ESTIMATING A PARAMETRIC MODEL OF TEMPERATURE DISTRIBUTION FROM AN ULTRASOUND IMAGE SEQUENCE DURING HIFU THERAPY

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ABSTRACT

This paper presents a novel method to estimate a parametric model of temperature distribution from a High-Intensity Focused Ultrasound sequence using a Kalman filter approach. The Kalman filter enables an initial temperature map, derived from (say) the echo-strain method, to not only be smoothed along the heat conduction direction, but to adopt a shape similar to the defined parametric shape of a sensor model. Effects of the model parameters and the covariances of the Kalman filter are investigated. Experimental results on phantom data show that the overall quality of the resulting temperature map is improved using our approach, enabling the extent of tissue “damage” caused by heating to be readily estimated through a visual display.

1. INTRODUCTION

HIFU (High-Intensity Focused Ultrasound) is a relatively new non-invasive cancer therapy method which has recently been introduced into clinical practice [1]. It ablates a tumour by generating and focusing high-power ultrasound in a relatively small area. A tumour is ablated through tissue necrosis mainly caused by the high temperature which is converted from the high-power ultrasound. HIFU has many advantages over alternatives such as targeted treatment, no incision, no radiation, short hospitalization time. However, the lack of a general monitoring protocol for the quality assessment of the treatment is one of the main difficulties in extending the use of HIFU clinically.

Some attention has been given to measuring temperature during treatment using US or MR. Ultrasound-based temperature measurement has advantages of relatively low cost, real-time imaging and easy aligning with a HIFU transducer. Ultrasound temperature estimation methods are generally based on the change of speed of sound due to the change of temperature. One of the principal methods is based on estimating echo strain which is linearly related to temperature change.

In the echo-strain approach the displacement between two images is first estimated and then differentiated along the axial direction to produce local echo strain. The temperature change is linearly related to the echo strain [2, 3]. Some filters are usually applied to smooth the estimated displacement and a least square line fitting method introduced to differentiate the displacement to attain echo strain [4].

The result of the echo strain method has been found to be acceptable for high signal-to-noise ratio data and for a small range of temperature change [2, 3]. However, in practice, the use of smoothing filters along the axis and lateral directions during echo strain estimation tends to distort the heat distribution. Further in the real HIFU situation, one needs to accommodate a large temperature range and data can have a low signal-to-noise ratio. To overcome these limitations, in this paper we investigate estimating a parametric model of temperature distribution from ultrasound data using a Kalman filter approach. Using phantom data we show that estimating a simple parametric model of temperature improves the overall quality of the temperature map and can be used to estimate the extent of tissue “damage” caused by heating.

2. THEORY & METHOD

Previous temperature estimation methods involve image post-processing operations such as smoothing which do not take into account any prior knowledge of the process being imaged. Although an accurate model of the heating effect is difficult to derive for the true HIFU case, one can make simple assumptions about the heat distribution that leads to a model that can be estimated robustly and efficiently as shown next.

2.1. The Parametric Model

During the HIFU treatment, the heat source is introduced by the high acoustic intensity in the focal zone of a HIFU transducer, so the shape of the heat distribution is likely to depend on the shape of the focal zone. Many studies [5] shown that a 3dB focal zone is an ellipsoid, such as about 3 mm diameter in the centre and 30 mm length. Therefore, we can assume that the heat source displayed on the image across the centre of the focal zone along axial direction is an
ellipse-shape. We further assume that heat conducts equally away from the heat source into a relative large homogeneous media with uniform ambient temperature. In this case the heat distribution will be an elliptical shape near the heat source tending towards a circular shape [6].

Referring to the co-ordinate system shown in Fig.1, a family of ellipses with the same aspect ratio \((a/b)\) parameterized by \(r\) can be expressed (in its principal co-ordinate system) by the following equations.

\[
x_r = C_x - a \cdot r \cdot \sin(\theta)
\]
\[
y_r = C_y + b \cdot r \cdot \cos(\theta)
\]

where \(x_r\) and \(y_r\) denote points on the ellipse, \(r\) controls the size of the ellipse, \(\theta\) is the angular variable of the ellipse, \(C_x\) and \(C_y\) are the centre of the ellipse, and \(a\) and \(b\) are parameters that determine the shape of the ellipse. For a circle, \(a\) is equal to \(b\). Changing the ratio of \(a\) to \(b\) (the aspect ratio), different elliptical shapes are attained.

![Fig. 1. The elliptical shaped heat distribution.](image)

2.2. Kalman Filter

We assume the temperature distribution follows an elliptic distribution parameterized by \((a, b)\), and the location of the centre of the heat distribution is known (in practice this is easy to find as the local maximum in temperature). Then iso-contours of temperature are elliptic in shape. We use this fact to smooth the data (temperature) for a given \(r\) around a number of elliptical contours using a 1D-Kalman filter in theta-space. We can increase \(r\) from a small value (we use 0.5 pixels) in increments \(\Delta r\) (=0.5 pixels in our work) to cover a region of the temperature map. The increments of \(\Delta \theta\) are changed for different \(r\) to keep the same spatial sampling along the ellipses, in order to provide the same sampling frequency for the Kalman filter.

The model for the Kalman filter is a linear stochastic difference equation governed by the following system:

\[
T(k) = T(k-1) + w(k)
\]

where the states \(T(k)\) and \(T(k-1)\) are the temperatures at location \(k\) and \(k-1\) along the contour and \(w(k)\) is assumed to be Gaussian white noise with a covariance of \(Q\).

As the measurement model \(z(k)\) we take a Gaussian smoothed estimate of temperature in the direction of heat conduction (normal to the ellipse contour). Specifically:

\[
z_r(k) = \sum_{i=-\infty}^{\infty} T_r(k)x_i + \nu(k)
\]

\[
x_i = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(T_r(k)-T_r(k))^2}{2\sigma_i^2}\right)
\]

where the \(x_i\)’s are samples of a Gaussian distribution with a variance of \(\sigma_i^2\) and with a length of \(2N+1\) along the normal to the ellipse distribution. \(\nu(k)\) is Gaussian white noise with a covariance of \(R\). We assume that both \(Q\) and \(R\) are constants in this work. The ratio \(Q/R\) determines the relative importance of the model and measurements, hence the degree of constraint imposed by the underlying model assumptions.

The following steps summarize the Kalman filter filtering process in an ellipse with given \(r\) [7]:

1. Predict temperature:

\[
T_r(k | k-1) = T_r(k-1 | k-1)
\]

2. Update the prediction covariance:

\[
p_r(k | k-1) = p_r(k-1 | k-1) + Q
\]

3. Calculate the Kalman gain:

\[
G_r(k) = \frac{p_r(k | k-1)}{p_r(k | k-1) + R}
\]

4. Update the temperature prediction:

\[
T_r(k | k) = T_r(k | k-1) + G_r(k)[z_r(k) - T_r(k | k-1)]
\]

5. Update the state covariance:

\[
p_r(k | k) = [1 - G_r(k)]p_r(k | k-1)
\]

3. RESULTS

3.1. Data Acquisition:

To well-define the shape of a heat source, a resistor was horizontally embedded inside a gelatin phantom. A heat distribution was generated by applying electric pulses to the resistor. The resistor was a cylinder approximately with a 2 mm diameter and 7 mm in length. One would thus expect the shape of temperature contours to be rectangular or elliptical. The ultrasound image plane was set about 2 mm away from the resistor to avoid distortion from the metallic effect of the resistor. RF data was acquired using an ultrasound system (Analogic 3500, Analogic Corporation, USA). This system has a sampling frequency of 40 MHz. A linear array transducer with 192 elements uniformly spaced in the length of 30 mm and in a centre frequency of 8 MHz was used for data acquisition.

After applying a series of pulses to the resistor at room temperature of around 11 °C, the temperature map (Fig. 3) was estimated using an echo strain method [2, 3]. Cross-correlation with a window of size 1.9 mm by 0.16 mm was used to estimate the displacements. A median filter of size 3 mm by 3 mm was used to filter the displacement map and a least-squares line fitting method [4] was used to produce the smoothed echo strain.

3.2. Image Processing Results:

Figure 2 shows the temperature map (left) and its contour map (right) before applying the Kalman filter. It is unlikely to show genuine fluctuations since the gelatin phantom was homogenous at this scale. The fluctuations are mainly
caused by the low signal-to-noise ratio of the original data. In addition, during temperature estimation the smoothing by the median filter and the least-squares line fitting method in the axial direction is done without considering the physics of the heat flow, and therefore may distort the result.

The Kalman filter in contrast is based on a simple physical model of heat flow. It was applied to the temperature map (Fig.2), with the ellipse centre automatically selected as the highest temperature point on the temperature map and hence assumed to be the centre of the source. In practice the final result is sensitive to the initialization conditions and also the order in which measurements are integrated into the estimation process. To minimize these effects, the Kalman filter was applied in both directions (clockwise and anticlockwise) and the final result was taken to be the average of both directions (Fig. 3).

Figure 4 and Fig. 5 show respectively the temperature maps and their contours after Kalman filtering. \(a/b\) controls the shape of the model and \(Q/R\) controls the relative weighting between model and measurement. From the first row to the third row in Fig. 4 and Fig. 5, \(a/b\) was 1, 0.6 and 0.3 respectively. A value of \(a/b=1\) gives a circular shaped model, and \(a/b=0.6\) (0.3) is an ellipse-shaped model which has a ratio of 0.6 (0.3) between the minor and major axis. From the first column to the third column in Fig. 4 and Fig. 5, \(Q/R\) was 0.1, 0.01 and 0.001 respectively. A smaller \(Q/R\) leads to a low pass filter which not only smooths the heat distribution but also deforms the heat distribution to the shape of the defined model. The effect of \(Q/R\) also depends on the spatial resolution (=0.156 mm/pixel in our work) of the temperature map. A higher image spatial resolution defines a smaller spatial distant between two system states in the linear stochastic difference equation (Eqn.2). This requires a smaller value of \(Q/R\) because the dynamic is relatively small for a small spatial distant.

Figure 6 shows the heat diffusion process after heat was applied. The temperature maps after the Kalman filter are smoother than those where the Kalman filter has not been applied. Whilst heat was conducted away from the heat source (from row 1 to row 3 in Fig. 6), the peak temperature decreased and hence the surrounding temperature increased. When using a threshold of 14 °C, the contours in Fig. 7 show the areas above 14 °C increase with time and the contour shape after Kalman filtering appears smooth and elliptical in shape.

Fig. 2. The temperature map (left) and its contour map (right) before Kalman filtering. The colorbar indicates the temperature. The contours show the temperatures range from 13.4 °C in a step of 0.1 °C towards the heat source.

Fig. 3. Effects of the direction in the Kalman filter. The black line shows the temperature sampled on a particular contour from Fig. 2. The green line and the blue line are the temperature after applying a Kalman filter on anticlockwise (\(\theta=0\rightarrow2\pi\)) and clockwise (\(\theta=2\pi\rightarrow0\)) direction respectively. The red line is the average temperature on both directions.

Fig. 4. Temperature maps after Kalman filtering. The colorbars indicate the temperature. Row 1: \(a/b=1\); Row 2: \(a/b=0.6\); Row 3: \(a/b=0.3\). Column 1: \(Q/R=0.1\); Column 2: \(Q/R=0.01\); Column 3: \(Q/R=0.001\).

Fig. 5. Contour maps corresponding to Fig. 4 respectively. The contours show the temperatures range from 13.4 °C in a step of 0.1 °C towards the heat source.
4. CONCLUSIONS

This paper has introduced a new model-based framework for temperature estimation. This model utilizes the prior information derived from the heat conduction equation. A Kalman filter was used to combine the model and the temperature measurement map which was estimated by a conventional echo strain method. Compared to the temperature map without the model, the model-based result has produced fewer spurious responses. The resulting images could offer a method to enhance the visual monitoring during HIFU treatment by a simple visualization of iso-temperature contour movement. We will investigate this in the next phase of our research.

The Kalman filter used in our method could be extended to provide a data association framework to incorporate other temperature measurements such as those from a mean scatterer method [8], measures such as backscattering intensity or a more sophisticated temperature model [5] (e.g. the true solution to the heat equation). In this work we have preferred to adopt a simpler model that was relatively fast to compute and hence is suitable for the real-time needs of our application (providing feedback during a treatment).

The ratio \(a/b\) controls the shape of the heat distribution model, and future work will look at how the most appropriate model could be selected for a real HIFU treatment. The ratio \(Q/R\) determines the degree of constraint imposed by the model. A method to direct and validate the choice of \(Q/R\) will be investigated further in future work.

Further work to validate the actual temperatures of each contour is needed as well through further experiments. We will look at extending the model to a fully spatial-temporal model. In practice this would need to take into consideration respiration motion either by a pre-processing registration step or in the estimation process itself. Other areas to be examined are inhomogeneities: in tissue (particularly blood vessels which cause significant heat conduction) and on the ultrasound field itself from heating related changes.

5. REFERENCES


