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Feature extraction techniques for ultrasonic signal classification

G. Simone[a], F.C. Morabito[a], R. Polikar[b], P. Ramuhalli[b], L. Udpa[b] and S. Udpa[b]
[a]*NeuroLab, Faculty of Engineering, University of Reggio Calabria, Via Graziella - Feo di Vito, 89100 Reggio Calabria, Italy*
Tel.: +39 0965 875 224; Fax: +39 0965 875 220; E-mail: simoneg@ing.unirc.it, morabito@unirc.it; Web: http://neurolab.ing.unirc.it
[b]*MARG, Iowa State University, 391 Durham Center, IA 50011-2252, Ames, USA*
E-mail: rpolikar@iastate.edu; rpradeep@iastate.edu; lalita@iastate.edu; udpa@iastate.edu; Web: http://marg.ee.iastate.edu

Abstract. In this paper, we present two feature extraction techniques for the classification of ultrasonic NDE signals acquired from weld inspection regions of boiling water reactor piping of nuclear power plants. The classification system consists of a pre-processing block that extracts features from the incoming patterns, and of an artificial neural network that assigns the computed features to a particular class of defect present on the inspected pipe. The two techniques are respectively based on the discrete Gabor transform (DGT) and on the discrete wavelet transform (DWT); a third feature extraction technique, based on the clustering of the wavelet coefficients, is also presented. The results carried out by artificial neural networks trained and tested using the described feature extraction techniques, demonstrate the usefulness of the clustered DWT method with respect to the well known techniques of DGT and DWT.

1. Introduction

Efficient signal processing techniques are of significant importance in Non Destructive Testing and Evaluation (NDT/NDE) of materials where defects need to be detected in order to prevent catastrophic outcomes. One of the most commonly used NDT techniques is ultrasonic inspection [9], which employs a piezoelectric transducer that produces mechanical oscillations inside the inspected material, and acquires the reflected ultrasonic wave from discontinuities in the material. In this study ultrasonic NDT is used to inspect welding regions of piping in boiling water reactors to detect intergranular stress corrosion cracking [4,7]. The received signal can hence be reflected from a crack, a counterbore or a rootweld. Counterbores and rootwelds are related to the geometry of the weld and do not impose a threat to the integrity of the material. Therefore, the automatic classification system has to be able to distinguish cracks from counterbores and rootwelds, all of which appear in the heat affected zone (Fig. 1). Ultrasonic signals typically contain reflections from discontinuities, which result in time varying spectral characteristics of the signal. Consequently, the conventional Fourier decomposition technique is not well suited to extract useful information from the measured signal. Time-frequency techniques are therefore more useful for understanding the behavior of the signal. In this paper, the discrete Gabor transform (DGT) [2,4,8] and the discrete wavelet transform (DWT) [5–7] are used to analyze the input signal. Furthermore, two DWT based techniques of feature extraction are presented. The first one uses a subset of the wavelet

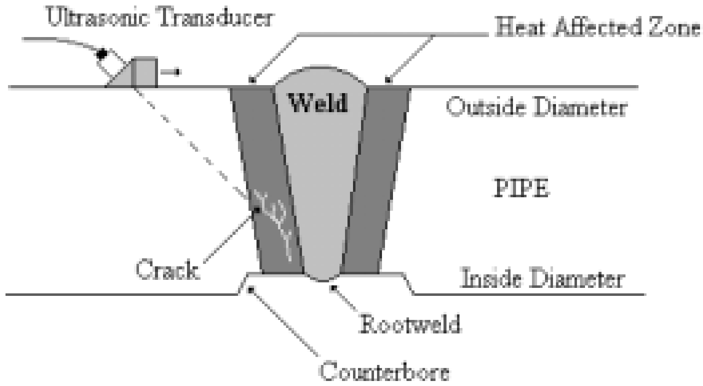

Fig. 1. Weld geometry for ultrasonic inspection.

coefficients, whereas the second one uses a clustering algorithm to cluster the wavelet coefficients, and the energy of each cluster is used as a feature. The computed features are then classified by a multilayer perceptron [1,3] that outputs the class of each ultrasonic signal.

2. Discrete Gabor transform (DGT) feature extraction technique

DGT has been proposed by Gabor [2] to characterize a time function in time and frequency. For signal, the Gabor expansion is defined as:

$$s(t) = \sum_{m=-\infty}^{+\infty} \sum_{-\infty}^{+\infty} C_{m,n} h_{m,n}(t) \text{ where } h_{m,n}(t) = h(t - mT) \exp(jn\Omega t) \tag{1}$$

where T and Ω represent time and frequency sampling intervals. Although the Gabor expansion (Eq. 1) has been recognized as very useful for signal processing, its applications were limited due to the difficulties with computing the Gabor coefficients: $C_{m,n}; h_{m,n}(t)$ do not form an orthogonal basis unless the corresponding elementary function $h(t)$ is badly localized in either time or frequency. Therefore the selection of the Gabor coefficient $C_{m,n}$ in general is not unique. One solution to this problem [8] is to introduce an auxiliary function $\gamma(t)$ and then compute the Gabor coefficient $C_{m,n}$ by the usual inner product rule for projecting $s(t)$ onto $\gamma(t)$, i.e.,

$$C_{m,n} = \int_{-\infty}^{+\infty} s(t)\gamma^*_{m,n}(t)dt \text{ where } \gamma_{m,n}(t) = \gamma(t - mT) \exp(\text{in } \Omega t) \tag{2}$$

The DGT scheme presented in [8], applies for both finite as well as infinite sequences, whereas the standard algorithm works very well when the length of analyzed sequences is small. The following synthesis function has been used in this approach [8]:

$$h(t) = A \cdot \exp\left[-\frac{1}{2} \cdot \left(\frac{t - t_0}{\sigma}\right)^2\right] \tag{3}$$

Table 1
Classification Percentages for the DGT, DWT and Clustered DWT featuring techniques

	DGT			DWT			Clustered DWT		
	CR	CB	RW	CR	CB	RW	CR	CB	RW
CR	67.6	18.0	14.4	83.0	9.2	7.8	89.6	2.0	8.4
CB	15.3	71.2	13.5	4.8	89.8	5.4	0	100	0
RW	11.8	10.2	78.0	6.0	5.7	88.3	5.8	0.2	94.0

where t_0 is fixed to the center of the window, and t varies from the start to the end sample of the window. By using this algorithm (Eqs 1, 2, 3), the magnitudes of the computed Gabor coefficients are used as features describing the incoming pattern: the featuring scheme has been optimized by changing the time-frequency resolution and the standard deviation of the synthesis function, on the basis of the considered study case.

3. Discrete wavelet transform (DWT) feature extraction technique

The wavelet transform is very similar to the Gabor transform: it is a multiresolution analysis technique, that can be used to obtain the time-frequency representation of the incoming signal. It is based on the expansion of the incoming signal in terms of a function, called mother wavelet, that is translated and dilated in time. From the computational point of view, the DWT analyzes the signal by decomposing it into its coarse and detail information, which is accomplished by using successive highpass and lowpass filtering operations, on the basis of the following equations:

$$y_{\mathrm{high}}(k) = \sum_n x(n) \cdot g(2k - n) \tag{4}$$

$$y_{\mathrm{low}}(k) = \sum_n x(n) \cdot h(2k - n) \tag{5}$$

This procedure is repeated for further decomposition of the lowpass filtered signals. The highpass filter outputs of these multiple decompositions are the features used for classification [7]. This technique has been optimized, by looking for the frequency band where the discriminating information is retained: this is useful also to reduce the number of the wavelet coefficients used as features.

4. Clustered DWT

In this paper, we compare these two techniques with an additional technique that uses the energy of the different bands to cluster the coefficients [6]. In current methods, energy values are computed based on the detail and approximation wavelet coefficients belonging to the same scale. This helps in overcoming the well-known problem posed by the fact that wavelet coefficients are not time invariant. The clustering algorithm exploited in this paper, proceeds in an unsupervised mode by clustering the coefficients on the basis of the average energies at different scales and within the same scale, as described in [6]. The clusters are formed by using a set of representative signals that belong to the training dataset.

5. Classification scheme and experimental results

In this application, we use a feed-forward neural network (commonly known as MultiLayer Perceptron, MLP) for classifying signals obtained from weld inspection into three classes, namely, crack, counterbore, and rootweld; the data have been acquired by using 1 MHz frequency. A training database of 33 crack, 25 counterbore and 25 rootweld signals was used; each pattern consists of 256 samples. This database was mapped to the feature domain by using DGT, DWT and the cluster energy features generating three different training databases. Three different networks were trained using these training data: the exploited neural architecture consists of 2 sigmoidal hidden layers. The results of the feature extraction/classification algorithm are compared using a test database of 65 crack (CR), 48 counterbore (CB) and 50 rootweld (RW) signals. The classification results in percentage are summarized in Table 1.

6. Conclusions

Three time-frequency based feature extraction techniques have been compared in this paper; namely, the discrete Gabor transform, the discrete wavelet transform and energy of clustered wavelet coefficients. The clustered DWT provided the best results. In this case, clusters computed in an unsupervised mode on the energies of the wavelet coefficients, are used as boundaries for feature extraction during the training/testing of the MLP.

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