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A DEEP-LEARNING-BASED METHOD FOR DAMAGE IDENTIFICATION OF COMPOSITE LAMINATES

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Abstract

Carbon Fiber Reinforced Plastic (CFRP) laminates have been widely used in aircraft primary structures. However, delamination, one most common damaging pattern in CFRP, could deteriorate its mechanical properties considerably. Guided-wave is employed for damage detection and the core challenge is to quantify the damage index through comparing baseline and monitoring signals. This process is highly expertise-dependent, and the threshold of damage index varies from case to case. Therefore, a deep learning method called Temporal Distributed Convolutional Neural Network (TDCNN) is proposed, which partly addresses the difficulties of deep-learning application in structural health monitoring, such as inadequate data samples, severe class skewness, and non-uniform data length. Moreover, LSTM module is innovatively used in this model to relate signal features over a chain of data fragments. TDCNN could dig damage features more effectively from original signals, and is less expertise-dependent. Through validation, this method proves to be efficient with a high accuracy.

Keywords: composite laminate; damage detection; guided-wave; convolutional neural network

1. General Introduction

Equipped with superior features over traditional metallic materials, such as high stiffness and strength ratio, tailorable design and integrated manufacturing, Carbon Fiber Reinforced Plastic (CFRP) laminates have been widely used in aircraft primary structures[1]. However, laminates are susceptible to delamination, which is induced by Foreign Object Impact (FOI) or manufacturing defects[2, 3], and its mechanical properties can be significantly impaired. For promoting flight safety, Guided-waves are employed as an approach of damage detection [4, 5]. Guided-waves are a specific case of surface-guided waves that travel within a thin (relative to propagating wavelength) single elastic and homogeneous plate of large areal extent [6, 7]. When they meet boundaries or damages during propagation, they reflect and scatter. By analyzing these suspected reflecting or scattering signals[8], the structural state, damaged or undamaged, or even the size of damage, could be diagnosed [9, 10].

The prevailing method now of guided-wave-based damage detection is called Damage Index (DI), which analyzes the signal variation before (baseline signals) and after (monitoring signals) suspected damaging event, and generalizes them into a single value. By comparing the value with a threshold, the structural state is estimated [11, 12]. DIs are presented in the form of combination of some guided-wave features, such as amplitude and energy. A single feature is hardly able to characterize structural state, therefore, in the form of combination of some features, namely DIs, are proposed. By far, there are at least 12 patterns of DIs [9, 10]. However, DIs are susceptible to environmental factors, such as temperature and loading state, and they are highly expertise-dependent and of poor performance in generality[13].

On the other side, machine learning is a potent tool to address problems like this kind. Especially, deep learning, due to the considerable breakthrough of artificial neural network in recent years, is being widely studied for damage detection[14-16] and localization[17-19]. However, there are some practical obstacles encountered when it is applied in the field of structural health monitoring.1, there is a severe shortage of training samples. Structures, which require SHM, are usually of high-value. It is impractical to generate sufficient physical damages for model training. An alternative method is to use artificial damages[13], but the magnitude can still not meet the requirement. For example, 516 pieces of data are generated through numerical simulation in finite element model of a composite plate[14]. Therefore, some other measures must be adopted; 2, The severe phenomenon of class skewness. Commonly the magnitude of monitoring data of undamaged case is considerably greater than that of damaged one, which easily misleads the deep learning model to make preferential estimation towards undamaged conclusion; 3， non-uniform data length. In practical application, the setting of data length varies from case to case. However, the uniform data length is essential as the input format for Convolutional Neural Network (CNN). There are some common measures, however, most methods (e.g., padding technology, sequence truncating technology, grouping technology, etc.) influences greatly the precision of the deep neural network (DNN) models. For example, the padding technology may result in the significant increase in convergence time of a DNN model[20], and gradient vanishing problem[21] caused by excessively long data; The sequence truncating technology may discard part of the discrete signal or reduce the sampling rate in the continuous signal exceeding a fixed length, which will inevitably lead to the loss of information[21, 22]; Grouping technology which groups the recordings that have the same length and won't cause any loss or distortion to their information as it doesn't change the original signals. But, as the distribution of the recording lengths is extremely uneven, a group may contain just one or two recordings, resulting in a big variety of batch sizes. Besides, there is some uncertainty in the prediction by a DNN model when it receives a recording with an unknown length[20].

A novel deep learning model, Temporal Distributed Convolutional Neural Network (TDCNN) [23] is proposed in this paper. It augments the amount of data samples to an extent to alleviate its severe shortage while concerning the issue of class skewness. It also unifies the data length before input and it takes not only the local features of each data fragment but also the overall trend into account to improve the accuracy of damage recognition.

2. Experiments

2.1 Brief Introduction of in Guided-Wave-Based Damage Monitoring

The layout of sensor network is like the pattern presented in Figure 1 (a). The sensor is made of PZT, which could work as either signal exciter or receiver due to its piezoelectric effect. When excited at proper electric voltage, the PZT chip (as exciter) oscillates to generate guided waves, which transmit over the structural panel to reach the destinating PZT chips (as receiver), and are transferred back to electrical signals for analysis. The straight line connecting any two PZT chips defines a monitoring path, and all PZT chips in the sensor network work like this in turn to have the structure scanned by the guided wave (Figure 1(b)). As signals of guided wave transmitting over a damaged area (named as monitoring signals) may differ from the ones along the exactly same path but before damage (baseline signals) is induced, the basic idea of damage detection based on guided-wave is realized by recognizing signal variations.

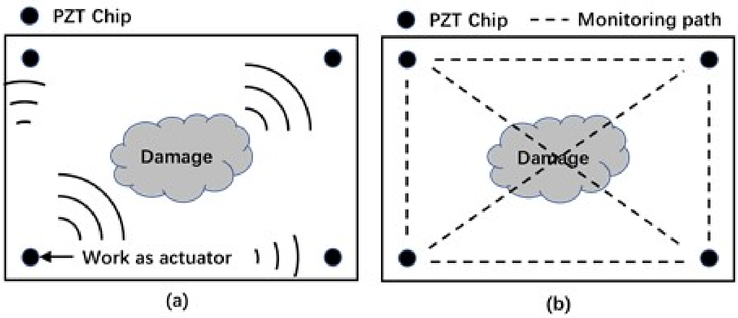

Figure 1 – Schematic configuration of PZT sensor network.

2.2 Stiffened Panel with Simulated Damage

The stiffened panel is made of CFRP CCF300/BA9916. Its geometric dimensions and layout of sensor network are sketched in Figure 2, from which total 28 monitoring paths are established. Damages in this case are not really induced as only one specimen is available, but simulated by attaching a M16 steel bolt on various positions of the surface[10]. Meanwhile, a number of signals are collected when the bolt is not attached on the panel, and the signals are labeled as "undamaged".

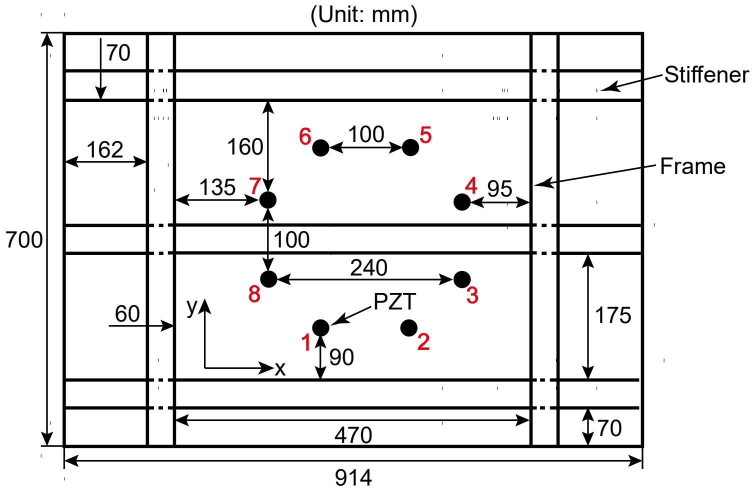

Figure 2 – Schematic demonstration of stiffen panel and sensor network

For the signals collected at the case of bolt attachment, it is impractical to label them all as "damaged" ones, because some monitoring paths in such cases are far from "damaged" position and their corresponding signals produced are less affected. Therefore, a threshold is needed to divide these signals into two classes, damaged and undamaged. In this paper, the damage index SDCC is employed and the threshold value based on SDCC is obtained according to following principles. Firstly, the signal, of which the SDCC value is the greatest in each case of bolt attachment, is labelled as "damaged". Secondly, the average value of SDCCs among signals collected in cases of NO bolt attachment is selected and multiplied by 4 as the threshold value. Any monitoring signal in that case, of which the SDCC value is greater than that threshold value, is labelled as "damaged". 750 pieces of signals are finally collected, and its composition is listed in Table 1. The distribution of SDCC values of all signals are demonstrated in Figure 3. It is seen that a relatively clear boundary exists to divide the damaged and undamaged into two parts.

Table 1 – Distribution of simulated damage monitoring data of composite stiffened plate

Type	Data length		Total
	6000	5000	
Damaged	39	215	254
Undamaged	111	385	496
Proportion of damage (%)	0.26	0.36	0.34

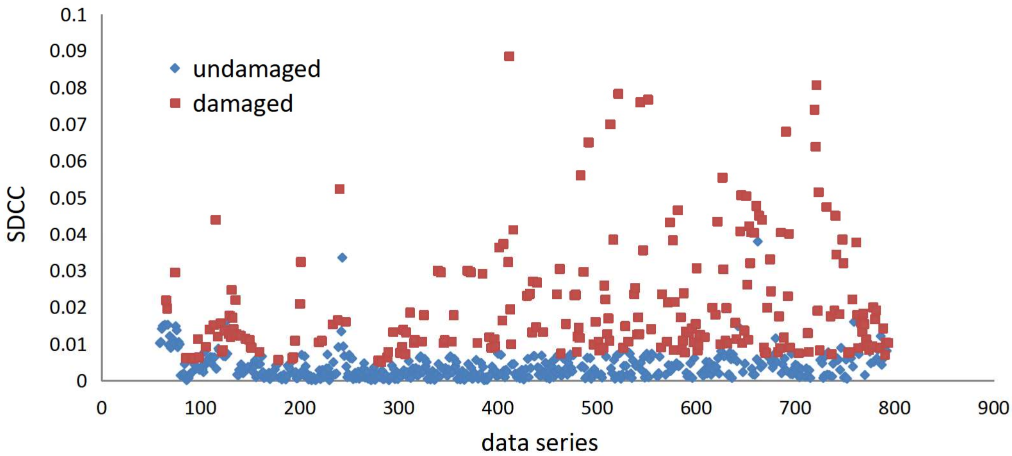

Figure 3 – SDCC value distribution of stiffened panel

2.3 Laminates with Impacted Damage

There are 10 laminates made of CFRP T300/BA9916. Its layup sequence is $[0/90/\pm 45]_s$ and thickness is 2mm. The geometrical dimension and the layout of sensor network is sketched in Figure 4. The excitation signal is a five-cycle tone burst modulated by a Hanging window. The excitation signal center frequency is selected as 90KHz and the sampling rate for sensor data acquiring is set at 10MHz. the collected signal length is 0.5ms. The impact damage is induced by drop weight, which is headed with a steel ball in diameter of 18mm.

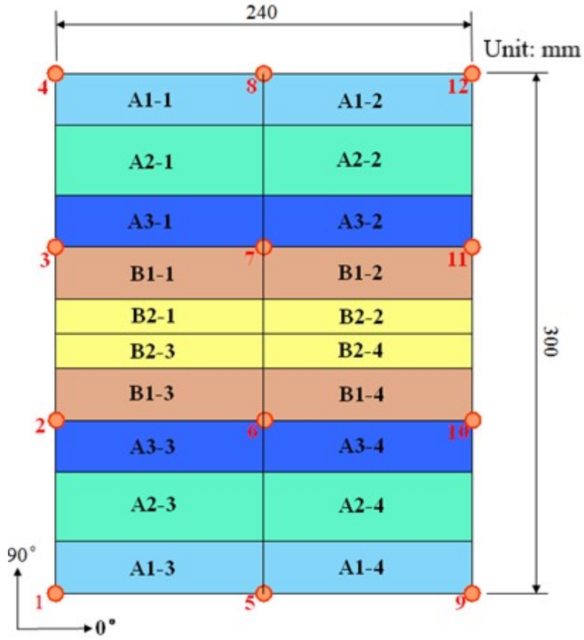

Figure 4 – Sensor network layout of composite laminate for impact damage introduction

Practical issues from 3 aspects are considered when introducing impact damages. 1, to produce more signals of damaged samples; 2, to enlarge the distance of neighbouring impacted positions in order to alleviate their influence on guided-wave transmitting; 3, to select the impact positions randomly. Therefore, according to these 3 requirements, the total amount of impacts and respective impacting positions are determined like this:

Firstly, divide these 10 laminates into 2 groups equally, and each laminate is partitioned into 20 regions as shown in Figure 4. In the first group (Laminate 1 to 5), impact damages are only induced in region A1, A3 and B2 (the dark region in Figure 4). Contrarily, impact damages are only induced in region A2 and B1 (the bright region in Figure 4) in the second group (Laminate 6 to 10).

Secondly, no more than 2 impacts are induced in each region in one laminate. Sum up the total amount of impacts in the same region over 10 laminates.

Finally, impact positions in each region according to the total impact amount are defined through Randn Function in Software Matlab, and then spread evenly over the 10 laminates.

The sizes of impacted damages induced by drop weight are generally greater than 170mm2. 137 impacts are eventually induced, and 1479 pieces of signals are collected. The highly-susceptible sensor network is defined as the one formed by 4 closest sensors surrounding the impacted position, while the lowly-susceptible one formed by the remaining sensors. However, in this case, there doesn’t exist such a clear line to partition the signals between the highly and lowly susceptible ones if they are presented in the form of SDCC (Figure 5). This is probably due to the fluctuation of damage size, and individuality differs from laminate to laminate. Therefore, the principle to label the signals in this case is to assign the signal with maximal SDCC value in the highly-susceptible sensor network as “damaged” one only. According to this principle, 137 pieces are labelled as “damaged”, accounting for 9.26% of the total signals. The SDCC value distribution according this labelling law is presented in Figure 6. In contrast with Figure 3, it is seen that the SDCC value is obviously higher. This is because SDCC, as well as other patterns of Damage Index, are susceptible to environmental factors, such as material systems, structural configuration, and sensor network.

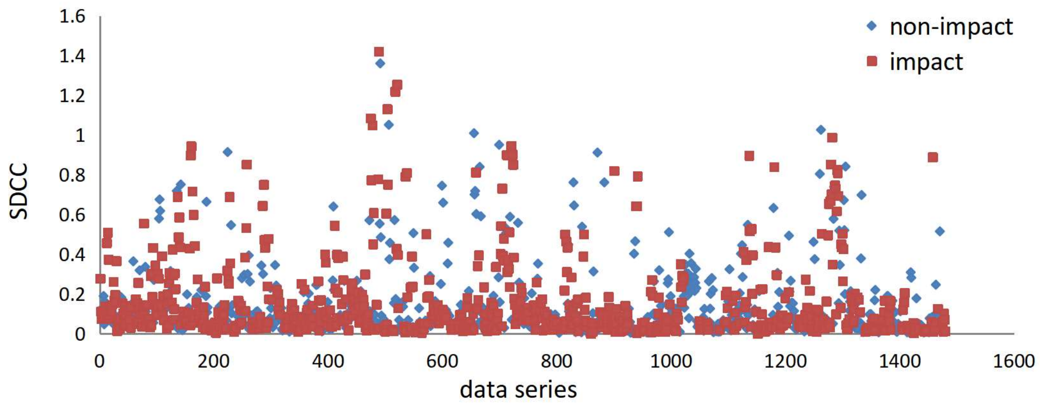

Figure 5 – SDCC distribution of 10 impacted laminates classed by impact and non-impact area

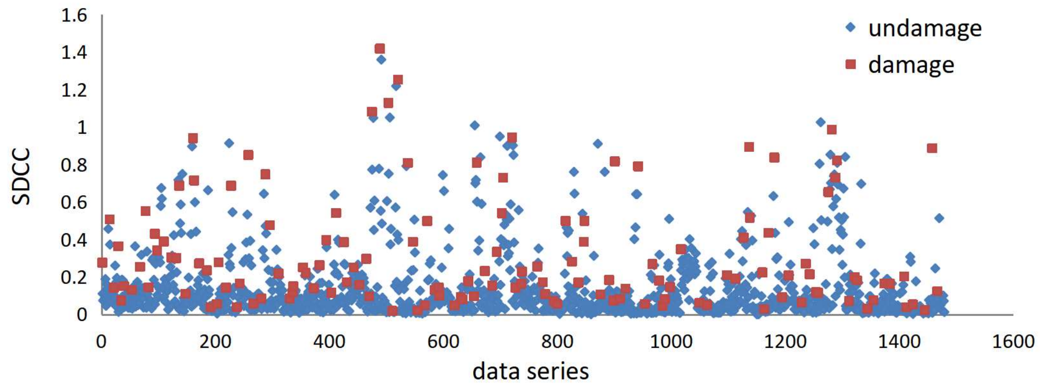

Figure 6 – SDCC distribution of 10 impacted laminates classed by damage and undamage

3. Deep Learn Model TDCNN

3.1 Data Augment and Class Skewness Alleviation

When deep learning methods are applied for guided-wave-based damage detection, some practical problems are encountered.

- severe shortage of data samples. Generally, over 100,000 samples are essential for model training[24]. The level of 1,000 samples collected in this paper is far apart. Therefore, some measures must be made to alleviate this negative effect;
- severe class skewness. In real application, the "damaged" signals generated are much less than the "undamaged" ones. For example, less than 10% in the case of impacted laminates. This easily misleads the deep learning model to make preferential estimation towards undamaged conclusion;
- non-uniform data length. In practical application, the setting of data length varies from case to case. However, the uniform data length is essential as the input format for Convolutional Neural Network (CNN).

In order to tackle above problems, the module of data augment is induced to increase the amount of data samples, as well as to alleviate class skewness.

- for the data, of which the length is shorter than the requirement, some meaning-less figures are added to extend its length;
- for the data, of which the length is longer, a strideCi of sliding window is defined in Equation (1) to cut out segments from original data (schematic illustration in Figure 7.

$$stride_{C_i} = \left\lceil MS * \frac{|samples\ labeled\ C_i|}{\max_{j=1}^{m} |samples\ labeled\ C_j|} \right\rceil \quad (1)$$

Where, MS is the maximum stride length. It is a super parameter, and its value ranges between 50 and 300 empirically. C is the label set, $C = [C_1, C_2, \ldots, C_m]$, where m is the pattern of label. In this paper, $C=[C_1, C_2]$=[damaged, undamaged]. The symbol of absolute value is to obtain the magnitude of that labelled samples. According to Equation (1), the amount of data samples for stiffened panel are augmented to 28230, in which “damaged” ones are 15240, accounting for 54%. For laminates, 35542 augmented samples are produced, in which “damaged” ones are 18481, accounting for 52%.

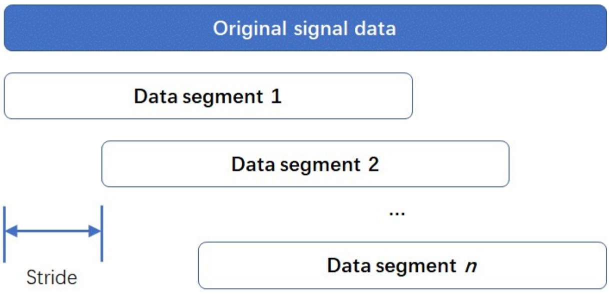

Figure 7 – Schematic diagram of using sliding window step to intercept the original data

3.2 Frame of TDCNN

The frame of TDCNN is illustrated briefly in dashed rectangle in Figure 8. “Distributed” in TDCNN signifies the partition of data segment into 10 fragments. The purpose of this procedure is to extract local features of each fragment by CNN with co-shared weights. “Temporal” represents the extraction of sequential features of all fragments by using LSTM module.

In detail, the network consists of a 6-layer Convolutional Neural Network (CNN) block, which takes the short fragments of each data as the input. Each CNN layer has a filter length of 32 and have 128 filters. In addition, before each convolutional layer we apply Batch Normalization and a rectified linear activation, adopting the pre-activation block design. We also apply Dropout[25] and Adam[26] between the convolutional layers to avoid over fitting, in order to improve the generalization of the model. Then, we use Bi-directional Long-Short Term Memory (Bi-LSTM) cells which can capture long term trend by utilizing the local morphological feature extracted from the fragments of the labelled augmented segments. Then, the predictions are made by a fully connected layer and a Softmax layer.

The conclusion of damage recognition is presented by taking recognizing result of each fragment into account. Here, a simple polling mechanism is involved.

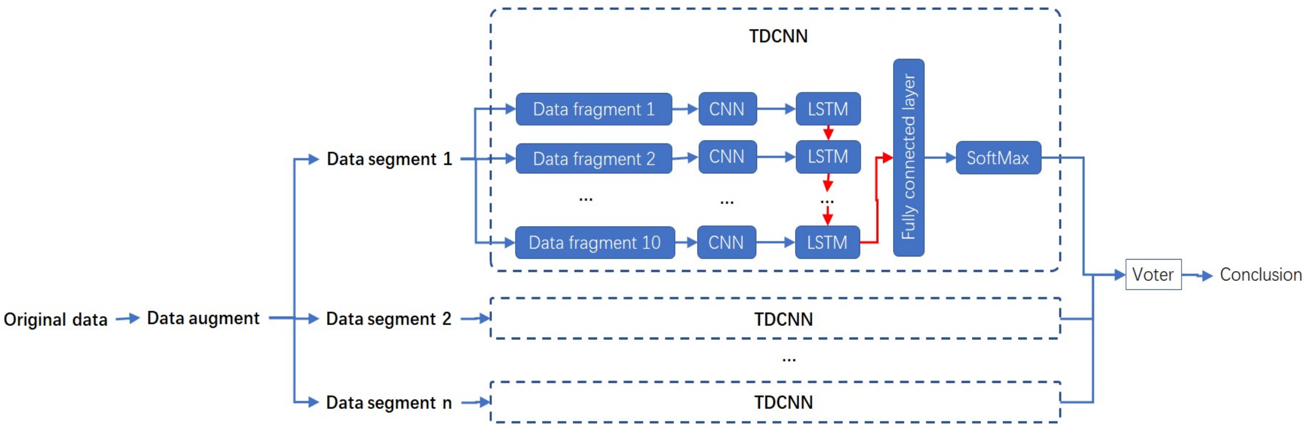

Figure 8 – Work flow of TDCNN based structural damage identification model

4. Analysis and Discussion

Here, we define the signals produced from stiffened panel as “Data of stiffened panel”, and corresponding TDCNN model as “Model of stiffened panel”. Similarly, we define the “Data of laminate” and “Model of laminate”.

Firstly, we validate “Model of stiffened panel” and “Model of laminate” by using respective simulated data. These simulated data are produced by overlapping a random signal, of which the amplitude is no more than 30% of original signal. 440 and 330 pieces of simulated data are produced for the validation of “Model of stiffened panel” and “Model of laminate”, respectively. The performance of these models is evaluated by indexes of accuracy, recall and F1, respectively (see Table 2 and 3). These indexes are defined in Figure 9, in which A is the “undamaged” samples who are recognized as undamaged, B the “undamaged” samples recognized as damaged, C the “damaged” samples who are recognized as undamaged, and D the “damaged” samples recognized as damaged.

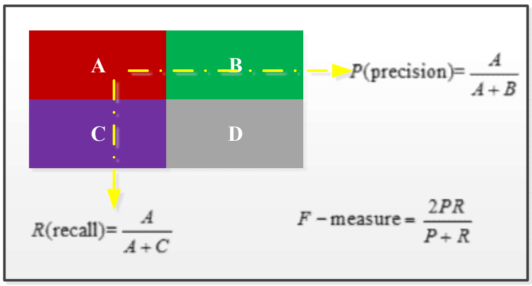

Figure 9 – Schematic of model performance evaluation index

Table 2 – Testing result of Stiffen Model based on Stiffen Data

Data	Amplitude	F1	Precision	Recall
1-110	0.1	1.0	1.0	1.0
	-0.1	1.0	1.0	1.0
	0.2	1.0	1.0	1.0
	-0.2	1.0	1.0	1.0
110-220	0.1	0.98	1.0	0.97
	-0.1	0.98	1.0	0.97
	0.2	0.98	1.0	0.97
	-0.2	0.97	1.0	0.94
220-330	0.1	0.95	0.90	1.0
	-0.1	0.95	0.90	1.0
	0.2	0.95	0.90	1.0
	-0.2	0.93	0.86	1.0
500-610	0.1	0.99	1.0	0.98
	-0.1	0.99	1.0	0.98
	0.2	0.99	1.0	0.98
	-0.2	0.96	0.94	0.98
Average		0.98	0.96	0.99

Table 3 – Testing result of Plate Model based on Plate Data

Data	Amplitude	F1	Precision	Recall
1-110	0.1	0.87	0.76	1.0
	-0.1	0.93	0.87	1.0
	0.2	0.81	0.68	1.0
	-0.2	0.86	0.8	0.92
110-220	0.1	0.89	0.80	1.0
	-0.1	0.92	0.92	0.92
	0.2	0.81	0.73	0.92
	-0.2	0.83	0.83	0.83
220-330	0.1	0.86	0.82	0.9
	-0.1	0.8	0.67	1.0
	0.2	0.78	0.69	0.9

Data	Amplitude	F1	Precision	Recall
	-0.2	0.83	0.71	1.0
Average		0.85	0.77	0.95

After self-validation, the “Model of stiffened panel” and “Model of laminate” are mutually tested using the counterpart’s data. The testing result is shown in Table 4.

Table 4 – Testing result for crossed validation

Model	Data	F1	Precision	Recall	Accuracy
Stiffen Model	Plate Data	0.17	0.09	1.0	0.10
Plate Model	Stiffen Data	0.08	1.0	0.04	0.68

From Table 2 to 4, it is seen that both models perform well in respective data set. However, the performances deteriorate significantly when tested in counterparts’ data. This is because the damage patterns, structural configurations, sensor network layouts will affect the guided-wave signal considerably, it is difficult to generalize a widely-applicable deep learning model for damage recognition based on guided-wave. However, it is impossible to develop customized deep learning model for every application case, as there are inadequate samples for model training. Therefore, the economic approach is to develop models for some typical scenarios, such as wing panel or door frame, based on a large amount of physical testing data. This enables the models to acquire a certain degree of generalizing capability, and applicable to damage recognition of other similar structures.

It is worth to emphasize that although both models perform well in respective data set, it is suspicious to over fitting because of the shortage of sample amount. Limited by expensive physical experiments, the practical method now is to produce simulated damages by means of foreign material attachment or numerical simulation, for example. However, whether the simulated damage can represent the physical one is rarely investigated by far[27-29].

5. Conclusion

- a novel deep learning model, TDCNN, is proposed for damage recognition of composite structures based on guided-wave. It augments the amount of data samples to an extent to alleviate its severe shortage while concerning the issue of class skewness. It also unifies the data length before input and it takes not only the local features of each data fragment but also the overall trend into account to improve the accuracy of damage recognition;
- TDCNN models work well in respective cases of stiffened panel and laminate, but perform poorly in crossing validation. This implies that it is difficult to generalize a widely-applicable deep learning model of damage recognition over most situations. The economic approach is to develop models for some typical scenarios based on a large amount of physical testing data. This enables the models to acquire a certain degree of generalization capability, and applicable to damage recognition of other similar structures;
- At least one author has registered as a Congress delegate by 15 July 2020.although the module of data augment could alleviate the severe shortage of data samples to some degree, there is a still pressing demand to generate more samples. The practical method now is to produce simulated damages by means of foreign material attachment or numerical simulation, for example. However, whether the simulated damage can represent the physical one is rarely investigated. Therefore, one further work is to search for a practical way to generate adequate samples to support the model training.

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7. Copyright Statement

References

[1] 杜善义. 先进复合材料与航空航天. *复合材料学报*, Vol. 24, No. 1, pp 1-12, 2007.
DU Shanyi. Advanced composite materials and aerospace engineering. *Acta Materiae Compositae Sinica*, Vol. 24, No. 1, pp 1-12, 2007(in Chinese).

[2] Talrejia R and singh C v. *Damage and failure of composite materials*, 1st edition, Cambridge University Press, 2012.

[3] Ip K H and Mai Y W. Delamination detection in smart composite beams using Lamb waves. *Smart Materials & Structures*, Vol. 13, No. 3, pp 544, 2004.

[4] Osmont D L, Dupont M, Lemistre M B and Gouyon R. Damage and damaging impact monitoring by PZT sensor-based HUMS. *Proceedings of Spie the International Society for Optical* 2000.

[5] 郭永跃. *基于压电晶片阵列的复合材料层合板损伤检测研究*. 哈尔滨工业大学, 2016.
GUO Yongyue. *Research on damage identification for composite laminates with piezoelectric wafer active sensors array*. Harbin Institute of Technology, 2016(in Chinese).

[6] 袁慎芳. *结构健康监测*, 第 1 版, 国防工业出版社, 2007.
Yuan S F.*Structure health monitoring and damage control*,1st edition,National Defense Industry Press,2007(in Chinese).

[7] Maierhofer C, Reinhardt H-W and Dobmann G. *Volume 2: Non-Destructive Testing Methods*, in *Non-Destructive Evaluation of Reinforced Concrete Structures*, Woodhead Publishing Series in Civil and Structural Engineering, 2010.

[8] 王强. *Lamb 波时间反转方法及其在结构健康监测中的应用研究*. 南京航空航天大学, 2009.
WANG Qiang. *Research on lamb wave time reversal technique and its applications in structural health monitoring*. Nanjing University of Aeronautics and Astronautics, 2009(in Chinese).

[9] Torkamani S, Roy S, Barkey M E, Sazonov E, Burkett S and Kotru S. A novel damage index for damage identification using guided waves with application in laminated composites. *Smart Materials & Structures*, Vol. 23, No. 9, pp 95015, 2014.

[10] Zhanjun W, Kehai L, Yishou W and Yuebin Z. Validation and evaluation of damage identification using probability-based diagnostic imaging on a stiffened composite panel. *Journal of Intelligent Material Systems and Structures*, Vol. 26, No. 16, pp 2181-2195, 2015.

[11] Yao P, Zheng B, Dawood M, Huo L and Song G. Real time monitoring of spot-welded joints under service load using lead zirconate titanate (PZT) transducers. *Smart Materials & Structures*, Vol. 26, No. 3, pp 35-59, 2017.

[12] 刘国强, 孙侠生 and 肖迎春. 基于 Lamb 波和 Hilbert 变换的复合材料 T 型加筋损伤监测. *复合材料学报*, Vol. 31, No. 3, pp 818-823, 2014.
LIU Guoqiang, SUN Xiasheng and XIAO Yingchun. Damage monitoring of composite T-joint using Lamb wave and Hilbert transform. *Acta Materiae Compositae Sinica*, Vol. 31, No. 3, pp 818-823, 2014(in Chinese).

[13] Dworakowski Z, Ambrozinski L, Packo P, Dragan K and Stepinski T. Application of artificial neural networks for compounding multiple damage indices in Lamb-wave-based damage detection. *Structural Control & Health Monitoring*, Vol. 22, No. 1, pp 50-61, 2015.

[14] Sbarufatti C, Manson G and Worden K. A numerically-enhanced machine learning approach to damage diagnosis using a Lamb wave sensing network. *Journal of Sound & Vibration*, Vol. 333, No. 19, pp 4499-4525, 2014.

[15] Worden K and Manson G. The application of machine learning to structural health monitoring. *Philosophical Transactions*, Vol. 365, No. 1851, pp 515-537, 2007.

[16] Atashipour S A, Mirdamadi H R, hemasian H and Amirfattahi R. An effective damage identification approach in thick steel beams based on guided ultrasonic waves for structural health monitoring applications. *Journal of Intelligent Material Systems and Structures* Vol. 24, No. 5, pp 584-597, 2013.

[17] Yan G. A Bayesian approach for damage localization in plate-like structure using Lamb waves. *Smart Materials & Structures*, Vol. 22, No. 3, pp 035012, 2013.

[18] Su Z and Lin Y. Lamb wave-based quantitative identification of delamination in CF/EP composite structures using artificial neural algorithm. *Composite Structures*, Vol. 66, No. 1-4, pp 627-637, 2004.

[19] Agarwal S and Mitra M. Lamb wave based automatic damage detection using matching pursuit and machine learning. *Smart Materials & Structures*, Vol. 23, No. 8, pp 085012, 2014.

[20] Liu Y, He R and Wang K. *Automatic Detection of ECG Abnormalities by Using an Ensemble of Deep Residual Networks with Attention*, in *Machine Learning and Medical Engineering for Cardiovascular Health and Intravascular Imaging and Computer Assisted Stenting*, Cham, 2019.

[21] Yan J, Qi Y and Rao Q. LSTM-Based Hierarchical Denoising Network for Android Malware Detection. *Security & Communication Networks*, Vol. 2018, No. 5249190, pp 1-18, 2018.

[22] Ratadiya P and Mishra D. An Attention Ensemble Based Approach for Multilabel Profanity Detection. *2019 International Conference on Data Mining Workshops (ICDMW)*. 2019. IEEE.

[23] Kant N A, Dar M R, Khanday F and Psychalinos C. Analog Implementation of TDCNN Single-Cell Architecture using Sinh-Domain Companding Technique. *IEEE International Conference On Recent Trends In Electronics Information Communication Technology*. 2016. IEEE.
[24] Chen F C, Jahanshahi R M R and NB-CNN. Deep Learning-based Crack Detection Using Convolutional Neural Network and Naïve Bayes Data Fusion. *IEEE Transactions on Industrial Electronics*, Vol. pp, No. 99, pp 1-1, 2017.
[25] 任沙. *基于深度学习的手写数字集特征提取算法*. 湖南师范大学, 2016.
REN Sha. *A feature extraction algorithm for handwritten digits based on deep learning*. Hunan Normal University, 2016(in Chinese).
[26] Kingma D and Ba J. Adam: A Method for Stochastic Optimization. *Computer Science*. 2014.
[27] Jeong-seok L, Gyuhae P, Chun-gon K and Farrar C r. Use of Relative Baseline Features of Guided Waves for In situ Structural Health Monitoring. *Journal of intelligent material systems and structures*, Vol. 22(2), No. pp 175-189, 2011.
[28] Sohn H, Park G, Wait e R, Limback N P and Farrar C R. Wavelet-based active sensing for delamination detection in composite structures. *Smart Materials and Structures*, Vol. 13, No. 1, pp 153, 2003.
[29] Andrew S R, Brian F E, Daniel B, Hundhausen R J and Park G. Active Piezoelectric Sensing for Damage Identification in Honeycomb Aluminum Panels. *Proceedings of the 24rd IMAC Conference on Structural Dynamics*. 2006.