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A SVM-based Quality Assessment using Thermal Image DATA in Sealer Dispensing Process

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Abstract

As manufacturing environments are getting global and complex, the automated and systematic ways of product quality monitoring are becoming more popular in the global manufacturing sector, especially in automotive industry. In a number of manufacturing processes, however, the process of quality assessments in production is still highly dependent on manual inspections due to the complex patterns of defects and lack of input data in both products and processes. In this paper, thus, a case of the automated quality assessment system in an automotive company is investigated. To enhance the quality monitoring capability of the production system, the infrared thermal image, which includes nominal dimensions and temperatures, is analyzed using support vector machine (SVM) algorithm. The thermal image data can provide multi-dimensional quality information which may not be possible to be assessed by human visions. At the end of this paper, a sealer dispensing in an automotive parts assembly process is illustrated to verify the applicability of the system.

Keywords
Thermal image, Quality monitoring system, SVM (Support vector machine),

1. Introduction
Throughout the years, mass production systems have become automated to enhance both the productivity and cost efficiency. However, several quality assessment tasks, with high level of intelligence and classification capability, still requires a role of human experts. Recently, however, the automatic system has been replacing the human expert to inspect products' quality by virtue of the advances in sensor technologies and data analysis capabilities. In order to make the automated system not only efficient, but also effective, a quality monitoring system is often embedded in the manufacturing process for inspection purpose. To provide more accurate inspection results, machine learning and data mining have been studied to reduce errors in the classification results based on a variety of the data analysis method (Li et al. 2013). In this work, an accurate and reliable quality monitoring system of the primer-sealer dispense process is presented. Note that primer sealer dispensing process is used to glue a frame and a glass in a various manufacturing industry. Under the proposed monitoring system, the thermal image are collected and analyzed using

several algorithms including the SVM (support vector machine), and other image processing algorithms. Several studies have provided effective data analysis methods and frameworks using SVM methods in various fields. However, the sensed data in the manufacturing process of the dispensed sealer cannot be directly used into the traditional SVM. Thus, the proposed monitoring system provides the data preprocessing method to ensure data compatibility with SVM framework. The rest of the paper consist of four sections: first, we discuss the related works; second, we explain the specific steps to get the inspection result using the suggested system. Third, the proposed model is applied to an industrial case study with real process data. And last, we discuss and summarize the result.

2. Related Work

2.1 product quality monitoring system

In manufacturing industry, especially in the assessment of machine conditions, the development of monitoring and diagnosis system have been centered on various data-driven pattern analysis methods along with SPC (Statistical Process Control). While all failure modes cannot be detected using historical data (Zhu, 2008; Lee et al., 2010; Ertunc et al., 2001); the use of historical data boost the credibility of the monitoring system. Historical data are used to build and train smart and intelligent maintenance systems with the capability of predicting specific failure modes.

The applications of an automated maintenance, which perform efficient maintenance practices, have been provided (Kirikos. et al. 2008). The machine condition can directly affect the quality of products manufactured in the system and can also be considered as a decisive factor in evaluating the process efficiency in terms of the manufacturing enterprise. On the other hand, in a complex supply chain environment, part quality from suppliers become the main interest for the vendors. Online product quality evaluation from suppliers' manufacturing processes is also one applicable area of the product quality forecasting.

In comparison to other major classification method such as k-means algorithm, apriori algorithm and CART, SVM is relatively new (Wu et al., 2008). However, several cases have shown that SVM performance is often far superior to other algorithms, thus it has been applied in various field such as machine condition monitoring and manufacturing process fault detections (Widodo and Yang, 2007; Ge et al., 2004). Furthermore, the SVM can be used in the classification of non-linear data. It can as well be used to determine the optimal margin classifier for the hyper plane (Duan et al., 2003). Similar to solving quadratic programming problem, the optimization of margin classifier problem can be formulated as follow:

$$\begin{aligned} &min_{\alpha} \ \frac{1}{2}\sum_{ij}\alpha_i\alpha_j K(x_i, x_j) \\ &subject\ to: 0 \le \alpha_i \le \frac{1}{v_i} \\ &subject\ to: \sum_i \alpha_i = 1 \end{aligned} \tag{1}$$

where:

α_i : Lagrange multiplier

v: Control parameter of the trade-off between maximizing distance of hyper plane from the origin data points

$K(x_i, x_j)$: The kernel function to project input data into a high dimensional

Assuming a high dimensional space map for nonlinear decision boundaries:

$$\emptyset : X \rightarrow R^N \tag{2}$$

where $\emptyset$ shows the training vectors from input data space X. Thus, the kernel function is defined as:

$$K(x_i, x_j) = \{\emptyset\ (x), \emptyset\ (y)\} \tag{3}$$

The selection of optimum controllable parameters is realized through the application of n-fold cross validation in which data is randomly separated in each fold, and the process is repeated N times (Duan et al., 2003).

3. Product quality inspection process

The quality classification system of primer-sealer dispense process starts with gathering data using thermal camera, and the results of the inspection are displayed on the monitor of kiosk pc. The required number of thermal camera needed for data collection depends on both the product size and curved angle. Thus, as shown in Figure 1, the proposed classification system flow includes: 1) deciding a required number of thermal camera; 2) finding proper sensing timing of thermal image based on PLC (Programmable Logic Controller) sequence; 3) inspecting a sealer-interruption on the thermal image; 4) classifying the product quality after the SVM testing; and 5) displaying the classification result of the product quality. The system gives a warning alarm when the product is deemed defective part by the monitoring system.

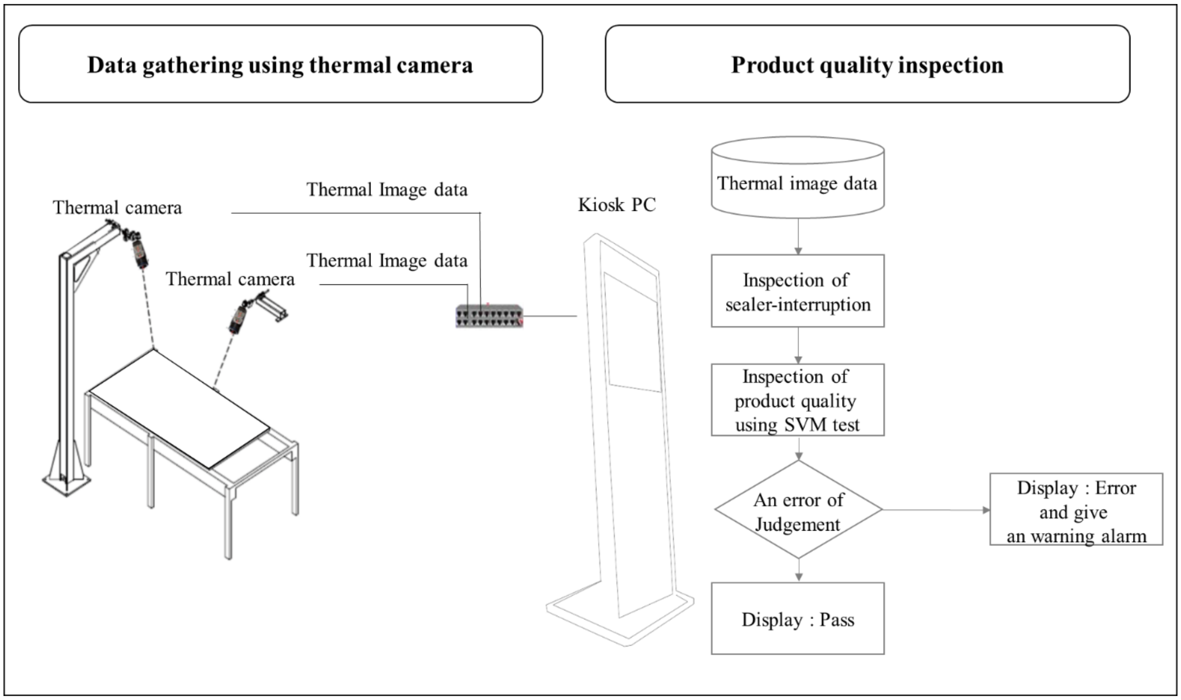


Figure 1. The layout design of a product quality inspection system for the sealer dispensing

3.1 Preparation of the quality classification system installation

To install the quality monitoring system, the appropriate thermal camera and its location should be decided based on the environment and product information. Once the system is set up, we collect all data that may affect the product quality in bonding processes. For example, in our case study, the thermal image data includes the topologies (width and height) of dispensed sealer patterns and its discontinuities. The data gathered from the system is then fed into the proposed monitoring system. As noted earlier, there are three important product quality factors on the primer-sealer dispense process: continuity, width and height of dispensed sealer. The three major quality factors were considered after interviewing expert operators. For example, when the dispensed sealer has some interruption points, an operator glues a sunroof window and frame after the sealer dispensing on a sunroof frame of a car, due to it can cause a leakage of water.

The system installer determines a specific thermal camera model based on the required image quality necessary for the product quality analysis, according to the guidelines. Then, the length of a pixel can be calculated with a camera angle, a camera lens information, and distance between the thermal camera and the product (see Figure 2). Depending on the length of a pixel, the quality classification system provides a minimum standard of product quality classification. The formulation of calculating pixel size is as follows:

$$\text{Length of a pixel} = \frac{length\ of\ an\ image}{resolution} \tag{4}$$

$$, where\ length\ of\ an\ image = f(DCA) \times \tan(\text{camera angle} + \text{camera lens angle}) - \tan(camera\ angle - camera\ lens\ angle)$$

$$, where\ \ f(DCA) = Distance\ from\ a\ camera\ to\ a\ product \times \cos(camera\ angle)$$

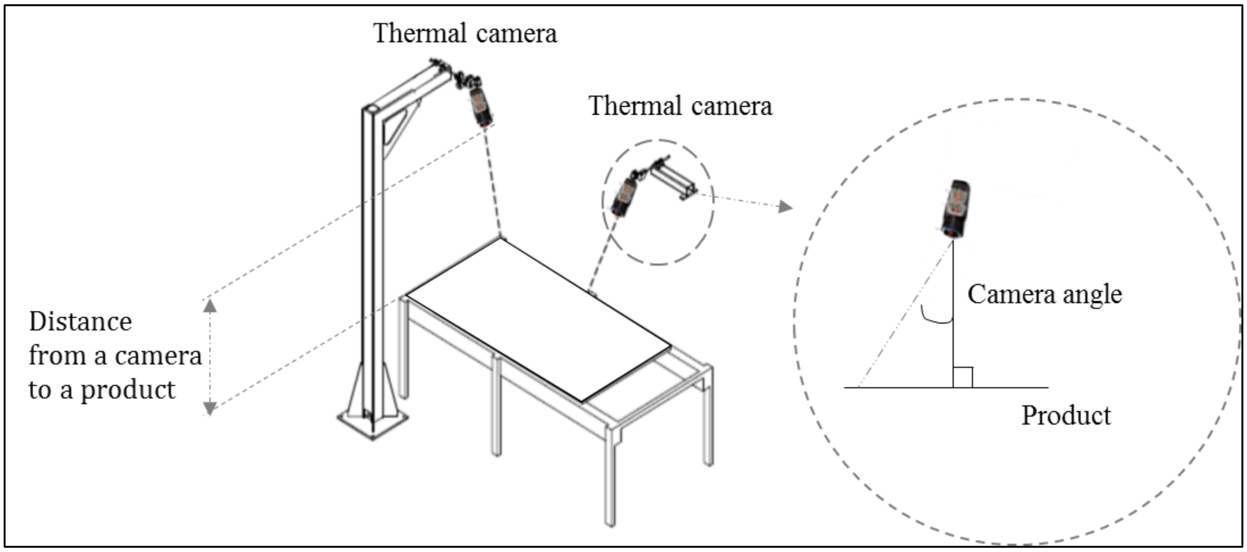


Figure 2. An illustration of camera angle and distance from a camera to a product

A system installer needs to find the proper timing to get the optimal thermal image without any disruptions. Also, the thermal image needs to be taken twice based on PLC sequence in order to compare the product temperature before and after processing the primer-sealer dispensing. Since the temperature can be affected by external environment factors. Our monitoring system utilize the gap in temperature of the two images to block the external factors.

The thermal image includes temperature information per each pixel. The analysis of all pixels is inefficient due to the checkup time. Thus, to find sealer-interruption, we separate a thermal image into two parts, one includes sealer and the other part includes frame sheets and environment temperature. The sealer part can be obtained using skeleton algorithm after transforming the image into a black and white photograph. Once the required image data is acquired, to find sealer-interruption we examines each pixel group in the following steps:

Step 1. Get number of group from the pixel number of center line.
Step 2. Make a group as {N-1, N, N+1} where 0< N< maximum number of group
Step3. Analyze each sample (a set of thermal image data) to make decision whether the interruption is occurred or not.
Step4. Transfer the group information, N, and the analyzing results of each sample.

3. SVM training and test using thermal image

The suggested quality classification system detects defective parts based on the SVM, which is widely used in a variety of engineering applications (Li et al. 2013; Widodo and Yang 2007). The temperature data of thermal image needs to be properly pre-processed for SVM training. Our system uses quality factors as inspection standard.

The thermal image-based inspection data for each sample needs to match the operators' inspection results. Due to aforementioned discrepancy; our analysis compares two images of the primer-sealer taken at different time in order to reduce seasonal and environment effects. Along with the thermal image data, the product quality analysis requires the following information: machine ID, production time, operator inspection results, and comparison result between before and after the image of primer-sealer dispense process, and production time. The operator inspection results are used as classification standard in SVM training. To train the SVM with balanced data, defective group data sets are combined with goods group data sets on equal proportions. The defective points occurs rarely on real process line. Instead of using real process data, we intentionally made various defective types and gather that data sets.

Although, sealer-interruption classification is "good" at the interruption points, further analysis are still needed to produce the final quality classification result. The quality classification system assesses the product quality based on the combined inspection result of the SVM test result and inspection results of sealer-interruption. The reason for combining results is to find out defective points and to reduce type II error. In other words, the quality monitoring system does not detect defective parts when the inspection result is of Type II error. Also, this way gives higher accuracy more than utilizing each quality inspection method separately.

4. Case study

4.1 Illustration of the current manufacturing process

We apply the proposed quality monitoring system to the sunroof assembly process line of an automobile. The required inspection time of this process line is three seconds. This time excludes checkup time by an operator that occurs when the system gives a warning alarm. Based on the survey for installing the suggested system, at least, two thermal camera are required. There are three reasons: First, the longer side of sunroof frame is over two meter. Second, a thermal camera needs be installed at the front and rear points due to a working area of the robot arm. Third, a sunroof has high curved angle at a longer side. In other words, the installation of only one camera results in a distorted thermal image. To decide specific inspection guideline of the system, a pixel size equal to 1.82mm was used based on equation (4) as. For each product tested, the monitoring system will assess its quality and display the result on kiosk pc. There are three kind of results: good, defective, or simply a warning. The warning alarm goes off once the system does not have enough data necessary for classification. In the following figure, the eighth failure mode is an interruption case which is detected at sealer-interruption step or SVM test; the other different failure modes are explained Table 1.

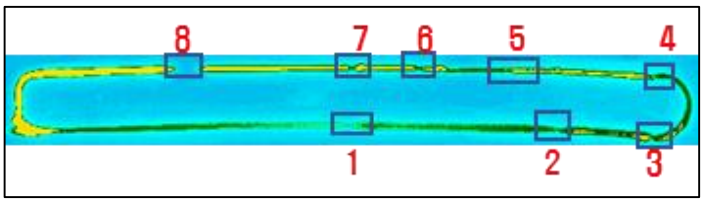
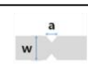
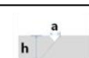
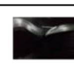
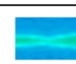
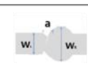
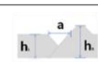
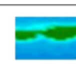
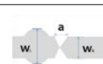
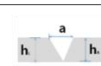
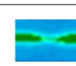
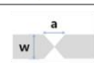
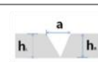
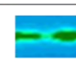
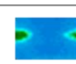
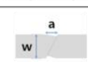
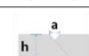
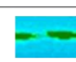
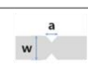
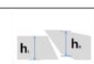
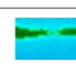


Figure 3. An example thermal image of defective part

The CAD model helps to understand different possible defective part. The image shows two different views: top view and side view. In table 1, the defective part column shows the real photography of a 'Defective part'. And the thermal image column shows the image (Thermal image) obtained from the thermal camera.

Table 1. Types of defectives (in Figure 3)

Case No.	Cross section of defective part		Defective part	Thermal image
	Top view	Side view		
1				
2				
3				
4				
5				
6				
7				

a: length of disconnected area, w: width of sprayed sealer, h: height of sprayed sealer

4.2 Data preparation for quality inspection

The input data sets for the SVM training consist of temperature data from each thermal image as well as machine ID, production time, operator inspection results(Good or NG), and comparison result between before and after image of the primer-sealer dispense process. At first, we find a center line of dispensed sealer using skeleton algorithm, and make data group with 13 points from the center line of dispensing sealer (see Figure 4).

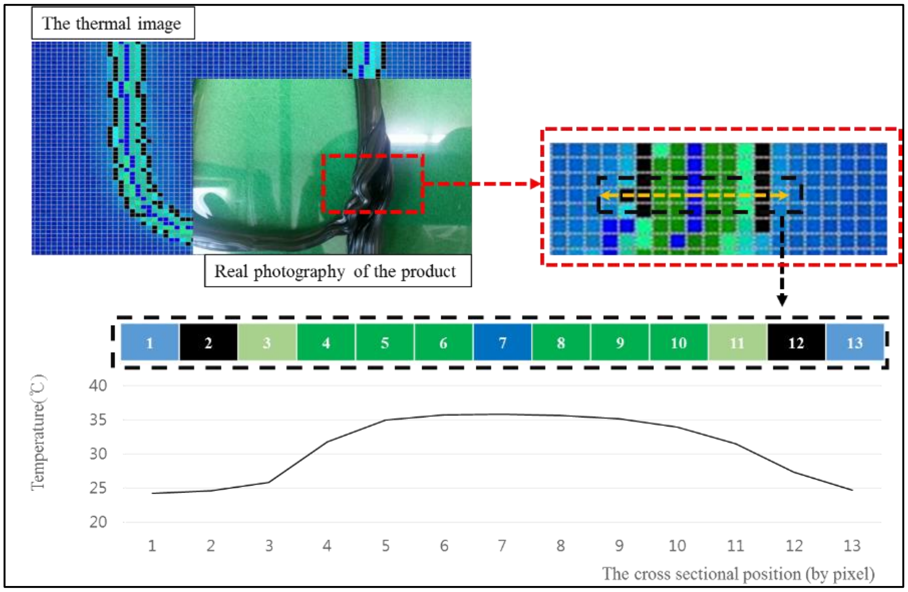


Figure 4. An illustration of the data group having the cross sectional positions

The temperature data group of the primer-sealer dispense process is investigated to find the minimal level of input data for SVM training. The temperature pattern of real process line is similar to Figure 5. The seventh temperature is center line data of dispensed sealer. The sealer typically covers four to five pixels on right and left side of the centerline.

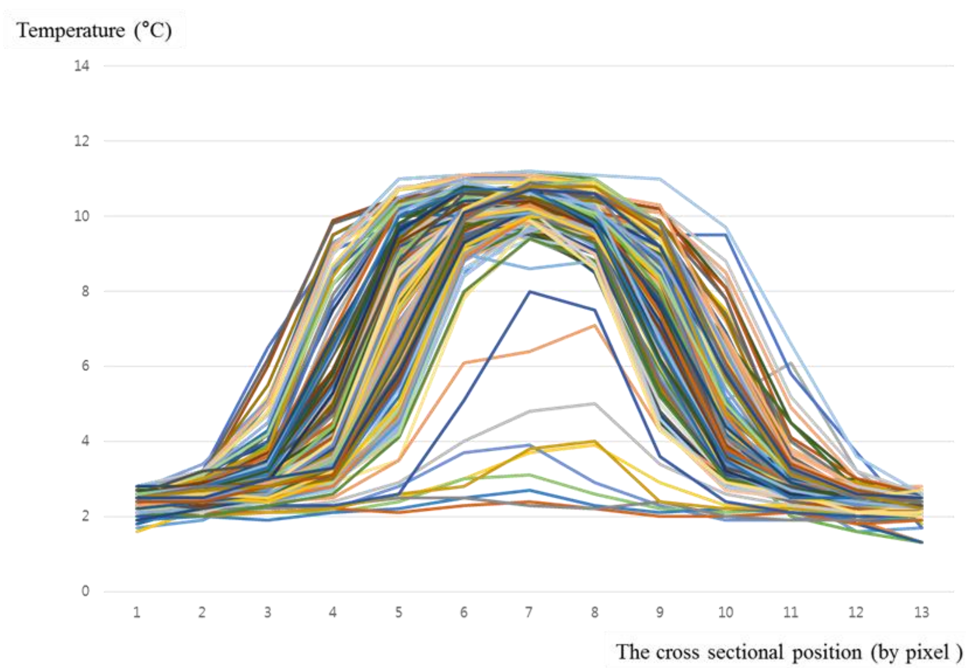


Figure 5. Temperature distribution of 200 measuring points in a sample

Each input data group of SVM training is the difference between before and after the thermal image for each sample data set. Each reference output data comes from the operator inspection results (true or false). The operator results e mbed manual inspection result of each quality factors which are interruption, width, and height. Although, the height of dispensed sealer is normally difficult to measure in thermal images, the faulty dispenses such as discontinuity and narrow dispensing are relatively easily detected using the thermal images.

Kernel functions are used to handle the non-linear data classification problems. In this paper, a radial basis function (RBF) is chosen after considering the features and data type (Veillard et al., 2012; Sahak et al., 2012). The RBF kerne l function is as:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (5)$$

4.3 Comparison result between SVM test and operator inspection

To verify the quality classification system, the combined quality inspection result of sealer-interruption and SVM test are compared with manual inspection results (assumed to be true). Table 2 summarizes the quality classification system accuracy. Each sample has around 3000 measuring points, which is the total number of cross section data group. As shown in Table 2, the proposed inspection system have an average accuracy of 93.91%, which is good enough to be used as a decision support tool for quality inspection process.

Table 2. The accuracy test results of the assessment system (with 18 different samples)

	Sample No. 1	Sample No. 2	Sample No. 3	Sample No. 4	Sample No. 5	Sample No. 6	Sample No. 7	Sample No. 8	Sample No. 9
Test Accuracy	97.51%	97.89%	97.42%	97.03%	97.99%	97.80%	98.47%	97.70%	96.94%
	Sample No. 10	Sample No. 11	Sample No. 12	Sample No. 13	Sample No. 14	Sample No. 15	Sample No. 16	Sample No. 17	Sample No. 18
Test Accuracy	88.97%	93.41%	93.74%	93.95%	87.26%	82.55%	84.36%	93.31%	94.01%

The temperature patterns of defective group data set are shown in Figure 6. This pattern tends to follow the real dimensional shape of the sealer surfaces. However, there exists up to 2 mm errors of sealer width measurements between manual inspections and thermal image data. In the future, the improvement of the quality monitoring algorithm is required to reduce the errors caused by the thermal image errors from environmental conditions.

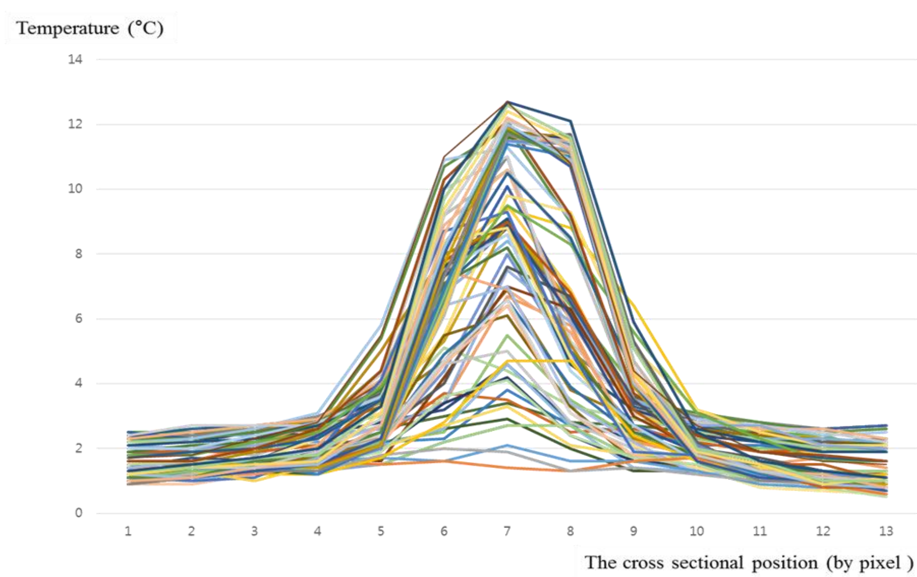


Figure 6. The temperature pattern of defective group data set

5. Conclusion

This research presents a SVM-based quality assessment using thermal image data in the sealer dispensing process. The quality classification system presented in this paper consists of the following four steps. First, the size of each pixel and the number of thermal cameras including their respective locations are determined based on both the size and the curved angle of the product. Second, the inspection of the interruption point is made using thermal image data. Third, the infrared thermal image, which includes topological information of nominal dimensions and temperatures, is analyzed using SVM algorithm. Fourth, the overall results are displayed based on both the SVM-based quality assessment and the interruption-based inspection. The model proposed in this paper was verified using the data from a sealer dispensing in an automotive assembly process. Based on the test results from 18 different samples, the proposed model showed an average accuracy of 93.91%. In the future, the model needs to be applied to other case to verify its applicability. It is expected that the proposed method can be a decision support tool for quality inspection, in which human operators have played a major role in product quality assessment.

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