On the Design of Acousto-Ultrasonics - Pattern Recognition Classifiers for the Identification of Material Response States

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ABSTRACT

This paper deals with the design procedure of computer-based Pattern Recognition (PR) Classifiers, when the Acousto-Ultrasonics (AU) technique is employed for the identification of material response states. For this purpose, material specimens presenting different mechanical response states are processed to retrieve AU signals in the form of digitalized records. The retrieved AU data are, then, grouped in distinct classes, each pertaining to a known response state of the material under consideration. These AU data are, subsequently, identified by pattern vectors, the components of which represent values of characteristic features in certain domains of description. PR-classifiers built from these pattern vectors are subsequently used to identify unknown response states of the material by classifying their pertaining AU signals as belonging to one of the predefined classes.

In the paper, AU-experimental work in conjunction with PR-computational results are presented to illustrate the design procedure and testing of PR-classifiers for the purpose of identifying various low-energy repeated-impact states of a class of polymeric material; namely, Polyvinylchloride (PVC).

KEYWORDS: Mechanical, Response, Acousto-Ultrasonics, Pattern Recognition, Classifiers, Impact.

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1. INTRODUCTION

The Pattern Recognition and Classification approach offers a suitable methodology for multivariate analysis of data. In this approach, pattern vectors are identified as belonging to a class by means of a PR-system. In particular, this methodology can be used for the discrimination between different response states of a material property, as given by data-measurements taken from various material specimens representing these states.

Acousto-Ultrasonics is a relatively new “quantitative” non-destructive examination technique that combines aspects of conventional Ultrasonics and Acoustic Emission practice. It constitutes a suitable methodology for examining microstructural states and related mechanical properties of polymer-based materials, which characteristically show high attenuation of ultrasonic waves; e. g., /1/.

In the AU-technique, stress waves, that resemble acoustic-emission waves, are ‘simulated’ into the material without disrupting the microstructure. In this technique, Fig. 1, a broad band transducer is employed to transmit a repetitive series of ultrasonic pulses into the test specimen. Meantime, a receiving acoustic-emission (AE) transducer, placed in contact with the surface of the specimen, at a specific distance from the sender-transducer, intercepts the resulting stress waves after having propagated through the microstructure. Although a number of test configurations are possible, the most effective experimental configuration was found to be the one in which the sending and receiving transducers are located on the same side of the specimen; e.g. /2,3/. The sender transducer emits longitudinal waves normal to the specimen surface. The resulting stress waves, which may consist of different components, propagate into the material specimen; interacting with a significant portion of the microstructure along their path. Thus, they can be affected by those microstructural and morphological properties which determine material performance. In many situations, it is possible to obtain information on the mechanical behaviour of the material from measured AU wave propagation data. In this context, Acousto-Ultrasonic waveforms have been shown, for instance, to be sensitive to interlaminar and adhesive bond-strength variations /2,4/. The technique has been used to estimate the variation in strength of composite systems /1/, as well as, in the evaluation of residual strength and degradation of such materials due to cyclic fatigue and impact; e.g., /5,6/. Acousto-Ultrasonics have been

Fig. 1: A schematic illustration of the acousto-ultrasonic technique; see also Fig. 4.

proven to be useful in assessing micro-porosity and micro-cracking produced by fatigue cycling; e.g., /7/. The strength of ceramic materials and the effect of hydrothermal aging on composites have also been evaluated successfully using the acousto-ultrasonic approach /8/.

Since the interactions of the ultrasonic-waves with the microstructure often result in quite complicated waveforms, the PR and Classification method is seen in this study as a convenient approach for the analysis of the pertaining retrieved data. In this context, when applying the PR and Classification methodology to the identification of AU signals, a discrete number of predefined classes would pertain to corresponding states of the tested material-property. Thus, for the purpose of building a PR-system, the retrieved AU signals can be identified by multi-dimensional characteristic quantities called "*pattern vectors*", the components of which are the values of describing features, as extracted from the pertaining AU signals. In this, the problem of recognition and classification of patterns can be understood as that of generating "*decision boundaries*", also called "*decision functions*", to separate pattern classes. The set of decision functions, which can be established by using the AU data from material specimens of known mechanical response states, constitutes a "*Pattern Recognition Classifier*" of the AU data and, hence, of the corresponding mechanical response states of the material. This classifier can be, subsequently, employed to identify unknown response states of the material by classifying their pertaining AU signals as belonging to one of the predefined classes.

2. DESIGN AND TESTING OF A PATTERN RECOGNITION SYSTEM

2.1. Design of Pattern Recognition Classifiers.

The task of a PR-system may be defined as the categorization of input data into identifiable classes via the extraction of significant features or attributes from a background of relevant data. This is accomplished on the basis that the "degree of similarity" among members of the same class would be higher than between members of different classes. Evaluation of this "degree of similarity" is made by using particular decision functions of the pattern vectors involved.

There are two main approaches to generate decision functions; i.e., *deterministic* and *statistical*. The deterministic approach comprises those decision rules that are established from the assumption that a minimum of a function of generalized distance between a pattern and a class indicates that the pattern belongs to this class. The statistical approach, however, is based on the minimization of the mathematical error of classifying a pattern as belonging to a class, when it actually belongs to another /9,10,11/.

In Pattern Recognition, decision functions are established by the so-called "*learning and estimation*" procedures. They are implemented by means of a computer-based set of rules which constitutes the pertaining *Pattern Recognition Classifier*. In this presentation, the following four decision functions are employed in the design of corresponding PR-classifiers:

- I. Empirical Bayesian,
- II. Linear Discriminant,
- III. K-Nearest Neighbour, and

IV. Minimum Distance Classifiers.

Operationally speaking, a PR-classifier would perform the following transformation:

$$P_s \rightarrow F_s \rightarrow C_s \quad (1)$$

where the “*Pattern Space P_s* ” comprises the sets of feature values extracted from either analogical or digitalized descriptions of the objects to be recognized; the “*Feature Space F_s* ” comprises the pattern vectors formed by a selection of those features which carry the discriminatory power between classes for the given problem; and the “*Classification Space C_s* ” is the frame of defined classes where a pattern of unknown classification is identified as belonging to a known class. The design of a *Pattern Recognition Classifier* implies the establishment of a series of procedures to perform transformation (1).

2.2. Feature Extraction and Normalization of Pattern Vectors.

Figure 2 presents schematics of the procedures used in this study to perform partial transformation from the *Pattern Space P_s* to the *Feature Space F_s* . With reference to Figure 2, AU signals in each class are

Fig. 2: Schematics of the feature extraction and normalization procedures.

divided in two sets; namely, “Classifier” and “Testing” Sets, each pertaining to two different groups of material specimens. *Classifier Sets* are used for building of the classifiers, as well as for further testing of their “Training” and “Evaluation” performances. *Testing Sets* are used for testing of their “Classification Performances”.

In general, PR-classifiers have to deal with values of features of diverse order of magnitude, originating from several domains of object description. Thus, a normalization procedure is necessary to make the obtained values numerically tractable and comparable in an N-feature space. In this study, we adopt the “Method of Zero-Mean Unit-Variance Mapping” for carrying out the required normalization of the involved features. In this method, the normalized feature value ξ_j for feature j is obtained from the corresponding unnormalized value x_j of a pattern vector $\mathbf{x}$ as follows

$$\xi_j = \frac{x_j - \mu}{s} \quad (2)$$

where μ is the mean of the values of the j -feature for all pattern vectors under consideration; and s is the standard deviation of the values of j -feature for all classes being dealt with. In our study, the so-called “global mean” of all values of the j -feature is used as the mean μ , while the average of the standard deviation values for all the classes is taken as s . Normalized values will be, thus, loosely bounded by the limits $(-1,1)$, measured in standard deviation units.

Equation (2) is generally intended to carry out normalization with respect to a certain set of values of the feature. For such normalization to be consistent, these sets of values must be extracted from the same set of patterns for all the features used in the PR process. This set of reference pattern-vectors is referred to as “Normalization Tree (NT)”. Normalization Trees are structured as hierarchical arrangements of computer-based files which are used for building and/or testing the PR-classifiers. The NT shown, for instance, in Figure 2 is employed in this study for building a PR-classifier from a set of limited-size samples of patterns and, hence, it is called “Classifier Tree”, e.g., /6,9/.

Various *Normalization Trees* can be proposed for the normalization of the involved Testing Sets. According to Equation (2), the choice of different sets of reference patterns may imply different mean and/or standard deviation values for the normalization procedure and corresponding normalization outcomes. In the following Sections we discuss the suitability of a number of *Normalization Trees* for an adequate testing of PR-classifiers.

2.3. Building and Training of Classifiers.

Figure 3 presents schematics of the procedure used in this study for building and testing of Classifiers by features files. They correspond to the partial transformation from the *Feature Space* F_S to the *Classification Space* C_S . For each particular classification problem, it is possible to establish a ranking of the feature’s discriminating-ability between classes. In this study, the “Fisher Distance”, also called “Fisher

Fig. 3: Procedures for building and testing of classifiers /6/.

Discriminatory Ratio", is used for the tasks of ranking of features and of corresponding feature selection /6,12/.

As previously discussed in Subsection 2.1, the designed Classifiers work on the basis of decision functions. The ability of these decision functions to discriminate between the pattern vectors that were used to build them can be tested and, subsequently, expressed as the percentage of the pattern vectors that are correctly classified. This percentage is referred to as "*Training Performance*", as it represents the effectiveness of the Classifier training to recognize the pattern vectors used in its training.

Meantime, a PR-classifier may be also evaluated by the percentage of correct classification, when classifying pattern vectors obtained from the same specimens employed in its design. This percentage is referred to as "*Evaluation Performance*" of the Classifier.

Training and Evaluation performances are often determined during the course of building the PR-classifier. If the latter is to be used further in the identification process of unknown material response states, excellent training and evaluation performances would be, obviously, essential prerequisites for such Classifier.

2.4. Testing of Classification Performance.

With reference to Figure 3, the performance of each designed classifier may be tested by using limited-size Testing Sets, obtaining the so-called “*Classification Performance*”. The Classification Performance for any tested class is expressed as the percentage of pattern vectors, from the respective Testing Set, that are correctly classified in the class. Such Classification Performance gives the effectiveness of classifying pattern vectors that were not used in the process of building the Classifier. As was discussed in Subsection 2. 2, careful design of the Normalization Trees is needed for the adequate appraisal of the Classifier performance.

3. EXPERIMENTAL WORK

3.1. Experimental Setup

The AU experimental set-up used in the present investigation is schematically shown in Fig. 4; see also /3/. The pulsar-sender is a printed circuit board capable of pulse generation. It emits electric voltage pulses to the piezoelectric sender-transducer at a predetermined rate, resulting in acoustic pressure waves that have frequencies in the ultrasonic range of 1-20 MHz. The emitted waves interact with the microstructure of the material specimen before being captured by the receiving transducer. The latter, as shown in Fig. 4, is connected to a preamplifier and, in turn, to an AE-testing facility. The AE-facility receives the captured waveforms, one at a time, converts the signal from an analog form to a digital one and then transfers the latter to a digitization board. The digitization board possesses a signal processing capability. It digitizes the signal with the use of a specialized real-time data acquisition and signal processing software. As soon as a signal is

Fig. 4: The AU experimental set-up /9/.

digitized, the digitizer triggers the pulsar to emit a second wave. This, in turn, interacts with the microstructure and the sequence of operations mentioned above is repeated. After digitization, the pertaining data are stored in separate data files on the computer hard disk for later analysis.

The rate of emission of input pulses is determined by a 'repetition rate' utility which is operated by the controlling software. This software allows, further, easy selection of threshold setting, gains and their values, damping, frequency, etc. Moreover, it initiates waveform generation and reception.

In this paper, we present the experimental and computational results concerning the design and testing of PR-classifiers for retrieved AU signals, as pertaining to different low-energy repeated-impact states in Polyvinylchloride specimens.

Three classes of low-energy repeated impact are considered, as represented by the number of impacts applied by a 0.9 kg-weight falling vertically from a height of 1.2 m /9/:

- Class A: No impact,
- Class B: Five impacts, and
- Class C: Twenty impacts.

In the AU experiment, both the input and receiver transducers were located on the same side of the specimen. A rectangular PVC specimen (with rectangular cross-section), of dimensions 210 mm x 25.4 mm x 4.76 mm, was used. Table 1 presents relevant controlled parameters, as pertaining to the transducer configuration and instrumentation setup that were used for the study.

Table 1
Controlled parameters for AU data acquisition.

CONTROLLED PARAMETER	Set Value
Voltage Range	0 to +12 Volts
Gain	30 decibels
Wave Frequency	750 KHz
Sampling Rate	3.125 MHZ
Distance between transducers	19 mm
Couplant Medium	Ultragel II™

A specially designed software is used in the present study to control the emission of the ultrasonic pulse and to obtain a digitalized record of the received AU waveform. Two sets of AU-records, representing two samples of material specimens, are obtained for each of the previously defined impact states (classes). These two sets constitute the Classifier and Testing sets, with both sets being associated with one of the impact states considered. The three Classifier Sets are employed for building the PR-classifiers and testing their Training and Evaluation performances, by following the procedures described in Section 2. Four PR-classifiers are built, each pertaining to one of the four types of decision functions previously described in Subsection 2.1, by choosing the 12-best discriminating features in five different domains of description; namely, time, frequency, phase, cepstral and autocorrelation domains.

Experimental work was carried out by the authors concerning the influence of different Normalization Trees on the testing of PR-classifiers by the same Testing Sets. In this context, the following Normalization Trees were employed:

NT(i): Normalization Tree (i), of Figure 5, comprises the three Testing Sets.

NT(ii): Normalization Tree (ii), Figure 6, constitutes the pattern-vectors pertaining to a single specimen from one of the classes and the entire Testing Sets for the two other classes.

NT(iii): Normalization Tree (iii), of Figure 7, includes the entire "Testing Set" for one of the classes.

NT(iv): Normalization Tree (iv), of Figure 8, pertains to the "Testing Set" for one of the classes plus the three Classifier Sets previously used for building the PR-classifier.

The above types of Normalization Trees are examples of the normalization arrangements that may be proposed for the testing of PR-classifiers.

NT(i) should be optimal for the employed normalization procedure and it may be a reference case for comparison with other Normalization Trees. Design of **NT (i)** requires, however, a priori complete knowledge of classification for the Testing Sets. It demands, before any normalization or classification to be

Fig. 5: Normalization Tree (i). Arrangement of AU-data for the normalization of testing sets.

Fig. 6: Normalization Tree (ii). Arrangement of AU-data for the normalization of testing sets.

Fig. 7: Normalization Tree (iii). Arrangement of AU-data for the normalization of testing sets.

Fig. 8: Normalization Tree (iv). Arrangement of AU-data for the normalization of testing sets.

carried out, that patterns be correctly identified into pertaining *Testing Sets*. Thus, building of $NT(i)$ would not be possible if dealing with pattern vectors of unknown classification. Given this, $NT(i)$ may be inadequate for testing the PR-classifiers.

$NT(ii)$ is a special case of $NT(i)$. It presents the situation that may arise in practice when normalizing by $NT(i)$ a set of either known or unknown-classification patterns that comprises fewer patterns for one class than for the other two classes.

$NT(iii)$ is a special case of $NT(i)$. It presents the situation that may evolve when normalizing by $NT(i)$ a set comprising only unknown-classification patterns which actually belong to a single class.

$NT(iv)$ is the proposed arrangement to solve the problem of adequate normalization in this study. The case represented in Figure 8 pertains to the use of $NT(iv)$ for testing the PR-classifiers by means of known-classification Testing Sets. If $NT(iv)$ is employed for the normalization of unknown-classification patterns, they should be arranged as displayed in Figure 9.

Fig. 9: Normalization Tree (iv). Arrangement for the normalization of unknown-classification of AU data.

3.2. Experimental Results

Table II displays the experimental results for the four types of PR-classifiers when employed for testing recognition performances for the considered three impact states of the material. The results of classification are presented, for each situation, as percentages of correctly identified pattern vectors, as were normalized by each of the above proposed types of Normalization Trees.

Results of Table II show, for the same type of PR-classifier, when identifying the same material state, significant differences of classification performances if the pertaining Testing Set was normalized by different Normalization Trees. In general, testing by $NT(ii)$ shows the highest classification performances, while $NT(iii)$ shows the lowest classification performances. For $NT(iv)$, however, classification performances are quite close to those of those pertaining to $NT(i)$, specially for high rates of recognition.

Table II

“Testing Performances” for PR-classifiers of low-energy repeated-impact states in PVC specimens when using different “Normalization Trees” for the “Testing Sets”.

TYPE OF CLASSIFIER	CLASS	NORMALIZATION TREE			
		(i)	(ii)	(iii)	(iv)
(I) Empirical Bayesian Classifier	Class A	93.33%	96.00%	20.67%	88.00%
	Class B	74.00%	75.00%	54.00%	79.00%
	Class C	75.00%	79.00%	6.00%	74.00%
	Average	80.78%	83.33%	26.89%	80.33%
(II) Linear Discriminant Classifier	Class A	99.33%	100.00%	38.67%	90.00%
	Class B	27.00%	30.00%	21.00%	34.00%
	Class C	57.00%	60.00%	39.00%	44.00%
	Average	61.11%	63.33%	32.89%	56.00%
(III) K-Nearest Neighbours Classifier	Class A	98.67%	100.00%	44.67%	91.33%
	Class B	66.00%	65.00%	27.00%	63.00%
	Class C	52.00%	62.00%	2.00%	47.00%
	Average	72.22%	75.67%	24.56%	67.11%
(IV) Minimum Distance Classifier	Class A	93.33%	100.00%	18.67%	88.00%
	Class B	75.00%	74.00%	54.00%	75.00%
	Class C	70.00%	84.00%	10.00%	65.00%
	Average	79.44%	86.00%	27.56%	76.00%

4. DISCUSSION OF EXPERIMENTAL RESULTS

Experimental results of Subsection 3.2 show that the normalization process can strongly influence the testing performances.

Fig. 10: Probability density function for the best ranked feature (greatest peak amplitude in the wave autocorrelation domain).

Previous work of the authors showed that pattern vector discrimination is influenced by the overlapping of the probability density functions, of occurrence of a given feature-value in a class, between classes; e.g., /3,6,12/. Figure 10, for instance, shows the probability density functions for the first-ranked feature (greatest peak amplitude in the wave-autocorrelation domain of description) in the three classes, as experimentally obtained for the *Classifier Sets* of Subsection 3.1.

In general, the more the referred to probability density functions are separated for any two classes, the higher the corresponding classification performances for these classes. Further, probability density functions are usually described, in the assumption of Gaussian normality, by the mean and standard deviation of the corresponding statistical distribution.

Case *NT(ii)* can be analysed on the basis of the normalization expression (2). If the hypothesis is made that the global mean $\mu_{(ii)}$ of *NT(ii)* is not larger than the global mean $\mu_{(i)}$ of *NT(i)*, i.e., when,

$$\mu_{(ii)} \leq \mu_{(i)} \quad (3)$$

$$x_j - \mu_{(ii)} \geq x_j - \mu_{(i)} \quad (4)$$

where x_j is the unnormalized value of feature j in pattern vector $\mathbf{x}$.

It can be reasonably assumed, for the purpose of this analysis, that the standard deviation $s_{(ii)}$ for $NT(ii)$, as average of corresponding values for all classes, where one of them is represented by a sample of pattern vectors pertaining to a single specimen, is not larger than $s_{(i)}$, obtained for the three classes considered in $NT(i)$:

$$s_{(ii)} < s_{(i)} \quad (5)$$

By applying the above inequalities (4) and (5) to the normalization equation (2), it follows that:

$$x_j - \frac{\mu_{(ii)}}{s_{(ii)}} \leq x_j - \frac{\mu_{(i)}}{s_{(i)}} \quad (6)$$

$$\xi_{j(ii)} \geq \xi_{j(i)} \quad (7)$$

where in the above equations (6) and (7), ξ_j is the normalized value of feature j for the pattern vector x , and subscripts (i) and (ii) refer, respectively, to $NT(i)$ and $NT(ii)$.

Equation (7), above, indicates that $NT(ii)$ may give higher values for normalized features than those correspondingly obtained by $NT(i)$, Equation (3). When, on the contrary, the mean of the feature values for the class is higher than the global mean of the Classifier, no such relation can be predicted for the normalized values. The analysis of equations (3) through (7) is schematically shown in Figure 10, where the probabilities of occurrence p_j of feature j are assumed as Gaussian distributions.

Figure 11 displays the probability density functions of unnormalized feature j for the concerned classes in $NT(ii)$. This figure shows, also, the distributions of feature j as normalized by $NT(i)$. Figure 11 suggests that normalization by $NT(ii)$ may reduce the overlapping of the probability density functions distribution for the class under consideration. Thus, it may lead to higher classification performances as confirmed by the corresponding results in Table II.

In general, Classifier performances for a given class, as tested by $NT(ii)$, depend on the relative position of the mean of the unnormalized class with respect to the global mean, for each of the concerned features. Since $NT(ii)$ is a particular case of $NT(i)$, the latter may not be adequate for the normalization of Testing Sets in Classifier testing.

Analysis of the case $NT(iii)$ on the basis of the normalization expression (2) is trivial. Since global mean $\mu_{(iii)}$ and standard deviation $s_{(iii)}$ are those of the single class in the $NT(iii)$, the normalized distribution will be centred around zero-mean. Figure 12 presents schematics that can be used to compare the results pertaining to $NT(iii)$ with those of $NT(i)$, where the probabilities of occurrence p_j of feature j are assumed as Gaussian distributions. It shows that $NT(iii)$ gives, for the class under consideration, a normalized density function which may strongly overlap with the other two classes. This may explain why the classification performances are the lowest when experimentally tested by $NT(iii)$. Since $NT(iii)$ is a particular case of $NT(i)$, the latter may not be adequate for the normalization of Testing Sets in testing the Classifier.

Fig. 11: Schematics of the effects of Normalization Tree (ii) on the probability density function of the pertaining class.

Classification performances for $NT(iv)$ are very close to those of $NT(i)$, specially for high percentages of recognition. $NT(iv)$ may be adequate for testing, given that PR-classifiers will be employed only when showing high recognition rates for the considered classes. Further, an important advantage of $NT(iv)$ is that such normalization arrangement can always be built for both known and unknown classification patterns, as respectively, displayed in Figures 8 and 9. Thus, when using a PR Classifier, the operator must be provided with files containing the Classifier Sets, by which an $NT(iv)$ can always be determined. Given this condition, testing of Classifiers by $NT(iv)$ may give an adequate estimate of the probability of correct recognition for pattern vectors of *a priori* unknown classification.

Fig. 12: Schematics of the effects of Normalization Tree (iii) on the probability density function of the pertaining class.

5. CONCLUSION

The presented study shows the influence of the “normalization procedure” on the testing of computer-based Classifier performance. There are a number of Normalization Trees that can be built in a multiple-class problem. However, a critical examination of the most intuitively obvious “*Normalization Tree (i)*” for the normalization of pattern vectors shows that such a normalization arrangement may be inadequate for the testing of PR-classifiers.

Design of appropriate testing procedures requires, however, special consideration to the fact that testing of PR-classifiers is performed in the practice by pattern vectors whose classifications are *a priori* known. The

intended purpose of such testing is to give an estimate of the Classifier success for pattern vectors of unknown classification.

The testing of the Classification Performances requires that the Normalization Tree employed in the testing process should be available for the further normalization of pattern vectors of unknown classification. This study proposes a Normalization Tree comprising pattern-vectors from Testing and Classifier sets, which can always be built, irrespective of whether known or unknown classification was used for the concerned patterns. Experimental results show that testing of PR-classifiers by such proposed normalization arrangement may be adequate for the estimation of PR-classifier performances.

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