CANCOM2024 – CANADIAN INTERNATIONAL CONFERENCE ON COMPOSITE MATERIALS

DEVELOPING AN MACHINE LEARNING MODEL FOR DISTINGUISHING FIBER ORIENTATION USING ACTIVE ULTRASONICS

Bedrosian, A[1], Thompson, M[1*], Hrymak, A[2] and Lanza, G[3]
[1] Department of Chemical Engineering, CAPPA-D/MMRI, McMaster University, Hamilton, Canada
[2] Department of Chemical and Biochemical Engineering, University of Western Ontario, London, Canada
[3] Institute of Production Science (wbk), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany
* Corresponding author (mthomps@mcmaster.ca)

Keywords: *Active Acoustics, Non-Destructive Testing, Signal Processing Techniques*

ABSTRACT

This study evaluated the capabilities of signal processing techniques and supervised learning models to differentiate between similar acoustic signals for the purpose of predicting the fiber orientation within a polymer composite. Projection of latent structures had poor predictive capabilities compared to artificial neural networks. A time-based analysis of the data demonstrated the frequencies of the signal change with time based on the sample fiber orientation. Processing the signal using the continuous wavelet transform, instead of the fast Fourier transform, improved the predictive capabilities of the artificial neural network. The artificial neural network acting as a regressor instead of a classifier improved the predictive capabilities for fiber orientation. Acoustic signals for samples with multiple orientations contain artifacts of the separate individual orientations. The results of this work highlight the capabilities for composite material predictions using active acoustic testing and the capabilities to integrate this technology into a continuous in-line system.

1 INTRODUCTION

The industrial digitization of a system using sensors and computational modelling methods for improved performance is of significant interest. The ability to acquire, analyze and react on data in real time to maximize production, while limiting errors associated with a process, is allowing standard manufacturing systems to operate with improved performance [1]. This digitization is still in the preliminary stages of implementation, meaning there are a variety of challenges industries must overcome. An early adopter of industrial digitization is the automotive sector, which will have significant use of composite materials. Artificial intelligence (AI) paired with technologies that can monitor composite materials allows for more discriminating monitoring tools since the AI tools can be trained from historical data. Ultrasonic spectroscopy using active acoustic testing was chosen for investigation due to low capital cost relative to other sensor technologies, ease of integration within manufacturing systems and non-destructive testing capabilities. With limited signal attenuation over relatively long distances, active acoustics utilizing the frequency-domain allows for large inspection areas for a given material [2]. The purpose of this study was to identify signal processing techniques capable of deconvoluting similar acoustic signals and combine them with robust AI models to correlate a changing material property, i.e. the fiber orientation. The capability in discerning material differences from acoustic signals will open the door for active acoustics to be used as an accurate and cost-effective monitoring tool for composite quality assurance.

2 MATERIALS AND METHODS

2.1 Specimen Preparation

Dow-Corning sized chopped glass fibers sized to 4 mm length, 14 μm diameter (data provided by supplier) was used as the reinforcement material. A 3D-printed grooved rig constrained the glass fibers to a single orientation in a specimen. Pressure sensitive adhesive paper was used to transfer the fibers into a 3D-printed mold at dimensions of 25.4 mm x 38.1 mm x 2 mm. The fibers were orientated to either 0, 15, 30, 45, 60 or 75 degrees of the length of the mold. West System 105 Epoxy Resin mixed with West System 207 Hardener supplied by West System (Michigan, USA), in a 3:1 volumetric ratio. The mixture was gradually poured into the mold to half its thickness, where heated air from a hot air gun (Weller) would dissipate entrapped air bubbles within the mixture. The specimens cured for 24 h, and then flipped over. Additional epoxy mixture was gradually poured into the mold, and cured for 48 h. This method allowed for the fibers to lie within the middle of the specimen at a single orientation. The process was adjusted to allow for specimens with two fiber orientations. After the specimens were flipped, fibers at a different orientation were transferred to the mold prior to the resin mixture being added. The overall glass content for each specimen was 15 wt %, divided evenly for the two orientation samples.

2.2 Acoustic Setup

The active acoustic setup for monitoring the fiber orientation is shown in Figure 1. Two 2.25 MHz acoustic transducers (Olympus) acting as the emitter and receiver were affixed to Polyether Ether Ketone (PEEK) rods. Silicone vacuum grease (Dow Corning) acted as a coupling agent between the sensors and the PEEK rods. The setup is designed for testing within an extruder system, the rods function as a buffer between the sensors and the heated extruder. The tips of the mounting rod were set on either side of the test specimen without an offset allowing for the transmission of the emitted acoustic signal through the thickness of the part.

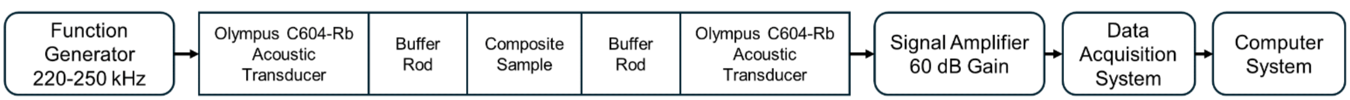

Figure 1. Acoustic testing setup used during testing of composite material.

An emitting sensor sends 31 Square waveforms in series ranging from 220 to 250 kHz in a 1 kHz step from a WaveForm generator (Agilent) with a cycle of 10 evolutions. The frequency range was chosen to target the calculated resonance frequency of the glass fibers (approx. 245 kHz). The received signal spans 700 μs, where it is amplified by a 60 dB gain using a signal amplifier (Mistras). A 10 MHz 12-bit 4-channel data acquisition system (DAQ) (National Instruments) records the signal, using a reference noise threshold of 0.1 volts. Using code developed in Python 3.7 with the SciPy and NumPy libraries, the recorded signals are processed using either the fast Fourier transformation (FFT), short time Fourier transformation (STFT) or continuous wavelet transformation (CWT). An example of each is shown in Figure 2.

2.3 Signal Flattening and Averaging

Each of the 31 transformed spectra were condensed into a singular spectrum for a given test. The spectra were first flattened into a 2-dimensional representation. The FFT can only be expressed in a 2D form (the frequency band and associated amplitude), and this was necessary for the STFT and CWT which consider time and frequency simultaneously with amplitude. As a result, the STFT and CWT were expressed as frequency-time bands and associated amplitude. This was done for all 31 spectra in each test. The 31 spectra are then converted into an averaged representative spectrum, which highlight the spectral regions that are consistent across all the tested frequencies while reducing redundancies. This process was repeated for all tests, and from which the averaged spectrums were mean centered and scaled across the entire testing dataset. More information about the averaging process can be found in previously published work [3].

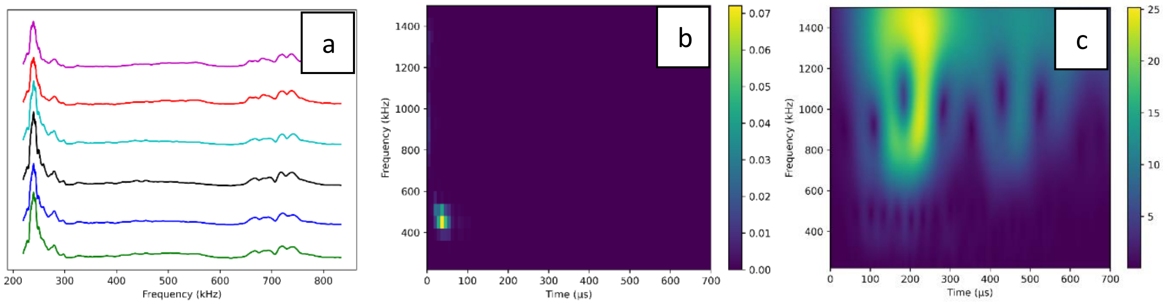

Figure 2. Signal representation of acoustic data for the various transformations. (A) Fast Fourier transformation. (B) Short time Fourier transformation. (C) Continuous wavelet transformation.

3 MODELLING

3.1 Projection of Latent Structures (PLS)

The averaged FFT spectra for the different fiber orientations were randomly divided into training and testing sets in a 75:25 split and then modeled using Projection of Latent Structures (PLS). The training set represents the data the model learns from to train the parameters, with the testing set used to validate the trained parameters. The number of components for the PLS model was chosen by comparing both the explained variance R^2 and predicted variation Q^2. Components were incrementally added until overfitting (R^2 continues to increase while Q^2 plateaus with each component). If the model demonstrated excellent classification capabilities on the testing datasets, the data were further divided into a 60:20:20 split of training, testing and prediction sets and then retrained.

3.2 Artificial Neural Networks (ANN)

The transformed time domain spectra, being either STFT or CWT, were divided into training and testing sets in a 75:25 split and then modelled using artificial neural networks (ANN). The input variables to these models were the mean-centered and scaled amplitude values at each frequency-time band described above and the output variables were the classification of the fiber orientation. Optimization of the ANN hyperparameters was done, by varying the number of hidden layers (2 to 7), model optimizer (RMSProp, Adam, SGD), activation function (ReLU, Softsign, Tanh) for each layer, learning rate (0.001, 0.01, 0.1) and number of epoch (1 to 500). For each layer, 50 nodes were chosen. The loss function was chosen to be the mean absolute error. Categorical cross-entropy was chosen as the loss function. The same training, testing, prediction data allocations as for the PLS models were considered for the ANN models.

3.3 Multiple Orientation

If the results for both the PLS and ANN based models demonstrated adequate testing capabilities, the multiple orientation filled samples were tested and evaluated. If the models were unable to learn from the unidirectional samples and accurately predict the multi-orientated ones, both the unidirectional and multi-orientated datasets would be combined and then randomly divided, with the model retrained to improve prediction. The model would be changed from a singular classification result to a probability distribution, outputting the probability it determines for each fiber orientation based on the inputted signal.

4 RESULTS

4.1 PLS with FFT Model

The results for the testing data results on the PLS regression model on the FFT data can be seen in Table 1. Overfitting began to occur after five components were used for the model. The results show the model was unable to predict any form of orientation based on the tested signal. Due to the poor predictive capabilities this technique was not considered for further evaluation.

Table 1. Projection of latent structures results of the fast Fourier transformation data.

0	15	30	45	60	75
25.76 ± 10.4	25.35 ± 6.04	26.00 ± 5.96	29.21 ± 8.63	39.46 ± 14.3	43.01 ± 18.8

4.2 ANN with STFT Model

The optimization of the hyperparameters for the ANN STFT model was found to be a 6-hidden layer model consisting of Softsign-ReLU-Softsign-Softsign-Softsign-Softsign as the activation functions for the respective layers. The SoftMax activation function was used for the output layer. The model optimizer was RMSprop, with a learning rate of 0.001 with 150 epochs. The testing data results on the model are shown in Figure 3, where a mean absolute error of 16.3 ^{o} was found on the classification results. The results show the model was somewhat accurate for a few orientations in classifying the signals to the respective orientation; however, the amount of error associated with the incorrect classifications resulted in the inclusion of a prediction set as well as the orientation distribution method not pursued.

4.3 ANN with CWT Model

Through early optimization of the hyperparameters it was found that the classification results seen in Figure 3 for the testing data resulted in a mean absolute error of 5.4 ^{o}, much lower than the STFT model. Due to the excellent classification of the testing set, the entire dataset further divided to include the prediction dataset and retrained. The resulting optimization led to a model with 3-hidden layers consisting of ReLU-ReLU-ReLU as the activation functions, and the SoftMax activation function for the output layer. The model optimizer was Adam, with a learning rate of 0.001 with 150 epochs. The results on the prediction data, seen in Figure 4(A) for the model resulted in a mean absolute error of 8.8 ^{o}. Due to most of the samples fiber orientation correctly predicted, this technique of using the ANN model with the CWT dataset was further evaluated with multiple orientation samples.

4.4 ANN with CWT for Multiple Orientations

The results for the classification of the samples with two fiber orientations on the model described in section 4.3 is shown in Figure 4(B). The classification results were very poor, with the model always predicting at least one orientation to be 0 ^{o}. This required the need to retrain the ANN models with the inclusion of multiple-oriented signals and using regression instead of classification. After training the ANN model with both datasets, the results for the unidirectional signals can be seen in Figure 5(A) and for the multiple orientation signals in Figure 5(B). The unidirectional samples mean absolute error decreased to 7.7 ^{o}, and for each of the six multiple orientation samples, both dominant fiber orientations were correctly captured by the regression.

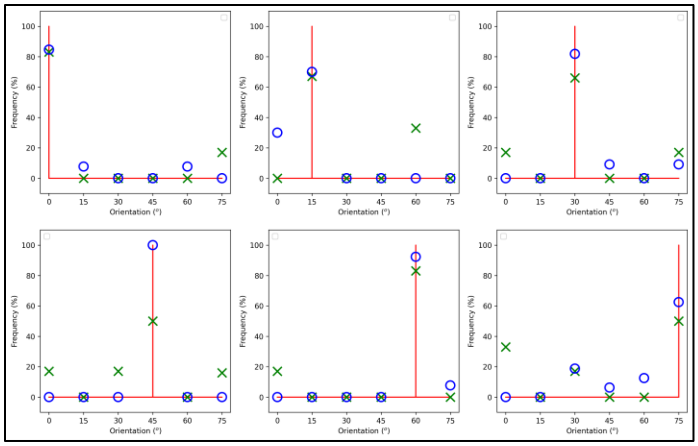

Figure 3. Results for the testing data of (x) artificial neural network on short time Fourier transform data and (●) artificial neural network on continuous wavelet transform data compared to actual orientation (—).

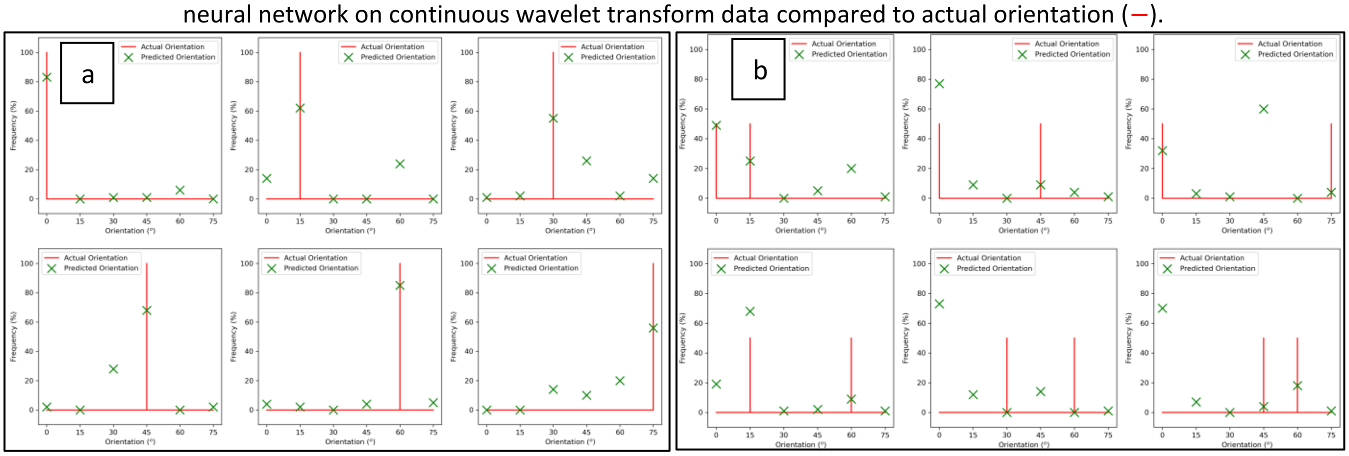

Figure 4. Results for predicted data of artificial neural network on continuous wavelet transform data trained from unidirectional data. (A) Unidirectional samples. (B) Multiple orientation samples.

5 DISCUSSION

The results of the different processing techniques and computational modelling showed clear differences in their capabilities of deconvoluting similar acoustic spectra. Including the time domain within the analysis, as opposed to only the frequency domain, vastly improved the capabilities. This suggests the affected frequencies are not changing uniformly over the signals time duration, however, are varying based on the orientation of the fibers. This would explain why the STFT and CWT were able to recognize changes that the FFT could not. The improvements seen in the CWT over the STFT indicate the need for maximizing the frequency information retained within the signal. The STFT, which uses finite time windows of the recorded signal limit the frequency resolution as only that portion of the signal is explored and transformed [4]. The CWT use longer time windows at the respective frequency bands allowing it to retain more of the frequency information than that of the STFT [4], [5]. This is interesting as although the inclusion of the time-domain vastly aided in differentiation the different orientations, the extent at which the frequency information changes with time was of greater importance and helps explain why the mean absolute error for the CWT was reduced to almost one-third of the mean absolute error of the STFT, the CWT has greater frequency resolution than the STFT. Finally, it was shown the signals for multiple orientations were quite different from the combination of the two unidirectional ones. The improvements to the ANN model when trained on both the singular and multiple orientation datasets indicate there are key differences in the scattering nature of the multiple orientation sample. The improvement from Figure 4(A) to 5(A) demonstrated the ANN model could identify and learn from artifacts seen in both data sets. Although the multiple orientation signals were not the combination of the two singular orientations, they still contained key artifacts that can be identified and aid in prediction.

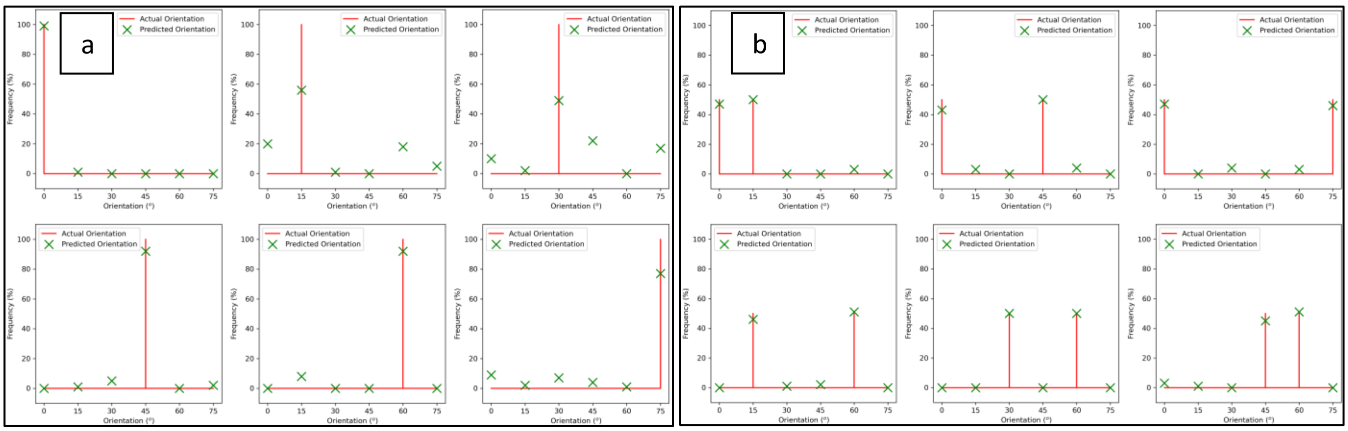

Figure 5. Results for predicted data of artificial neural network on continuous wavelet transform data trained on both unidirectional and multiple orientation data. (A) Unidirectional samples. (B) Multiple orientation samples.

6 CONCLUSION

Composite samples at six different orientations were tested with active acoustics to predict the orientation. The acquired signals were very similar to one another requiring the need for adequate processing techniques matched with modelling to adequately differentiate them. The use of amplitude-frequency information was found to have very limited capabilities, requiring the need for the time-domain to obtain accurate predictive capabilities. Using the CWT transformation with greater frequency resolution than the STFT was shown to have aid greatly in the model predictive capabilities. Orientation-based artifacts can be discovered and learned from the multiple-orientation signals that correspond to each of the fiber orientations. The use of the CWT paired with ANNs is a promising technique for fiber property information.

7 REFERENCES

[1] A. G. Frank, L. S. Dalenogare, and N. F. Ayala. “Industry 4.0 technologies: Implementation patterns in manufacturing companies”. *Int J Prod Econ*, vol. 210, no. January, pp. 15–26, 2019.

[2] O. Putkis, R. P. Dalton, and A. J. Croxford. “The anisotropic propagation of ultrasonic guided waves in composite materials and implications for practical applications”. *Ultrasonics*, vol. 65, pp. 390–399, 2016.

[3] A. D. Bedrosian, M. R. Thompson, A. Hrymak, and G. Lanza. “Developing a supervised machine-learning model capable of distinguishing fiber orientation of polymer composite samples nondestructively tested using active ultrasonics”. *J Adv Manuf Process*, vol. 5, no. 1, Jan. 2023.

[4] T. Bartosch and D. Seidl. “Spectrogram analysis of selected tremor signals using short-time Fourier transform and continuous wavelet transform”. *Annali di Geofisica*, vol. 42, no. 3. pp. 497–506, 1999.

[5] D. Komorowski and S. Pietraszek. “The Use of Continuous Wavelet Transform Based on the Fast Fourier Transform in the Analysis of Multi-channel Electrogastrography Recordings”. *J Med Syst*, vol. 40, no. 1, pp. 1–15, 2016.