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Ultrasonic signal classification and imaging system for composite materials via deep convolutional neural networks

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ABSTRACT

Automated ultrasonic signal classification systems are finding increasing use in many applications for the recognition of large volumes of inspection signals. Wavelet transform is a well-known signal processing technique in fault signal diagnosis system. Most of the proposed approaches have mainly used low-level handcraft features based on wavelet transform to encode the information for different defect classes. In this paper, we proposed a deep learning based framework to classify ultrasonic signals from carbon fiber reinforced polymer (CFRP) specimens with void and delamination. In our proposed algorithm, deep Convolutional Neural Networks (CNNs) are used to learn a compact and effective representation for each signal from wavelet coefficients. To yield superior results, we proposed to use a linear SVM top layer in the training process of signal classification task. The experimental results demonstrated the excellent performance of our proposed algorithm against the classical classifier with manually generated attributes. In addition, a post processing scheme is developed to interpret the classifier outputs with a C-scan imaging process and visualize the locations of defects using a 3D model representation.

1. Introduction

Ultrasonic methods are the most successful non-destructive testing (NDT) technique for quality assessment and detection of flaws in engineering materials and the pulse-echo is the most commonly used for its simplicity and efficiency [1]. In this technique, a piezoelectric ultrasonic transducer is used to generate ultrasonic waves which propagate through metal plate. Thus, they are reflected by defect and return back to transducer surface. The same ultrasonic transducer receives the reflected waves and converts them to electrical signals. These signals, called A-scan signals, contain information about the type, size and orientation of the defect [2].

The identification of defects on A-scan signal is not a trivial task and usually called *ultrasonic pattern recognition* [3]. The results usually depend on the experience and knowledge of the experts. To minimize errors due to human subjectivity, automatic signal classification system (ASCS) is becoming increasing important and has the advantage of detecting flaws and interpreting ultrasonic signals consistently and accurately [4]. Some researchers [2,3,5,6] define three major tasks to such systems: preprocessing raw data, feature extraction and classification. The preprocessing task normalizes the raw data signals values to a suitable range for other tasks. The feature extraction task is responsible to obtain attributes from normalized A-scan signals. The obtained attributes must be able to characterize the flaws. Finally the classification task aims to analyze the attributes from an A-scan signal and indicates one from a known set of flaws. The algorithm that implements a classification task is called *classifier*. Several approaches have been proposed to build a classifier, such as traditional statistical classifiers, rule-base classifiers and learning-base classifiers [7], which typical examples are artificial neural network (ANN) [8,9] and support vector machine (SVM) [10–12].

As one of the most important techniques, feature extraction will directly affect the accuracy and reliability of signal classification. Deep learning using neural networks develop rapidly recently and have achieved success in a wide range of tasks. We propose to use deep learning to extract powerful representations from the input signals. Instead of low-level handcraft features, we train Convolutional Neural Networks (CNNs) to get high-level features to improve the performance for signal classification. Wavelet transformation can divide the signal gradually in multi-scale by means of dilation and translation. Inspired by [13], the wavelet transform coefficients are re-organized into a 2D feature matrix which is taken as the input to the CNNs to facilitate the training process and utilize the convolutional characteristics of CNNs. The deep CNNs are

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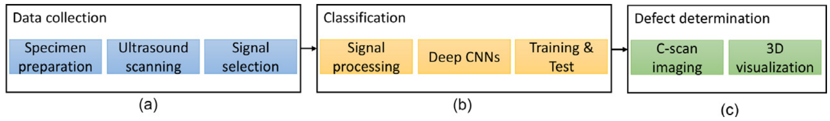

Fig. 1. Flowchart of our proposed approach. (a) Data collection including specimen preparation, ultrasound scanning and signal selection is carried out during the experimental procedure; (b) Signal classification tasks are completed through signal processing, deep architecture construction and training/testing. (c) Defect determination is performed through C-scan imaging and 3D visualization representation.

devoted to learn a compact and effective representation for each signal from wavelet coefficients in our framework. In this manner, the proposed deep CNNs are trained as a multi-class classifier to predict the class of the input signals.

As an alternative to softmax, support vector machine (SVM) is widely used for classification. In [14], the L2-SVM objective was used for the output layer of a deep Convolutional Neural Network to obtain more discrimination power of classification. This kind of output layer for classification using the hinge loss as cost function is also proposed in [15] to make comparison with the commonly applied softmax. Smoother learning curve and slightly increased accuracy are obtained when using this objective in our deep architecture. Thus a linear SVM top layer instead of softmax is proposed to train the networks to yield superior results for signal classification task.

For defect determination, it is usually beneficial to obtain a two-dimensional representation through a C-scan imaging process [16]. Other than the C-scan image obtained purely depending on the signal amplitude, we propose a post processing scheme to compute the C-scan image which takes the classifier outputs as input and further create the three-dimensional (3D) model representation to visualize the locations of defects. To our knowledge, it is the first attempt to present the defects in 3D view which provides new potential ways to localize and characterize the defect for ultrasound testing in the future.

This work conducts a study on ultrasonic signals very similar to each other obtained from artificial inserts in a carbon fiber reinforced polymer (CFRP) plate. First, a process was developed to produce CFRP laminates and artificial defects with void, delamination were collected for our experiments. Then we present an automated signal classification system based on the deep convolutional neural networks to process A-scan signals acquired with the ultrasound transducer. To complement the system, an additional post processing is developed to interpret the classification results with a C-scan imaging process and visualize the locations of defects using a 3D model representation. The flowchart of our proposed approach is shown in Fig. 1.

1.1. Contributions

The main contribution of this work is three-fold:

- A deep learning based framework is proposed to classify ultrasonic signals from carbon fiber reinforced polymer specimens in an automated signal classification system.
- A linear SVM top layer is used in the training process of signal classification task to yield superior results.
- A post-processing scheme is developed to interpret the classifier outputs and present the defects in 3D view.

1.2. Related work

In the last years, various efforts have been made in devising an automated signal classifications system such that we restrict the discussion to the most important aspects including feature selection techniques and classification algorithms.

Simone et al. [9] presented serval techniques including discrete Gabor transform, discrete wavelet transform (DWT) and clustered DWT methods for ultrasonic signals classification. ANN are trained based on the these features and the results demonstrated the effectiveness of the clustered DWT method for feature extraction. Matz et al. [10] used the DWT based method for filtering of ultrasonic signal in combination with SVM to automatically classify ultrasonic signals of in the form of different fault echoes. Cacciola et al. [11] proposed an heuristic approaches based on the use of DWT and PCA in feature extraction and selection. The SVM classifier trained on these features has good performance for classifying the ultrasonic echoes measured on defective CFRP specimen. Wang [5] utilized the DWT and wavelet packet transform (WPT) for feature extraction. ANNs and SVMs are trained to validate the effectiveness of different wavelet transform based features for classifying the ultrasonic flaw signals from CFRP specimens. Like most of the methods mentioned above, we adopted wavelet transform based methods for feature extraction in this paper due to the non-stationary characteristics of ultrasonic flaw signals.

For the classification purposes, the classifiers of choices are mainly learning-based classifier, which typical examples are ANN and SVM. recently as a subfield of machine learning, deep learning have been widely applied in traditional artificial intelligence domains such as natural language processing [17], transfer learning [18] and computer vision [19–21] and many more. we refer the reader to a recent more complete survey [22]. Hong et al. [23,24] proposed hypergraph regularized autoencoder for feature extraction with deep learning for image-based human pose recovery. Yu et al. [25] developed a deep multi-modal distance metric learning method based on the click and visual features for image ranking. It is worth noting that A-scan signals are very similar to each other and only have subtle variances that are very difficult to classify. In our study, we first attempt to use deep learning to process A-scan signals for ultrasonic flaw classification.

1.3. Outline

This paper is organized as follows. Section 2 gives a brief introduction to the wavelet transform. Section 3 demonstrates the experimental procedure. The deep learning architectures are described in Section 4. Experimental results are presented in Section 5. Section 6 introduces a post processing algorithm to localize and characterize defect information followed by conclusions in Section 7.

2. Wavelet transform

The wavelet transform is a windowing technique with variable-sized regions, which allows the use of long time intervals to obtain more precise low frequency information and shorter regions where high frequency information is required [26]. The structure of wavelet packet transform (WPT) is similar to discrete wavelet transform (DWT) [27]. The main difference in these two techniques is, the WPT can simultaneously break up detail and approximation versions but DWT only breaks up as an approximation version. Therefore, the WPT have the same frequency bandwidths in each resolution and DWT does not have this property. The WPT suits signal processing, especially non stationary signals because the same frequency bandwidths can provide good resolution