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Wood species identification using feature-level fusion scheme

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ABSTRACT

In this paper, we propose a robust wood species identification scheme by using a feature-level fusion scheme. First, a novel wood feature acquirement system is devised, which can get the curve of 1D wood spectral reflectance ratio and the 2D wood surface color image. Second, the 4 wood color features, the 4 principal texture features, the 4 secondary texture features and the 4 spectral features are established, respectively. Third, a fuzzy BP neural network is proposed to perform the classification work, which consists of 4 sub-networks based on the color feature, texture feature and spectral feature. We have experimentally proved that this scheme improves the mean recognition accuracy to approximately 90% for 5 wood species. Moreover, our feature-level fusion scheme is superior to the recognition schemes which use color feature and texture feature.

1. Introduction

Wood species recognition is a significant issue in the wood industry so as to judge the physical property and economic value of different wood species correctly [1]. It can be used in some fields of the wood industry such as the wood assortment and the wood price so as to decrease the economic losses from the wood species misclassification. Some visual image characteristics have been used in the wood species recognition, and can be divided into two general categories: wood surface's texture analysis [2,3] and its color analysis [4,5]. For example, we propose a wood species identification scheme based on the image blur information [6]. In this scheme, the blur-invariant-moment features are used in the recognition. The allowed maximum translation speed of the detected wood is also calculated by using image blur information. Recently, the wood spectral reflectance characteristics are also exploited for the species classification. The more common schemes in the literature consider the vibration spectroscopy [7,8] and the Raman spectroscopy [9]. For example, Piuri and Scotti present a scheme for the wood species classification based on the analysis of fluorescence spectra [10]. The proposed scheme partitions the input spectra in different bands equally spaced. The energy contained in each band is used in input to the classifier. This simple experimental setup and the limited computational complexity permit the realization of wood species classification in real-time applications.

In recent years, multi-sensor data fusion is widely used in many fields such as military science, biomedical engineering, robotics and remote sensing [11]. It consists of three level fusion schemes: the signal-level fusion, the feature-level fusion and the decision-level fusion. Especially, the multi-sensor data fusion has also been used in biological species identification by using image processing. For example, the color, texture and spectral features are combined to perform the weed species recognition in agricultural engineering [12,13]. Similarly, the airborne LIDAR data and multi-spectral imagery are fused in the classification of woodland species, land cover classification or coastal classification mapping [14–16]. In wood species recognition, Filho et al. combine the 18 color histogram features and 24 texture features based on the gray-level co-occurrence matrix (GLCM) to perform the wood species recognition of the Brazilian flora. They demonstrate experimentally that the feature-level fusion for color and texture information can improve the wood recognition accuracy [17]. However, the current wood species recognition based on color features is sometimes poor especially for those wood species which have similar color structure information. Moreover, for every wood species, the color variations of wood panels usually occur with different growing conditions, exposure time in air, sapwood/heartwood, earlywood/latewood. Therefore, the individual wood panel's color difference consists of the intraspecific color variation and the interspecific color variation. The mixture of these two color variations may decrease the wood recognition accuracy, since the intraspecific color variation may blanket the interspecific color variation. A similar case occurs for the wood texture feature. Therefore, to

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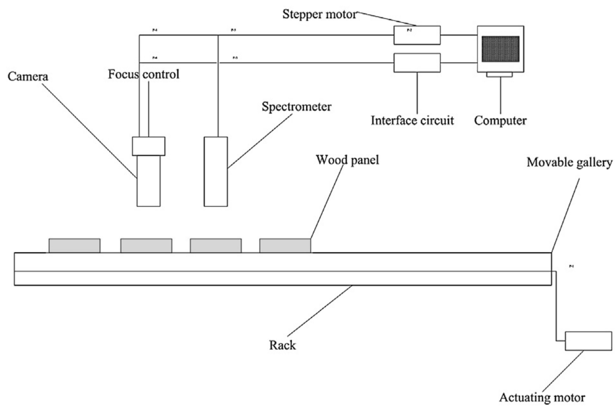

Fig. 1. The structure graph of our wood feature acquirement system.

mitigate the intraspecific color variation, Filho et al. segment the original image into 25 sub-images and the final decision is produced by the voting method based on the classification decisions of these 25 sub-images [17].

On the other hand, the spectral features such as the spectral reflectance ratio are relatively stable for every wood species. The intraspecific spectral reflectance variation is much smaller than the interspecific variation [10]. However, spectral reflectance features maybe easily influenced by the operation environmental conditions such as the illumination, dust or smog. To make full use of these complementary features, we provide a fundamental feature-level fusion framework for a robust/accurate wood species recognition work. This framework can effectively integrate the color, texture and spectral features so as to identify the wood species and judge the physical property and economic value of different wood species panels correctly. It can be used in some fields of the wood industry such as the wood assortment and the wood price so as to decrease the economic losses from the wood species misclassification.

2. Materials and methods

2.1. Wood feature acquirement system

One novel wood image acquirement system is devised as in Fig. 1. An image aiming system is the main part of the wood image acquirement system. In Fig. 1, the ray from the radian goes through the collimation path and is projected onto the detected object's surface (i.e. the wood panel). The wood panel image is picked up by a color CCD camera. After a photoelectric transform, this image is sent into the computer by the interface circuit to form the digital image which will be used in the wood recognition task. When multiple wood panels are measured, the working gallery should be moved with a uniform velocity in the X or Y direction, to make every panel's surface enter the view field of the aiming CCD camera sequentially. This operation can be performed by the software operation interface in the computer. In our experimental setup, a Sony WV-CP240EXCH color camera is used to obtain the wood panel images with resolution 768×576. The LED circular radian is used to obtain the uniform lighting conditions as illustrated in Fig. 2 with structure parameters $d_1 = 45$ mm, $d_2 = 100$ mm, $h = 17.2$ mm, $\alpha = 116°$. The Navitar zoom optical system is used with structure parameters such as working distance $37\,\text{mm} \le wd \le 234\,\text{mm}$, numerical aperture $0.018 \le NA \le 0.1$. This zoom system consists of the frontal lens group, zoom lens group and rear lens group. As for the accurate measurement of wood spectral reflectance ratio, a FieldSpec Pro FR portable multi-spectral spectrometer is used whose sample interval is 1.4 nm and whose measurement wavelength range is 340–1070 nm.

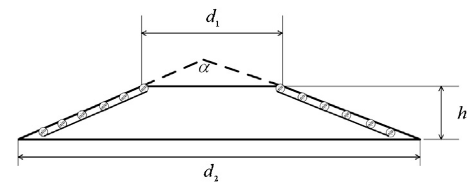

Fig. 2. The structure graph of our circular radian.

2.2. Classification feature extraction

For the color wood panel images, the RGB color base does not appear to give accurate colorimetric information when images are acquired under variable light conditions. In this case, the color levels depend on lightness, which has to be separated from chromatic values. Here the RGB color base is transformed into the HSI color base, and the three color moments are computed as follows based on the H component:

$$\begin{cases} u_1 = \dfrac{1}{MN}\displaystyle\sum_{i=1}^{M}\sum_{j=1}^{N} f_{ij} \\ u_2 = \left[\dfrac{1}{MN}\displaystyle\sum_{i=1}^{M}\sum_{j=1}^{N}(f_{ij}-u_1)^2\right]^{1/2} \\ u_3 = \left[\dfrac{1}{MN}\displaystyle\sum_{i=1}^{M}\sum_{j=1}^{N}(f_{ij}-u_1)^3\right]^{1/3} \end{cases} \tag{1}$$

Therefore, as for the wood color feature extraction, the color moments u_1, u_2, u_3 of the H component and the S component variance are used as the 4 color classification features, which are represented by T_1–T_4.

As for the wood texture feature extraction, again the RGB color base is transformed into the HSI color base. The S component gray-level image is transformed into a 6 gray-level image on which the co-occurrence matrix is calculated. The gray-level co-occurrence matrix (GLCM) based 8 features are computed with the spatial distance of 1 pixel and angle $\theta = [0°, 45°, 90°, 135°]$:

$$\begin{cases} T_5 = \displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} iP(i,j) \\ T_6 = \displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (1-i)^2 P(i,j) \\ T_7 = \displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)^2 \\ T_8 = -\displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)\log_{10} P(i,j) \end{cases} \tag{2}$$

$$\begin{cases} T_9 = \max(P(i,j)) \\ T_{10} = \displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \dfrac{1}{1+(i-j)^2} P(i,j) \\ T_{11} = \displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i-j)^2 P(i,j) \\ T_{12} = \displaystyle\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i+j-2u)^4 P(i,j) \end{cases} \tag{3}$$