Neural Network Analysis of Bone Vibration Signals to Assesses Bone Density

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Abstract. Osteoporosis is a systemic disease, characterised by low bone mineral density (BMD) with a consequent increase in bone fragility. The most commonly used method to examine BMD is dual energy X-ray absorptiometry (DXA). However DXA cannot be used reliably in children less than 5 years old because of the limitations in the availability of required normative data. Vibration analysis is a well-established technique for analysing physical properties of materials and so it has the potential for assessing BMD. The overall purpose of this study was development and evaluation of low frequency vibration analysis as a tool to assess BMD in children. A novel portable computer-controlled system that suitably vibrated the bone, acquired, stored, displayed and analysed the resulting bone vibration responses was developed and its performance was investigated by comparing it with DXA-derived BMD values in children. 41 children aged between 7 and 15 years suspected of having abnormal BMD were enrolled. The ulna was chosen for all tests due to the ease with which it could be vibrated and responses measured. Frequency spectra of bone vibration responses were obtained using both impulse and continuous methods and these plus the participants' clinical data were processed by a multilayer perceptron (MLP) artificial neural network. The correlation coefficient values between MLP outputs and DXA-derived BMD values were 0.79 and 0.86 for impulse and continuous vibration methods respectively. It was demonstrated that vibration analysis has potential for assessing fracture risk.

Keywords: Medical Signal Processing, Bone Vibration Analysis, Bone Mineral Density.

1 Introduction

Osteoporosis is a silent systemic disease, characterised by low bone mineral density (BMD) resulting in bone becoming thinner and less dense increasing fracture risk. The most common sites of fracture due to osteoporosis are the spine, hip and wrist, but almost all bones can be affected [1-2]. Men and women over 60-years-old are at highest risk of osteoporosis. Nevertheless, it is possible to have osteopenia (low bone mass) at a much earlier age. Osteogenesis imperfecta (OI) commonly called “brittle

bone disease" is the name given to a group of heritable disorders, affecting the bones and connective tissue resulting in osteopaenia in childhood [3-5]. It is very important to monitor BMD during childhood (especially for children with chronic disorders) with the aim of preventing osteoporosis in later life [6].

BMD can be measured using a variety of non-invasive methods, the most common of which is dual energy x-ray absorptiometry (DXA). Other measurement methods are quantitative ultrasound (QUS) and quantitative computed tomography (QCT). Each method, DXA, QUS and QCT, has its own advantages and disadvantages [7].
Vibration analysis is a well-established industrial method for structural health monitoring. In the last few decades, its potential for bone health assessment in orthopaedics has been considered. In theory, by stimulating bone mechanically and analysing its response, it is possible to monitor various conditions from fractures through to osteoporosis [8-9]. Lippmann [10] in 1932 was the first to use a vibration test to examine bone. He vibrated the clavicle by tapping it and listening to the resulting sound using a stethoscope. There was no further significant research until the early 1970s when investigators tried to apply low frequency vibration analysis to orthopaedics. As technology has improved since the late 1980s, a considerable number of investigations have been carried out to develop a useful clinical tool based on vibration analysis techniques [11-17]. However, effectiveness of vibration analysis as a diagnostic tool in orthopaedics is still under investigation.

Like the other methods (DXA, QCT and QUS), vibration analysis is painless and requires no injections, invasive procedures, sedation, special diet, or any other advance preparation. It is a completely safe (no x-ray radiation), quick and cost effective method. This study aims to assess feasibility and reliability of vibration analysis for *in vivo* BMD assessment.

2 Methodology

Ethics approval for the study was obtained from Sheffield Hallam University, Sheffield Research Ethics Committee and the local NHS Research & Innovation Department. Forty one children aged 7 to 15 years old were recruited from those referred to Sheffield Children's Hospital (SCH) to have DXA scans as part of their routine management. DXA scans were undertaken using a fan-beam GE Lunar iDXA densitometer. All children and their carers completed assent/consent forms to enter the study. The patients included 19 females and 22 males. They were asked to indicate their dominant hand and whether or not they had any previous hand fracture. Four patients were left handed and the rest right handed. The patients' whole body BMD, height and weight were obtained from their medical records following their DXA scan. Patient details are summarised in Table 1.

Table 1. Summary of patient details.

Variable	Statistical Measure	Value
Age (years)	Mean ± SD	11.1 ± 2.9
	Median	11.2
	Range	7 to 15
Sex	Male (%)	22 (54)
	Female (%)	19 (46)
Height (cm)	Mean ± SD	137.9 ± 16.3
Weight (kg)	Mean ± SD	39.0 ± 18.9
BMI centile	Mean ± SD	58.1± 37.2
Arm length (cm)	Mean ± SD	21.2 ± 3.2
Whole body BMD (g/cm^2)	Mean ± SD	0.70 ± 0.19

2.1 Vibration Signal Acquisition

The recording set up is shown in Figure.1. In order to record the data, the participant sat on a chair. The ulna was chosen for the study because of the ease with which it can be vibrated and its vibration responses be recorded from sensors placed on the skin [18]. The hand to be tested was placed on a soft support placed on a table of suitable height. The support was designed to provide a suitable position for the ulna to allow performance of the vibration test. The distance between the olecranon process and the ulnar head was measured and divided into 5 equal parts. The bone inducing tapping point (to induce vibration) was one fifth of the distance from the olecranon.

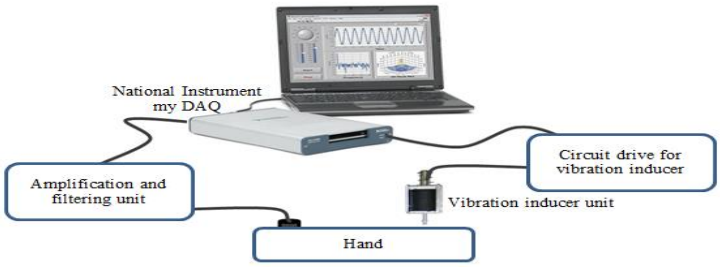

Fig. 1 Bone vibration response recording system set up.

Two schemes were used to excite the ulna: impulse and continuous. In the impulse method, a miniature computer controlled electrical tapper was developed by adapting a solenoid [19]. The solenoid shaft was fitted with a small steel cylindrical top with a diameter of 4mm made to ensure appropriate contact with the bone. The developed tapper was housed in a suitably designed vice which allowed its position to be adjusted horizontally and vertically. Using this vice, the tapper could be positioned easily in any orientation. In order to maintain a fixed distance between the tapper and the ulna, the tapper was encapsulated with a small hollow plastic cylinder (inner diameter 4.5 mm). The cylinder once placed on the ulna, allowed the moving part of the tapper to move freely and impact the bone. The developed tapper's voltage supply

was 6 volts. This produced sufficient force to excite the ulna without causing pain. The Laboratory Virtual Instrument Engineering Workbench (LabVIEW) software and its associated hardware (myDAQ) were used to control the tapper. A square pulse with an amplitude of 5 volts and a duty cycle of 4% was generated using LabVIEW. This pulse was sent through myDAQ to the MOSFET power transistor that drove the tapper. The ulna was tapped 10 times. The time interval between the taps was 1 second. In order to ensure consistency of results, the impulse scheme was repeated twice; therefore two vibration signals were obtained. Each vibration signal consisted of 10 vibration responses to the 10 taps.

The continuous method of inducing bone vibration used an encapsulated eccentric rotating mass (ERM) vibration motor (model type: Precision Microdrives, 307-100). The motor supply voltage was 3 volts providing motor vibration frequency and amplitude of 230 Hz and 6 g respectively. The motor in this condition could adequately vibrate the ulna without inducing pain.

The CM-01B vibration sensor was positioned on the skin above the ulnar head using Mefix self-adhesive fabric. The signal was fed to the signal conditioning system, amplified and low pass filtered with a cut-off frequency of 2 kHz. The resulting signal was then digitised using the NI myDAQ and transferred into the laptop computer for display and storage. The signal sample rate for both the impulse and continuous vibration schemes was 100,000 and duration of recording was 10 seconds.

2.2 Vibration Signal Processing

Impulse Scheme. Two sets, each consisting of 10 vibration responses were obtained using the impulse scheme for each participant. The vibration responses were individually low-pass filtered with a 7^{th} order Butterworth digital filter and cut-off frequency of 2 kHz then their magnitude frequency spectra were obtained. The resulting twenty magnitude frequency spectra were averaged to reduce bias towards a single trial. The averaged magnitude frequency spectra for the subjects were used for further analysis with an artificial neural network (ANN). The type of ANN used in this study was the multilayer perceptron (MLP). The inputs for the neural network were the frequency parameters up to 2 kHz which were normalised so that they lay between +1 and -1. Relevant parameters (sex, height, weight, age in days, dominant hand and length of the right hand) were also used as inputs to the MLP after normalising between +1 and -1. Sex was taken into account as +1 and -1 for females and males respectively. Similarly the dominant hand was assigned as +1 and -1 for the right and left hand respectively. The MATLAB function mapminmax was used for mapping the data between -1 and +1, formulated as follows

$$y = (y_{max} - y_{min}) \times (x - x_{\min)})/(x_{max} - x_{min}) + y_{min} \quad (1)$$

where y_{max} and y_{min} were +1 and -1 for x_{max} and x_{min} respectively.

The MLP had two hidden layers. According to Masters [20] the initial number of

nodes in the hidden layer can be computed as: nodes in the first hidden layer $= mr^2$ and nodes in the second hidden layer $= mr$
where n and m are the number of nodes (neurons) for input and output layers respectively and

$$r = \sqrt[3]{\frac{n}{m}} \quad (2)$$

This formula was used as the initial estimate to determine the number of nodes in the hidden layers. The exact number used was then determined through training and evaluating the MLPs with different number of nodes that varied slightly from the calculated values.

To optimise the network, the patients were randomly divided into the training, validation and test sets in the proportion 45%, 30% and 25% respectively, using the MATLAB dividerand function. The transfer function for the network was the hyperbolic tangent for the two hidden layers and the linear for the output layer.
Through training and observing the MLP performance, suitable values for the learning rate and momentum were selected as 0.01, 0.6 respectively.

Continuous Scheme. One continuous vibration response was obtained from each participant. The response signal was low pass filtered with a 7th order Butterworth digital filter, cut-off frequency of 2 kHz and the magnitude frequency spectrum of each vibration response was obtained. The resulting frequency parameters were then normalised to be between -1 and +1. The frequency parameters up to 2 kHz were further analysed using the MLP network explained in the impulse scheme. Like the impulse scheme, relevant parameters (sex, height, weight, age in days, dominant hand and length of the right hand) were also used as inputs to the MLP after normalising between +1 and -1. The number of nodes for the hidden layers of the network was adjusted based on the number of input values, however the other specifications of the network remained the same.

3 Results and Discussion

3.1 Impulse Scheme

Figure 2 shows the typical vibration signals obtained from a subject using the impulse method and the individual vibration responses for the two trials.

Both trials have similar patterns indicating the consistency of the method to record the signals. Magnitude frequency spectra of 20 vibration responses obtained from each patient were averaged and the resulting spectrum shown in Figure 3 was used as input to the ANN.

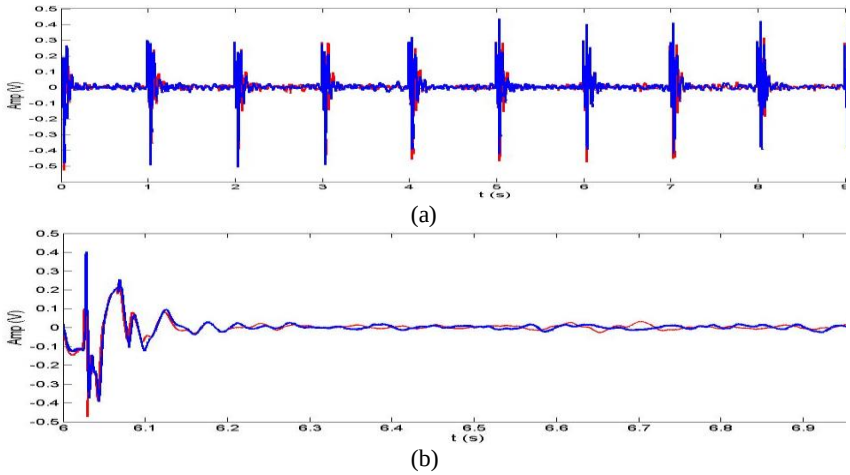

Fig 2. (a) Typical vibration signals obtained from the ulna and (b) An individual vibration response from two trials recorded from a single patient.

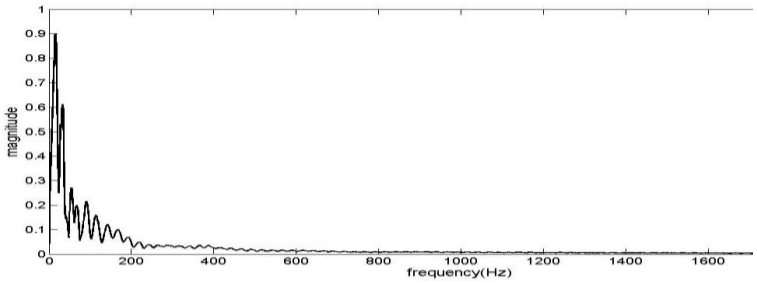

Fig 3. The typical magnitude frequency spectrum of the ulna in the impulse scheme.

Figure 3 shows that the main peaks are located below 200 Hz. Frequency parameters were normalised between -1 and +1 using Formula 1 and used for the neural network analysis. Magnitude frequency spectra of all participants showed that the largest peaks were located below 50 Hz. These frequency parameters (i.e. 50 frequency values, separated by 1 Hz, per patient) together with the patient's physical parameters (i.e. 6 values indicating sex, age, height, weight, dominant hand and length of the right hand) were fed into the MLP.

Considering the number of nodes for the input layer to equal 56 (i.e. *n*) and one node for the output layer (i.e. *m*), Formula 2 was used to estimate the number of nodes in the hidden layers. Then through experiment the numbers that gave best results were selected. The best results were obtained when the numbers of nodes for the first and second hidden layers were selected as 16 and 6 respectively. The training set was used to optimise the neural network weights, the validation set was used to ensure over fitting did not take place and the test set was used to evaluate the network on unseen cases.

The input values were fed into the trained network to estimate the corresponding

BMD values. Figure 4 shows the comparison between the DXA-derived BMD values and the calculated values obtained from the MLP using frequencies of up to 50 Hz as its inputs. The correlation coefficient value between the actual BMD values and the neural network calculated BMDs was 0.79, calculated by using.

$$(A,B) = \frac{1}{N-1}\sum_{i=1}^{i=N}\left(\frac{A_i-\mu_A}{\sigma_A}\right)\left(\frac{B_i-\mu_B}{\sigma_B}\right) \quad (3)$$

where N is the number of patients, μ_A and σ_A are the mean and standard deviation of A respectively, μ_B and σ_B are the mean and standard deviation of B respectively. A and B represent DXA and MLP calculated BMD values.

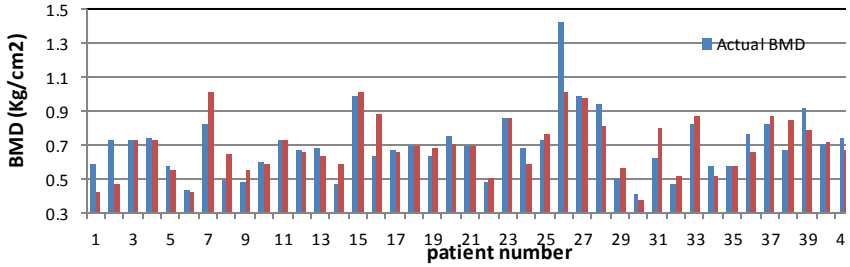

Fig4. Actual DXA-derived BMD values and the values calculated from the MLP for

Figure 5 shows the percentages of relative errors for the BMD values calculated from the MLP using the frequencies up to 50 Hz as inputs.

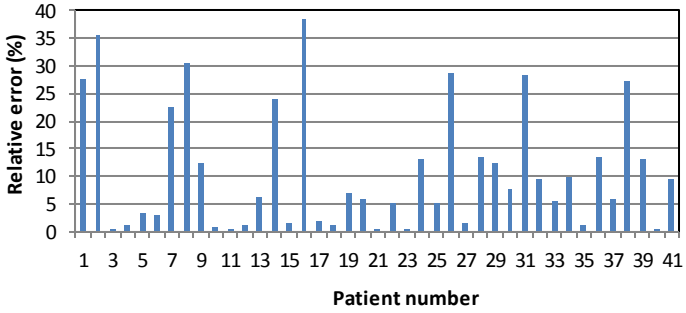

Fig 5. Relative error calculated by comparing the DXA-derived BMD values and the values determined from the MLP used in the impulse scheme study.

The method provided an accuracy of 89.3%, determined using

$$\%Accuracy = \left(1 - \frac{|BMD_{DXA} - BMD_{ANN}|}{BMD_{DXA}}\right) \times 100 \quad (4)$$

The accuracy, given the amount of data used to train the MLP is acceptable. The BMD values for three subjects; one from the training set, one from the validation set and one from the test set, had more than 30% relative error, however the majority of the obtained values had less than 15% relative error where the BMD for 16 subjects were calculated with less than 5% relative error.

The results of the impulse scheme showed that the MLP was best trained when its

inputs were limited to the low frequency parameters. It indicated that input information related to the BMD was contained in frequencies less than 50 Hz. This result is in agreement with the results obtained in [18] using the manual method for vibration analysis to assess BMD in children.

3.2 Continuous Scheme

Figure 6 shows a small section of a typical vibration response and a typical vibration frequency spectrum obtained from the ulna using the continuous scheme.

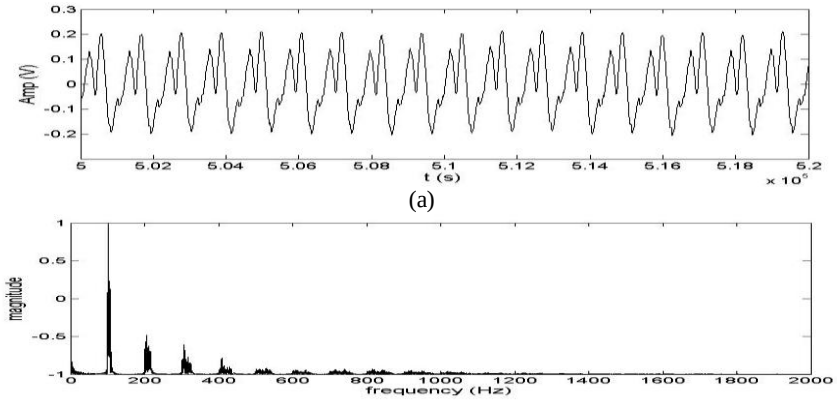

Fig 6 A typical vibration signal (a) and its corresponding frequency spectrum (b) obtained from the ulna using the continuous scheme.

The magnitude frequency spectrum of the vibration signal was obtained and its parameters were mapped between -1 and +1. The two highest peaks in the magnitude spectrums were in the frequency range of 50 Hz and 250 Hz. This frequency range included 2000 values that were used as input values for the MLP network. The input data was randomly divided into the training, validation and test groups with the proportions of 65%, 20% and 15% respectively. The numbers of nodes for the first and second hidden layers set to be 160 and 25 respectively. The other specifications of the network remained the same as those used for the impulse scheme.

Figure 7 shows the estimated BMD values obtained from the MLP in the continuous scheme in comparison with the actual DXA-derived BMD values.

The correlation coefficient value between the DXA-derived BMD values and the MLP-calculated BMD values was 0.87. Figure 8 shows the relative errors for the BMD values calculated by the MLP in the continuous scheme. The continuous scheme showed better results than the impulse scheme. However it should be considered that the network in the continuous scheme was tested with only 15% of the data sets compared to 25% for the impulse scheme.

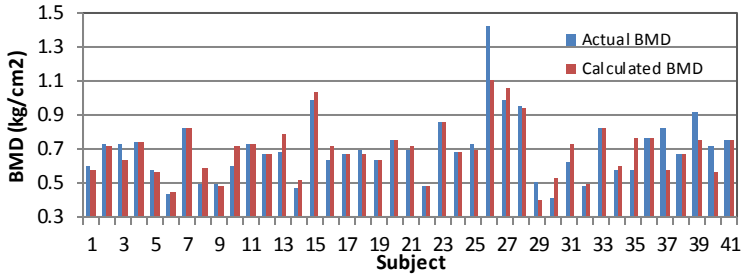

Fig 7. Actual DXA-derived BMD values and the values calculated from the MLP for the continuous method.

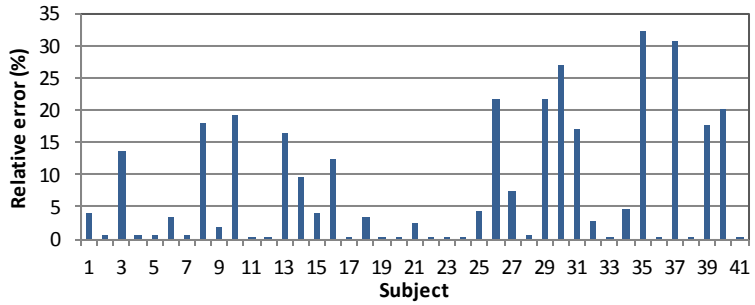

Fig 8. Relative error calculated by comparing the DXA-derived BMD values and the values determined from the MLP used in the continuous scheme.

4 Conclusion

Vibration analysis was performed on 41 children aged 7 to 15 years using the impulse and continuous schemes. The vibration signals were obtained from the children's right ulnae. The magnitude frequency spectra of the recorded signals were obtained and were further analysed using an artificial neural network model called multilayer perceptron (MLP). Bone mineral density (BMD) values obtained from MLP analysis were compared with the DXA-derived BMD values. The correlation coefficient value between BMD values obtained using the MLP and the DXA-derived BMD values was 0.79 and 0.86 for impulse and continuous schemes respectively.

The study showed that vibration analysis implemented either in the impulse scheme or the continuous form using the MLP may have potential in examining BMD in children, but further work is needed to make it clinically deployable.

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children included in the study.

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