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A Classification Method for Wood Types using Fluorescence Spectra

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Abstract *– The analysis of the wood types is important in many industrial sectors such as the furniture industries and the wood panel production. Different woods have different aspects, properties and costs. The analysis of the wood type is very important to guarantee that the final product has the required features and characteristics. Unfortunately, the analysis made by human experts is not rapid and it presents a not standardized accuracy due to the operator's capabilities and tiredness.*

The presented paper shows how that it is effectively possible to accurately classify the wood types by the analysis of the fluorescence spectra in real time and during the production activities. In particular, the paper presents a prototype schema and a set of techniques suitable to extract features from the spectra and how to used the extracted feature to train an inductive classification system. Results show that a good accuracy in the classification can be achieved, and that the proposed setup can be used also in real-time industrial processes.

Keywords *– Automatic Wood Classification, Wood Spectra Analysis, Computational Intelligence Algorithms.*

I. INTRODUCTION

The automatic classification of the wood is a problem which is present in many industrial contests such as the furniture industries and the wood panel production [1]. The need to correctly identify the wood type is related to that fact that different woods have different aspects, properties and costs. The correct classification of the wood type is very important to guarantee that the final product has the required features and characteristics.

For example in the production of wood panels the choice of the wood type can influence the needed quantity of the glue that must be present in the panel to guarantee the proper mechanical properties. In addition the glue has a great impact on the final cost of the panel and it effects the overall environmental impact of the wood panel production. In the paper industry, the wood type is related to the final quantity of the cellulose in the paper, and hence to the quality of the paper [2].

Most of the time, the analysis of the wood type is performed by human experts by observation, but this activity is not rapid and it presents a not standardized accuracy due to the operator's capabilities and tiredness. More expensive chemical test are available, but they are slow and can be done only on samples of the production.

The paper we present describes the design of an accurate and standard method for the automated classification of the wood types by a contact-less measurement and classification of the wood by visible and near infrared spectra. Experiments has been made in order to test a classification capability up to 21 different wood types.

The paper is structured as follows. Section 2 focuses on the proposed approach to the problem and compares it with respect to the literature. Section 3 shows the experimental results obtained by applying the proposed method. The description of the creation of the dataset of wood spectra is given, then the section describes how to create and train different models of inductive classification systems such as the k-nearest neighbor classifiers, linear and quadratic Bayesian classification systems. Finally, it follows the discussion of the accuracy and the performances of the overall system.

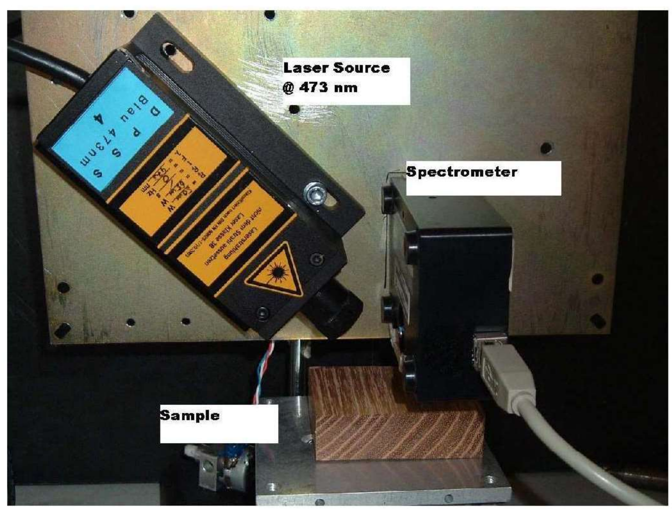

Figure1. Picture of the experimental setup: the 473 nm DPSS laser (left) excites fluorescence of wood sample (bottom right), while the miniature spectrometer above acquires the emission spectrum. The laser line is blocked by an optical long pass filter placed on the spectrometer.

II. THE MEASUREMENT SYSTEM

The characterization of wood samples has been carried out by fluorescence spectroscopy. Such approach presents some advantages in comparison with those proposed in literature which are mainly based on vibrational spectroscopic methods: such near-infrared (NIR) [3], mid-infrared (MIR) [4, 5], and Fourier-Transform Raman [6, 7] spectroscopies .

Vibrational spectroscopies, despite the richness of the providing information, present several drawbacks for the industrial application both for costs and experimental difficulties for its implementation in on-line and real time measurement systems operating in industrial environment. For example, all these techniques require normally long integration times and expensive cooled detectors. In particular IR measurements are affected by the some environmental variables which are not easily controllable in the production line: such the presence of thermal sources, dust and humidity. As a matter of fact the tail of the thermal radiation in the detectors sensitivity range produces a noisy background, the random presence of dust produces several artifacts in a long time measurement and some water vapor absorption bands overlap the wood spectral features useful for the recognition.

Fluorescence spectroscopy, on other hand, working in the visible spectral region has a higher signal to noise ratio unaffected by thermal noise or water absorption and furthermore the high sample rate for example allows to reject measurement on flying particles. Fluorescence represents also convenient choice due to the availability of lower cost components: as the modern high performance silicon based CCD (charge coupled device) detector and high power DPSS (diode pumped solid state) laser. The use of the modulation capability DPSS laser (up to 100 KHz) together with a synchronous detection, allows a further improving of the signal to noise ratio, fast measurements and subtraction of the environmental light. All these features make fluorescence spectroscopy particularly suited for real time measurement system operating in an industrial environment.

The prototype measurement system we set up, consists of a miniature spectrometer (Ocean Optics USB2000) and a frequency doubled DPSS laser operating at 473 nm, respectively for fluorescence detection and excitation. In the setup (see Figure 1) the exciting laser beam, with modulable optical power up to 50 mW, impinges on samples at 45 degrees respects to the vertical direction corresponding to the axis of the collection optics. The spectrometer, provided with an adjustable objective lens focusing the collected light into the entrance slit, is positioned few centimeters above the sample. A long pass filter, with cutoff wavelength of 500 nm inserted between the sample and spectrometer, removes the laser line from the collected light.

The fluorescence intensity is then measured in the spectral range between 500-1000 nm at 1 nm resolution and with 10 ms of integration time. The intensity of fluorescence spectra have been normalized using as reference signal the intensity of laser sub-harmonic (at 946 nm) or of the pumping diode (at 808 nm), in order to correct the effects due to sample absorption. Such reference signals, which will be employed as feedback for an autofocus system, has been manually maximized during the experiment.

Figure 2 plots the input spectra of the following wood types: Wild Cherry, Oak Chestnut, Walnut and Larch. Figure 2 shows only the most significant part of the spectra qualitatively estimated in the range from 490nm to 750nm. The main assumption we assume is that the emitted spectra of the different wood types are enough different to be classified with accuracy.

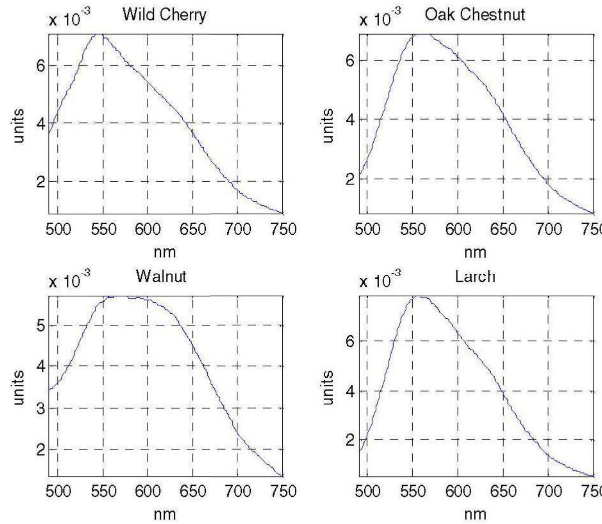

Figure 2. Examples of inputs spectra.

III. THE CLASSIFICATION SYSTEM

The exact relationship between the shape of the spectra and the wood types is not well known, hence it is not possible to directly design an algorithm for a classification system. On the contrary, the capability of the inductive classifiers to learn input-output relationships from examples can be exploited to create a proper classification system [8, 9]. In our study we propose different kinds of classification systems such as the k-nearest classifiers, linear and quadratic classifiers Bayesian classifiers.

Since the acquisition system produces vectors of 242 samples for each wood acquisition, the cardinality of the input is very high. It cannot be considered as adequate to be directly used as input to the classifiers, hence a reduction of the number of the input features has to be considered (features selection/extraction phase [9]).

The reduction of the dimensionality of the input space can be achieved using different methods [8]. The most popular is the Principal Components Analysis (PCA) which can compress most of the variation measured in the overall spectrum into a minor number of components [10]. Since the PCA-like mapping mixes the input components into a reduced set of new features, the direct relationship between the regions of the spectra and their importance in the wood classification is less explicit [11]. Similar approaches in the literature are based on the neural networks [6] and the genetic algorithms [7]. In [12] the linear prediction models were produced using multivariate analysis and regression methods on a very specific application: the compression wood in Norway spruce (Picea abies). In [13] the spectra coming from a satellite spectrometer has been classified using Self-Organizing Maps.

The approach we propose integrates the spectral energy into N fixed bands producing a vector of N elements which can be used as input to the classification system. This approach permits very easily to test the functioning of the system with different spectral definitions of the spectrometer, and to directly identify which bands of the spectrum are more relevant into the classification problem.

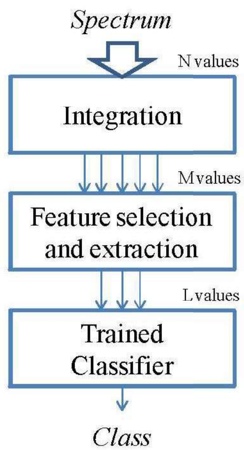

Figure 3. Structure of the proposed classification system.

The final classification system can hence be designed by considering the following four phases (Figure 3):

1) acquisition of the input spectra (N sample vectors);
2) integration of the spectrum in M contiguous bands;
3) feature selection/extraction of the L values;
4) classification of the wood using the L values.

In the next section it will be described the four phases, the creation of the dataset, the creation of the classifiers, the training phase of the classifiers and the accuracies of the proposed classification systems.

IV. EXPERIMENTAL RESULTS

A set of the 21 different wood types (of certified origin purchased at Woodtechnology Gmbh) belonging the most common species has been analyzed. Twenty spectra for each sample have been acquired in different points by moving the samples under irradiation. During the measurements we ensured to probe all wood zones namely heartwood, sapwood, and growth ring. The 21 wood types belonging to the dataset with the caption number assigned by the provider are the following: (1) Wild Cherry; (2) Oak Chestnut; (3) Walnut; (4) Larch; (5) Wild Pear Tree; (6) Poplar; (7) Cembar Pine ; (8) Beech Tree; (9) Alnus incana; (10) Linden Tree; (11) Alnus incana; (12) Scots Pine; (13) Oak tree; (14) Spruce; (15) Maple; (16) Taxus baccata; (17) Elm; (18) Silver Fir; (19) Birch Tree; (20) Black Locust; (21) Carpinus betulus.

The first classification problem we considered -*Problem A*- is the binary classification between the *confier* and *broad-leaved* wood spectra. This problem is related to the fact that, in some specific applications such as the wood panel production, the properties of the wood types belonging to the same class (conifer or broad-leaved) can be considered as similar. The second classification problem we considered -*Problem B*- is the classification of the 21 different wood types. Problem B can be considered as more difficult than Problem A since the number of classes is 10 time more.

The capability to classify the wood types via fluorescent spectra has been tested using different classification paradigms. The first model we adopted is the Linear Bayes Normal Classifier (LDA in the following), a method which builds a linear classifier between the classes of the dataset by assuming normal densities with equal covariance matrices in the input data [14]. Based on similar hypothesis, but using instead a second-order mapping of the input, we considered the Quadratic Bayes Normal Classifier (QDC) [11, 15]. As third family of classifier systems, we adopted the well-known k-Nearest Neighbor classifier with odd values of the parameter k (1,3,5). In order to test the real advantage of using feature extraction techniques in this applicative case, we considered the application of the PCA technique as preprocessing for the LDA and kNN (k=1) classifiers. In the following we refer to these systems as PCA+LDA and PCA+1NN.

The classification error of the cited systems has been estimated using the cross-validation technique (using 10 rotations) [14]. The test has been applied to all cited classifiers producing the mean classification error and its standard deviations.

In order to understand the effect of the spectral resolution of the available power spectra, the values of each spectrum have been integrated in M bands of the same size, as discussed in the previous section. Results for Problem A and Problem B have been plotted in Table A and Table B. The tables report the classification errors and its standard deviations for the tested classifiers, with respect to the number M of used bands. Tables A and B do not report the classification error of the PCA+LDA and PCA+1NN classifiers since the application of the PCA does not significantly affect the classification errors with respect to the LDA and 1NN classifiers.

Table A shows that the classification between confier and broad-leaved woods can be suitably achieved with different classification systems. All tested classifiers behave with similar accuracies. The minimal classification error value is about 2.9% with a standard deviation of 0.1% for the QDC (13 bands). Similar classification errors are achieved by the 1-NN classifier and by the LDC with an error of 0.3% (81 bands) with a 0.2% standard deviation.

Results of the classification of the 21 wood types (Table B) show that the classification can be achieved with a classification error of 6.4% (with a 0.9% standard deviation) by the QDC algorithm.

The errors related to the two classification problems are very promising since they are obtained by using a single spectrum acquisition. A second method can be also be considered: more than one spectrum acquisition can be taken from the same point (or considering points that are in a narrow neighborhood of the same wood sample). In this case, it is possible to achieve different operations of classification from the same points/area of the sample, and then to process an average/voting operation on the class outputs. More experiments will be done to control if the averaging/voting method can effectively further reduce the classification errors.

All the tested classifiers achieve the classification in a computational time which ranges between 1ms and 45ms, depending on the number of inputs (the M bands) and the complexity of the algorithms. LDCs and 5NNs classifiers have the minimum computational times and the maximum computational times, respectively. All tests have been performed using a Pentium 1,7GHz, 1GB RAM, using Windons XP Professional. The whole system has been implemented in Matlab by exploiting the available Toolboxes.

The obtained computational times suggest that is possible to adopt the proposed classification method in real time applications.

TABLE A - Conifer / Broad-leaved										
	LDC		*QDC*		*1-NN*		*3-NN*		*5-NN*	
Bands	err.	std.	err.	std.	err.	std.	err.	std.	err.	std.
121	0.714	*0.000*	0.179	*0.017*	0.033	*0.003*	0.038	*0.003*	0.034	*0.003*
81	0.712	*0.001*	0.173	*0.014*	**0.030**	*0.002*	0.038	*0.002*	0.036	*0.003*
61	0.034	*0.001*	0.115	*0.009*	**0.030**	*0.003*	0.036	*0.002*	0.035	*0.001*
49	0.032	*0.002*	0.059	*0.005*	0.032	*0.002*	0.039	*0.002*	0.033	*0.003*
31	0.032	*0.003*	0.031	*0.002*	0.032	*0.004*	0.039	*0.002*	0.034	*0.002*
25	0.035	*0.002*	0.031	*0.003*	0.036	*0.004*	0.036	*0.002*	0.035	*0.003*
13	**0.030**	*0.002*	**0.029**	*0.001*	0.033	*0.003*	0.037	*0.002*	0.036	*0.003*
9	0.031	*0.001*	0.035	*0.003*	0.033	*0.002*	0.034	*0.002*	0.038	*0.002*
7	0.035	*0.001*	0.037	*0.005*	0.036	*0.002*	0.037	*0.002*	0.042	*0.003*
5	0.034	*0.002*	0.054	*0.009*	0.036	*0.004*	0.039	*0.002*	0.036	*0.002*
4	0.033	*0.001*	0.052	*0.008*	0.053	*0.005*	0.047	*0.004*	0.053	*0.003*
3	0.108	*0.002*	0.130	*0.011*	0.113	*0.005*	0.085	*0.004*	0.091	*0.006*

TABLE B - 21 wood types										
	LDC		*QDC*		*1-NN*		*3-NN*		*5-NN*	
Bands	err.	std.	err.	std.	err.	std.	err.	std.	err.	std.
121	0.950	*0.000*	0.949	*0.003*	0.194	*0.004*	0.205	*0.007*	0.206	*0.006*
81	0.919	*0.004*	0.932	*0.008*	0.194	*0.009*	0.209	*0.003*	0.209	*0.008*
61	0.121	*0.005*	0.901	*0.006*	0.193	*0.006*	0.204	*0.004*	0.204	*0.003*
49	0.110	*0.006*	0.794	*0.016*	0.194	*0.006*	0.206	*0.007*	0.207	*0.005*
31	0.097	*0.007*	**0.064**	*0.009*	0.191	*0.006*	0.206	*0.006*	0.206	*0.008*
25	0.104	*0.004*	0.097	*0.010*	0.194	*0.007*	0.209	*0.005*	0.209	*0.004*
13	0.123	*0.003*	0.135	*0.013*	0.215	*0.007*	0.215	*0.005*	0.223	*0.005*
9	0.144	*0.006*	0.115	*0.005*	0.220	*0.009*	0.227	*0.006*	0.228	*0.005*
7	0.196	*0.006*	0.135	*0.005*	0.228	*0.004*	0.243	*0.005*	0.221	*0.003*
5	0.215	*0.007*	0.160	*0.008*	0.245	*0.008*	0.250	*0.004*	0.240	*0.007*
4	0.252	*0.005*	0.202	*0.008*	0.323	*0.009*	0.304	*0.006*	0.294	*0.008*
3	0.376	*0.007*	0.373	*0.014*	0.387	*0.008*	0.361	*0.004*	0.338	*0.008*

V. CONCLUSIONS

The paper presented a method for the automated classification of wood types based on the analysis of fluorescence spectra. The proposed method partitions the input spectra in different bands equally spaced. The energy contained in each band is used in input to an inductive classifier. Results show a good classification accuracy up to 21 different wood types. The presented approach has a general validity, and it can be used with spectrometers of different resolutions and with different classification systems, encompassing k-nearest neighbor classifiers, linear and quadratic Bayesian classification systems. The simple experimental set set-up and the limited overall computational complexity permit the adoption of the proposed method in real time applications.

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