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Onset Time Detection of Acoustic Emission Signals for Structural Monitoring with Deep Learning

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Abstract. The Acoustic Emission (AE) technique is widely employed in structural engineering as a non-destructive testing method for detecting defects and monitoring structural health. AE captures signals emitted by structures due to damage, providing valuable insights into cracks propagation and durability. This study focuses on the identification of the onset time of AE signals, a critical parameter for structural monitoring. Traditional signal analysis methods are often inadequate due to background noise similarities, necessitating novel approaches. In this study, the signal onset time identification is tackled by performing a one-dimensional segmentation task on the AE time series. To do so, a U-net is implemented, which is an artificial Neural Network (NN) specific for segmentation. The dataset comprises signals obtained from a Pencil Lead Break (PLB) test, closely resembling AE signals. The U-net assigns probabilities to each signal point, enabling accurate differentiation between the AE signal and background noise. Averaging probabilities with neighboring points mitigates false positives. The presented methodology offers real-time, continuous monitoring without the need for extensive preprocessing or temporal window separation, making it practical for AE-based structural health monitoring.

Keywords: Acoustic Emissions · Structural Health Monitoring · Deep Learning · Crack Location · Artificial Neural Network · Time Series · Segmentation.

1 Introduction

The Acoustic Emission (AE) technique [1] is extensively utilized in structural engineering to detect defects and imperfections in structures. Its popularity stems from being classified as a non-destructive testing (NDT) method [2], allowing for structural monitoring without the need for sampling or causing any damage [3,4]. Additionally, AE is a passive monitoring technique that records signals emitted by the structure as a result of structural damage, without the requirement of applying external stimuli. These inherent characteristics make AE an invaluable option for monitoring crack propagation and assessing the damage to structural elements during service conditions. Furthermore, the utilization of acoustic emissions enables the estimation of the energy released during fracture propagation, providing valuable insights into the durability performance of the structure [5].

The principle behind the AE technique is that the formation and propagation of a fracture release energy, generating an elastic wave that propagates through the medium [6,7]. Through piezoelectric sensors, which are coupled to the material, it becomes possible to convert the measured elastic wave into an electrical voltage, and subsequently transform it into a digital signal. AE signals contain vital information about fractures, enabling the localization and characterization of structural damage. This article focuses on the identification of the onset time of AE signals, a critical parameter in structural monitoring. By employing an adequate number of sensors and utilizing the triangulation technique, the onset time can assist in pinpointing the fracture location [8].

Over the years, various techniques have been explored for onset time identification in AE signals [9,10,11]. However, this remains a challenging task, particularly in monitoring concrete structures, where background noise often exhibits similar frequencies and amplitudes as the AE signals. Traditional signal analysis methods, involving the application of filters, are often unsuitable as they risk compromising the main signal and leading to information loss. In this study, the identification of the onset time was approached using a U-net [12], an artificial Neural Network (NN) commonly employed in segmentation tasks. First, we tackled a one-dimensional segmentation problem, by assigning each time step a label that indicates whether it belongs to the background noise or AE signal. Then, the onset time is retrieved by looking at where the predictions change from background to signal.

The dataset utilized for training and testing the neural model comprises signals obtained through a Pencil Lead Break (PLB) test [13]. This widely employed test is specifically designed for calibrating instrumentation used in acoustic emission monitoring. During the PLB test, the tip of a pencil is intentionally fractured against a monitored material block, and the resulting elastic waves propagating through the medium are recorded as signals. The advantages of this approach are that (i) the obtained signals exhibit a remarkable resemblance to AE signals, ensuring their relevance and applicability, and (ii) the precise origin point is known a prior, since it coincides with the fracture point in the pencil lead.

The U-net architecture was employed to assign a probability to each point in the signal, determining its association with either the AE signal or the background noise. To mitigate

the occurrence of false positives resulting from intense background noise oscillations, the assigned probability for each point was smoothed by averaging it with the probabilities of its 50 neighboring points. The significant advantage of this technique lies in its ability to be applied directly to continuous signals, eliminating the need for preprocessing and temporal window separation required by other commonly used onset time identification methods. This characteristic makes the presented methodology an effective and practical option for continuous, real-time monitoring using the acoustic emission technique.

2 Methodology

The identification of onset time is of utmost importance in the analysis of AE signals as it enables the determination of the precise location of fracture occurrence. Under the simplified assumption that the elastic wave generated by the fracture propagates in a straight line from the fracturing source to the sensors where it is recorded [8], the time for a stress wave to travel from the source at (x_0, y_0, z_0) to a transducer A located at (x_A, y_A, z_A), considering c the wave speed can be calculated as:

$$T_A = \frac{\sqrt{(x_0 - x_A)^2 + (y_0 - y_A)^2 + (z_0 - z_A)^2}}{c} \tag{1}$$

Due to the lack of knowledge about the absolute time of the source event, Equation 1 cannot be directly used for determining the source location. However, the relative arrival times Δt_A at each transducer are known. It is possible to rewrite the equations by subtracting the wave arrival time from a reference transducer (T_R) from both sides of each equation. This allows us to calculate the relative signal arrival time Δt_A to transducer A considering the reference transducer T_R as follows:

$$\Delta t_A = T_A - T_R = \frac{\sqrt{(x_0 - x_A)^2 + (y_0 - y_A)^2 + (z_0 - z_A)^2}}{c} - T_R \tag{2}$$

The equation involves four unknowns: the coordinates representing the fracture position (x_0, y_0, z_0) and the propagation velocity of the elastic wave in the medium, denoted as c. This implies that by measuring the elastic wave with at least four piezoelectric sensors, it is possible to construct a system of four equations with four unknowns that can be solved to obtain the exact position of the fracture.

2.1 Dataset description

The dataset utilized to train and test the neural network model is taken from [13]. It is a collection of 298 time series generated through a Pencil Lead Break (PLB) test on a concrete beam: a 0.3 mm HB pencil lead is intentionally broken on the surface of the beam to simulate the propagation of elastic waves caused by the formation of a crack. Signals are sampled at 1

MHz ($\Delta t = 1\ \mu s$ between two consecutive time points), and each record has 1024 time steps. The onset time is fixed at $256\ \mu s$, so it is possible to assign the label 0 (*background*) to all the points at $t < 256\ \mu s$ and 1 (*signal*) to the others.

We joined all the time series in a random order, to create a unique one. Then, we split it into training and validation sets (respectively the first 75% and the last 25% points).

2.2 Model implementation and training

We introduced a novel method based on deep learning to identify the onset time. We framed the problem as a one-dimensional binary segmentation task: each point of the AE wave is assigned a label that indicates whether it belongs to the background noise or the signal. The model is based on the U-net architecture [12].

The U-net is a Convolutional Neural Network (CNN) designed for segmentation tasks (natively on images), where the goal is to assign a class label to each pixel. Its structure combines an encoder-decoder design, enabling it to capture both local and global contextual information. It comprises two main components: the contracting path (encoder) and the expansive path (decoder). The key feature in the U-Net is the inclusion of skip connections, which directly connect feature maps from the contracting path to corresponding blocks in the expansive path. These enable the decoder to access and leverage multi-scale information from earlier stages of the network, facilitating precise and detailed segmentation. At the end of the expansive path, a 1×1 convolutional layer with a softmax activation function is employed to generate a pixel-wise probability map of belonging to the specific class.

We adapted it to process one-dimensional inputs (Figure 1). For each time step in the input signal, the NN outputs the probability that the observed value corresponds to an AE signal. By setting a threshold to these probabilities, we can assign to each time step the label *background* or *signal*. The predicted onset time (also called *event* in this work) is identified when there is a switch from *background* to *signal* (Figure 2).

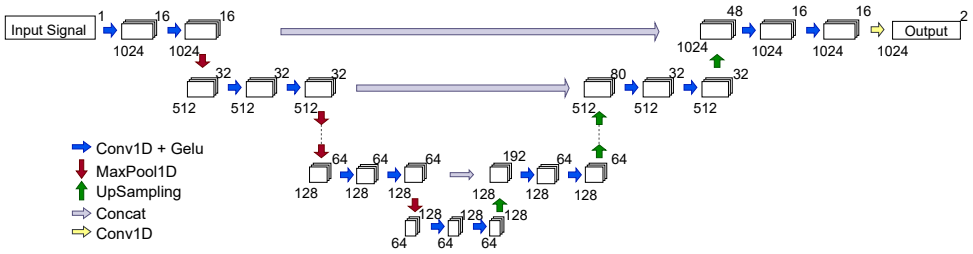


Fig. 1. Architecture of the U-net model implemented in the analysis of AE signals. The output is the probability for each time stamp to be *signal* rather than *background* noise.

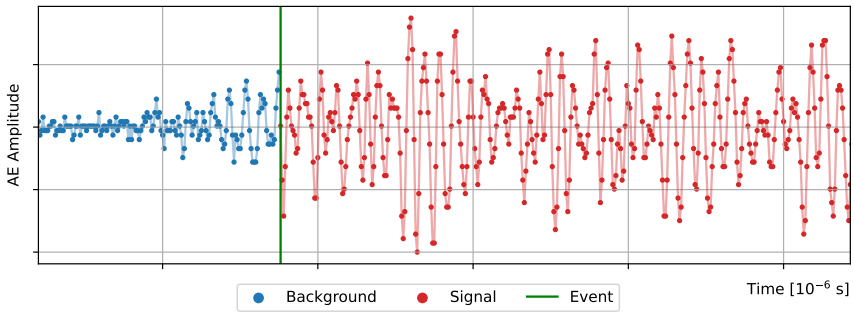


Fig. 2. Each point in the time series is classified as *background* or *signal* by a U-net. The onset time (*event*) is detected when the label changes from *background* to *signal*.

Model training was conducted by setting a maximum number of 200 epochs, with an early stopping based on the validation loss with patience of 20 epochs. We used the ADAM optimizer with a learning rate of 10^{-4}, and a binary cross-entropy loss. We tested different variations of the U-net architecture by changing the input sequence length (that is the number of time stamps of the input time series), and the depth of the model (i.e. the depth of the encoder/decoder). Metrics on training and validation sets are displayed in Table 2.

2.3 Rolling Average correction on the U-net predictions

Given an input signal $s = (s_1, \dots s_N)$, the U-net network generates a vector $q = (q_1, \dots q_N)$ where each q_i represents the probability of s_i being classified as an *signal*. To get the final label, we set a threshold T, and all points with a probability $q_i > T$ are classified as *signal*. However, if the network outputs rapidly change, this can lead to errors that cause the algorithm to detect multiple spurious *events*, as shown in the top panel of Figure 3.

We decided to smooth the U-net output by applying a rolling average with a window size of 50 time steps (center panel in Figure 3). Then, we set the threshold $T = 0.5$ on the smoothed values, and we assigned at each time step the label $\hat{y}_i = 1$ if $\bar{q}_i \geq 0.5$, and $\hat{y}_i = 0$ otherwise.

3 Results and Discussion

In this section, we present the results obtained by our analysis. Table 2 shows the metrics recorded during the training of different models, varying the length of the input sequence and the depth of the U-net architecture. All the models achieve comparable performances and converge during the training (Figure 4 shows the training history for the model with a sequence length of 1024 and a depth of 4, but all the architectures show a similar behavior); early stopping is needed, since the models are prone to overfit.

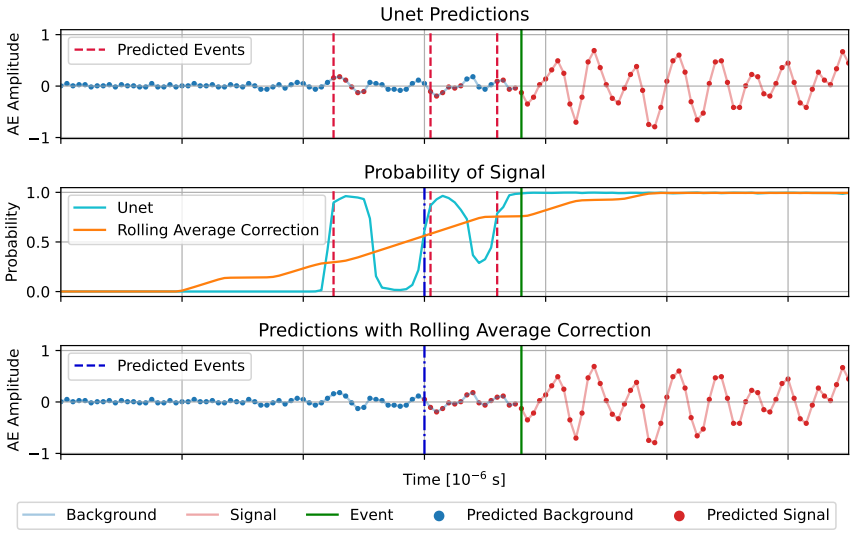


Fig. 3. Effects of the rolling average correction on the U-net outputs. [Top] Predictions directly with the model output probabilities. [Center] Comparison between the U-net probability and the smoothed version by performing a rolling average with a window of 50 time steps. [Bottom] Predictions after the correction.

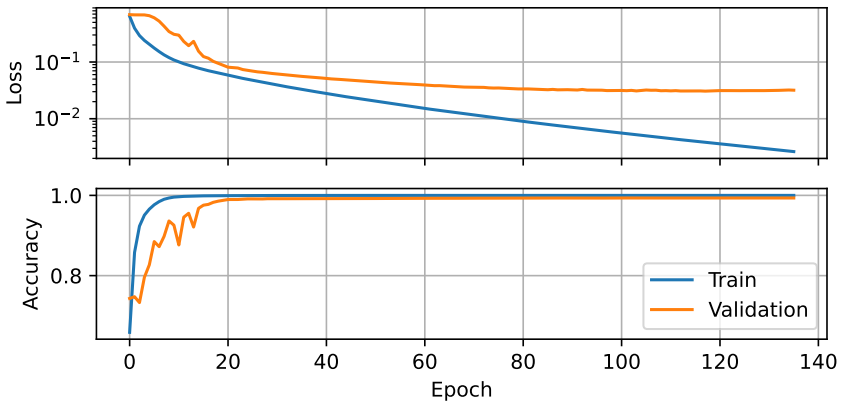


Fig. 4. Training and validation loss and accuracy for the U-net model with 1024 time steps in the input sequence, and a depth of 4. The other models show similar behaviors.

Model		U-net Predictions		R.A. Correction	
Seq. Len.	Depth	Train	Validation	Train	Validation
2048	4	0	19	0	1
2048	3	0	57	0	10
2048	2	191	242	9	13
1024	4	0	21	0	2
1024	3	0	56	0	7
1024	2	485	270	32	24
512	4	5	22	2	2
512	3	0	70	0	5
512	2	625	282	37	21

Table 1. Number of spurious *events* detected by directly using the U-net outputs, or by applying a rolling average (with a window of 50 time steps) to smooth the probabilities. This correction greatly reduces the number of false positive onset times detected, especially in the validation set.

The obtained results demonstrate a high level of performance; however, some considerations need to be taken into account. These metrics assess the ability of the model to correctly classify each point in the time series as either an *signal* or *background*, but they can be misleading in the specific context of onset time identification. In fact, in this setting achieving a high accuracy does not necessarily guarantee the precise localization of the *events*. Far away from the real onset times, it is relatively easy to classify most points as belonging to either the *signal* or *background*; the challenge lies in accurately identifying the transitional points between the two. Since these constitute a small fraction of the entire time series, even if a few misclassifications occur within this window, the overall evaluation metrics may still yield high scores. However, these mistakes can lead to significant errors in determining the onset time and, consequently, accurately locating the crack. This issue is further exacerbated by the high propagation speed of acoustic waves in structural materials, such as concrete, which can reach velocities of up to 4000 m/s. In addition, the algorithm finds an *event* when there is a transition between *background* and *signal*. In this context, small groups of points erroneously labeled cause the detection of spurious onset times, as shown in the top panel of Figure 3.

In order to reduce the number of false positive *events* detected, we smoothed the output of the network with a rolling average, as described in Section 2.3. Table 1 shows how this approach greatly reduces the number of spurious *events*.

Another important quantity to monitor is the difference Δt in time between the real onset and the predicted *event*, as illustrated in Figure 5. This evaluation directly relates to the final precision achievable in fracture localization, which is the final objective of the research.

Table 3 presents the average absolute distances between real and predicted onset times in μs for all the tested neural networks. The table includes results obtained from both direct classifications using the probabilities calculated by the U-net and the smoothing method em-

Model		Train						Validation					
Seq. Len.	Depth	Loss	Acc	MAE	RMSE	F1	AUC	Loss	Acc	MAE	RMSE	F1	AUC
2048	4	0.006	1.000	0.006	0.007	1.000	1.000	0.037	0.992	0.014	0.084	0.995	0.997
2048	3	0.010	1.000	0.010	0.013	1.000	1.000	0.065	0.985	0.026	0.115	0.990	0.991
2048	2	0.031	0.997	0.028	0.056	0.997	1.000	0.108	0.973	0.052	0.153	0.980	0.986
1024	4	0.004	1.000	0.004	0.005	1.000	1.000	0.031	0.994	0.011	0.072	0.996	0.998
1024	3	0.007	1.000	0.007	0.010	1.000	1.000	0.061	0.986	0.021	0.109	0.991	0.991
1024	2	0.055	0.991	0.047	0.096	0.991	0.999	0.103	0.972	0.062	0.151	0.978	0.990
512	4	0.012	0.999	0.008	0.019	1.000	1.000	0.032	0.993	0.015	0.072	0.996	0.998
512	3	0.008	1.000	0.007	0.013	1.000	1.000	0.059	0.985	0.023	0.112	0.990	0.993
512	2	0.052	0.987	0.040	0.095	0.990	0.999	0.092	0.971	0.054	0.148	0.978	0.993

Table 2. Metrics on the training and validation sets for different lengths of the input sequence and varying the depth on the U-net.

ploying the rolling average described in Section 2.3. The application of the correction on the model outputs improves the precision of the proposed method, and the best model results in an average error of 7μs (which reflects in an error in position around 2.8 cm considering an acoustic wave propagating at 4000 m/s). The gain due to the correction is related to the reduced number of false positive *events* detected since spurious onset times increase the mean difference with the correct ones.

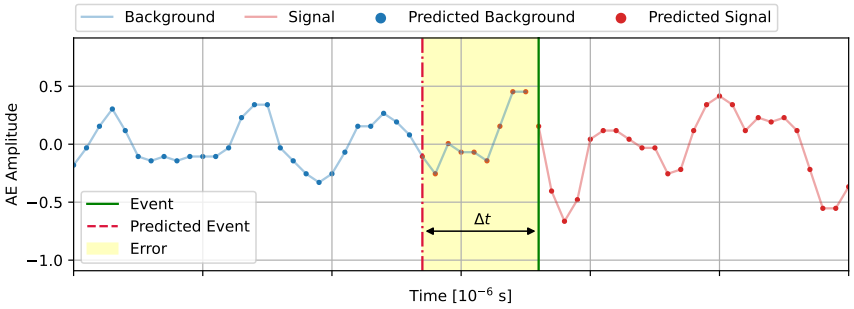


Fig. 5. The distance between the real onset time and the predicted one: the metric for the evaluation of the models.

It is worth noting that the achieved high precision is obtained without the need for data preprocessing or considering the potential accuracy enhancement that can be achieved by incorporating multiple signals from piezoelectric sensors simultaneously. Although these techniques have the potential to further improve the precision of the method, they are beyond the scope of this study, which focuses on developing a deep learning technique for real-time identification of the onset time in continuous signals.

Model		U-net Predictions		R.A. Correction		
Seq. Len.	Depth	Train	Validation	Train	Validation	Δx (cm)
2048	4	0	14.63	0	7.03	2.812
2048	3	0	86.27	0	21.34	8.536
2048	2	142.83	201.98	4.74	28.56	11.424
1024	4	0	25.58	0	10.62	4.248
1024	3	0	81.71	0	22.12	8.848
1024	2	211.24	207.67	19.59	35.64	14.256
512	4	5.46	33.53	3.39	9.01	3.604
512	3	0.11	89.39	0.11	16.51	6.604
512	2	242.55	210.33	25.37	36.02	14.408

Table 3. Average Δt (10^{-6} seconds) between the predicted and the real onset times. A greater number of spurious detected *events* leads to a higher error, showing again the importance of the rolling average correction. For the validation set with the correction, it also displayed an estimate of the error in the position, assuming an acoustic wave propagating with a speed of 4000 m/s.

4 Conclusions

In this work, we presented a deep learning-based approach for the identification of the onset time in acoustic emission signals. The proposed method makes use of the U-net architecture and demonstrates promising results in accurately classifying acoustic emission events and distinguishing them from background noise. By assigning probabilities to each point in the signal and applying a threshold-based heuristic, the method achieves effective *event* identification capabilities.

The evaluation of the models was carried out using specific metrics tailored to the problem at hand, particularly focusing on the reduction of spurious onset times and the temporal distance between the real and predicted ones. The results show the ability of the proposed method to accurately localize fractures, with an average error of $7\,\mu s$ achieved through the application of a sliding average correction on the network output.

It is important to note that the proposed technique showcases high precision without requiring data preprocessing, and without considering the potential benefits of multi-sensor fusion techniques. Further improvements in precision could be achieved by incorporating these procedures, which may be explored in future research.

Overall, the developed deep learning technique provides a valuable tool for real-time identification of the onset time in continuous acoustic emission signals. Its potential applications extend to various fields, such as structural health monitoring and non-destructive testing, where accurate fracture localization is crucial. The presented method serves as a foundation for future advancements in this area and opens up possibilities for further research and refinement of the approach.

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