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APPLICATION OF EAR-BRAIN ANALOGY FOR SOUND SPECTRAL RESPONSE CHARACTERISATION IN NON-DESTRUCTIVE MATERIAL EVALUATION

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ABSTRACT

The ability of the human's ear-brain system in recognising distinctive sound patterns has been used to develop a non-destructive testing system that is able to evaluate the strength class of material. The work involves the development of the most appropriate and effective configuration of devices and software to observe the response of specimens of wood composites to externally induced excitation of sound in form of white noise. This system predicts the strength class, and eventually the elastic and strength properties, of the specimens non-destructively. The unique sound spectral response of each group of specimens is captured by a microphone, filter and amplifier system that mimics the human 'ear'. The 'brain' is made up of a computer with an adaptive neuro-fuzzy analysis capability. The net amplitude readings of the spectral response changes according to the species and the frequency levels but generally higher density specimens absorb more sound energy resulting in lower readings. Virtual specimens were generated using Weibull distribution to enhance the training and validation, and it was found to be appropriate for the biological material being evaluated. Fuzzy inference model of sound response of the wood composites has successfully been used to classify them according to their density ranking.

1 INTRODUCTION

The human's ear and brain works seamlessly as a system to provide auditory capability and also the sense of physical balance. The vestibulocochlear and vestibular nerves carries impulses for both hearing and balance from the ear to the brain. The normal effective frequency range of sound waves that humans can hear is between 20 and 20,000 Hz. Loudness is the force of sound waves against the ear and it is measured in decibels (dB).

The brain recognises the unique features of sound passed though the ear by repetitive and adaptive learning. As such, the human's ear-brain system also has the capability in learning unique features of sound passed through a material (Fig.1). The resulting features of sound depend on the physical properties of the material such as density and biological properties such as the cell structure. The human biological system may not have the capability to exactly quantify the properties, but through learning and familiarisation, in hearing the unique sound features that pass through the material, the type of material can be recognised. The methodology of this work was inspired by this capability, but nevertheless, the full hidden biological function of

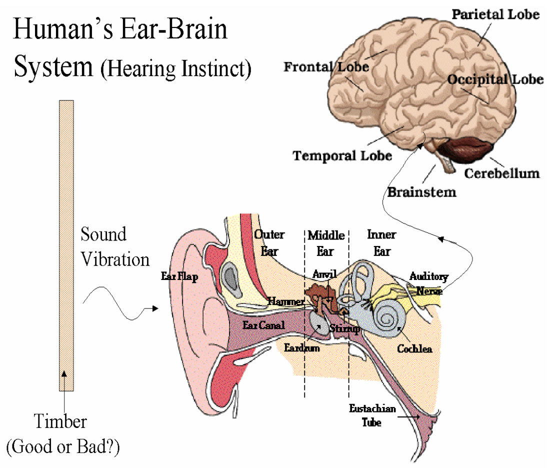

Fig. 1. The human's Ear-Brain system

the ear-brain system cannot be exactly engineered due to its complexity.

This paper describes the development of an intelligent system, based upon existing knowledge and technology, in evaluating the strength properties of wood composite without causing permanent damage to the tested specimens. The work involves the development of the most appropriate and effective configuration of devices and software to observe the response of specimens to externally induced excitation of sound and vibration, and this configuration is used as a system to predict the strength class, and eventually the elastic and strength properties non-destructively. These findings can be applied as a quality control to the general production line since it will be possible for the expected strength of each specimen to be stamped directly on its surface without the need to perform destructive test on only some representative samples of the production batch. This can expedite the classification of the products into their strength class prior to packaging and shipment, and interested parties would have greater confidence in the materials that are being used.

2 NON-DESTRUCTIVE TESTING AND APLLICATION OF SOFT COMPUTING

To determine the strength properties of a material, it has to be tested either by destructive or non-destructive method. Destructive method is usually done on certain percentage of representative specimens of a population of a material. The specimens are subjected to physical force that would cause damage and render the specimens to be useless after the testing is done. Due to several uncertainties in production the strength properties of the whole batch of material have to be modified by statistical reduction that takes into account the standard deviation of the tested specimens. Usually the reduction in strength is determined by using the exclusion limit formula:

$$EL = \bar{x} - ts \qquad (1)$$

where EL is the exclusion limit of the strength values, $\bar{x}$ is the mean strength values, t is the *Student's t* value and σ is the standard deviation of the tested specimens. The exclusion limit value, which are the lower exclusion limit, are to be taken as the characteristic strength of the material that shall be used in engineering design. As the variability of the material increases the standard deviation, σ, will also increase; and the resulting characteristic strength will be lower. To achieve higher reliability more specimens have to be tested to reduce the standard deviation. This practice is not favourable to be done on expensive or scarce material, and to material produced from depleting natural resources.

Conversely, non-destructive method can be applied on every sample of the population or a larger percentage of the population since the specimens will not be destroyed and can be used again. Non-destructive testing offers a better alternative such that strength values can be assigned to each individual specimen, thereby improving the reliability of material usage. Moreover, non-destructive testing also permits evaluation of individual pieces without damage due to overloading (Bodig, 1982).

But for biological based material such as wood composite, linear model will not be the right choice to predict its strength, since the production of trees are affected by many natural factors such as soil type, soil constituents, sunlight intensity, water supply, genetic inheritance and final processing method. Due to this, biological based material tends to possess properties of high variability. To apply non-destructive testing based on linear assumption of the material's behaviour can be problematic since a linear model is not suitable to be used.

Soft computing offers a better alternative to conventional mathematical means for solving highly complex and computationally intensive problems. Artificial neural networks (ANNs) learn by adjusting the weights in the interconnections of layers while fuzzy inference systems (FIS) use fuzzy *if-then* rules to map the relationship between input and output data. For a strength classification of highly variable biological material a model-free application of fuzzy logic, neural network or hybrid of both approaches i.e. neuro-fuzzy can prove to be a more effective solution. To allow the degree of the membership of the fuzzy model to be tuned through adaptation, the learning capability of ANN is incorporated into the Sugeno fuzzy model. The same concept of adaptive networks as in ANN that computes gradient vectors systematically gave birth to adaptive neuro-fuzzy inference system (ANFIS) as proposed by Jang (1992).

Fuzzy logic uses simple rules to describe the system of interest rather than analytical equations, thus it is easy to be applied in classification work. System based on fuzzy logic possesses the ability to reach distinct decisions even though there are overlapping and noise contaminated data. The combination of neural network and fuzzy logic enables the system to learn and improve its performance based on past data. A neuro-fuzzy approach can be used to incorporate pattern recognition capabilities of neural networks with modeling advantages of the rule based fuzzy logic. This combination significantly improves the classifier's performance and provides a mechanism to incorporate past observations into the classification process. For a neural network scheme the training process builds the system, but in a neuro-fuzzy scheme the system is built by fuzzy logic definitions and then it is refined using neural network-type training. Also for a neuro-fuzzy system, extensive training from the beginning does not necessarily give high performance, but future data collection can be used to refine the system further (Liu and Chandrasekar, 2000).

Wu, *et al*. (1990) stated that the conventional method of postulating the property of material would only work when the presumed mathematical model fitted the behaviour of the material. The model would only be true when all of the assumptions were also true. The limitation with conventional method is that the mathematical model might not be able to encompass complex material behaviour.

3 METHODOLOGY

The system prototype as shown in Fig. 2 was made up of a soundproof box to isolate the internal part from surrounding noise interference. Sound in form of white noise was generated using the digital signal analyser through a piezoelectric transducer. The sound was imparted onto the flat surface of one side of the specimen. A microphone, which could be considered as the 'ear', was used to capture the remnant sound that passed through the specimen. The weak signal was boost up using a signal amplifier before being passed to the digital signal analyser for hardware signal processing. The system's 'brain' consisted of a computer for software signal processing including fast-Fourier transformation (FFT), and Matlab's ANFIS toolbox for data analysis.

For this work, wood composites specimens designated as KE, MS, MSP species were tested to observe the capability of the system to categorise them into their appropriate strength class. The specimens were each having gross dimensions of 34 cm x 34 cm x 0.46 cm (width x length x thickness). The frequencies of the sound that passed through the specimens were between 0 Hz to 25 kHz. FFT was done in real time to produce spectral parameters of each specimen in the frequency domain.

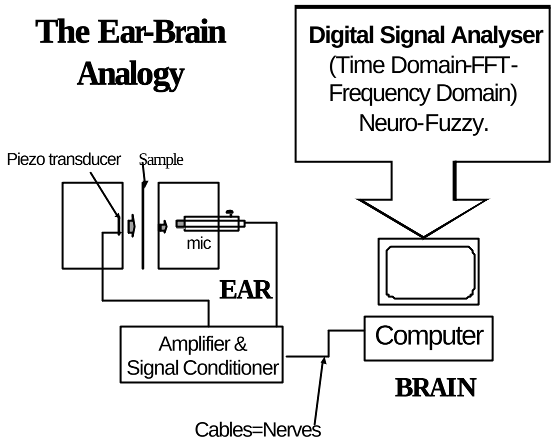

Fig. 2. The Ear-Brain analogy-*The system prototype*

4 VIRTUAL SPECIMEN GENERATION BY WEIBULL DISTRIBUTION

The work of Waloddi Weibull (1939) gave birth to the Weibull distribution that is widely accepted as an appropriate analytical tool for modeling the breaking strength of materials. Current usage also includes reliability and lifetime modeling. Bodig (1982) mentioned that a normal distribution give both positive and negative values due to it having infinite tails in both directions, but for properties such as strength of material negative values gives no meaning. Many simulation input quantities must be positive to make sense.

The Weibull probability density function (pdf) is expressed as

$$f(x) = gx^{(g-1)} \exp(-(x-m)/a)^{g}$$
$$x > m, g, a > 0 \qquad (2)$$

where g is the shape parameter, m is the location parameter and a is the scale parameter. The typical shape of the distribution appropriate for the material tested for this work is as shown in Fig.3.

Since the amount of actual wood composite specimens to be tested in this work was limited, the fuzzy inference system (FIS) model obtained after training will not be robust enough to encompass the range (or known also as the universe of discourse) of the strength properties of the material.

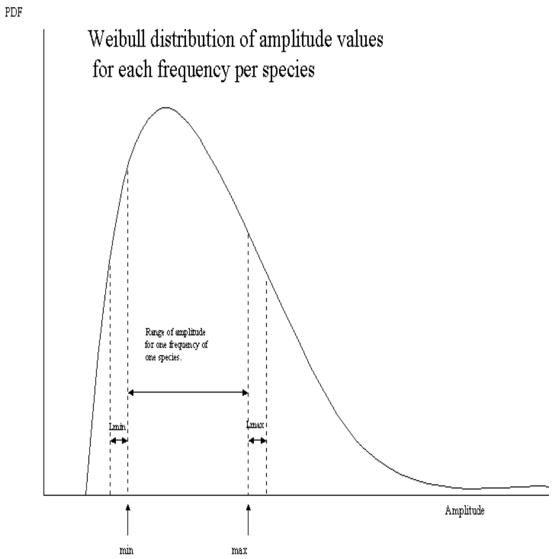

Fig.3 Weibull distribution of amplitude values for each frequency per species with implementation of Lmin and Lmax tolerance.

Therefore a systematic method of data generation was made by applying Weibull distribution to produce virtual specimen data that would augment the limited amount of actual data. The Weibull parameters were determined from the spectral data of amplitude of frequency of each species. To reduce the possibility of lengthy computation time due to the 'curse of dimensionality' only amplitudes values of three frequencies were chosen. The frequencies were 11500, 11625 and 11750 Hz., and they were chosen after being found to show significant difference among the three species. There were 10 original specimens for each species that gave 10 amplitude readings for each frequency. For each species and frequency these 10 corresponding amplitude readings were fitted into a Weibull distribution and their Weibull parameters were determined. The procedure was done to generate virtual specimen for training as well as validation data set.

Due to its nature, the generation of the virtual specimen using Weibull distribution will create two tails, one below the minimum and one above the maximum of the actual amplitude values of each frequency. In these tails are the virtual specimens that fall outside of the range of the amplitude values found by testing of the original specimens, but are valid specimens since the behaviour of the whole population besides the tested sample is assumed to follow the Weibull distribution. During training of the ANFIS, however, not all of the generated virtual specimens can be included because it was found that there would be large error during validation.

Using only the data that lies between the maximum and minimum amplitude of each frequency would produce fuzzy inference system that is only valid specifically in that range. As a compromise, two tolerance values, Lmin and Lmax, were introduced to set the range of values to be extracted from the total generated virtual specimens (Fig.3). These tolerance values were adjusted to produce the best prediction when the fuzzy inference model is tested with the real amplitude data obtained from the experiment.

5 Results and Discussion

In order to observe the feature of the sound that was projected onto the specimens the following steps were performed:

1) With no specimen placed between the piezoelectric transducer and the microphone, the amplitude readings corresponding to every frequency of the sound produced by the white noise were recorded. These values were denoted as AMP_ref to represent the reference reading of the microphone.

2) With a specimen placed between the piezoelectric transducer and the microphone, the amplitude readings corresponding to every frequency of the sound produced by the white noise were recorded. These values were denoted as Amp, to represent the corresponding readings of the microphone for the specimen being tested.

3) The difference between two amplitude readings of AMP and AMP_ref was then calculated.

The test and analysis were initially done on only the highest density species, KE, and the lowest density species, MSP. These observed readings were then scrutinised visually by graphical method to detect any significant difference found between the species. As shown in Fig. 4, the significant difference could only be observed in the frequency range of 10000 to 15000 Hz. Species KE showed lower amplitude valleys and peaks as compared to species MSP. The most probable reason was because species KE was much denser than MSP such that the tighter packed molecules absorbed more sound energy. A more detailed graphical representation, i.e. narrowing to the frequency range of 10000 to 15000 Hz, of the response of the two species is as shown in Fig. 5.

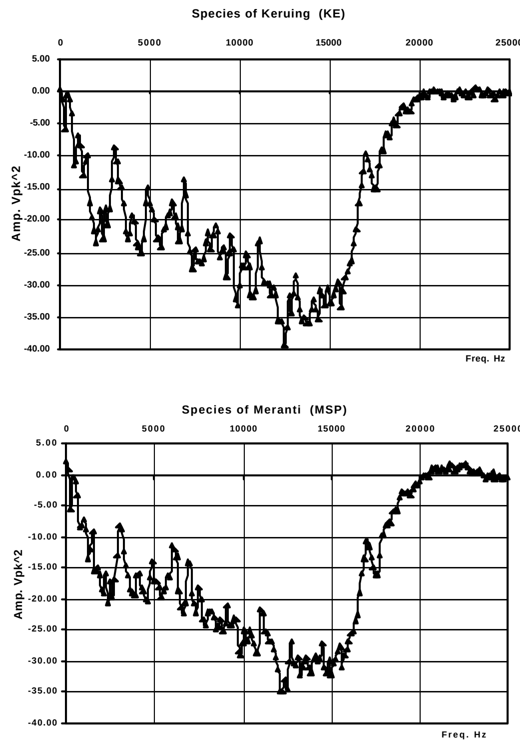

Fig. 4. The frequency domain of white noise imparted on two species of timber

It is noted that the amplitude readings of KE is generally below the amplitude readings of MSP. Using this feature alone it was envisaged that a dividing boundary line could be drawn in between the two species amplitude readings.

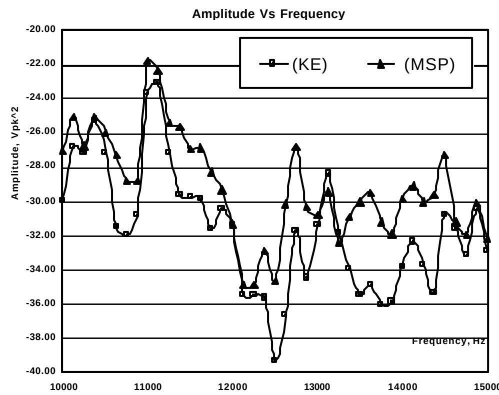

Fig. 5. A detailed frequency and amplitude response for two species

For initial analysis to observe the possibility of separation between the species by neuro-fuzzy approach the following steps were done. The frequency and the extra prior knowledge, i.e. the expected strength class, were used as the inputs while the net amplitude readings Amp-Amp_ref as the output. The training consisted of 246 data set and the validation consisted of 82 data sets. At this moment only the actual data were used and no virtual specimen data were added. Gaussian membership function was used on the inputs. It was found that using this approach the network was able to separate the groups corresponding to their density levels very well. The separation line was able to go in between the peaks and the valleys of the species of amplitude versus frequency graph.

The third species, MS, which had density values between that of species KE and MSP was then tested using the system. Species MS data sets were then added to the network, increasing the training data set to 369 and the validation data set to 123. The analysis was run again but now with the added species. The network was successful in placing the third species in between the two initial species. This placing coincided with density level of MS that fell between KE and MSP. The output of the network is as shown in Fig. 6.

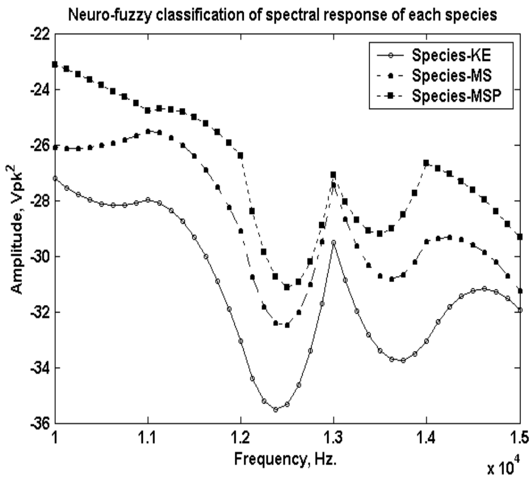

Fig. 6. Neuro-fuzzy classification of spectral response of each species

Since the inputs were frequency and strength class, and the output was net amplitude, the neuro model as shown above was not directly applicable to be use as a strength class predictor. The graphical representation of the network as in Fig.6 can be used to choose the region where the analysis could be concentrated to obtain distinct classification.

To produce a neuro-model that could directly predict the strength class from net amplitude values, the previous training configuration was altered so that the inputs were vectors of net amplitudes of selected frequencies, and the output was the strength class. But since one specimen can only provide one amplitude value for each corresponding frequency the total amount of training and validation data was not adequate. Due to this, the virtual specimen data that were created using the Weibull distribution were added. To reduce the computational time only amplitudes of three frequencies were chosen for the inputs. Data pruning was performed to eliminate the region where the net amplitude for a particular frequency of all the species tends to overlap. From Fig. 6 it is observed that the region between 12500 to 13500 Hz has a very narrow separation between the species, and this region can be eliminated. It was sufficient to actually choose the region between 11125 to 11750 Hz, inclusive, to perform the strength class prediction. The selected frequencies were 11500, 11625 and 11750 Hz., and these frequencies lies in the region where the separation among the species was clearer.

Each input was a column vector with each of the rows consisted of the net amplitude values corresponding to each frequency label. Each row was to represent reading taken from one specimen. The configuration is such that:

$$Input = [\, A_{sf} \,] \text{ and } Output = [\, C_{sf} \,]$$

where, A_{sf} is the net amplitude value and C_{sf} is the strength class of specimen s = 1,....n, with n representing number of actual plus virtual specimens, corresponding to each frequency f = 11500, 11625 and 11750 Hz, i.e. the three selected frequencies. The network was trained and validated using the new configuration, and the number of membership function for all of the three frequencies was three to reflect the strength classes of 1, 2 and 3 for the species KE, MS and MSP respectively. After the training, the model was then implemented into the ear-brain system prototype for actual online prediction task. New actual specimens that were not used for training of the system were tested, and the procedure similar to the training was followed. The net amplitude readings were calculated by getting the difference between the current amplitude readings (AMP) with the reference amplitudes readings (AMP_ref). The net amplitude readings were then implemented into the neuro-fuzzy model obtained from the training to give the output that was the strength class of the specimen. The accuracy of the prototype system was determined by simply getting the ratio of correct strength class prediction over the total number of tested specimens of the known strength class.

It was found that the system was able to predict the strength class of species KE very well, i.e. 100% correctness, and for species MSP, 80% correctness was achieved. However, for species MS, which was in between the two other species in terms of their density values, the correctness level achieved was 70%. This was obvious due to the reason that, by being in the middle, frequency response of species MS overlapped with the frequency response of species KE and MSP such that the strength class boundary was not distinct enough to make correct prediction. The tolerance limit Lmin and Lmax for each species were adjusted to get the optimum prediction accuracy.

The outcome of the analysis and prediction is as shown in Table1.

N_T= 140, N_V=40 F11625, F11500, F11750												
Tolerance level						**Error**			**Strength Class Prediction %**			
Class 1 Species KE		**Class 2 Species MS**		**Class 3 Species MSP**		**Training**	**Validation**					
Lmax_1	**Lmin_1**	**Lmax_2**	**Lmin_2**	**Lmax_3**	**Lmin_3**	**Training**	**Checking**	**Test**	**1**	**2**	**3**	**Epoch**
0.05	0.05	0.045	0.045	0.045	0.045	0.35762	0.38219	0.40290	100	60	80	1000
0.05	0.05	0.04	0.04	0.05	0.05	0.35434	0.38338	0.38810	100	70	70	1000
0.05	0.08	0.04	0.04	0.08	0.05	0.35096	0.47449	0.44082	100	70	80	1000
0.05	0.10	0.04	0.04	0.10	0.05	0.34372	0.45005	0.49733	90	50	70	1000
0.05	0.08	0.04	0.04	0.10	0.05	0.34372	0.45005	0.49733	90	50	70	1000
0.05	0.10	0.04	0.04	0.08	0.05	0.35078	0.44185	0.47670	100	70	80	1000
0.05	0.10	0.04	0.04	0.08	0.05	0.35047	0.44351	0.47969	100	70	70	1800
N_T= gross number of generated virtual specimen for training before extract (per species) **N_V**= gross number of generated virtual specimen for validation before extract (per species)												

Table 1: Strength class prediction with the implementation of virtual specimen using Weibull distribution

6 CONCLUSION

A method based on frequency-domain analysis of sound signal combined with classification capability of adaptive neuro-fuzzy inference system has been developed and validated. The accuracy of a non-destructive testing system rely very much on the accurate translation of the measured physical parameters to the required engineering properties that depends on certain assumption to the way the material behaves. Normally mathematical relations based on linear model are being used and only suitable for materials that have linear properties. Linear model to predict strength will not be the right choice for biological based material because they tend to possess properties that have high variability. The human's ear and brain system is able to recognise by instinct certain properties of material if the sound response is learned and familiarised. Using this ear-brain analogy, this work has succeeded in linking the appropriate hardware and software that is capable to evaluate the strength class of material made from biological elements. Only sound was passed through the specimens and they could be used again because no permanent damage was imposed. Soft computing offers a better alternative to conventional mathematical means for solving highly complex and computationally intensive problems. Virtual specimens were generated using Weibull distribution that was found to be appropriate for the material being tested. Spectral data of these virtual specimens were added to the actual specimens to enhance the training and validation process. These outcomes show the capability of the system to used sound frequency response in combination with neuro-fuzzy analysis as a means to determine the strength class of wood composite material non-destructively.

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