TEMPERATURE DETECTION BASED ON NONPARAMETRIC STATISTICS OF ULTRASOUND ECHOES

MICHAŁ BYRA, BARBARA GAMBIN

Institute of Fundamental Technological Research
Pawińskiego 5B, 02-106 Warsaw, Poland
mbyra@ippt.pan.pl, bgambin@ippt.pan.pl

Different ultrasound echo properties have been used for noninvasive temperature monitoring. Temperature variations that occur during the heating/cooling process induce changes in a random process of ultrasound backscattering. It has already been proved that the probability distribution of the backscattered RF (radio frequency) signals is sensitive to temperature variations. Contrary to previously utilized methods, which explored models of scattering and involved techniques of fitting histograms into a special probability distribution, two more direct measures of changes in statistics as temperature markers are proposed in this paper. They measure the "distance" between probability distributions. The markers are the Kolmogorov Smirnov distance and Kulback-Leiber divergence. The feasibility of using such nonparametric statistics for noninvasive ultrasound temperature estimation is demonstrated in the ultrasounds data collected during series of heating experiments in which the temperature was independently registered by either a classical thermometer or thermocouples.

INTRODUCTION

Two types of the thermal treatment of human soft tissue should be supported by temperature field monitoring. The first case is local hypothermia, in which the elevation of the temperature to 43°CC results in the cells' defensive biochemical reaction, namely the production of the so-called heat shock proteins (HSP). HSPs are chaperones, and they serve to ”repair” the affected proteins, which can be observed, for example, in Alzheimer's disease. Such a temperature range does not cause irreversible changes in living cells. The second case is radiofrequency ablation therapy (thermoadlation), which involves the thermal destruction of parts of ill tissue. This requires raising the temperature above 43°C. Special ultrasonic heating transducers can be used in both of these treatments; in the first therapy low-intensity focused ultrasound (LIFU) is used, and in the second, high intensity focused ultrasound (HIFU). It is clear that the quality of both of these therapies is related to the current control of the temperature field, i.e. the volume of the heated area and the temperature level. For several years, studies have been conducted on the possibility of the non-invasive precise monitoring of the temperature field by registering the variations in the backscattered ultrasound field, see [1], [2] and references therein. The statistical properties of the backscattered signal amplitude depend on the scatterers' according reflectivity and as well as their geometrical distribution. Due to the fact that both of these features can change during heating, some statistical characteristics should accordingly be sensitive to temperature variations. In papers [3] and [4], this idea was explored. Firstly, the signals were subjected to band-pass filtering around the transmit frequency and a compensation of attenuation was performed. Then the random amplitude data was matched to different probability distributions, which are commonly used to describe the nature of the scattering from soft tissues, cf. [5], [6], [7] – in particular, the Rayleigh distribution, Nakagami and K-distributions were studied. We found that the statistical properties of amplitudes are very sensitive to the methods of attenuation compensation, and consequently, also the statistical parameters of the probability distributions are dependent on such data preprocessing. Notwithstanding, the shape parameters of the K and Nakagami distributions were proposed as temperature markers. To become independent of data processing, we decided to perform a statistical analysis upon another basis. The only signal filtering, we caried out was to limit the bandwidth of the received echoes to the nearest range of transmit frequency. Then, after calculating the signals' amplitudes, changes in their statistics which were caused by heating and cooling will be measured by the most direct method: the "distances" between the probability distribution functions. In this way we omit the determination of a class of distribution, and on top of this, as regards the chosen distribution. We have used two different measures of 'distance' between distributions, namely the Kolmogorov-Smirnov distance and the Kullback Leiber divergence. Furthermore, this analysis is performed to demonstrate why these measures can be used as markers of temperature variations. The paper is organized as follows. In Section 1 a brief description of performed experiments is given. Section 2 contains the main results and the final remarks are given in Section 3.

1. EXPERIMENTS

Two types of tissue mimicking materials were used in experiments, namely the PVA-c (polyvinyl alcohol - cryiogel) sample and the AGO (Agar-Oil) samples; details of the experiment are given in [8]. The PVA-c sample was heated by water bath. The temperature of the bath was increased linearly from 20.6°C to 48.8°C within the space of one hour. Next, the heating was switched off, and over the next two hours, the temperature decreased to 25.8°C. RF signals were registered by means of ultrasound (ULTRASONIX SonixTOUCH, British Columbia, Canada) with the linear transducer L14-5/38 at a frequency of 8 MHz. RF signals were recorded every halfminute (361 times) during the hour long heating and two-hours cooling periods. Heating of AGO (Agar Oil) samples were performed with the use of the spherical ultrasonic transducer (central frequency 2.2MHz, diameter 44mm, 44.5mm focal length, area S = 15.2cm2) over the course of 10 minutes. The temperature within the sample was firstly recorded by thermocouples along the beam axis during heating and following that, there was 10 minutes of cooling. Secondly, the imaging transducer registered frames every 5 seconds for the 20 minutes of the same heating/cooling process as in the first case. The same imaging system as in the PVA-c experiment was used, but in addition to this, time synchronization was conducted on the heating and imaging transducers in order to preserve the imaging process from acoustic noise, which was possibly coming from the heating beam. The sampling rate (sampling frequency) was 40MHz and the imaging frequency was 8MHz. The measurements were repeated for two of the heating transducer's heating powers, that is to say powers of 4 W and 6 W. The temperature range measured by thermocouples was between the range of 20°C and 48°C.

2. MEASURES OF DISTANCE BETWEEN STATISTICAL DISTRIBUTIONS

In what follows as a random one dimensional variable, the amplitude values of FR signals at the fixed moment in time is understood. The Rf signals are backscattered from square areas with dimensions of 3mm x 3mm, which are marked in Figures 1 and 2 as different ROI's (region of interest) located at different points within the samples. The empirical histogram from every ROI at any fixed moment in time during the heating process was also determined. The aim of this contribution is to demonstrate that the two measures of distance defined below between two particular distributions, namely the random amplitude at the starting point of the thermal process and the random amplitude distributions for every successive time moments in the process, both calculated from within the same sample region, can both be used as excellent temperature markers. The first nonparametric statistics we have is the Kolmogorov-Smirnov distance (KS statistics), which is the distance between the two empirical distributions, computed as the maximum absolute difference between the cumulative curves. Firstly, in order to determine this distance, the cumulative distribution function from the empirical histograms must be calculated. The second distance is the Kullback-Leibler divergence (or relative entropy). This is the most commonly used measure of dissimilarity between two probability distributions. For discrete probability distributions P and Q, the Kullback–Leibler divergence (KL statistics) of Q from P is defined as

$$D_{\mathrm{KL}}(P\|Q) = \sum_i P(i)\,\ln\frac{P(i)}{Q(i)}. \tag{1}$$

The above expression means that the KL divergence is the expectation of the logarithmic difference between probabilities P and Q, where the expectation is made by using probabilities P. The KL distance is not a distance in the typical (metric) sense, due to its lack of symmetry and triangular inequality, and so can be used in places in which directionality is meaningful. The KL distance was calculated from the empirical distribution function estimated using the kernel density estimation method, with the Gaussian kernel.

3. RESULTS

The ”distances” between the initial statistics of the signal amplitude from the statistics of the amplitudes at successive time moments within the thermal process were calculated using MATLAB. In Fig. 1, the ROI areas are indicated on the B-mode images: the PVA-c sample is on the left, the AGO on the right, respectively. The echo amplitude from this area formed the data which was used in calculations.

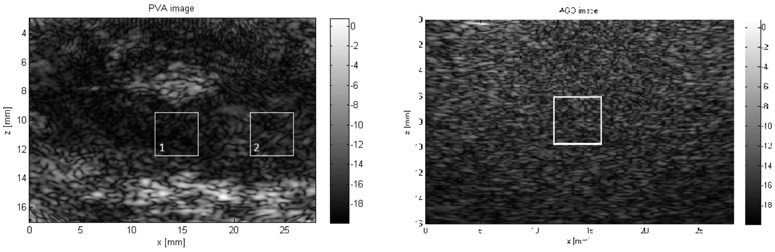

Fig. 1. The USG image of the PVC-c sample with two marked ROI's: ROI1 located centrally and ROI2 close to the sample side, left the USG image of AGO sample with fixed ROI located near the center of the sample, right.

The KS distance between the probability distribution function of the echo amplitude recorded at the initial moment and the consecutive probability distribution function over the next moments of the thermal process creates a time-variable map of the "warming-up" of the material in the PVA-c sample. As an illustration of this, in Figs. 2 and 3, we are able to observe in the maps in ROI1 and ROI2 the situation 5 minutes after the start of the process then after 1 hour of heating (which is to say the point at which there is the maximum increase in heating) and finally the situation after a further two hours of cooling.

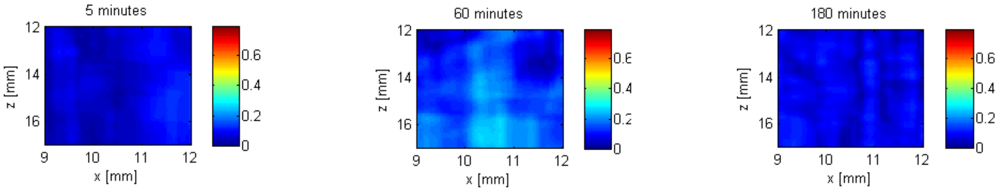

Fig. 2. The map of KS distances calculated for the PVA-c sample in the centrally located ROI1 for 3 different time moments in the thermal process, from left to right 5 minutes after the starting of heating, 60 minutes later, and then 180 minutes later.

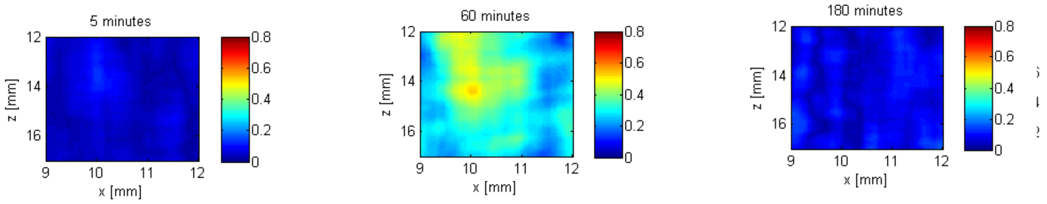

Fig. 3. The map of the KS distances calculated for the PVA-c sample close to the side located at ROI2 for 3 different time moments in the thermal process, from left to right 5 minutes after the starting of heating, 60 minutes later and then 180 minutes later.

It should be noted that the magnitudes of the KS distance depend on the position of the ROI in the sample. A centrally located ROI1 gives a much smaller increase in KS distance than when the ROI2 is situated closer to the edge of the sample. As the temperature was measured by recording the water bath temperature and the structure of the PVA-c material, which is highly heterogeneous, there is a high probability that in such a low temperature range, even despite a relatively lengthy heating time, that the sample volume will most probably not warm up uniformly. In Fig. 4, the comparison of the KS distance as a function of time, with the time-variation measured by thermometric temperature variations in the water bath can be seen.

Like the KS distance, KL divergence was calculated throughout the whole heating/cooling process. Fig. 5 compares the relationship between changes in KL divergence magnitude with changes in temperature levels in the water bath during this process. For further comparison, linear regression was utilized in order to calculate the directional coefficients for temperature and nonparametric statistical variations.

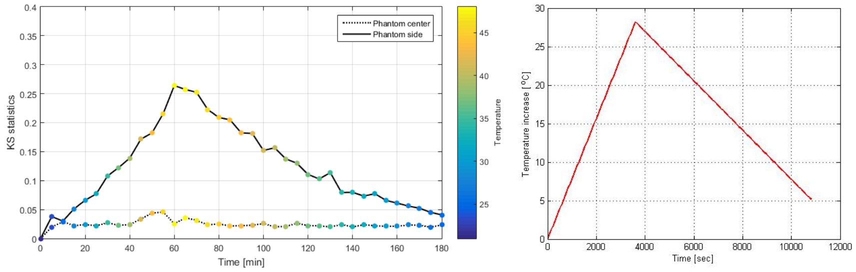

Fig. 4. The KS distance variations, left, and water bath temperature variations during process, right.

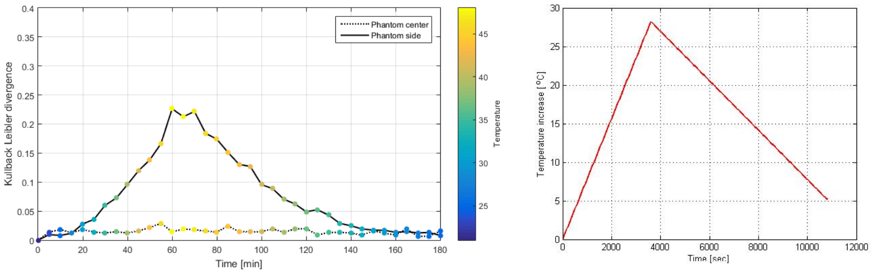

Fig. 5. The KL distance variations, left, and water bath temperature variations during process, right.

Bearing in mind that the heating and cooling process performed with the AGO samples was wholly different, it was therefore interesting to demonstrate that the same measures, namely the KS and KL distances proposed in this study play the role of temperature estimators which are qualitatively superior to those seen in the first experiments. Let us underline here that the heating process takes place in the AGO sample experiment six times more rapidly than previously: it only takes 10 minutes now, and the source of the temperature rise is concentrated inside the sample in the acoustic focused beam not at the boundary of the sample, as was the case in the PVA-c experiment. In Figs. 6 and 7, the variables over the time distances KS and KL are compared with the curves of the temperature time dependence, measured by thermocouples, during the whole heating/cooling process in the AGO sample.

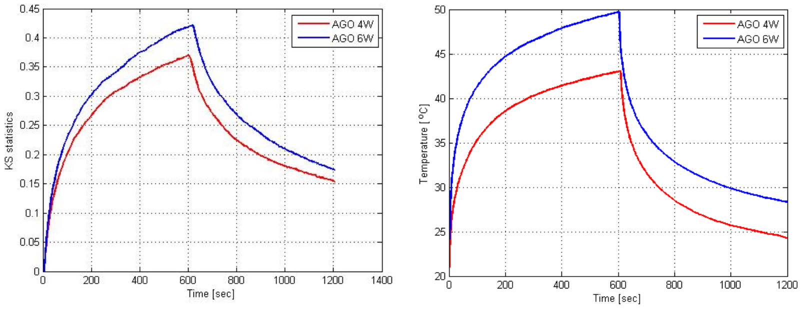

Fig. 6. The KS distance variations, left, and the temperature registration by thermocouples during the process, right, for two different powers of heating.

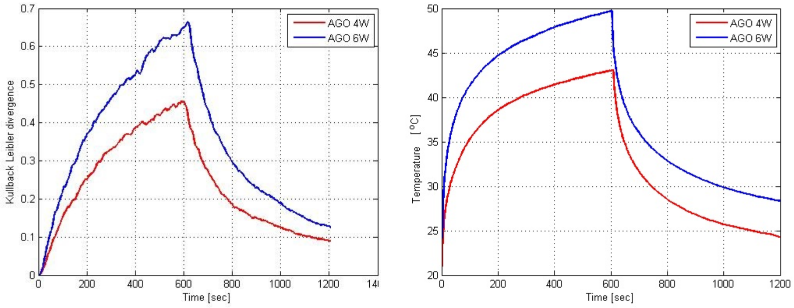

Fig. 7. The KL divergence variations, left, and the temperature registration by thermocouples during the process, right, for two different powers of heating.

4. FINAL REMARKS

Linear regressions were calculated for the rising and falling temperatures in the PVA-c sample for the measured experimental curve and the curves obtained from the herein introduced both measures of distributional distances. Obtained directional coefficients of the straight lines has the same signs so the rise and the fall in temperature and KS and KL distances took place in the same period of time but, what is even more interesting the rate of temperature variations coincides. This means that the ratio of the heating to cooling rate is the same (with an accuracy of up to 3%) for calculations carried out by the distributional distances and experimentally measured temperatures.

In the AGO sample experiments, the KS and KL distances as functions of time are highly nonlinear. Yet in this thermal process, the temperature variations measured by thermocouples also exhibit clear nonlinearity. The calculated and experimental curves are extremaly similar. In particular, the maximum values of all curves calculated for both the KS distance and KL divergence, in both experiments, correspond accurately with the maximum temperatures determined by the experimental curves. In conclusion, the KS distance and KL divergence between the probability distributions of the echo amplitudes which are present in different thermal processes may be used as temperature markers.

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