Improved temperature measurement and modeling for 3D USCT II

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Abstract

Medical visualization plays a key role in the early diagnosis and detection of symptoms related to breast cancer. However, currently doctors must struggle to extract accurate and relevant information from the 2D models on which the medical field still relies. The problem is that 2D models lack the spatial definition necessary to extract all of the information a doctor might want. In order to address this gap, we are developing a machine capable of performing ultrasound computer tomography and reconstructing 3D images of the breasts - the KIT 3D USCT II.

In order to accurately reconstruct the 3D image using ultrasound, we must first have an accurate temperature model. This is because the speed of sound varies significantly based on the temperature of the medium (in our case, water). We address this issue in three steps: so-called super-sampling, calibration, and modeling. Using these three steps, we were able to improve the accuracy of the hardware from ±1°C to just under 0.1°C.

Keywords: Temperature modelling, calibration, super resolution

1 Introduction

Breast cancer is the most common form of the affliction that there is, affecting more than 1.7 million women in 2012 alone. There is still a major problem with breast cancer screenings, as the images collected using the most common method, mammography, are two-dimensional. They therefore lack the spatial information that is often necessary for an accurate and confident judgement. At KIT, we seek to address this problem. Our novel imaging method uses ultrasounds computer tomography to reconstruct a 3D image of the breast. The prototype of this technology is currently being used in a clinical study called 3D-USCT II.

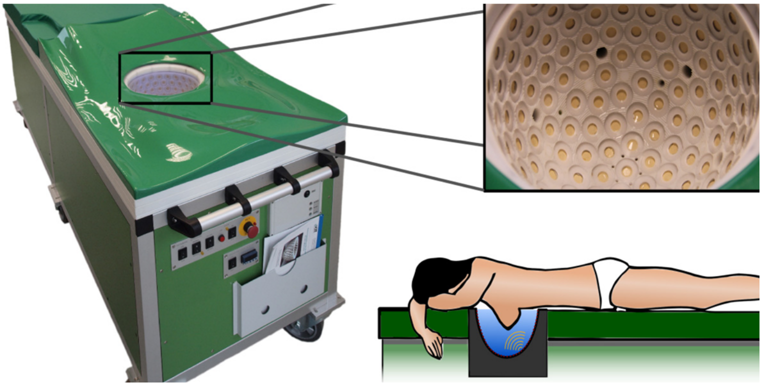

Figure 1: KIT 3D USCT II demonstrator (left), aperture (right top) and schematic

This technology functions based on the use of 3D synthetic aperture focusing, or SAFT, applied to unfocused spherical waves that are iteratively emitted and received by individual transducers. The measurement of these waves takes place in a semi-ellipsoidal water-filled container (17cm x 24 centimeters, height x width), which can be both lifted and rotated. Thousands of transducers have been strategically placed along the walls to form the imaging aperture. These transducers have a resonant frequency of 2.5 MHz at 50% relative bandwidth and a directivity of ±23° at 6dB. The system images and processes the data based on several imaging techniques, such as the previously-mentioned SAFT technique and transmission tomography-based approaches [1].

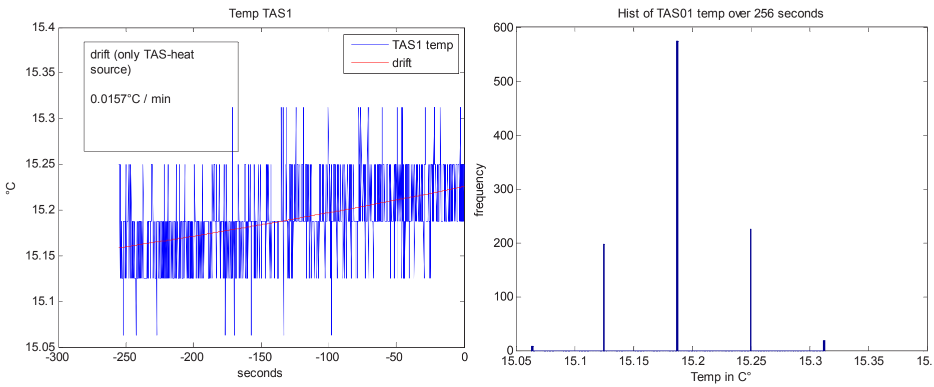

Figure 2: Left: temperature measurement over four minutes (blue curve). Visible noise and temperature drift. Red curve is the low order polynomial fit. Right: histogram of the measurement

2 Motivation

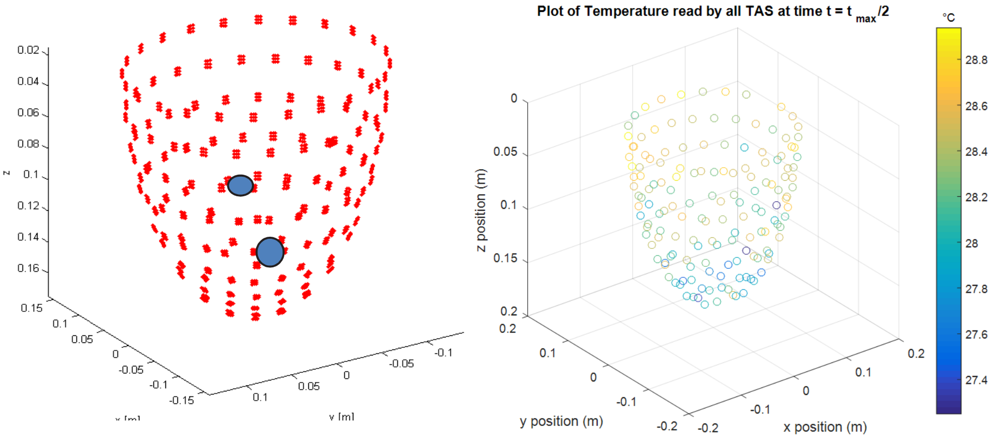

Figure 3: Left: Distribution of temperatures sensors, red dots indicate TAS temperature sensor position in space, blue dots are the 2 high quality JUMO sensors; right: temperature distribution over aperture surface and sensors.

The key point about the previous paragraph to understand for this paper is that the imaging techniques mentioned require accurate time-of-arrival and speed of sound values such that they can calculate back to identify the depths of possible lesions and cysts. The fidelity of these values is called into question by several factors. However, by far the biggest culprit in engendering errors is the variation of the speed of sound due to variations in medium temperature. The speed of ultrasound waves in water is significantly temperature-dependent [1].

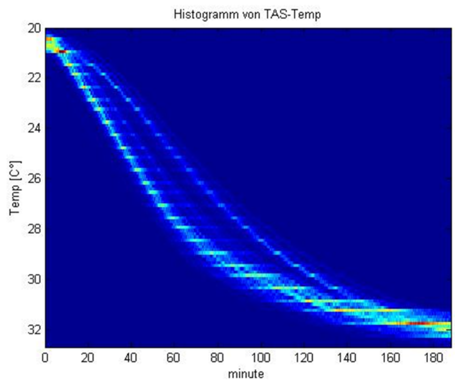

Figure 4: Temperature drift and spatial spread as 2D histogram over all TAS temperature sensors during 3D USCT heat up. X-axis is time, y-axis is temperature, color coding frequency of temperature. Around minute 80 the spread is the biggest, the system has “settled” after three hours.

There are several factors that may lead to poor temperature data. These include the outside air temperature, heating due to the systems DAQ electronics (roughly 1kW), heat dissipation at the water‘s surface, heating from the patient‘s body (roughly 100W), and mixing of the water due to the patient‘s motion.

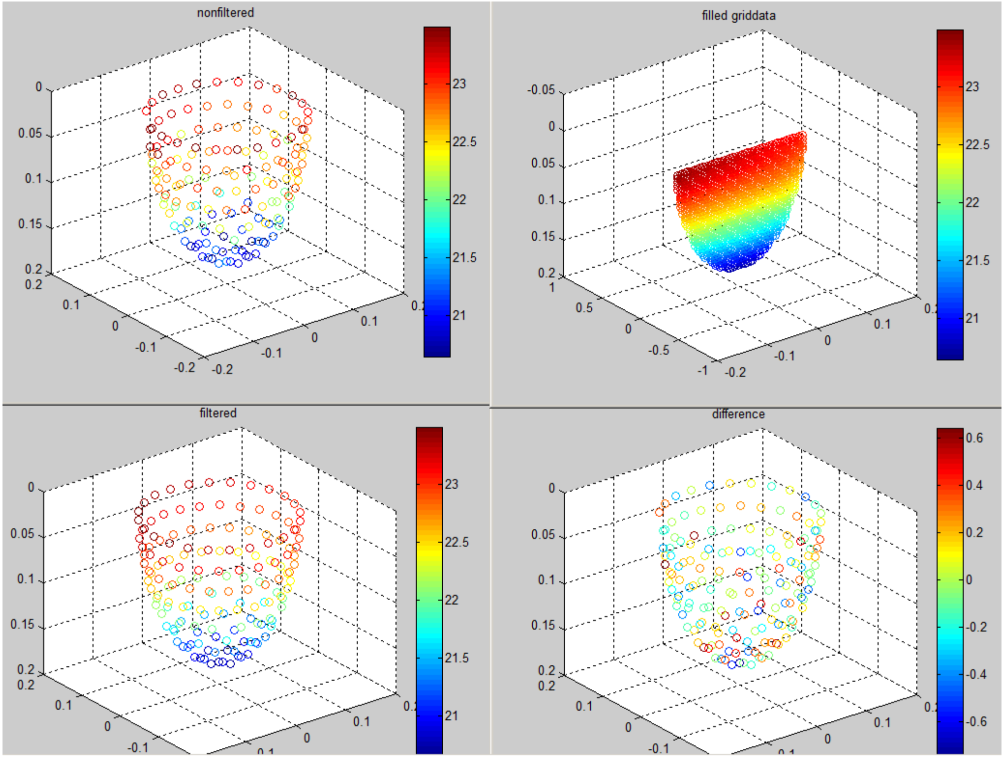

Figure 5: top left: raw temperature distribution, bottom right: filtered temperature, top right modelled and extrapolated for the water, bottom right: difference temperature filtered vs unfiltered

We pre-heat the water to match the patient‘s body temperature to mitigate the effects of the patient‘s body temperature as much as possible. However, even this is often impractical in the dynamic situations presented in hospital environments.

To summarize, the behavior of the temperature of the water is complicated and difficult to regulate into the required margins. As a result, we found it necessary to actively collect temperature data across space and time to develop a robust temperature model with which the images can be accurately reconstructed.

3 Hardware Setup

The USCT system utilizes 157 Transducer Array Sensors (TAS), each of which is outfitted with nine receivers, four emitters, and one MAX6627 temperature sensor. According to its datasheet, the MAX6627, hereafter referred to as TAS, has an accuracy of ±1°C and offers 12-bit resolution. It therefore has a temperature resolution of 0.0625°C-per-bit. The temperature measurement cadence is limited to about 320 milliseconds.

The system additionally contains two, high-accuracy temperature sensors, the JUMO dTRANS T03 B Typ 707031 Pt100 (DIN EN 60751), hereafter referred to as JUMOs. The datasheet reports the JUMOs‘ accuracy as 0.08°C and offers 10-bit resolution. This makes its temperature resolution similar to that of the TAS.

3.1 Constraints and Requirements

We have estimated that our required speed of sound accuracy should be within 1m/s. This translates to a temperature-accuracy of approximately 0.1°C, as opposed to the ±1°C offered by the TAS. Another constraint is that the collection of temperature information should not disturb or slow down the overall USCT measurement process, which, for a typical patient, is on the order of several minutes.

4 Methods

We take three steps in order that the necessary resolution and temperature accuracy are acquired. The path of the data is as follows. We begin with the raw temperature data from the 157 TAS. This raw data is passed through our super-resolution step, which is meant to increase accuracy and compensate for drift. The compensated data is then passed into the calibration step, in which we attempt to mitigate the effects of the hardware parameters of the TAS. The calibrated data then moves into our final step in which we determine a suitable spatial and temporal temperature model and remove outliers. These steps are described in more detail in the following sections.[2]

4.1 Super-Resolution

The analog-to-digital converter (ADC) has a standard deviation of 0.0405°C. This value correlates to having a standard-error-derived confidence interval and reliability of 68% at 0.081°C (1.29 bits) and to having a reliable of 95.5% at 0.162°C (2.59 bits).

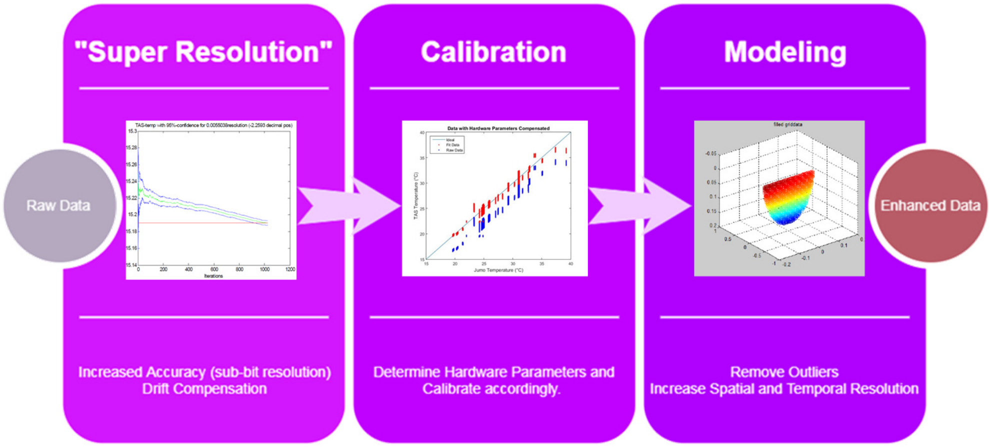

Figure 6: 3 step process for temperature data handling

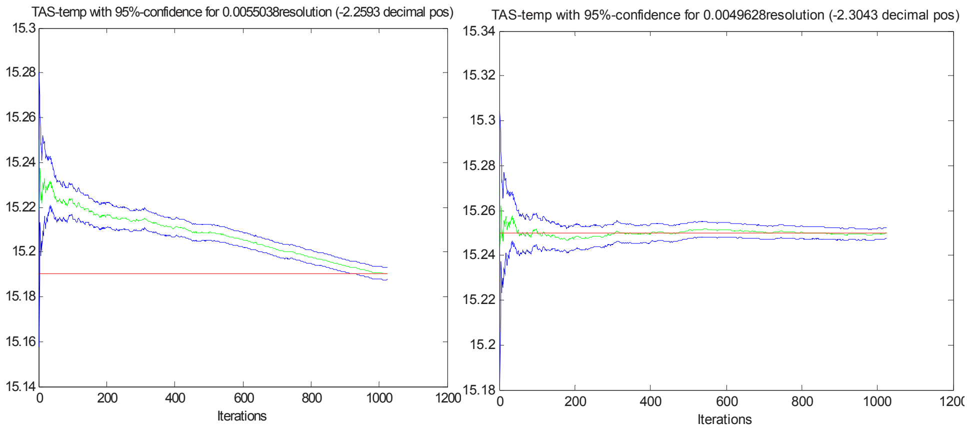

Figure 7: Blue lines 95% confidence interval, green line actual temperature measurement value, red line final end result. Left: Temperature measurement without drift compensation, red line leaves the confidence interval. Right: with drift compensation, the red line is always inside the confidence interval.

We know from signal processing and sampling theory that oversampling by simply averaging over time can achieve a higher reliability and accuracy, given that the noise is distributed normally. However, due to us having a limited measurement read-out speed, and as we expect to see a significant effect of drift over time, we cannot apply simple averaging. Rather, we must begin by compensating for the observed drift.

In order to do so, we began by changing the modus operandi of the temperature measurement from a synchronous on-demand action to an autonomous measurement. This process is handled by the TAS internal TI430 microcontroller, which fills in an internal memory buffer at a 0.5 second cadence.

We then used this data to model the drift with a first-order polynomial fit over the measurement time. This substitute of the simple averaging technique suggested by signal processing and results in an improved accuracy as well as super-resolution (resolution below 1 bit).

4.2 Calibration

After the applying the previous step to all TAS measurements, we pass the compensated data into our calibration step. The TAS temperature data suffers from a significant offset due to hardware parameters. This is in large part due to bad coupling with the water medium, as each TAS is insulated by a 0.4 millimeter ceramic plate. We have also noticed that the TAS see small heating effects from the DAQ electronics surrounding them. When compared with the generally good temperature measurements of the JUMO sensors, which are topped with a stainless steel tip that extends directly into the water, the TAS measurements need to be significantly adjusted.

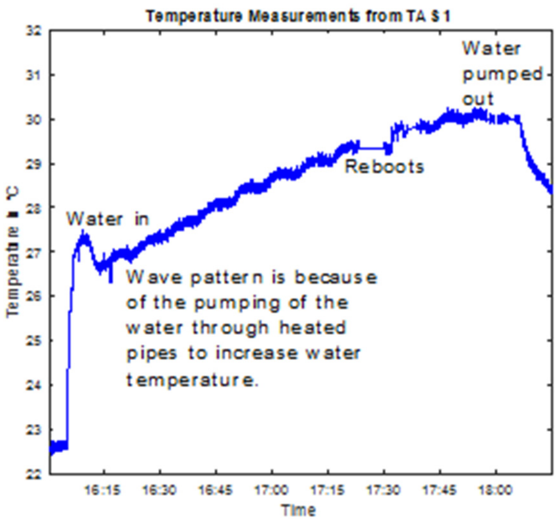

Figure 8: Temperature measurement monitoring the heat up of the system. Approx. over three hours.

4.3 Spatial and Temporal Temperature Modeling

Our final step begins with us removing the outliers from our newly calibrated data. We do this by removing the TAS measurements that are more than ten standard deviations away from the median of its 10 closest neighbors' temperatures. Having removed outliers, we can now begin to determine an overarching temperature model. We apply a second-order polynomial fit over the spatial domain, which assumes that the temperature change happens very slowly over space. This has been experimentally shown to be a safe assumption.

5 Results

Our process increases the accuracy and prevision of the TAS temperature measurements by more than an order of magnitude, 36.3x and 12.6x, respectively. This is well beyond the original 1 bit resolution. Though the datasheet specifies ±1°C for the TAS, for a 512 second measurement period with 1024 samples, we achieves 0.00496°C with a 95% confidence interval.

6 Conclusion and Future Work

Though we have, for the most part, achieved the goal, which we had set out to achieve, when we plot the temperatures seen by our TAS, we see layering effects. These layering effects are quite significant, up to around 1°C. We are currently investigating the possible causes of such a phenomenon. We have recently begun to collect more data about possible confounding variables such as air temperature above the ellipsoid, air temperature around the ellipsoid, heating due to the DAQs and piping that run around the ellipsoid, and initial water temperature. We are currently using manual sensors with the same accuracy as the JUMOS (0.08°C) to measure these effects and correlate them to patterns we see in our TAS data.

Figure 9: left and middle: calibration of Greisinger temperature measurement probes, right: setup for measuring the heat-up of the 3D USCT 2.0 and air temperature for improved calibration

References

[1] Ruiter et al., „Realization of an optimized 3D USCT," *SPIE 7968, Medical Imaging 2011: Ultrasonic Imaging, Tomography, and Therapy,,* 2011.

[2] Zapf, Michael & Menshikov, Alexander & Ruiter, Nicole. (2016). Temperature model for 3D ultrasound computer tomography. 1-4. 10.1109/ULTSYM.2016.7728723.