Real-Time Organ Tracking in Ultrasound Imaging Using Active Contours and Conditional Density Propagation

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Abstract. Ultrasound tracking of organs or target volumes is a promising means to correct the displacement caused by respiration and errors from repositioning in medical applications e.g. in radiation therapy. However, one major problem of ultrasound images is their inherent low contrast and clutter which often makes standard algorithms instable for this purpose. In this work we present the adaption and application of a probabilistic tracking approach based on conditional density propagation (condensation) for real-time tracking on ultrasound images. This approach promises to facilitate robust real-time tracking with 5 degrees of freedom (translation and scaling in x-/y- direction, rotation) of anatomic structures on noisy and low contrast ultrasound images. The real-time performance and precision of the algorithm are investigated with ultrasound data from the liver. The tracking results of the algorithm are compared with results obtained from image registration. It is shown that this algorithm is real-time capable with processing time less than 5 ms per frame and robust on low contrast target structures with a precision below 1.6 mm in translation. Compared with an independent image co-registration method, this method leads to a superior displacement correction in pre-delinated target structures.

1 Introduction

In modern radiotherapy, the procedures of delivering prescribed dose are always affected by the inevitable organ motion though machines have precision in millimetre range. Real-time tracking of the organ motion can help to improve the precision by simultaneously and synchronically adjusting the target position. Due to its real-time, portable and non-invasive nature, ultrasound imaging suggests itself a good choice for tracking. Although substantial work has been done to facilitate ultrasound tracking of organ motion the problem of robust motion detection is still partly unsolved. The substantial clutter and low contrast forms a

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major obstacle in motion control in ultrasound images. For non-real time applications feasible solutions have been proposed to e.g. retrospectively segment organ boundaries on ultrasound series in echocardiography [1,2,3]. Also, the tracking of slowly moving surgical instruments, which generally exhibit high contrast and a known shape, has been successfully pursued with ultrasound images [4]. However, robust (i.e. noise insensitive) real-time tracking of tissue regions still remains a challenge. Although some promising methods have been suggested to track resparitory motion in abdominal ultrasound images, these methods are generally computationally costly and require the incorporation of other imaging modalities [5] or additional markers [6].To overcome these obstacles we used an active contour algorithm that possesses beneficial properties to track noisy, low contrast ultrasound image structures. The algorithm relies on a bayesian probabilistic approach with conditional density propagation (condensation) which was first proposed by Isard and Blake [7,8]. The statistical nature of this approach makes the process stable against image noise and hence suits ultrasound image sequences well. This process was proved to be fast enough to operate and control the motion in real-time [9].

In this work we implemented the 2D real-time ultrasound tracking and investigated the motion tracking behaviour in-vivo within the liver. To facilitate ultrasound tracking with this algorithm, a dedicated measurement and weight calculation procedure was introduced. The precision of extracted trajectories was determinated by inverstigating the variances between different real-time runs of the algorithm. Besides, this contour tracking algorithm have been compared to an independent (non-real-time capable) co-registration of the ultrasound frames.

2 Methods and Meterials

2.1 Contour Tracking Algorithm

To track motion with cluttered and noisy ultrasound images an algorithm for contour tracking using a stochastic random sampling procedure (condensation algorithm) [8] was adopted in this work and a dedicated measurement and weight calculation procedure was introduced to meet the special requirements for ultrasound tracking. As a first step, a contour on a target structure is delineated manually by marking several points in one frame of the ultrasound data. In this delineation procedure points expected to be bright are marked with a bright point marker and points expected to be dark with a dark point marker. In this way a base contour with M_b bright points M_d dark points(M_b+M_d=M) is generated. To represent the movement of the base contour, a contour state s that consists of the transform parameters in 5 degrees of freedom(x and y translation, x and y scaling and rotation) is used. The tracking procedure takes a Bayesian approach and starts with the initialization of a N size contour state set $\{s_0^{(n)}, n = 1, ..., N\}$ with a gaussian number generator (in this work N was set as 1000 to enable a real-time tracking). In subsequent procedures a probability

distribution of current state set $\{s_k^{(n)}, n = 1, ..., N\}$ for current ultrasound image is calculated and a predicting state set is derived in the following steps:

1. Observation on the ultrasound data: For each sample an observation Z_k is derived by measuring the gray values I_b of bright markers and I_d of dark markers in the ultrasound frame k . The observation density $p_z(s_k^{(n)})$ for a certain sample $s_k^{(n)}, n \in \{1, ..., N\}$ is generated in the following way:

$$p_z(s_k^{(n)}) = p(Z_k|X_k = s_k^{(n)}) \propto (\frac{1}{M_b} \cdot \sum_{i=1}^{M_b}((I_b)_i) - \frac{1}{M_d} \cdot \sum_{i=1}^{M_d}((I_d)_i))^2 \quad (1)$$

Then a weight set $\{\pi_k^{(n)}, n = 1, ..., N\}$ which represents the probability of respective state set is generated as follows:

$$\pi_k^{(n)} = \frac{p_z(s_k^{(n)})}{\sum_{i=1}^{N}(p_z(s^i)}, n \in \{1, ..., N\}. \quad (2)$$

2. Sample selection: As a preparation for the next step, samples in the prior set $\{s_k^{(n)}, n = 1, ..., N\}$ with high weight are selected preferentially to generate a new N-size selected set $\{s'^{(n)}_k, n = 1, ..., N\}$, that is to say, the propagation posibility of a certain sample $s_k^{(n)}, n \in \{1, ..., N\}$ is proportional to the respective weight $\pi_k^{(n)}$.

3. Propagation: The selected set $\{s'^{(n)}_k, n = 1, ..., N\}$ then serves as the base for the following autoregressive diffusion process to generate a posterior set $\{s_{k+1}^{(n)}, n = 1, ..., N\}$:

$$s_{k+1}^{(n)} = \overline{s_k} + A \cdot (s'^{(n)}_k - \overline{s_k}) + \sigma \cdot G(0, 1), n \in \{1, ..., N\} \quad (3)$$

and

$$\overline{s_k} = \sum_{n=1}^{N} \pi_k^{(n)} \cdot s_k^{(n)}, \quad (4)$$

where $G(0, 1)$ is a Gaussian diffusion term with a width σ adjusted according to the tracking problem, while A is the factor defining the process scaling which describes the weight of the propagated sample relative to the stochastic diffusion process in the model(in this work A=0.4 was set).

The three steps above iterate themselves to complete a tracking of the target structures over all the frames in a ultrasound data. To extract a propagated contour a consensus contour is calculated as a weighted mean of all samples in the current sample set. The mean state parameters $\overline{s}$ serve to generate movement parameters for the control of a medical device.

2.2 Materials

In this work, the algorithm was implemented in C++ on a PC with 2 Pentium XEON 3.2MHz processors and 1GB RAM. The software makes use of DirectX

9 to stream ultrasound data and can be used with on-line ultrasound imaging or off-line with stream playback from a hard-drive. The algorithm performance was tested in-vivo with respect to real-time tracking of respiratory motion. The ultrasound data of the liver with approximate sagittal view were acquired in a volunteer during around 10 deep breathing cycles with an ultrasound system (Echo Blaster 128 1-Z)from Telemed Inc. (LT). For image generation a curved linear array transducer (Vermont Inc., 3.5. MHz, 128 lines, FoV=220mm) was used. The data were acquired in real-time with a frame rate of 25Hz and subsequently stored to a hard drive. The algorithm was run on the data by playing them back with the same frame rate as acquired.

3 Results

To demonstrate the feasibility of robust tracking, the proposed method was evaluated on liver ultrasound data. The parameters in the algorithm were set as follows: sample number=1000, σ(x-translation)=σ(y-translation) = 0.01, σ(x-scaling) =σ(y-scaling)= 0.005, σ(rotation) = 0.01, and the base contour was generated by manually picking up 28 contour support points (13 bright and 15 dark points) on the diaphragm and vena portae in the first frame of the ultrasound series. During the tracking, displacement parameters in 5 degrees of freedom for each ultrasound frame were recorded. An exemplary raw data frame with corresponding contour delineation is shown in Figure 1. The algorithm tracked the delineated features in real-time with a average computing time of 3.4 ms for each frame. Visual inspection of the tracking contour shows that the tracking contour follows the target structures very closely.

3.1 Algortithm Precision

To obtain a measure for the reproducibility of our stochastic procedure, several real-time runs of the algorithm on the same liver dataset were compared. In

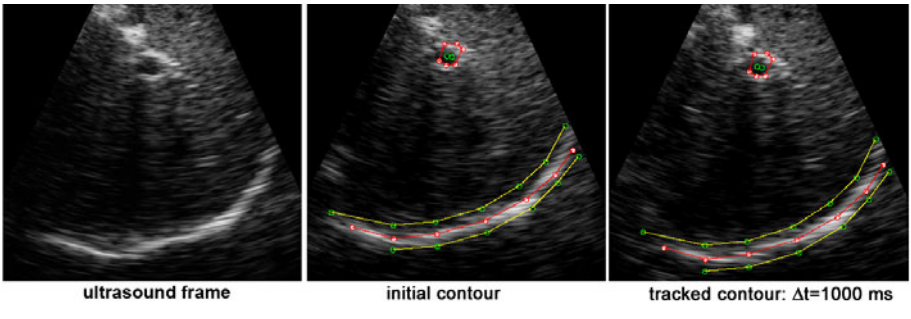

Fig. 1. Left: The field of interest in a ultrasound frame. Middle: The initial contour(28 points) overlayed on the first frame(Δt=0 ms) of the liver ultrasound data. Right: The tracking contour from our real-time algorithm overlayed on a later frame during deep breathing (Δt=1000 ms).

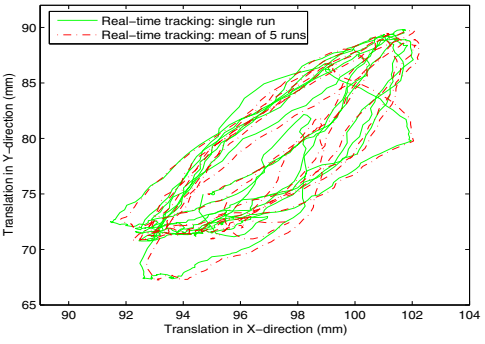

Fig. 2. x-y Trajectory of the contour with a single real-time tracking and the mean of 5 runs on the liver ultrasound data(36s, 909 frames) during deep breathing with 28 contour points(13 bright and 15 dark points). Tracking parameters were set as followed: sample number=1000, 5 degrees of freedom, σ(x-translation)=σ(y-translation) = 0.01, σ(x-scaling) =σ(x-scaling)= 0.005, σ(rotation) = 0.01.

Table 1. Standard deviation of 5 real-time runs in all the degrees of freedom with contour tracking(1000 samples, 28 contour points)

Standard deviation	Translation -X[mm]	Translation -Y[mm]	Scaling -X [100%]	Scaling -Y [100%]	Rotation [rad]	Computing time [ms]
Average	0.40	0.17	0.46	0.21	0.007	0.025
Minimum	0.071	0.027	0.082	0.036	0.002	0.001
Maximal	1.54	0.66	1.24	1.27	0.027	1.855

Figure 2 a typical real-time x-y trajectory of the contour (approx. 10 breathing cycles) is shown together with the mean over 5 independent runs of the experiment. From the figure, it can be seen that the real-time trajectory generally follows the mean trajectory within a distance of less than 1 mm. As a general measure for algorithm reproducibility the standard deviation for 5 independent real-time tracking runs on the same dataset was calculated. The maximal, minimum and average values of standard deviation in the time course are shown in Table 1, from which it can be seen that for typical situations the displacements of the live structures can be determined with a precision well below 1.6mm with the computing time for each frame less than 5ms.

3.2 Algorithm Comparison with Image Co-registration

As an independent measure of tracking quality, the results from the tracking procedure were then compared with an independent frame-by-frame image co-registration. Due to the relative poor quality of ultrasound images, all the frames of the ultrasound data were prepocessed with a mean filter of 9-by-9 neighborhood. Then co-registration was implemented using the ITK library, in which *Affine Transform,Linear Interpolator, Mean Squares Metric* and *Regular Step*

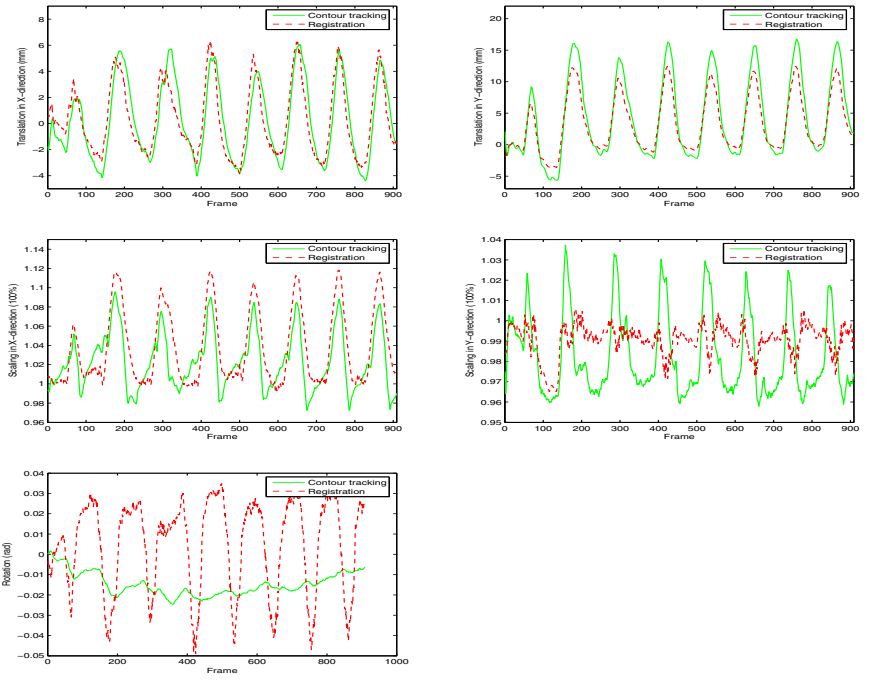

Fig. 3. Time courses of the 5 transform parameters(x-/y- translation, x-/y- scaling and rotation) for the liver movement during 8 breathing cycles resulting from the contour tracking algorithm and the co-registration method

Gradient Descent Optimizer are used [10]. Frame 15 in the liver data was defined as the base frame and then registered to all the other frames one-by-one to get the transform parameters. In this way, a continual spatial transform parameter set was generated as a contrast of the contour tracking algorithm.

Figure 3 shows the results of the 5 transform parameters with the contour tracking algorithm and co-registration method, in which frame 15 was adopted as a reference frame for both results. As we can see, the co-registration and contour tracking algorithm yielded rather similar time-courses for x-/y- translation and x-scaling. However, certain differences in y-scaling and rotation is notable.

Table 2. Transform parameters from frame 15 to frame 180 using registration and the contour tracking algorithm

Method	Translation -X[mm]	Translation -Y[mm]	Scaling -X [100%]	Scaling -Y [100%]	Rotation [rad]	Computing time [ms]
Registration	4.8271	11.8720	1.1139	0.9973	-0.0372	1626640
Contour tracking	4.9212	16.0640	1.0878	0.9845	-0.0195	3.461509

Also, the y-translation in the maximum inhaled and exhaled states proves several millimeters bigger when estimated from the contour tracking algorithm than from registration. Although in the some degrees of freedom there are large differences between the tracking algorithm and image co-registration method, it makes no sense to investigate the difference in each degree of freedom separately, because parameters only make sense as a whole other than considerded as separate numbers. To clarify the effect of the paramter sets on the actual ultrasond images the frame 15 was compared to a later frame 180 which has a large displacement. Respective transform parameters resulting from the contour algorithm and registration are shown in Table 2. To have a visual judgement on the transform quality, the resampled frame 15 with transform parameter sets from each method was subtracted from frame 180, and then the rescaled results are shown in Figure 4. From the figure, we can see that the major displacements around the diaphragm from the original images were corrected with the transform results of both methods. It was also shown that the contour tracking algorithm works better around the vena portae, while the registration yields a superior match at places where the ultrasound probe was contacted to the skin. These differences can mainly be attributed to the fact that the contour tracking

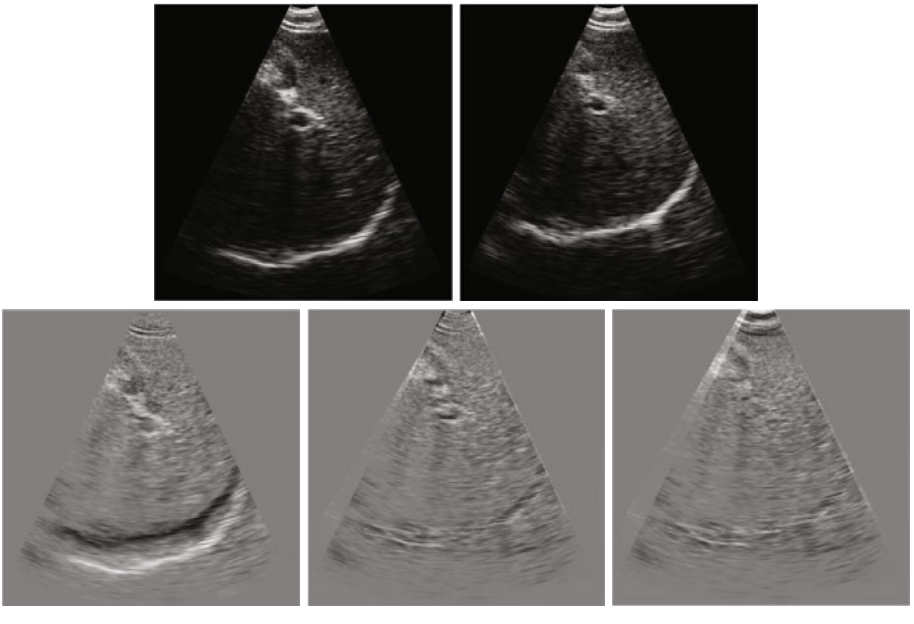

Fig. 4. Upper left: the ultrasound frame 15 in the liver data. Upper right: the ultrasound frame 180 in the liver data. Lower Left: the rescaled subtraction of frame 180 from frame 15. Lower middle: the rescaled subtraction of frame 180 from transformed frame 15 using the result of registration. Lower right: the rescaled subtraction of frame 180 from transformed frame 15 using the result of contour tracking.

algorithm tends to only match the structures a user delineated contour relevant, while the registration takes into account more or less all the image regions.

4 Conclusion

In this work we presented a method to track organ structures on ultrasound images using an algorithm based on conditional density propagation [8]. It was shown that with the method it is feasible to track relevant liver structures real-time on 2D ultrasound images with computing time in the order of milliseconds. The algorithm proves to be robust on low contrast target structures and insensitive against image noise and is therefore well suitable for ultrasound applications. As demonstrated the method provides high reproducibility. Because of the lack of ground truth in vivo tracking, an independent image co-registration registration method was introduced to determine the tracking quality. The comparison shows that the contour tracking algorithm tends to only match the structures a user delineated contour relevant, while the registration takes into account more or less all the image regions, which can be the main reason of the differences between these two methods. As the tracking algorithm leads to superior displacement correction in structures that was previously delineated as part of the contour, a good tracking of the target in real-time can be yielded with delineation of relevant structures on the image and using the suggested algorithm.

This ultrasound tracking method can then be beneficially used in several medical applications eg. the compensation of organ movements in radiation therapy to improve the accuracy of dose delivery to the target, and the real-time reduction of motion artifacts in diagnostic imaging modalities such as CT and MRI. For further clinical utilization, we are now developing the 3D tracking algorithm based on this proposed method.

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