CALIBRATION-FREE MARKERLESS AUGMENTED REALITY IN MONOCULAR LAPAROSCOPIC CHOLECYSTECTOMY

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Abstract: In this paper we present an augmented reality system for laparoscopic cholecystectomy video sequences enhancing. Augmented reality allows surgeons to view, in transparency, occluded anatomical and pathological structures constructed preoperatively using medical images such as MRI or CT-Scan. The deformable nature of digestive organs leads to a high dimensionality N-degrees of freedom detection and tracking problem. We describe a knowledge-based construction method of powerful statistical color models for anatomical structures and surgical instruments classification. Thanks to a new wavelet based multi-resolution analysis of the virtual reality models and the anatomical color space; we can detect and track digestive organs to ensure markerless laparoscopic monocular camera pose and preoperative 3D model registration. Results are shown on both synthetic and real data.

1 INTRODUCTION

Augmented reality allows viewing in transparency anatomical and pathological 3D models reconstructed preoperatively using medical images (MRI, CT-Scan) in the surgeon field of view. However, one of the major challenges that limits augmented reality massive use in clinical laparoscopic abdominal surgery is the difficulty of markerless registration of preoperative digestive organs 3D models within the laparoscopic view. Indeed, digestive organs are highly deformable and variable. Therefore, we believe that a clinical use of augmented reality in abdominal laparoscopic surgery system has to ensure markerless registration with knowledge-based interactive functionalities. In this paper we propose a novel method to ensure 3D models alignment and tracking of digestive organs directly onto laparoscopic cholecystectomy videos.

Cholecystectomy is the first surgical intervention in the United States with more than a half million operations done each year. Since the first cholecystectomy of Langenbuch(Traverso, 1976), it is established as the standard procedure for surgical treatment of gallbladder diseases such as gallstones. Cholecystectomy consists in the complete removal of the gallbladder with different techniques such as open or laparoscopic(Reynolds, 2001; Litynski, 1999) procedures. However, the video-assisted laparoscopic cholecystectomy is actually the gold standard technique with more than 98% of interventions(Bittner, 2004).

The rest of the paper is organized as follows. In the second section, we present a number of significant augmented reality systems and methods applied to digestive surgery. Next, we describe the proposed method used for statistical abdominal organs color model construction and its application to detect and track anatomical structures and surgical instruments in order to register the preoperative virtual model using a new wavelet based multi-resolution analysis of deformable objects and particles swarm optimization (PSO). In section 4, experimental results on synthetic and real data show the effectiveness and robustness of our method. Finally, we present our conclusion and perspectives.

2 RELATED WORKS

In the last few years, researchers of augmented reality community have proposed many systems for various medical domains and applications. According

to tracking devices and methods, augmented reality systems in digestive surgery can be classified in two categories, vision-based and hybrid systems. In their work, (Nicolau et al., 2005b) proposed a low cost and accurate guiding system for laparoscopic surgery with validation on abdominal phantom. The system allows real time tracking of surgical tools and registration using markers by optimization of a given criterion (EPPC)(Nicolau et al., 2005a). In the other side, (Feuerstein et al., 2008) propose a hybrid system composed of optical and electromagnetic tracking systems to determine the position and the orientation of the intra-operative imaging devices, such as mobile C-arm, laparoscopic camera and flexible ultrasound, allowing direct superimposition of acquired patient data in minimally invasive liver resection without need of registration.

3 PROPOSED METHOD

In this section we outline the principal components of our markerless augmented reality system for laparoscopic cholecystectomy. Taking into consideration temporal coherence according to the principal steps of standard laparoscopic cholecystectomy, the first component detects all anatomical and pathological structures in the surgical 2D laparoscopic view using a statistical color model of digestive organs. As a result, we have for each organ an initial segmentation represented by a sparse binary image. Then, false positives are filtered using an adaptation of particles swarm optimization (PSO) algorithm. thus, we have a set of particles with different radius in the 2D image for each organ.

In laparoscopic cholecystectomy, the most important organ is the gallbladder and its vascular supply. The same principle is applied on preoperative CT-Scan images to build a particles-based 3D model of the gallbladder and the liver. The novel proposed wavelet-based multi-resolution analysis allows to have coarse models either of 3D virtual organs or 2D images. Finally, we make a 2D/3D registration for each resolution level.

In order to build a statistical color model, a set of 16735 colored laparoscopic images (IRCAD source) from a video of laparoscopic surgeries is used. The images have 240 x 320 RGB coded pixels with 256 bins per channel (24 bits per pixel). The video sequence is acquired at a frame rate of 30 Hz.

3.1 Anatomical Color Model

According to the cholecystectomy intervention workflow step (t), we construct for each anatomical region (i) a statistical color model using a histogram with 256 bins per channel in the RGB color space. Each color vector (x) is converted into a discrete probability distribution in the manner:

$$P_{i,t}(x) = \frac{c_{i,t}(x)}{\sum_{j=1}^{N_{i,t}} c_{i,t}(x_j)}, t = t_1 \ldots t_6, i = 0 \ldots S_t. \quad (1)$$

where $c_{i,t}(x)$ gives the count in the histogram bin representing the *rgb* color triple (x) and $N_{i,t}$ is the total count of the *rgb* histogram entries returned by the histogram bins number of the structure region (i) during the intervention step (t). The number of detected structures S_t varies according to the step. According to the European standard and common laparoscopic cholecystectomy installation and intervention workflow, the number of structures classes is limited to four. In practice, the step (t) denotes a time interval represented by a set of consecutive laparoscopic images $t = \left[I_{v,1}^t \ldots I_{v,n}^t \right]$ in the videos (v) that compose the training dataset.

After analysis of the laparoscopic video, we have observed that it contains at most 10017 RGB color bins over the whole sequence with a mean of 1997 RGB triples in each frame. Therefore, the RGB histogram is mostly empty with 99,94% of the 256^3 RGB bins that are not used. Figure 1, shows the evolution of RGB bins count in the training laparoscopic cholecystectomy video.
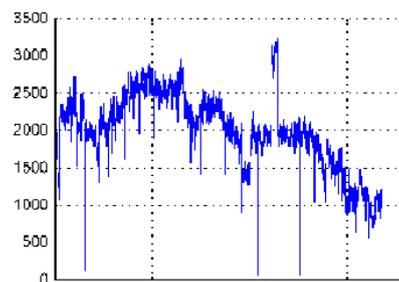

Figure 1: Evolution of RGB bins count in the sequence.

3.2 Spherelet : Wavelet-based Multi-resolution Analysis

In this section we propose a new multi-resolution analysis of 3D objects modeled as a set of elementary non intersected particles defined by their centers and radius. The virtual model of the anatomical structure

is subdivided into a set of particles, that we will call '"Spherelet"'. The closest greatest sphere to the preoperative 3D model gravity center represents the root of the Spherelet model. The Spherelet root is used to initiate 2D/3D rigid registration. Hence, the root definition has to ensure the most stability and less deformation during the whole sequence. The root represents the coarsest resolution level of the virtual model. We suppose that $[S^j]$ is the Spherelet at the resolution level (j). We have :

$$S^j = \left[S_{j,1} S_{j,2} \ldots S_{j,i} \ldots S_{j,n_j} \right]^t \qquad (2)$$

where $(S_{j,i})$ is the (i^{th}) particle of the virtual model at the resolution (j). (n_j) is the length of the Spherelet at the resolution level (j) denoting its particles count. The initial resolution level is $[S^0]$ and the coarsest one is $[S^r]$ corresponding to the Spherelet root. The relation between two successive resolution levels is given by:

$$\begin{aligned} S^{j+1} &= A^{j+1} S^j \\ D^{j+1} &= B^{j+1} S^j \end{aligned} \qquad (3)$$

with $[D^j]$ represents the wavelet detail coefficients of the resolution level (j):

$$D^j = \left[D_{j,1} D_{j,2} \ldots D_{j,i} \ldots D_{j,n_j} \right]^t \qquad (4)$$

The $[A^j]$ and $[B^j]$ matrices are called the analysis filters of the resolution level (j).

To reconstruct the superior resolution level we use two matrices $[P^j]$ and $[Q^j]$ called synthesis filters. The initial resolution level is given by:

$$S^j = P^{j+1} S^{j+1} + Q^{j+1} D^{j+1} \qquad (5)$$

The relation between the analysis and synthesis filters is formulated by:

$$[A|B]^t = [P|Q]^{-1} \; then \; [A|B]^t [P|Q] = I \qquad (6)$$

The detail information relative to eliminated particles contains their inter-distances or volume ratios in the logarithmic scale. In the simplest case, the transformation to an inferior resolution level (j) of the 3D Spherelet volumetric model consists in replacing two particles of the resolution level $(j-1)$ by a representative one. We have then:

$$\begin{aligned} A^j &= [I|0] \\ B^j &= [-I|I] \end{aligned} \qquad (7)$$

The $[A^j]$ filter is used to select elements of the next inferior resolution level and $[B^j]$ to extract wavelet coefficients of each level. Hence, the analysis process is formulated by:

$$\begin{aligned} S^r &= A^r S^{r-1} = A^r A^{r-1} \ldots A^2 A^1 S^0 \\ D^r &= B^r S^{r-1} = B^r B^{r-1} \ldots B^2 B^1 S^0 \end{aligned} \qquad (8)$$

Therefore, the synthesis filters are given by:

$$\begin{aligned} P^j &= [I|I]^t \\ Q^j &= [0|I]^t \end{aligned} \qquad (9)$$

Assuming that the initial Spherelet is composed of (2^r) spheres. We have, $S^{(j=0)} = \left[S_{0,2^0} S_{0,2^1} \ldots S_{0,i} \ldots S_{0,2^r} \right]^t$ with $n_{(j=0)} = 2^r$ and r gives the number of levels to reach the coarsest representation corresponding to the Spherelet root.

3.3 Anatomical Structures Tracking

We propose a tracking by detection method of digestive organs using particles swarm optimization (PSO). The classical PSO is a global search strategy for optimization problems(Kennedy et al., 1995) and it is based on the social evolution simulation of an arbitrary swarm of particles based on the rules of Newtonian physic. Assuming that we have an N-dimensional problem, the basic PSO algorithm is formulated by position $x_m(t)$ and velocity $v_m(t)$ vectors representing the time evolution of M particles with random affected initial positions. Hence, we have:

$$x_m(t) = [x_1(t) x_2(t) \ldots x_N(t)]^T \qquad (10)$$
$$v_m(t) = [v_1(t) v_2(t) \ldots v_N(t)]^T \qquad (11)$$

The evolution of the particles in the classical algorithm is done by the following equations:

$$\begin{aligned} v_m(t+1) &= f_{m_i} v_m(t) + f_{m_c} [D_c]_N (x_m(t_c) - v_m(t)) \\ &\quad + f_{m_s} [D_s]_N (x_{opt}(t_s) - v_m(t)) \end{aligned} \qquad (12)$$

Thus, the new position of the particle m is given by:

$$x_m(t+1) = x_m(t) + v_m(t+1) \qquad (13)$$

Where $(v_m(t))$ and $(v_m(t+1))$ are, respectively, the past and the new velocity vectors of the particle (m). (f_{m_i}) is the inertia factor of the particle m, (f_{m_c}) is its the cognitive factor and (f_{m_s}) is the social factor. $([D_c]_N)$ and $([D_s]_N)$ are the N-dimensional diagonal matrices composed of statistically independent normalized random variables uniformly distributed between 0 and 1. (t_c) is the iteration where the particle m has reached its best position given by (x_m). (t_s) is the generation that has found its best global particle-member defined by its components (x_{opt}).

The Spherelet root of each organ, mainly that of the gallbladder, is determined in the 2D UV space of the image by optimization of the following proposed cost function:

$$F_\Theta = |1 - k| + |1 - d| \qquad (14)$$

with

$$k = \frac{\alpha}{\sum_{i,j} I_b(x)}, \qquad (15)$$

and

$$d = \frac{\sum_{i,j} I_b(x)}{x_r^2}, \qquad (16)$$

where, α, models the priori-knowledge and , d, the density of the particle.

The 2D/3D registrations is ensured by minimizing the distance between the projection of the 3D Spherelet (S_{3D}) of the virtual model reconstructed using preoperative slides and the 2D Spherelet (S_{2D}) in the laparoscopic image. Therefore, for each 3D Spherelet particle we compute the pose using (PSO) assuming the stability of previously computed coarse levels registration. For each resolution level, the function to be minimized is given by:

$$F_\Phi = |\Phi_{3D}(x) - S_{2D}| \qquad (17)$$

where Φ_{3D} is the rendering function of (S_{3D}).

4 EXPERIMENTAL RESULTS

First, we have applied the method on synthetic images (made by hand) to validate detection and tracking method (Figure 2).
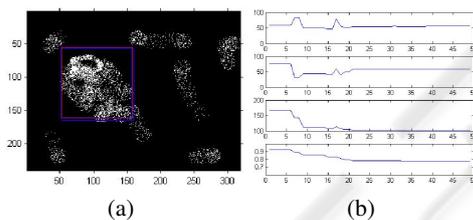

(a)   (b)

Figure 2: Tracking of synthetic gallbladder.

Then, we have tried the method on real laparoscopic images as shown below (Figure 3).

(a) Original image.   (b) Detection
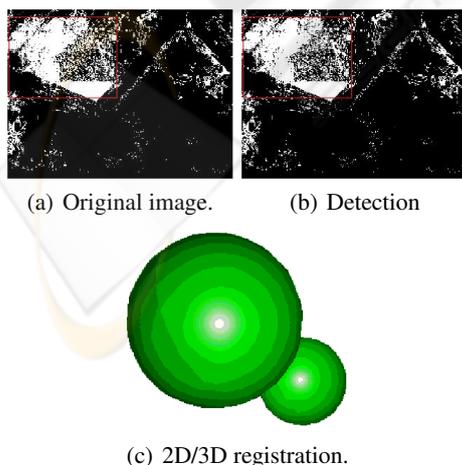

(c) 2D/3D registration.

Figure 3: Real laparoscopic image augmentation (IRCAD).

5 CONCLUSIONS

In this paper we presented a novel method for augmenting images of video based laparoscopic cholecystectomy. A new statistical color model is proposed to detect anatomical and pathological structures. A new criterion is used to detect and track organs using particles swarm optimization. A new wavelet based multi-resolution analysis of 2D laparoscopic images and 3D particles-modeled objects is used to register the preoperative model within the real scene. Experiments have shown the effectiveness of the proposed method.

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