A monitoring method for detecting and localizing overheat, smoke and fire faults in wind turbine nacelle

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ABSTRACT

This study presents a monitoring method that utilizes 3D object classification to accurately detect mechanical and electrical components of a wind turbine by combining a geometric and statistic feature extractor (GSFE) with a multi-view approach. The proposed monitoring method also detect outlier after executing object detection to localize overheat faults in these components with fused Optical or Infrared/LiDAR measurements. The proposed method has three key characteristics. First, the proposed outlier detection allocates two extremes of normal and faulty clusters by using 2D object classification/detection model or measuring the standard deviation of temperature with sensor fusing measurements. Specifically, the outlier detection with sensor fusing measurements extracts the position coordinates and temperature data to localize overheat faults, effectively detecting an overheat component. Second, the GSFE utilizes a group sampling approach to extract the local geometric feature information from neighboring point clouds, aggregating normal vectors and standard deviation. This method ensures the high accuracy of object classification. Third, a multi-view approach focuses on updating local geometric and statistic features through a graph convolution network, improving the accuracy and robustness of object classification. The proposed outlier detection is verified through overheat/fire field tests. The effectiveness of the proposed 3D object classification method is also validated by using a virtual wind turbine nacelle CAD dataset and a public CAD dataset named ModelNet40. Consequently, the proposed method is practical and effective for monitoring a fire and overheat component because it can accurately detect critical components with only a few virtual datasets because gathering bigdata for training a neural network is extremely difficult.

1. METHODOLOGY

The method for monitoring and detecting overheat, smoke, and fire faults in wind turbine nacelle structures comprises three phases. In phase 1, a 3D nacelle map is created using an octomap method that utilizes 3D point cloud data and motor state data of pan/tilt system to identify the nacelle environment and minimize blind spots (Hornung et al, 2013). In phase 2, two outlier detection methods are used to detect overheat, smoke, and fire faults in the nacelle. In phase 2-1, hotspot detection is used to detect overheat faults by extracting position coordinates and temperature data using fused LiDAR and Infrared (IR) measurements (Jiarong, L., & Fu, Z. 2022). Especially, overheating is defined as a temperature reading that is 3 standard deviations (3σ) from the mean temperature measured by the IR camera. In phase 2-2, a 2D object classification/detection method with an optical camera is used to classify the fire, smoke, and normal classes and detect the localization of fire/smoke faults. The position of fire/smoke faults is then transformed from 2D pixel coordinates to 3D coordinates using an extrinsic parameter between 3D LiDAR and optical camera. Next, in phase 3-1, the position of fire, smoke, or overheating is matched with one of the classified nacelle components using a 3D object classification model called GSFE-GCN. This proposed model utilizes an effective local feature extractor called Geometry and Statistical Extractor (GSFE), which creates a new aggregated feature combining group normalization with normal vector, and a Graph Convolution Network (GCN) that improves the accuracy and robustness of network through view-graph that represents the relationships among single-views (Xin, W. et al, 2020). In detail, this GSFE method suggests a local feature extractor. It is important to create local groups corresponding to the entire point cloud data using Farthest Point Sampling (FPS) and K-nearest neighbor (KNN). And the GSFE extracts the new input feature, aggregated by geometry and statistical feature. The statistical feature is the normalized point clouds of the local groups, which is conducted as follows:

$$X_{i,j} = \frac{X_{i,j} - X_i}{\sqrt{\frac{1}{k \times n \times d}\left(X_{i,j} - X_i\right)^2}} \quad (1)$$

where $X_{i,j}$, X_i, k, n and d denote the statistical feature in grouped local neighbor, the center of grouped, the number of the point cloud, the number of neighbor and the dimension of the point cloud, respectively.

The geometry feature calculates the normal vector by choosing two vectors on the plane that are not parallel to each other, which is conducted as follows:

$$a_{i,j}(x - x_i) + b_{i,j}(z - z_i) + c_{i,j}(z - z_i) = 0, \quad (2)$$

$$t_{i,j} = (a_{i,j}, b_{i,j}, c_{i,j}), \quad (3)$$

where x_i, y_i, z_i, $a_{i,j}$, $b_{i,j}$ and $c_{i,j}$ denote the x, y, z component of the centroid and the normal vector, respectively.

An aggregated function combines the geometry feature with statistical feature, which is conducted as follows:

$$u_{i,j} = \sum_{j}^{K} \left| \frac{X'_{i,j}}{\left|X'_{i,j}\right|} \cdot t_{ij} \right|, \quad (4)$$

This new aggregated input feature ($u_{i,j}$) ensures more effective group sampling to extract the local geometric feature information. This input feature is processed by PointNet++ and transformed into a more optimal embedding space for classification (Charles, R. Q. et al, 2017). Finally, in Phase 3-2, the pan/tilt system is used to localize and extinguish the fire sources. The aiming and extinguishing system converts the selected aiming point into angle data for each pan/tilt motor, which are controlled to approach the origin of the extinguishing system coordinate.

2. Field Test and Experiment

The proposed method was validated through a field test and two quantitative experiments. The first field test is based on ISO 7240 standard and Under Laboratories (UL) 268 B, which suggest about detail of fire field test. Therefore, a pan/tilt system equipped with three sensors (3D LiDAR, IR camera and optical camera) was used to scan a fire test room with dimensions of $10 \times 6 \times 6$ m based on ISO 7240-9. The system was automatically controlled at distances ranging from 1 to 7 m from the ignition point. Also, this test was executed in several fire situation by UL 268 B, including n-Heptane fire (Size [H × V]: $135 \times 228\ mm$) and overheat (Size [H × V]: $1{,}388 \times 197\ mm$). A total of 239 detection experiments were conducted to evaluate the accuracy of the proposed method for detecting fire and overheating faults. Figure 1 (a) shows the result of the proposed method for hotspot detection, which successfully detected all overheat regions with their temperature and depth position, enabling the identification of the incipient fire. Figure 1 (b) shows the result of the proposed method for smoke/fire detection and hotspot detection, which successfully detected and aimed at all fire sources.

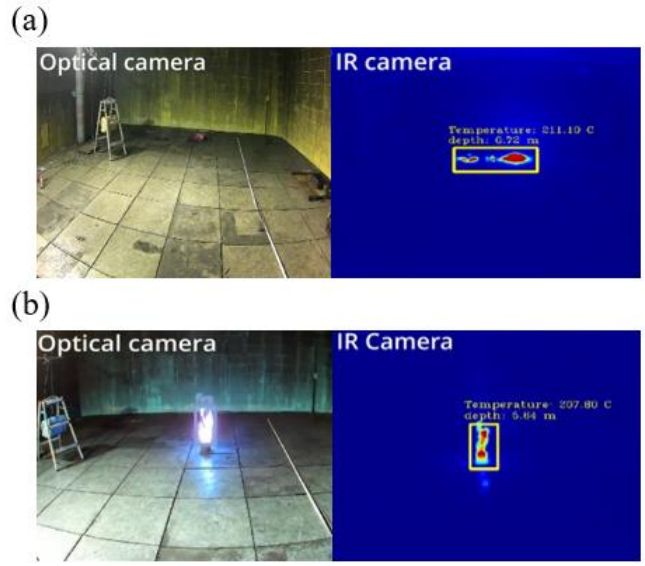

Figure 1. (a) Result of the hotspot detection and (b) Result of the smoke/fire detection.

Two quantitative experiments were conducted to validate the accuracy and robustness of the GSFE-GCN model, using a nacelle dataset and a public dataset named ModelNet40. The nacelle dataset included five classes of main components of a nacelle: generator, gearbox, brake system, main bearing, and others, where overheating, smoke, and fire incidents are likely to occur. Table 1 shows the result of the GSFE-GCN method for nacelle dataset, demonstrating accurate classification of all nacelle components. In particular, the pre-train model (GSFE) improved the accuracy compared to other classification model, indicating that the geometry and statistical features were sufficient to extract local information from point cloud data. Furthermore, the difference in accuracy between GSFE and GSFE-GCN highlights the effectiveness of the graph convolution network in improving the accurate classification. Next, Table 2 shows the result of the GSFE-GCN method for the ModelNet40 dataset, which contains 9843 training models and 2468 test models divided into 40 categories. The GSFE-GCN achieves 94.7 %, outperforming PointMLP by a significant margin of 0.5 %. Furthermore, the proposed method, which only uses point cloud data, showed comparable performance to the ULIP+PointMLP method, which uses various input features such as language, image, and point cloud data.

Table 1. Result of classification on Nacelle dataset.

Method	The accuracy of each nacelle components (%)				
	Generator	Gearbox	Main bearing	Brake system	Others
PointNet++ (Qi et al, 2017)	88.5	89.7	95.0	95.0	91.6
GSFE	96.5	98.6	100	100	98.3
GSFE-GCN	100	100	100	100	100

Table 2. Result of classification on ModleNet40

Method	Overall Accuracy (%)	Mean Accuracy (%)
PointNet (Qi et al, 2017)	89.2	86.0
PointNet++	90.7	88.4
DGCNN (Wang et al, 2019)	92.9	90.2
RSCNN (Lui et al., 2019)	93.6	-
Point-BERT (Yu et al., 2022)	93.2	-
PointMLP (Xu et al., 2021)	94.5	91.4
ULIP+PointMLP (Le et al., 2019)	94.7	92.4
GSFE-GCN	**94.7**	**92.2**

3. CONCLUSIONS

In conclusion, this study proposes a monitoring method that detect and localize the overheat, smoke, and fire faults with several classification/detection models. The proposed method has three key characteristics: First, it can allocate two extremes of normal and faulty clusters by using object classification/detection model and measuring the standard deviation of temperature with sensor fusing. Second, it can accurately detect several nacelle components by creating the new aggregated geometric and statistical feature using the GSFE. Third, it can further improve the accuracy and robustness of component detection using GCN. The fire field test demonstrates the effectiveness of the proposed method. And two quantitative evaluations using the nacelle dataset and ModelNet40 confirm the accuracy and robustness of GSFE-GCN model. Additionally, the proposed method can be effective for fire and overheating detection in many other real-world applications including manufacturing plants, factories, power plants and other infrastructures that require a robust and highly accurate fire detection system.

ACKNOWLEDGEMENT

This work was supported by Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE) (20213030020260, Development of Fire detection and protection system for wind turbine).

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