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Wood species identification using stress-wave analysis in the audible range

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ABSTRACT

Stress-wave analysis is a powerful and flexible technique to study mechanical properties of many materials. We present a simple technique to obtain information about the species of wood samples using stress-wave sounds in the audible range generated by collision with a small pendulum. Stress-wave analysis has been used for flaw detection and quality control for decades, but its use for material identification and classification is less cited in the literature. Accurate wood species identification is a time consuming task for highly trained human experts. For this reason, the development of cost effective techniques for automatic wood classification is a desirable goal. Our proposed approach is fully non-invasive and non-destructive, reducing significantly the cost and complexity of the identification and classification process.

1. Introduction

Stress-wave analysis is a relatively simple and powerful technique for material inspection. Compared with other non-destructive testing methods, stress-wave measurements for wood are relatively new [1,2]. The properties of wood vary with respect to species, growth rate, grain angle, moisture content, defects, anisotropies and many other factors. As a consequence, it is not uncommon that several specimens cut from the same tree can exhibit larger differences in some of their properties than specimens from different wood species. Stress induced waveforms in wood are very complex and so variable, that other resonance acoustic techniques successfully developed for other materials cannot be directly applied in the case of wood. Besides, sound attenuation is greater in wood than in other materials like ceramics or metals.

Automatic systems for wood species analysis have been tried using several techniques. The most successful ones to date have used texture analysis of wood images [3], spectral analysis in the near-infrared [4], fluorescence spectroscopy [5], and thermal properties [6]. Acoustic properties of many wood species have been studied due to their importance as materials for musical instruments [7–10]. In spite of the similarities with our experimental method, relatively few works deal specifically with the development of a classification system for wood using its acoustical properties. From a musical point of view, the main research goal is just the opposite, to characterize the acoustic properties of known wood species. Other acoustic approaches have been used for wood classification purposes: acoustic resonance spectrometry [11], and neural network analysis of ultrasonic signals [12].

Most stress-wave studies use ultrasonic frequencies [12–14]. Ultrasounds offer several advantages, but also some disadvantages, like a more costly equipment and low penetration depth in wood. The use of common low cost microphones and commercial PC sound cards for inspecting and identifying wood is studied in this work. These media reduce the accuracy and spectral range of the results, but allow for a very cost effective and flexible experimental setup. The obtained results indicate that this simple equipment could be enough for species characterization of many common wood species.

Our technique is fully non-invasive and non-destructive. The stress induced waveforms are recorded while a low weight hard plastic pendulum is hitting a thin square veneer of wood at the centre. The reproducibility of the waveforms and frequency spectra are compared in order to study the reliability of the method. Finally, the deleterious influence of sample thickness in raw pine samples is analysed.

2. Experimental setup

The experimental setup is very simple as can be seen in Fig. 1. The microphones and the protractor used for the actual recordings are not shown for clarity. Several microphone configurations were tried to maximize the quality of the recordings. Finally, all recordings were made with the microphone parallel to the veneer plane, as near to the impact point as possible. An square frame, made from expanded polystyrene foam, was vertically placed over a thick plate of the same material, in order to reduce unwanted

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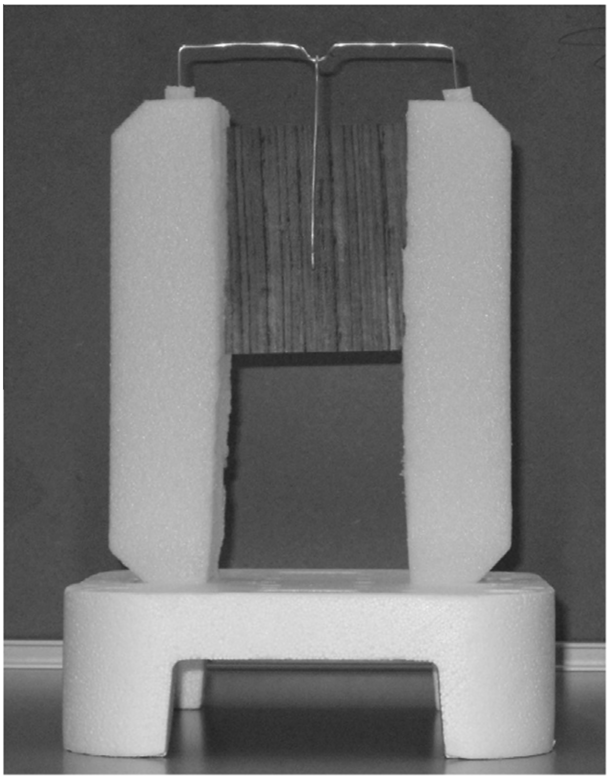

Fig. 1. Simple experimental setup for stress-wave studies in wood veneers.

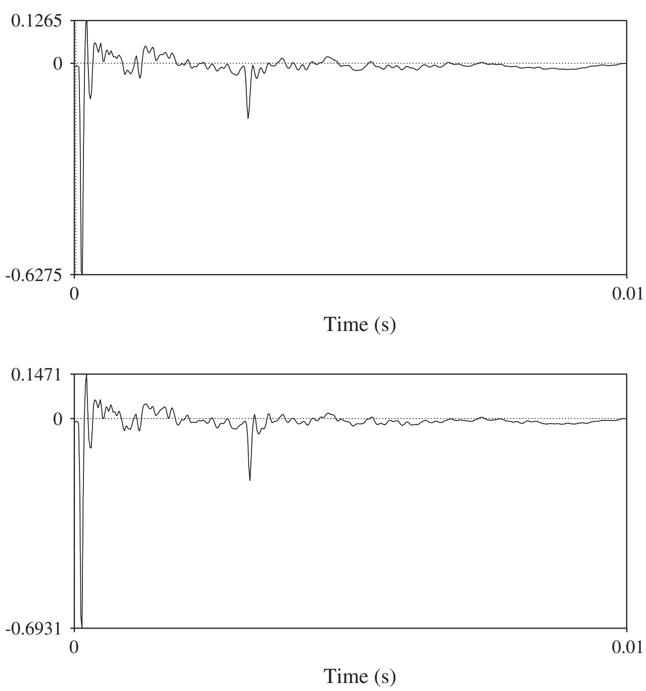

Fig. 2. Waveforms of the sound produced by pendulum impact of two chestnut veneer samples.

vibrations. The wood veneer sample was placed in such a frame. A hard plastic pendulum, weighting a few grams, was located in front of the wood sample in order to hit it at the centre. After some experiments, we found that a light hard plastic pendulum

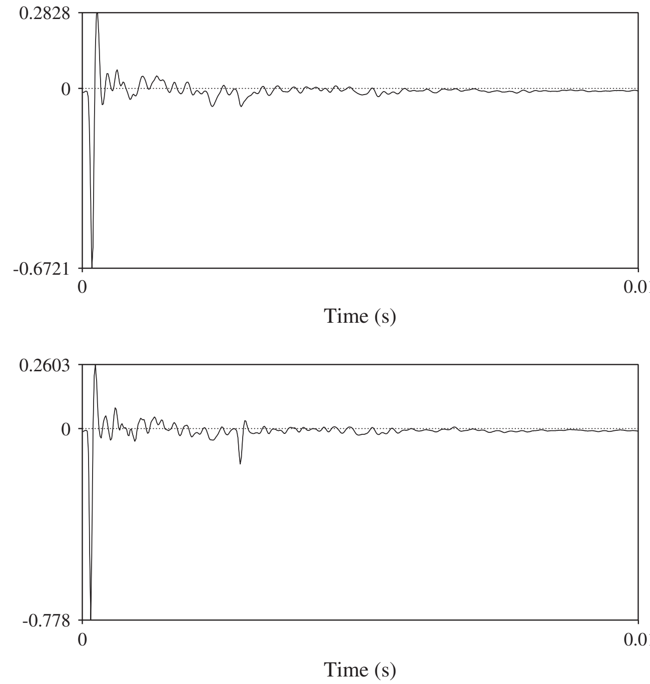

Fig. 3. Waveforms of the sound produced by pendulum impact of two cherry veneer samples.

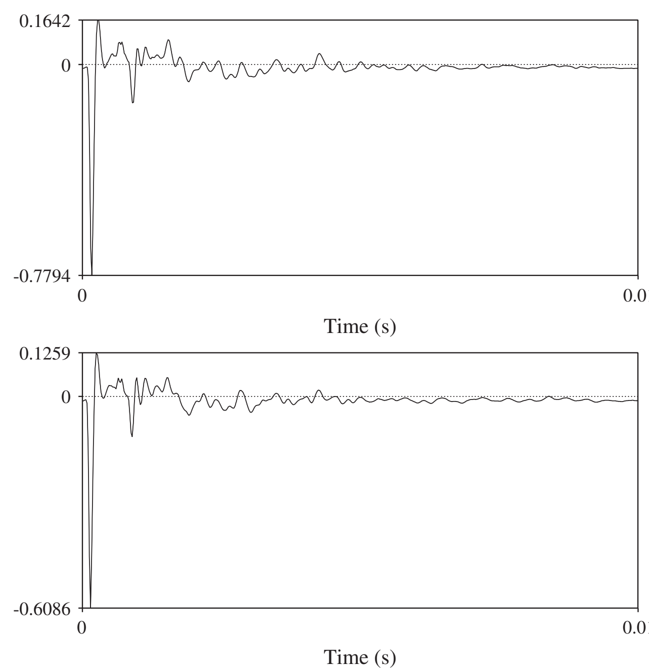

Fig. 4. Waveforms of the sound produced by pendulum impact of two European beech veneer samples.

produced clearer sounds and less damage than metallic, ceramic or glass balls.

The sounds were recorded with several commercial low cost microphones in order to verify the consistency of the results. In general, the agreement was excellent. A common sound card able to 192 kHz recordings, inside a PC, was used and controlled by the Praat program [15]. The results were confirmed using a different sound card. Besides, a previous calibration of the response

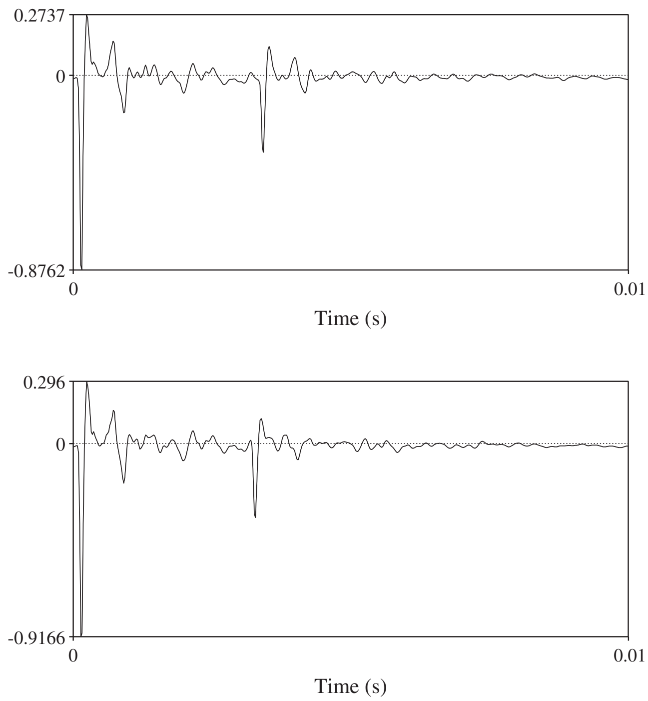

Fig. 5. Waveforms of the sound produced by pendulum impact of two sycamore maple veneer samples.

curve of the first sound card was performed using a pure sine signal generator for selected frequencies in the audible range. The sound recordings were made in quiet, but not anechoic, conditions.

The sounds from 10 pendulum beatings for each wood sample were recorded and analysed. Larger pendulum angles produced more intense sounds, but worse reproducibility, so that beatings from 45° were used as a compromise between intensity and accuracy.

Wood properties are prone to change under different ambiental conditions. Moisture content is the main variability factor. In order to minimize errors, temperature was kept to a constant value of 22 °C and moisture content was measured by conductance methods for all studied samples in the same conditions. All wood veneer moisture ratios were in the range of 13 ± 2%.

3. Experimental results and discussion

In order to verify the suitability of stress-wave analysis by pendulum impact to identify wood species, five different samples of six different wood species were analysed. The samples were cleanly cut veneers, 10 × 10 cm squares, with 0.3 mm thickness. This kind of wood samples are typically used for covering furniture made with cheaper particle board or plywood. The studied species were five common European trees: chestnut (*Castanea sativa*), cherry (*Prunus avium*), European beech (*Fagus sylvatica*), sycamore maple (*Acer pseudoplatanus*), European pear (*Pyrus communis*) and two pine species (*Pinus taeda* and *Pinus sylvestris*). All samples were free of visible defects, although the pine samples presented considerably more complex patterns. The samples from the same species had similar grain patterns.

The two most different recorded waveforms from each veneer species can be seen in Figs. 2–7 for comparison purposes. They have been recorded in the same conditions. Only the first 0.01 s of each pulse are shown, because most of the information is in this range. After this time, the sound is practically attenuated. In all cases, the amplitude of the waves are less than 1% of the value of the highest peak after 10 ms.

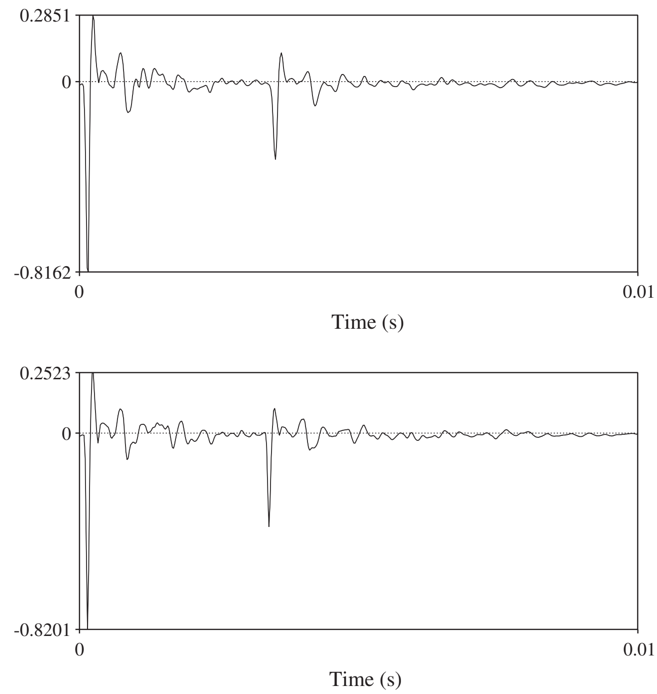

Fig. 6. Waveforms of the sound produced by pendulum impact of two European pear veneer samples.

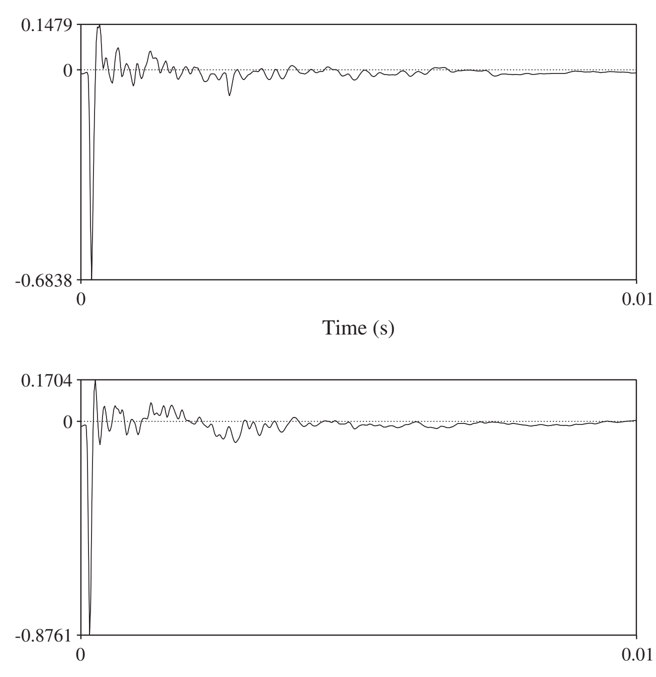

Fig. 7. Waveforms of the sound produced by pendulum impact of *Pinus taeda* and *Pinus sylvestris* veneer samples.

The shape of the stress induced waveforms is very similar among the samples of the same species. The waveforms from different wood species are qualitatively different. The position of the most relevant waveform peaks and their relative distances are preserved within a 5% range except in those cases in which very different grain patterns or defects are present in the samples.

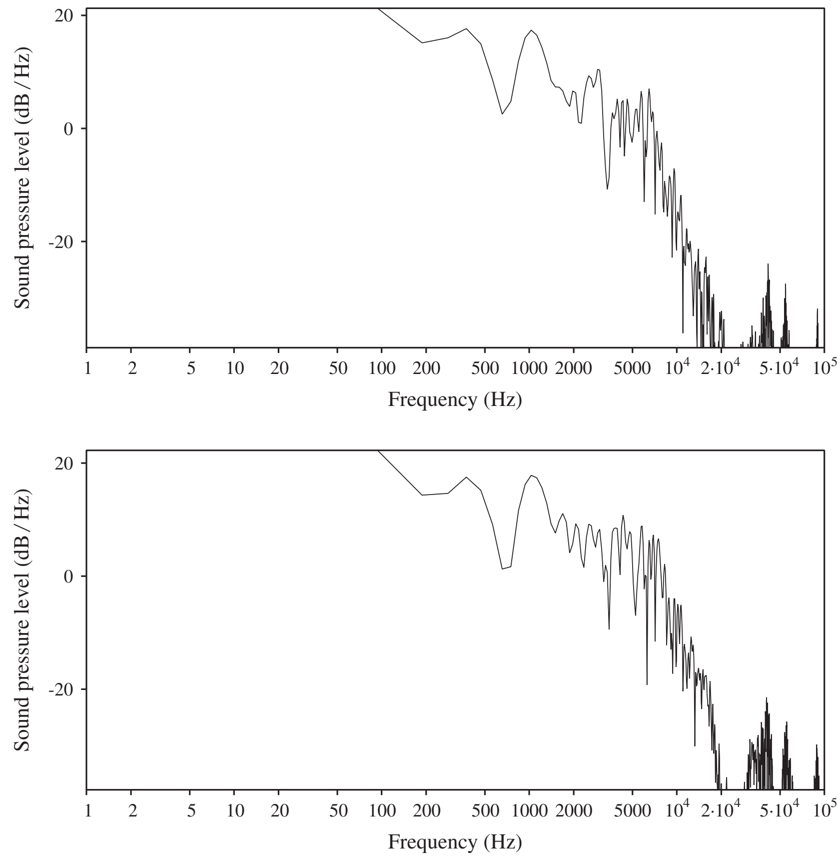

Fig. 8. Logarithmic frequency spectra of the sound produced by pendulum impact of two chestnut veneer samples.

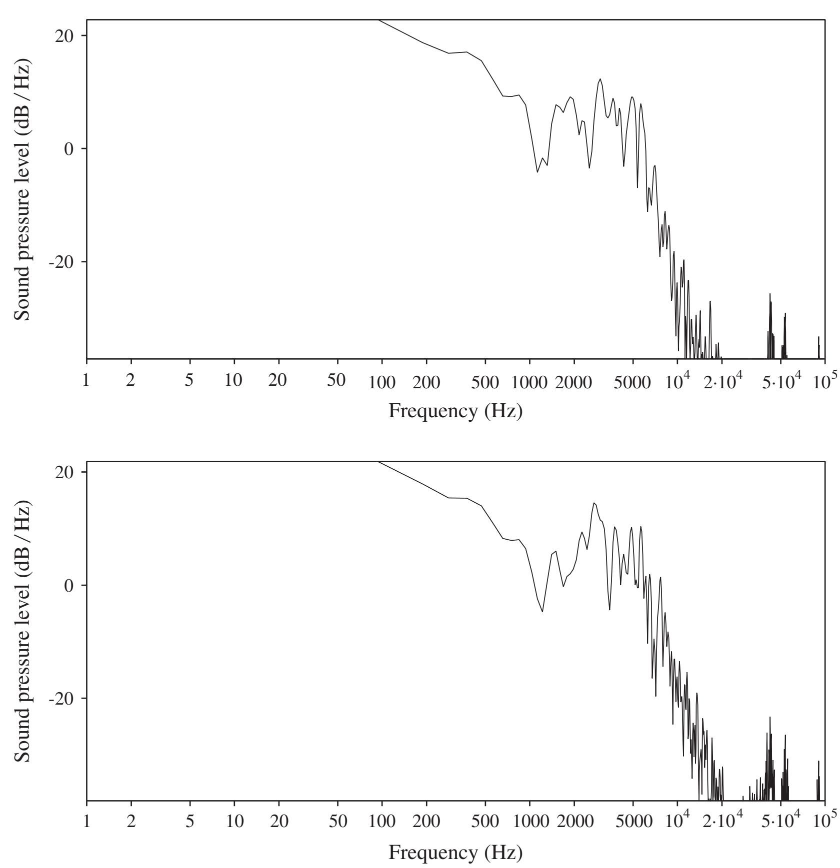

Fig. 9. Logarithmic frequency spectra of the sound produced by pendulum impact of two cherry veneer samples.

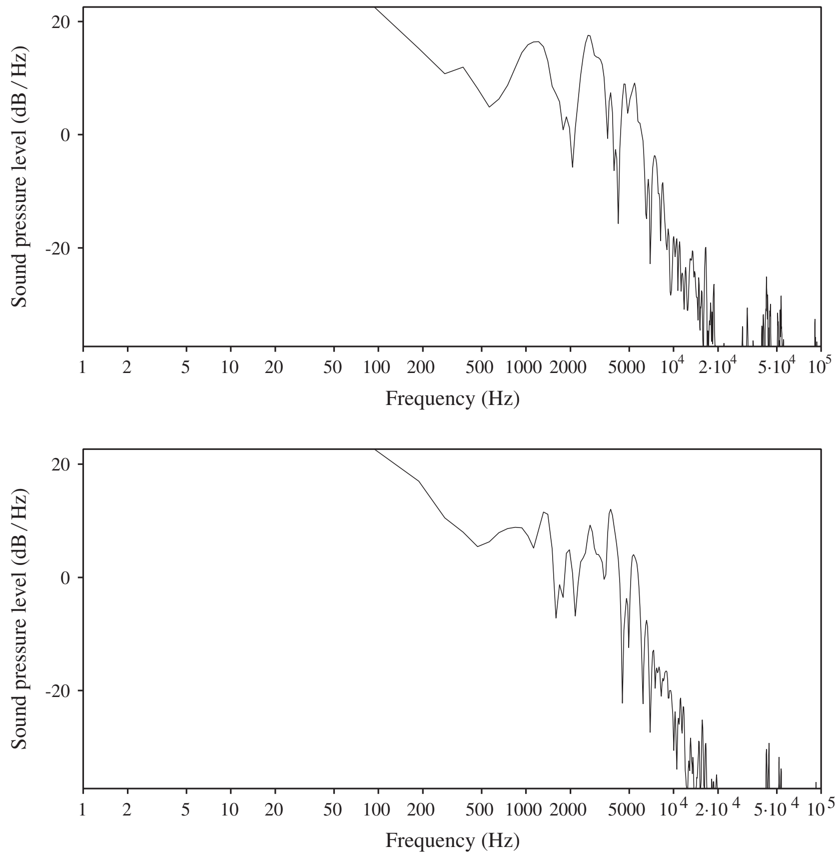

Fig. 10. Logarithmic frequency spectra of the sound produced by pendulum impact of two European beech veneer samples.

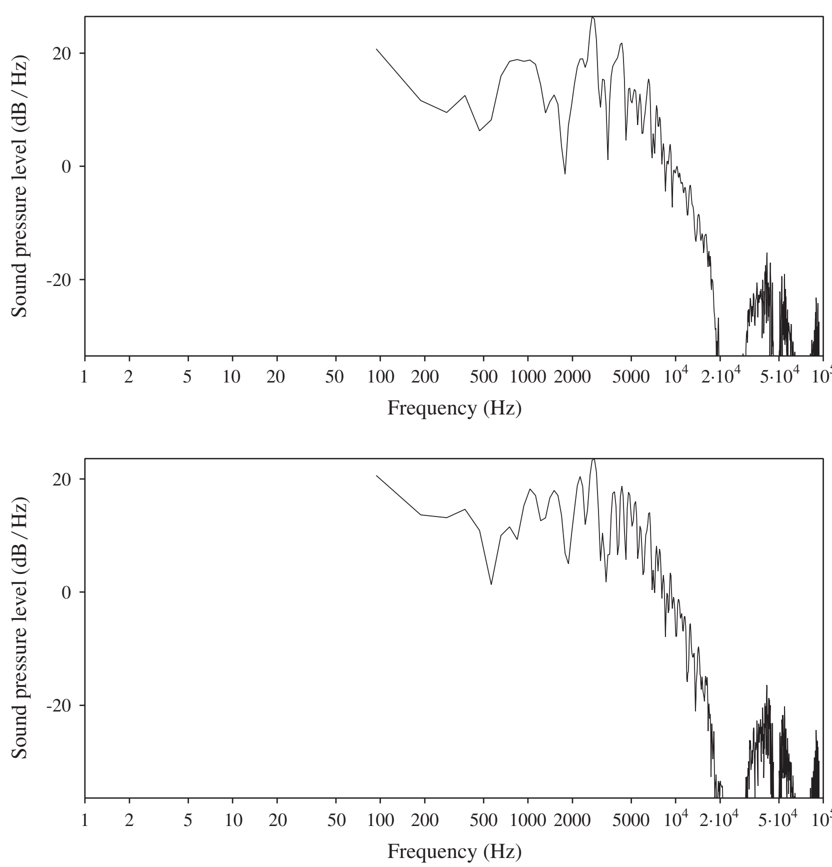

Fig. 11. Logarithmic frequency spectra of the sound produced by pendulum impact of two sycamore maple veneer samples.

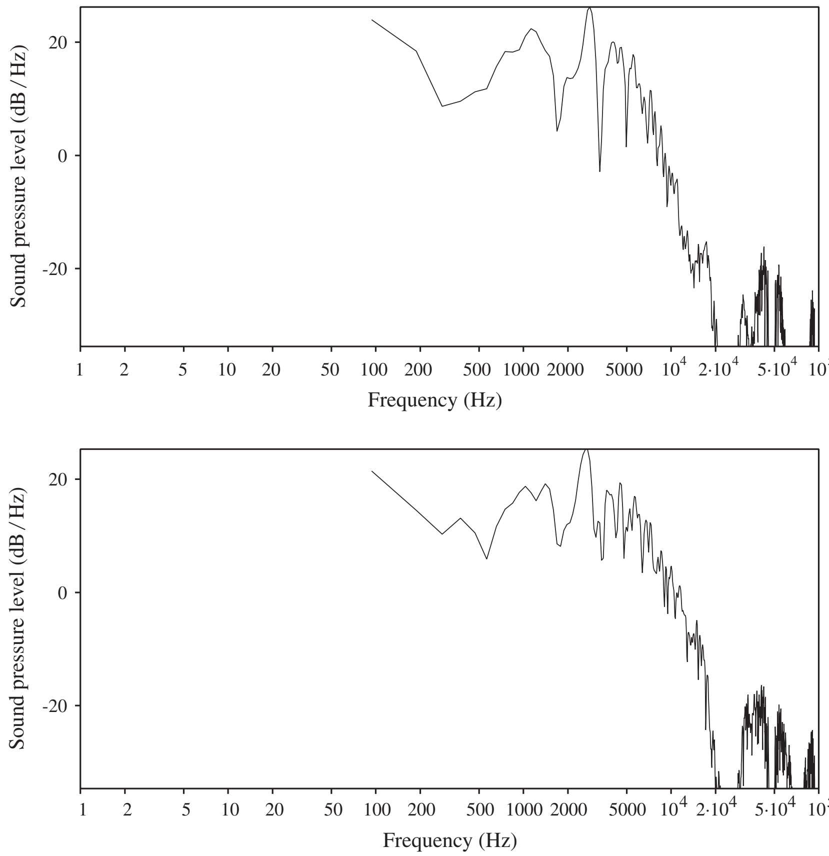

Fig. 12. Logarithmic frequency spectra of the sound produced by pendulum impact of two European pear veneer samples.

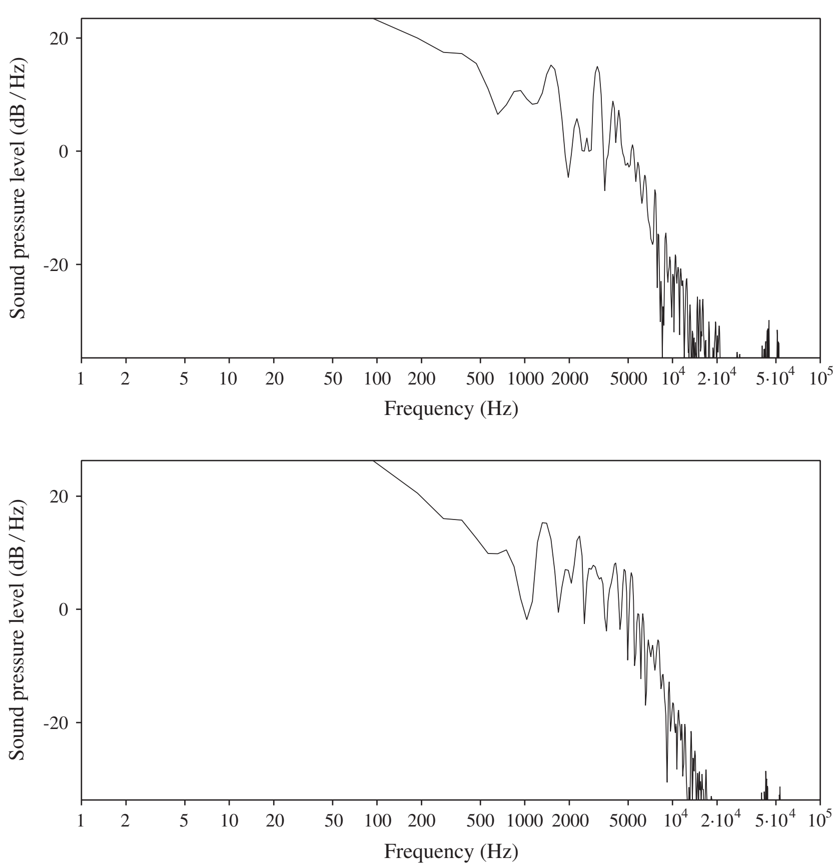

Fig. 13. Logarithmic frequency spectra of the sound produced by pendulum impact of two different pine species.

Table 1
Summary of stress-wave parameters of five studied veneers. D: Duration of the pulse, RDC: Ring-down count, AN: Amplitude of the deepest negative peak (in arbitrary units), AP: Amplitude of the highest positive peak (in arbitrary units), RT: Rise time, FP: First highest isolated peak in the frequency spectrum, I: Mean intensity of the wave.

Wood	Stress-wave measured parameters						
	D (ms)	RDC	AN (au)	AP (au)	RT (ms)	FP (Hz)	I (dB)
Chestnut	5.45 ± 0.06	30 ± 2	−0.67 ± 0.10	0.12 ± 0.03	0.16 ± 0.01	4330 ± 767	70 ± 1
Cherry	3.49 ± 0.04	17 ± 1	−0.71 ± 0.04	0.23 ± 0.06	0.17 ± 0.01	534 ± 22	73 ± 1
E. beech	4.78 ± 0.27	20 ± 1	−0.70 ± 0.10	0.14 ± 0.01	0.20 ± 0.01	1588 ± 85	71 ± 2
S. maple	6.31 ± 0.23	27 ± 1	−0.90 ± 0.03	0.29 ± 0.01	0.18 ± 0.01	2774 ± 267	73 ± 1
E. pear	8.73 ± 0.48	33 ± 2	−0.69 ± 0.14	0.23 ± 0.05	0.18 ± 0.01	2650 ± 1	69 ± 2

Table 2
Ratios between the standard deviation and the mean of the parameters of five studied veneers. D: Duration of the pulse, RDC: Ring-down count, AN: Amplitude of the deepest negative peak (in arbitrary units), AP: Amplitude of the highest positive peak (in arbitrary units), RT: Rise time, FP: First highest isolated peak in the frequency spectrum, I: Mean intensity of the wave.

Wood	Stress-wave measured parameters						
	D (%)	RDC (%)	AN (%)	AP (%)	RT (%)	FP (%)	I (%)
Chestnut	1.1	6.7	14.9	25.0	6.3	17.7	1.4
Cherry	1.1	5.9	5.6	26.1	5.9	4.1	1.4
E. beech	5.6	5.0	14.3	7.1	5.0	5.3	2.8
S. maple	3.6	3.7	3.3	3.4	5.6	9.6	1.4
E. pear	5.5	6.0	20.3	21.7	5.6	0.4	2.9

These pathological cases deserve a different study. However, the peak amplitudes are more variable. The first, most prominent peaks are less affected and their amplitudes generally do not vary more than 20%. These intense peaks, produced during the first 5 ms s of sound emission, are the most important for the identification of the wood species.

However, some woods can exhibit differences among samples of the same species which can be confused with other species, as can be seen in Fig. 7 for two different pine veneers. Both pine waveforms have distinctive features in general, but the presence of defects or other grain patterns can affect the reliability of the identification. Averaging techniques from several impact areas could improve the characterization process.

Physical models of impact produced sounds in wood are extremely complex due to their anisotropic and heterogeneous nature. Such models would imply very heavy numerical methods and they could not be directly related with the actual samples under study. Due to these difficulties, we have not tried a complete physical description of the waveform parameters, because they are not needed for wood identification purposes. Useful semi empirical acoustic models will be developed in future works.

Many acoustic identification schemes use the frequency spectrum instead of the waveform. In order to obtain the frequency spectra, we have calculated the FFT of the first 10 ms of the recorded pulses with a Hamming window and 1024 points of resolution. The results can be seen in Figs. 8–13 in logarithmic scale. Linear spectra exhibit too many complex features and they are too variable to be useful in most cases. Logarithmic scale spectra are more stable and can be a good starting point for wood characterization in many cases. The main differences among species are located in the 200–5000 Hz band. Lower frequencies have very similar patterns in all wood veneers and higher frequencies are very variable.

Qualitative estimations are a good starting point for approximate human directed classification, but they are not enough for a rigorous statistical identification. Several data can be used to extract useful parameters for stress-wave based wood identification. Such parameters must refer to a common amplitude threshold in order to be comparable. In our case, a 1% wave amplitude below

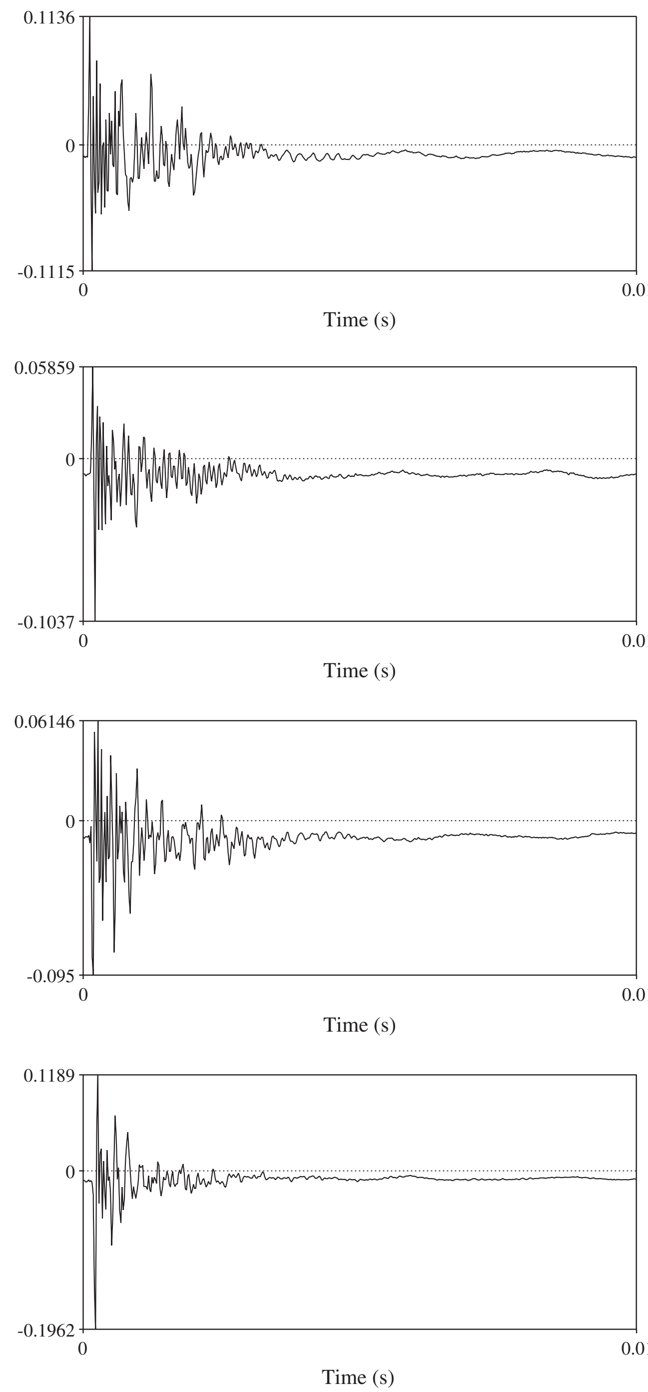

Fig. 14. Waveforms of the sound produced by pendulum impact of four 1 cm thick *Pinus sylvestris* wood samples.

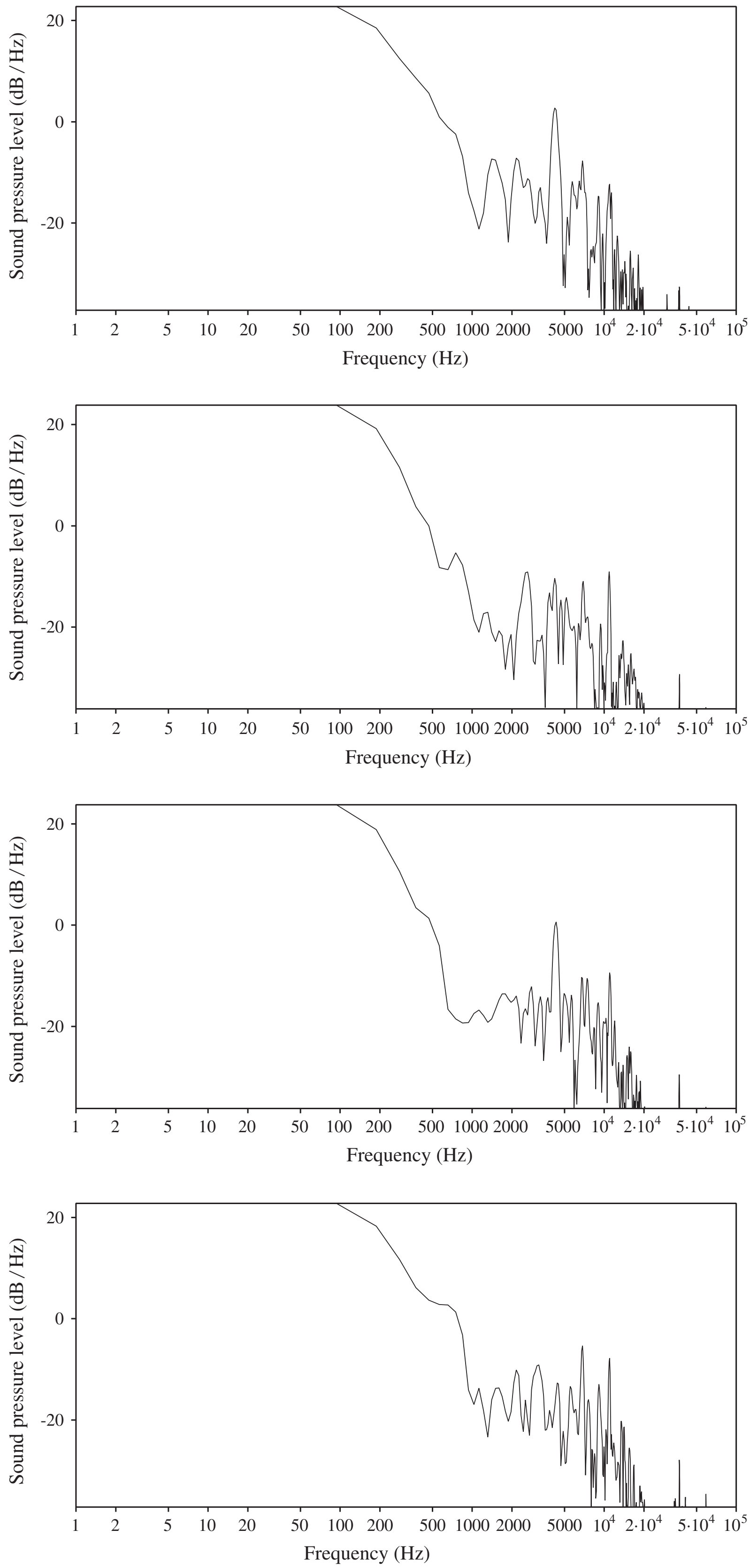

Fig. 15. Logarithmic frequency spectra of the sound produced by pendulum impact of four 1 cm thick *Pinus sylvestris* wood samples.

the highest positive peak has been used to define the pulse duration. The most common parameters used for the analysis of acoustic pulses are:

- Duration of the pulse.
- Ring-down count (number of peaks in the wave amplitude).
- Amplitude of the deepest negative peak.

- Amplitude of the highest positive peak.
- Rise time (from the beginning of the pulse to the highest positive peak).
- First highest isolated peak in the frequency spectrum.
- Mean intensity of the wave.

These parameters have been chosen because they can be easily measured and are well defined. Many acoustics works and non-destructive testing procedures describe the same parameters. A summary of seven measured parameters for five of the studied woods can be seen in Table 1. The arithmetic mean and standard deviation of the data are presented.

The results in Table 1 show that a combination of these seven parameters can be used to unambiguously identify the veneer samples. In order to study which parameters are the most important, the ratio between the standard deviation and the mean value of every measured parameter is presented in Table 2.

The analysis of these seven parameters and their relative variation indicates that the most reliable ones are duration, ring-down count, rise time, frequency peak and mean intensity. Peak amplitudes are too variable to follow a clear wood species pattern. However, rise time and mean intensity of the waves are too similar among samples for classification purposes. They are only useful as a refinement in a classification scheme. The most informative parameters in this case are the duration of the pulse and peak frequency. These two parameters are enough to identify the wood species in the studied veneer samples, under the present experimental conditions.

Variability in one parameter is not related with a similar deviation in the other parameters. For example, chestnut presents the smallest deviation in duration, but the greatest in peak frequency. The opposite case can be observed in European pear. In fact, these ratios can also be considered a valuable aid to identification, in addition to the mean parameters. No overlap among mean values for duration and peak frequency are observed, considering their uncertainty, except in one case. In such cases, more peaks in the frequency domain could be measured to resolve the overlap.

Pine samples show greater variability, sometimes greater than 25%, due to some irregularities observed in the samples. Pine identification is more complex than in the previous cases. A detailed study will be devoted to this problem in forthcoming works.

Figs. 14 and 15 reveal that sample thickness greatly increases the complexity of both the waveform and spectrum patterns. In this case, four 1 cm thick wood samples from different pines of the same species (*P. sylvestris*) were studied. Remarkably, in thick samples the logarithmic frequency spectrum seems a better identification tool than the waveform. The sound propagation in three-dimensional samples shows a far greater complexity than in the almost bi-dimensional veneer case.

Waveforms in thick samples are attenuated more quickly and have a larger number of lines of shorter time duration in the first 5 ms. Although the linear spectrum is more complex than in veneers, the logarithmic representation greatly simplifies the pattern. Variations among the samples are notorious, but some common features can be extracted from their spectra, not visible in their waveforms. These common features appear fundamentally in the 2–5 kHz region of the spectrum.

4. Conclusions

Our results show that stress-wave analysis in the audible range can be a viable and robust technique for identification of wood veneers. Waveform patterns are distinctive in most cases and can be used as wood signatures without further processing. Linear frequency spectra are too complex, but logarithmic scaled spectra are also a good starting point for wood identification. Quantitative results show that an unambiguous identification of the wood species can be obtained combining only seven wave parameters. From these, pulse duration and peak frequency are the most informative.

The analysis of thick samples is much more complex and perhaps a full physical inverse problem should be solved prior to characterization. In this case, logarithmic spectra are more easily compared. In future works, semi empirical models could be fitted to experimental waveforms in order to extract physically meaningful information. The definition of standard measurement procedures and the creation of stress-wave parameter databases are needed for a full scale development of this technique. Finally, advanced pattern classification approaches could be used to build fully automated identification systems in wood industries.

References

[1] Kawamoto S, Williams RS. Acoustic emission and acousto-ultrasonic techniques for wood and wood based composites – a review. Gen tech rep FPL-GTR-134, Madison, WI: US Department of Agriculture, Forest Service, Forest Products Laboratory; 2002.
[2] Beall FC. Overview of the use of ultrasonic technologies in research on wood properties. Wood Sci Technol 2002;36:197–212.
[3] Bremananth R, Nithya B, Saipriya R. Wood species recognition system. Int J Intell Syst Technol 2009;4(1):54–60.
[4] Tsuchikawa S. A review of recent near infrared research for wood and paper. Appl Spectrosc Rev 2007;42:43–71.
[5] Piuri V, Scotti F. Design of an automatic wood types classification system by using fluorescence spectra. IEEE Trans Syst Man Cybern Part C: Appl Rev 2010;40:358–66.
[6] Tarrío-Saavedra J, Naya S, Francisco-Fernández M, López-Beceiro J, Artiaga R. Functional nonparametric classification of wood species from thermal data. J Therm Anal Calorim 2011;104:87–100.
[7] Wegst UGK. Wood for sound. Am J Bot 2006;93:1439–48.
[8] Brancheriau L, Baillères H, Détienne P, Kronland R, Metzger B. Classifying xylophone bar materials by perceptual, signal processing and wood anatomy analysis. Ann For Sci 2006;63:73–81.
[9] Aramaki M, Baillères H, Brancheriau L, Kronland-Martinet R, Ystad S. Sound quality assessment of wood for xylophone bars. J Acoust Soc Am 2007;121:2407–20.
[10] Brancheriau L, Baillères H, Détienne P, Gril J, Kronland R. Key signal and wood anatomy parameters related to the acoustic quality of wood for xylophone-type percussion instruments. J Wood Sci 2006;52:270–3.
[11] Mills TP, Jones A, Lodder RA. Identification of wood species by acoustic-resonance spectrometry using multivariate subpopulation analysis. Appl Spectrosc 1993;47:1880–6.
[12] Jordan R, Feeney F, Nesbitt N, Evertsen JA. Classification of wood species by neural network analysis of ultrasonic signals. Ultrasonics 1998;36:219–22.
[13] Bucur V, Lanceleur P, Roge B. Acoustic properties of wood in tridimensional representation of slowness surfaces. Ultrasonics 2002;40:537–41.
[14] Bucur V. Acoustics of wood. Springer; 2006.
[15] Boersma P, Weenink D. Praat: doing phonetics by computer (version 5.0.24) [Computer program]; 2008. <http://www.praat.org/> [retrieved 14.05.08].