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Localized damage detection in wind turbine rotor blades using airborne acoustic emissions

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Abstract. The human-induced climate change is one of the biggest threats for modern society. Wind energy turbines play a key role in the necessary transformation of the energy sector and their reliable, low-maintenance operation with short downtimes is therefore of particular interest. To this end, automated structural health monitoring (SHM) gained a lot of interest in research and economy. In this work, we propose an algorithm for damage detection in rotor blades using airborne acoustic emissions (AE). Our algorithm inherently uses a localization approach and is therefore not only able to detect a structural damage but also to estimate its position using time differences of arrival (TDoA) of airborne sound waves. Since we intend only an approximate localization of the impulsive damage sounds, we suggest a simple yet effective method based on cross-correlation of energy-envelope functions to estimate the TDoA. For the task of damage detection and localization, only two line-of-sight microphones are required, which makes this approach very economic for SHM. We evaluate our method on two large-scale fatigue tests conducted on a 34-meter and a 30-meter rotor blade under laboratory conditions. During the fatigue tests, we continuously recorded airborne sound signals with multiple microphones placed inside the rotor blades. With our proposed method, we are able to detect and correctly assign the two significant structural damages in both rotor blades to a two-meter-long rotor blade zone without having any false-positive alarms throughout more than 350 hours of continuous audio recordings. Airborne acoustic emissions therefore may be a promising alternative to other conventional monitoring solutions based on structure-borne sound, which usually require considerable denser sensor networks.

Introduction

Climate change and its consequences are a central topic in politics, research and our daily life. There is no doubt that especially the industrialized countries need to reduce their carbon dioxide emissions by decreasing the use of fossil fuels and expanding renewable energies. Next to hydropower, wind energy is the most prevalent form of renewable electricity generation [1]. Due to the heavily increasing construction of offshore wind turbines [2] and the growing economic pressure on wind turbine operators, the demand for automated structural health monitoring (SHM) is becoming more apparent. Even though, the wind turbine's rotor blades are not the most prevalent component in terms of frequency of damage occurrence, they are considered to be a critical subassembly with respect to downtime of the wind turbine [3]. Therefore, various methods have been proposed to monitor the structural health of wind turbine rotor blades, including but not limited to operational modal analysis (OMA), guided wave testing (GWT) and automated visual inspections using computer vision [4–6]. While especially modal parameters, such as natural frequencies and mode shapes extracted from structure-borne sound signals are widely studied with regard to damage assessment of large civil infrastructures, aspects like their dependency on environmental and operational conditions as well as the limited sensitivity with respect to smaller

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damages are still part of ongoing research [7]. With the availability of affordable, commercially available computer hardware and storage media, acoustic emission testing (AET) became suitable for applications in the field of structural health monitoring [8, 9]. Conventionally, AET belongs to the passive non-destructive testing methods and refers to the analysis of structure-borne sound waves in the ultrasonic frequency range resulting from the sudden energy release caused by damage events within the structure [10]. However, more recently researchers also suggested to use airborne sound signals for the task of damage assessment using acoustic emissions caused by the damage event itself or by analyzing the change of the characteristic environmental acoustic signature [11–13]. While the latter approach is mostly studied under controlled laboratory conditions, Krause et al. also validated their acoustic emission-based method on recordings acquired on an operating wind turbine. Using multiple microphones mounted inside the rotor blade, the suggested decision tree is capable to detect the significant structural damage that occurred during the large-scale fatigue test without showing any false-positive alarms during the analysis of the operational recordings [11]. However, the suggested decision tree relies on several spectro-temporal features with specified thresholds whose generalization needs to be further evaluated. In order to avoid establishing a discriminative feature representation of the damage events, Solimine et al. [12] proposed an anomaly detection algorithm based on different features, such as linear predictor cepstral coefficients. They evaluated their approach on a subset of audio signals recorded during another large-scale rotor blade fatigue test and were able to detect anomalous sound caused by external noise as well as the disbonding of foam inside the rotor blade. However, a structural damage did not occur during this test and could therefore not be detected. On the basis of these previous studies, we propose another simple and intuitive approach for detecting damages in wind turbine rotor blades using airborne acoustic emissions (AE). Our algorithm is based on the cumulative acoustic emission energy often utilized in the field of materials research [14]. In contrast to other methods, the proposed algorithm relies on only two user-defined power-related thresholds and inherently utilizes a localization approach allowing for a localized damage detection that none of the earlier discussed algorithms is capable of. The localization approach is based on time differences of arrival (TDoA), which can be estimated i) by detecting the signal's onset time in each recording channel separately or ii) utilizing cross-correlation based methods, such as the generalized cross-correlation phase transform (GCC-PHAT) [15]. The latter approach is well-studied and successfully applied in various domains. However, multipath propagation introduces ambiguities that may result in poor localization performance. Hence, we adapt the idea of a signal envelope used in time of flight (ToF) estimation in ultrasonic testing [16] and estimate the TDoA based on the peak-normalized cross-correlation of the moving root mean square of the percussive damage sound signals.

In the next section, we will first introduce two large-scale fatigue tests of a 34m- and a 30m rotor blade, which form the experimental basis for our work. In Section 3, we give a detailed description of the proposed algorithm for the localized damage detection. Section 4 summarizes the results on the two datasets of audio recordings acquired during the previously mentioned fatigue tests. Section 5 closes with a brief summary and an outlook for interesting research directions.

Experiments

For the evaluation of our suggested algorithm, we utilize continuous audio recordings acquired during two large-scale rotor blade fatigue tests. During both rotor blade tests, the airborne sound was continuously recorded with a sampling frequency $f_s = 96\ kHz$. For the calibration of each microphone, we utilized a sound calibrator with a defined sound pressure level of 114 dB at 1 kHz.

Fatigue test of 34 m rotor blade. The first equipped rotor blade under test had a total length of 34 m. Inside this rotor blade, we installed one microphone in the chamber of the leading edge close to the root and two more at the trailing edge in approximately 3 m and 15 m distance to the root.

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The optical microphones used throughout the experiment were omnidirectional and had a frequency range from 20 Hz to 40 kHz (+/- 6 dB). The sensor layout is depicted in Fig. 1. A regular interruption of the fatigue test allowed for visual inspection and documentation of the rotor blade's structural condition. Based on these visual inspections, excitation load was slowly increased to provoke a relevant structural damage within the limited test period. After the occurrence of the structural relevant damage, the external load was reduced and then stepwise increased again to allow for further damage propagation. Table 1 gives a brief summary of the experimental details including the number of load cycles and the analyzed hours of audio recordings used for the later evaluation of our method. The last column indicates the occurrence of the structural relevant damage and its approximate position. Several more minor damages, such as adhesive cracks, were also observed but found to be structurally irrelevant meaning that those damages would not lead to any repair measures if observed in an operating wind turbine.

Table 1: Overview of test procedure for 34m and 30m rotor blade fatigue test

Blade	No. of load cycles	Analyzed audio recordings	Notes
34m rotor blade	~ 1.243.600	231 hours	Structural relevant damage at $D_r = 6.2\ m$ (see Fig. 1); (16th of July, 18:30 h); Initial crack size approx. 44 cm
			Progression of damage (18th of July, 09:00 h)
30m rotor blade	~ 666.000	137 hours	Structural damage on 28th of April, 11:30 h; $D_r = 8\ m$ at leading edge (see Fig. 2); Final crack size up to 100 cm;

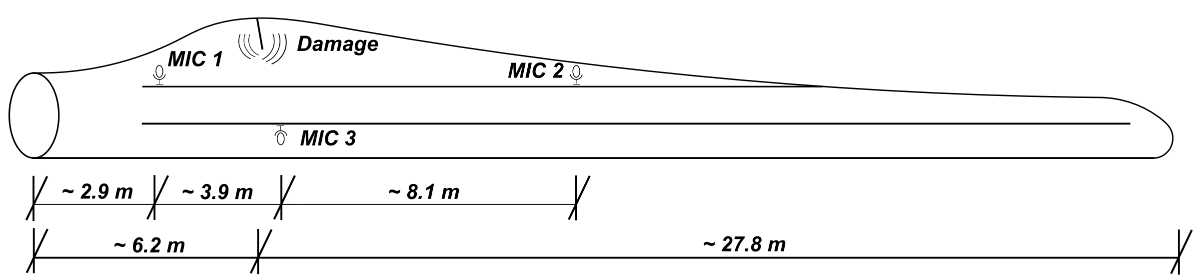

Figure 1: Sensor layout for acoustic monitoring of a 34 m rotor blade during fatigue test

Fatigue test of 30 m rotor blade. The second rotor blade considered in this study was slightly smaller, having a length of approximately 30 meters. In agreement with the sensor layout of the previously described fatigue test of the 34m rotor blade, we again installed three microphones inside the rotor blade as depicted in Fig. 2. However, this time we used omnidirectional electret microphones with a flatter frequency response in the audible frequency range (30 Hz – 18 kHz, +/- 1 dB). The fatigue test was conducted in several steps including adjustments of the excitation load to ensure the occurrence of a structural relevant damage within the test period. In regular time intervals, visual inspections as well as dynamic tests were carried out to assess the structural condition. In contrast to the rotor blade described before, only a minor increase of the external load was necessary throughout the test procedure indicating a more fatigue-related occurrence of damage than before. Some test parameters as well as the details of the damage are briefly summarized in Tab. 1. Minor damages such adhesive cracks were also observed during the regular inspections. However, since these damages would not lead to any actions if observed in a rotor

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blade of an operating wind turbine, those were not considered as structural relevant damages in the later evaluation.

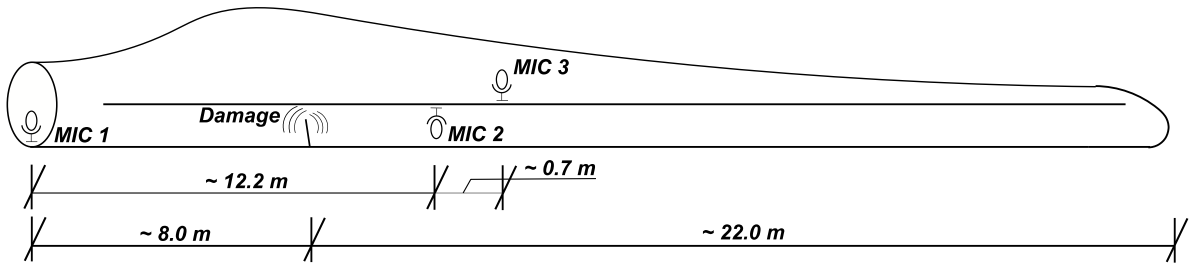

Figure 2: Sketch of the 30m rotor blade and the installed microphones for continuous monitoring

Methodology

For detecting damages in rotor blades using airborne sound, we propose an algorithm based on cumulative acoustic emission energy (AE energy), which we extend by a zonal localization using time differences of arrival (TDoA). AE energy is often utilized in materials research to reveal information about damage progress throughout the experiment, when a manual interruption of the test is not desired [10]. Conventionally, acoustic emissions of ultrasonic structure-borne sound signals are analyzed. Here, we apply this method to airborne sound signals in the audible frequency range. Since significant structural damages in fiber-reinforced composites do not necessarily result in a single, sudden energy release but can also progressively grow and therefore result in multiple AE events with slightly less energy, we suggest the use of cumulative AE energy within a fixed time period. We hypothesize that a structural relevant progress of damage shall result in an observable increase of AE energy and can therefore be detected by means of accumulated energy. To further facilitate this approach for rotor blade monitoring, we employ a TDoA-based localization technique which may i) reduce the false alarm rate when more AE events occur at the same time but in different regions of the rotor blade and ii) inherently gives information about the potential damage position, which is of specific interest for further decision-making. In the following, we will introduce the simple amplitude threshold-based detection of damage events and the incorporation of the TDoA-based zonal localization.

Detection of audio events with elevated peak sound pressure level. At first, all channels of the audio stream $a_{M,i}[n]$ are preprocessed using a high-pass butterworth filter with a cutoff-frequency of 5 kHz. This is done to reduce environmental noise and enhance the signal-to-noise ratio as it is also suggested in [11]. After this filtering step, we arbitrarily choose one reference sensor (here: MIC 1) and process the corresponding audio stream $a_{M,1}[n]$ with a simple threshold on the peak sound pressure level. To achieve a good sensitivity, the threshold was set to $L_p = 80\ dB\ SPL$ here. Once a threshold crossing is detected at index i_{thr}, we determine the absolute maximum amplitude within an approximate 224 ms long time window (Eq. 1) and finally extract a fixed length audio segment $a_{seg,i}$ according to Eq. 2 in all channels $a_{M,i}[n]$ of the audio stream. Whenever an audio segment is extracted, the trigger is locked for $T_{Lock} \approx 171\ ms$ to avoid multiple detections within the same time window. This definition of a lockout phase can be often found in conventional AE systems [17].

$$k = \arg\max_n \ a_{M1}[i_{thr} + n] \quad with \quad n \in \{0,1,2,\dots,16383\}. \tag{1}$$

$$a_{seg,i}\,[n] = a_{M,i}\big[\,(i_{thr} + k) - t_{pre}, \dots, (i_{thr} + k) + 3.2 * t_{pre}\big] \; with \begin{cases} t_{pre} = 5120 \\ i \in \{1,2\} \end{cases}. \tag{2}$$

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Once the audio segments of the different channels are selected, it is firstly verified that within each specific time segment, the threshold L_p is also crossed in the corresponding line-of-sight microphone (here: MIC 2). If this is the case, a moving root mean square (RMS) $R_{M,i}[n]$ is calculated for both zero padded signals (Eq. 3) and the time difference Δt_{12} of the two peak normalized moving RMS signals $R_{Mn,i}[n]$ is estimated using the cross-correlation function. Before applying Eq. 4, a peak picking algorithm is employed on the RMS signals $R_{Mn,i}[n]$ to discard anomalous audio segments with small pulse widths or multiple peaks with similar prominences [18].

$$R_{M,i}[n] = \sqrt{\frac{1}{960}\sum_{t=n-959}^{t=n} a_{seg,i}[t]^2} \; with\, i \in \{1,2\}. \tag{3}$$

$$CC_{1,2}[n] = \sum_{k=-L-1}^{k=L-1} R_{Mn,1}[k+n] * R_{Mn,2}[k] \; with\, L = 21504. \tag{4}$$

Based on the estimated time differences of the two signals Δt_{12} and a simplified one-dimensional view of the rotor blade, the position of the audio source signal, i. e. the distance to the rotor blade's root D_r is obtained using Eq. 5.

$$D_r = \begin{cases} D_{M,1-r} + \frac{1}{2}\left(D_{M,2-M,1} - v_{air} * \Delta t_{12}\right) & for\ \Delta t_{12} \leq 0 \\ D_{M,1-r} + \frac{1}{2}\left(D_{M,2-M,1} + v_{air} * \Delta t_{12}\right) & for\ \Delta t_{12} > 0 \end{cases}. \tag{5}$$

Here, $D_{M,1-r}$ is the distance between MIC 1 and the rotor blade's root, $D_{M,2-M,1}$ is the distance between the two line-of-sight microphones MIC 2 and MIC 1 and v_{air} is the estimated speed of sound (343 m/s at 20 ° C). Signal pairs with an estimated time difference that does not satisfy the inequality in Eq. 6 are discarded. This is done to filter out signals whose estimated source position lies outside the surrounded area of the two microphones. Consequently, we suggest that two line-of-sight microphones (here: MIC 1 and MIC 2, see Fig. 1 / 2) shall be used to monitor the area between these two microphone positions only.

$$|v_{air} * \Delta t_{12}| \leq D_{M,2-M,1}. \tag{6}$$

Finally, we calculate the arithmetic mean of the two corresponding audio segments $S_{E,mean}$ in a limited frequency band (Eq. 7) and save it together with the approximate timestamp of the audio segment and the previously estimated source position to a database for further analysis. In Eq. 7, $A_{seg,i}[k]$ is the discrete Fourier transform of $a_{seg,i}[n]$ and f_s is the sampling frequency. The frequency band limits b_1 and b_2 correspond to a lower frequency of 15 kHz and an upper frequency of 20 kHz, respectively. The overall processing workflow is illustrated in Fig. 3.

$$S_{E,mean} = \frac{1}{2L} * \left[\sum_{k=b_1}^{b_2} |A_{seg,1}[k]|^2 + \sum_{k=b_1}^{b_2} |A_{seg,2}[k]|^2\right] * \frac{1}{f_s}. \tag{7}$$

Zonal acoustic emission activity using estimated sound source location. For the analysis in terms of accumulated AE energy, we partition the rotor blade in equally sized zones of two meter length and assign the accumulated energy of acoustic emissions within a fixed time period of one hour to the rotor blade zones based on their estimated source position. That way, we can finally monitor the course of AE energy per time unit and rotor blade zone to detect anomalous AE activity

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throughout the fatigue tests. For the detection of a damage, we finally introduce a second threshold T_{AE} = 2 [Pa²ms / h].

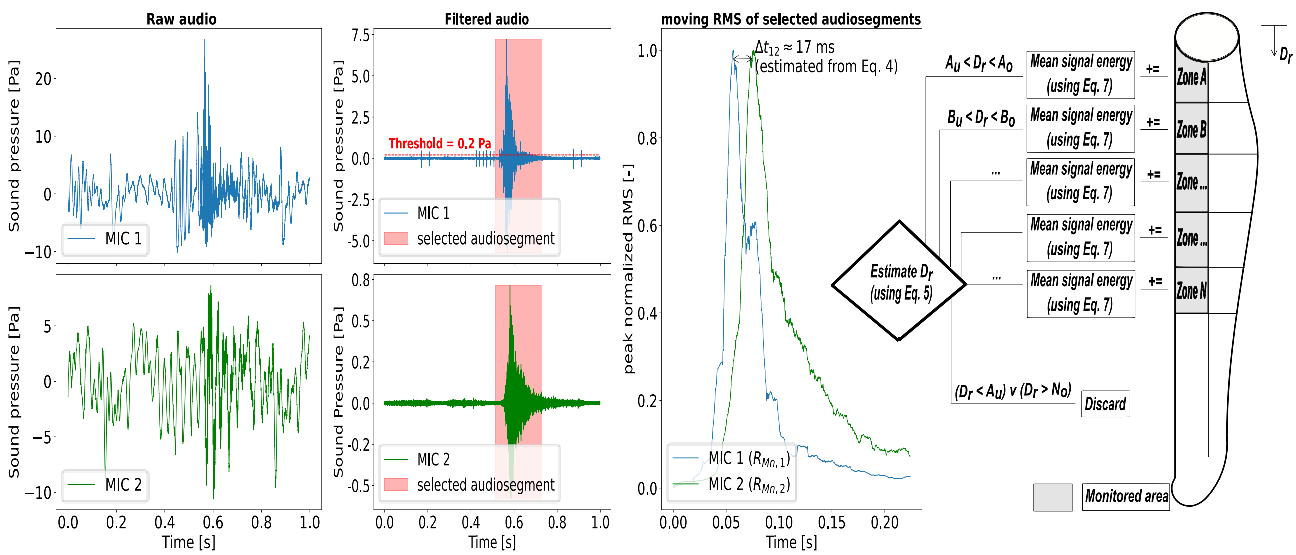

Figure 3: Illustration of the processing workflow for localized damage detection in rotor blades

Results

For the evaluation of the proposed method, we processed the continuous audio recordings from two different rotor blade fatigue tests described previously. After removing time periods in which the test was not running, we obtained more than 350 hours of audio recordings (see Tab. 1) that we processed with our algorithm as detailed in the previous section. The corresponding results are depicted in Fig. 4. For both rotor blade fatigue tests, it is possible to detect the structural relevant damages indicated by a shaded grey area using a simple threshold on the accumulated acoustic emission energy per hour. Further, our algorithm correctly identifies the rotor blade's zone in which the damage occurred and therefore estimates the approximate position. Despite these promising results, the acoustic emission activity throughout the two rotor blades should be noted. During the 30 m rotor blade fatigue test, an elevated level of acoustic emission energy several days before the actual damage can be observed. Therefore, airborne sound acoustic emission activity may also allow early-stage indication of damages. In contrast, however, this increase of the acoustic emission energy before the actual damage cannot be observed in the 34m rotor blade fatigue test. A possible reason may be the heavy increase of the external load in this fatigue test which lead to a more sudden occurrence of damage and therefore did not show any fatigue-related indications beforehand.

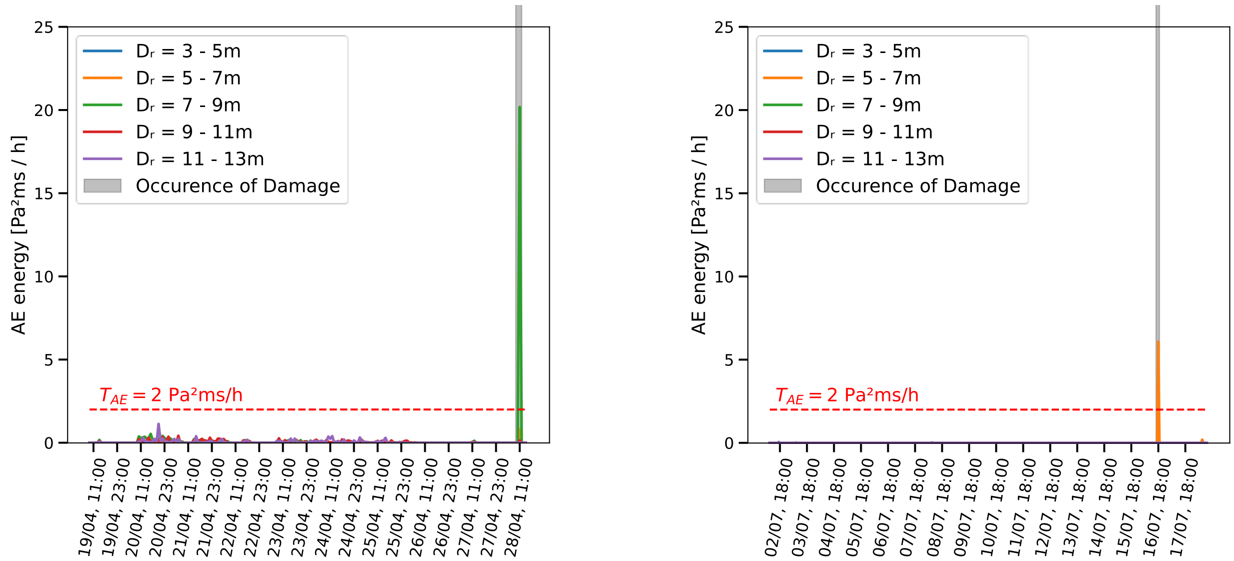

Figure 4: Cumulative acoustic emission energy throughout the entire test period of the 30m rotor blade fatigue test (left) and the 34m rotor blade fatigue test (right). The different colors indicate the rotor blade zones, to which the detected acoustic emissions were assigned.

Conclusion

In this study, we proposed the use of localized airborne acoustic emission energy for damage assessment of rotor blades. For the evaluation of our method, we processed audio recordings of two different large-scale rotor blade fatigue tests and successfully detected the structural relevant damage in each of these rotor blades. Further, our algorithm correctly estimated the approximate position of the structural damage. Due to its simplicity, the algorithm is likely to have a good generalization performance and additionally provides good interpretability considering that one is able to listen to the selected audio events in case of a detection. Further, our algorithm utilizes only two simple thresholds whereby the second (T_{AE}) can also be discarded, when the acoustic emission activity curve is inspected by humans, e.g. in a control room. However, more experiments should be conducted to further verify this approach. Another open research question is the applicability of the algorithm under real environmental and operational conditions with respect to false detections. If this turns out to be a limitation, further research could focus on the incorporation of additional damage-related features as suggested in other publications [11, 12]. With regard to the zonal localization, more sophisticated methods for the estimation of time differences of arrival (TDoA) could be investigated.

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