Imagification Technology and Deep Learning Accelerating Defect Detection in Non-Destructive Testing for Wind Turbine Blades

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Wind power generation is a fast-growing type of renewable energy that is highly recognized for its potential. Turbine blades are a crucial part of power generation systems, and they bear substantial loads in operation. Therefore, quality inspection standards during production are extremely strict in order to meet critical to quality (CTQ) requirements. Quality inspections include ultrasonic non-destructive testing (NDT) methods, for instance, which involve an engineer's detailed examination of ultrasonic testing (UT) scan image data covering a length of approximately 75 meters to identify possibly defective parts of a few centimeters. This is a time-consuming process, and human error is always a risk. Fujitsu Laboratories of Europe Ltd. has developed a unique technology, Imagification, and combined it with an image-recognition deep learning engine to develop a system for automating defect detection, helping to reduce the inspection load and prevent human errors. We have further developed the system by digitizing and integrating customer knowledge and expertise in blade structure, ultrasonic NDT procedures and know-how in defect characterization to build a new automated quality inspection solution. This paper explains the newly developed defect detection system and describes the process of digital co-creation with customers to realize commercial applications of the technology.

1. Introduction

Wind power generation is one of the fastest growing renewable energy resources. As an unlimited source of energy that does not cause CO_2 emissions, it is in demand all over the world.[1)]

Wind power turbines are huge and complex systems, and turbine blades in particular are a crucial component for power generation. Their length ranges from several tens of meters to about 100 meters, they are curved in shape and each blade varies in thickness along its length. Since very large loads are applied to the blades when the turbine is in operation, it is crucial that the blades meet structural integrity requirements to avoid potential risks in the field. Blade manufacturing is a complicated process, and advanced quality assurance procedures have been developed to detect any small flaws and defects that may be present in the structure. Next to visual inspection, ultrasonic non-destructive testing (NDT) is one of the key quality control methods especially for inspection of thick laminates where visual inspection is not an option. Ultrasonic testing (UT) consists in scanning the blade with ultrasonic waves to image internal defects, and an inspection technician interprets the scan images. Since the aim is to identify potential defects in the order of just a few centimeters from the full scan of a blade with a total length of 75 m, expertise and suitable experience are required for the interpretation of the imaging data. Moreover, since defect images are complex and it is difficult to classify them by patterns, efficiency improvement using AI technology has been considered.

Since Fujitsu announced the FUJITSU Human Centric AI Zinrai in 2015,[2)] we have offered AI technology in the form of application programming interfaces (API) and cloud services.[3)] Fujitsu Laboratories of Europe Ltd. (hereafter, FLE) has been promoting the social implementation of AI technology, from the fields of design and manufacturing to finance and retail. FLE successfully developed the Imagification technology for imaging non-imaging data, enabling feature recognition using the deep learning engine for image recognition (hereafter, DL engine).[4]

This paper describes the development of highly efficient NDT using AI technology realized through digital co-creation.

2. Challenge of quality control in turbine blade manufacturing

As mentioned in the previous section, ultrasonic NDT has been introduced for the quality inspection of blades. The scans are analyzed in detail to detect potential defects such as transverse wrinkles (fiber waviness), dry glass, foreign objects, etc., in the laminates. Any defects that are detected in this way are repaired according to the specified working instructions. Manufacturers of wind turbine blades are actively developing technology for improving quality, and the possibility of the occurrence of such defects is extremely low. Still, even a single defect remaining in a blade increases the risk of damage or breakdown after installation. It was therefore previously necessary for the inspection technician to interpret, and analyze all inspection images on a screen.

Due to massive size of the blades, a large amount of data is generated from the UT scans, and its manual evaluation is quite a time consuming process. Thus, our objective was to develop an automated system that can highlight only a small portion (20%) of the data containing potential defects and disregard the remaining 80%. By allowing inspection to focus on only a small portion of the data, this system would shorten the data evaluation time and reduce human error, thus increasing inspection effectiveness.

3. Imagification technology and its application to NDT of turbine blades

Imagification is a created word consisting of the term "image" and the suffix "-fication" (to make), and it means "imaging." This section describes the relationship between Imagification technology and DL engine, and the application of these technologies to NDT.

3.1 Challenges for the application of deep learning

Operating deep learning at a practical level requires from tens of thousands to millions of data items to learn the features of the object. However, it is rare for customers to be able to prepare such vast amounts of data, and thus it is difficult to achieve practical performance based on sufficient learning.

Moreover, the quality of the data used for learning is also important, and in particular, the labeling of the data determines accuracy to a great extent. Since expert knowledge is required for the interpretation of ultrasound images, it is important to exchange information such as expertise about data. This is discussed in the next section.

3.2 Imagification technology

Imagification technology aims to enhance the learning effectiveness of the DL engine even when only a small amount of data is available, and it has the following two features.

(1) Imaging of non-imaging data

The types of data to which Imagification technology can be applied, besides 2D imaging data, include 3D CAD models, financial data such as stock price movements, measurement data such as 3-axis accelerometer data, and time-series data such as system logs of registers. As shown in **Figure 1**, Imagification technology is applied to raw data such as sensor and CAD model data, which are input to a DL engine to create learning models.

(2) Pre-processing to achieve effective learning

Parameter adjustments for the data imaged in (1) above are performed to maximize learning efficiency. Examples of parameters are image brightness and contrast. As a more practical example, in automatic part detection using a 3D CAD model,[5] similar parts were extracted using feature values. In the 2D imaging of the 3D CAD model shown in the lower left of Figure 1, the camera angle is used as a parameter and information such as the component size and area is incorporated for further improvement of accuracy. Imagification technology realizes efficient learning data creation by extracting features by a combination of image processing and signal processing techniques.

3.3 Application of Imagification technology to NDT

The input data in this case are the following two types.

1) Raw data

Numerical data of blade scan images using UT

2) Metadata (CSV file)

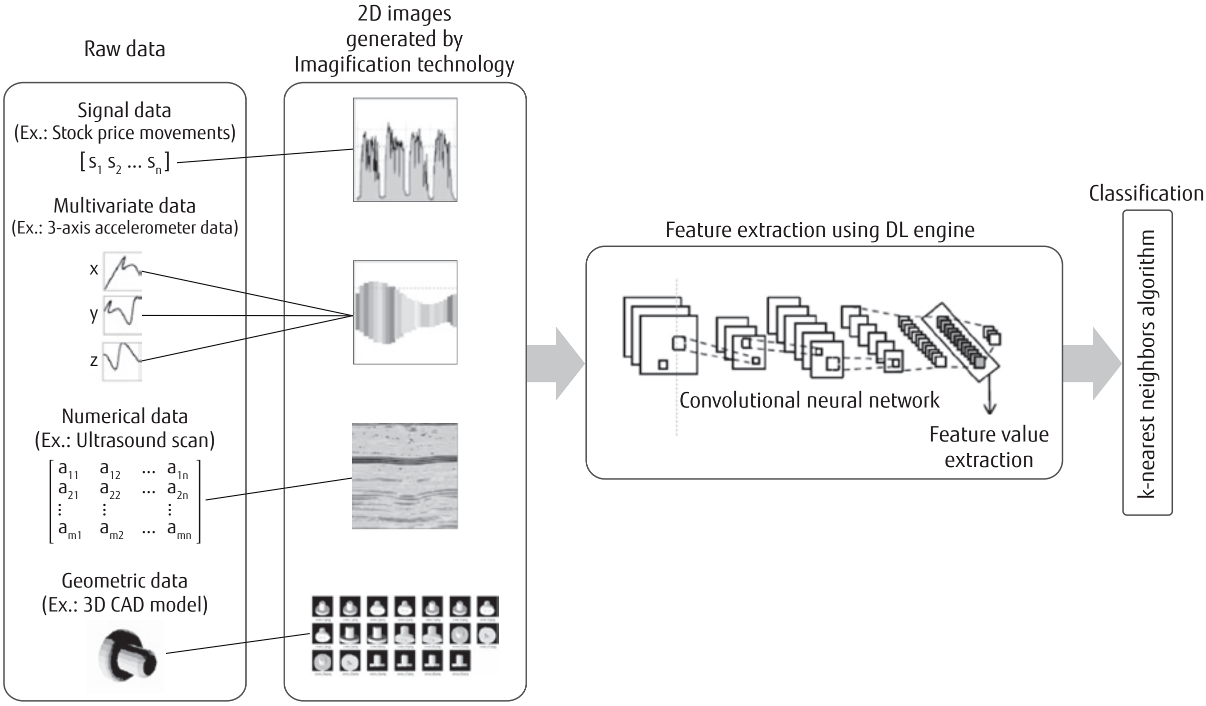

Figure 1
Imaging by Imagification technology and classification by features using DL engine.

Supplementation information linked to raw data, coordinates of potential defects, defect classes, data numbers, and so on

Figure 2 shows the flow of a series of processes using Imagification technology and DL engine developed for NDT data. First, scan plotting to image the raw data is performed, and then image patching to divide the image of the 75-meter long blade into segments of an appropriate length. As preparation, the data is divided into data for learning and data for testing, and the data for learning is further classified based on metadata. This learning data is input to the DL engine, and potential defect image patterns are learned. Next, the validity of the learning model is evaluated using the test data. If sufficient performance cannot be obtained, the parameters are adjusted and learning is performed again.

The results of an evaluation run using a new data set to confirm the effectiveness of this series of processes are shown below.

- Potential defect location detection rate[note 1)]: 89.5%
- Inspection volume per blade[note 2)]: 28.4%

4. Digital co-creation for application to manufacturing sites

This section describes the creation of a solution applying the system, whose validity was confirmed in the previous section, to a manufacturing line.

This project began with the establishment of evaluation criteria, and the identification of technical requirements suitable for business development. The application requirements for the manufacturing line were set as follows.

- Potential defect location detection rate: 95% or higher
- Inspection volume per blade: 20% or lower

note 1) Percentage of defects detected correctly by the DL engine.

note 2) Taking the entire image as 100%, the percentage represented by the parts pointed out by the DL engine as defects.

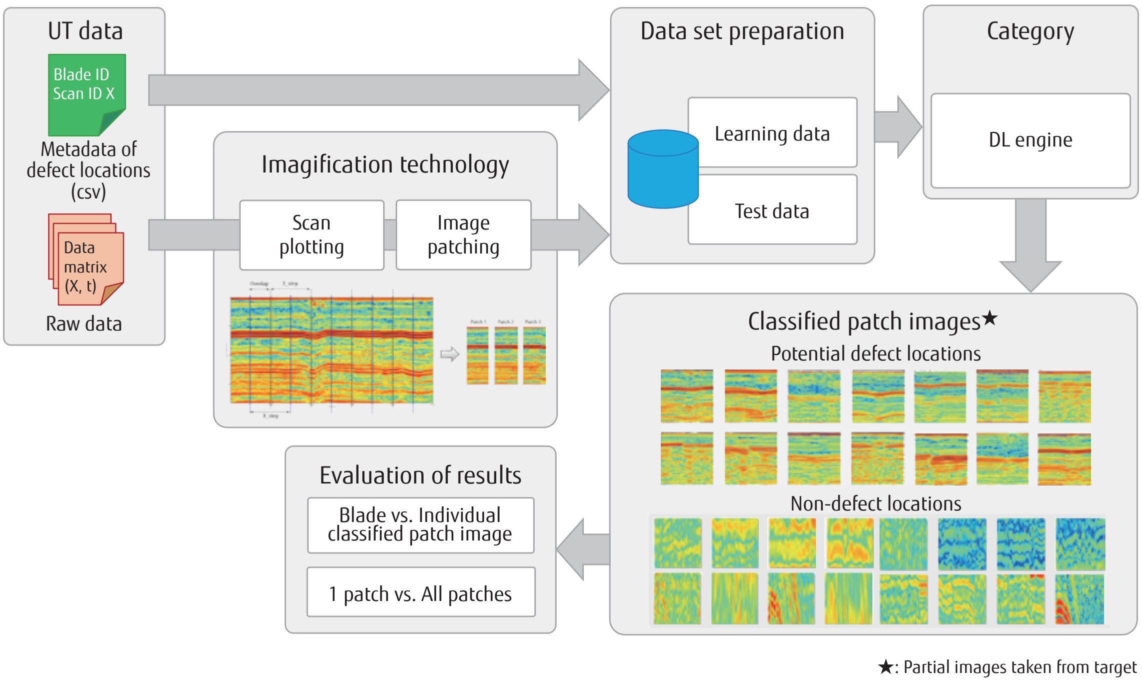

Figure 2
Imagification technology for UT data and process flow.

As mentioned earlier, each company has already refined blade manufacturing methods through repeated trial and error, and the number of defects itself is small. Therefore, it was necessary to satisfy the above requirement from a learning data sample more limited than expected.

4.1 Implementation of digital co-creation

As mentioned in the previous section, since the quality of the learning data greatly affects the accuracy of the final system, it is important to understand the data based on expert knowledge of the inspection process and ultrasonic NDT procedure. In executing the project, the following expertise was provided to FLE by the customer's NDT quality control engineers:

- Expertise regarding blade structural integrity requirements
- NDT procedure, know-how on UT, and setting test plans
- Data analysis and validation for learning and verification of deep learning system. Delivered meaningful sub-classified data extracted from many years of database and experience in NDT of blades.

The key elements required for problem solving are data and related knowledge and experience with blade inspection. To satisfy the practical level of performance, it is necessary to digitalize the tacit knowledge of the inspection process held by technicians. To that end, we held repeated conversations with members of the quality control group. Based on years of experience in NDT, they analyzed and evaluated images, classified the types of defects derived from the database and their occurrence probability in detail, and provided all this information to FLE. The verification of mutual understanding combined with the review and assessment of test results for systems built by FLE were complex tasks for those who provided their image expertise as this required them to deliver and analyze dedicated image patterns and test materials for the learning and validation of each specific pattern recognition algorithm.

FLE repeatedly verified the effectiveness of the following three procedures in order to improve the accuracy of the learning model, using the provided training data.

- Extraction of issues regarding application of the technology
- Functional enhancement of Imagification technology

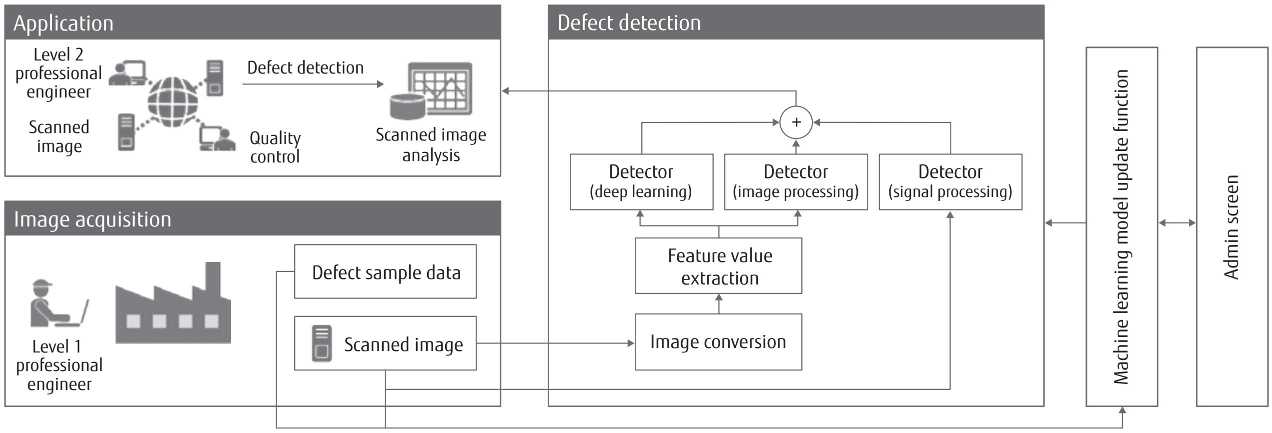

Figure 3
Configuration of defect detection support solution.

- Optimization of Imagification technology and DL engine after functional enhancement

We also held several workshops and created an agreement regarding the system's execution capabilities and the objectives of the proposed solution. The know-how for defect characterization using real data and knowledge of the NDT procedure, together with the system built by FLE by combining the Imagification technology and DL engine, make up the defect detection support solution shown in **Figure 3**. This is a made-to-order solution specifically designed for solving issues of ultrasonic NDT.[6]

In the final evaluation of the system, which was developed over a short period of 3 months, the following results were obtained and the application requirements for the production line were satisfied.

- Potential defect location detection rate: 95%
- Inspection volume per blade: 18%

For digital co-creation, it is essential to extract expert knowledge and know-how on site, and dialogue with the customer is a must. In some cases, however, this may hinder daily work activities at the site. This requires developing relationships of trust and time management, and thus we carried out development with a constant focus on implementing efficient dialogue. In a process we called Sprints, we held telephone conferences with the customer every two weeks to share progress information and repeat the process of trial and error. Furthermore, we also held a face-to-face workshop twice. As a result, we were able to meet the requirements.

5. Future tasks and outlook

We have demonstrated the potential for defect detection and achieved accuracy of a practical level through research and development work so far. Further perfecting of the system is required for its future practical use in production environments. Additional functionalities and requirements will have to be investigated during the pilot phase at the production site. This also includes the realization of a high-speed display for the scan viewer capable of rendering images within 1 second, and enhancement of color profiles.

Further, a point to be taken into consideration when running deep learning is that the detection accuracy is lower for new types of defects. Blades have a laminated structure made of composite materials, and most of the manufacturing processes are manual. As a result, the image patterns of defect are complicated and difficult to classify. Therefore, to maintain the accuracy of the quality inspection, regular updates of the learning model are required.

Since it is also necessary to collect new defect images for re-learning, a re-learning environment that minimizes the burden on the operation side is needed. Moreover, if the system is applied to different blade types, it is necessary to re-evaluate the current learning model and apply necessary parameter tuning and adjustments, and systematization of after-sales service is a challenge.

The initiative introduced so far is a project that extends across countries and departments. A blade manufacturer initiated contact with FLE through Fujitsu

A/S in Denmark and the sales department of Fujitsu Technology Solutions in Germany, prompting FLE to commence technological development with the support of Fujitsu Laboratories Ltd. in Japan. Business implementation was led by Fujitsu A/S and Fujitsu Advanced Technologies Ltd. in Japan.

Imagification technology has the potential to be widely used for a broad range of applications and industries beside NDT. Fujitsu Services in the UK is currently building Fujitsu Advanced Image Recognition Solution based on this case, and we are aiming for further practical applications across industries.

6. Conclusion

This paper introduced the case of digital co-creation for development of a solution using Imagification technology and deep learning in order to improve the efficiency and effectiveness of quality inspections for blade manufacturing.

Looking ahead, we will aim to enhance further the value of this solution by developing additional functionalities and learning modules and deploying this solution to other industries as a Fujitsu Advanced Image Recognition solution.

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