Deep Acoustic Emission Detection Trained on Seismic Signals

Deep acoustic emission detection trained on seismic signals

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Abstract. In the structural health monitoring field, the acoustic emission technique (AE) is one of the most important and extensively applied methods. AE is a non-destructive testing (NDT) method which investigates acoustic ultrasonic waves caused by a sudden energy release due to cracks and micro-cracks opening in the investigated material, that can be analysed for structural health monitoring (SHM) purposes. Two essential qualities of the AE method are the capability to detect and locate the damage/crack, through a reliable and accurate onset time detection, and the ability to identify the cracking mode from recorded parameters. The aim of the present contribution is the automatic detection of the Onset time of AE signals with the help of artificial intelligence algorithms, more specifically artificial neural networks (ANN). Two different approaches have been used for automatic onset time detection. The foremost is related to adopting a convolutional neural network (Faster R-CNN) with a pre-training on a very large dataset, it was possible to employ the transfer learning (TL) technique. The main benefits of TL include: speed up training considerably, saving of resources, improving the efficiency and removing the need for a large set of labelled training data. The latter approach involves the use of a convolutional recurrent neural network (CRNN), developed in the field of the sound event detection (SED). The SED's objective is to identify sound events in a recording and their related starting and ending time instances. Considering the obvious parallelism between AE signals and seismic signals, the training of the two networks has been carried out with the latter, because of their larger availability. The dataset composed of seismic signals has been collected thanks to ITACA, Italian ACcelerometric Archive.

Keywords: Acoustic emission · Artificial Neural Network · Source location · Seismic signals · Crack location · Onset time determination.

Introduction

The importance of monitoring the structural safety of structures has been long stated [1,2,3,4,5,6,7]. Many in-service structures experience accumulated damage as a result of overloading and fatigue cracks as they age. To predict the service life of existing buildings and save maintenance costs, an engineering construction monitoring tool that is both trustworthy and thorough is necessary [8,9,10]. Non-destructive evaluation (NDE) techniques are frequently used to estimate the safety and performance of structures in their actual conditions [11,12,13]. NDE, also known as nondestructive testing (NDT) consist in evaluating the testing objects without altering or damaing it in any way. The main idea is to determine the presence of discontinuities or conditions that may affect the object's utility or serviceability [14]. One of the powerful techniques in NDT is acoustic emission (AE) [15,16]. AE testing is a technique to detect the formation and growth of cracks not only on the surface but also inside the material [17,18]. This technique measures the transient elastic waves that arise during any crack propagation event to monitor the structure in real-time [19]. Piezoelectric sensors can be used to detect elastic waves that are generated by the crack and that are propagating through the material [17]. These sensors transform the energy of the transient elastic wave into an electric waveform which is digitized and stored [1].

In the field of structural health monitoring and civil engineering the AE method has been widely used in particular[16,20,8] for concrete [21,11,19] and masonry structures [22,23]. In addition, the AE technique can also be used to monitor the emergence and development of material corrosion, such as the corrosion of steel bars in concrete [24], stainless steel [25] and stay cable high-strength steel [20].

The capacity to locate damage/crack based on AE events is one of the most important aspects of the AE technology [26,27,28,1]. Determining the source position allows for an accurate overall evaluation of a structure as well as previous knowledge of the precise damaged/cracked location [8]. In order to localize the damage, onset time determination of the transient signal is important, since it directly results in the accuracy of crack event location and source mechanism analysis [21,29,30,31,32].The time of arrival (TOA) approach, a typical method

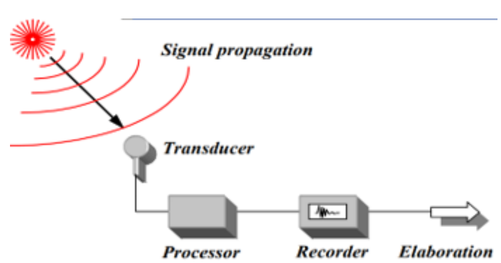


Fig. 1. AE technique

for two-dimensional source detection, has been broadly utilized to find AE sources in structures made of isotropic materials, on the basis of the detection time of arrival of signals at specific sensors. However, this method is not always ideal for practical monitoring as wave dispersion and attenuation effects may influence the definition of the TOA of the signal [33]. Any inaccuracies in the signal arrival time calculation will result in an additional decrease in precision in the estimated source locations.
Recently, many AE signal processing algorithms for automated onset time detection have been presented. The huge amount of data acquired during an AE test makes automatic onset detection a highly preferable state. Automatic detection methods include an improved approach based on the Akaike Information Criterion (AIC) [21], but also artificial intelligence techniques like artificial neural networks [8].
Another feature of the AE method is the capability to recognize the cracking mode from recorded parameters (e.g. amplitude, energy, and average frequency) [34,17,1]. Through this technique is possible to classify the active cracks in material into tensile and shear cracks.
In the present study, two different deep learning models are used to automatic detect the onset time. The two methods are described in the next section. Then, the networks are trained and applied to earthquake accelerograms, because of the parallelism with AE signals. The last part of this study presents the outputs provided by the two networks and the related metrics used to evaluate their performance.

Methodology

To automatically detect the onset time of acoustic emission signals, two different approaches were used. These are two deep artificial neural networks (ANN): a convolutional neural network (CNN), called *Faster R-CNN*, and a recurrent convolutional neural network (CRNN), developed in the field of the sound event detection (SED). Due to the similarity with AE signals, seismic signals were used to train ANNs for AE detection. Indeed, an earthquake represents the same phenomenon of AE but on a different scale. The data of earthquake accelerograms was obtained from ITACA database [35]. The onset time was manually identified on 410 seismic events time series on the basis of the operator experience [18]. The first method of automatic detection consists in fine-tuning a Faster R-CNN pre-trained on a very large dataset. Faster R-CNN [36] is a deep convolutional network used for object detection, which can accurately and quickly predict the position of various objects. The architecture of this network consists of 2 modules: a Region Proposal Network (RPN) and Fast R-CNN. An RPN is a CNN that produces regional proposals with different scales and aspect ratios, while Fast R-CNN [37] detects objects in the proposed regions. The merge of RPN and Fast R-CNN into a single network occurs by sharing their convolutional features. The advantage of this method is that by using a pre-trained network on a very large dataset, it was possible to use the transfer learning method [38]. This technique is an advanced Machine Learning method that allows reusing most of the parameters (weights) of a pre-trained model on a similar problem to the one to be solved, through the use of one or more levels of the same. In this way, the

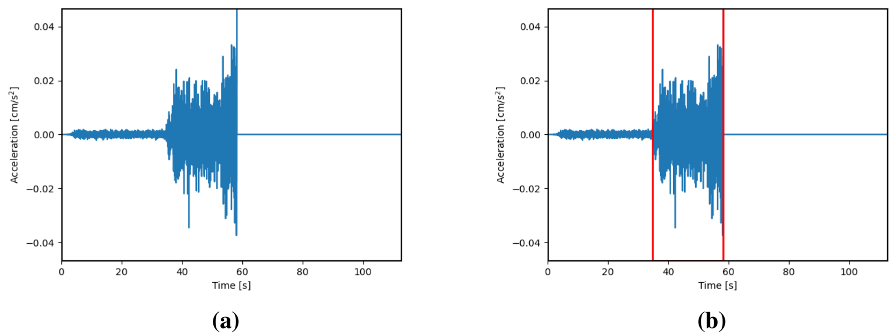
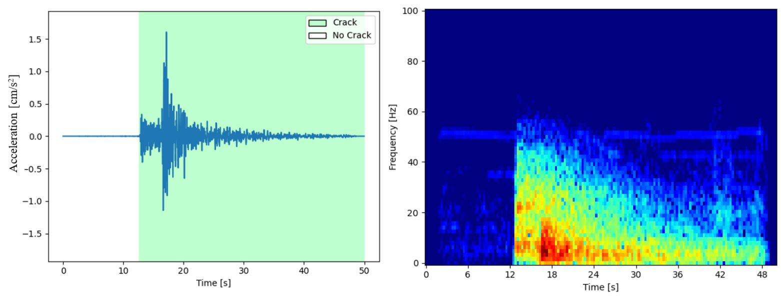


Fig. 2. An example of seismic signal extracted from the dataset and relative bounding box

training will dwell on the last layers, which are usually those dedicated to the classification and/or regression of the features obtained with the previous layers. The main benefits of this technique, which represents a great alternative to training ANNs from scratch, include: speeding up training considerably, saving computational resources, improving efficiency, and removing the need for a large set of labeled training data.

The dataset with 410 signals is divided into 328 (*sim* 80% of the dataset) for training and 82 (*sim* 20% of the dataset) for testing. The dataset contains the seismic events time series [18], e.g. a seismic signal is illustrated in Fig.2 (a). Furthermore, for each signal, a text file containing metadata, i.e. essential information for representing a bounding box of the seismic event (Fig.2 (b)). To help the network in detection, we force the signal plotting to zero once the absolute maximum is reached. The text file, on the other hand, contains the following information expressed in pixel coordinates and normalized according to the image size: label, coordinates (x,y) of box center, box width and box height. In order to label the data, it was previously necessary to identify manually the onset time.

The second method of automatically detection consist in a CRNN, adopted in the of the sound event detection (SED) field [39,40]. SED scopes are to recognize the sound events even considering their location on the time series. This makes them able to recognize the initial time of the signal as it is required for the scope of this paper. The CRNN is a popular network design for sound event recognition, especially for problems where temporal sequence modeling is useful. In a single design, CRNN combines the capabilities of a CNN, a RNN, and FC. Convolutional layers extract features, whereas recurrent layers learn the temporal development of the data. Lastly, the feedforward layers provide the probabilities related to the sound event activity on the basis of the output of the previous recurrent layer. Further details of the adopted SED model and hyperparameters can be found in [18].



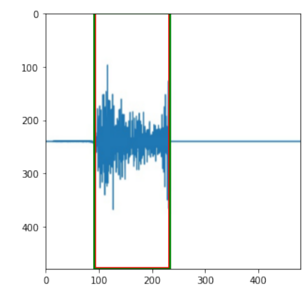
(a) **(b)**

Fig. 3. CRNN input

To evaluate intrinsic characteristics in both the temporal and frequency domains, the network takes inputs in the form of spectrograms. The vertical axis of a spectrogram displays the signal's frequency components, while the horizontal axis indicates the time dimension. Lastly, a color map graph represents the frequency component intensity, where the lowest intensity frequencies are represented in blue and the greatest are depicted in red. To train the SED-based network methodology, spectrograms based on the quick Fourier Transform method were computed using time series [41]. An example of a seismic accelerogram spectrogram is represented in Fig. 3 (b). The input data for supervised learning is labeled as follows (Fig.3 (a)): from 0 to the starting point of the signal'*No crack*' label is assigned, while the '*Crack*' label to time series representing the signal.

Results and discussion

Once the two networks have been trained, their performance can be evaluated by analyzing the outputs. In addition, performance evaluation metrics will be used for each network. An example of output returned by the first network is depicted in Fig. 4:



(a)


```
{'boxes': tensor([[ 92.9167,   0.0000, 232.8496, 477.7464]], device='cuda:0'),
 'labels': tensor([1], device='cuda:0'),
 'scores': tensor([0.9993], device='cuda:0')}
```


(b)

Fig. 4. Faster R-CNN output

In Fig. 4 (a) the green rectangle is the ground-truth box and the red represents the network prediction. Instead, in Fig. 4 (b) there is useful information to return to the expression in seconds of the onset time prediction. In order to evaluate network performance, two evaluation metrics were used: mean squared error (MSE) and mean percentage error (MPE). The metrics values obtained are presented in Table 1:

MSE	MPE
0.3026 s^2	3.54 %

Table 1. Faster R-CNN metrics

MSE measures the average squared difference between the estimated values and the actual value; whereas, MPE is the computed average of percentage errors by which estimated values differ from actual values.
The second approach returns as output the initial and final instant of the event and its label. An example of a graphical representation of the network output is depicted in Fig. 5:
When the reference annotation and system output are compared, the properly and incorrectly recognized events are counted in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) (FN). In this situation, the metrics employed are F-score and error rate (ER). They are defined as follows, depending on the numbers of accurate

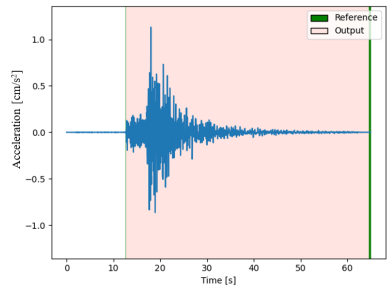


Fig. 5. SED output

and incorrect detections:

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$F = \frac{2PR}{P + R} \tag{3}$$

$$ER = \frac{S + D + I}{N} \tag{4}$$

ER considers a combined occurrence of a false positive and a false negative as a single substitution error S, whereas P, R, and F-score regard and count the mistakes independently. The remaining insertions I are false positives unaccounted for in S, while the remaining deletions D are false negatives unaccounted for in S [39]. An ideal SED method has an ER of 0 and F of 1. The metrics values obtained are presented in Table 2:

	Error rate (ER)	F-score
ideal values	0	1
obtained values	0.012080	0.99197

Table 2. CRNN metrics

Conclusions and future developments

Although both networks achieved the intended goal, for the first one, the Faster R-CNN [37], it was necessary to introduce a forcing in the plotting of the accelerograms to help the network in detection. Among the two networks adopted, the second one, i.e. the CRNN [39], appeared to be the more advantageous one for the case under consideration. This is due to the fact that, in addition to having achieved values of the evaluation metrics very close to the ideal values, the network is also able to identify the cracking mode. In reality, the adopted CRNN approaches the problem of the onset time detection as a classification problem. Thus, it is possible to use it as classifier for different crack typologies on the basis of the signal shapes in such a way that it can be employed for the onset time detection and both for the crack classification. Ultimately, the suggested work's future developments could be using the presented strategy to classify fracture's mode. Furthermore, the proposed method can be applied and test on experimental data obtained from laboratory experiments on concrete samples.

Acknowledgments

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