Expert Systems with Applications 36 (2009) 5113–5118

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Automated visual inspection expert system for multivariate statistical process control chart

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ARTICLE INFO

Keywords:
Multivariate control chart
Automated visual inspection
Expert system

ABSTRACT

Automated manufacturing is increasingly common; however, automating inspection as a part of quality management processes is problematic, creating producer and consumer risk. Manufacturing plants can suffer several defect types. These defects result from different processes and cause different product failures. Numerous scenarios currently exist that require simultaneous monitoring or control of two or more quality-related process characteristics and in which online quality control is appropriate. Monitoring these quality characteristics automatically and simultaneously is essential to quality management. This study integrates image processing technologies and multivariate statistical process control chart to design an automated visual inspection expert system. The expert system thus developed can enhance decisions based on inspection of several quality variables and is easy to implement in a mass production environment.

1. Introduction

Owing to the growing popularity of computers, expert systems have been applied in various industries, including IC manufacturing, healthcare and machinery (Hsieh, Tong, & Wang, 2007; Übeyli, 2007; Wu, Wang, & Bai, 2007). The expert system has more business applications than any other intelligent system. Organizations with complex decisions to make or problems to solve frequently turn to experts for advice. These experts have specific knowledge and experience in the problem area, and are aware of alternative solutions, success probabilities, and costs that organizations may incur if the problem is not solved. Experts can diagnose problems correctly and solve them satisfactorily within a reasonable time frame. Advice becomes more specialized as situations become less structured. However, employing human experts is costly, and availability is not guaranteed. Expert systems have thus been developed as an alternative means of problem diagnosis. An expert system is a tool to assist human decision-making. To solve automated surface inspection problems, automation inspection technologies and multivariate statistical process control are applied to implement an automated visual inspection expert system (Liao, Enke, & Wiebe, 2004).

As a result of upgraded and more automated technology, manufacturing processes increasingly use automation to reduce labor requirements and costs, reduce factitious error and boost production capacity. The automation process stresses efficiency and monitoring of various quality variables, resulting in the widespread adoption of multivariate control chart (Bersimis, Psarakis, & Panaretos, 2007). Automatic inspection is desirable because human inspectors are not always consistent in their product assessments (Prieto, Redarce, Lepage, & Boulanger, 2002). Automated vision inspection (AVI) systems achieve superior performance in terms of processing speed and detection accuracy for the integrated circuit (IC) industry (Hou, 2001). Modern products are frangible or small, and surface defects can be identified using automated inspection technology (Schmitt, Riddington, Young, Budgett, & Chatwin, 2000; Tien, Yeh, & Hsieh, 2004).

Modern industries involve numerous situations that require simultaneous monitoring or control of two or more related quality-process characteristics. Independently monitoring these quality characteristics can be extremely misleading. Processes monitoring of problems involving several related variables are collectively known as multivariate statistical process control. The quality control chart is the most useful tool for multivariate statistical process control. Multivariate process control techniques (Hotelling's T^2) were designed by Hotelling in his pioneering 1947 study. In practical problems, the T^2 control chart is typically recommended for performing preliminary of multivariate observations required for process monitoring applications. Sullivan and Woodall (1998) discussed the problem of adapting control charts for preliminary analysis of multivariate observations, and also recommend a method for preliminary analysis of multivariate observations that requires no simulation to determine the exact control limit, and which is

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doi:10.1016/j.eswa.2008.06.047

almost as effective as the multivariate CUSUM (MCUSUM) and multivariate EWMA (MEWMA) control charts for step shift detection. With regards to monitoring several variables, numerous studies have discussed multivariate control charts in detail, such as, Hotelling's T^2 control chart (Aparisi & Haro, 2001; Chou, Chen, & Chen, 2006; Ngai & Zhang, 2001; Tsung & Apley, 2002), multivariate CUSUM (Bourke, 2001) and the multivariate exponentially weighted moving average control chart (Del Castillo & Rajagopal, 2002; Fan, Jiang, Jen, & Wang, 2002).

Automated vision inspection (AVI) system involves the construction of explicit and meaningful descriptions of physical objects based on images. AVI is synonymous with automated vision and embodies several processes. Images are obtained using a physical image sensor, and dedicated computational hardware and software are used for image analysis with the aim of performing a predefined visual task. AVI is also recognized as the integrated use of devices for frangible optical sensing and computing, and decision processes for automatically receiving and interpreting real world imagery. The technology aims to duplicate human vision by electronically perceiving and understanding an image. Horst and Negin (1992) used two charge-coupled device (CCD) and computer server over Internet to process digital image. They built a real-time system for inspecting textiles. Their system was applied to inspect textile thickness, and to transform and plot the control chart for mean and standard deviation. The system was used to increase inspection speed, as well as for real-time quality control. The proposed system is only applied in single variable control chart.

In real world environments, supervisors generally control several quality variables during automatic process, and thus this investigation adopts an integrated view of the implementation of AVI for multivariate control chart and enhances quality decision effectiveness.

2. Inspection expert system

The system environment and framework of the expert system are illustrated in Fig. 1, and includes the manufacturing workshop, main processor, and monitoring equipments. The manufacturing workshop includes an automating-machine, queuing component and camera device, and communicates between the processor and the network or general transmission line (like RS-232 transmission line). The main processor occupies the center of the processing system, which incorporates three databases and four functions. These four functions include image input device, standard binary image inverter, image analysis and multivariate control chart. These functions include three procedures, namely image processing, plotting multivariate control chart, and interpreting outlier signal.

2.1. Database

These three databases include original image structure, formatted image structure, and component eigenvalue. In the original image structure database, the image input device inverts the analog image into a digital image and forms the standard image structure on the monitor. In the formatted image structure database, the original image structure is used to preprocess the image, acquire an automatic threshold, invert the binary image, and construct a binary structure. In the eigenvalue of the component database, the formatted image structure is applied to analyze, compute and obtain the eigenvalue. This value is used to calculate and plot the multivariate control chart. The database includes the original image structure, formatted image structure, and component eigenvalue, and explains them as below:

1. Original image structure: the image-input-device inverts the analog image into a digital image, and presents the standard image structure on a monitor.
2. Formatted image structure: This procedure uses the original image structure to perform preprocessing for the image, auto-threshold acquisition, inversion of the binary image, and construction of a binary structure. This procedure is necessary for component inspection, and is known as the formatted image structure.
3. The component eigenvalues: The value that analyzes the formatted image structure, computes and acquires a feature of the inspecting component. This value is used to calculate and plot the multivariate control chart.

2.2. Algorithm of system function

2.2.1. Procedure 1. Image processing

Procedure 1 (image processing) comprises four steps. Step 1 is image preprocessing, which transforms the primary RGB (Red, Green, Blue) value in each pixel of the image form into YIQ (where Y denotes luminance, while I and Q represent chrominance). Step 2 is threshold acquisition, which extracts the gray difference between the object and background in the image. An optimum threshold is used to obtain two grouped pixels in a segment of a gray-level image to obtain automatic threshold acquisition. Step 3 comprises binary image, and involves the storage of a binary image in a form that can easily be processed for other purpose. This step is used to set the gray value of the image coordinates, as well as the threshold and processed value of the binary image. Step 4 comprises edge detection, which separates the object from the background and accurately positions the object within the picture.

2.2.1.1. Step 1. Preprocessing. This step transforms the primary RGB value in each pixel of the image form into YIQ.

2.2.1.2. Step 2. Threshold acquisition. Threshold acquisition extracts the gray difference between the object and the image background. Using the optimum threshold to obtain two grouped pixels in the gray-level image segment, the threshold is automatically determined. Threshold acquisition extracts the gray difference between the object and background in the image. Using the optimum threshold to obtain two grouped pixels in the segment of the gray-level image, the threshold can be automatically obtained.

p_i denotes the probability of gray-level value i in inspecting object, $1 \leqslant i \leqslant L$, the pixel number of i is n_i,

$$p_i = \frac{n_i}{\sum_{i=1}^{L} n_i} \tag{1}$$

The optimum threshold k^* is

$$\sigma_B^2(k^*) = \operatorname*{Max}_{1\leqslant k\leqslant L} \frac{(\mu_\tau \times \omega_{(k)} - \mu_{(k)})^2}{\omega_{(k)} \times (1-\omega_{(k)})} \tag{2}$$

where
$\omega_{(k)} = \sum_{i=1}^{k} p_i,\ \mu_{(k)} = \sum_{i=1}^{k} i \times p_i,\ \mu_\tau = \mu_{(L)} = \sum_{i=1}^{k} i \times p_i,\ i = 1, \ldots, L.$

2.2.1.3. Step 3. Binary images. Binary images are easier to store and process. The procedure is to set $F(x,y)$ as the gray value of image coordinate (x,y), while setting T as threshold, and $F'(x,y)$ as the processed value by this step. If $F(x,y) > T$, then $F'(x,y) = 1$, else, $F'(x,y) = 0$.

2.2.1.4. Step 4. Edge detection. Edge detection separates on object from its background and thus accurately positions an object within a picture. Edge detection is processed using the method below.

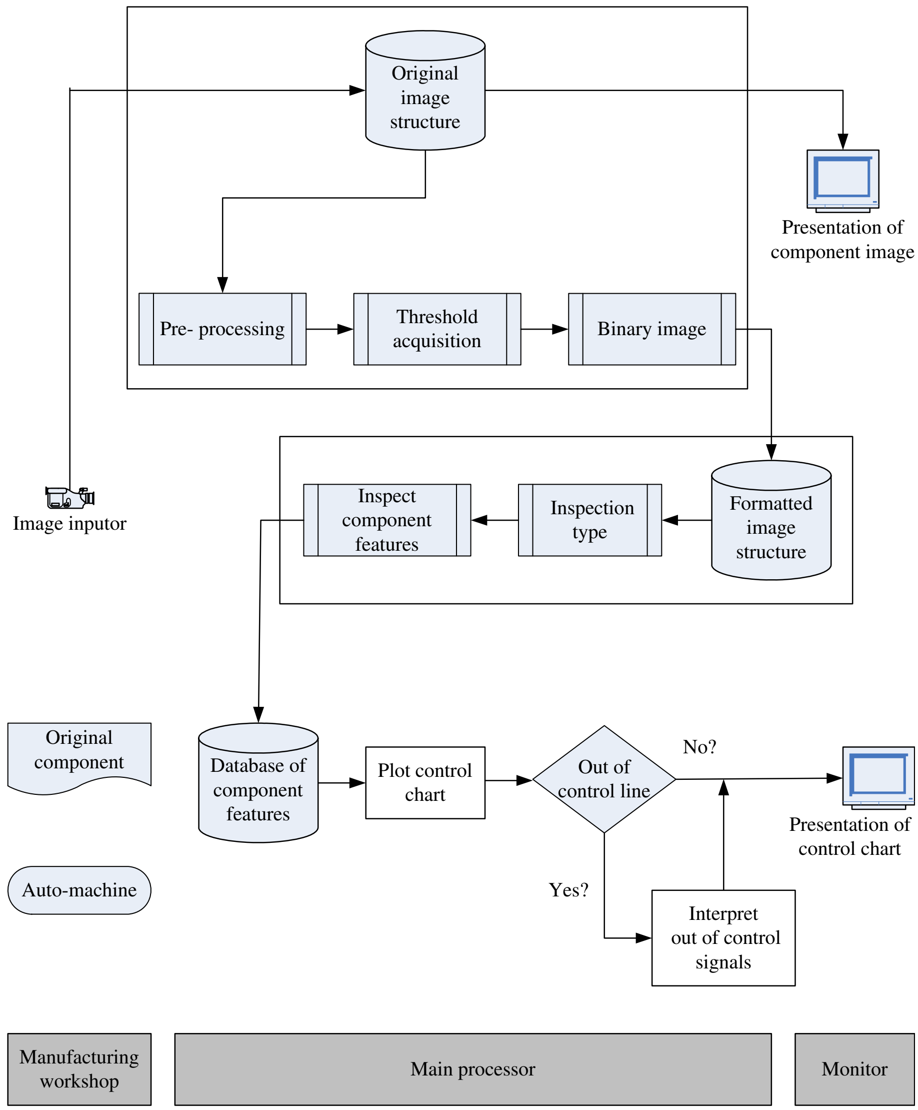

Fig. 1. Automated visual inspection expert system.

Let (x,y) denote an image coordinate, while $f(x,y)$ represents the gray-level value of (x,y),

$$G(x,y) = \left\{[f(x,y) - f(x+1,y-1)]^2 + [f(x+1,y) - f(x,y-1)]^2\right\}^{1/2} \tag{3}$$

If $G(x',y') > \theta$, boundary coordinate (x',y') denotes the point in boundary of all (x,y), where users employ θ as the boundary standard (Michael, 1988).

2.2.2. Procedure 2. Plotting multivariate control chart

This procedure is used to plot the multivariate control chart. Moreover, χ^2, Hotelling T^2 and MEWMA are used to plot the multivariate control chart.

2.2.2.1. Step1. Chi-square (χ^2) method. $X_t = (x_{1,t}, x_{2,t}, \ldots, x_{p,t})^{\mathrm{T}}$, $x_{j,t}$ denotes the jth observations at time t, $X_t \sim$ i.i.d $N_p(\mu, \Sigma)$, Σ represents the covariance matrix ofX_t, and μ_0 is the vector of the mean,

$$\chi^2 = (X_t - \mu_0)^{\mathrm{T}} \Sigma^{-1} (X_t - \mu_0) \tag{4}$$

If $\chi^2 > \chi^2_{p,\alpha}$, $\chi^2_{p,\alpha}$ denotes the upper control limit (UCL) of χ^2, X_t is out of control.

2.2.2.2. Step2. Hotelling T^2 control chart. Where $\mu_0$and Σ are unknown, sufficient data is gathered to identify $\bar{X} = \mu_0$ and $\Sigma = S$. Two cases can occur when using this, as follows:

Case 1 ($n = 1$)

$$T^2 = (X_t - \bar{X})^{\mathrm{T}} S^{-1} (X_t - \bar{X}) \tag{5}$$

$$\mathrm{UCL} = \frac{p(m+1)(m-1)}{m^2 - mp} F_{\alpha,p,m-p} \tag{6}$$

where the value of $F_{\alpha,p,m-p}$ is based on an F distribution with p degrees of freedom for the numerator and $m-p$ degrees of freedom for the denominator, m denotes the original sampling group, n represents sample size, p is quality characteristics and α denotes significance level.

Case 2 ($n > 1$)

$$T^2 = n(\bar{X}_f - \bar{\bar{X}})^{\mathrm{T}} \bar{S}^{-1} (\bar{X}_f - \bar{\bar{X}}) \tag{7}$$

$$\mathrm{UCL} = \frac{p(m+1)(n-1)}{mn - m - p + 1} F_{\alpha,p,mn-m-p+1} \tag{8}$$

where $\bar{X}_f$ denotes the sample mean of fth group, $\bar{\bar{X}}$ represents the overall sample mean.

2.2.2.3. Step 3. MEWMA control chart. The vector of the exponentially weighted moving average is represented as

$$Z_i = RX_i + (1-R)Z_{i-1},\ \ i=1,2,\dots,R=\mathrm{diag}(r_1,r_2,\dots,r_q),\ 0\leqq r_j\leqq 1,\ j=1,2,\dots,q$$

$$T_i^{\mathrm{T}} = (Z_i-u_0)^{\mathrm{T}}\sum_{Zi}^{-1}(Z_i-u_0)$$

Average run length (ARL) in the zero, steady state and worst states is used to simulate the UCL.

2.2.3. Procedure 3. Interpreting outlier signal

Procedure 3 is used to interpret the outlier signal, as are the Doganaksoy method (Doganaksoy, Faltin, & Tucker, 1991) and Fuchs & Benjamin's MSSD (mean square successive difference) method (Fuchs & Benjamini, 1994).

3. An example

The inspected component has the shape of a concentric circle, or example a compact disk, screw nut, hoop, and tube. Since circles are measured based on their radius, the component cannot be measured by inspector with a gauge. This study inspected the inner and outer diameters of concentric circles to obtain the value of image pixel of inspecting object. In this empirical work, the internal and external diameters of the standard concentric circles were 2 cm and 3.5 cm, respectively. This study used a 2 cm × 2 cm square as the standard model and calculated the pixel value before the component inspection. The pixel value of the verticality is 0.023697 cm, while the parallelism is 0.023585 cm. After using the standard distance between the two pixels, the component size is obtained from the standard distance between the two pixels, with the numerical data being listed in Table 1.

In an empirical study of 35 images of centric circles, this study calculated samples mean, matrix of covariance and inverse matrix of covariance, and used the T^2 control chart to compute and plot the multivariate control chart, UCL = 11.6656, $m = 35$, $p = 2$, $\alpha = 0.01$, with the numerical data being listed in Table 2.

3.1. Basic interface set-up

In this multivariate automated inspecting system, users only set up the menu values to perform automated inspection and analysis, and the menu of the system is illustrated in Fig. 2 and explained below.

3.1.1. Step 1. Elementary set-up

The sample size n is 1, and the initial sample group size n_0 is 20, where α is 0.01. The smoothing exponent is also 0.1. The inspected component is concentric circles; while the quality variables are the inner diameter and outer diameters.

Table 1
Coordinates of concentric circles

	Inner circle	Outer circle
Coordinates of circle (X,Y)	85,170	53,170
	170,170	201,170
	125,130	125,98
	125,214	125,245
	105,136	89,108
	105,208	89,235
	147,135	163,107
	147,209	163,236
The center of a circle	127,174	126,176
Diameter (cm)	2.04486	3.546

Table 2
Data of concentric circles for T^2 control chart

	Inner circle		Outer circle
Samples mean $\overline{X}$	2.0176 cm		3.5105 cm
Matrix of covariance Σ	0.000211976		0.000130077
	0.000130077		0.000155611
Inverse matrix of covariance Σ^{-1}	9685.786296		−8096.439303
	−8096.439303		13194.10518

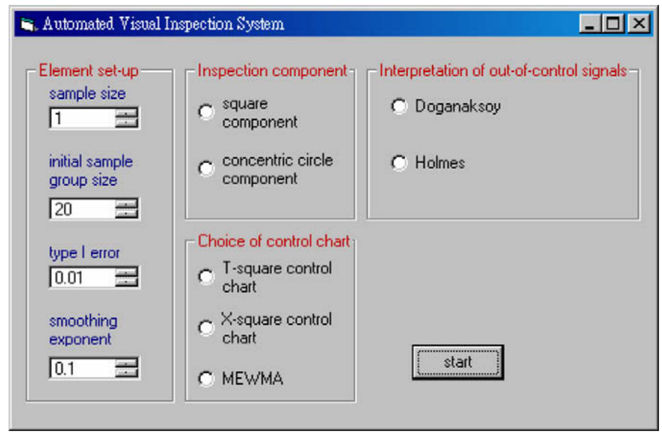

Fig. 2. Basic interface set-up.

3.1.2. Step 2. Control chart selection

Three multivariate control charts for user are used to perform quality inspection including χ^2, T^2, and MEWMA control chart.

3.1.3. Step 3. Out-of-control signals interpretation

Interpretation of out-of-control signals includes the Doganaksoy and MSSD methods.

3.2. Image processing

The study chose black concentric circles and a white background as a means of separating the object from the background in the picture. Obtaining a dynamic image involves using a CCD camera to take seven pictures per second. The image thus obtained is continuously exhibited using Win Cap software. The background is not white because this CCD is self-sensitive and the illumination is adjusted via software installed in the CCD camera. This method avoids excessively bright light resulting in color deviations. The following procedure involves transforming a dynamic image into static image that can be saved and analyzed. This study created a program for obtaining a tableau derived from a dynamic image for display in another window. Because image size obtained using a CCD camera is 320 × 240, the size of the static image is set to 340 × 250 to cover the tableau and the image is saved in a standard BMP (bit mapped) format. This standard image is saved simultaneously with the BMP file. The procedure for image processing is as follows:

1. *Preprocessing*: While reading the formatted file, the RGB point of the image is transformed into a luminance value between 0 and 255. Following the transformation there is little difference in the choice of components and background color. Before the transformation, the gradual layer of luminance is dim, while after the transformation, the gradual layer of luminance is clear.

2. *Calculating the optimum threshold*: Before obtaining the binary image, it is necessary to calculate the optimum threshold. Using the algorithm of calculating threshold, the optimum threshold for the image is 90.
3. *Transformation into a binary picture*: Every point of luminance in the gray-level image is compared with the optimum threshold. If the luminance exceeds the optimum threshold, the binary picture is to be set to white, otherwise it is set to black. Fig. 3 shows the picture.

3.3. Plotting multivariate control chart

Multivariate control chart is plotted as Fig. 4. The 35th concentric circle is an outlier in the χ^2 control chart. Based on image analysis, the inner diameter is 2.04486 cm, and the outer diameter is 3.55782 cm.

3.4. Interpreting outlier signal

Using the Doganaksoy method, the 35th inner and outer concentric circles are out of the control. Using the MSSD method of Fuchs and Benjamin, this inner circle of concentric is controlled, while the outer circle is not controlled. MSSD method differs from the Doganaksoy method owing to the Doganaksoy method being required to establish an acceptable probability, which can be adjusted based on sample size, type I error and covariance matrix.

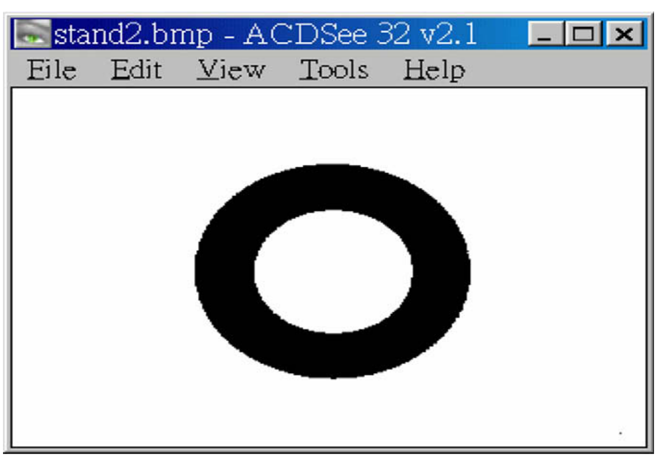

Fig. 3. Transformed binary picture.

4. Conclusions

Based on the research findings and empirical study, six conclusions are reached:

1. To interpret the outlier, the Doganaksoy method must establish an acceptable probability, which can then be adjusted according to sample size, type I error and covariance matrix. This adjustment will result in analytical error. This study used the approximate data simulated using Doganaksoy method, and the results contained some error. For ease of operations, MSSD method is used in every case, and there is no need to simulate the needed parameters.
2. This project examines the circular component and finds that the curvy component is not suitable for binary picture.
3. This investigation finds that the waiting component is too small; reducing the distance between the camera lenses with component will grow the image to get unclear picture according to the deviation of focus.
4. The random movement of the camera lens or component will affect image quality and precision, and operators should use the camera, which can automatically focus, to target some fixed position and thus obtain a consistent quality and high precision image.
5. When the image of a circle is transformed into a binary picture, the circle edge is found to be ladder-shape. This case will affect the precision of the inspecting component. Curvy component thus are not suitable for binary pictures.
6. The MEWMA control chart can easily monitor long-term trends. However, without an appropriate smoothing exponential, there is a high likelihood of making wrong decisions.

This empirical study demonstrates the feasibility of the proposed system. Simultaneously, the multivariate control chart is used to monitor the outlier. This investigation provides a speedy, consistent, and multi-feature system for inspection that is suitable for practical applications.

Further study could examine the development of the integrated investigation of multivariate quality control using automated inspection systems. Specific focuses for future research could include the following:

1. The expansion of inspecting types and techniques.
2. Future studies can include additional inspection types such as true circle, parallel degree, vertical degree, concentric degree and different shaped components. Inspection techniques can use robots, X-ray and ultrasonic waves to increase system application.

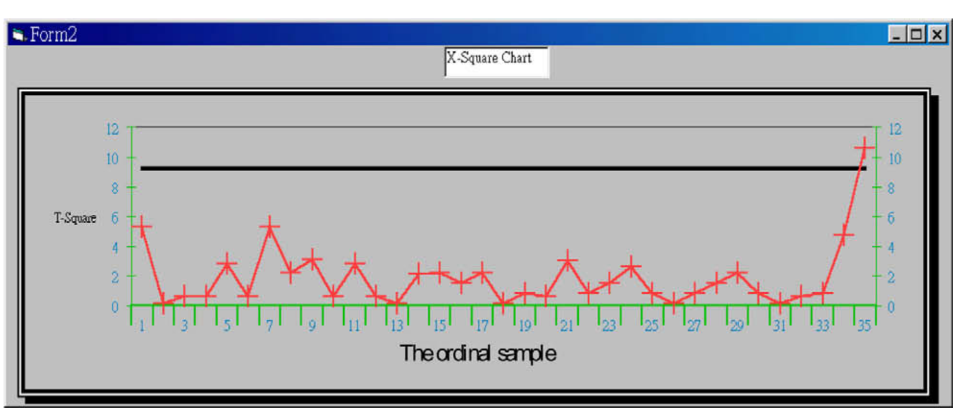

Fig. 4. Chi-square (χ^2) control chart (concentric circles, $m = 35$).

3. Establishing a choice mode for outlier interpretation. Differences in outlier interpretation can be used in appropriate cases to increase benefit. The following investigation established a selection mode for outlier interpretation to help supervisors select more appropriate modes and thus obtain more accurate results.
4. Developing testing rules for multivariate control chart. Analyzing the multivariate control chart, it is possible to determine whether the process is stable based on the outlier, but it is impossible to examine manufacturing process variation. Future study can develop rules for testing multivariate control chart, such as run tests, or zone tests for Shewart control chart.

Acknowledgments

The authors would like to thank the National Science Council of the Republic of China, Taiwan for financially supporting this research under Contract No. NSC 89-2416-H-066-026. Mr. BoNian Chen is appreciated for his technical assistance in this paper.

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