Evaluation of Dental Implant Osseointegration Using Ultrasonic Spectrometry: A Phantom Study

HAMED HAMID MUHAMMED(1), SATYA V.V.N. KOTHAPALLI(2)

(1) Division of Informatics, Logistics and Management
(2)Division of Medical Engineering
School of Technology and Health STH
Royal Institute of Technology KTH
Alfred NobelsAlle 10, SE-141 52 Huddinge – Stockholm
SWEDEN

E-mail: hamed.muhammed@sth.kth.se
Tel: +46(0)8-7904855 , URL: http://www.sth.kth.se/hamed/

Abstract: - One of the challenging and important problems that still needs solution within the field of dental implant surgery is to monitor the osseointegration process. Therefore, this work aims to achieve a reliable noninvasive automatic method to evaluate dental implant stability which is directly related to the grade of osseointegration. For this purpose, an experimental phantom study was performed to simulate this process and evaluate it. Ultrasonic spectrometry was proposed and used to take measurements that were processed and analyzed to estimate the stability of the simulated dental implant. The phantom that was designed and used in the experiments simulated a jawbone with a dental implant and was made of a little pool filled with soft-tissue-equivalent material (with respect to ultrasound waves) and a solid cylinder of fresh oak-wood immersed into it to simulate the jawbone. A metal screw was used to simulate the dental implant. By screwing this screw into or out of the wooden cylinder, varying grades of stiffness and contact between the screw and the wooden tissues were obtained. And by this way, varying screw stability grades which simulate varying osseointegration grades were achieved. Pulse-echo ultrasound was used to measure the power spectra of the received ultrasonic echo-signals. These power spectra were, at first, processed and normalized then analyzed by using the partial least squares method to estimate the corresponding implant stability or stiffness grades. The number of screwing turns (for the screw into or out of the wooden cylinder) was used as a measure of stiffness grade.The feasibility of this approach was investigated through experimental tasks and promising results were achieved. A coefficient of determination R^2 of 96.4% and a mean absolute error of ±0.23 screwing turns were achieved when comparing real and estimated stiffness-grade values, indicating the high efficiency and good accuracy of this approach.

Key-Words: -Screw dental implant stability; stiffness grade; contact grade; partial least squares PLS; pulse-echo ultrasound; spectroscopy; spectral analysis; power spectra;

1 Introduction

In recent years, dental implant surgeries became common among almost all patients categories; female, male, young and elderly patients. In general, this type of surgeries is performed in a series of four phases that are different. The most critical phase of such a surgery is the second one, which is called the osseointegration phase (Branemark*et al.*, 1969 [2]), during which the integration of the dental implant into the living jawbone occurs gradually. The progression of the osseointegration process depends on many factors, such as age, gender, bone tissue density and the pathological condition of the patient. Therefore, the completion of the osseointegration phase may take a longer or a shorter period of time. Consequently, it is important to not to disturb the osseointegration process as long as that is possible. For this reason, as well as other usually desired clinical considerations, it is required to use a non-destructive, risk-free and mobile clinical routine to evaluate the osseointegration process by measuring the stability or the fixation of the dental implant in the jawbone.

In 1929, Sokolov had already proposed his novel idea to use ultrasound for non-destructive testing of castings (Sokolvo, 1929 [18]). About 20 to 25 years later, industrial ultrasonic flaw detectors were developed and sold by a number of companies in different countries and a World-wide competition was started.

In 1981, Fitting and Adler [6] suggested to use ultrasonic spectral analysis for non-destructive testing purposes. Eighteen years later, Chambers and Tucker (1999) [3] used ultrasonic spectroscopy for industrial inspection of bonding quality of composites in aerospace products. Therefore, by using this technique which fulfills the requirements mentioned above, it sounds promising to test the hypothesis that ultrasonic spectral measurements can be performed to evaluate the biomechanical stability or the stiffness of the bone-implant interface which is proportional to the osseointegration grade.

Later on, Lin *et al.* (2001) [10] then after that, Pan and Ying (2005) [13] proposed and used the resonance frequency analysis (RFA) technique to evaluate the grade of osseointegration. They found that the resonance frequency was proportional to the mechanical stability of the dental implant. The frequencies considered in these studies were in the range of 60-120 Hz to be able to study the vibration of the whole piece of dental implant imbedded into Bakelite (which is a gypsum model). The results that were achieved and presented by using this technique were only showing if the grade of stiffness was high or low.

The results achieved by Valderrama*et al.* (2007) [20] indicated that the recently introduced magnetic resonance frequency analysis device could give comparable results as the original electronic RFA variant. However, Pattijn*et al.* (2007) [14] discovered that the energy of the signal measured by the RFA technique was displacement/position and angle dependent and could change considerably when the measurements were performed at different positions or parts of the dental implants and from different directions or angles.

Almost simultaneously, De Almeida *et al.* (2007) [4] introduced a new approach and called it quantitative ultrasound (QUS). Here, a transmission ultrasound technique was used to inspect a phantom made of a threaded metal piece (which simulates the dental implant) imbedded into a metal block (which simulates the bone). An ultrasonic transducer with 1 MHz central frequency was used in this study. The results showed that the stiffness of the structure of this phantom could be estimated, because it was proportional to the mean value of the ultrasonic signal detected during a certain (short) time period.

Mathieu *et al.* (2011) [12] performed an *ex vivo* study on rabbit femur with titanium dental implant. They showed that the QUS technique could be used to compute a quantitative parameter which was significantly sensitive to the amount of bone tissue (rabbit femur) in contact with a cylindrical titanium dental implant. The transducer that was used in this study had a central frequency of 10 MHz to allow for distinguishing different echoes that were originating from different implant interfaces. Furthermore, it was important to retrieve enough information from the dental implant to be able to compute that quantitative parameter or indicator. Therefore, a long-enough signal duration was required to be used in this study; 25 times longer than the signal duration that was used by De Almeida *et al.* (2007) [4].

In this research work, a new approach is proposed aiming at simulating and evaluating the microstructure of bone and soft tissues around a dental implant. For this purpose, a proper phantom, simulating a jawbone with a dental implant, is designed and used in the experiments. In these experiments, pulse-echo ultrasound is utilized and the reflected echo-signals from the phantom are measured. Then the power spectra of these measurements are computed and analyzed. In other words, ultrasonic spectral analysis is utilized to detect changes in the shape of the curve of the power spectrum of the ultrasonic echo-signals reflected from the phantom. An automatic statistical-modeling method is developed and utilized to analyze each obtained power spectrum and estimate the contact and stiffness grade between the dental implant simulator and the surrounding tissues simulating jawbone and soft tissues in the used phantom.In 2012, preliminary results were published by the authors, Hamid Muhammed and Kothapalli [8], showing how ultrasonic spectrometry can be used to estimate the stability of a dental implant phantom.

Regarding the statistical modeling method used in this research work, two common problems or limitations that are usually associated with this type of methods are addressed. These two problems are as follows: 1) Large number of variables and few observations. 2) Explanatory and dependent variables are collinear. The solution proposed in this work for these two problems are to, at first, preprocess and normalize the data (which are a number of power spectra and the corresponding

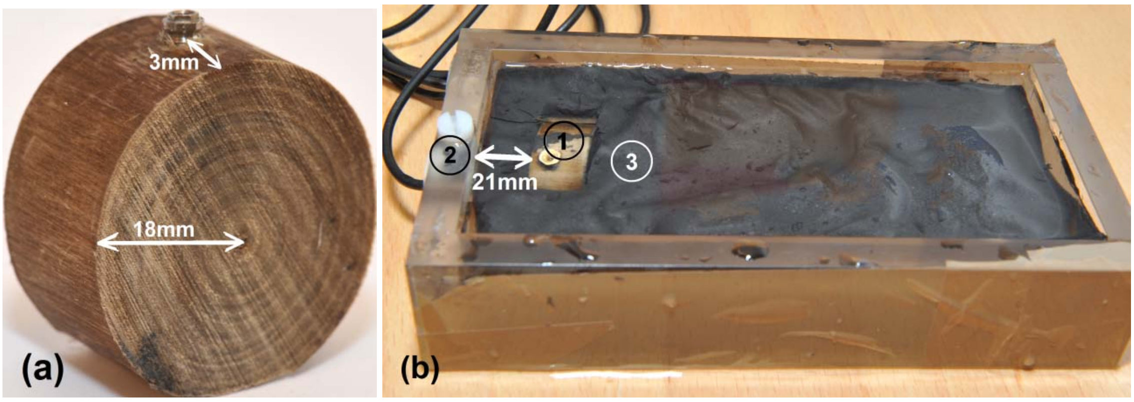

Fig. 1. (a) A metal screw inserted or screwed into a disc or a solid cylinder of fresh oakwood. (b) The experimental setup where the phantom, labeled with (1) and presented in Fig. (1a), is immersed into a little pool filled with a soft-tissue equivalent material, labeled with (3), and water. An ultrasonic transducer, labeled with (2), is mounted at a distance of 21 mm away from the edge of the phantom, labeled with (1).

implant stability measures) in an efficient way, then to analyze these normalized data by using a suitable Partial Least Squares (PLS) algorithm that is able to manage non-linear processes or relationships among the data to be able to achieve the desired results.

2 Materials and Methods

2.1 Phantom and experimental setup

A disc or a solid cylinder of fresh oak-wood, immersed in water continuously to keep it fresh, was used to simulate a jawbone. Using this solid wooden cylinder or disc to simulate the jawbone is motivated by the following reasons (Hereafter, this jawbone simulator is called the wooden cylinder). The speed of sound is around 3800 m/s in oak-wood (Walker, 2005 [21]), compared to about 3500-4000 m/s in bone tissue. Hence, it is obvious that the acoustic impedance of oak-wood is close to that of the jawbone. In addition to that, Tampieri*et al.* (2009) [19] produced bone implants that had the same spongy microstructure of wood. They could show that these wood-based bone-implants were functioning more efficiently, mainly because of the spongy microstructure of the (used) wood tissue that was retained after the calcification process which resulted in a bone implant.

To simulate a dental implant, a metal screw was used and screwed into this wooden cylinder, as shown in Fig. (1a). Hereafter, this dental implant simulator is called the screw. A little pool was filled with water and a soft-tissue equivalent material and that wooden cylinder was immersed into it. The soft-tissue equivalent material, which looked like a black-colored mixture, was composed of 93% water, 4% graphite and 3% agar (Madsen *et al.*, 1978 [11]). An immersion ultrasonic transducer was mounted at a distance of 21 mm from the edge of the wooden cylinder, as shown in Fig. (1b), because the focal length of this non-focused transducer was 24 mm and the distance between the edge of the wooden cylinder and the surface of the metal screw was 3mm.

The fundamental or central frequency of the used ultrasonic transducer is 2 MHz, and its frequency band is ranging from 1.8 MHz to 2.2 MHz, as shown in Fig. (2). The central or fundamental frequency is defined as the local maximum peak frequency of the frequency band which covers the frequency region between the two -3dB level frequencies around the central or fundamental frequency of the ultrasonic transducer.

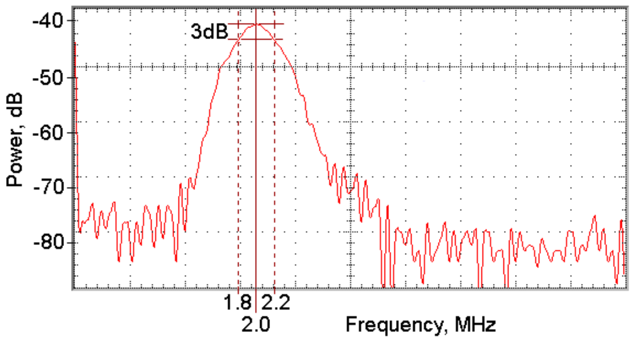

Fig. 2. The power spectrum of the response of the ultrasonic transducer (L20) used in the experiments.

A pulse generator with an amplifier (an ultrasonic pulser/receiver of type 5072PR, from Panametric-NDT, Waltham, MA, USA) was used to

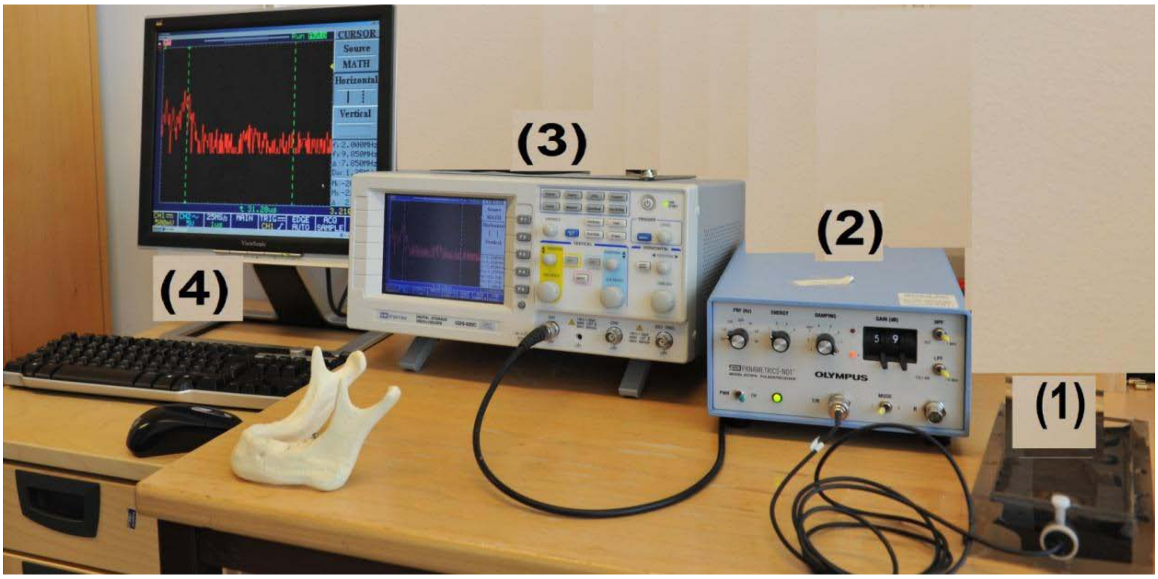

Fig. 3. The experimental setup consisting of an ultrasonic transducer attached to the phantom labeled with (1), an ultrasonic pulser/ receiver labeled with (2), an oscilloscope labeled with (3) and a personal computer labeled with (4).

excite a single-crystal piezoelectric ultrasonic transducer (L20, from Ceram AB, Lund, Sweden) to emit an ultrasonic pulse. The same transducer was also used to receive the echo signal reflected from the phantom through all surrounding environment. The detected signal was transferred through that amplifier to an oscilloscope (GDS-820c DSO, from GW Instek, Taiwan). A power spectrum of the received echo signal was generated by the oscilloscope by using the fast Fourier transform (FFT) technique. This process was repeated continuously and a sequence of power spectra was generated and obtained in real time. The resulted power spectra were directly (in real time) transferred to a personal computer (PC) by using the freeVIEW ® software (from Innovative Elektroniksysteme GmbH, Bad Breisig, Germany), where it was saved and finally analyzed (afterwards, off-line) by using MATLAB ® (from The Mathworks Inc., Natick, MA, USA). Fig. (3)shows the experimental hardware setup, including the experimental setup presented in Fig. (1), the amplifier, the oscilloscope and the PC. It also shows the resulted power spectrum of one measurement (of the sequence of pulse-echo measurements) plotted on the monitor of the PC by using the freeVIEW ® software, which shows an identical copy of what is plotted on the little monitor of the oscilloscope.

2.2 Dataset

The pulse-echo ultrasound system described previously in this paper and illustrated in Fig. (1) and (3), was used to acquire 30 measurements. The used parameters were a Pulse Repetition Frequency (PRF) of 100 Hz and a Gain value of 59 dB. Thereafter, 30 power spectra were computed for the measured signals and transferred to a PC. Each power spectrum was consisting of 660 points (or power spectral lines) and was corresponding to a certain contact and stiffness grade between the screw and the wooden cylinder. The record length of the acquired power spectrum was 660 points (not equal to power of two) because a dump of the display of the oscilloscope was transferred by the freeVIEW ® software to the PC-screen (as shown in Fig. 3). The contact and stiffness grade is measured or expressed in number-of-turns when screwing the screw out or into the wooden cylinder.

Initially, the screw was inserted or screwed firmly into the wooden cylinder. This case was called the initial tight screw state. Thereafter, it was screwed out of the wooden cylinder, with a half turn each time, to decrease the stiffness and contact grade between the wooden cylinder and the screw gradually, until reaching 5 full turns. Afterwards, the process was reversed and the screw was screwed into the wooden cylinder also with a half turn each time, until reaching 5 full turns, which corresponds to the initial tight screw state. Finally, the process was reversed again and the screw was screwed out the wooden cylinder also with a half turn each time, until reaching 5 full turns.

Hence, the dataset that was made available for this work was consisting of 30 power spectra and the corresponding contact and stiffness grades expressed in number-of-turns ranging (with a step of 0.5 turn) between 0 and 5, which were corresponding to the initial-tight-screw-state and the loose-screw-state, respectively. By this way, 10 different contact and stiffness grades, linearly distributed between 0.5 and 5 turns, were simulated three times and the corresponding power spectra were obtained as described previously.

2.3 Methodology

2.3.1 Partial Least Squares (PLS)

Partial Least Squares (PLS) is a multivariate statistical framework, which includes a wide class of approaches and methods. The PLS technique is used for processing, interpreting and analyzing data, measurements and observations in a wide range of fields and in many applications, including social sciences, natural sciences, life sciences, various technological fields as well as numerous applied and industrial applications. An overview of the PLS technique and its applications is presented by Rosipal and Kramer (2006) [16].

The pioneering work of proposing and introducing the PLS technique was mainly performed by Herman Wold in 1966 [22] and 1975 [23], where the first variants of the PLS methods and approaches were introduced. Since then, the PLS technique has received great attention and interest within many research fields. The basic and common principle of the PLS algorithms is to find a small number of uncorrelated variables (known as components or latent variables) and use them to explain as much covariance as possible between two blocks of variables: the block of explanatory variables denoted as $\boldsymbol{X}$ and the block of dependent variables denoted as $\boldsymbol{Y}$; where these $\boldsymbol{X}$ and $\boldsymbol{Y}$ are matrices and each column of the $\boldsymbol{X}$-matrix and $\boldsymbol{Y}$-matrices contains one explanatory variable, while each column of the $\boldsymbol{Y}$-matrix contains one dependent variable.

Usually, at the first step of any PLS algorithm, the input variables which are $\boldsymbol{X}$- and $\boldsymbol{Y}$-variables should be preprocessed and normalized to achieve the best possible performance and obtain results with the highest achievable accuracy. Therefore, it is important to make the distributions of the $\boldsymbol{X}$- and $\boldsymbol{Y}$-variables fairly symmetrical. One efficient way to do that is by using the n^{th} root transformation (where n is a real number) to compress the dynamic range of these variables so that the result of dividing the mean value by the standard deviation (of each of these variables) will be around one. Thereafter, a normalization technique called whitening is utilized and it results in scaling the data into values of zero-mean and unit-variance. Details about whitening can be found in Eldar and Oppenheim (2003) [5] and a discussion about its efficiency can be found in Koivunen and Kostinski (1999) [9]. And the result is said to be whitened.

The general PLS model is described as follows:

$$\boldsymbol{X} = \boldsymbol{T}\,\boldsymbol{P}^T + \boldsymbol{E}$$
$$\boldsymbol{Y} = \boldsymbol{T}\,\boldsymbol{Q}^T + \boldsymbol{F} \qquad (1)$$

where $\boldsymbol{X}$ is an $n \times m$ matrix of predictors, $\boldsymbol{Y}$ is an $n \times p$ matrix of responses, $\boldsymbol{T}$ is an $n \times l$ matrix of factors, $\boldsymbol{P}$ and $\boldsymbol{Q}$ are $m \times l$ and $p \times l$ loading matrices (of weight coefficients), respectively, and matrices $\boldsymbol{E}$ and $\boldsymbol{F}$ contain error terms.

There exist a number of PLS algorithms to estimate the factor and loading matrices $\boldsymbol{T}$, $\boldsymbol{P}$ and $\boldsymbol{Q}$. Most of these algorithms estimate the linear regression between $\boldsymbol{X}$ and $\boldsymbol{Y}$ as follows:

$$\boldsymbol{Y} = \boldsymbol{X}\,\boldsymbol{B} + \boldsymbol{N} \qquad (2)$$

where$\boldsymbol{Y}$ contains n cases and m dependent variables, $\boldsymbol{X}$ contains n cases and p independent variables, $\boldsymbol{B}$ contains $p \times m$ regression coefficients (reflecting the covariance structure between $\boldsymbol{Y}$ and $\boldsymbol{X}$), and $\boldsymbol{N}$ is a noise term of the same size as $\boldsymbol{Y}$.

2.3.2 Using PLS Analysis

There exist many approaches and different algorithms that can be used when performing PLS analysis. In this research work the non-linear iterative partial least squares algorithm (NIPALS), (Wold, 1975 [23]) is used. The first step of the NIPALS algorithm (i.e. the starting iteration) is to construct the matrices $\boldsymbol{E} = \boldsymbol{X}$ and $\boldsymbol{F} = \boldsymbol{Y}$, as explained in Eq. (1). The columns of matrix $\boldsymbol{X}$ contain the measured ultrasonic power spectra which are our independent variables, while matrix $\boldsymbol{Y}$ contains the corresponding dependent variables or the target parameters that are desired to be estimated. However, matrix $\boldsymbol{Y}$ consists of only one column (i.e. it is actually a vector) because only one single target parameter (namely: the contact and stiffness grade expressed in number-of-turns) is involved in the case study of the current paper.

The next step, which is very important as mentioned previously in this section, is to preprocess and normalize both of $\boldsymbol{X}$ and $\boldsymbol{Y}$. Each element of vector $\boldsymbol{Y}$ is transformed by choosing an appropriate power value and raising each element of $\boldsymbol{Y}$ to this power value. The power value is selected so that the result of dividing the mean value of the transformed ***Y***-vector by its standard deviation will be around one.

After that, the whitening transformation is applied to the ***Y***-vector to make its elements have values of zero-mean and unit-variance.Matrix ***X***, which is two dimensional, is also whitened by employing two iterative normalisation approaches that are based on utilizing a series of one-dimensional whitening operations.

In both approaches, a number of alternating spectral-wise (denoted as Sw and performed row-wise in matrix ***X***) and band-wise (denoted as Bw and performed column-wise in ***X***) whitening operations are performed, as described by Hamid Muhammed (2005) [7]. When performing Sw-whitening, each spectrum (which corresponds to one row in ***X***) is whitened, while each column of ***X*** (which corresponds to one spectral band) is whitened when Bw-whitening is performed. In the first iterative whitening normalisation approach, a series of alternating Sw- and Bw-whitening operations, beginning and ending with Sw-whitening operations, are performed. On the other hand, the second variant of the iterative whitening normalisation process starts with a Bw-whitening operation and ends with a Sw-whitening operation.

Thereafter, the training dataset is selected out of the preprocessed and normalized data and the chosen PLS algorithm, which is also iterative (i.e. the operations are performed repeatedly on the data until convergence of the result is achieved), is applied on this training dataset to estimate the factor and loading matrices ***T***, ***P*** and ***Q***. finally, these factor and loading matrices are fed as input parameters to the PLS algorithm to process the rest of the (preprocessed and normalized) data samples in matrix ***X*** which are considered together with the rest of the corresponding ***Y***-vector elements as the test dataset. At this point, the whole set of latent variables are calculated (i.e. estimated values for these ***Y***-vector elements are obtained), as explained by Abdi (2003) [1].

One of the important issues, in order to avoid over modeling, is to decide the number of latent variables that should be included in the PLS model. A general rule of thumb that can be used here is that one latent variable can be added and used in the final PLS model for each group of additional five or six independent observations (which correspond to power spectra in our application) that are included in the training dataset; Rhiel*et al.*, (2001) [15].

By this way, an upper limit for how many latent variables to include in the PLS model can be defined. The remaining question, which is also very important, is to know how many of these latent variables are enough to be included in the PLS model. A popular approach to know the answer to this question is by calculating the relative error value for the estimated ***Y***-vector elements when comparing them to the real ***Y***-vector elements values.

The obtained relative error value is zero when perfect prediction or estimation is achieved. Otherwise, it is always a positive value. Therefore, the PLS model will be improved as long as adding more latent variables lowers the resulting relative error value. The optimal number of latent variables is found when the relative error value begins to increase when adding a new latent variable (Abdi, 2003 [1]).

Another important issue is to make sure that the system of equations is well conditioned. This can be simply performed by resampling the power spectra vectors to get a quadratic ***B***-matrix (which contains the regression coefficients) as explained in Eq. (2).

2.3.3 Cross Validation

It is necessary to evaluate the usefulness and efficiency of the used PLS model. Cross validation is a common approach that is utilized for this purpose. Leave-One-Out Cross Validation (LOOCV) is an efficient evaluation method when only few observations are available for the study. In the experimental part of this work, 30 power spectra each of which consists of 660 elements are acquired. Only one pair of variables, consisting of one dependent variable and one independent variable, at a time is removed from that dataset. The excluded dependent parameter is considered as unknown and the goal is to estimate it. While the rest of the data samples pairs are considered as training data for the used PLS model. The excluded measured spectrum, which is our independent variable, is fed into the trained PLS model to estimate the corresponding dependent parameter which is also excluded.

Obviously, by using the LOOCV approach, all data samples are efficiently used in evaluating the performance of the PLS model on hand. The estimated parameter values (which are ***Y***-vector elements) are finally compared to the real values, to obtain an evaluation measure of the performance of the used PLS model. Both of the relative error E_{rel} and the coefficient of determination R^2 can be used to produce such an evaluation measure. Computing R^2 requires computing the correlation coefficient R (which has a value within the range from -1 to +1) and the corresponding P-value for testing the hypothesis of no correlation. A rule of thumb is that the P-value should be smaller than 0.05 to get a reliable correlation measure R. Otherwise, the resulting correlation coefficient R cannot be considered as significant and is consequently useless.

3 ExperimentalResults

In reality, the gap (which may correspond to bone tissue loss) between the jawbone and the dental implant may vary between zero and about 50-100μm when inserting a screw-type dental implant, as stated by Schenk and Buser (1998) [17]. The gap-size variation corresponds to a variation of the contact and the stiffness grade between the dental implant and the jawbone. However, what is more interesting and important to know is if the osseointegration process is complete or not, as well as whether this process is progressing towards decreasing the gap-size and obtaining a better intimate contact between the bone tissue and the dental implant, or not. When the osseointegration is complete, a convergence towards a zero gap is supposed to be achieved. This means that it is in our study more important to measure and evaluate small gaps in the order of few tens of micrometers, down to zero.

Therefore, an efficient method to simulate varying grades of osseointegration is to use the experimental setup and the phantom described in the previous sections. As described previously, the metal screw is inserted and screwed into the wooden cylinder firmly. Then when it is screwed out gradually of the wooden cylinder, the contact grade between the screw and cylinder will be decreased, because small cavities are generated around the threads of the screw. The depth of thread (i.e. the height from the root to the crest of the thread) of the dental implant screw shown in Fig. (4a) is around 300μm, while the depth of thread of the screw used in our experiments (and shown in Fig. 4b) is around 450μm. This means that, in reality, the gap between the dental implant and the jawbone, may be slightly smaller than the gap, obtained in our experiments, between the wooden cylinder (which is made of fresh wood immersed in water continuously) and the used metal screw. However, on the other hand, the elasticity of bone tissue is much less of the elasticity of fresh wood tissue. Therefore, the gap between wood tissue and the threads of the screw may vanish and can be considered as being approximately zero when the screw is firmly tightened, because the continuously-immersed-in-water fresh-wood tissue is soft enough to be able to fill in all cavities between the threads of the metal screw.

The experimental setup described previously was used to acquire ultrasonic spectral measurements from the phantom shown in Fig. (1b). The penetration and nonlinear propagation of the ultrasonic waves through the wooden cylinder, the metal screw and the water-filled gap between them will gradually deform the shape and wavelength of the ultrasonic waves. Therefore, because of this complicated nonlinear process, in addition to the effect of Fourier transforming the time-signals that are received by the transducer, higher harmonic frequencies (defined as integer multiples of the fundamental frequency of the ultrasonic transducer) appear in the resulting power spectra.

Visual inspection of the obtained power spectra shows that the local-maximum-peak frequency of the first harmonic (which is the fundamental of central frequency of the used ultrasonic transducer) was shifted from 2 MHz down to 1.92 MHz. The local-maximum-peak frequency of the second harmonic was around 3.84 MHz, the third one was around 5.76 MHz and so on, as shown in Fig. (5a). Low pass filtering was used extensively to suppress the noise and obtain the smooth spectra shown in the figures. A large number of measured power spectra were acquired, for exactly the same stiffness and contact grade and by using exactly the same experimental setup and holding the same conditions, during 20-30 seconds in realtime by the oscilloscope and transferred to a computer where the mean power spectrum was computed. In addition, the resulting mean power spectrum was further smoothed by using average filtering.

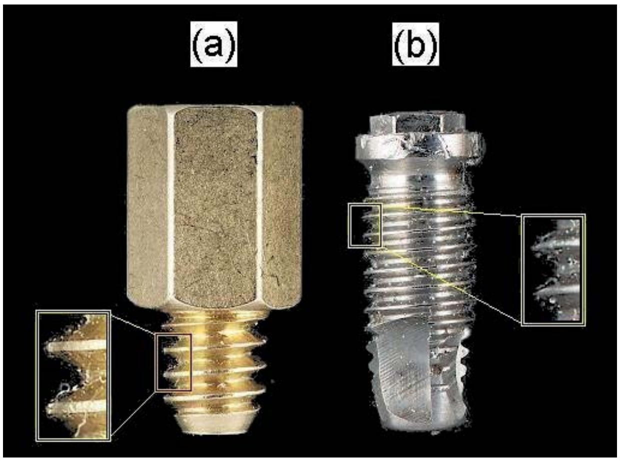

Fig. 4. A microscopic image showing two screws: (a) The metal screw used in the phantom. (b) A titanium dental implant screw. Two screw-thread regions, one from each screw, are zoomed-in with the same grade to show a comparison between the depth-of-thread values in both cases.

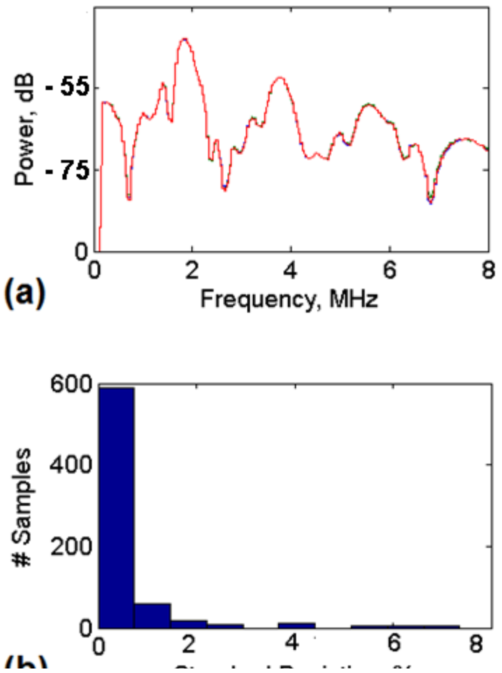

Fig. 5. (a) Three overlapping power spectra of the same experimental settings (the same stiffness and contact grade). (b) Histogram showing the standard deviations for these three spectra.

It is essential to ensure the repeatability and reproducibility of the experiments to validate the capability and robustness of the ultrasonic measurement system. Therefore, the experimental tasks (during each of which, power spectra were acquired in realtime in 20-30 seconds) were repeated using different initial conditions. The resulting mean power spectra were compared by using MATLAB ®. Fig. (5b) shows a histogram of the standard deviations for the power spectra obtained from repeating one of the experiments (exactly the same experiment) three times; when screwing out the screw with the same number of turns, which corresponds to the same stiffness and contact grade between the metal screw and wooden cylinder. This figure shows that the obtained standard deviations were mainly limited to 1%. This result indicates the robustness of the used method in achieving reproducible measurements, because the power spectra can be obtained with sufficient accuracy.

Fig. (6) shows a comparison between two power spectra; one corresponds to the tight screw state and the other one is obtained in the case of loose screw. It is possible to observe differences between these spectra, at the higher harmonics, by using visual inspection. These differences are automatically utilized by the PLS algorithm to be able to estimate the corresponding stiffness or contact grade which is measured in number-of-turns when screwing the metal screw out or into the wooden cylinder. Before applying the PLS algorithm, the power spectra were preprocessed and normalized according to the guidelines mentioned previously in this work.

Fig. (7) presents a comparison between real and estimated stiffness and contact grades expressed in number-of-turns, as explained previously. The correlation coefficient R between the resulted two curves of the real and the estimated values in this figure is 0.982 (i.e. 98.2% correlation) and the corresponding P-value is 1e-21 (too small; near 0). This R-value corresponds to a coefficient of determination R^2 of 96.4% and a mean absolute error of ±0.23 turns for the screw into (-) or out of (+) the wooden cylinder; i.e. a tighter or a looser state. In this experiment, the screw was gradually screwed out (made looser from 0.5 up to 5 turns), then gradually screwed in (made less loose or tighter from 5 down to 0 turns) and finally screwed out again in the same manner, as shown in Fig. (7).

4 Discussion and Conclusions

The success story of the approach proposed in this research work begins the smart design of the used phantom (a metal screw screwed into a solid fresh-wood cylinder) which made it possible to efficiently simulate slightly varyingosseointegration grades by screwing in or out the metal screw gradually. Thereafter, when the reproducibility and repeatability of the measurements were proven by simply looking at the standard deviations (which were mainly limited to 1%) for repeated measurements acquired by using the same experimental setup and correspond to identical grade of stiffness, conditions and constraints. An essential issue is, of course, to preprocess and normalize the data properly to achieve the best possible performance and accuracy of the system.

The promising results, that were obtained with a coefficient of determination R^2 of 96.4% and a mean absolute error of ±0.23 turns, indicate the usefulness and efficiency of the approach in this work. However, in the experiments, a piece of fresh oak-wood (a solid cylinder) was used instead of a jawbone, and a metal screw was used instead of a titanium dental implant.

Future experiments should be performed *in vitro* on a piece of bone with a dental implant screwed into it. Furthermore, the experimental setup was designed to work successfully in a well or rather fully controlled laboratory environment.

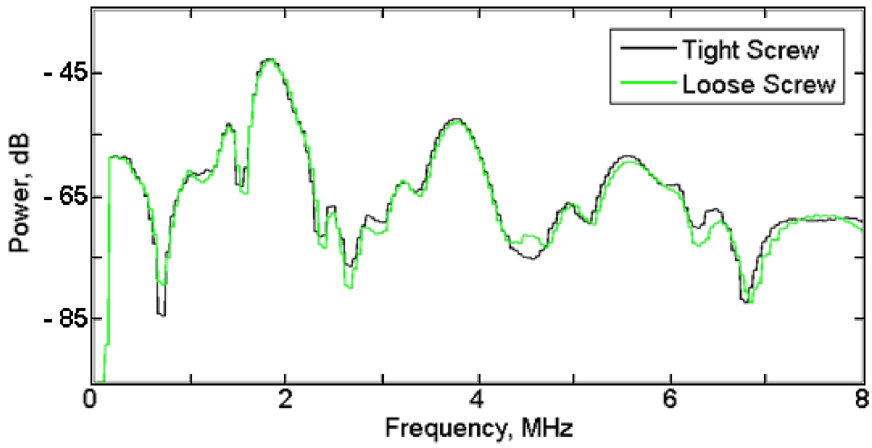

Fig. 6.A comparison between two power spectra; a power spectrum for the tight-screw state and another one for a loose screw.

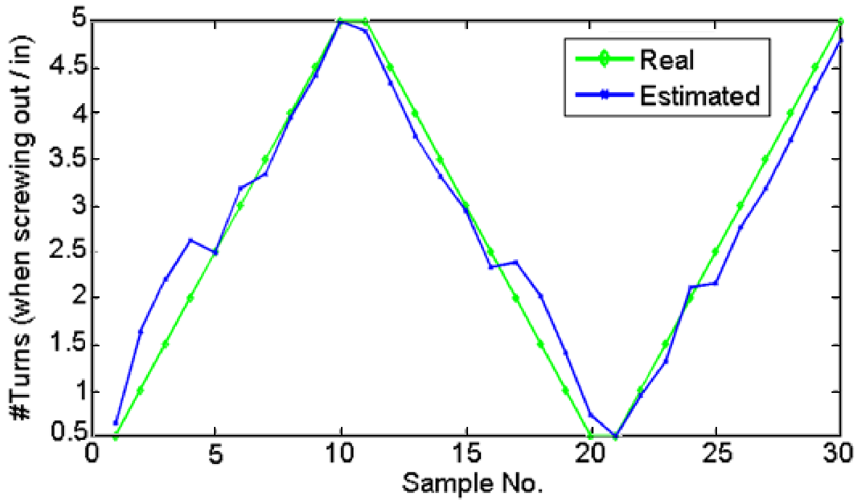

Fig. 7. A comparison between real and estimated number-of-turns when screwing the screw gradually out of the solid wooden cylinder (starting from the tight screw state), then into it (gradually until reaching the tight screw state) and finally out of it again. Increasing or decreasing the number of turns corresponds to various stiffness grades of the screw-in-wooden-cylinder structure.

The transducer was attached to the phantom at approximately the same position and direction during the whole experiment for all measurements. Minor changes or variations occurred when trying to screw in or out the metal screw.

Therefore, the challenge is to find a measuring procedure and/or a preprocessing and normalization method to be able to perform measurements at different occasions, where the transducer and the phantom are removed totally from the experimental setup after each series of measurements then the computation of an average power spectrum. A successful measuring, preprocessing and normalization procedure, which results in a robust, repeatable and accurate system, should make it possible to perform independent measurements on the same implant, then evaluate and compare them accurately.

The spectral measurements acquired, so far, are angle and displacement or position dependent. Therefore, these measurements will change considerably when measuring at different parts of the phantom and from different angles or directions; e.g. when the transducer is tilted by (even slightly) different degrees with respect to the phantom. However, it is possible to normalize the obtained average power spectra by using an efficient procedure and make it possible to compare such spectra anyway.

Good results were obtained in this research work because the method proposed and used in this work didn't rely on comparing amplitudes of one or several peaks found at certain frequencies or frequency intervals in the average power spectrum (as it is the case in many traditional spectral analysis approaches). The new method makes instead use of the shape of the whole power spectrum curve, which resulted in an efficient approach as proven by the obtained results. Therefore, it should be possible to proceed in the same manner to make this approach even more efficient and practical so that it can be used and applied on measurements performed outside the laboratory environment (i.e. in the clinic) without the need for a fixed experimental setup and/or well controlled measuring conditions.

Furthermore, another advantage of using the new approach is that it is not necessary to identify (e.g. by manual visual inspection or by automated analysis) the most useful spectral regions of the power spectrum (where e.g. most variations among the spectra are visible) to be included in the dataset processed by the proposed procedure. The algorithm can automatically include or exclude certain spectral regions of the power spectrum during the training phase. In other words, the system is able to differentiate between what is useful of the data and improves the performance and accuracy of the system to include it in the computations, and on the other hand, what is not and might degrade the performance of the system and therefore exclude it.

It is for instance possible to design, develop and use a self-optimizing and self-training system that can find its way and solve a system of equations as efficiently as possible in addition to the ability to still learn or to learn more while it is used (i.e. such a system can gain more experience the more you use it in systematic way, of course).

The significance of the new method for evaluating dental implant osseointegration can be summarized in enjoying a number of must-have advantages, such as that the new approach is safe (risk free), non-invasive, fast, robust, noise insensitive, accurate, fully automatic, reproducible/ repeatable, that it requires minimal patient preparation in addition to that it considerably reduces the reliance upon subjective measures.

The conclusion that can be drawn here is that the good correspondence between real and estimated dental-implant stiffness-grade values makes this approach promising (after further optimization and adaptation for *in vivo* studies) for monitoring and tracking the osseointegration process after dental implant surgeries.

Conflict Of Interest

There are no conflicts of interest relevant to this research work to be declared here.

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