REAL TIME TRACKING OF EXTERIOR AND INTERIOR ORGAN SURFACES USING SPARSE SAMPLING OF THE EXTERIOR-surfaces

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ABSTRACT
This paper presents a new algorithm for real time tracking of the exterior and interior surfaces of organs using sparse sampling of the exterior surfaces. The tracking is based on identifying subspaces in which the coefficients of spherical harmonic representations of the surfaces live. It uses pre-operative CT/MRI scans during training, and needlescopic images acquired during tracking. We study different strategies for sampling the exterior organ surface using the needlescopic images and also apply the method to 3D frame interpolation. Specially, we provide (1) the first demonstration of real time interior organ surface reconstruction using sparse sampling of exterior surfaces with error rate as low as 0.095%, and (2) algorithms’ application in 3D cardiac frame interpolation with error rate of only 1.15% while reducing radiation rate by 90%.

Index Terms— Organ deformation, spherical harmonics, orthogonal subspace pursuit, surface representation

1. INTRODUCTION
Organ deformation during operations can prevents doctors from performing precise diagnosis and surgery. For instance, the recently developed surgical approach of Natural Orifice Transluminal Endoscopic Surgery (NOTES) [1] confronts the problem of organ distortion due to gas insufflation inside the abdomen, which substantially degrades the precision of the prior surgical plan. Also, surgeons during NOTES operation have very limited field of view, which may increase the risk of complications during surgery. Therefore visualizing deformations and having extended view are the most critical issues for developing minimum invasive surgery.

Many efforts have been put into the investigation of modeling and measurement of 3D organ deformation. The most widely used methods are based on MRI/CT images [2][3]. For example, tagged MRI [2] has been used to construct the displacement field of left ventricle. Sparse points along tag lines measured in different frames and in various directions are used to determine the nonrigid movement followed by interpolation. Instead of using CT/MRI images, [4] presents a spatio-temporal adaptive sampling strategy for modeling dynamic viscoelastic deformable objects. The adjusted sampling density is derived from the Green strain tensor laws on the fact that time-dependent spherical harmonics (SH) are solutions to the wave equations, given the prior information about the motion cycle of the organ.

Most of the previous approaches only work under certain conditions. [2][3] requires CT/MRI images which are unavailable during interventional surgery. Methods in [4] and [5] depend on specific properties for the organs (e.g. viscoelasticity and periodicity). On the other hand, traditional algorithms are too costly to be implemented in real-time for their demanding computation resources. Moreover, none of those works addressed tracking the deformations involved in both interior and exterior surfaces, such as bladder. The main contributions of this paper include: (1) generalizing our earlier works [6][7] to design a new method for tracking interior unobservable surfaces from the exterior observable images; (2) studying different sampling strategies to achieve real time tracking with limited field-of-view; and (3) presenting verification results using simulation data and clinical CT data to demonstrate the effectiveness of the approach in terms of reconstruction accuracy and radiation reduction. The tracking method first uses preoperative CT or MRI scans for training and then acquires samples from fiber optic “needlescopic” cameras during surgery for deformation rendering. The 3D view of both interior and exterior provides surgeons with better field-of-view and awareness of the critical region such as tumors.

2. DESIGN OF ALGORITHM
The main algorithm involves three steps: (1) subspaces in which the deformed surfaces can be efficiently represented are identified; (2) three sparse sampling strategies are designed to track the interior and exterior deformation using samples from exterior only; (3) the deformed surface is reconstructed in the best-fit subspace using selected samples.

2.1. Step 1: Subspace Identification and Efficient Surface Representation
A large set of 3D training deformations obtained from preoperative CT/MRI images is plugged into this step to identify the deformation subspaces in which each deformation can be represented with a low dimension vector.

2.1.1. Spherical Harmonic Transform(SHT)
For an organ including both interior and exterior surface, individual parameterization [8] is conducted for both sides. We
denote \( \vec{x}^{in} \) and \( \vec{x}^{ex} \) \((1 \leq k \leq K)\) as the interior and exterior surface in the training frames, respectively. Then each pair of \( \vec{x}^{in} \) (with \( N_1 \) vertices) and \( \vec{x}^{ex} \) (with \( N_2 \) vertices) can be approximated by SH basis in a matrix format as

\[
\begin{bmatrix}
\hat{\vec{x}}^{in}_k \\ \hat{\vec{x}}^{ex}_k
\end{bmatrix} =
\begin{bmatrix}
\vec{Y}^{in} & O \\ O & \vec{Y}^{ex}
\end{bmatrix}
\begin{bmatrix}
\vec{f}^{in}_k \\ \vec{f}^{ex}_k
\end{bmatrix}
\]

where \( \vec{Y}^{in} \) of size \( N_1 \times (L+1)^2 \) and \( \vec{Y}^{ex} \) of size \( N_2 \times (L+1)^2 \) denote the SH basis matrix for interior and exterior respectively, each of which consists of discrete harmonics up to level \( L \). \( \vec{f}^{in}_k \) and \( \vec{f}^{ex}_k \) are the corresponding harmonic coefficient vectors. Therefore, each deformation can be represented by vector \( \vec{f}_k = \begin{bmatrix} \vec{f}^{in}_k \\ \vec{f}^{ex}_k \end{bmatrix} \), and all \( K \) training frames can be characterized by \( F = \bigcup_{k=1}^{K} \{ \vec{f}_k \} \).

2.1.2. Subspace Pursuit and Vector Clustering

Initially, \( J (J \geq 1) \) subspaces \( \{ U_i \}_{i=1}^{J} \) are identified from vectors \( \{ \vec{f}_k \}_{k=1}^{K} \) via Orthogonal Subspace Pursuit (OSP) [11]. Each subspace is spanned by \( n_i \) vectors. Then all vectors of matrix \( F \) are clustered into those subspaces \( U_i \) and the coefficients \( \vec{p}_i \) are calculated accordingly using LS approximation. So, each \( \vec{f}_k \) can be approximated in its subspace as:

\[ \vec{f}_k = U_i \vec{p}_i \]

2.2. Step 2: Sampling Strategy Design

With obtained matrix \( G_i \), the sampling strategy design aims to determine the sampling locations on the exterior to reconstruct the deformation on both interior and exterior. The samples can be obtained through the fiber optic camera with a rotating off-axis aperture [10] or sparse time sampling of CT scans. The following section: completely random sampling, patch sampling and localized sampling.

2.2.1. Randomly Sampling

We denote \( \vec{h} = \begin{bmatrix} \vec{h}^{in} \\ \vec{h}^{ex} \end{bmatrix} \) as the deformed surface to be constructed and subset \( \vec{h}^{ex} \) as the \( m_i \) samples to be chosen from the exterior. Let \( G_i \) stands for the sub-matrix containing \( m_i \) \((n_i < m_i < N_2)\) rows of \( G_i \). The philosophy behind the sampling design is to find an index set \( S_i = \{ s_{i,q} \mid 1 \leq i \leq m_i \} \) with each atom within \([N_1 + 1 \ N_1 + N_2]\) to form a well conditioned sub-matrix \( \tilde{G}_i \) and corresponding sample set \( \tilde{h}^{ex} \), such that the over-determined linear system

\[ \tilde{h}^{ex} = \tilde{G}_i \tilde{p}_i \quad \text{for} \quad i = 1 \ldots J \]

can be well solved under LS constraints for coefficient vector \( \tilde{p}_i \) in each subspace \( G_i \). Then the subspace with the least error at the known samples is chosen as the best-fit subspace for reconstructing the overall surface \( \vec{h} \).

Considering the fact that the computational complexity of finding \( G_i \) with the smallest condition number grows exponentially with the scale of the matrix, a “random walk” searching is adopted for simplicity: randomly pick \( m_i \) out of the lower \( N_2 \) rows from \( G_i \) to form \( \tilde{G}_i \) for a predefined number of trials (e.g., 1000 times in our simulation), and choose \( S_i \) as the index set which constructs \( \tilde{G}_i \) with the smallest condition number. Then atoms in \( S_i \) are used as the desired sampling positions, that is, the sample set in subspace \( G_i \) can be formulated as \( \tilde{h}^{ex} = [h(s_{i,1}) \ldots h(s_{i,m_i})] \). Notice that each \( s_{i,q} \) is in the range of \([N_1 + 1 \ N_1 + N_2]\), so every selected sampling position must locate on the exterior.

2.2.2. Sampling with Localization

Realizing the fact that, in reality, only a few observation instruments (such as fiber optics) or limited field of view to the exterior of the organ is available, completely random sampling is hard to implement. To reduce the overall monitoring area, certain sampling localization constraints can be introduced while determining index set \( S_i \) for each subspace.

1. Random Patch Sampling

In this sampling mode, all the surface vertices are initially grouped into patches of size \( n(n < m_i) \) which can be taken using a single fiber optic camera. Each patch contains \( n \) nearest neighbors without overlapping among patches. Thus, there are \( R = \lceil N/n \rceil \) patches, and \([a] \) stands for the integer that is closest to but smaller than \( a \). The number of patches to be chosen is \( r = \lceil m_i/n \rceil \) with \([a] \) as the smallest integer that is larger than \( a \). To seek a well-conditioned \( G_i \), randomly select \( r \) out of \( R \) patches for a predefined times and choose the \( r \) patches whose index generates \( G_i \) with smallest condition number.

2. Localized Sampling

This strategy is the combination of completely random sampling and patch sampling, which takes random samples from one concentrated area. Similar to patch sampling, surface vertices are grouped into patches of size \( n \) and \( R = \lceil N/n \rceil \), but \( n \) is at least 3 times larger than \( m_i \). Within each patch, run the same “random walk” searching process and record the resulted index set as \( S_{i,p} \) \((1 \leq q \leq R)\). After exhausting all the patches, the index set \( S_{i,p} \) leading to the best-conditioned \( G_i \) is chosen as the desired sampling location \( S_i \) for that subspace and the corresponding patch is the localized area monitored by a few fiber cameras.


2.3. Step 3: Deformation Construction

The final step is to decide which subspace the deformation best fits in and to construct the whole surface using the samples taken from the previous step.

For $J$ subspaces, each coefficient vector $\tilde{p}_i (1 \leq i \leq J)$ can be estimated as:

$$\tilde{p}_i = (\tilde{G}_i^T \tilde{G}_i)^{-1} \tilde{G}_i^T \tilde{h}_i (1 \leq i \leq J) \quad (5)$$

The construction error at sampling points for each subspace is used as the parameter for deciding the optimal subspace $G_i^*$ to which the current deformation $\tilde{h}$ belongs. That is, $i^* = \min_{1 \leq i \leq J}(\|h_i - \tilde{G}_i \tilde{p}_i\|_2)$. Then the overall surface can be simply reconstructed as $\tilde{h} = G_{i^*} \tilde{p}_{i^*}$.

Compared with compressed sensing MRI (e.g. [9]) conducted in Fourier domain, the proposed strategy uses samples in the spatial domain. Furthermore, it specially exploits subspaces rather than the sparseness of a representation of the object in a particular domain (e.g. wavelet), which enables the block sparse sampling strategy. As shown in Section 3, the proposed method features extremely sparse sampling in both deformation tracking and 3D frame interpolation.

3. EVALUATION

In order to verify the feasibility of the proposed algorithm, both synthetic data from 3D surgical simulators and clinical data of dynamic CT images are applied in the experiments.

3.1. Evaluation with Synthetic Data

3.1.1. Setup

An initial finite element volume model of bladder including interior and exterior walls is deformed with ABAQUS to mimic its interaction with an instrument. The surface mesh of each deformed volumetric bladder is extracted as testing data. Simulation is run on MATLAB 7.1 with a desktop of 2-GB memory. The bladder model has $N_1 = 4434$ and $N_2 = 4274$ vertices in the interior and exterior, respectively. SH level $L$ is set to be 30. $K = 90$ frames are used for training and 30 different frames are tested for tracking.

3.1.2. Computation Cost

According to the evaluation results, the overall memory occupation during tracking of the bladder deformation is only 7MB and each deformed surface (including both interior and exterior) can be reconstructed in milliseconds with the proposed method. In contrast, with the standard SHT method, the SH matrix occupies 100MB in memory and the computation time is at the level of tens of minutes. Therefore, the proposed method achieves more than one magnitude of computational cost saving. More theoretical analysis of computation cost can be found in [6][7].

3.1.3. Deformation Tracking

Three sampling strategies (as described in Section 2) are tested for tracking, including random sampling, patch sampling and localized sampling on the exterior of the bladder surface. To quantify the construction error, a parameter $EOF$ defined as the normalized Euclidean distance between the original surface and the reconstructed surface is applied.

<table>
<thead>
<tr>
<th>Samples</th>
<th>Global</th>
<th>Patch</th>
<th>Local</th>
</tr>
</thead>
<tbody>
<tr>
<td>EOF</td>
<td>0.091%</td>
<td>0.098%</td>
<td>0.095%</td>
</tr>
</tbody>
</table>

Table 1. Results of Three Sampling Methods

Table 1 summarized the test results for the three strategies with reference to the reconstruction accuracy using SHT. The completely random sampling strategy results in EOF 0.098% with 90 samples uniformly distributed on the exterior bladder surface. For patch sampling, four patches (i.e. $160/40$) with size 40 are required to achieve high reconstruction accuracy ($EOF = 0.095\%$). With localized sampling, only around 10% ($400/4274$) of the exterior bladder surface is under monitoring for tracking the overall deformation with EOF 0.110\%.

To summarize, the three sampling methods can achieve high tracking accuracy compared with the SHT, and patch and localized sampling approaches require much less monitoring area as opposed to random sampling.

Fig. 1 and Fig. 2 compare the reconstruction results of two example bladder deformations using SHT and the proposed method. The concave and convex part on interior and exterior of...
3.2. 3D Surface Frame Interpolation

The proposed tracking interior deformation using samples from exterior can be directly applied to 3D surface sequence interpolation. This is achieved by treating every two consecutive deformations as interior and exterior of a whole object, and then following the same training and sampling design as described in 2. Therefore the second (“interior”) deformation can be completely estimated with samples from the first (“exterior”) deformation.

A sequence of dynamic cardiac CT images is applied to verify the feasibility of interpolating the cardiac cycle. The CT image set involves 11 phases of a cycle, and 446 slices are taken for each phase with a spatial resolution of 0.39mm.

3.2.1. CT Data Preparation

The 2D CT images are reconstructed with MIMICS®. The resulted 3D triangular meshes are further re-sampled and remeshed via the following steps to use a common SH matrix during SHT: (1) construct an icosahedron of $M$ vertices ($M = 4002$ in this experiment) with radius large enough to embrace the largest heart volume among the sequence; (2) move the center of the 3D surfaces to the origin of icosahedron; (3) for each segment originated from the origin point to every different vertex on the icosahedron, find the triangle on the heart mesh that intersects with the segment; (4) calculate the intersection point accordingly and use it as the new surface point. Notice that, due to the “star-like” shape of the heart, there is always one and only one intersection between each line segment and the surface.

3.2.2. Interpolation Accuracy

In this experiment, 10 of the 11 phases are randomly chosen for training, and the remaining one are used for testing the performance of phase interpolation. The SH level $L$ is set to be 10 and patch sampling strategy is applied.

The evaluation result shows that, with 45 samples from 3 patches located in the first (“exterior”) deformation, the average interpolation error for the testing frame is EOF=1.15% as opposed to EOF=1.07% with SHT method. In Fig. 3, the interpolated heart shape at phase 8 using the proposed method are compared with the corresponding results using SHT. Two different views are shown for the reconstructed phase 8. We can see that the interpolation method features high accuracy. Since only 12% (45/4002) of the heart surface needs to be imaged to construct the current and the following frames, we are able to reduce the number of CT images to less than 10% of the number acquired in the traditional routine.

4. CONCLUSION

This paper introduced an efficient approach for tracking 3D deformations involved in both interior and exterior of the organ with sparse samples taken from the exteriors only. Experiments with synthetic data and clinic CT images show that the presented approach only requires 5-10 needlescopic fiber cameras to achieve real time tracking. Thus, this low sampling density enables its application in minimum invasive surgery [1] when only limited visual access to the organ is available. Meanwhile, it can be directly applied in 3D temporal interpolation in dynamic function analysis to reduce the CT/MRI radiation suffered by the patients.

5. REFERENCES


