DEVELOP A MODEL FOR FABRIC DEFECT PROGNOSTIC AND CLASSIFICATION

XÂY DỰNG MÔ HÌNH PHÂN LOẠI VÀ DỰ BÁO LỖI SẢN XUẤT VẢI

Huynh Nhat To*

The University of Danang - University of Science and Technology

*Corresponding author: hnto@dut.udn.vn

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Abstract - Classifying and prognosticating defects can assist manufacturers to reduce cost and increase the benefit and quality. Many studies have been done in high-tech industries but only few studies have focused on others such as textile, ceramic, and so on. Moreover, most these manufacturers are operating manually and with backward technologies. With changing quickly in manufacturing technologies, these companies need to find their way to catch up and compete with others. Furthermore, defects in textile industry have some difference with ones in high-tech industry. This study aims to proposed a framework for defect prognostic and classification for textile manufacturing. The framework has been validated based on experiements.

Key words - Classification; Defect prognostic; Neural network; Textile manufacturing

Tóm tắt - Việc phân loại và dự báo lỗi sản phẩm giúp cho các nhà sản xuất giảm thiểu chi phí, đồng thời nâng cao chất lượng và lợi nhuận. Nhiều nghiên cứu đã được thực hiện đối với các ngành sản xuất công nghệ cao. Tuy nhiên, chỉ có vài nghiên cứu được thực hiện đối với sản xuất vải, gạch men,… Hầu hết các nhà máy sản xuất này đang vận hành hệ thống phân loại thủ công và công nghệ lạc hậu. Với sự thay đổi nhanh chóng của nền sản xuất, các nhà máy cần phải đẩy mạnh qua trình quản lý vận hành của mình. Nghiên cứu này đã xây dựng một mô hình có thể phân loại và dự báo lỗi sản phẩm trong việc sản xuất vải. Dựa trên các kết quả đánh giá đã cho thấy được tính hiệu quả của mô hình.

Từ khóa - Phân loại sản phẩm; dự báo lỗi; mạng nơ-ron; sản xuất vải

1. Introduction

To increase the benefit and product quality companies need to reduce product defects. Prognosticating defects can help to reduce the cost and enhance the productivity. Many studies have been developed defect prognostic model in high-tech industries. Only few studies focused on others industries such as textile, ceramic, and so on.

In high-tech industries, defected products need to rework or repair. However, in textile industry, defected products can be classified into many groups which are repaired group and acceptable group. There are many factors affect the quality of textile product in manufacturing process such as moisture, floating fiber, color grade, material quality, human factor, material handling, dye type, yarn size, fiber density, machinery, and so on. So this study aims to develop a framework for defect prognostic and classification for textile manufacturing. In addition, experiments was designed to validate the proposed framework.

2. Literature review

Minimizing defects in production is an important factor because defects will affect productivity, product quality and cause potential reliability problems [1]. Reducing manufacturing defects helps to improve product quality and reduce the costs of operation. Chi et al. [2] developed the Adaptive Intelligent Production System (AIMS) for the production process and implemented AIMS appropriately, modifying the process model when the predicted errors were significant. The results show that AIMS has both explanatory and predictive power. Choudhary et al. [3] has researched and explored knowledge and data mining applications in the field of production. The study specifically emphasizes the type of functions that will be performed on data, including characterization and description, association, classification, prediction, clustering and evolution analysis. Ciflikli et al. [4] has considered improving the production process through data mining. The research has built models to predict defects, consider defects compared to non-disability scenarios to identify important causes of disabilities. Harding et al. [5] applied data mining in production, especially in operation, error detection and product quality improvement. Kusiak [6] used structures such as decision tables, decision maps and maps for decision making in areas and service production. The research also applies data mining in the field of pharmaceuticals, health and production. However, most of these studies failed to diagnose the root cause of the defects, so the company had to spend a lot of money on reworking and repairing. These analyzes do not systematically and proactively identify the exact models of factors such as process changes, costs of disability and signs of potential defects. Jackson [7] and Turban et al. [8] have combined statistical and analytical techniques to understand how to use data in the most effective way. Wang [9] has applied data mining to the zero-defect production system (ZDM) to ensure no errors in the products produced. In order to achieve ZDM, a close combination of not only product quality but also device status and performance degradation is required. Dean [10] introduced large data models and how they can be applied in decision making. Some researches studied the impact of raw materials on each product and any working condition-related factors including the time, shift and level of experience assigned by the workers to determine where the problems begin. Previously, there were many analyzes using data analysis techniques to predict disabilities. Tan et al. [11] and Yuen et al. [12] used decision trees, logistic regression and neural network models to determine the root cause of defects, increase the rate of perceived defects and support decision-making in disability classification.

There are many studies that have been done in the field of high technology. Hsu and Chien [13] used data mining and knowledge discovery techniques such as Kruskal-Wallis test, k-mean clustering and variance decomposition criteria to determine possible causes to improve the yield of fabricated wafers. Hsieh et al. [14] and Hessinger et al. [15] apply data mining methods to determine and quantify root causes of yield loss from defects in the semiconductor industry. The main objective of this method is to examine, classify different defects and distribution types of defects. In recent years, data mining and analysis are also being used to anticipate abnormalities that may occur in wind turbines. Many high-tech companies have also adopted an integrated approach to business analysis to improve productivity management and ensure that products are being produced at the right time [16]. Perzyk et al. [17] summarized various data mining techniques to handle defects diagnosis for production process parameters. However, only a few studies have been done in the textile sector.

The textile manufacturing process is a complex process going through many stages, from small to large [18]. Therefore, process testing is a preventive test that is not usually conducted. Instead, people often only check products after finishing, it means, check for defects in the final fabric product. Historically, there have been many surveys on Automatic Visual Inspection (AVI). Typically four surveys on AVI. Chin and Harlow [19] conducted a physical examination, seeking to identify both functional and aesthetic defects, applying visual inspection automation to improve product quality. Jain [20] have studied automated testing systems and systems. The study by Thomas et al. [21] also examined their technical properties, size tolerances and effects on disability testing. Patil et al. [22] studied optimized parameters of machines in the manufacturing process.

Conci and Proença [23] have used the estimate of Fractal dimension (FD) on inspection images to detect fabric defects. They performed differential box counting methods with a few modifications to minimize computational complexity. The decision to declare an error is based on the variant of FD. This method is simple in calculation but the accuracy of the detected defects is very poor. Kumar [24] has studied the problem of fabric defects using the feed-forward neural network (FFN). Recently, Hung and Chen [25] have used the back propagation neural network, with the fuzzification technique (fuzzy logic), to achieve the classification of eight different kinds of fabric defects along with the defect-free fabric.

However, most of these studies do not focus on prognosticating fabric defects but only present the overall inspection problem. In recent years, VAI techniques in fabric error analysis have made important progress, many new algorithms on fabric testing are also proposed. Sheen et al. [26] presented an ultrasonic imaging system for web textile inspection. Cole and Deak [27] illustrated the use of reflected infrared frequencies during fabric testing using knowledge-based systems to track Fabric defects which were proposed by Srinivasan et al. [28]. Many studies have identified five major categories of features for texture analysis: statistical, geometrical, structural, model-based and signal processing features [29], [30], [31]. However, due to the elasticity of yarn, fabric movement, pile, noise, and so on existing methods cannot efficiently solve the problem. Therefore, this study aims to propose a framework for defect prognostic and classification which predicts defects according to each group.

3. Research framework

As mentioned in section 1, defected products in textile industry have its own characteristics and can be repaired or used. A research framework of defect prognostic and classification model is proposed as in Figure 1.

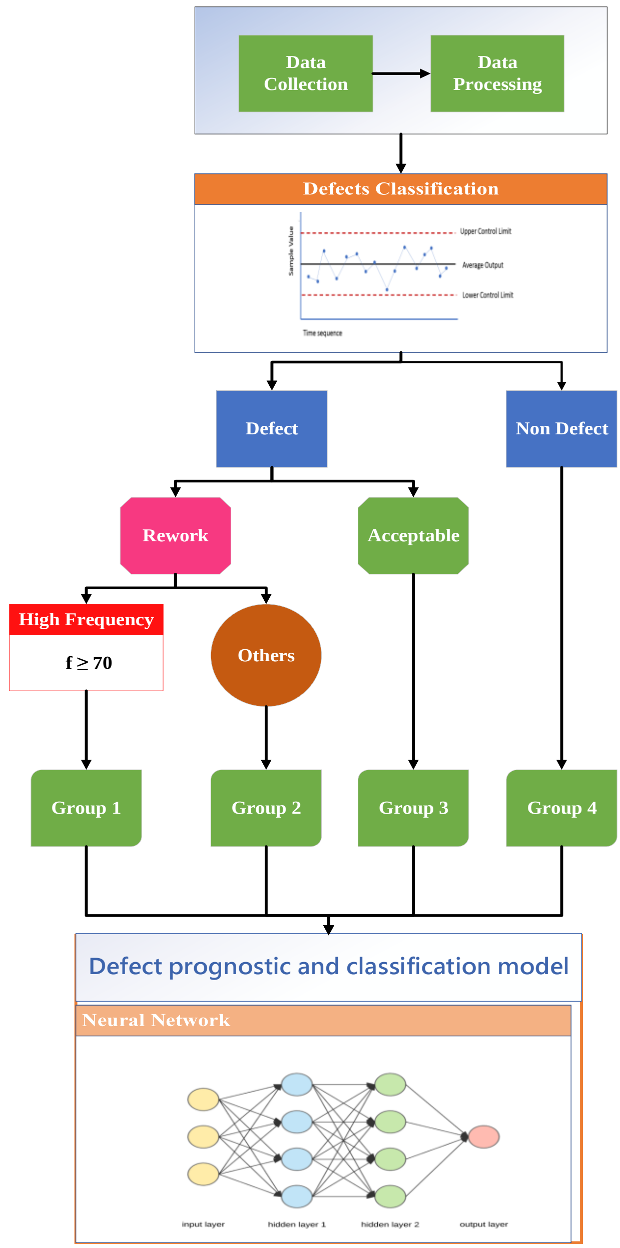

Figure 1. *Framework of defect prognostic and classification*

3.1. Data collection and processing

To begin the process of defects classification, all related data is collected such as moisture, floating fiber, color grade, material quality, human factor, material handling, dye type, yarn size, fiber density, machinery, and so on. The collected data then be processed to clean and repair missing data.

3.2. Defects determination

In this step, control chart is used to determine defect products and non-defect products. The defect products include ones which are upper and lower the control limits (upper control limit and lower control limit). For products without defect, they are group into group 4. The defect products will go to next step for other classification.

3.3. Defect classification

In textile manufacturing, some type of defects can be acceptable for using. So the defect products will be classified into acceptable defect products and repaired products. The defect product without repairing can be sold with lower price or used in different purposes. These products named as group 3 in this study.

3.4. Repaired defect product classification

The defect products which must be repaired will be classified based on its occurring frequency. The products appear more than 70 percent will be group in group 1 and the other for group 2.

Each product group may be affected by different factors and should be treated by different methods. A defect prognostic model is develop to solve this problem in section 3.5.

3.5. Defect prognostic and classification model

Neural network is used to develop the defect prognostic model. The proposed model can prognosticate the type of defect (group 1, 2, 3, or 4) based on the input data. The collected data is separated into 70 percent for training the model and the rest for testing the model. The proposed framework and model was validated based on a case of textile manufacturing as shown in section 4.

4. Experiement and discussion

4.1. An experiment of textile manufacturing

To validate the proposed framework, an experiment of textile manufacturing was designed. The manufacturing process is described as following.

The first step is to produce fibres from natural material. Next step is yarn preparation that includes blending, scutching, carding, combining and drawing. The output of this phase will be primary yarn which will be spinned in yarn manufacturing phase. After finishing these 3 phases, companies already produced yarn and ready to go in to main processes of manufacturing. In this process, yarn will be winded, wrapped, sized and then be weaved and knitted. Last step is finishing process including desizing, scouring, stone-washing, bleaching, dyeing and printing, and polishing. In this process, after bleaching, the products are dyed and printed according to the customers' requirements. These printed, dyed textile products will be polished to make them become cleaner and more valuable to be sold to customers.

There are many factors that can affect the quality of textile products. In this case, some main factors were generated. As shown in Table 1, the factors are separated according to the machines for easily control. Ten records or products are shown in this example. Each one has its factors since the factors may be changed during the time and the type of products. For winding machine, 3 main factors used include speed, clearer setting, and tension. The speed of the winding machine in 10 measurements is in the range from 1120 rpm to 1550 rpm. An important machine in manufacturing process is weaving machine which has seven main factors used to identify and predict the defects. The factors include speed, solid content, viscosity, squeeze roller pressure, size pick up, total stretch, and saw box temperature. The other import factors include fabric fiber density, fiber size, fiber maturity, and humidity.

Table 1. *An example of generated data*

No.	Factors		Record No.									
			1	2	3	4	5	6	7	8	9	10
1	Winding machine	Speed	1120	1450	1130	1350	1450	1450	1150	1550	1350	1250
		Clearer setting	3.0	4.1	3.2	4.5	4.7	5.1	5.8	5.0	4.8	4.8
		Tension	26	27	26	27	27	27	29	27	27	27
2	Weaving machine	Weaving speed (rpm)	350	330	340	320	360	365	377	345	320	350
		Solid content%	10	9	9	9	8	8	9	8	8	9
		Viscosity	8	10	9	8	8	8	9	9	10	8
		Squeeze roller pressure	17	16	18	19	18	17	18	16	15	17
		Size pick up%	12	10	14	17	12	10	11	12	11	11
		Total stretch	0.8	0.9	0.9	0.7	0.8	0.8	0.9	0.8	0.8	0.9
		Saw box Temperature	87	88	85	84	85	87	86	81	88	85
3	Fabric fiber density (number of yarns per 10 cm2 of fabric)		140	180	145	190	200	195	130	199	205	210
4	Fiber size (mm)D		0.158	0.158	0.190	0.20	0.199	0.190	0.199	0.2	0.180	0.180
5	Fiber maturity		0.60	0.75	0.65	0.8	0.79	0.80	0.74	0.81	0.79	0.80
6	Humidity (%)		8.2	7	7.5	87.9	8.5	8.6	8.8	9.0	8.8	8.6

4.2. Results and discussion

The total generated data are 2000 records. Following the proposed framework in section 3, the control chart was used to identify the products in group 4 (non-defect products). The remaining products or records then were classified into group 3. The rest ones were classified into group 1 and group 2. The group 1 has frequency greater than 70 percent. Based on the data in the example, the output of each records or products is shown in Table 2. The record (or product) number 1 was classified into group 1 (G1), product number 2 is classified into group 4 (G4), and so on. All records or products of 4 groups were used for training and testing the prognostic model.

The neural network model consists 5 hidden layers according to some trails. Based on the proposed framework, 1400 the records were used for training the prognostic model, and 600 records for testing. The results are shown as in Table 3.

As shown in Table 3, the misclassification rate of the model is 0.2814 for training and 0.2920 for testing. Similarly, the average square error is very low which is 0.2010 for training and 0.2116 for testing. In general, the proposed defect prognostic model is good to predict the types of defects.

Table 2. *Group of each records or products*

Record No.	1	2	3	4	5
Group	G1	G4	G2	G4	G4
Record No.	6	7	8	9	10
Group	G4	G3	G4	G4	G4

Table 3. *Experiment results*

No.	Measurement	Training	Testing
1	Misclassification rate	0.2814	0.2920
2	Average square error	0.2010	0.2116

5. Conclusion

This study proposed a defect prognostic and classification framework for textile manufacturing which classifies products into four groups. Each group has own its characteristics and can be solved easily compared with other prognostic models. This model can help manufacturers reduce cost of defect products and increase the benefit and quality of product. The proposed framework was validated based on an experiment of textile manufacturing. The results have shown the reliability and efficiency of the framework.

This proposed framework also can be used in other industries such as ceramic, steel, and so on. Further research will combine another classification techniques to improve the efficiency of prognostic and classification model.

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