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Pulse Compression Favourable Thermal Wave Imaging Approach for Estimation of Osteoporosis: A Numerical Study

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***Abstract*—Infrared thermography is emerging as a vital non-invasive testing and evaluation tool in biomedical applications in order to identify surface and sub-surface abnormalities in biomaterials. Among various active infrared thermographic approaches, recently introduced aperiodic modulated pulse compression favorable thermographic techniques gained their importance as these approaches provide higher sensitivity and resolution for the extraction of anomalies located deep inside the material under test. Further, these techniques facilitate the usage of moderate heat inputs unlike traditional pulse-based thermographic methods and provide better depth resolution compared to lock-in thermography. This paper highlights the merits of novel pulse compression favorable frequency modulated thermal wave imaging method, a widely accepted non-stationary thermographic approach, to detect the severity of osteoporosis in modeled human bone. Detection is achieved by estimating the effusivity of the bone at different stages of osteoporosis with the help of correlation coefficient values obtained from the compressed pulse. A 3-D finite element analysis is carried out on a multilayer bone model with different thermo-physical properties of bone to characterize different stages of the osteoporosis. The obtained correlation-based results are compared with the extensively used principal component analysis approach.**

***Index Terms*—osteoporosis, frequency modulated thermal wave imaging, pulse compression, principal component analysis, COMSOL Multiphysics**

I. Introduction

Osteoporosis is one of the most common diseases in human bones that degrades the strength of the bone and may lead to increased liability to fractures likely in the spine, hip, and wrist [1]-[5]. Even though a variety of the testing modalities are widely in use for diagnosis of osteoporosis such as Quantitative Computed Tomography (QCT), Peripheral QCT (pQCT), Quantitative Ultra-Sound approaches (QUS), Digital X-ray Radiogrammetry (DXR), Radiographic Absorptiometry (RA), High-Resolution CT (HRCT), Dual Energy X-ray Absorptiometry (DEXA), and peripheral DXA (pDXA), the most widely used bench mark diagnosis method is Dual Energy X-ray Absorptiometry (DEXA) for estimating the bone quality by measuring the Bone Mineral Density (BMD). BMD is a parameter to determine the important score known as T-score that determines the stage of the osteoporosis. Superior properties of DEXA uncover the prospective for new medical applications and researches. The scheme proposed in this paper overcomes the traditionally used gold standard, DEXA, such as limited area of examination and use of ionizing radiation. The present work proposes a novel non-contact, non-destructive, non-ionizing, safe, reliable and wide-area monitoring technique known as infrared thermography, to estimate the severity of osteoporosis. In this method, the condition of objects is monitored by means of observing temperature variations over the surface of the object under examination. This may be realized either in passive or in active manner. In passive method, thermal history over the test object is recorded in the absence of any external heat input. However, the usage of this approach is restricted due to its inability to quantify the anomalies and restricted depth of probing. Contrary to this, active thermographic approach leads to identification of anomalies hidden deep inside the material with better sensitivity and resolution. Active optical thermographic methods involve the heating of the surface of sample under test by heat stimulus of known amplitude, duration and bandwidth. The predefined frequency modulated thermal stimulus with known bandwidth and amplitude levels facilitates to provide the quantitative information about the stage of osteoporosis. In active method, several excitation approaches have been proposed to introduce sufficient contrast between the defective and the non-defective region. Based on the applied thermal stimulus, these methods can be categorized as pulse-based or modulated thermographic modalities. Pulse Thermography (PT) and Pulse Phase Thermography (PPT) are well-known pulsed infrared imaging modalities. However, the pulse-based thermographic techniques PT & PPT require high peak power heat sources in order to improve the test resolution [6]-[10]. Modulated thermographic methods may be periodic or aperiodic. Lock-in Thermography (LT) is a popular modulated thermographic technique in which the heat sources are modulated in a sinusoidal manner at a particular frequency to launch a certain wavelength into the test object. The resulting temperature history is captured during active heating and is further analyzed to get phase information similar to PPT. Although LT makes use of moderately low power heat sources to reveal anomalies hidden inside the test object, however the introduced thermal wave with single wavelength restricts its use in detecting anomalies located at various depths within the material. In order to conquer the aforesaid limitations, the present work attempts to test the capabilities of non-stationary aperiodic modulated pulse compression favorable thermographic technique which provides complete depth scanning in a short time span using low peak power thermal inputs [6-12]. The considered approach provides a quantitative evaluation for estimation of the stage of the osteoporosis by using high-resolution Linear Frequency Modulated Thermal Wave Imaging (LFMTWI) technique. This method utilizes a frequency modulated heat stimulus to launch a desired range of frequencies into the test object. The temperature history captured over the object under test is analyzed using correlation-based pulse compression approach. Further the results are compared with the traditional Principal Component Analysis (PCA)-based infrared thermographic technique named as principal component thermography. The presented results show that PCA-based data analysis response is nearly like mean-zero temporal thermal distribution having reduced dynamic range, whereas correlation-based pulse compression analysis localize the supplied energy to narrow duration rather than redistributing the imposed energy within the whole excitation period.

II. Linear Frequency Modulated Thermal Wave Imaging

In this technique, a linear frequency modulated (chirp) thermal excitation within desired band of frequencies with significant and equal energies is deposited onto the object under test. Due to the imposed thermal stimulus, thermal waves are generated which diffuse into test object and cause an analogous time varying thermal distribution over the object. The flow of heat is modified due to the presence of hidden anomalies which leads to generation of thermal gradient over the surface of the object. The resulting thermal distribution is attained from the one-dimensional (1-D) Fourier conduction equation in the absence of heat source or sink within the object given as [13-16]:

$$\frac{\partial^2 T(x,t)}{\partial x^2} = \frac{1}{\alpha}\frac{\partial T(x,t)}{\partial t}, \tag{1}$$

where $T(x,t)$ is the instantaneous temperature at a certain spatial location x, at a given time t and $\alpha = K/\rho c$ is thermal diffusivity of material, K- thermal conductivity, ρ- density and c- specific heat.

Considering boundary conditions (x=0, $\phi(t)$- surface temperature varying with time t and $x \to \infty$,T- ambient temperature) and initial condition ($T(x,t=0) = 0$), the obtained solution to heat equation for a semi-infinite solid is expressed as:

$$T(x,t) = \frac{2}{\sqrt{\pi}}\int_{x/2\sqrt{\alpha t}}^{\infty} \phi(t - \frac{x^2}{4\alpha\mu^2})e^{-\mu^2}d\mu. \tag{2}$$

The thermal stimulus applied over the test material is written as:

$$Q(x=0,t) = Q_0 e^{2\pi j(ft+\frac{Bt^2}{2\tau})}, \tag{3}$$

where Q_0 is the peak heat flux, B is the bandwidth of the applied stimulus, f is the initial (start) frequency of the chirp and τ is the excitation duration.

A similar thermal distribution is generated over the surface of object under test that is represented as:

$$T(x=0,t) = T_\infty + T_0 e^{2\pi j(ft+\frac{Bt^2}{2\tau})} \tag{4}$$

and

$$T_\infty = \lim_{x\to\infty} T(x,t), \tag{5}$$

where T_0 - peak temperature and T_∞ is the temperature attained using boundary condition $x \to \infty$. Assuming that boundary condition T_∞ is zero, and dynamic variations in temperature data are taken into consideration. Thus, (4) may be expressed as:

$$T(x=0,t) = T_0 e^{2\pi j(ft+\frac{Bt^2}{2\tau})}. \tag{6}$$

So, the resulting temperature response of (1) may be represented as:

$$\begin{aligned} T(x,t) &= T_0 e^{2\pi j(ft+\frac{Bt^2}{2\tau})} e^{-x\sqrt{\frac{\pi}{\alpha}(f+\frac{Bt}{\tau})}} e^{-jx\sqrt{\frac{\pi}{\alpha}(f+\frac{Bt}{\tau})}} \\ &- \frac{2T_0}{\sqrt{\pi}} e^{2\pi j(ft+\frac{Bt^2}{2\tau})} \int_0^{x/2\sqrt{\alpha t}} e^{\frac{-\pi j x^2}{2\alpha\mu^2}(f+\frac{Bt}{\tau})} e^{-\mu^2} d\mu. \end{aligned} \tag{7}$$

The second part of (7) corresponds to transient response which decays with the increase in time t and hence only the first steady-state term remains.

As the thermal wave propagates through the material, it gets attenuated. Thermal diffusion length is depth where energy of thermal signal reduces to $1/e$ times of its surface value and it can be obtained as:

$$\mu' = \sqrt{\frac{\alpha}{\pi(f+\frac{Bt}{\tau})}}, \tag{8}$$

where B/τ is sweep rate of FM excitation. Whole depth scanning is assured by employing an appropriate range of frequencies in a test run as is described by the relation between bandwidth of the imposed stimulus and the diffusion length. The diffusion length formulation equals the diffusion length obtained for LT (Lock-in Thermography), if B/τ (sweep rate of frequency) is made zero.

Thermal wavelength (λ) for LFMTWI is represented as [17-19]:

$$\lambda = 2\pi\mu' = 2\pi\sqrt{\frac{\alpha}{\pi(f + \frac{Bt}{\tau})}}. \quad (9)$$

The thermal wavelength relies upon the frequency sweep of the imposed heat flux, which helps to detect the pores of different lateral dimensions situated at different depths inside the bone in a single experimentation cycle.

III. Acquired Data Post-Processing Methods

To enhance the anomaly signature, suitable post-processing analysis methods are realized on the captured temperature data. Several data processing methods have been developed to improve the performance of the thermographic systems in terms of resolution and sensitivity. In this work, correlation-based data processing method is implemented for estimating the stage of the osteoporosis and further compared with the results obtained using PCA approach. The two considered approaches are employed as presented below:

A. Correlation-based Pulse Compression Approach

In this method, cross-correlation $g(\tau)$ between zero-mean observed temporal temperature data of the healthy bone $T_{ref}(x,t)$ and the temporal thermal distribution of osteoporotic bone sample $T(x,t)$ is computed as:

$$g(\tau) = \int_{-\infty}^{\infty} T(x,t)T_{ref}(\tau + t)dt. \quad (10)$$

Pulse compression is advantageous as it concentrates the imposed energy to localized time period that enhances the performance of the thermographic system.

B. Principal Component Analysis

In order to compute principal components, the captured thermal data is arranged in a three dimensional (3-D) thermal matrix $T(i,j,k)$, where $i = 1, 2, \dots, N_x$, $j = 1, 2, \dots, N_y$, and $k = 1, 2, \dots, N_t$. Here, N_x is number of pixels along length corresponding to number of rows, N_y is the number of pixels along breadth corresponding to number of columns and N_t refers to the number of thermograms. The obtained 3-D matrix is reorganized in a 2-D matrix so that the temporal variations appear column-wise and the spatial variations appear row-wise i.e. the columns contain the information about each thermogram and the row contain number of thermograms. The principal component coefficients and the corresponding variances are calculated by Eigen functions of covariance data matrix. The obtained variances are arranged in descendent order, the coefficient matrix is arranged in the same way. Further principal components are attained by multiplying standardized data with the obtained descendent order coefficient matrix. At last, 3-D matrix is formed using the resultant data.

In the present work, finite element analysis is carried out to simulate a multilayer human bone model. The modeled sample comprises of four different layers- skin, fat, muscle, bone with thickness of 0.5, 0.5, 0.5 and 3 mm respectively. The model sample dimensions are 10mm*10mm*4.5mm as illustrated in Fig. 1. The thermo-physical properties of the considered layers are presented in Table I. Further, the fourth layer (Bone) is considered to have different thermo-physical properties as given in Table I to represent different stages of osteoporosis (S1, S2, S3 and S4). The modeled sample is considered at normal body temperature (310.15K).

IV. Results and Discussion

A linear frequency modulated thermal stimulus of 100 W/m^2 with frequencies varying from 0.005 Hz to 0.5 Hz for a duration of 200 s as shown in the Fig. 2, is imposed onto the front side (skin) of the considered model.

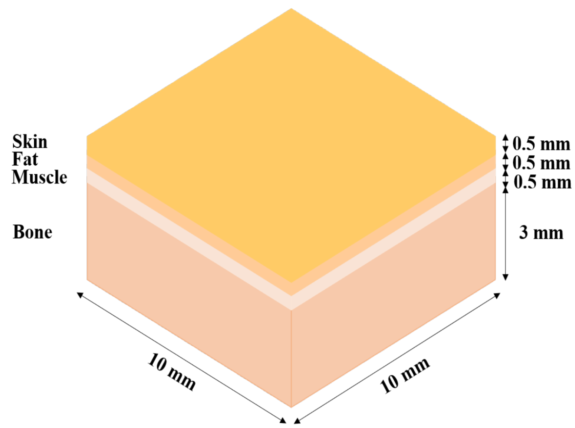

Fig. 1. Three-dimensional representation of modeled multilayered bone sample with skin, fat and muscle.

TABLE I
Thermophysical Properties of Tissue Layers [17-20]

Region	*Density (ρ) kg/m^3*	*Thermal conductivity (K) W/mK*	*Specific heat (c) J/kgK*	*Thermal effusivity ($e = \sqrt{K\rho c}$) $Ws^{1/2}/m^2K$*
Skin	1109	0.37	3391	1179.589
Fat	911	0.21	2348	670.2208
Muscle	1090	0.49	3421	1351.723
Bone	2420	0.616	1430	1460.044
S1	2310	0.588	1365	1361.636
S2	2200	0.56	1300	1265.543
S3	2090	0.532	1235	1171.824
S4	1980	0.504	1170	1080.54

The resulting temporal thermal history over the skin layer is obtained at a frame rate of 10 Hz. To this thermal response, Additive White Gaussian Noise (AWGN) having Signal to Noise Ratio (SNR) of 120 dB is added to validate the capabilities of the considered LFMTWI method under

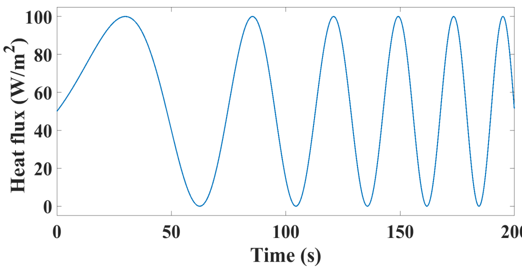

Fig. 2. Linear frequency modulated thermal excitation signal employed to heat the modeled osteoporosis sample.

practical conditions. The obtained noisy thermal distribution for different stages of osteoporosis (S1, S2, S3 and S4) is illustrated in Fig. 3.

To reconstruct zero-mean temperature distribution, a pulse of 200 s duration is applied on the sample. The concerned thermal response is recorded and is removed from the temperature distribution obtained from the given frequency modulated thermal excitation to obtain a mean zero thermal response. Fig. 4 and Fig. 5 show pulse heating response and zero-mean temporal temperature distribution respectively.

Then the noisy temperature data is analyzed with PCA approach and the zero-mean thermal data is processed using correlation-based analysis scheme. The obtained temporal temperature distribution reconstructed using the first principal component is shown in Fig. 6. To implement correlation-based pulse compression approach, the zero-mean temporal temperature data of healthy bone is cross-correlated with the zero-mean temporal temperature data of osteoporotic bone of various stages. The obtained correlation profiles for different osteoporotic stages are illustrated in Fig. 7.

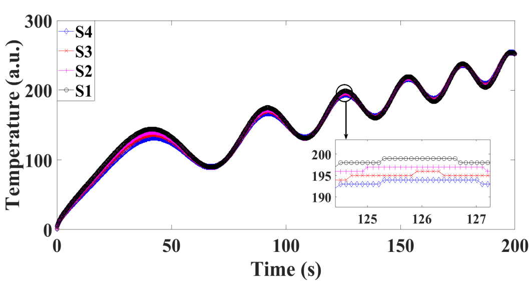

Fig. 3. Obtained temporal temperature distribution over the simulated bone sample for linear frequency modulated thermal stimulus with AWGN of 120dB for various stages of osteoporosis in the modeled bone sample

It is clear from the results obtained from both the PCA as well as correlation-based pulse compression approach that the PCA merely reduces the dimensionality of large thermal data sets as it is a dimension reduction scheme and does not provide any energy concentration capabilities as the correlation-based pulse compression approach. The reconstructed thermal profiles from the first principle component is more or less similar to the raw temperature profile except there a reduction in the dynamic range of temperature profiles.

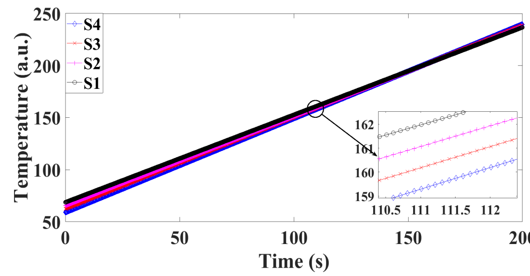

Fig. 4. Obtained temporal temperature distribution over simulated bone sample with pulse heat input for various stages of osteoporosis in the modeled bone sample

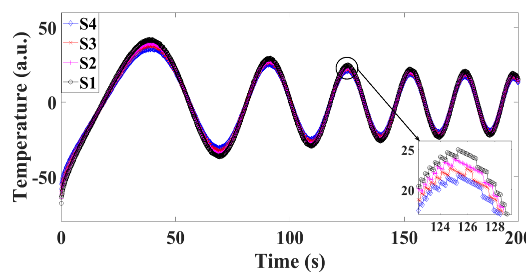

Fig. 5. Obtained zero-mean temporal temperature distribution for various stages of osteoporosis in the modeled bone sample

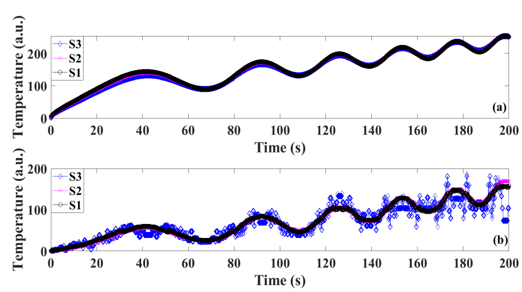

Fig. 6. Obtained temporal thermal distribution at a chosen location from first principal component for various stages of osteoporosis in the modeled bone sample

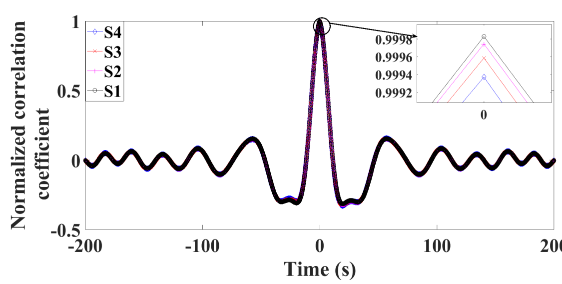

Fig. 7. Reconstructed compressed pulse obtained from correlation approach for various stages of osteoporosis in the modeled bone sample

Fig. 8 shows the effect of effusivity on the obtained correlation coefficient of the compressed pulse. It is clear that the effusivity of the osteoporotic bone decreases with its severity (osteoporosis) which results a change in the correlation coefficient in comparison with the sound bone. The trend clearly shows the increase in correlation coefficient with the increase in severity of the osteoporosis.

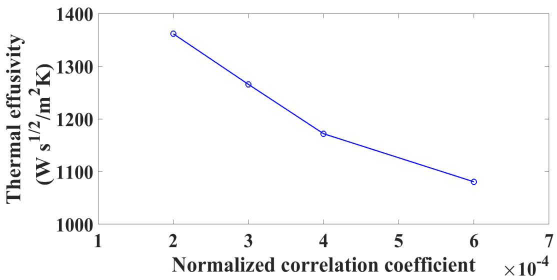

Fig. 8. Thermal effusivity versus correlation coefficient for the simulated bone model

V. Conclusion

This work introduces pulse compression favorable Linear Frequency Modulated Thermal Wave Imaging (LFMTWI) for the estimation of various stages of osteoporosis. The capabilities of the proposed approach are studied by employing the correlation-based pulse compression approach and are compared with the results obtained from traditionally used principal component-based post-processing scheme. It is observed from the obtained results using the adopted post processing approaches that principal component thermography is just a dynamic range reduction of temperature response and does not have the capabilities in providing the energy concentration as in the case of correlation-based post processing approaches for estimation of stage of osteoporosis. Even though the proposed method seems to be promising due to its above mentioned merits, it has to be validated through experiments to determine future applicability for real clinical studies. In addition, effects of parameters such as peak power of illuminating sources, sweeping bandwidth of modulating source and penetration depth need to be investigated thoroughly before adopting for clinical studies.

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