Vibration-based SHM System: Application to Wind Turbine Blades

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Abstract. This study presents an vibration-based system designed for structural health monitoring of wind turbine blades. Mechanical energy is introduced by means of an electromechanical actuator mounted inside the blade. The actuator's plunger periodically hits the blade structure; the induced vibrations propagate along the blade and are measured by an array of accelerometers. Unsupervised learning is applied to the data: the vibration patterns corresponding to the undamaged blade are used to create a statistical model of the reference state. During the detection stage, the current vibration pattern is compared with the reference state, and the novelties can be associated with damage. The vibration pattern is described by the covariance matrix between the accelerometer signals. The mid-range frequencies are used: this range is above the frequencies excited by blade-wind interaction, thus ensuring a good signal-to-noise ratio. Simultaneously, the frequencies are low enough to be able to propagate the entire blade length, so good results can be obtained even using only one actuator. The system is demonstrated on a real 34m blade mounted on a test rig. Using the suggested approach, the system enables detection of, e.g., a 20cm long trailing edge opening under realistic noise conditions. It is also demonstrated that the system provides rough information about damage location. Progression of damage, if any, can also be detected.

1. Introduction

Wind turbine blades today are extremely complex and expensive structures; from the cost perspective, they constitute a significant asset for wind turbine owners. Therefore, monitoring of their structural health becomes economically rational, especially for big, remote (offshore) turbines.

There are many different approaches to SHM of wind turbine blades, varying by utilizing different physical phenomena, sensor types and signal processing; a detailed review can be found, for example, in [1]. The present study introduces a vibration-based, active system. *Vibration-based* means that changes in mechanical vibrations of the blade serve as a feature indicating blade damage. Active means that the vibrations are introduced artificially, by using a dedicated *actuator* mounted inside the blade; this contrasts with other vibration-based approaches which rely on ambient vibration of the blades due to wind. In authors knowledge, so far there is no evidence that the latter can provide damage detection resolution satisfying industry's demand. The suggested technique differs from another well-known active approach, *guided waves*, in the

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frequency range used. If, in the guided waves case, the tens of kHz range is typical, the vibration frequencies excited by the suggested electromechanical actuator are normally below 1 kHz.

The vibrations induced by the actuator are picked by a number of accelerometers distributed over the monitored structure. The recorded signals are processed by the set of algorithms that determine whether or not the blade is damaged and find the location of the damage. A video demonstrating the SHM in action can be found in [2].

The *medium* frequency range which utilizes the proposed SHM is a compromise between the propagation range and detection resolution. Low-frequency vibrations can propagate long distances but are very insensitive to small areas of damage. It is well documented, see, for example, [3], that the modal parameters of the lowest blade modes are quite insensitive to blade damage, thus SHM systems utilizing changes in the modal parameters can only detect very significant damages. Ultrasonic range frequencies employed in the guided waves approach have good damage-detection resolution but the vibrations at such high frequencies quickly decay and cannot propagate long distances. This means the monitored blade has to be equipped with a large number of actuators and sensors, making such a system economically infeasible. The proposed approach utilizes the medium frequency range. Being well above the very low frequencies, where the blade is mainly excited by the wind, ensures satisfactory signal-to-noise ratio of the acceleration signals picked up by the accelerometers. At the same time, the frequency range is low enough for the vibrations to propagate long distances, and the experiments showed that a single actuator is sufficient to excite even a long modern blade. This also provides a good signal-to-noise ratio of the measured acceleration signals. On the other hand, the utilized frequency is high enough to ensure that the level of detection resolution is satisfactory for wind turbine owners; as it will be shown later, e.g., the system can detect a 20cm long trailing edge opening of a 34m blade.

Data-driven models for damage detection have been employed in numerous studies, for example, [4], with positive results. The experiments presented are often performed in laboratory conditions with models trained in a supervised setting where measurements from undamaged and damaged structures were available for the fitting. In contrast, the approach presented here is based on unsupervised anomaly detection, and thus does not require the learning of the damaged states. The SHM system is to be installed on an operational wind turbine continually monitoring the state so the algorithm must be robust to changing conditions such as wind, precipitation, and the operational modes such as changing rotational speeds and blade orientation. These phenomena may result in false alarms and the influence must therefore be investigated to implement a practical SHM system.

2. SHM system implementation on an SSP34m blade

Instead of making a general description of the proposed SHM system, this section uses one example of its implementation (namely, in application to an SSP34m blade). It is thought, however, that it should be easy to get a general idea about the concept of the proposed system and its usage. Before installing the SHM system on an operating wind turbine, its concept was

Figure 1. SSP34m blade mounted on the test rig

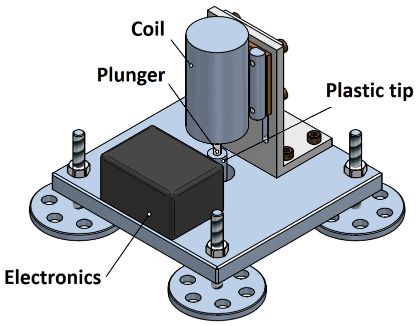

Figure 2. Design of electro-mechanical actuator.

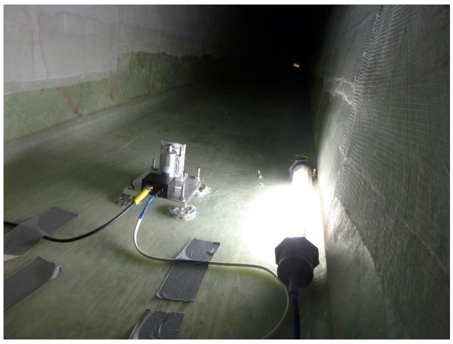

Figure 3. Mounting inside an SSP34m blade

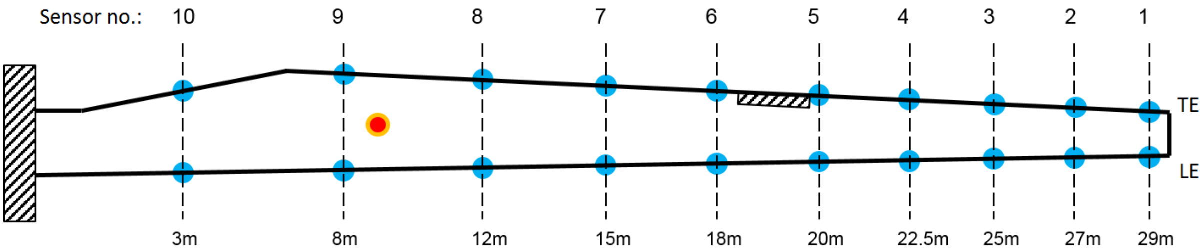

Figure 4. Test setup. Location of the actuator (●), accelerometers (●) and the damage (▨).

validated in laboratory conditions. An SSP34m blade, mounted on a test rig at DTU Wind Energy facilities in Roskilde, Denmark (figure 1), was instrumented, and a series of experiments were conducted on the blade in undamaged and damaged states.

2.1. SHM system hardware

The hardware of the SHM system consists of an electromechanical actuator and array of accelerometers.

The actuator is an electromechanical device consisting of two main parts (figure 2): a steel plunger and a coil. Driven by an electrical pulse, the coil 'shoots' the plunger towards the structure; after the hit, the plunger returns to its initial position by spring. Though, there is an advantage of measuring the injected force, the practical implementation of such sensors would be quite difficult and thus omitted in this study.

The actuator is meant to be mounted inside the blade, on the shear web or the spar cap (figure 3), in the root section of the blade, i.e., at the first third of the blade length. This area is typically easily accessible in most modern blades. From a few pretests, it became obvious that even one actuator can excite the entire blade. The chosen location of the actuator is shown in figure 4.

The blade was also instrumented with 20 Brüel & Kjær accelerometers Type 4524-B, ten on the leading edge (LE) and ten on the trailing edge (TE) (figure 4). The same accelerometer setup was used for modal analysis, therefore triaxial accelerometers were used [3]. However, in the experiment described, only the data from one axis, perpendicular to the blade surface, was used.We acknowledge that mounting sensors on wind turbine blades is a difficult task, especially in a retrofitting scenario. However, the last years advances in sensing technology, e.g. the fiber optic sensing, can make blade instrumentation feasible in the nearest future.

It should be mentioned that we did not use any systematic approach for selecting the number of accelerometers, their placement and the placement of the actuator. As mentioned before, the accelerometers were reused from another modal analysis experiment, and the placement of the actuator was mainly driven by ease of access and a few pretests. A systematic approach to sensor/actuator placement may significantly improve the effectiveness of the SHM system and contribute to its cost reduction by reducing the number of sensors (and hence, data acquisition channels) by placing them at most optimal points. The first steps in this direction were taken by Parker, who used a genetic algorithm [5], and Lagerbon, who utilized a topology optimization approach [6].

A Brüel & Kjær data acquisition unit (see [3] for more details) was used for collecting the acceleration data. The unit also contains a signal generator, which was set to generate a rectangular pulse, which, after amplification, was fed to the actuator, resulting in an actuator hit. The data acquisition was triggered by this pulse, set to collect vibration data for a few milliseconds before and a few seconds after the pulse. Using the trigger significantly reduces the amount of data collected for the analysis.

The damage-detection algorithms are based on statistics to make detection more robust. In order to collect the necessary statistics, the blade in undamaged and damaged states was subjected to about fifty hits at each state. To speed up the experiment, the time between the successive hits were selected quite small, varying from one to five minutes. In real life application, the time between hits could be, for example, an hour or more.

2.2. Artificial damage

Only one type of damage was tested in the presented study: a trailing edge opening (figure 5). This damage is typical for many types of wind turbine blades, caused by de-bounding of the shells forming the pressure and suction sides of the blade. The damage was introduced into the blade gradually; we started with a 20cm trailing edge opening, drilling a series of holes through the glue between the pressure and suction sections of the blade. Then, using a saw, the holes were merged into one opening. After that, using a chisel and saw, the crack was gradually extended to 120cm; thus we had four damaged states: 20cm, 60cm, 90cm and 120cm. The data acquisition were conducted for each state, including the initial undamaged state, using about fifty actuator hits for each state.

Figure 5. Blade damage in the trailing edge, with the chisel used to introduce the damage

Figure 6. Bolts and metal plates used to change damage size in the second experiment.

When the damage was introduced, it was realized that operating with a heavy hammer and chisel can introduce some other unwanted changes into the blade, which can be erroneously associated with the effect of the damage. To avoid this, the experiment was repeated: the de-bounded parts of the blades were connected by bolts, placed 10cm from each other. The glue

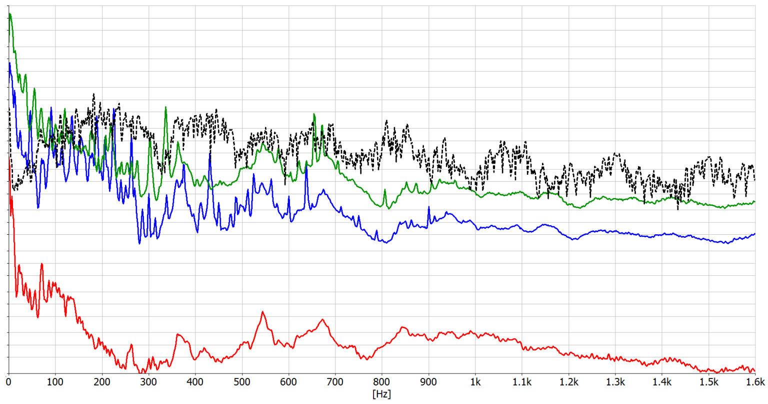

Figure 7. Power Spectral Densities (PSD) of the acceleration measured at the blade tip. V27 wind turbine: —— idle condition, moderate wind; —— operating at 32RPM, moderate wind; —— operating at 43RPM, strong wind, ······ response from actuator measured on SSP34m.

removed between the pressure and suction parts was replaced by thin metal plates (figure 6). By tightening and loosening the bolts, it was easy to control the size and location of the opening without using the chisel.

2.3. Modelling of noise

Noise in the data is known to be a factor that can significantly reduce the robustness of damage-detection algorithms. In the case of operating wind turbines, the acceleration responses due to the actuator hits will overlap with the vibrations due to blade-wind interaction, and the vibrations due to the numerous mechanisms of the wind turbine, such as gearbox, generator, yaw and pitch mechanisms, cooling system, etc. To mimic such noise, vibration data measured on the blades of an operating Vestas V27 was used. This data was obtained during another measurement campaign, which is described in detail in [7]. Though the V27 and SSP34m blades are quite different (for example, the first one is 13m long, while the second is 34m), using this noise data was considered the best among other alternatives. Figure 7 shows the PSD of the acceleration measured at the tip of an operating V27 wind turbine under the different operating conditions. It should be mentioned that the presented study did not model the possible effects of varying weather conditions, such as temperature, wind speed and direction, etc. We also did not model the effects of different rotor speed and blade orientation (azimuth and pitch angles), which may strongly affect the robustness of the damage-detection algorithms.

3. Damage-detection method

The proposed damage-detection algorithm is based on an unsupervised anomaly detection method [8]. The method is based solely on modelling data obtained from the blade in a healthy state. This is in contrast to many earlier data-driven approaches that use supervised methods to detect a limited number of areas of damages introduced in experiments [4]. The supervised approach is consequently too restrictive for an operational system such as a wind turbine where it is impossible to perform experiments for all imaginable damage scenarios.

The damage-detection method is therefore based on a *training phase*, where we establish a model of the normal state exclusively from healthy state data, and subsequently a *detection phase* where a new sample is compared to the normal-state model.

The modelling of the normal state takes as input the multivariate accelerometer signal recorded from the sensors. The processing for the model can be split into three parts; preprocessing, feature extraction and statistical modelling.

The set of accelerometer signals for each hit requires some preprocessing steps to enhance the damage detection. The first step is *windowing*, in which the signal is truncated to start at the actuator trigger signal and end when the impulse from the strike has died out, i.e., after 1s.

Figure 7 compares the spectra of the blade tip response due to wind and due to the actuator hit. As mentioned before, the wind mainly excites low-frequency vibrations, while the actuator excites a wider range. If at low frequencies, the signal due to the actuator is buried in the noise due to wind, at higher frequencies the situation is the opposite, and one can expect a good signal-to-noise ratio if the low frequencies are filtered out. This observation helps select the cut-off frequencies of the applied high-pass or bandpass filter that is applied in the filtering step of the preprocessing.

3.1. Damage indicator

The data-driven modelling approach employed in this study requires the definition of a compressed representation of the state of the structure. A damage metric based on the covariance matrix between the time histories, similar to the one introduced in [5], is employed. Structural damage will change the energy propagation paths from the actuator to the accelerometers, and the vibration pattern due to actuator hit. Since the cross-covariance function is a measure of the similarity between two signals, the change in vibration pattern can be very well characterized by the change of the covariance matrix. The cross-covariance between signals x_1 and x_2 of length N is calculated as:

$$c_{x_1x_2}(m) = \begin{cases} \sum_{n}^{N-m-1} \left(x_1(n+m) - \frac{1}{N}\sum_{i=0}^{N-1} x_1(i)\right)\left(x_2(n) - \frac{1}{N}\sum_{i=0}^{N-1} x_2(i)\right) & , m \geq 0 \\ c(-m) & , m < 0 \end{cases}. \quad (1)$$

In this application, only the cross-covariance for lag 0, $m = 0$, is used for the damage indicator. Calculating the covariance for a set of M sensors, produces $M(M-1)/2$ distinct values for each hit that constitutes the damage indicator. Figure 8a and 8b show the covariance features for the SSP34m blade in an undamaged state and with an opening at 120cm. It is seen that the feature values change for the covariance between sensor $c_{x_2x_{10}}$, $c_{x_4,x_{10}}$, and $c_{x_5,x_{10}}$, depicted in the lower left corner of the plots. Inspection of the covariance-feature vectors reveal that

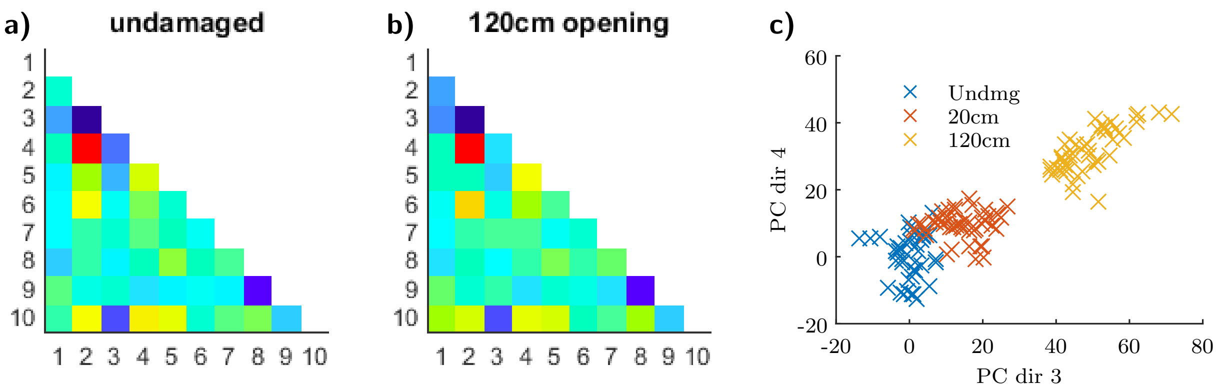

Figure 8. Covariance-based damage indicator using the 10 trailing edge accelerometers for the undamaged blade and the blade with 1.2m opening in trailing edge. The third panel shows the 3rd and 4th principal component dimensions for undamaged and two damage sizes

many of the dimensions are correlated, and in addition the dimensionality of the feature vectors grows quadratically with the number of sensors which could impede a statistical model of the samples. The dimensionality of the covariance-feature vectors is reduced using principal component analysis (PCA) [9]. The PCA is estimated using the samples from the undamaged case which produces a principal component space, that all samples are projected into. This projection is seen to separate damaged and undamaged samples quite well as illustrated in figure 8c.The dimensionality, i.e., the number of principal components, used for the PCA was chosen using a heuristic method. The method chooses the minimal number of principal components such that 99% of the variance in the data is accounted for.

3.2. Damage-detection metric

To evaluate whether a sample vector in the PCA-space, $\mathbf{y}$, is normal or damaged we use the Mahalanobis distance. The Mahalanobis distance is calculated as the distance between the normal-state samples $\mathbf{X}_n$, summarised by the mean $\boldsymbol{\mu}_{X_n}$ and the covariance matrix $\boldsymbol{\Sigma}$, and the new sample:

$$d(\mathbf{y}, \mathbf{X}_n) = \sqrt{(\mathbf{y} - \boldsymbol{\mu}_{X_n})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{y} - \boldsymbol{\mu}_{X_n})}. \tag{2}$$

To make the decision whether a new sample $\mathbf{y}$ is anomalous/damaged, a threshold must be chosen. This choice of threshold must either be based on observations of data from normal and from damaged blades, or chosen based on the normal-state data only. The former approach of supervised tuning of the threshold will have superior performance but requires that the system is trained on all damages seen. The current system uses the latter approach by calculating the distance for each normal-state sample $\mathbf{x}_{n,i}$ and then choosing the threshold as the maximum among the $d(\mathbf{x}_{n,i}, \mathbf{X}_n)$. This choice of threshold will thus classify all data in the training as normal.

3.3. Damage localization

The proposed SHM system also provides a rough damage localization. The localization is based on evaluation which elements of the covariance matrix are most affected. The damage is likely to be located between the sensors whose signals cross-covariance significantly changed (cf. figure 8a and 8b). Typically, several most affected elements of the covariance matrix indicate the damage position with precision, sufficient for damage severity evaluation and facilitation of its particular location for the repair.

4. Results

The damage-detection method was tested using data for the undamaged state and six different damage sizes of 20, 40, 60, 80,100, and 120cm. The performance was evaluated using tenfold cross-validation to get unbiased estimates of the error rates shown in table 1. The results show a very low error rate already with the use of the 5 sensors at the trailing edge (TE) and has approximately similar performance for all damage sizes and as we add more sensors. A realistic instrumentation that uses both leading-edge (LE) and trailing-edge (TE) sensors also reaches the lowest observed error rates. As mentioned earlier, the algorithm was also tested with added

Table 1. Results of damaged vs. undamaged classification with different sensor configurations. The table shows the mean error rate (in %) from the tenfold cross-validation followed by the 95% confidence interval of the mean in brackets.

State	20cm	40cm	60cm	80cm	100cm	120cm
No. samples	53	52	52	48	49	53
TE1-5	2.0 [0.2;7.2]	2.1 [0.3;7.3]	2.1 [0.3;7.3]	2.2 [0.3;7.6]	2.1 [0.3;7.5]	2.0 [0.2;7.2]
TE1-6	3.1 [0.6;8.7]	3.1 [0.6;8.8]	3.1 [0.6;8.8]	3.2 [0.7;9.1]	3.2 [0.7;9.0]	3.1 [0.6 8.7]
TE1-7	5.1 [1.7;11.5]	5.2 [1.7;11.6]	5.2 [1.7;11.6]	5.4 [1.8;12.1]	5.3 [1.7;12.0]	5.1 [1.7;11.5]
TE1-10	2.0 [0.2;7.2]	2.1 [0.3;7.3]	2.1 [0.3;7.3]	2.2 [0.3;7.6]	2.1 [0.3;7.5]	2.0 [0.2;7.2]
TE1-5,LE1-5	2.0 [0.2;7.2]	2.1 [0.3;7.3]	2.1 [0.3;7.3]	2.2 [0.3;7.6]	2.1 [0.3;7.5]	2.0 [0.2;7.2]

artificial wind noise from an operational turbine to test the robustness of the damage-detection method in real operation. The results of these experiments are shown in figure 9. The wind noise is measured in terms of signal-to-noise ratio (SNR) between the clean signal in trailing edge sensor 1 from the arrival of the strike and 0.25s forward and the generated wind noise signal. The performance is measured using the well-established Area Under the (ROC) Curve (AUC) [10] that scores a binary classifier from perfect classification with a score of 1 to random guessing at a score of 0.5 independently of the chosen detection threshold. It is clear that all damage can be detected down to an SNR level of 0dB while larger areas of damage are detectable at even lower SNR levels.

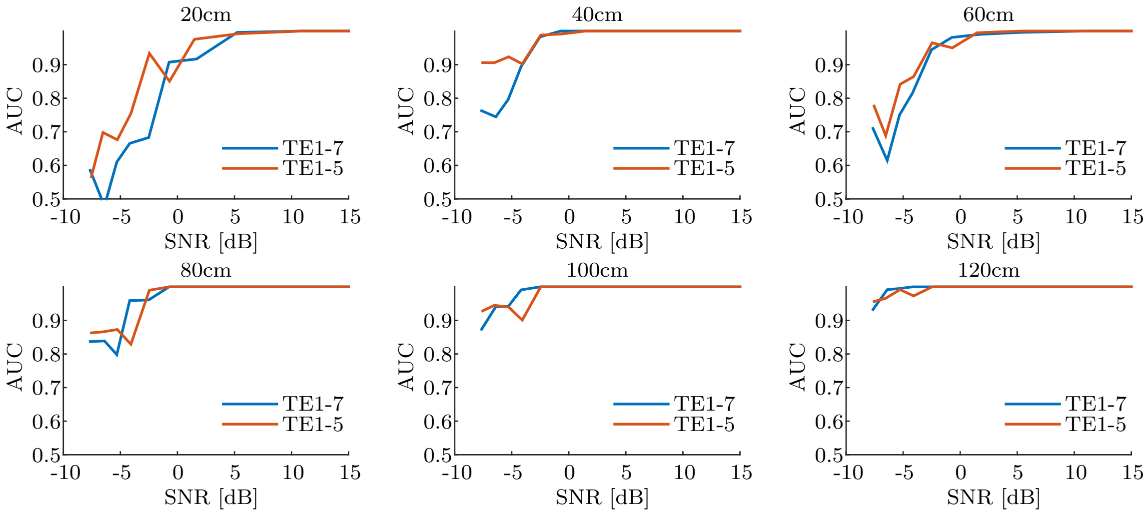

Figure 9. AUC for experiments with added wind noise. The legend in the figure shows the numbers of the trailing edge sensors used.

5. Conclusion

The paper presented a prototype of a vibration-based SHM system for wind turbine blades. The proposed approach is based on active excitation of the blade by an electro-mechanical actuator and measurements of the exited vibration by an array of accelerometers. The unsupervised abnormality detection method is employed for the analysis of the response signals for damage detection and localization. The method is demonstrated on a 34m wind turbine blade mounted on a test rig. It is shown that the proposed system is able to detect a 20cm length of trailing edge damage in presence of realistic (though artificial) noise.

Acknowledgments

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