Analysis of the Density of Wooden Components in Ancient Buildings by Micro-Drilling Resistance, Using Information Diffusion

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Wooden components were removed from ancient buildings and used as experimental materials. The drilling curve and feed curve were generated from data collected by a resistograph, and the wood density was predicted by using the information diffusion model. A significant correlation was observed between the data for micro-drilling resistance and wood density. The information diffusion methodology was able to predict the wood density by the nonlinear method very well. Using the two-curve effect weight, when the drilling curve data and the feed curve data were 0.2 and 0.8, respectively, the error was minimum, with an average relative error of 3.82%. Therefore, the data supported on-site ancient building repair work.

Keywords: Micro-drilling resistance; Timber structural; Wood density; Information diffusion

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INTRODUCTION

Ancient Chinese buildings consist of timber structures, which contain many valuable historical, scientific, artistic, and social values in their structures and in each of their components (Yang *et al*. 2012; Liu *et al*. 2013). Density is one of the important performance indexes of wood, and many mechanical properties of wooden components are correlated with the density of the selected tree species. Therefore, accurately determining the density of wood is an important prerequisite for the protection of ancient building wooden components (Xu 2006; Xu and Qiu 2011; Sun 2012). According to the current Chinese national standard of (GB/T1933 2009), wood needs to be sawn into a standard test size for the traditional density measurement *via* the volume method. The wood density value obtained by this method is more accurate, but it is not suitable for the testing of ancient building wooden components in use and repair (Fikret and Li 2003). Therefore, obtaining the density information of wooden components by nondestructive (micro-destructive) testing is very useful for on-site ancient building repair work.

Currently, micro-drill resistance technology is used to test internal defects and material properties of standing wood and ancient architecture wooden components (An *et al*. 2008; Gwaze and Stevenson 2008; El-Kassaby *et al*. 2013). The principle is to drill a probe with a diameter of 1.5 mm into the interior of a timber at a constant rate to collect the relative resistance value on the test path and present changes in wood density on the test path in the form of a resistance curve. This makes it an intuitive basis for judging internal conditions of the wood section (Huang *et al*. 2007; Imposa *et al*. 2014; Newton 2017; Fundova *et al*. 2018). The micro-drill resistance value has a strong correlation with the wood dry density measured by the traditional method (Lima *et al*. 2007; Icel and Guler 2016; Karlinasari *et al*. 2017). However, the use of wood micro-drill resistance technology to test the mechanical properties of wood has been considered in some studies, and most of them adopt a resistance value as a reference variable for simple linear fitting. Based on this, the IML micro-drilling resistance meter used in this study sets two variables of the probe at constant values, *i.e*. drilling speed and feed speed (Li *et al*. 2016), and it collects two sets of parameter data, *i.e*., drilling relative resistance value (R) and feed relative resistance value (F) as reference variables for data fitting of wood density. Furthermore, a theoretical model of information diffusion to select the above two parameters as input variables to predict wood density was introduced for predicting wood density more accurately and quickly under the conditions of full-scale components on the site.

EXPERIMENTAL

Test Materials

The wooden components materials were obtained from the ancient building repair works in Beijing, Shanxi, and Anhui provinces in China. According to the tree species identification form from the Chinese Academy of Forestry Sciences, they were Chinese pine (*Pinus tabulaeformis*), Simon poplar (*Populus simonii* Carr), and fir (*Cunninghamia lanceolata*), as shown in Fig. 1.

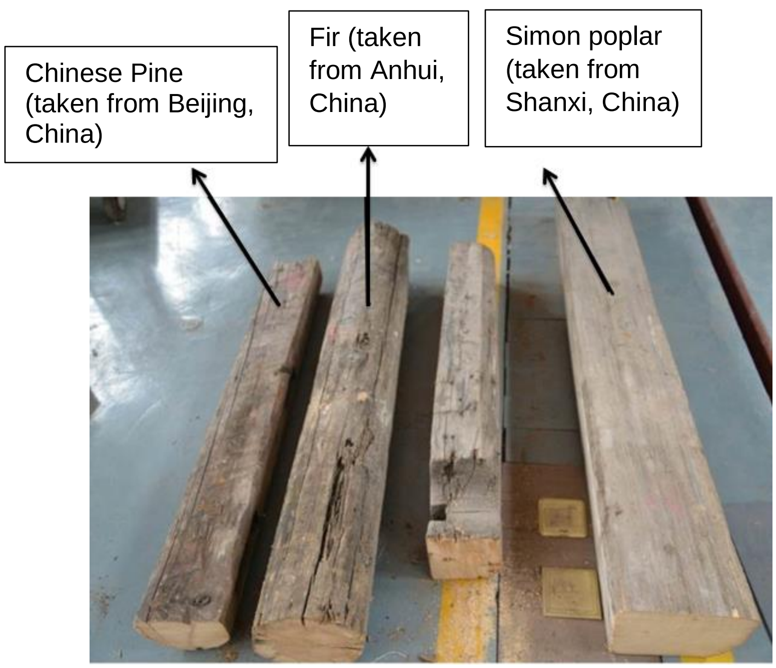

Fig. 1. Test materials selection

According to the national standard on the size requirements for test specimens (GB/T1933 2009), the specimen was sawn along the rift grain direction of the old wooden components to a size of 20 mm × 20 mm × 500 mm and screened by visual inspection; 10 test specimens without obvious defects were selected for each species.

The test specimens were grouped and numbered, and the water content was balanced to 9% to 12% to simulate the general moisture content of wooden components in the natural environment. Each test specimen was sawn into two parts: Sub-testing Specimen A and Sub-testing Specimen B, whose dimensions were as follows: 20 mm × 20 mm × 20 mm for Sub-testing Specimen A, used for data acquisition of air-dry density test; and 20 mm × 20 mm × 480 mm for Sub-testing Specimen B, used for data acquisition of micro-drill resistance test, as shown in Fig. 2.

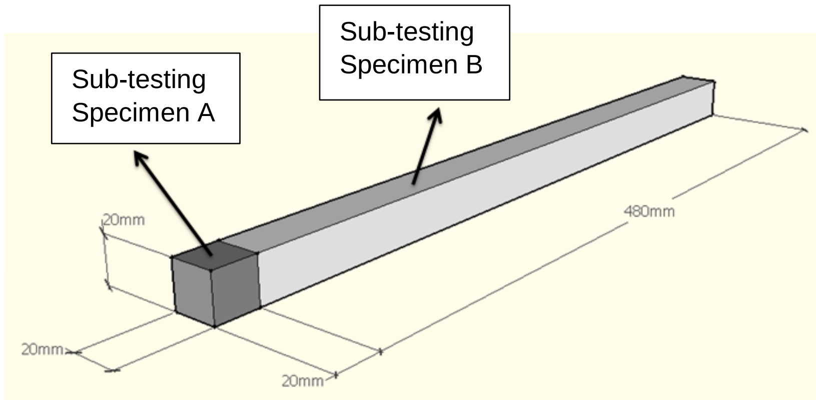

Fig. 2. Dimensions of testing specimens

Air-dry Density Data Collection

For Sub-testing Specimen A, the volume (v) and mass (m) were measured respectively by the digital vernier caliper (SF2000) (GUANGLU Experimental Instrument Co. Ltd., Guilin, China) and the electronic scale (JJ224BC) (G&G Measurement Plant, Changshu, China). The air-dry density (D) of the specimen was calculated by the formula, $D = m/v$.

Micro-drill Resistance Data Collection

The micro-drill resistance data acquisition equipment used in this test was the IML Resistograph PD-Series (IML Co., Ltd., Wiesloch, Germany), as shown in Fig. 3. To avoid accidentality of the test data, the test was designed to uniformly arrange four test points along the rift grain direction of the Sub-testing Specimen B and conduct the micro-drill resistance test perpendicular to the direction of the timer annual rings. The probe drilling parameters were set to 5000 $r{\cdot}min^{-1}$ for drilling speed and 200 $cm{\cdot}min^{-1}$ for feed speed. A drilling resistance curve and a feed resistance curve were obtained. Figure 4 is a test curve graph of a certain test point, which represented the relative magnitude of resistance value by an amplitude ratio curve. The arithmetic mean of each resistance curve was taken as the drilling relative resistance value R_n (n = 1, 2, 3, and 4), and the feed relative resistance value F_n (n = 1, 2, 3, and 4) of the test point, wherein R_n and F_n had no units and was expressed with percentage. Through Eq. 1 and Eq. 2, the average value of the data measured by the 4 test points was obtained as the micro-drill drilling relative resistance value R and the micro-drill feed resistance value F of the sub-testing specimen.

$$R = \frac{\sum_{i=1}^{n} R_i}{n} \quad (n=1,2,3,4) \tag{1}$$

$$F = \frac{\sum_{i=1}^{n} F_i}{n} \ (n=1,2,3,4) \tag{2}$$

Fig. 3. Micro-drilling resistance test

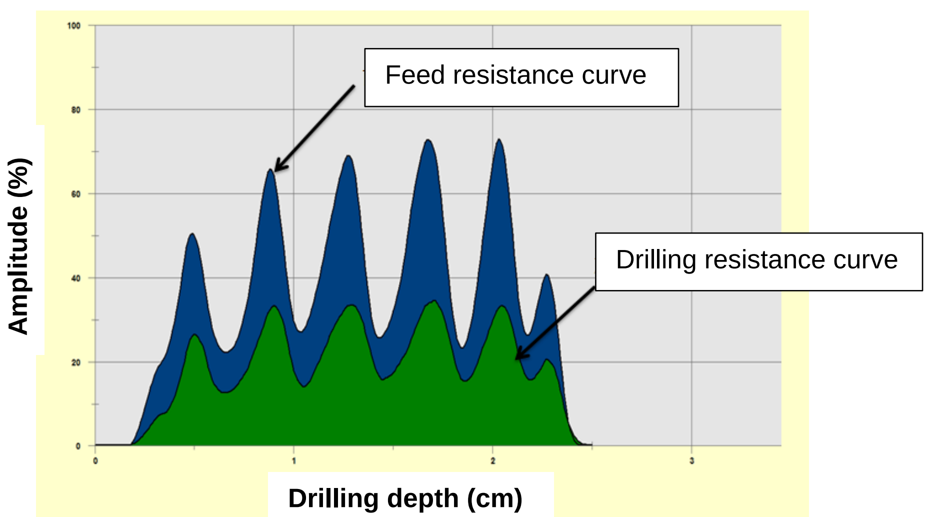

Fig. 4. Example of micro-drilling resistance curve

The results of the two types of test data collected for each tree test specimen are as shown in Table 1.

Table 1. Data Preparation for Model Building

Tree Species	Drilling Relative Resistance (*R*) (%)	Feed Relative Resistance (*F*) (%)	Wood Density (*D*)/(g·cm^{-3})
Chinese pine (*Pinus tabulaeformis*)	22.385	61.875	0.683
	23.105	57.717	0.686
	19.979	54.987	0.650
	24.030	61.192	0.693
	24.159	61.518	0.708
	21.499	64.412	0.680
	23.581	59.086	0.690
	27.129	69.345	0.723
	23.973	60.462	0.696
	21.521	59.890	0.668
Simon poplar (*Populus simonii* Carr)	21.200	30.660	0.430
	17.241	26.134	0.405
	20.600	30.447	0.431
	18.031	30.112	0.405
	17.744	26.834	0.400
	22.483	36.604	0.460
	18.049	26.443	0.399
	19.170	27.345	0.401
	21.311	35.644	0.444
	20.241	32.704	0.427
Fir (*Cunninghamia lanceolata*)	12.607	17.571	0.406
	20.867	23.142	0.439
	17.047	18.097	0.401
	19.879	23.875	0.420
	10.610	18.032	0.398
	11.709	17.695	0.407
	20.069	23.417	0.408
	15.178	20.759	0.403
	17.285	17.937	0.400
	11.349	17.540	0.398

RESULTS AND DISCUSSION

Information Diffusion Principle

Information diffusion model is a fuzzy mathematics method established and developed based on the information distribution method. The basic idea is to directly transfer the original information to the fuzzy relationship in a certain way, conduct extremal mathematical processing to samples, and maximize the original information carried by the data, thereby avoiding the gain of membership function (Zhang *et al*. 2003; Zhu *et al*. 2011). Therefore, under the condition of incomplete information, the method can predict the relationship between variables by a certain diffusion function from the sample. Information diffusion can be divided into two types: one is to distribute the information of single-valued samples at different control points to achieve data fuzziness; and the other is to gain the information matrix determined by the control points of multiple domains of discourse to obtain a fuzzy relationship between them (Li *et al*. 2014). In this study, the drilling relative resistance value and the feed relative resistance value of the micro-drill resistance meter were the input variables, wood density was the output variable, and the relationship model between the input and output variables was established with the second information diffusion method.

Establishment of Matrix Model

First, the fuzzy relationship among the drilling relative resistance (*R*), the feed relative resistance (*F*), and the wood density (*D*) was analyzed separately. Taking the drilling relative resistance (*R*) as an example, as can be seen in Table 1, the numerical range of the drilling relative resistance (*R*) varied from 10.610 to 27.129, and the numerical range of the wood density (*D*) varied from 0.398 to 0.723. Therefore, the domain of discourse of the two was taken as,

$$U_R = \{9.0,\ 13.5,\ 18.0,\ 22.5,\ 27.0,\ 31.5\};\quad V_D = \{0.30,\ 0.43,\ 0.56,\ 0.69,\ 0.82\}$$

where U is the domain of discourse of drilling relative resistance, with a step size Δ = 4.5; and V is the domain of discourse of wood density, with a step size Δ = 0.13.

This study selected the two-dimensional normal diffusion drop formula:

$$Q = f_m(u,v) = \frac{1}{2\pi n h^2}\sum_{j=1}^{n}\exp\left[-\frac{(u'-u'_j)^2+(v'-v'_j)^2}{2h^2}\right] \tag{3}$$

where $u' = (u-a_1)/(b_1-a_1)$; $v' = (v-a_2)/(b_2-a_2)$; $u_j' = (u_j-a_1)/(b_1-a_1)$; $v_j' = (v_j-a_2)/(b_2-a_2)$; $a_1 = \min\limits_{1\le j\le n}\{u_j\}$, $b_1 = \max\limits_{1\le j\le n}\{u_j\}$, $a_2 = \min\limits_{1\le j\le n}\{v_j\}$, $b_2 = \max\limits_{1\le j\le n}\{v_j\}$; u_j and v_j are discrete points of U and V, respectively. The variable h = 1.4208 / (n-1), where n is the number of samples.

According to Eq. 3, the original information distribution matrix $Q_{R,D}$ could be obtained, and then the original information was carried out by normalization processing to obtain the fuzzy relation matrix $T_{R,D}$ between the drilling relative resistance value (*R*) and the wood density (*D*). Calculated with MATLAB software (MathWorks, Inc., Natick, MA, USA), the results are shown in Table 2.

Table 2. Initial Information Distribution Matrix $Q_{R,D}$

	D_1 (0.30)	D_2 (0.43)	D_3 (0.56)	D_4 (0.69)	D_5 (0.82)
R_1 (9.0)	0.000	0.048	0.000	0.000	0.000
R_2 (13.5)	0.000	0.524	0.000	0.000	0.000
R_3 (18.0)	0.000	2.579	0.000	0.005	0.000
R_4 (22.5)	0.000	1.943	0.000	6.666	0.000
R_5 (27.0)	0.000	0.000	0.000	0.262	0.000
R_6 (31.5)	0.000	0.000	0.000	0.000	0.000

$$T_{R,D} = \begin{vmatrix} 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.002 & 0.000 \\ 0.000 & 0.291 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \end{vmatrix}$$

Similarly, by applying the above equation, the fuzzy relation between the feed resistance value (*F*) and the wood density (*D*) of the micro-drill resistance meter could be obtained, and then the original information distribution matrix $Q_{F,D}$ and the fuzzy relation matrix $T_{F,D}$ could be obtained, as shown in Table 3.

Table 3. Initial Information Distribution Matrix $Q_{F,D}$

	D_1 (0.30)	D_2 (0.43)	D_3 (0.56)	D_4 (0.69)	D_5 (0.82)
F_1 (10)	0.000	1.000	0.000	0.000	0.000
F_2 (22)	0.000	1.000	0.000	0.000	0.000
F_3 (34)	0.000	1.000	0.000	0.000	0.000
F_4 (46)	0.000	1.000	0.000	0.306	0.000
F_5 (58)	0.000	0.000	0.000	1.000	0.000
F_6 (70)	0.000	0.000	0.000	1.000	0.000
F_7 (82)	0.000	0.000	0.000	1.000	0.000

$$T_{F,D} = \begin{vmatrix} 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.306 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \end{vmatrix}$$

Fuzzy Approximate Reasoning

In the construction of this model, the approximate inference formula,

$$B_i = A_i \times R$$

was used for prediction, where A_i in the formula was calculated as follows:

when $a \le a_{\min}$, $a_{\min} \in A_i$, $A_i = [1,0,\cdots,0]$

when $a \ge a_{\max}$, $a_{\max} \in A_i$, $A_i = [0,0,\cdots,1]$

when $a_{\min} \le a \le a_{\max}$, $A_i = \left[\max\left(0, 1 - \frac{|a - a_i|}{\Delta}\right) \right]$.

The above is the first-order fuzzy approximation inference process. If only a single measurement variable is introduced to predict the wood density, the above calculation results are conducted information concentration to obtain the predicted value. In this study, the drilling relative resistance and the feed relative resistance of the micro-drill resistance meter have different degrees of influence on wood density prediction. Therefore, the second-order fuzzy approximation inference should be carried out based on comprehensive consideration of the influence weight of each variable. According to Eq. 4, the result of the second-order fuzzy approximation inference can be obtained by the combination operation of Weight Array A' and Fuzzy Matrix R'.

$$B' = A' \times R' \tag{4}$$

In Eq. 4, A' is the influence weight of each variable. In this study, the A' value was determined by a cross-combination operation of two measured variables under different influence weights. Upon calculation, when the influence weight of the drilling relative resistance and the feed relative resistance is $A' = [0.2, 0.8]$, the average relative error of the predicted value is minimal, which is 3.82%.

Information Concentration

In order to obtain the best predicted value, B' is substituted into Eq. 5, and the result is the final predicted value.

$$D = \frac{\sum_{i=1}^{n} (B_i^{'})^m \cdot D_i}{\sum_{i=1}^{n} (B_i^{'})^m} \tag{5}$$

where, D is the final predicted value of wood density; D_i is the grade value of wood density; m is a constant as appropriate, and $m = 2$ in this study.

Analysis

Table 4 compares the model prediction results and the values measured with conventional methods. Through data analysis, the information diffusion principle can be used to better quantify the testing data of micro-drill resistance and establish its relationship with the wood density value. The method neither needs to know the distribution of the samples nor needs to construct a membership function. The amount of data required is small and the prediction accuracy is high. Under the condition that the influence weight of the two parameters is determined, the minimum average relative error is 3.82%, and the correlation coefficient between the predicted value and the actual value is $R^2 = 0.990$. Compared with the method of binary linear regression, the calculation error was reduced by 1.26 percent. As far as the tree species data is concerned, it can be found that the bigger the wood density value of a tree species, the smaller the testing error is. For example, the Chinese pine with the highest density’s predicted average relative error is 1.45%, while the fir with the lowest density’s predicted average relative error is 5.87%.

The larger the density of the tree species, the denser its texture is in the measuring path of the probe. When the probe of a micro-drilling resistance meter drills, subject to the power supplied by a motor, the contact between the wood tissue on the measuring path and the probe is more sufficient, and the feedback effect of the material itself on the probe power output is also more complete and direct; on the contrary, the smaller the density of the tree species, the looser its texture is in the measuring path of the probe when a large amount of wood chips are generated due to the high-speed rotation of the probe. This causes a certain interference to the power output of the probe, thereby affecting accuracy of the measured data.

Table 4. Contrast of Predicted Value and Measured Value of Wood Density

Tree Species	Actual Value of Wood Density/(g·cm^{-3})	Predicted Value of Wood Density/(g·cm^{-3})	Relative Error
Chinese pine (*Pinus tabulaeformis*)	0.683	0.689	0.008
	0.686	0.689	0.004
	0.650	0.646	0.006
	0.693	0.690	0.005
	0.708	0.690	0.026
	0.680	0.688	0.011
	0.690	0.689	0.001
	0.723	0.690	0.045
	0.696	0.690	0.009
	0.668	0.688	0.030
Simon poplar (*Populus simonii* Carr)	0.430	0.436	0.015
	0.405	0.430	0.062
	0.431	0.434	0.008
	0.405	0.430	0.062
	0.400	0.430	0.076
	0.460	0.451	0.020
	0.399	0.430	0.077
	0.401	0.431	0.074
	0.444	0.440	0.008
	0.427	0.433	0.014
Fir (*Cunninghamia lanceolata*)	0.406	0.430	0.060
	0.439	0.435	0.008
	0.401	0.430	0.072
	0.420	0.432	0.028
	0.398	0.430	0.080
	0.407	0.430	0.057
	0.408	0.433	0.059
	0.403	0.430	0.068
	0.400	0.430	0.076
	0.398	0.430	0.080

Besides, the Fir has the material characteristics of large differences in heartwood and sapwood density. Therefore, when making standard size specimens, it is bound to cause the dispersion of the data collected among the specimens to be large, thereby increasing the prediction error. However, in general, this method is still an effective method for predicting wood density based on micro-drill resistance data, and the applicability and effectiveness of this method for other different tree species will be further studied.

CONCLUSIONS

1. Through the micro-drill resistance testing method, information about the internal state of the wood can be obtained quickly and conveniently under the micro-destructive conditions, and a correspondence between the detected value and the density value of the measured wood can be established to provide data support for inferring various

mechanical properties of wood. This method is especially suitable for testing at a protection and repair site of wooden structure historical buildings.

2. With the information diffusion principle to predict wood density, the described method can avoid the gain of membership function. The prediction accuracy and stability are good. The minimum average relative error is only 3.82%, indicating that the protocol is an effective means and method for predicting the mechanical properties of wooden components with non-destructive testing. It also provides a new idea for the mining application of micro-drill resistance testing data. The principle can determine the influence weight of different measured variables on prediction results. The calculation shows that when the influence weights of the drilling relative resistance value and the feeding relative resistance value are 0.2 and 0.8, respectively, the predicted relative error against wood density is minimal.
3. Because wood is a anisotropic non-homogeneous biomaterial, the factors affecting its micro-drill resistance testing value are very complex, such as early and late wood, moisture content, nodular scarring distribution, *etc.* Therefore, under different conditions, the prediction of wood density by micro-drill resistance testing will be further explored.

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