SOLVING THE REGISTRATION PROBLEM
2.1. Parameterization of the 3D transformations
In order to register the 2D CT-Fluoro slice with the 3D CT-Volume, the latter should be projected onto a gray-scale image after having being subject to a 3D rigid transformation. Such transformation can be described by a \((4 \times 4)\) matrix \(T\) that belongs to the Special Euclidean group \(SE(3)\) and that has the following form:

\[
T = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix}
\]

where \(R \in SO(3)\) is the 3D rotation matrix and \(t \in \mathbb{R}^3\) is the translation vector. Such matrix has 6 d.o.f and can be parameterized using the Lie-Algebra \(se(3)\) that corresponds to the Lie group \(SE(3)\) through the exponential
map. Let \( A_i \), with \( i \in \{1, \ldots, 6\} \), be a basis of the Lie algebra \( \mathfrak{se}(3) \). Any matrix \( A \in \mathfrak{se}(3) \) can be written as a linear combination of the matrices \( A_i \):

\[
A(x) = \sum_{i=1}^{6} x_i A_i
\]

where \( x = [x_1, \ldots, x_6]^T \) and \( x_i \) is the \( i \)-th element of the base field. Let the vectors \( b_x = [1, 0, 0]^T \), \( b_y = [0, 1, 0]^T \) and \( b_z = [0, 0, 1]^T \) be the natural orthonormal basis of \( \mathbb{R}^3 \). Knowing that the dimension of the matrices \( A_i \) is \( (4 \times 4) \), the generators for the translation are:

\[
A_1 = \begin{bmatrix} 0 & b_x & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 0 & b_y & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad A_3 = \begin{bmatrix} 0 & b_z & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\]

and the generators for the rotation are:

\[
A_4 = \begin{bmatrix} [b_x]_x & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad A_5 = \begin{bmatrix} [b_y]_x & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad A_6 = \begin{bmatrix} [b_z]_x & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}
\]

where \([b_i]_x\) is the skew matrix associated to the vector \( b_i \). The exponential map links the Lie algebra to the Lie Group: \( \exp : \mathfrak{se}(3) \to \mathbb{SE}(3) \). It exists an open cube \( \mathcal{V} \) such that \( \mathcal{V} \) is smooth and one-to-one onto, with a smooth inverse.

Hence given a coefficient vector \( x = [x_1, x_2, \ldots, x_6] \), the corresponding transformation matrix \( T \) is obtained as:

\[
T(x) = \exp\left(\sum_{i=1}^{6} x_i A_i \right), \quad (1)
\]

See for example [8] for more details concerning this parameterization.

### 2.2. Iterative registration method

A pixel in the 2D CT-Fluoro slice (fixed image) is the result of the projection of a voxel \( \mathcal{X} \). Its intensity in this image is \( \mathcal{I}^{\ast}(\mathcal{X}) \). Further, let \( T \) be the transformation matrix defining a certain pose estimate of the 3D CT-Volume. When projected at this pose, the volume results in an image \( \mathcal{I}(T\mathcal{X}) \). Ideally, registering the 2D CT-Fluoro slice with the 3D CT-Volume consists in finding the transformation matrix \( \hat{T} \) such that:

\[
\forall \mathcal{X}_i, \quad \mathcal{I}(T\mathcal{X}_i) = \mathcal{I}^{\ast}(\mathcal{X}_i) \quad (2)
\]

Due to the high non-linearity of the problem, the registration problem is generally solved iteratively by estimating at each iteration an incremental pose update \( T(x) \) that should be composed with the current estimate \( \hat{T} \) such that a cost function is minimized. The cost function is generally based on the sum-of-squared differences of pixel intensities and, in practice, it does not give satisfactory results for the following reasons: the severe and natural noise of CT-Fluoro slices, due to the low dose applied; the high contrast difference between the pre-interventional volume and the interventional CT-Fluoro slices; the presence of needle in the interventional CT-Fluoro slices. That is the reason why we are using the M-estimators and the Iteratively Reweighted Least Squares (IRLS) process in order to compute the update parameters for the incremental pose \( T(x) \). The cost function considered for this purpose penalizes the largest residues:

\[
f(x) = \sum_{\mathcal{X}_i} \rho \left[ \mathcal{I}^{\ast}(\mathcal{X}_i) - \mathcal{I}(\hat{T}T(x)\mathcal{X}_i) \right] \quad (3)
\]

where the function \( \rho \) is called the robust loss function. There exist many possibilities for the \( \rho \) function e.g. Huber, Cauchy or Beaton-Tukey functions [9]. Basically, they all play the same role: they permit to give different weights to the image differences by putting at a disadvantage the larger residues and at a favor smaller ones (in different manners depending on the function used). The minimization process consists in estimating the weights (that reflect the confidence of each intensity difference), evaluating the vector \( x \) by solving the weighted
system, then reiterate until convergence. With all minimization techniques [10], e.g. Gradient descent, Newton, Gauss-Newton or Levenberg-Marquardt, this approach automatically rejects the outliers, the noise, the needle presence and the high contrast differences (that are not solved by the image normalization). Therefore, the registration does not suffer from spurious measurements and the real global minimum can be better localized.

2.3. Some details concerning the minimization

A Gauss-Newton minimization is used in a multi-resolution approach in order to speed up the process and to help avoiding local minima trap. Specifically, we use an iterative-reweighted least squares [9] to minimize the cost function $f$.

Let $d_i = I(x_i) - I(TTx_i)$, $d$ be the vector containing all the intensity differences $d_i$ and $r_i = |d_i - median(d)|$ denote the case median centered intensity difference residuals with associated variance $\sigma_i$. The median is calculated according to the median of medians algorithm [11], this algorithm insuring linear time calculation. Introducing a weight function $w$ by $\rho'(d) = \psi(d) = w(d) \sigma_i$, we arrive at the following weighted equation system to solve:

$$\sum_{x_i} w(r_i/\sigma_i) J_i^T J_i x = \sum_{x_i} w(r_i/\sigma_i) J_i^T d_i$$

(4)

Here, $J_i = \frac{\partial r_i}{\partial x}$ stands for the Jacobian of the residual, which can be derived as follows: Starting from a first order Taylor approximation of the residual, we have to calculate

$$\frac{\partial I(TT(x),\lambda)}{\partial x} \bigg|_{x=0} = \frac{\partial I(T\lambda)}{\partial \lambda} \cdot \frac{\partial T\lambda}{\partial T} \cdot \frac{\partial T(x)}{\partial x} \bigg|_{x=0}$$

(5)

The first term is a $(1 \times 3)$ matrix and represents the gradient of the image corresponding to the projection of the volume at the pose $T$. The image gradient is computed before the registration process for the whole volume. The second term is a $(3 \times 12)$ matrix, which depends only on the homogeneous coordinates of the considered voxel $\lambda$:

$$\frac{\partial T\lambda}{\partial T} = \begin{bmatrix} \lambda^T & 0 & 0 \\ 0 & \lambda^T & 0 \\ 0 & 0 & \lambda^T \end{bmatrix}$$

(6)

since the gradient generalization to the matrices $\frac{\partial T}{\partial T}$ corresponds to the derivative with respect to each entry of the matrix $T$ (taken line after line). The third term represents the Jacobian of the exponential map with respect to the motion parameters:

$$\frac{\partial T(x)}{\partial x} \bigg|_{x=0} = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 & a_6 \end{bmatrix}$$

(7)

where $\forall i \in [1,6]$, $a_i$ is a $(12 \times 1)$ vector containing the entries of the matrix $A_i$ taken line after line.

As M-estimator, we chose the popular Beaton-Tukey biweight function, which is a strict outliers rejector since it descends very fast toward zero with increasing error differences:

$$\rho(d) = \begin{cases} \frac{a^2}{\sigma^2} \left( 1 - \left( \frac{d}{\sigma} \right)^2 \right)^3, & |d| \leq a \\
\frac{\sigma^2}{a^2} \frac{d}{\sigma}, & |d| > a \end{cases}$$

where the parameter $a = 4.6851 \hat{\sigma}$ and where $\hat{\sigma}$ is a robust estimation of the standard deviation of the inliers. It is usually defined by the Median Absolute Deviation (MAD) given by: $\hat{\sigma} = 1.4826 r_i$.

2.4. Registration results

Here, despite that the projection of the 3D CT-Volume at the initial pose (Fig. 1(b)) is far from the reference 2D CT-Fluoro slice (Fig. 1(a)), the proposed approach succeeds to converge toward the minimum (Fig. 1(c)). The weights image makes it possible to detect the spurious measurements, the noise, the needle presence and the regions suffering from a high contrast differences (see the dark regions in Fig. 1(d)). Figure 1 shows a result of the proposed approach on real data.
3. ADAPTIVE VISUALIZATION

For better spatial orientation, and to increase the confidence in the registration result, not only the minimizer of the registration function $f$ is visualized as a 2D view, but also other views “close” to the minimizer. For this, we choose a set of parameters for which the cost function attains almost minimal value. The corresponding views (along with the minimizing view) are then visualized in a smooth animation. We will now make this precise, starting with the notion of “close views”.

The visualization of the 3D volume on this trajectory brings more information than the single slice. It gives the intuition of slowly exploring the volume in the neighborhood (in real space) of the minimizer. In addition, since the function associating a set of parameters to a 2D view is continuous, projecting the volume with the parameters on this trajectory gives a smooth evolution of the image intensities in the closed loop passing by the minimum (obtained at the registration) and the different points on the isosurface.

3.1. Finding parameters close to the minimizer

For a given $\alpha \in \mathbb{R}^+$, an isosurface of the cost function $f$ defined in the equation (3) is a set $\mathcal{C}(\alpha) \subset \mathbb{R}^6$ given by

$$\mathcal{C}(\alpha) = \{ x \in \mathbb{R}^6 : f(x) = \alpha \}$$

See Fig. 2(a) for an illustration of isosurfaces in $\mathbb{R}^2$ (i.e., isolines). Now, let $\bar{x} \in \mathbb{R}^6$ be the estimated minimizer. To find a certain number of parameters $x_i$ around the minimizer, we use a line search in different directions for points on the isosurface $\mathcal{C}(f(\bar{x}) + \varepsilon)$, where $\varepsilon$ defines the size of the neighborhood in parameter space. In section 4, we explain how, in practice, we choose the directions of the line search and the $\varepsilon$ defining the size of the neighborhood. Each of these points corresponds to a certain pose and therefore to a certain projection of the volume. We call these views cost-equivalent projections (CEPs). See Fig. 2(b) for an illustration of the line search approach and the sampling of an isoline close to the minimizer of a function in $\mathbb{R}^2$. Once the minimizer of the function $f$ is identified and a number of samples on a given isosurface are determined, it is possible to define a trajectory interpolating these points. See Fig. 2(b) for an illustration of a such trajectory.

3.2. Trajectory waypoints

In order to visualize the volume smoothly, we first need to find an optimal trajectory from the minimizer through all of the isosurface sample points $x_i$. Ideally, this trajectory follows the shortest path from the minimizer towards the isosurface, stays on the latter exactly, and aims for the minimizer again.

As the isosurface itself is not analytically known, we use the sample points computed previously as waypoints, and rearrange them in a way that we visit each point once while following a trajectory of minimal length. We expect this path to be of similar merit in our visualization as the ideal trajectory, while being faster to compute. This task is an old problem of theoretical computer science – the Traveling Salesman Problem (TSP) – and cannot be solved deterministically in polynomial time. Therefore, we use the Minimum Spanning Tree (MST)
3.3. Trajectory interpolation

Here, we create a smooth path passing by the ordered points $x_i$ defined above. We interpolate these points in parameter space as elements of the Lie algebra $se(3)$ and convert these vectors via the exponential map into the Lie group $SE(3)$. The transformation matrices denote now the position and orientation of the virtual camera. Since the rotational parameters are small between each CEP, global distortion errors occurring from the flat topology of $se(3)$ which is mapped into the non-flat topology of $SO(3)$ will not occur (cf. [14]). We are using piecewise cubic Hermite interpolation [15] to interpolate between the sample points $x_i$. The desired gradients at these anchor points are approximated by computing the difference between the next and the previous point in relation to the respective anchor point. Having thus obtained suitable values for $g(0) = x_i$, $g(1) = x_{i+1}$, $g'(0) = x_{i+1} - x_{i-1}$, and $g'(1) = x_{i+2} - x_i$ for two successive anchor points $x_i, x_{i+1} \in \mathbb{R}^6$, we can compute a cubic polynomial $g : [0, 1] \rightarrow \mathbb{R}^6$ that can be used to interpolate between these two. Repeating this procedure for all pairs of successive (with respect to the trajectory) points yields a sufficiently smooth curve through the parameter space.

4. EXPERIMENTS AND RESULTS

The volume datasets are downsampled in $x$ and $y$ from $512 \times 512$ to $256 \times 256$ to fit the CT-Fluoro slices, which have an image size of $256 \times 256$. The registration is performed with a coarse-to-fine strategy, starting at $64 \times 64$ and increasing to $128 \times 128$ and $256 \times 256$. Each time the estimated values are taken as initialization for the next resolution. The optimization procedure is started from the pose obtained by the DICOM Image Position Patient since the patient is not moved from the table. The following experiments were run on a PC with 1.80GHz Intel Pentium processor and 1GB of memory. The average time for the registration for the clinical images was $5.5 \text{s}$ with a minimum of $2 \text{s}$ and maximum of $16 \text{s}$. The computation of the set of solutions on the isosurface took in average $15 \text{s}$ for one $\varepsilon$. A solution set of 18 sampling points on the isosurface is used. The points result from search directions obtained by combinations of out-of-plane parameters, i.e. translation along the $z$ axis, rotations about the $x$ and $y$ axis. Here, six CEPs result from the three out-of-plane parameters in $+$ and $-$ direction, and twelve CEPs result from the combination of each of two parameters in $+$ and $-$ direction. More precisely, at every search step in one direction, we are computing the weights based on the actual intensity residuals between
the projected slice in the volume and the CT-Fluoro slice with the Beaton-Tukey biweight function and use these weights to reach the isosurface. The same procedure is used for the parameter combination to reach the isosurface. The reason for using further a weighted search is that the estimated minimum is not any more a local minimum when the SSD cost function is used.

4.1. Linking $\varepsilon$ with the volume

Based on results of the literature, e.g. [16], [17], the deformation in the liver can reach up to 19 mm from the predicted rigid position, while the average across tissue yields about 6 mm. Therefore, we would like the CEPs to represent an average movement between 6 mm – 7 mm. We start with an initial guess of $\varepsilon$ and adapt it using a line search until the average motion of all 3D points $X_i$ considered in the volume between the minimum view and the views at the CEPs will be in the interval [6 mm, 7 mm].

4.2. Experiments with synthetic derived slices without deformation

To test the registration algorithm, we created a set of Ground-Truth (GT) slices simulating a CT-Fluoro slice. We used from one patient a noisy reconstructed volume [18] where we extracted at different poses including rotations and translations four slices. These slices were registered to the same pre-interventional volume but reconstructed without noise. An average RMS between the starting positions and the GT pose is about 35.75 mm for translation and 7.22° for rotation. The results of the RMS calculations between registered noisy slices and the GT give an average RMS for translation of 0.88 mm and for rotation 0.28°.

![Figure 3. 2D Views. (a) is showing a 2D CT synthetic slice including noise. (b) is showing the starting position for optimization with an RMS of 20.12 mm for translation and 5.4° for rotation. (c) is showing the estimated minimum with an RMS of 0.86 mm for translation and 0.004° for rotation. (d) is showing the weights image in the estimated minimum.](image)

4.3. Experiments with synthetic derived slices including deformation

For deriving synthetic 2D slices that also include deformations, we are using two CT-Volumes of one patient, the pre- and the post-interventional datasets. The pre-interventional CT-Volume (the template volume) is elastically [19] registered to the post-interventional CT-Volume (the reference volume). Since after the intervention, the patient is not any more able to achieve the full inspiration breath-hold as before the intervention, the registration of the pre-interventional toward the post-interventional scan is mimicking a possible expiration movement. This post-interventional scan is not used any more for the next steps, only the deformed volume is used. The displacement field for the achieved deformation will map the voxels of the deformed volume into the pre-interventional scan. In this way by extracting axial slices of this deformed volume, adding noise (cf. [20]) and adding for some of them a previously segmented needle of real CT-Fluoro slice, each of these slices represent hypothetical CT-Fluoro slices. We are using six axial slices extracted every 1 cm, and we run the robust minimization for each of them. Figure 4 shows such a registration result. For each synthetic CT-Fluoro slice we map each voxel into the pre-interventional volume resulting in a deformation surface. Starting with an initial guess of $\varepsilon = 0.25$ the corresponding average movements and $\varepsilon$ are shown in the table below:
Visually, we clearly see that the deformation of all slices of the liver voxels is included by the estimated CEPs.

Figure 4. 2D Views. (a) is showing a 2D CT synthetic slice including deformation, noise and needle. (b) is showing the same axial position in the pre-interventional volume as the position where the synthetic slice was extracted in the deformed volume. This position is used as starting position for optimization. (c) is showing the estimated minimum. (d) is showing the weights image in the estimated minimum.

### 4.4. Experiments with real CT-Fluoro slices

We are using 8 datasets from 8 different patients, all routinely acquired with a 4 detector-row CT, Siemens Somatom Sensation4 and a 16 detector-row CT, Siemens Somatom Sensation16. The CEPs are generated for each slice starting with $\varepsilon = 0.25$. The figures 6 and 7 are showing examples for two slices from two different datasets the generated CEPs. In the tables below we show the corresponding results:

<table>
<thead>
<tr>
<th>Patient1</th>
<th>Patient2</th>
<th>Patient3</th>
<th>Patient4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slice</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>0.17</td>
<td>0.5</td>
<td>0.24</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Patient5</th>
<th>Patient6</th>
<th>Patient7</th>
<th>Patient8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slice</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>0.16</td>
<td>0.2</td>
<td>0.14</td>
</tr>
</tbody>
</table>

The estimation of the CEP’s takes from 1 to 3 iterations. This can be parallelized starting with two different $\varepsilon$, such that the procedure can be speed up. Assuming a linear model of the increase of $\varepsilon$ with increasing RMS, an estimation of $\varepsilon$ can succeed in most of cases after 3 iterations.

### 5. EVALUATION OF ADAPTIVE VISUALIZATION

Three experienced interventional radiologists evaluated independently the CEP visualization versus the visualization of a single slice. Six datasets were evaluated with corresponding three CT-Fluoro slices, which results in eighteen examples. Two of the radiologists considered in all eighteen times (100%) the CEP visualization more valuable than one slice. One of them voted eleven times (61%) for the CEP visualization. The advantage of this automatic visualization of the subvolume is that it shows the relationship between needle-tip and the target lesion in the 3D space, thus reducing the need for further CT-Fluoro acquisitions. It gives the interventional radiologist a scale of how far the lesion is away from the actual slice and can display this as a 3D coronar view to visualize the cranio caudal direction as well. All relevant features (vessels and lesion(s)) of the liver can be
Figure 5. 3D Views of the example showed in fig.4. (a) is showing an axial view of the deformed surface where the cranio-caudal depth is coded from dark to light. (b) is showing a sagittal view on the recovered deformed surface and the estimated minimum slice intersecting the surface. (c) is showing the same configuration as (b) from different viewpoints plus the CEPs at an average movement of 6.56 mm and $\varepsilon = 0.3$. All the liver voxels are included into the volume defined by the CEPs.

included in the CEP visualization, with the volume being larger when the target is farther away. This helps to know which direction to take and how to angulate the needle. A single slice in the CT-Volume will confirm or not the right position, but it misses further guidance and neighborhood assessment. On the other hand, this visualization ties up to the familiar view in the radiology.

6. CONCLUSION

In this paper, we have presented a robust slice-to-volume registration method to overcome the noise and the difference between the conditions of the pre-interventional and the interventional acquisitions. The method was evaluated with simulations on synthetic noisy slices with and without deformations. We also proposed an adaptive visualization that includes views of the CT-Volume determined along flat directions of the out-of-plane motion parameters next to the minimum pose, where the optimization encounters uncertainty. The views are generated at poses that represent an average movement reported in the literature. In this way the deformation caused by the breathing should be included into the volume defined by the views. The proposed method gives very good results in a reasonable time with a standard computer. The result of the registration and the adaptive visualization were assessed by three experienced interventional radiologists on real CT-Fluoro data. The evaluation outcome supports that such visualization in the intervention room allows the examiner better to orientate and estimate the path to the lesion. A user interface permitting stopping and scrolling the
Figure 6. 6(a) 2D CT-Fluoro slice, 6(b) initial pose in the CT-Volume, 6(c) estimated minimum in the CT-Volume, 6(d) weight image at the minimum, 6(e) 3D coronal and sagittal view of CEPs around minimum at an average movement of \(6.34 \text{mm}\) and \(\varepsilon = 0.3\).

Visualization manually could further improve the usability of the proposed approach. Finally, in addition to the proposed visualization, a display for the scale of distance to the target and a 3D coronal view for incorporating the cranio-caudal direction eases the perception of depth and orientation of the needle.

REFERENCES

Figure 7. The 2D views represent CEPs at motions from out-of-plane parameters starting from the estimated minimum in negative and positive directions of the example showed in figure 1. 7(a) CEP in negative z translation direction, 7(b) CEP in negative x rotation direction, 7(c) CEP in negative y rotation direction, 7(d)-7(f) CEP in positive directions. 7(g) shows a 3D coronal and sagittal view of CEPs around the minimum at an average movement of 6.99mm and $\varepsilon = 0.25$.


