Published in final edited form as:

Phys Med Biol. 2015 October 7; 60(19): N345–N355. doi:10.1088/0031-9155/60/19/N345.

Optimization of tissue physical parameters for accurate temperature estimation from finite-element simulation of radiofrequency ablation

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Abstract

Computational finite element models are commonly used for the simulation of radiofrequency ablation (RFA) treatments. However, the accuracy of these simulations is limited by the lack of precise knowledge of tissue parameters. In this technical note, an inverse solver based on the unscented Kalman filter (UKF) is proposed to optimize values for specific heat, thermal conductivity, and electrical conductivity resulting in accurately simulated temperature elevations. A total of 15 RFA treatments were performed on *ex vivo* bovine liver tissue. For each RFA treatment, 15 finite-element simulations were performed using a set of deterministically chosen tissue parameters to estimate the mean and variance of the resulting tissue ablation. The UKF was implemented as an inverse solver to recover the specific heat, thermal conductivity, and electrical conductivity corresponding to the measured area of the ablated tissue region, as determined from gross tissue histology. These tissue parameters were then employed in the finite element model to simulate the position- and time-dependent tissue temperature. Results show good agreement between simulated and measured temperature.

Keywords

Radiofrequency ablation; Temperature simulation; Finite element analysis; Unscented Kalman filter; Inverse problem

1. Introduction

Radiofrequency ablation (RFA) is a standard minimally invasive treatment for unresectable liver cancer and other soft tissue tumors (Wong et al., 2010). Magnetic resonance (MR) is used for temperature mapping (Lepetit-Coiffé et al., 2010), and ultrasound imaging-based thermometry methods have also been proposed, including echo strain imaging (Anand et al., 2007; Daniels et al., 2007), echo decorrelation imaging (Mast et al., 2008; Subramanian et al., 2014), and other temperature mapping approaches (Rivens et al., 2007). For validation of such methods, tissue temperature in the image plane is often estimated using numerical methods such as the finite element method (FEM) (Daniels et al., 2007). Tissue parameter values for these computations are usually obtained from measurements reported in the literature. However, tissue parameter values vary among different tissue samples, and

uncertainty in these values strongly affects simulated tissue temperature (Tungjitkusolmun et al., 2000; Schutt and Haemmerich, 2008; dos Santos et al., 2009). To validate image-based thermometry methods accurately, tissue parameter values must be optimally estimated for the individual tissue samples employed.

Sample-specific tissue properties can be estimated using iterative inverse techniques (Fuentes et al., 2013; Audigier et al., 2014), which typically require a large number of computations before convergence. As a typical 3D FEM simulation of RFA requires about 1 h to complete, these methods can be computationally expensive (dos Santos et al., 2009). Also, there is no guarantee that convergence to a global minimum will be achieved, as the initial guess needs to be close to the optimal solution (Fuentes et al., 2013).

The unscented Kalman filter (UKF) developed by Julier and Uhlmann (2004) is a computationally inexpensive technique commonly used for state estimation and system identification problems. In this paper, an inverse solver based on UKF is proposed for optimization of tissue parameters to accurately simulate tissue temperature during RFA. In this approach, the unscented transform is used to approximate the mean and variance of the ablated tissue area through a nonlinear transformation of known mean and variance of tissue parameters (dos Santos et al., 2009). The mean-square error between simulated and measured ablated areas is minimized to recover a set of tissue parameters for accurate temperature simulation, appropriate for validation of image-based temperature mapping methods.

2. Methods

Below, methods are presented for accurate finite element (FE) simulation of temperature elevations from a series of *ex vivo* RFA experiments. For the geometry and exposure conditions of each experiment, a fixed number of FE simulations were performed using deterministic sampling of the specific heat, thermal conductivity, and electrical conductivity parameters. These simulations were used to approximate the mean and variance of the simulation outcome (area of the ablated tissue region) as well as a nonlinear mapping between the input tissue parameters and the ablated area. The Kalman filter was implemented to recover a set of tissue parameters minimizing the mean-square error between measured and simulated ablated areas. The following sections describe methods for the RFA experiments, FE simulation, and UKF implementation.

2.1. Experiments

RFA treatments were performed on fresh bovine liver tissue acquired from a local slaughterhouse using the experimental setup shown in figure 1(a). Liver tissue samples were cut with dimensions matching the sample holder ($85 \times 85 \times 60 \text{ mm}^3$), then stored in a bag filled with phosphate buffered saline (PBS) and placed in ice prior to treatment. A 1.5 mm diameter, custom-made needle electrode with an exposed length of 22 mm along with two 1 mm diameter thermocouples (Omega, Stamford, CT) were inserted through a custom made guide such that all were aligned parallel to each other, with the two thermocouples at a distance of 8 mm from the electrode. A grounding pad was placed at the distal end of the tissue relative to the RF probe. A 500 kHz sine wave was produced by a signal generator

(33220A, Agilent, Santa Clara, CA) with voltage amplitude 280–320 mV_{pp}, amplified using a 50 dB gain RF power amplifier (3100L, ENI, Rochester, NY), and supplied to the needle electrode.

15 RFA treatments were performed with 31–34 V_{RMS} input voltage and treatment durations 1–6 min. For each experiment, RFA treatment was stopped when the impedance near the RF probe increased due to tissue vaporization at high temperatures (> 100 °C), as indicated by large fluctuations of the amplifier's built-in power meter. Initial power readings from the amplifier's built-in power meter were within the range 60–80 W; these readings included both forward and reflected radiofrequency power and thus substantially exceeded the electrical power absorbed by the tissue. This range of exposure conditions was chosen because, in preliminary experiments, it resulted in thermal lesions of diameter 1–2 cm after treatments of 1–3 min duration.

Ultrasound imaging was performed using a 192 element, 7 MHz linear ultrasound array (L7, Guided Therapy Systems, Mesa, AZ) as part of a concurrent study (Subramanian, 2015), in which the ability of ultrasound echo decorrelation imaging method (Mast et al., 2008; Subramanian et al., 2014) to monitor treatment was assessed. The ultrasound image plane (figure 1(b)) was aligned to include the RFA electrode tip as well as the two thermocouple tips. Temperature measured by the thermocouples was recorded throughout all treatments using a digital data logger (HH309A, Omega, Stamford, CT).

After completion of each treatment, the liver sample was placed in a container matching the sample holder size and frozen in a –80 °C freezer to retain shape for the purpose of accurate image registration (Mast et al., 2008). Samples were sectioned parallel to the image plane as part of the concurrent study (Subramanian, 2015). The tissue section closest to the ultrasound image plane was scanned using a flatbed scanner (V600, Epson, Long Beach, CA) at 600 dpi. The thermal lesion was manually segmented based on gross discoloration of the tissue, with all the pixels within the lesion boundary defined as ablated. This region of discoloration, in which ablated tissue appears paler than normal tissue (Graham et al., 1999), comprises a conservative estimate for the extent of thermal necrosis during *in vivo* thermal ablation (Thomsen, 1991). The ablated area was quantified as the total area of all pixels within the segmented lesion boundaries (Mast et al., 2008).

2.2. Finite element simulations

Tissue temperature was simulated using ABAQUS software (Hibbit, Karlsson and Sorensen, Inc., Pawtucket, RI), where 3D models of the needle electrode and liver tissue sample were created to match the geometry of each RFA experiment. A fine mesh was created near the electrode, where the temperature gradient is largest, while a coarser mesh was created near the tissue boundary. Convergence tests were performed to ensure a sufficient mesh size.

To estimate tissue temperature, FEM simulations solved the Pennes bio-heat transfer equation (Pennes, 1948) without perfusion, given by

$$\rho c \frac{\partial T}{\partial t} = \nabla \cdot k \nabla T + Q, \quad (1)$$

where T is the tissue temperature, ρ is the tissue mass density, k is the tissue thermal conductivity, c is the tissue specific heat, and Q is the heating power per unit volume generated by the RF electrode, $Q = \mathbf{J} \cdot \mathbf{E}$, where $\mathbf{E}$ is the electric field intensity and $\mathbf{J}$ is the current density. The electrical field intensity and current density vectors were determined at each time step by solving the Laplace equation $\nabla \cdot \kappa \nabla V = 0$ independent of the thermal equation, where V is the voltage and κ is the electrical conductivity.

The initial tissue temperature was set to the average starting temperature measured by the two thermocouples in the corresponding experiment. A constant voltage, equal to the RMS value of the experimentally applied input voltage, was set at the RF electrode. An insulated boundary condition was implemented for both the thermal and electrical problems, except at the position of the grounding pad, where the electrical boundary condition was set to 0 V.

The ablated area was computed using a MATLAB (The MathWorks, Natick, MA) script, in which the simulated temperature within the image plane was first spatially interpolated to a resolution of 0.1 mm. The thermal dose parameter (Sapareto and Dewey, 1984) approximating the thermal damage in the tissue was then determined as

$$EM_{43} = \sum R^{T(r,t)-43} \delta t / 60, \quad (2)$$

where δt is the time step in seconds, $R = 2$ for $T \geq 43^\circ\text{C}$, and $R = 4$ for $T < 43^\circ\text{C}$. The thermal lesion within the image plane was defined by assigning pixels exceeding $EM_{43} = 200$ min as ablated, based on a previously defined threshold (Mast et al., 2005) and consistent with experimental observations on liver heating (Graham et al., 1999; Karunakaran, 2012). The ablated area was estimated as the total area of these pixels.

To calculate the electrical power delivered to the tissue in the simulations, the computed current density profile was recorded at the electrode surface at the end of treatment. The power delivered was determined as the product of current density with the applied voltage, integrated over the surface area of the needle electrode. The impedance value was determined as V_{RMS}^2 / P , where P is the power delivered to the tissue.

2.3. Unscented transform

The unscented transform is implemented here to propagate literature-reported values for the mean and standard deviation of specific heat (Haemmerich et al., 2005; dos Santos et al., 2009), thermal conductivity (Valvano et al., 1985), and electrical conductivity (Gabriel et al., 1996) through a nonlinear transformation to obtain the true mean and variance of the ablated tissue area. Mean and variance values obtained from the nonlinear transformation are used in the unscented Kalman filter to estimate the tissue parameters.

Parameter values used as input to the unscented transform are listed in table 1. The standard deviation of the thermal conductivity measurements was not reported in Valvano et al. (1985), hence an uncertainty of 25% was assumed for this analysis. The electrical conductivity of liver has previously been assumed to increase 2% with every degree rise in tissue temperature (Berjano, 2006). This temperature dependence is equivalent to the expression $\kappa = \kappa_0 1.02^{T-37}$, where κ_0 is the electrical conductivity value measured at 37 °C and T is the temperature in °C.

The unscented transform was implemented similarly to dos Santos et al. (2009). In this implementation, let the n -dimensional random variable $\mathbf{x}$ represent tissue parameters x_1 , x_2 and x_3 , denoting specific heat, electrical, and thermal conductivity, with mean $\bar{\mathbf{x}}$ and covariance $\mathbf{P}_x$. The input random variable $\mathbf{x}$ is related to the ablated tissue area $\mathbf{y}$ through a nonlinear transformation $\mathbf{y} = g(\mathbf{x})$. A set of tissue parameter values called sigma points $\mathcal{X}$, with associated weights w , are then deterministically chosen such that application of the nonlinear transformation g to these points completely captures the first two moments of the ablated area (expected value and variance),

$$\bar{\mathbf{y}} = \sum_i w_i g(\mathcal{X}_i) \text{ and } \mathbf{P}_y = \sum_i w_i (g(\mathcal{X}_i) - \bar{\mathbf{y}})(g(\mathcal{X}_i) - \bar{\mathbf{y}})^T. \quad (3)$$

Selection of sigma points and associated weights is performed using a Taylor series expansion of the transforming function to form the set of equations (De Menezes et al., 2008)

$$\sum w_i = 1 \text{ and } \sum w_i \mathcal{X}_i^m = E\{u^m\}, \quad (4)$$

where u is a zero-mean random variable and m is the order of a central moment for this random variable. Using the known mean and covariance of the input random variables, the weights and sigma points can be determined by solving equation 4 up to the fourth moment (dos Santos et al., 2009). For n -dimensional input random variables, the minimum required number of sigma points is $2n+1$ (De Menezes et al., 2008). However, for multivariate inputs, the effect of interdependence between input random variables needs to be considered. To this end, the sigma points are considered to be located at the edges, main axis, and center of an n -dimensional cube, resulting in a set of $2^n + 2n + 1$ sigma points (De Menezes et al., 2008). The weights and sigma points obtained using equation 4 for the case $n = 3$ are

$$\begin{aligned} w_{\text{edges}} &= \frac{1}{48}; & w_{\text{axis}} &= \frac{1}{36}; & w_{\text{center}} &= \frac{2}{3} \\ \mathcal{X}_{\text{edges}} &= (\bar{x}_1 \pm \sigma_1 \sqrt{3}, \bar{x}_2 \pm \sigma_2 \sqrt{3}, \bar{x}_3 \pm \sigma_3 \sqrt{3}) \\ \mathcal{X}_{\text{axis}} &= \begin{cases} (\bar{x}_1 \pm \sigma_1 \sqrt{3}, \bar{x}_2, \bar{x}_3) \\ (\bar{x}_1, \bar{x}_2 \pm \sigma_2 \sqrt{3}, \bar{x}_3) \\ (\bar{x}_1, \bar{x}_2, \bar{x}_3 \pm \sigma_3 \sqrt{3}) \end{cases} \\ \mathcal{X}_{\text{center}} &= (\bar{x}_1, \bar{x}_2, \bar{x}_3), \end{aligned} \quad (5)$$

where $\bar{x}_1$, $\bar{x}_2$, $\bar{x}_3$, σ_1 , σ_2 , and σ_3 are the mean and standard deviation of the specific heat, thermal conductivity, and electrical conductivity listed in table 1.

These sigma points were used as inputs to the FE model for each RFA treatment and the simulated tissue temperature data was saved at 5 s time steps. Tissue parameters were updated during the simulations according to the temperature dependencies given in table 1. Changes in the electrical conductivity for temperatures greater than 100 °C, due to tissue vaporization (Berjano, 2006), were not implemented, as the RFA treatments were ceased when sudden increases in electrical impedance were observed. The ablated tissue area was then estimated for all sets of sigma points using equation 2.

2.4. Unscented Kalman Filter

The UKF was implemented as an inverse solver, similarly to Wan and Van der Merwe (2000). In this approach, the goal is to determine a set of input tissue parameters minimizing the mean-square error between predicted and measured ablated areas. This minimization is achieved through a series of iterations where the mean and covariance of input random variables are updated until acceptable error (within 2%) is achieved. To avoid the computational expense of FEM simulations for each iteration, a mapping between the input tissue parameters x_1 , x_2 and x_3 and the ablated area y is approximated using a second-order Taylor series expansion (dos Santos et al., 2009)

$$y=g(x_1, x_2, x_3)=a_0+a_1x_1+b_1x_2+c_1x_3+c_{12}x_1x_2+c_{13}x_1x_3+c_{23}x_2x_3+a_2x_1^2+b_2x_1^2+c_2x_3^2 \quad (6)$$

The coefficients of the mapping function (equation 6) defining the second order mapping between the tissue parameters and the ablated area were determined using the Moore-Penrose pseudo-inverse method (dos Santos et al., 2009).

Let $\bar{\mathcal{X}}_k$; and $\bar{\mathcal{Y}}_k$ represent the weighted average of the sigma points and corresponding ablated areas at the k^{th} iteration. The mean $\bar{\mathcal{X}}$ and covariance $\mathbf{P}_{x_k}$ were determined using the weighted mean and covariance of the sigma points as

$$\bar{\mathcal{X}}_k = \sum_i w_i \mathcal{X}_{i,k} \text{ and } \mathbf{P}_{x_k} = \sum_i w_i (\mathcal{X}_{i,k} - \bar{\mathcal{X}}_k)(\mathcal{X}_{i,k} - \bar{\mathcal{X}}_k)^T. \quad (7)$$

Initial values $\bar{\mathcal{X}}_0$ and $\mathbf{P}_{x_0}$ were determined using equation 7 with $k=0$ and the initial sigma points defined by equation 5 and table 1.

At the k^{th} iteration, the output variables can be determined for corresponding tissue parameters and sigma points using the mapping function g as

$$y_k=g(\mathbf{x}_k) \text{ and } \mathcal{Y}_k=g(\mathcal{X}_k). \quad (8)$$

The updates are performed by first computing the innovation $\mathbf{P}_{y_k y_k}$ and cross $\mathbf{P}_{x_k y_k}$ covariances, which are defined as

$$\mathbf{P}_{y_k y_k} = \sum_i w_i (\mathcal{Y}_{i,k} - \overline{\mathcal{Y}}_k) (\mathcal{Y}_{i,k} - \overline{\mathcal{Y}}_k)^T \text{ and } \mathbf{P}_{x_k y_k} = \sum_i w_i (\mathcal{X}_{i,k} - \overline{\mathcal{X}}_k) (\mathcal{Y}_{i,k} - \overline{\mathcal{Y}}_k)^T. \quad (9)$$

The Kalman gain ($\mathbf{K}$) is defined as

$$\mathbf{K}_k = \mathbf{P}_{x_k y_k} \mathbf{P}_{y_k y_k}^{-1}. \quad (10)$$

The update equations for the mean $\mathbf{x}_k$, and the input covariance $\mathbf{P}_{x_k}$ are

$$\overline{\mathbf{x}}_{k+1} = \overline{\mathcal{X}}_k + \mathbf{K}_k (y_{\text{meas}} - \overline{\mathcal{Y}}_k) \text{ and } \mathbf{P}_{x_k} = \mathbf{P}_{x_k} - \mathbf{K}_k \mathbf{P}_{y_k y_k} \mathbf{K}_k^T, \quad (11)$$

where y_{meas} is the ablated area determined from gross tissue histology. The percent error between the measured ablated area y_{meas} and the estimated area y_k from equation 8 was determined for each iteration. If the percent error was greater than 1%, new sigma points were determined using equation 5 with the mean defined as $\mathbf{x}_k$ and standard deviation defined as the square root of $\mathbf{P}_{x_k}$ (equation 11), which was determined via Cholesky decomposition. These sigma points were then iterated from equations 7–11 to predict the new ablated area and to estimate new tissue parameters, until the percent error fell below 1% or converged to a constant value, which was below 2% in all cases.

Optimized tissue parameters for a given experiment were then used in the corresponding FE model to estimate tissue temperature profiles in the image plane. To verify the accuracy of the simulated temperature, time-dependent temperatures recorded by the two thermocouples were compared to corresponding time-dependent temperatures simulated at the thermocouple locations. The RMS error of temperature prediction at the thermocouple locations was determined using these time-dependent measured and simulated temperature values from all experiments.

2.5. Sensitivity Analysis

To estimate the uncertainty in temperature estimates using the UKF approach described here, sensitivity analysis was performed. The main causes for experimental uncertainty were identified as imprecise knowledge of the thermocouple location and electromagnetic interference.

Thermocouple positions within the image plane were determined from B-mode images using the hyperechoic spots (enclosed by red circles in figure 1(b)) caused by the thermocouples. Thermocouple positions were estimated to be accurate within a radius of 2 mm (average radius of these bright spots) in the image plane and an out-of-plane distance of ± 2 mm (the average tissue-slice thickness). To determine the effect of this uncertainty on tissue

temperature, standard deviations of the final simulated temperatures within two cylinders of 2 mm radius and 4 mm length around the two thermocouples were determined for all treatments. The uncertainty in temperature due to imprecise knowledge of thermocouple positions was then determined by calculating the mean of these standard deviations across the simulations corresponding to all 15 treatments.

Uncertainty caused by electromagnetic interference to thermocouple measurements was usually observed as a dip in the measured temperature when the RF signal was switched on. This uncertainty was determined by estimating the RMS value of the apparent change in temperature observed at the two thermocouple locations at the beginning of all treatments. The combined uncertainty in the simulated tissue temperature was then estimated as the square root of the summed squares of these two uncertainties.

3. Results

The mean and standard deviation of thermal conductivity, electrical conductivity, and specific heat estimated using the UKF and corresponding coefficients of variation are listed in table 2. Estimated values of these tissue parameters for all 15 treatments are listed in Subramanian (2015). Notably, while the mean values of thermal conductivity and specific heat were within the range of literature-reported measurements (table 1), the electrical conductivity was higher than this range. This could be due to the addition of saline during the RFA experiments.

The calculated electrical power delivered to tissue in the 15 RFA simulations was 11.08 ± 2.82 W (mean $\pm$ standard deviation). This is consistent with estimates of the absorbed electrical power required for ablation of the observed thermal lesion volumes (Mast et al., 2005). The corresponding simulated impedance values were 104.6 ± 14.87 Ω .

Figures 2(a) and (b) show tissue temperature simulated by FEM using UKF estimated tissue parameters and the corresponding tissue sections for two representative RFA treatments. Qualitatively, simulated tissue temperatures agreed with the ablated region (enclosed by dashed black lines) in the corresponding tissue sections. The temperature uncertainty due to imprecise knowledge of the thermocouple position was estimated as 3.32 °C. The uncertainty caused by electromagnetic interference on temperature measurements was determined to be 0.53 °C. The combined uncertainty of the aforementioned effects on simulated tissue temperature was 3.36 °C.

Figure 3(a) shows a scatter plot of ablated areas estimated by the FEM using UKF-optimized tissue parameters vs. measured areas for all ($N=15$) treatments. The average ablated area for all 15 treatments was 140.5 ± 82.6 mm². The average simulated ablated area was 136.8 ± 80.3 mm². The RMS error between the measured and simulated ablated area was 5.35 mm². To assess the accuracy of temperature simulations, the time-dependent measured tissue temperature at each thermocouple location was divided into bins of width 1 °C. The mean and standard deviation of the corresponding simulated temperature at each thermocouple location was determined for each measured temperature bin. Figure 3(b) shows the mean (solid line) and standard deviation (shaded area) of the simulated

temperature, plotted against the measured temperature at the thermocouple locations. The RMS error between simulated and measured temperatures at the thermocouple locations was 3.74 °C, only marginally greater than the estimated experimental uncertainty of 3.36 °C, implying that the simulated tissue temperature was within acceptable experimental error.

4. Discussion

Numerical simulations are often used to understand, reproduce, and predict experimental outcomes during RFA. These simulations are usually limited by uncertainty in tissue physical parameter measurements, location of blood vessels, and other sample-specific properties. Most RFA simulation studies have used measured values of tissue physical properties, reported in the literature, to simulate temperature elevation, resulting in substantial uncertainty (dos Santos et al., 2009). However, for verification of potential ultrasound and other image-based thermometry methods, temperature within the image plane must be accurately known. The UKF implementation presented here allowed accurate simulation of tissue temperature, with good agreement between simulation and experimental measurements, in the absence of precise knowledge of tissue physical parameters.

While the tissue parameters estimated using the UKF-based optimization method fell within the range of measurements reported in literature, they may not accurately agree with independently measured values. However, the tissue parameter estimates from the UKF-method resulted in simulated tissue temperatures that agreed with time-dependent temperature data measured using thermocouples. Thus, tissue parameters estimated in this manner should be sufficient to estimate accurate temperature maps suitable for validation of image-based thermometry methods. Further testing would be needed to assess the absolute accuracy of these estimated parameters.

Previous studies focusing on optimization of RFA simulations for accurate computations have been performed for the purpose of patient specific treatment planning (Audigier et al., 2014; Chen et al., 2009). Optimization was performed using classical gradient-based (Chen et al., 2009) or gradient-free (Audigier et al., 2014) techniques, where a series of computations were performed until convergence to a minimum error was achieved. In contrast, the UKF-based optimization method presented here requires a fixed number of up-front computations to approximate the relationship between tissue physical parameters and the resulting ablated tissue area. This second-order polynomial approximation (equation 6) between tissue parameters and ablated area allowed for minimization of the mean-squared error without further FEM simulations, reducing the computational cost. Use of GPU-based processing could further increase the speed of these computations. This method could also be applied to patient-specific treatment planning, allowing for prediction of thermal lesion formation and thus aiding in treatment guidance.

As these treatments were performed *ex vivo*, the measurements and simulations did not account for blood flow in living systems. Consideration of blood perfusion would be important for application of the present UKF method to *in vivo* treatment optimization. To obtaining accurate *in vivo* temperature estimates using this method, blood perfusion would

also need to be estimated. Estimation of this additional parameter would require 25 FEM computations instead of 15 per trial (dos Santos et al., 2009).

A major limitation of the present FEM implementation was the assumption of a homogeneous tissue medium. However, the liver is heterogeneous in nature, with structure including hepatic arteries and veins. The presence of large arteries and veins in the liver samples caused some non-uniform heating due to trapped blood and PBS, as observed in the tissue sections shown in figure 2. As this heating is often directional, for simplicity these effects were ignored while performing temperature simulations. This simplification was a significant source of error in the temperature estimations, and thus contributed to the RMS error observed between simulation and measurements.

Another limitation of the present model is that only one constraint was placed on this model, i.e the ablated area. Hence, the results converged to a small tolerance value. Adding additional constraints could result in more robust estimation of the tissue parameters, but could also possibly cause the solution not to converge within the small errors (< 2%) reported in this paper.

In conclusion, an inverse method using UKF to optimize tissue parameters for finite element simulation of tissue temperature has been investigated. Tissue temperatures simulated using this approach agreed with measured temperatures, within acceptable experimental uncertainty. Temperature maps simulated using this method should be useful for validation of image-based thermometry approaches to monitoring of RFA.

Acknowledgments

This research was supported by NIH grant R01 CA158439.

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Figure 1.

(a) Schematic diagram for the 15 *in vitro* RFA treatments. (b) Ultrasound B mode image representing the image plane with RF electrode (yellow circle) and two thermocouples (red circles).

Figure 2.
 Simulated tissue temperature and the corresponding tissue sections with dashed black lines representing lesion boundaries for two representative treatments with exposure conditions of (a) $V_{\text{RMS}} = 36.8$ V and treatment time of 58 s (b) $V_{\text{RMS}} = 33.5$ V and treatment time of 93 s.

Figure 3.

(a) Measured vs simulated ablated area for 15 RFA treatments. (b) Mean (solid line) and standard deviation (shaded area) of simulated tissue temperature for all time-dependent temperatures measured using thermocouples within 1 °C bands for all 15 treatments.

Table 1

Temperature dependence of literature-reported liver tissue properties, means and standard deviations of the coefficients, and values of thermal and electrical properties for the custom stainless steel needle electrode.

	k (W/m ² /°C)	c (J/kg/°C)	κ (S/m)	ρ (kg/m ³)
Relationship	$k = k_0 + 0.001265 T$ $0 < T < 100^\circ\text{C}$	$c = c_0, T < 63.5^\circ\text{C}$ $c = c_0 + c_1(T - 63.5), T \geq 63.5^\circ\text{C}$	$\kappa = \kappa_0 1.02^{T-37}$ $23 < T < 100^\circ\text{C}$	1060
Coefficients	k_0 (mean = 0.4882 std. dev. = 0.1221)	c_0 (mean = 3399.9, std. dev. = 522.34), $c_1 = 28.9$	κ_0 (mean = 0.3, std. dev. = 0.075)	
Electrode	18	840	1×10^8	6450

Table 2

Mean and standard deviation of UKF-estimated tissue properties for 15 RFA treatments.

	k_0 (W/m ² /°C)	c_0 (J/kg/°C)	α_0 (S/m)
Values estimated from UKF	0.400±0.038	3005±149	0.465±0.073
Coefficient of variation	9.64%	4.82 %	15.71%