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Tracking Performance in Ultrasound Super-Resolution Imaging

Iman Taghavi¹, Sofie B. Andersen^{2,3}, Carlos A. Villagomez Hoyos⁴, Mikkel Schou¹, Sigrid H. Øygard¹, Fredrik Gran⁴, Kristoffer L. Hansen², Charlotte M. Sørensen³, Michael B. Nielsen², Matthias B. Stuart¹, Jørgen Arendt Jensen¹

¹Department of Health Technology, Technical University of Denmark

²Department of Diagnostic Radiology, Rigshospital, Denmark

³Department of Biomedical Sciences, University of Copenhagen

⁴BK Medical, Herlev, Denmark

Abstract—Tracking plays an important role in super-resolution (SR) ultrasound imaging, as it improves the quality and sharpness of the final SR images. Moreover, tracking enables quantification of clinically important parameters, such as blood flow velocity. However, the tracking performance degrades in the presence of complex particle patterns and localization uncertainty due to noise and motion. This work presents and discusses multiple approaches for tracking evaluation and compares a nearest-neighbor (NN) with a Kalman tracker through simulations and an in vivo experiment. It is shown that in the presence of a localization uncertainty with a standard deviation (SD) of $\lambda/5$, the bias and SD of the velocity estimates reach -1.04 ± 0.9 mm/s and -0.12 ± 0.72 mm/s in the NN and Kalman tracker, respectively (relative to the peak velocity of 10 mm/s). The precision of individual track positions is estimated for an in vivo experiment as $37.95 \pm 21.37 \mu\text{m}$ and $23.9 \pm 11.82 \mu\text{m}$ for the NN and Kalman trackers, respectively. The results indicate that the Kalman tracker achieves a better velocity estimation and reduces localization uncertainty.

I. INTRODUCTION

Ultrasound super-resolution imaging (SRI) has been studied by various research groups over the last years [1]–[7]. The approach employs detection and tracking of microbubble (MB) contrast agents to visualize the micro-vasculature including the capillary network. A detector estimates the centroids of the MBs, and several factors including the non-linear imaging scheme, the signal to noise ratio (SNR), complex and nonuniform MB concentrations, and various MB dynamics affect the centroid estimation and tracking of the MB positions. The centroid localization is uncertain, since the above mentioned factors produce non-symmetrical, overlapped, dissimilar, and shifted target spread functions for the various MBs during the scan. These conditions are even worse for in vivo measurements, as several other ultrasound artifacts, organ motion, and uncontrolled MB concentrations depending on the 3D vessel structure, affect the images.

The tracking methods aim to link the detected MBs from frame to frame. The methods range from simple nearest-neighbor (NN) [8] to multi-frame data structure and using explicit motion models (*e.g.* Kalman filtering) [6], [9]–[11].

This work investigates several performance metrics for tracking evaluation. A NN and a Kalman tracker are compared through both simulations with known ground-truth and in an in vivo experiment with unknown ground-truth. Finally, a new tracking strategy that will likely address tracking difficulties in a wide range of scenarios is suggested.

II. METHODS

A. Simulation

The simulations were made by generating MB positions, each with uniformly random lifetime and known ground-truth, moving with different velocities across an X-shaped phantom. A random localization error was added to each MB position. The various parameters of the phantom are listed in Table I. The ground-truth tracks with different MB density and trajectories of MBs with localization uncertainty are shown in Fig. 1. These simulations provided a wide range of scenarios, including various MB concentrations, velocities, and localization uncertainties.

TABLE I: Parameters used in the in-silicon X-phantom

Parameters	Value
Tube length	10 mm
Tube radius	250 μm & 125 μm
Peak velocity	10 mm/s & 5 mm/s
Velocity profile	Parabolic
Angle between tubes	60°
Point Spread Function (PSF)	Unsymmetrical Gaussian
Axial / Lateral FWHM	0.7 λ / 1.5 λ
Number of MBs per frame (mean $\pm$ standard deviation (SD))	Very low: 2 $\pm$ 2 Low: 8 $\pm$ 4 Medium: 28 $\pm$ 13 High: 49 $\pm$ 20
Uncertainty in localization (SD of localization error)	Very low: $\lambda/20$ Low: $\lambda/10$ Medium: $\lambda/5$ High: $\lambda/2$

B. In vivo measurement

The in vivo measurement was conducted using a modified BK5000 scanner, and an X18L5s transducer (BK Medical,

Fig. 1: Ground-truth tracks of various MB density scenarios for a (a) very low (b) low (c) medium or (d) high concentration. The tracks of uncertain MB positions with standard deviation of (e) $\lambda/20$ (f) $\lambda/10$ (g) $\lambda/5$ and (h) $\lambda/2$ for a low-density scenario are shown in the bottom row. The green dash lines show the wall of the tubes.

Herlev, Denmark) was used to record 10 minutes of contrast-enhanced and B-mode frames from a rat kidney with a frame rate of 53.85 Hz. A pulse amplitude modulation sequence was used for imaging with a transmit frequency of 6 MHz ($\lambda = 256 \mu\text{m}$). The transmit voltage was low with a corresponding mechanical index (MI) of 0.2 to prevent bursting of the MBs. The MBs (SonoVue, Bracco, Milan, Italy) were injected with a flow-rate of 100 $\mu\text{l}/\text{min}$ after a 1:10 dilution.

C. Tracking algorithms

In the NN tracker, the estimated MB positions in the next frame are linked to the MB positions in the current frame based on their minimum distance. Though NN is simple and fast, simple linking of MB positions generates false and flexuous tracks when the localization is uncertain. Considering the MB's smooth movement, more robust tracking is possible via Kalman filtering. This simple movement consideration can be modeled as $\vec{r}(t) = \vec{r}(t-1) + d\vec{r}(t) + \vec{\varepsilon}(t)$, where $\vec{r}(t) = (r_z(t), r_x(t))^T$ is the position of MB at time t , $d\vec{r}(t) = (dr_z(t), dr_x(t))^T$ is the displacement of the MB and $\varepsilon(t)$ is the uncertainty in the displacement. This model can be formulated within the Kalman framework as:

$$\begin{cases} \bar{x}(t) = \mathbf{F}\bar{x}(t-1) + \varepsilon(t) \\ \bar{z}(t) = \mathbf{H}\bar{x}(t) + \mathbf{v}(t), \end{cases} \quad (1)$$

where $x(t) = [\vec{r}(t), d\vec{r}(t)]^T = [r_z(t), r_x(t), dr_z(t), dr_x(t)]^T$, $\bar{x}(t)$ is the prediction of MB position in the next frame, $\bar{z}(t)$ is the estimated uncertain position,

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix},$$

$\varepsilon(t) \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, and $\mathbf{v}(t) \sim \mathcal{N}(0, \sigma_v^2)$.

In this study, the maximum linking distance was 500 μm , and the initial conditions of the Kalman filter were $\sigma_\varepsilon = 1 \text{ mm}$ and $\sigma_v = 100 \mu\text{m}$. After tracking, the velocity of the MBs was estimated by calculating the time derivative of track positions.

D. Evaluation

The first group of performance metrics, proposed in [12], was based on an assignment problem. To evaluate tracking performance using this approach, estimated tracks were paired with ground-truth tracks based on their minimum distance using Hungarian algorithm [13]. Hungarian algorithm provides fast optimal assignment of the two sets. The gate size is equal to λ , meaning that any tracks outside this gate range were considered as false positive (FP), tracks within the gate range were assumed as true positive (TP) or false negative (FN), if they are paired or unpaired to the ground-truth. The Jaccard Similarity Coefficient (JSC) is defined as $\text{JSC} = \text{TP}/(\text{TP} + \text{FP} + \text{FN})$, which determines the similarity of the set of estimated tracks and set of ground-truth tracks. The root-mean-square error (RMSE) of velocity estimates was calculated for each paired track (TP), and the number of unpaired (spurious) tracks was also counted as an extra performance metric. For the paired tracks, JSC of track positions and RMSE of the estimated positions can also be calculated to provide metrics at the position level.

The second performance metric was calculated by considering the known velocity profile of flow in the tubes as a ground-truth. In this approach bias and standard deviation of velocity profiles over different cross sections of the tubes were calculated.

The localization uncertainty in the in vivo data, used as the last performance metric, was estimated by RMSE of a fitted piece-wise least-square line to the MB positions.

III. RESULTS

The super-resolution (SR) images shown in Fig. 2 indicate that the Kalman filter has more smooth tracks in this scenario. All of the assignment-based performance metrics for various density and uncertainty scenarios at the track and position levels are listed in Table II and Table III (the green labels show a better performance). At the position level, the Kalman filter outperformed the NN almost in all scenarios. Notice that the RMSE of the track positions are relevant to the localization

TABLE II: Performance Metrics at Track Level (Color scheme: green → higher performance, yellow → roughly the same).

MB Density	Tracker	Unertainty in Localization											
		SD = $\lambda/20$ = 12.83 μm			SD = $\lambda/10$ = 25.67 μm			SD = $\lambda/5$ = 51.33 μm			SD = $\lambda/2$ = 128.34 μm		
		JSC	Spurious	RMSE	JSC	Spurious	RMSE	JSC	Spurious	RMSE	JSC	Spurious	RMSE
Very low	NN	0.731	14	0.01	0.731	14	0.01	0.731	14	0.05	0.132	250	0.33
	Kalman	1	0	0	1	0	0	1	0	0.03	0.528	34	0.01
Low	NN	0.961	13	3.19	0.953	16	0.01	0.835	64	3.22	0.148	1868	0.34
	Kalman	0.934	23	0.03	0.923	27	0	0.91	32	0.01	0.416	454	0.03
Medium	NN	0.892	104	0	0.839	165	0.02	0.642	478	0.9	0.104	7437	0.17
	Kalman	0.534	435	0.01	0.632	500	0.02	0.595	585	0.04	0.236	2194	0.19
High	NN	0.717	672	0.06	0.634	983	1.02	0.435	2209	0.3	0.095	16226	1.1
	Kalman	0.446	2079	0.04	0.418	2376	0.04	0.388	2681	0.01	0.215	6209	0.9

TABLE III: Performance Metrics at Position Level (Color scheme: green → higher performance, yellow → roughly the same).

MB Density	Tracker	Uncertainty in Localization							
		SD = $\lambda/20$		SD = $\lambda/10$		SD = $\lambda/5$		SD = $\lambda/2$	
		JSC	RMSE	JSC	RMSE	JSC	RMSE	JSC	RMSE
Very low	NN	0.639	15.02	0.639	29.49	0.576	52.27	0.127	135.23
	Kalman	1	11.99	1	20.34	0.937	37.63	0.584	88.92
Low	NN	0.754	14.3	0.672	25.12	0.557	38.86	0.154	115.25
	Kalman	0.92	13.96	0.836	22.18	0.788	36.61	0.463	76.55
Medium	NN	0.511	15.54	0.432	15.58	0.354	29.21	0.094	112.72
	Kalman	0.534	13.21	0.493	19.95	0.421	31.83	0.236	77.48
High	NN	0.446	16.52	0.36	22.62	0.266	40.09	0.078	111.92
	Kalman	0.432	15.98	0.38	22.92	0.319	38.99	0.189	79.75

Fig. 2: A comparison between (a) NN tracker, and (b) Kalman tracker for low-density scenario and uncertainty of $\lambda/5$ in the localization.

uncertainty. This will be used later to estimate the uncertainty of localization from the in vivo measurements. At track level, NN achieved a better rank in JSC, and the number of spurious tracks was lower in several scenarios. However, the velocity estimates of paired tracks were more accurate when a Kalman filter was employed. This diverse behavior of trackers through different scenarios is discussed in Section IV. It can be seen that in some scenarios the Kalman filter can reduce the number of spurious tracks by more than 67%.

To avoid the ambiguities in an assignment problem, the estimated velocity profiles over 14 cross-sections of the larger vessel in the final SR image are illustrated in Fig. 3. The velocity estimates and the resolution were improved by the Kalman filter. This shows the superiority of the Kalman over NN in a scenario with high MB concentration and uncertainty in the localization.

While there is no ground-truth for the in vivo measurement, less flexuous tracks are expected for more accurate localization or robust trackers. To measure the precision of the tracks positions, a piece-wise least-square line was fitted to MB positions tracked for more than 5 frames. Table IV lists the mean and SD of the localization error relative to the fitted line after NN and Kalman tracking. It shows that the Kalman filter has reduced the localization uncertainty. Fig. 4 shows SR images produced by the two trackers for 90 seconds of the in

Fig. 3: Velocity estimation statistics over 14 cross-sections of the large vessel for medium density scenario with localization uncertainty of $\lambda/5$. The NN estimates had a bias and standard deviation of -1.04 ± 0.9 mm/s, while these values for the Kalman estimates were reduced to -0.12 ± 0.72 mm/s.

Fig. 4: Super-resolution images of renal inner medulla created using the NN (left) and Kalman (right) trackers. The NN generated a lot of spurious and flexuous tracks. However, the Kalman tracker reduced these uncertainties. The structure is clearly distinguishable in the right image, as it is resolved down to 25.6 μm for almost every position.

vivo data. It is clear that the Kalman tracker outperforms the NN tracker.

Finally, velocity SR images of the entire kidney, shown in Fig. 5, demonstrate the difference between two trackers in terms of less spurious and less uncertain tracks.

TABLE IV: Tracking performance on localization uncertainty

Tracker	Precision of individual track positions
NN	$37.95 \pm 21.37 \mu\text{m}$
Kalman	$23.9 \pm 11.82 \mu\text{m}$

Fig. 5: Velocity SR images of the kidney show renal vascular tree with opposite flows (arteries and veins). The color wheel on top-right corner shows the flow direction of the color-coded tracks.

IV. DISCUSSION

Considering only the JSC and the number of spurious tracks, NN performed better than Kalman in some scenarios. Two key factors explain this behavior of the Kalman tracker. Firstly, based on the definition of optimal assignment, a unique estimated track must be assigned to a ground-truth track. A tracker might estimate a long track with multiple small tracks. In this case, while tracks are correct, the number of spurious tracks will increase, and JSC will decrease. Therefore, these two metrics cannot determine the overall performance of the tracker in all scenarios. Secondly, a single Kalman filter with specific initial conditions is employed for tracking in all scenarios. A Kalman filter might not reach a fair estimate within a short lifetime of these MBs. The question that may arise here is why we do not optimize the tracker for each specific scenario? The reason is that in an in vivo measurement, the tracker has to deal with a wide range of scenarios, as the MBs have uncontrolled concentrations as well as different velocities and flow dynamics when entering the blood stream. All of these scenarios are usually difficult to track with a simple tracking strategy. One solution would be tracking with a hierarchical structure. For example, a Kalman filter with a strict initial condition can apply to track slow flows. Then, the untracked MBs and the track positions with an overestimated velocity can be passed to another Kalman filter optimized to track faster MBs. This can be continued in a hierarchical structure to cover all range of scenarios [14].

V. CONCLUSION

Several performance metrics for the tracking algorithms in SRI were investigated. It was shown that in the presence of a high localization uncertainty, the Kalman tracker reached a better velocity estimate bias and SD of $-0.12 \pm 0.72 \text{ mm/s}$ compared to $-1.04 \pm 0.9 \text{ mm/s}$ in the NN relative to a peak velocity of 10 mm/s . The Kalman tracker reduced the precision of individual track positions in an in vivo experiment to $37.95 \pm 21.37 \mu\text{m}$ and $23.9 \pm 11.82 \mu\text{m}$ for the NN and Kalman trackers. Overall, the Kalman tracker was superior, as it estimated velocity with a higher precision and reduced localization uncertainty.

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