TEMPERATURE LEVEL AND PROPERTIES OF WAVELET APPROXIMATIONS OF BACKSCATTERED ULTRASOUND

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The aim of the paper is to find links between the dynamics of changes of statistical parameters and changes in spectral properties of the signal envelope of backscattered RF signals during the thermal process. We have shown previously that by using wavelet approximations these tendencies are better recognized in the case of the heating of a phantom sample than in the parallel analysis performed for a full signal envelope. Here we are currently expanding this statement to the case of heating a soft tissue sample in vitro. The shape parameter of the K- distributed random variable is considered as a statistical marker of temperature level changes. Additionally, the spectral properties of different levels of wavelet approximations are calculated and their sensitivity to temperature increase and decrease is demonstrated. Both approaches registering changes in temperature, are used in the case of the pork loin tissue sample in vitro, heated by an ultrasound beam with a different power.

INTRODUCTION

The studies of thermal processes in soft tissues due to the ultrasound irradiation are far advanced, their importance and different aspects are discussed in [1-5], cf. also references therein. Due to the fact that the changes in microstructure of the sample are invisible in the standard ultrasound B-scan during heating, cf. Fig.1, we are looking for a temperature measurement in the soft tissues sample by different approaches based on analysis of backscattered RF signal.

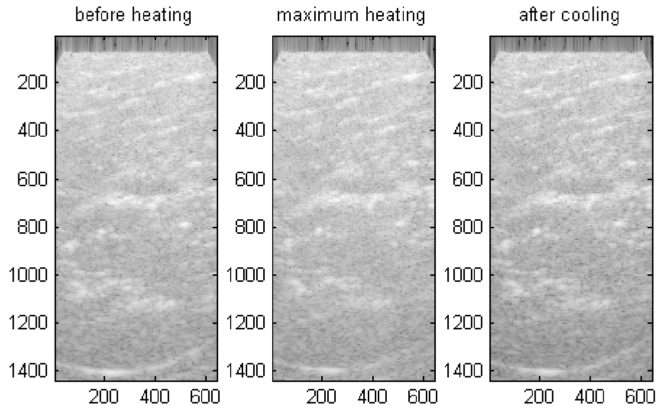


Fig. 1. The B-scan of the tissue sample. The left image shows the structure of the tissue at the initial moment and this, compared to the middle shows the structure when the heating has been stopped, i.e. for $t = 121$, and the last one is the end of the experiment for $t = 241$.

Linking the temperature increase with the received ultrasonic signal is very current field research, cf. e.g. [6-8]. At first, we are looking for "temperature tags" with a combination of the wavelet method with a statistical analysis of the signal envelope, what we have already done for the case of heating in a water bath a phantom sample made from Polyvinyl Alcohol – Cryogel, cf. [9]. Secondly, we present application of wavelet approximations to the visualization of changes taking place during the thermal process in the signal spectrum. One can assume that during heating the sample material changes their physical properties, and the microstructure varies particularly. Measuring or at least approximating the characteristic length of microstructural inhomogeneities by the ultrasonic backscattering signal is still a significantly challenging problem in parametric imaging methods, see [6]. Backscattering signals are random and sensitive to the type of random distribution of scatterers as well as their sizes and physical properties i.e. how strongly they scatter the signal. Therefore the backscattering signal has various spatial frequency bands and hence a signal decomposition method is required to analyze the ultrasonic backscattering signals. In this study, the discrete wavelet transform (DWT) using a MATLAB decomposition algorithm was applied to ultrasonic backscattered signals acquired at successive temperature levels. The ultrasonic backscattered signals were decomposed into two parts: high frequency components called "Details" and low frequency components called "Approximation". The latter is the low pass filter and we used it for improving the quality of temperature change differentiation. The paper is organized as follows. In Chapter 1 the experiment performed is described. In Chapter 2 the preprocessing of a signal is given and elements of the wavelet method are introduced. Chapters 3 and 4 contain the main results, i.e. links between temperature level and the statistical parameter, and links between spectrum changes and temperature level.

1. EXPERIMENT DESCRIPTION

The pork source sample has been heated by the ultrasound beam produced by a focused spherical transducer. The system for heating consists of generator (Agilent 332, Aprings Colorado, USA), an amplifier (ENI 1325LA, Rochester NY, USA), a spherical ultrasonic transducer (central frequency 2.2 MHz, diameter 44 mm, 44.5 mm focal length, area S = 15.2 cm^2) and an oscilloscope (Tektronix TDS3012B). Irradiation with 2 different powers: of 4W and 6 W (Watts) has been performed. During 10 minutes of heating and 10 minutes of cooling the temperature changes were recorded using thermocouples and registered by the USB module -TEMP. The temperature within the sample has been measured along the beam axis at different distances from the head. The geometrical focus was located c/a 44.5 mm of the surface of the transducer, while the maximum temperature observed in the pattern was located at a distance of 25 mm of the surface of the transducer , cf. Fig 2.

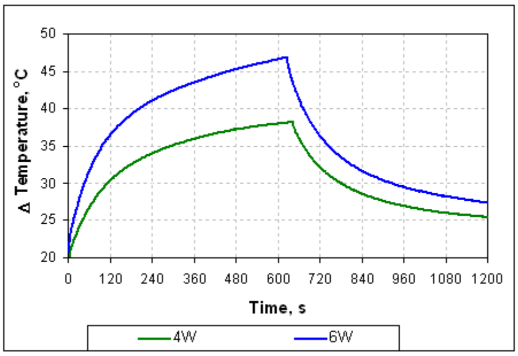


Fig. 2. The experimentally determined by thermocouples temperature changes at the point of focus (the highest heating) in the pork loin sample as a function of time / different values of power applied to the 4 and 6 W transducer, 10 min heating and 10 min cooling.

The linear transducer (L14-5/38) located across the heating beam at a distance of 40 mm from the transmitter has been used to produce images during heating by the focused transducer, see Fig. 3. Synchronization in time of both ultrasound sources has been carried out to ensure that the imaging process is free from the noise coming from the heating beam. The used ultrasound imaging system (Sonix TOUCH, ULTRASONIX, British Columbia, Canada) recorded images every 5 secs during 20 min of process. The sampling rate (sampling frequency) was 40 MHz and the imaging frequency was 8 MHz. The shape of the image scanned is a rectangle 36 mm x 16 mm, cf. Fig. 3.

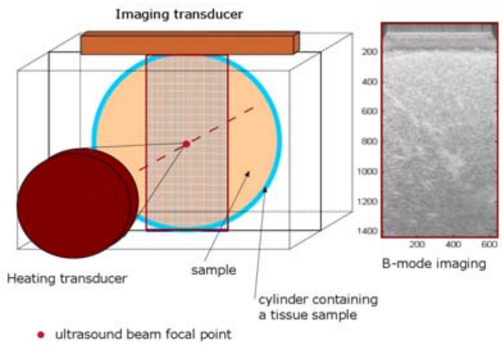


Fig. 3. The scheme of the experiment.

The date was collected with the help of Synthetic Aperture Technique.

2. PREPROCESSING OF A SIGNAL AND ELEMENTS OF WAVELETS

In order to perform the wavelet decomposition of the signal and the statistical analysis of the wavelet approximation it is necessary to carry out some previous transformations of the initial data. The dataset obtained from the experiment was modified by following steps.

The experiment data array of the size $1001 \times 501 \times 361$ had been reduced to the array $601 \times 501 \times 361$ by removing 200 points from each side. Let us define three dataset for each dimension: a set of points $X = 0, 1, ..., 600$, set of lines $Y = 0, 1, ..., 500$, and a set of images which is a scale discrete time-series $T = 0, 1, ..., 360$. Thus initial data may be assumed as a discrete function $f(x,y,t)$, where $x \in X$, $y \in Y$, $t \in T$. Fig. 4 represents the example of the signal function $f(x,y_0,t_0)$ for $y_0 = 240$ and $t_0 = 120$.

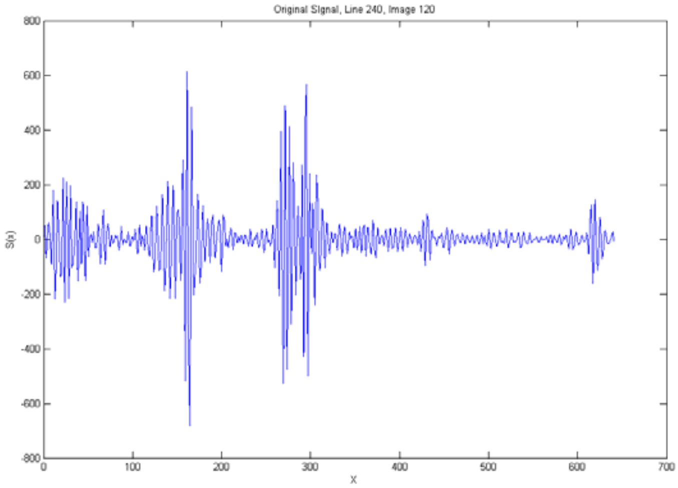


Fig. 4. Example of the signal, image 160 line 250.

Next, zero-phase digital filtering with the Butterworth filter has been performed [9]. Additionally a filter, which reduces the tendency of the changes with depth was used. The compensated signal will be denoted as $\tilde{f}(x,y,t)$. We consider the obtained signal as a function $f(x,y,t) = f_{y,t}(x)$, $x \in X$, $y \in Y$, $t \in T$.

In signal processing it is common to take into considerations the RF-envelope of the signal, which is an absolute values of the Hilbert transform of the function $f_{y,t}(x)$ with respect to the variable x. Hilbert (or RF) envelope was constructed with respect to the variable x. Let $\tilde{f}(x,y,t) = \tilde{f}_{y,t}(x)$, $x \in X$ then the Hilbert envelope represents the absolute value of the Hilbert transform of real-valued function

$$H(x) = \frac{1}{\pi} p.v. \int_{-\infty}^{\infty} \frac{f_{y,t}(x')}{x - x'} dx',$$

where $p.v. \int_{-\infty}^{\infty} \frac{f_{y,t}(x')}{x - x'} dx'$ means the principal value of the Cauchy integral.

The signal example together with its Hilbert envelope is shown in Fig. 5. Here the blue line represents the example of the signal and the red line represents the Hilbert envelope of the signal.

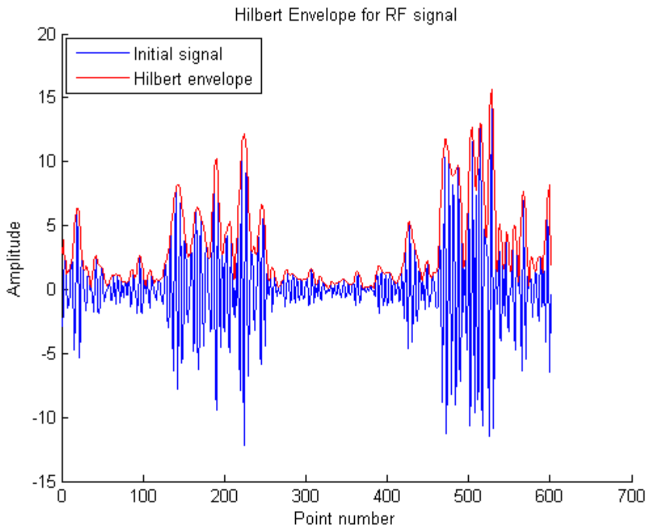


Fig. 5. The example of signal and its Hilbert envelope.

Then the data was averaged with respect to each line $\tilde{s}_{av}(x,\cdot,t_0)=\frac{\tilde{s}(x,\cdot,t_0)}{E(\tilde{s}(x,\cdot,t_0))}$ where $E(\tilde{s}(x,\cdot,t_0))$ is a mean value with respect to variable x for each $t_0 \in T$.

In order to have enough high number of values in the statistical ensemble the data of each line had been considered together. The 361 images considered as discrete functions of 300969 points had been constructed: $\bar{S}(x,t)=\bar{S}_x(t)=\bar{S}_t(x)$, $t \in T$, $x \in \tilde{X}$, $x \in \tilde{X} = 0, 1, ..., 300969$.

These signals $\bar{S}_x(t)$ have been normalized with respect to variable x: $S(x,t)=\frac{\bar{S}_x(t)}{\max\limits_{x\in\tilde{X}}\{\bar{S}_t(x)\}}$.

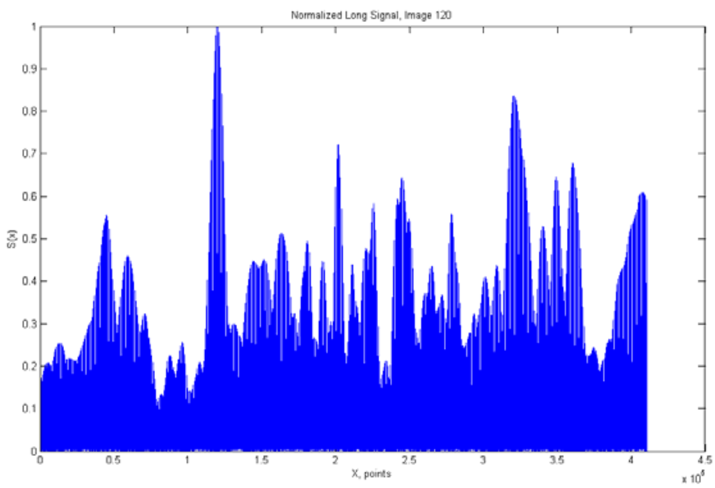


Fig. 6. Signal function after all pre-transformations.

The result of the pre-transformation steps for the image which corresponds to the $t = 160$ is shown in the Fig. 6.

This data is concidered as initial for the following approximation of the function $S_t(x)$ by using wavelet transform.

The main idea of this method is that any function integrable with the 2nd power $f(t)$ may be represented in the form $f(t)=\sum_k s_{j_n,k}\varphi_{j_n,k}+\sum_{j\geq j_n} d_{j_n,k}\psi_{j_n,k}$, where ψ is a chosen wavelet function, φ is corresponds to the scaling function. The set of functions $\{\psi_{j,k}\}$ is constructed as $\psi_{j,k}=2^{\frac{j}{2}}\psi\left(2^j t-k\right)$, the set $\{\varphi_{j,k}\}$ may be obtained by using the additional relations for functions ψ and φ (see, e.g. [9], [10]). The value of j_n denotes the level of decomposition whose scale coefficients s and detail coefficients d are calculated for each chosen family.

In our work the Daubechies 6 wavelets family [9] had been chosen as analyzing wavelet. This wavelet family is due to its possibility of pre-defined properties and also of the special form of the function which is similar to the shape of the transmit impulse signal (see Fig. 7).

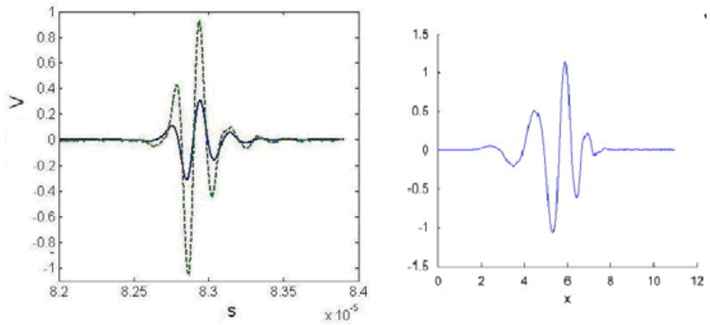


Fig. 7. Left: Reflected impulse signal in water - dashed line and the same signal transmitted through Phantom A and reflected – continuous line. Right: Daubechies 6 wavelet.

The function was decomposed $S_t(x)$ $j_n=4$ for statistical analysis and $j_n=6$ for spectral analysis. The whole procedure is described in [9], and it was also used for the investigation the RF-signals in [11-12].

3. STATISTICAL PARAMETER AND SPECTRAL PROPERTIES. TEMPERATURE DEPENDENCE

Firstly, several probability distribution functions (PDF) have been used to estimate the histograms of a signal at different levels of temperature, which means at different time points. K –distribution have been chosen as the best estimate of the histogram (in the sense of least mean square error). Its probability density function has the following from [6],[9]:

$$P_K(A|\sigma^2,\alpha)=\frac{4A^{\alpha}}{(2\sigma^2)^{(\alpha+1)/2}\Gamma(\alpha)}K_{\alpha-1}\left(\sqrt{\frac{2}{\sigma^2}}A\right),$$

where A represents the amplitude of the signal, $\alpha>0$, $\sigma>0$ is the shape and the scale parameter, respectively, Γ is the Euler gamma function, and K_p denotes the modified Bessel function of the second kind of order. Let us remember that the amplitude of the signal, scattered from infinitely many small, the same scatterers being non-uniformly distributed, is the K-distributed random variable. In the case when scatterers are grouped and in consequence, and K-distribution has the additional parameter measuring the degree of clusterization i.e. the shape parameter. The shape parameter is chosen here as a marker of temperature level, because one can expect the reorganization of the microstructure during temperature changes, which follows the changes of the values of the shape parameter. This is calculated from the real data with the help of the method of moments, cf. [6], which means that we approximate the values of the K-distribution shape parameter by the given function of the second and fourth moments alone. We compared the dependence of the calculated parameter, denoted by α0, to a temperature with the temperature dependence of α_0 calculated for wavelet approximations of different levels. The level of approximation has been chosen by the criterium, that is to say: to obtain the function of the temperature with a variance as small as possible with respect to the local average, and with a resolution better than without approximations, but with the use of a data set many times smaller, cf. [9]. The results are depicted in Fig. 8 and Fig. 9.

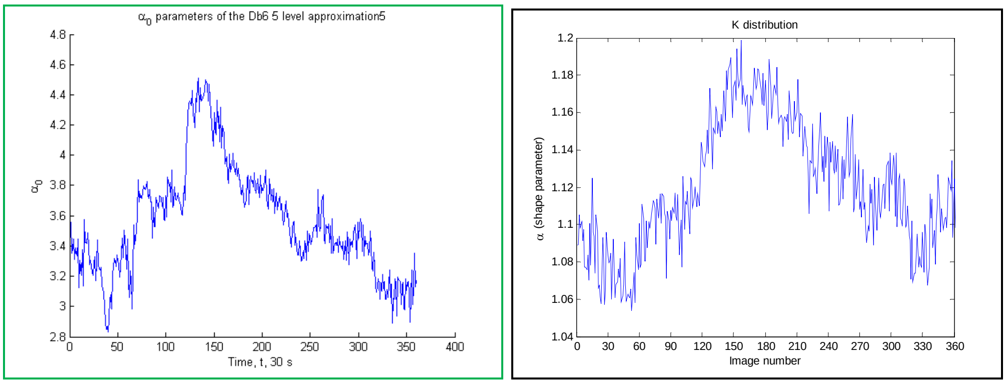


Fig. 8. Dependence of shape parameter on image number (time), left: with the use of the wavelet approximation of the 5th level, right: without any approximations.

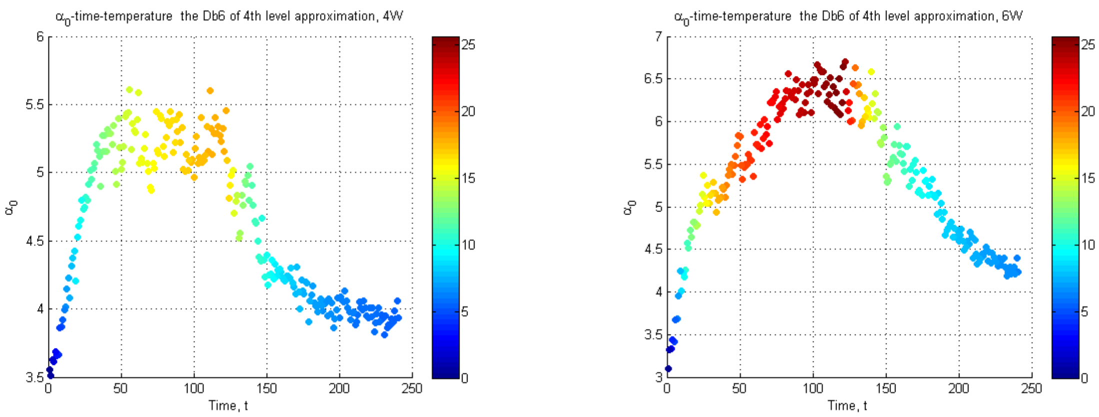


Fig. 9. Dependence of the shape parameter on time and temperature, for experiments with two powers of heating transducer, left image corresponds to the power of 4 W applied to the transducer and the right image corresponds to the power of 6 W.

The "long" signal obtained by the transformation described in Chapter 2 can be interpreted as the backscattered signal from one dimensional medium. The wavelet approximation, on some level, means that the frequency band is cut from above by the low pass filter. The FFT transform on initial data, which we named "transformed signal", is not illustrative for temperature increase, in contrast to the FFT performed for the wavelet approximation, see Fig. 10.

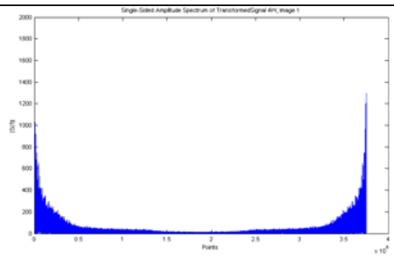
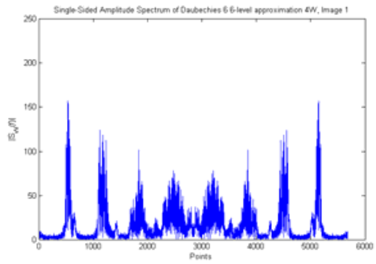
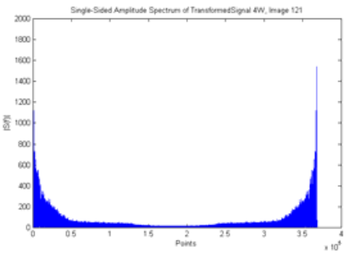
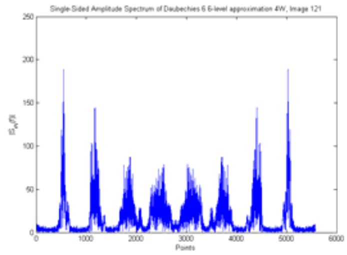
Image Number	Transformed signal	Daubechies 6, 6^{th}-level approximation
1 – beginning of heating, Temperature 20^0 C		
121- middle point of heating time, maximal temperature level 38^0 C		

Fig 10. FFT transforms of signal and wavelet approximations.

To identify the frequency range over which temperature changes are clearly visible, many estimations of FFT have been calculated. As the most informative we have found the polynomial approximations of the 10^{th} degree of the absolute value of a complex spectrum, see Fig. 11 and 12.

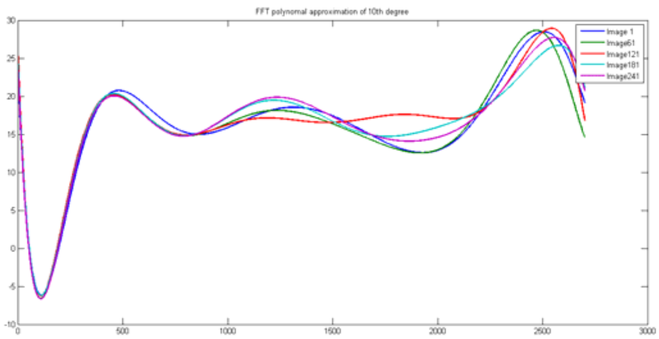


Fig. 11. Polynomial approximation of the 10^{th} degree of the Fourier transform absolute value with Daubechies 6, 6^{th} -level approximation of signal for different images; image 1 – 20^0 C, image 61 – 35,2 ^{0}C, image 121 – 38^0 C, image 181 – 27,6^0 C, image 241 – 25,6^0 C.

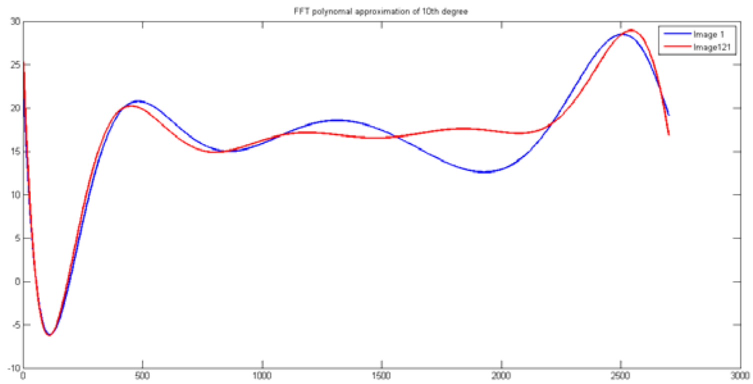


Fig. 12. Polynomial approximation of 10^{th} degree of the Fourier transform absolute value of Daubechies 6 6^{th} -level approximation for image 1 (20^0 C) and middle time of the heating process, Image 121 (38^0 C).

4. FINAL REMARKS

The shape parameter of K-distribution has been used by many researchers to differentiate the tissue microstructures of in vitro and in vivo samples. As far as we know there is no scientific paper, except our paper (in printing) [9], where this parameter is used as a temperature marker. Let us notice that in the Fig. 9 the rate of temperature changes is also well predicted by the parameter changes. This rate is strongly dependent on the power of the heating transducer and additionally, on the wavelet approximation level. The question of why there is a connection between the cutting off of some high frequencies from the signal (i.e. taking wavelet approximations) and a better fitting rate of temperature changes is the challenge for future research.

The main conclusion from spectral analysis is that using wavelet analysis we can identify the ranges of frequency which are the most sensitive on temperature changes. They correspond to the range of characteristic scale of inhomogeneities in the microstructure of the sample. This thesis has not yet been proved. Additionally, we observed division of the spectrum into four “effective” harmonics (that is to say a “group” of frequencies). The physical meaning of this fact has also until now not been clarified. We hope that we are able to find an answer of how to correlate microstructural properties of a sample material, i.e. soft tissue properties, and changes of temperature, which are measured by spectral properties and the shape parameter of K-distribution.

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