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Three-dimensional stress wave imaging of wood internal defects using TKriging method

Xiaochen Du[a,b], Hailin Feng[b], Mingyue Hu[b], Yiming Fang[b], Shengyong Chen[a,*]

[a] College of Computer Science, Zhejiang University of Technology, Hangzhou, China
[b] School of Information Engineering, Zhejiang A&F University, Hangzhou, China

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ABSTRACT

In order to detect the size, shape and degree of decay inside wood, a three-dimensional stress wave imaging method based on TKriging is proposed. The method uses sensors to obtain the stress wave velocity data sets by hanging around the timber randomly, and reconstructs the image of internal defect with those data sets. TKriging optimizes structural relationship between interpolation point and reference point in space firstly. The searching radius is used to select the reference points accordingly. Top-*k* query method is introduced to find the *k* value with relevant points. The values of the estimated points are calculated and three-dimensional image of the internal defect inside wood is reconstructed. The results show the effectiveness of the method and the accuracy rate is higher than that of basic Kriging method.

1. Introduction

Stress wave tomography technique has been widely used in non-destructive testing of wood. Ross et al. (1962) first time introduced stress wave detection technology on red oak decayed area for testing. The image observed by the stress wave imaging software could indicate the rotten wood's interior location, size and extent of decay (Gilbert and Smiley et al., 2004). Wang and Sun (2011) combined the diagnostic method of stress waves with the two-dimensional X-ray/CT image to determine the internal decay region of logs efficiently and accurately. Qi (2011) proposed the X-ray pattern to filter and sharpen which made the detailed wood internal defects more obvious. Wang et al. (2005) used eight sensors around the wood to test the initial by stress wave imaging technology. The experimental results showed that was 62% of the accuracy rate, but 8.5% of healthy wood was mistaken for rotten wood. Liang and Hu (2009) obtained timber tomographic image by stress wave tomography and then obtained the size, shape and other information of the internal defects of the timber. Yang and Wang (2005) presented the stress wave method for the internal decay detection about logs. The results showed that the stress wave tester could get the two-dimensional image of the basic shape of internal rotten wood and determine the serious decay of different tree species. These studies seldom focused on the stress wave imaging algorithm but the application of existing commercial imaging software for two-dimensional imaging research.

Feng et al. (2014) presented an image reconstruction algorithm which used the speed around the points to estimate the value of unknown grid points. The test results demonstrated the feasibility of this method. Choi et al. (2007) used the model of damage detection algorithm to locate the defect location and extent of decay. Du et al. (2015) proposed spatial interpolation, elliptic velocity compensation for trees and timber-based approach to plot the internal defect analysis and the timber internal defect image. However, there are few researches about three-dimensional stress wave imaging algorithm of defect detecting in wood.

The basic idea of Kriging is to predict the unknown regions based on the differences of the correlation and the spatial location between different regions (Quirante et al., 2015). Kriging algorithm designed simulation study was firstly used in mine exploration, groundwater, and applied in soil mapping. The method makes use of assuming that a smooth mathematical function can not be simulated because of space attribute is irregular changing continuously, but can be read by random surface representation (Webster and Burgess, 1980). This spatial change property, often referred to as "regional characteristic variables," is often used to describe the elevation, pressure and continuity features constantly changing. The algorithm, based on the spatial distribution of the unknown region, has got a good experiment result where the operation speed is fast, the use scope is broad, and the storage space is small.

Kriging algorithm exists the following problems when applied to three-dimensional stress wave imaging of wood internal defects: firstly, increasing the complexity of the algorithm because of the predicted results are related to all known points in the neighborhood; secondly,

* Corresponding author.
E-mail address: sy@ieee.org (S. Chen).

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neglecting the spatial structure of interpolation points because of the results of the prediction points are related to the distance between all known points in the neighborhood. The objective of this study is to detect the size, shape and degree of decay inside wood. We propose a TKriging (Top-k Kriging in short) algorithm which can be extended to estimate the relationship between the neighborhoods of three-dimensional space. Then, the algorithm is applied to reconstruct the 3D image of wood internal defects.

2. Materials and methods

2.1. Proposed method

Regionalized variable, the variable spatial distribution, can reflect the specific spatial distribution of various special properties. For example, those exist in space, meteorological factors, soil information, eco-hydrology, geological environment, maritime climate, and so on. They not only have a specific spatial attributes but also have a dual nature of the variable region. Then we can assume a random field $Z(x)$ to represent the numerical of regionalized variables observed before, after the observation, it is a value of a function that determines the spatial points (Liu et al., 2015). There are two major characteristics in regionalized variables:

(1) $Z(x)$, a random uncertain function, represents the amount of change in the region that main feature is random, localized and abnormal function.
(2) To some extent, the self-correlation should be: when x is a variable, the attribute at point $Z(x)$ and spatial distance deviation of the point at $Z(x+h)$ have some relationship, and its relationship has correlation with the characteristics of variable and the distance between two points.

In this paper, we propose a stress wave imaging algorithm using TKriging. We optimize the spatial structural about estimating points and known points in their neighborhoods, and increase the Top-*k* query technology to improve the calculation accuracy about estimating points.

It is supposed that $p_i'(x_i, y_i, z_i)$ $(i = 1, 2, \ldots, n)$ is the point in the internal region of wood, which satisfies the second-order stationary assumptions or intrinsic hypothesis. Therefore, $Z(q_i')$ is the point that have been measured as q_i' (x_i, y_i, z_i) $(i = 1,2, \ldots, m)$, and λ_i is the weighted coefficient, for an arbitrary predicted value $Z^*(p_i')$ of the estimating point are as follows:

$$Z^*(p_i') = \sum_{i=1}^{m} \lambda_i Z(q_i') \tag{1}$$

In the equation above, λ_i, the weighted coefficient of the known point, is not singly decided by the distance, which is calculated based on variogram at minimum variance unbiased condition. $Z^*(p_1')$ is good or bad by how to choose the weight coefficient λ_i.

In order to ensure the $Z^*(p_1')$ is calculated based on the unbiased estimate of $Z(q_1')$, which means the deviation of the mathematical expectation is zero; if the sum, square of the difference between the estimated value $Z^*(p_1')$ and the actual value $Z(q_1')$, is the minimum, the sum should satisfies the conditions:

$$E[Z^*(p_1') - Z(p_1')] = 0 \tag{2}$$

For obtaining the minimum variance of the estimated under the above constraints, λ_i needs to be constructed by the function of the Lagrange multiplier method, and μ is the Lagrange multiplier:

$$F = E\left\{[Z^*(p_1') - Z(p_1')]^2 - 2\mu\left(\sum_{i=1}^{m} \lambda_i - 1\right)\right\} \tag{3}$$

If there is a set of values λ_i to meet the requirements, the equations can be represented as follows:

$$\begin{cases} \sum_{i=1}^{m} \lambda_i = 1 \\ \sum_{i,j=1}^{m} \lambda_i Cov(q_i', q_j') - \mu = Cov(p_1', q_j') \end{cases} \tag{4}$$

The $m+1$ equations group is ordinary Kriging equations. According to the above formula, the matrix equations can be obtained as follows:

$$[K][\lambda] = [M] \tag{5}$$

The K, M, λ are respectively expressed as follows:

$$[K] = \begin{bmatrix} C_{11} & C_{12} & \ldots & C_{1n} & 1 \\ C_{21} & C_{22} & \ldots & C_{2n} & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ C_{n1} & C_{n2} & \ldots & C_{nn} & 1 \\ 1 & 1 & \ldots & 1 & 0 \end{bmatrix} [\lambda] = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \ldots \\ \lambda_n \\ -\mu \end{bmatrix} [M] = \begin{bmatrix} C_{01} \\ C_{02} \\ \ldots \\ C_{0n} \\ 1 \end{bmatrix} \tag{6}$$

The result of estimated variance is minimum by ordinary Kriging method, which is expressed as follows:

$$\sigma^2 = Var[Z^*(p_1') - Z(p_1')]^2 = Cov(p_1', p_1') - \sum_{i=1}^{m} \lambda_i Cov(p_1', q_i') + \mu \tag{7}$$

Wherein variogram function $r(q_i', q_j')$ can be represented as follows:

$$\gamma(q_i', q_j') = \gamma(q_i' - q_j') = \frac{1}{2} E[Z(q_i') - Z(q_j')]^2 \tag{8}$$

Wherein, the variation function $r(q_i', q_j')$ substitutes for the covariance $Cov(q_i', q_j')$, and brings into the equation to obtain the equation as follows:

$$\begin{cases} \sum_{i=1}^{m} \lambda_i = 1 \\ \sum_{i,j=1}^{m} \lambda_i \gamma(q_i', q_j') - u = \gamma(p_1', q_j') \end{cases} \tag{9}$$

And the corresponding ordinary kriging variance can be expressed as follows:

$$\sigma^2 = \sum_{i=1}^{m} \lambda_i \gamma(p_1', q_i') + \mu - \gamma(p_1', p_1') \tag{10}$$

Top-*k* discover technology is used mainly to search the most relevant *k* results from a large amounts of data (Le et al., 2013; Zheng et al., 2010), Kriging algorithm uses the Top-*k* query technology to find out the most influential *k* known points in the neighborhood range of estimated points and their properties. Top-*k* query is defined as follows: given *M* tuples as a collection *T*, each tuple has its own attribute. Then store the collection *T* as a column files collection, each column file is a binary array, wherein representing the object identifier and object property values at the property. The storage way of each column file is a monotonous decreasing sequence of each tuple's property value which is defined as the scoring function *F*. The formula is as follows (Shaikh and Kitagawa, 2014):

$$F(a) = \sum_{i=1}^{m} (\lambda_i \times au_i) \tag{11}$$

λ_i is a weight which was defined on the attribute values u_i by the scoring function. Usually, *F* is a monotonic function. The *k* subset of each tuples in the set *T* can be queried by Top-*k* query technology. Subsets each element in a group, by reading the *m* column which is a collection of files in descending order of columns *S*, read the sequence in order. When tuples appear, get the corresponding attribute value in another column file by random reading mode, and calculate their score value. If the value of *k* is the largest one ever seen, put the tuple and its relevant information to the optimal queue. For each column sequence,