Intelligent Inspection System Based on Infrared Vision for Automated Fiber Placement

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***Abstract*—This paper proposes an intelligent inspection system based on infrared vision for Automated Fiber Placement. It can improve composite materials production quality and production efficiency, shorten process design time, and reduce material waste. The system can realize the defect recognition and defect measurement, which can be used in intelligent decision-making, optimization of multi-parameters and quality traceability. Experiments are conducted to verify the feasibility and effectiveness of the presented system.**

Index Terms - Automated fibre placement, defect detection, infrared measurement system.

I. Introduction

Automated fiber placement (AFP) plays an irreplaceable role in composite manufacturing because of its high productivity. And the inspection system of AFP has a great influence on its production efficiency. However, there are still many problems of the AFP inspection system. Most of the current inspection method is manual which needs trained human inspectors to perform careful visual inspection and verification of each ply. For large composite parts such as a fuselage barrel requiring hundreds of plies, manual inspection and rework has significant influence on automated process efficiency, according to information presented at recent industry gatherings. For example, in a generic fuselage barrel and using an optimized AFP process, inspection and rework still made up more than 60% of the total part production time[1].

With the development application of composite material, and the pressure for higher production rates call for the new technologies for automated and in-process inspection. Groups around the world are working on this to develop an in-process inspection system for AFP process which can meet the efficiency requirements and make the quality traceable. In the aerospace industry, the traceability of materials information plays a critical role in ensuring materials auditability and their eventual qualification for safe use. It is the ability to track the trail of data generated during product development, so that one can follow the data to prove the performance and do quality assurance verifications for manufactured products. Defects identified with the system include: gaps, twists, overlaps, missing tows, foreign objects, debris, wrinkles, bridging, splices, and end of ply.

There are four main commonly used sensors in AFP inspection system: spectral cameras, short-wave infrared cameras, laser profilometers and thermal-infrared cameras. Using a spectral camera mounted on AFP head was first presented by Soucy K in 1996[2]. However, the black prepreg slit tapes prevent a high visual contrast in between the single tows and the plies on the tooling surface, which results in difficulties in defects detection[3]. A camera system with multi-lighting source illumination was presented by Tao to improve the accuracy of online detection, but it can only detect the gaps [4]. Boeing used shortwave infrared cameras with infrared filters and lighted up by near infrared light to detect defects in eight patents from 2005 to 2010 [5-12]. The defect detection effect has been improved. However, the entire inspection system is very complicated. Shadmehri et al. developed a Laser-Vision inspection system to detect the ply location, the fiber orientation and gaps but there is no complete solution for an inspection of the fiber placement process available, and in addition it is challenging to integrate the process monitoring in the process itself for an online inspection [13]. In 2014 Boeing Co proposed a method of detecting missing tows using thermal infrared camera and achieved a good efficiency. Afterwards, Berend realized an US patent to use thermal infrared camera, detecting all defects during the automated lay-up process and verified this method did a good performance. Carsten designed a thermal in-process monitoring system using this method [14] and analyzed the influence of AFP parameters [1]. J. Brüning proposed a machine learning algorithm for optimization of AFP processes based on the thermal in-process monitoring system.[15].

In general, the inspection systems based on spectral camera and short-wave infrared cameras can hardly detect multiple types of defects. And the one based on thermal infrared camera can only qualitatively detect all types of defects but has not yet realized quantitative measurement.

To address the current issues, a comprehensive inspection system based on infrared camera for AFP is presented in this paper. The recognition and measurement of defects in AFP process are implemented, so that the production quality can be traceable.

II. Intelligent Infrared Visual Inspection System Establish

The procedure of presented intelligent in-process inspection system is as shown in Fig 1. It consists of four modules including data collection, defects recognition, defects measurement and defects visualization.

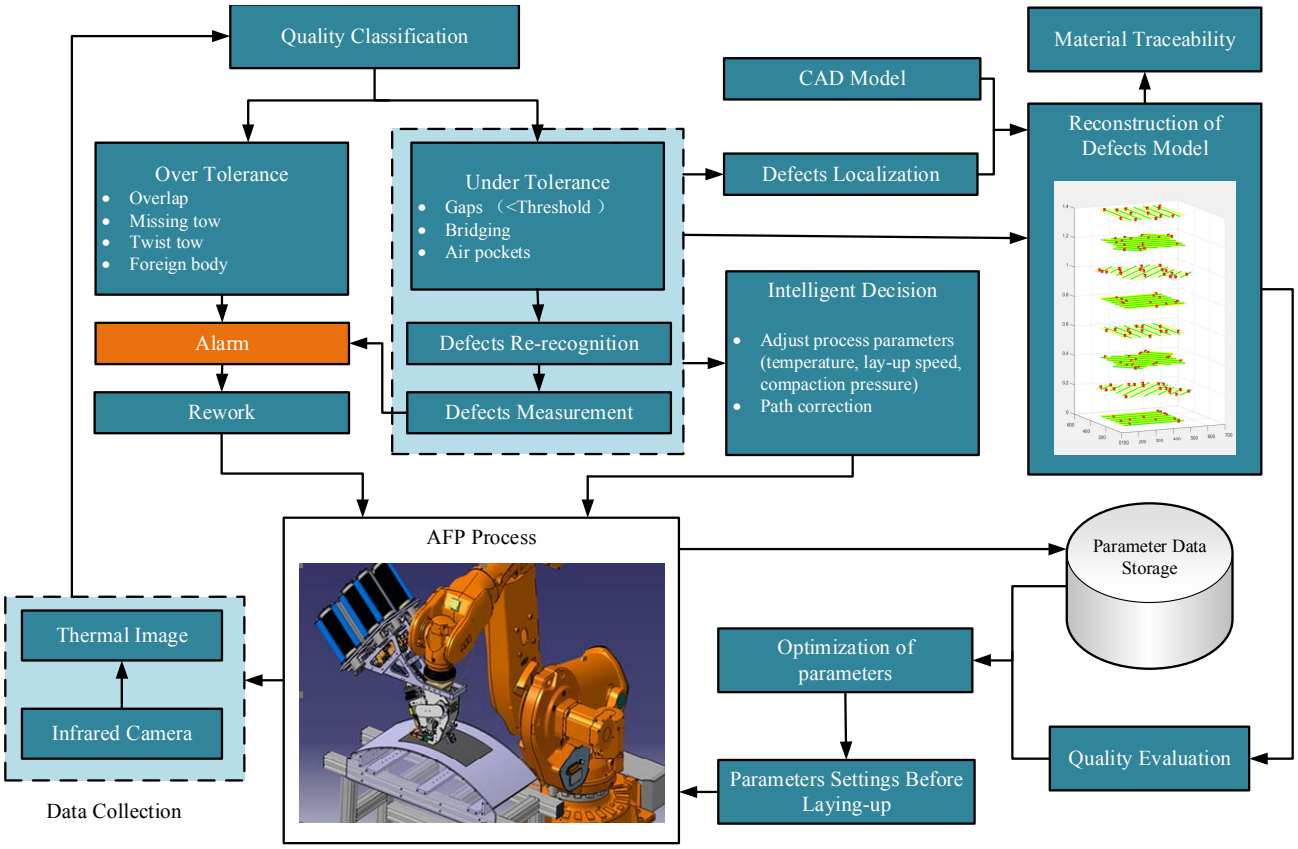

Fig.1 Intelligence in-process inspection system diagram

1. Data collection module

Thermal-infrared camera moves with AFP head in placement processing to scan the fiber surface and capture images. It can be seen from the thermal camera at the compaction point that there is a temperature contrast between the cool tows and the heated surface and it will bring a good contrast between the surrounding surfaces and the cool tows in thermal images. If there are gaps or overlaps of a certain size, their geometric shape will be imaged according to the infrared camera working principle. Therefore, the information of multiple types of defects is collected and transferred to the next module.

2. Defects recognition module

A classification network is designed to divide collected images into two categories, pass or failure, according to the identified defect types. Defects like overlap, missing tow, twist tow and foreign body are over tolerance in AFP processing while gaps(<Threshold)，bridging and air pocket are under tolerance. The significance of using classification network in this step to do initial recognition is that there are too many types of defects. If designing rules one by one to recognize each type of defects, the algorithm is too complex. The initial classification reduces the difficulty of defects recognition and improve the processing efficiency. Once the over tolerance defects are recognized by the classification network, the system will alarm and AFP needs to rework or repair. For defects belonging to pass category, the re-recognition rules are set for defects with low recognition accuracy in the initial classification like overlaps. In this way, we got the defects data with high recognition accuracy.

3. Defects measurement module

The extraction and segment algorithms are performed on those under tolerance defects to get their pixel position in the image in this step. The extraction results are combined with the calibration results to measure the size of defects and localize the defects points on lay-up tools. There are two main tasks in this module. First, for gaps detection, the width of gaps is an important indicator, so a threshold is set to judge whether the gap is under tolerance or not. Then, for other defects under tolerance, the information of their size and position are saved to reconstruct defect 3D model.

4. Visualization module

In this module, the detected defects information of each layer is matched to their CAD model and the defect 3D model is reconstructed. With the 3D model, it is possible to calculate the presence of pores in the produced composite material and realize comprehensive quality monitoring. The defects information including defect type, course number, defect number, X-position, Y-position, Z-position and repair action forms a report and output. The final evaluation result and defects model is visualized through the interactive interface like Fig.2.

The functions implemented by this presented intelligent inspection system have many uses. Defects information stored in this system can be used to do quality analysis of the composite products. The reconstructed defect 3D models can be used as product IDs for later traceability. The relationship between process parameters and defects can be established

from this system and applied in intelligent decision and parameters optimization. Process parameters like temperature, lay-up speed, compaction pressure have positive and negative correlations with defects, some of their relationships are shown in Table 1. The process parameters can be intelligently adjusted according to the recognition and measurement results of defects. We can set a reward function, once the parameters are adjusted the reward function will achieve a value according to next detect results. Through continuous learning from process, a learning model can be established and used in parameter optimization. The results of the monitoring module combined with the information of the path planning will be saved in an experience storage to generate process knowledge, that can be used to optimize the path planning and parameter adjustment of the AFP machine before placement.

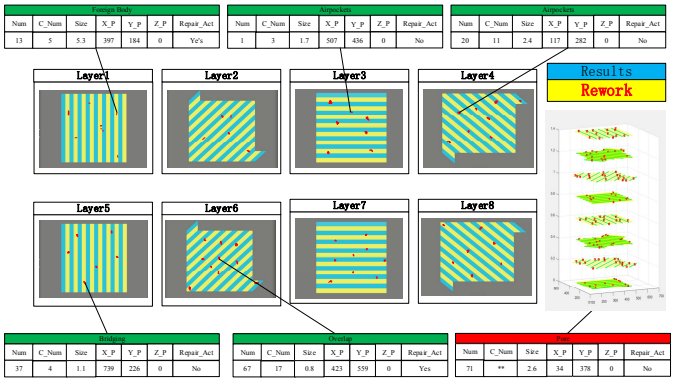

Fig.2 Inspection report

TABLE I

RELATIONSHIP BETWEEN PROCESS PARAMETERS AND DEFECTS

Relationship	Gaps	bridging	Air pocket
Temperature	NO	Negative	Positive
Lay-up speed	Negative	Negative	NO
Pressure	Positive	Negative	Negative

III. SYSTEM IMPLEMENTATION

The implementation algorithm of the presented system is shown in Fig.3. The inputs are the Fiber SIM or CPD and CAD model of each layer from which the total layer number LayN and path number of each layer {Path_Lay_n} can be gotten. The serial number of layer is recorded as Lay_n, when all layers have been laid, the algorithm stops. During the laying of each layer, the serial number of path is recorded as Path_r, when the whole paths in a layer are laid, the number of layers is increased by one. At the beginning of each path, the system will send a start signal, and then start collecting images from infrared camera. The collected image is first recognized by the trained classification model and divided into pass and failure. If this image is recognized as failure, the system will alarm and stop working, waiting for workers to repair, and after repair, the path will be re-laid. If the image is classified as pass, it will be re-recognized according to the set rules to identify whether there is an intolerable defect that is difficult to identify based on the network model, and if so, return to the alarm and repair step. Otherwise, proceed to the next step, extract the edge of the gaps and measure width of the gap. Return to the alarm and repair step when it exceeds the threshold or locate the gap when the width is within the threshold. Simultaneously extract the edges of other under tolerance defects and do measurement and location.

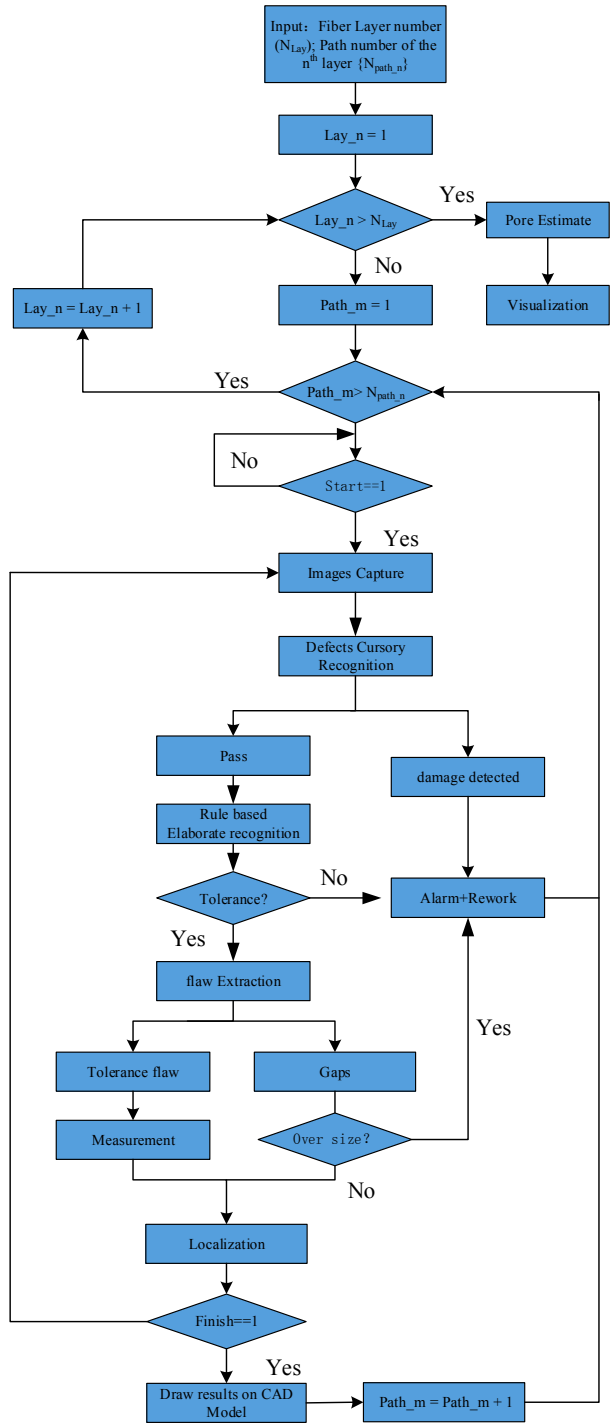

Fig.3 System implementation algorithm

The above operations are repeated for all the collected images until the stop signal of the path is received, the image acquisition stops, and it will continue until the start signal of the next path is set. When the placement of a layer is completed, the stored defect information is matched to the CAD model of the layer. Repeat the above steps until the

placement is finished, then create a three-dimensional model of the defect. Estimate the presence of air holes based on the three-dimensional model and generate the final inspection report.

IV. EXPERIMENTS

A. Experiment Platform

The experiment platform is the AFP as shown in Fig.3. An ABB 6640 robot is used in these experiments to verify the method. The infrared camera is i3-thermalexpert TE – EQ1. It has a resolution of 640×480 pixels and a frame rate of 60 f/s. It can see objects in the temperature range of -10□–120□. The thermal-IR camera is fixed to the end of robot. The distance between the camera and detected plane is about 15cm and the angle between them is about 45°.

Fig.4 Experiment platform

B. Defects Recognition

For this experiment, multiple ply laminates are placed to collect defect images as training samples. The experimental process and placement laminates are shown in Fig.5 and Fig.6.

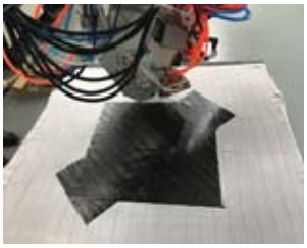

Fig.5 Experimental process

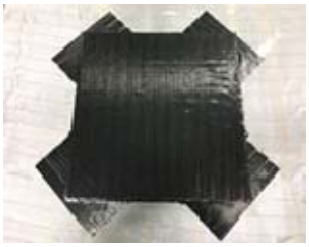

Fig.6 Placement laminates

Defects like gaps and overlaps will appear randomly during placement process. Missing tow, air pockets/bridging, cut failure and foreign body are actively injected. Fig.7 shows the collected images of typical defects.

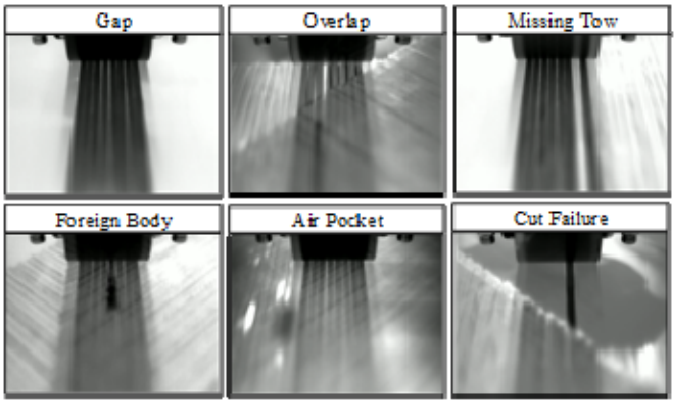

Fig.7 Defects images

Considering defect recognition as an image processing problem, the CNN network is applied in our work. We designed a classification network with 10 layers, including input layer, out layer, 4 convolutional layers, 2 pooling layers and 2 fully-connected layers. The architecture of the network is shown as Fig.8. The recognition accuracy of this model is 95.7%, which is a sufficient accuracy to initially screen of the defects. Then, based on the calculated confusion matrix, feature extraction rules can be set for the defect type with low recognition accuracy, and the re-recognition based on set rules is performed and the overall recognition accuracy can be improved.

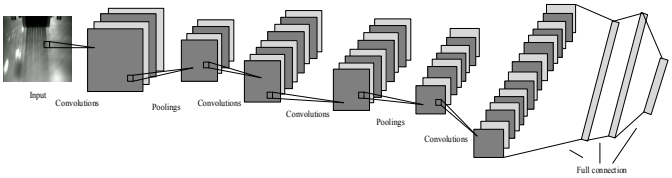

Fig.8 Recognition network architecture

C. Defects Measurement

To the best of our knowledge, there is no application of infrared camera in measurement being reported. The application of infrared camera to geometric measurements in AFP system has two main problems. On the one hand, infrared camera imaging relies on temperature contrast, this is easily affected by surrounding environment. On the other hand, thermal diffusion makes the geometry of the object in the infrared image change over time. Both of these two problems can impact on the accuracy of infrared camera measurements. So, in this part, we design the experiment to verify the feasibility of infrared measurement. The experimental steps are as follows:

1) Mark five reference lines on lay-up tooling as shown in Fig. 9 and Fig.10. Place a rectangular metal board along each reference line, assuring the lower edge of the rectangle coincides with the reference line. (Because the reference lines cannot be sensed in thermal image and use mental board to represent them when imaging. And reference lines are used to determine the position correspondence between the image and lay-up tooling.)

2) Find the image in the detected video stream, which is corresponded to the reference position marked in step1.

3) Search for the edge point of gaps in the image and fit the side lines .Calculate the width of gaps donated as Φ.

4) Measure the width of the gap on the lay-up tooling reference line with a Vernier caliper as the real value of gap width. There is a reading error with Vernier caliper, so each datum is measured three times and the average is taken donated as Φ.

5) Calculate the absolute error and relative error between infrared camera measured value and real value. All above are called experiment I.

6) Adjust the temperature of lay-up tooling to change the temperature difference between the tow and tooling, repeat the above experiment donated as experiment II. Change the bottom material to the tows and repeat the above experiment donated as experiment III.

The main parameters are set as:

- Environment temperature or tow temperature: 19℃
- Lay-up surface temperature:33℃ for experiment I and 39℃ for experiment II and experiment III.
- Material of lay-up surface: peel ply for experiment I and experiment II, laminates for experiment III.
- Place speed: 150mm/s
- Compaction pressure: 0.3Mpa
- Environment humidity: 40.5%

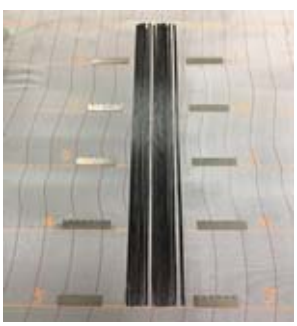

Fig.9 Lay up on toolings

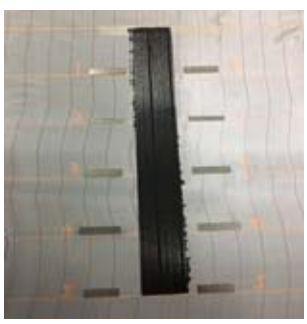

Fig.10 Lay up on laminates

There are eight fiber tows at each course and it will bring seven gaps or overlaps. In order to increase the universality of the experiment, the missing tow is designed at the second tow and it can be seen as a big gap. So, there are six gaps of each course (Overlap can be seen as a gap of width 0). Each course is marked five reference position and the AFP places two courses each time. Hence, we measure the width of gaps at these ten positions.

Fig.11 shows the absolute measurement error of experiment I. The axis of abscissa represents the 10 reference positions chosen in step1 and the axis of ordinates represents the absolute errors. Six lines with different colors represent measurement error curves of six gap widths. The abscissa indicates the 10 reference positions and the ordinate indicates the absolute measurement error at the corresponding reference position. The average and standard deviation of these errors can be calculated and the value are -0.223mm and 0.317mm. It can be obviously seen from the figure that errors and fluctuations in the error curves are small. The same conclusion can be achieved from Fig. 12 for experiment II and Fig. 13 for experiment III.

There are three main sources of errors. The first one is the Vernier caliper reading error. This make the real value of width of gaps not absolutely accurate and the error level is 0.01mm. The second one is the edge extraction error. In edge extraction process, choose points of which the changes of the gray gradient are the fastest as the edge point. Some blurry edges will interfere with the extraction algorithm, and cause extraction errors. The last one is the calibration error. There are still many difficulties in infrared camera calibration and the calibration error is about 0.1mm.

In the presence of these non-measurement error interference, the infrared camera measurements can achieve the effect as shown above, which means infrared camera is with high accuracy and stability of measurement in different situation. Therefore, the measurement have strong robustness and the presented system based on infrared camera is feasible.

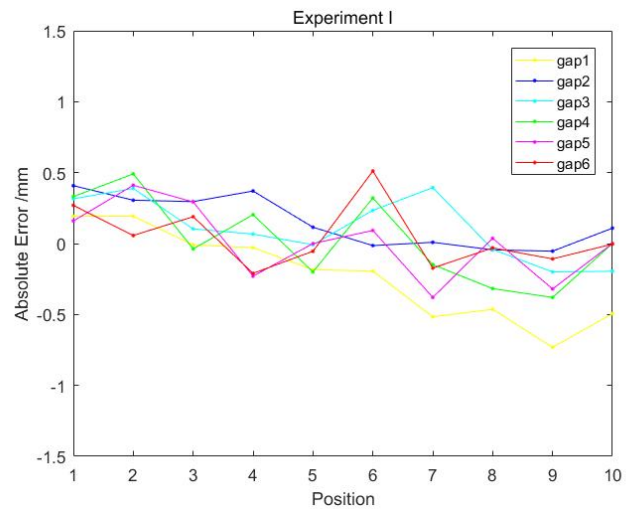

Fig. 11 Measurement error of experiment I

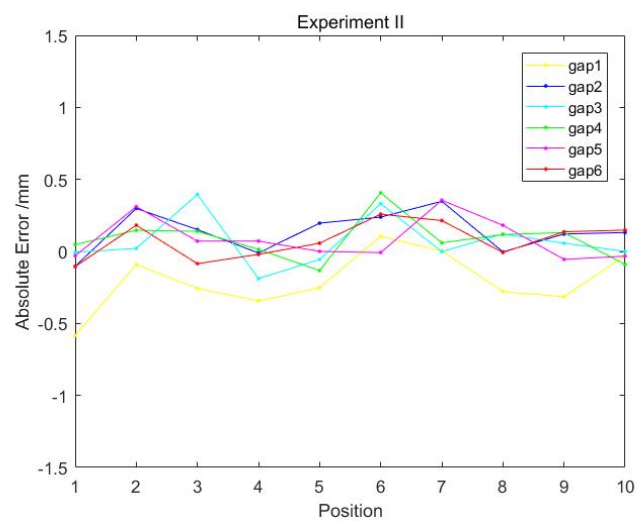

Fig.12 Measurement error of experiment II

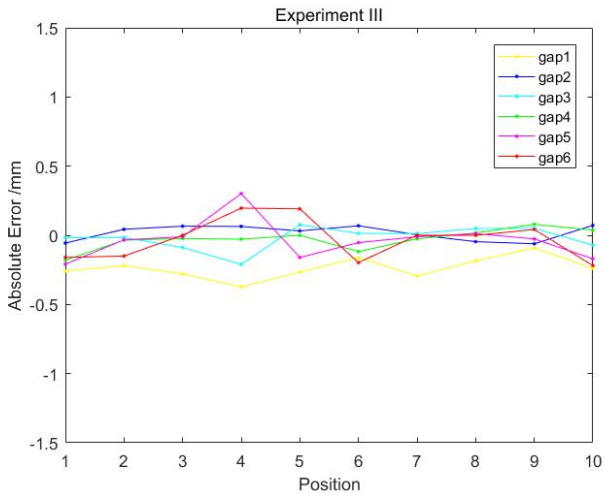

Fig.13 Measurement error of experiment III

V. CONCLUSION

In this paper, the recognition and measurement of defects in AFP process is implemented based on thermal image. Experiments verified the measurement of defects with infrared camera is accurate and stable. Therefore, the presented inspection system has a valid input and subsequent functions are achievable, which means the intelligent in-process inspection system based on infrared camera of the AFP process is feasible. It is essential to do more research on infrared camera measurement to improve the measurement accuracy and promote it to more application. The ideas and architecture of the intelligent inspection system presented in this paper can provide reference for all manufacturing inspection system and application of artificial intelligence in manufacturing.

ACKNOWLEDGEMENT

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REFERENCES

[1] Schmidt, C., et al., Influence of AFP Process Parameters on the Temperature Distribution Used for Thermal in-process Monitoring. Procedia CIRP, 2017. 66: p. 68-73.

[2] Soucy K. In-process monitoring for quality assurance of automated composite fabrication. In: Review of progress in quantitative nondestructive evaluation. New York: Plenum Press; 1996.

[3] Schmitt R, Pfeifer T, Orth A. Feasible production of fiber-reinforced composites through inline inspection with machine vision. In: Proc IMEKO world cong. Rio de Janeiro, Brazil; 2006..

[4] Tao, Y., et al., An online detection method for composite fibre tow placement accuracy. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2016. 230(9): p. 1614-1621.

[5] Engelbart, R.W. and C. Walters, System for identifying defects in a composite structure. 2005, Google Patents.

[6] Engelbart, R.W. and F.G. Speno, Systems and methods for using light to indicate defect locations on a composite structure. 2007, Google Patents.

[7] Engelbart, R.W., S.T. Holmes, and C. Walters, System and method for identifying defects in a composite structure. 2007, Google Patents.

[8] Engelbart, R.W., et al., Systems and method for identifying foreign objects and debris (FOD) and defects during fabrication of a composite structure. 2007, Google Patents.

[9] Engelbart, R.W., R. Hannebaum, and T. Pollock, In-process vision detection of flaws and FOD by back field illumination. 2010, Google Patents.

[10] Engelbart, R.W., R. Hannebaum, and T. Pollock, In-process vision detection of flaw and FOD characteristics. 2010, Google Patents.

[11] Engelbart, R.W., R. Hannebaum, and T. Pollock, In-process vision detection of flaw and FOD characteristics. 2008, Google Patents.

[12] Engelbart, R.W., et al., Systems and methods enabling automated return to and/or repair of defects with a material placement machine. 2006, Google Patents.

[13] Cemenska, J., T. Rudberg, and M. Henscheid, Automated In-Process Inspection System for AFP Machines. SAE International Journal of Aerospace, 2015. 8(2).

[14] Schmidt, C., et al., Thermal Image-based Monitoring for the Automated Fiber Placement Process. Procedia CIRP, 2017. 62: p. 27-32.

[15] Brüning, J., et al., Machine Learning Approach for Optimization of Automated Fiber Placement Processes. Procedia CIRP, 2017. 66: p. 74-78.