An Efficient Fault Detection Methods for Wind Mill using Haar Feautures

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Abstract--*In this paper, a new crack detection technique for wind turbine blades in operation using multi SVM Classifier. The framework included two phases, its development and deployment. The first phase developed a cascading classifier based on Haar-like features to identify images containing blade cracks.Haar-like features are applied to depict crack regions and train a cascading classifier for detecting cracks. Two sets of Haar-like features, the original and extended Haar-like features, are utilized. Based on selected Haar-like features, an extended cascading classifier is developed to perform the crack detection through stage classifiers selected from a set of base models, the LogitBoost, Decision Tree (DT), and Support Vector Machine (SVM). In the detection, a scalable scanning window is applied to locate crack regions based on developed cascading classifiers using the extended feature set.*

I INTRODUCTION

As commercial wind turbines (WTs) are typically located in remote wilds and exposed to harsh working conditions, they suffer from highly variable loads which

result in intense mechanical stresses and frequent failures [1]. A significant operations and maintenance (O&M) cost which accounts for 25% - 30% of the overall wind power generation cost has been reported [2]. A commercial wind farm can cover a broad region and contain numerous sparsely distributed large-size wind turbines. Thus, the O&M knowledge of traditional power plants is not directly applicable. Novel approaches for improving efficiencies of the wind farm O&M have attained a top priority in the recent demand of the wind energy industry.

There are many problems in the wind industry, some of which are as follows

(1) It is difficult to perform inspection and maintenance work considering the height of the turbine.

(2) Accidents have been reported, some of which have been fatal.

(3) The location of the wind turbine, usually at remote mountainous or rough sea regions, adds even more challenges to the task of maintenance and repair.

(4) For those countries which have poor lifting and handling equipment such as cranes, fork lifts, etc, yet are interested to generate power through wind turbines; the functionality of the turbine system is also a great concern.

(5) The stake becomes higher and higher when the price of the wind turbine increases together with the capacity to become a gigantic expensive structure.

(6) To improve safety considerations, to minimize down time, to lower the frequency of sudden breakdowns and associated huge maintenance and logistic costs and to provide reliable power generation, the wind turbines must be routinely monitored to ensure that they are in good condition .

Due to the aging of WTs, a growing rate of wind turbine blade failures has been observed. As a major component of WTs, failures of WT blades can lead to the significant capital loss and unscheduled downtime. Previous studies reported that each blade failure could result in a downtime of more than 7 days. Pulsating wind loads and environmental factors, such as the lightning, dust, and icy weather, actually make blades fragile parts of WTs. Therefore, approaches for monitoring the WT blade health are highly valuable and deserve more research efforts.

II LITERATURE SURVEY

Image processing approaches have been applied to the detection of cracks on public infrastructures. Tong *et al.* identified the shape of the crack on the concrete bridge bottom based on binarized images. Hutchinson *et al.* applied the Wavelet transformation and Bayesian decision approach to detect the crack on the concrete structure. Yamaguchi *et al.* proposed a percolation-based image processing method to perform an efficient crack detection on the concrete surface. Methods reported in were capable of identifying the crack from images with simple noises. However, as WT blade images taken by UAVs convey more complicated information, such as the surrounding environment, their analytics are more challenging. Powerful approaches for efficiently processing UAV-taken WT blade images and accurately identifying the crack information need to be developed.

Raisutis*et al.* applied the ultrasonic air-coupled technique with guide waves to investigate defects in WT blades. Jasiniene*t al.* proposed a novel inspection method combining contact pulse-echo and immersion techniques for identifying the shape and size of blade defects. Wei *et al.* assessed damage severities as well as failure modes and locations of WT blades by comparing features of AE signals with the blade mechanical properties. Anastassopoulos*et al.* utilized pattern recognition tools to construct the evaluation criteria of the integrity of blades based on AE signals so that alarms of impending failures could be issued. Menon*et al.* introduced the wavelet-based AE analysis method with adaptive thresholds to evaluate WT blade conditions. Munoz *et al.* applied a graphical method to locate the AE source for better detecting the blade damage. Alternative to AE sensors, the damage detection of WT blades based on ultrasonic techniques is also widely discussed.

III PROPOSED SYSTEM

. A schematic diagram describing the procedure of developing the proposed crack detection in the WT blades as shown in figure.

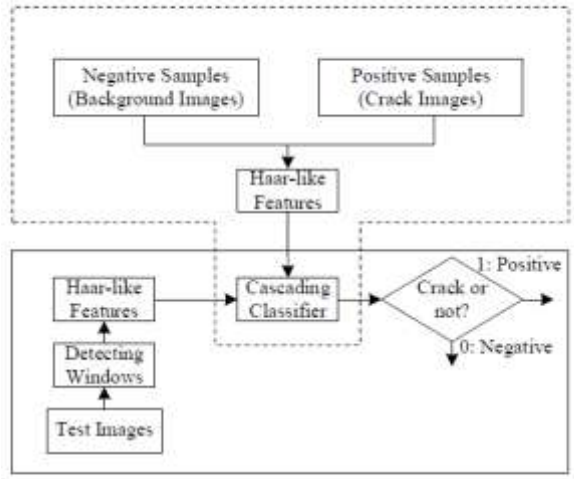


Fig. Proposed diagram

In this figure, both original and extended Haar-like features are firstly compared to determine a more suitable set of Haar-like features for depicting blade cracks. Next, cascading classifiers are developed based on the selected feature set to detect blade cracks. Detailed procedures of constructing the data-driven crack detection framework are summarized as follows:

Step 1 Constructions of training samples

Step 1.1 Collect WT blade images taken by UAVs

Step 1.2 Manually extract regions containing cracks from collected images as positive samples for training; select a set of images without blade cracks while containing all possible backgrounds as negative samples for training

Step 2 Computation of Haar-like features

Step 2.1 Transform training samples into grayscale images

Step 2.2 Compute values of Haar-like features based on the original and the extended Haar-like feature sets

Step 3 Development of the cascading classifier

Step 3.1 Set a number of stages for the cascading classifier

Step 3.2 Train cascading classifiers based on computed two sets of Haar-like features respectively. To speed up the training process, a higher false-positive detection rate is set at each stage to ensure a 100% true-positive detection rate

Step 4 Comparison of Haar-like features

Step 4.1 Classify the training images by trained classifiers

Step 4.2 Compare computational results and select a better feature set

Step 4.3 Apply training algorithms of cascading classifiers to develop crackdetection models based on the selected feature set.

HAAR-LIKE FEATURES

Haar-like features are an over complete set of two-dimensional (2D) Haar functions, which can be used to encode local appearance of objects . They consist of two or more rectangular regions enclosed in a template. The feature value f of a Haar-like feature which has k rectangles is obtained as in the following equation:

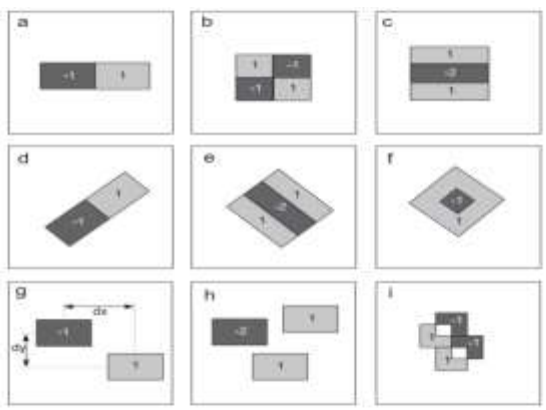


Figure. Haar like feauture

where μ(i) is the mean intensity of the pixels in image x enclosed by the ith rectangle. Henceforth we will refer to the quantity μ as the rectangle mean. In (1), w(i) is the weight assigned to the ith rectangle. Traditionally, the weights assigned to the rectangles of a Haar-like feature are set to default integer numbers such that the following equation is satisfied:

$$f = \sum_{i=1}^{k} w^{(i)} \cdot \mu^{(i)}$$

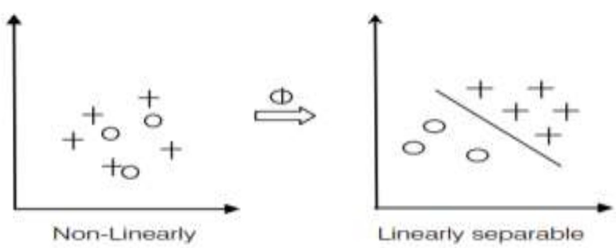
One of the main reasons for the popularity of the Haar-like features is that they provide a very attractive trade-off between speed of evaluation and accuracy. With a simple weak classifier based on Haar-like features costing just 60 microprocessor instructions, Viola and Jones achieved 1% false negatives and 40% false positives for the face detection problem. The high speed of evaluation is mainly due to the use of integral images, which once computed, can be used to rapidly evaluate any Haar-like feature at any scale in constant time.

SVM classification:

Forbinaryclassificationproblems,theideabehindSVMistosplitthedatainfinestmethod.Binaryclassificationisusedwhenweneedtoclassifythetwodatasets.Therearenumerousexamplesofbinaryclassificationliketry-outs(oneeithermakesorfailstomaketheteam),claimsize(largeclaimsareabovesome thresholdandsmallclaims below), andfingerprintidentification(matchedorunmatched).Supportvectormachinesareprimarilydesignedfor2-classclassificationproblems.

SupportVectorMachineconsider2SupportVectorMachineconsider2approaches-

1. Case whenthe dataare linearly separable
2. Casewhenthedataarenon-linearly separable



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IV SIMULATION RESULTS

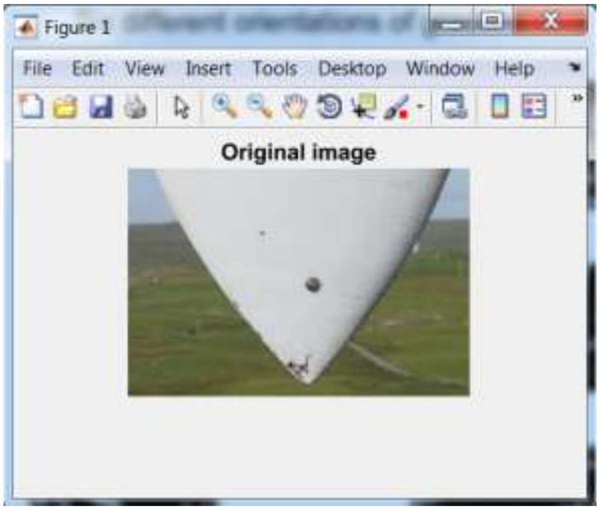

Fig :Input image

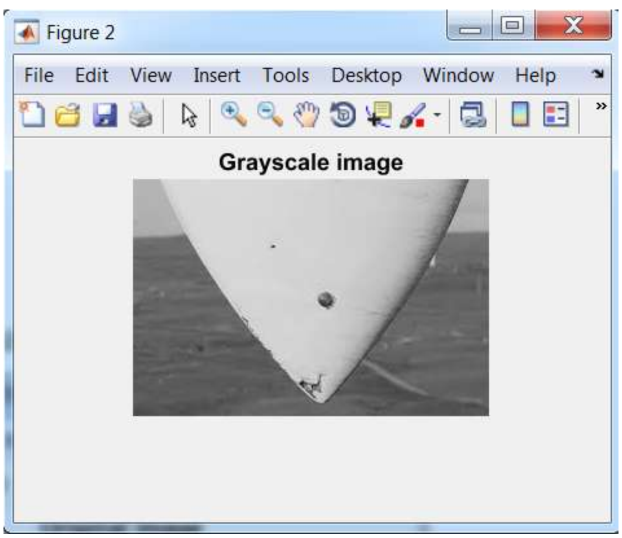

Fig: gray scale image

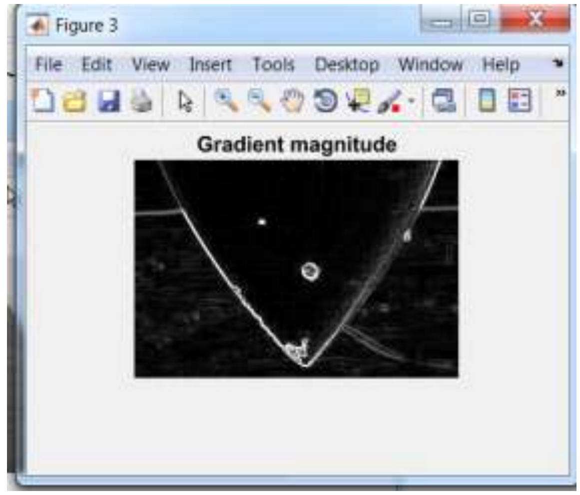

Fig: gradient magnitude

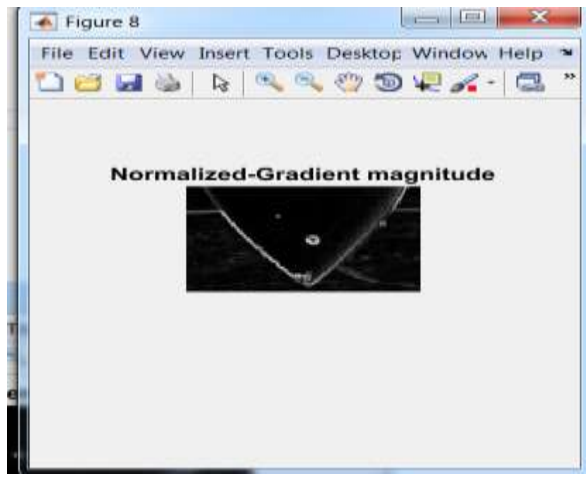

Fig: normalaized magnitude

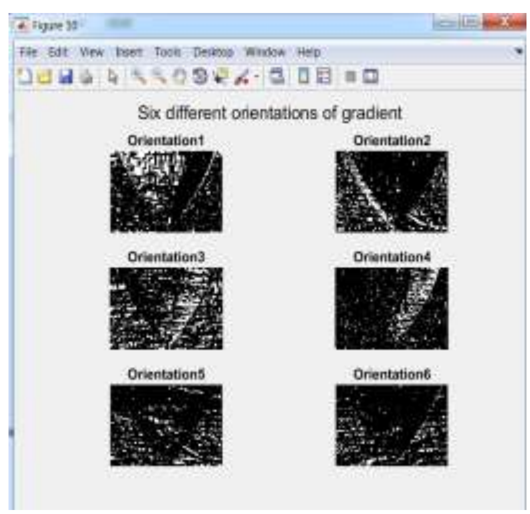

Fig: orientations of gradient

Fig: gradient direction

Fig classification result

V CONCLUSION

Wind turbines require a robust structural health monitoring strategy for wind turbine blades, and this work developed a new crack detection technique for wind turbine blades in operation using multi SVM Classifier . The framework included two phases, its development and deployment. The first phase developed a cascading classifier based on Haar-like features to identify images containing blade cracks. In the second phase multi class classifier proposed . In the experiment of the confirmation of the crack detection accuracy, it was proved that the proposed method showed comparable accuracy to the existing one.

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