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A Review and Perspective on Control Charting with Image Data

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Machine-vision systems are increasingly being used in industrial applications due to their ability to provide not only dimensional information but also information on product geometry, surface defects, surface finish, and other product and process characteristics. There are a number of applications of control charts for these high-dimensional image data to detect changes in process performance and to increase process efficiency. We review the control charts that have been proposed for use with image data in industry and in some medical-device applications and discuss their advantages and disadvantages in some cases. In addition, we highlight some application opportunities available in the use of control charts with image data and provide some advice to practitioners.

Key Words: Image-Based Monitoring; Machine-Vision Systems; Multivariate Image Analysis; Profile Monitoring; Shewhart Control Chart; Statistical Process Control.

Introduction

Recently there have been a number of industrial- and medical-device applications where control charts have been proposed for use with image data. The papers on this topic have appeared in a wide variety of subject-matter fields, where much of it has been developed independently of previous related work. A primary purpose of our paper is to review these applications and the proposed methods. Our goal is to bring this work on the use of control charting for image data into better focus and to encourage further work in this area.

Control charts were proposed by Walter A. Shewhart in the 1920s as a simple and yet effective method to visualize and detect the occurrence of assignable causes of variability in manufacturing processes. It is well documented in the quality-control literature that his control charts are most effective in detecting moderate to large shifts in the parameter being monitored. To improve the performance of the Shewhart control charts in detecting other types of unusual patterns, supplementary run rules were introduced (see, e.g., the Western Electric Company (1956)). There are several image-based approaches that are designed to aid in control-chart pattern interpretation; see, for example, Arpaia et al. (1999) and Lavangnananda and Piyatumrong (2005). These image-based tools are not included in our review because their inputs are standard control-chart data patterns rather than industrial or medical images. It should also be noted that we do not cover the application of control charts to video-sequence data for digital-image–processing purposes, such as for detecting noise-obscured signals in a sequence of frames, as in Vihonen et al. (2008), or for scene-recognition purposes as in Elbasi et al. (2005). We believe that three-dimensional (3D)-laser scanning represents much of the future of industrial measurement because it can rapidly provide thousands (or millions) of data points representing the entire geometry of a part. Megahed et al. (2010b) introduced the application of control charting to 3D–laser-scanning data and highlighted some future research opportunities on this subject. This type of data collection and analysis, however, is also not covered in our pa-

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per. Similarly, we do not include medical applications where the input to the control charts is a 3D image (such as in Lindquist et al. (2007)).

We assume that the reader is familiar with the construction and use of control charts (for detailed introductions, see Wheeler and Chambers (1992), Woodall and Adams (1998), or Montgomery (2008)). On the other hand, it is not assumed that the reader is familiar with the issues involved with image data. Therefore, a brief overview of image-data processing is given in the next section. This is followed by a section on some of the general differences between image-based control-chart applications and more standard control charting. We then offer some general advice to practitioners. Then there are several sections on various types of methods proposed for monitoring with image data, along with their advantages and disadvantages in some cases. Finally, our conclusions are given in the last section.

An Overview of Machine-Vision Systems

A machine-vision system (MVS) is a computer system that utilizes one or more image-capturing devices (e.g., cameras or X-ray devices) to provide image data for analysis and interpretation. The system involves the image-capturing step, the analysis of the image data, taking appropriate action based on the image analysis, and learning from experience so that the system's future performance can be enhanced.

In spite of some similarities between human and machine vision, there are significant differences between them. As Zuech (2000) stated, current machine-vision systems are primitive when compared with the human eye–brain capability because, for example, current MVSs are susceptible to variations in lighting conditions, reflection, and minor changes in texture, among other variations, to which the human eye can easily adjust and compensate. Despite these limitations, the use of MVSs is superior to visual inspection with respect to (1) monitoring processes with high production rates; (2) performing multiple simultaneous tasks with different objects; (3) their ability to cover all the ranges of the electromagnetic spectrum, as in the use of magnetic-resonance imaging (MRIs) and X-rays in medical applications; and (4) the lack of susceptibility to fatigue and distraction. In some cases, the use of MVSs is cheaper than the use of human inspectors and it is expected that the cost of MVSs will continue to decrease over time. These advantages position the use of MVSs as a much more attractive option than the use of human visual inspection in many cases, which helps to explain their widespread and increasing use in industrial and medical applications. Therefore, there is a consequent need for some statistical process-control (SPC) monitoring techniques.

The acquisition of an image is the first step in any application of machine vision. An image is often represented as a function $f(x, y)$ or a vector $\mathbf{f}(x, y)$, where x and y represent the spatial coordinates on the image plane, and the value (or values) at any location (x, y) is (are) commonly known as the intensity (or intensities). In digital images x, y, and the intensities take only nonnegative integer values. As the resolution of the image-capturing device increases, the image is divided into more elements (i.e., pairs of x and y) and thus the total number of elements (pixels) increases. On the other hand, the intensity values depend on whether the image is black and white (binary), grayscale, or in color. In the case of a binary image, each pixel can only have an intensity of either 0 (black) or 1 (white). If the image is grayscale, then $f(x, y)$ can take any integer value between 0 (black) and 255 (white) for eight-bit images. Finally, when the image is in color, $\mathbf{f}(x, y)$ is a vector of three individual components corresponding to red, green, and blue (RGB) with values between 0 and 255 for each component. Thus, in all three cases, each image can be viewed as a collection of multivariate, spatially distributed observations with dimensionality that depends on the number of pixels and the type of image. For 16-bit images, the intensity values can take values between 0 and $2^{16} - 1$.

Images in industrial applications are most often grayscale or binary images. These images are cheaper to obtain and analyze. In addition, there is limited time to analyze images in industrial settings with high production rates, so there are advantages in using simple analysis methods.

The intensity values for neighboring pixels within an image are often highly correlated. This correlation can result in a considerable amount of data redundancy, where the information contained at any given pixel location in an image is relatively small because its intensity can often be predicted accurately from the neighboring pixels.

Color (RGB) images are just one example of a larger class of hyperspectral images. A hyperspectral image consists of a stack of aligned (i.e., congruent) images, each of which covers a certain wave-

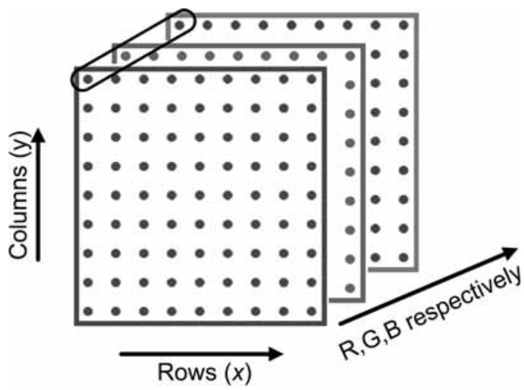


FIGURE 1. A Color Image Representation in Three Wavelength Channels (RGB). The ellipse indicates the red, green, and blue intensity values for a given pixel.

length band. Together, these congruent images form a three-way matrix $(x, y, \mathbf{f}(x, y))$. It should be noted that $\mathbf{f}(x, y)$ is a vector of the different wavelength intensities captured by the image-capturing device. For example, the representation of an RGB image in its three-way matrix form is illustrated in Figure 1. In part due to the correlated nature of the information contained across the different congruent images, hyperspectral images are usually referred to as multivariate images.

After an image is captured, it must be analyzed so that information can be extracted. Gonzalez and Woods (2007) divided this process into three subsequent levels: (1) low-level processes comprised of basic operations of noise reduction, image compression, and contrast enhancement, where the inputs and outputs are images; (2) mid-level processes, where the inputs are images and the outputs are attributes extracted from images such as edges, objects, and contours; and (3) high-level operations aimed at understanding and making sense of the data. For binary/grayscale images, the process of information extraction is referred to as digital image processing or image analysis. There are quite a few books on this topic, including Nalwa (1993), Jähne (2005), and Gonzalez and Woods (2007). Multivariate images are often analyzed through some multivariate statistical framework, such as principal component analysis (PCA) or partial least-squares (PLS) regression, for dimension reduction. The analysis process for multivariate images is commonly known as multivariate image analysis (MIA). We discuss MIA monitoring approaches in more detail in a later section. For more information on the well-developed area of MIA, the reader is referred to Geladi and Grahn (1996), Grahn and Geladi (2007), and Pereira et al. (2009).

Machine-vision systems are widely used in a variety of industries for inspection purposes, where "good" items are to be separated from "bad" ones. Megahed and Camelio (2010) categorized MVS inspection applications into the following three groups: (1) medical applications, where MVSs are used in detecting and diagnosing abnormalities in different body parts (e.g., Liu et al. (1996)); (2) transportation and construction applications, where MVSs are used in the identification and measurement of cracks, surface indentations, and protrusions in different construction materials and structures (e.g., Schmitt et al. (2000)); and (3) industrial applications. Malamas et al. (2003) reviewed in considerable detail the industrial use of MVSs to detect dimensional defects (comparing the product's shapes and dimensions with respect to the design tolerances), structural defects (checking for missing components in product assemblies), surface defects (inspecting surfaces for scratches, cracks, improper finish, and roughness), and operational defects (verifying the proper operation of inspected products). Despite their importance, we do not cover inspection applications in our paper unless control charts are directly involved.

General Differences from Standard SPC

The use of image-based control charts differs somewhat from the use of more traditional control charts. These differences can be attributed to a number of factors, which include the type of data being monitored, the rationale behind using control charts, and how the control charts are applied. Preliminary analysis of image data is required before control-charting methods can be used. Noise reduction, image compression, and other types of data processing may be necessary with image data before any monitoring can be done. This analysis is typically much more extensive than that required in standard control-charting applications. Data processing speed can become an issue with 100% inspection.

Human inspectors do not respond with equal sensitivity to all visual information. Gonzalez and Woods (2007) discussed how humans search for distinguishing features within an image, such as edges and/or textural regions, and mentally combine them into recognizable groupings. A person then uses prior knowledge to complete the image interpretation process. Feature-detection operations or multivariate analysis is needed with MVS data to perform an analogous type of interpretation.

In some applications, image-based control charts are not used to detect changes in images over time but in specifying where any flaws have occurred spatially on the objects being imaged. In these applications, the X-axis on the control chart can correspond to the location on the image. This is much different from traditional control-chart practice where time or the sample number is plotted on the X-axis. These applications are based on a sliding-window technique where the window (with a size based on target defect size to be detected) is moved progressively over the whole image area. A statistic is calculated for every window and a "spatial" control chart (due to the fact that the X-axis refers to the window's position within an image) is used for detecting defects. Spatial control charts are described in detail in a later section. The reader should note that the majority of the image-based control- charting methods discussed in this paper follow the standard SPC approach. Accordingly, unless otherwise specified, the X-axis of the discussed image-based control chart will correspond to either time or image number.

In process monitoring, it is very beneficial to carefully distinguish between the Phase I analysis of historical data and the Phase II monitoring stage. With Phase I data, one is interested in checking for stability of the process and in estimating in-control parameter values for constructing Phase II methods (see, e.g., Woodall (2000)). Phase I methods are usually evaluated by the overall probability of a signal, whereas run-length performance is typically used for comparison purposes in Phase II, where the run length is the number of samples before a signal is given by the control chart. In general, for current papers on image-based control charts, there is often not a clear distinction made between the two phases. Exceptions include much of the work on MIA monitoring approaches (see Lyu and Chen (2009), and the approach of Wang and Tsung (2005)).

Advice to Practitioners

There are many practical decisions that must be made when using images for process monitoring. These include the choice of the image-capturing device; the frequency of imaging; the set-up of the imaging to avoid lighting, alignment, and other problems; the software to use for image analysis; the preliminary image processing; and the type of monitoring method to employ. There are no currently existing guidelines for guiding the practitioner through all of these decisions. It may be possible to use images taken in industry for some other purpose, such as inspection or item alignment, for process monitoring. Our advice to practitioners who are to implement image-based monitoring is to find the paper (or papers) on the most similar applications in order to obtain implementation ideas. Because there is no standard approach to image monitoring in most cases, practitioners will have to adapt methods to their particular applications.

The choice of a method will be driven to a large extent by the purpose of the monitoring. Often, imaging is used for feature extraction, e.g., to obtain dimensional data on the imaged object. In this case, standard control-charting methods are used on the obtained data just as if they had come from a source other than through imaging. Of course the measurement system must be evaluated through a gage repeatability and reproducibility (gage R&R) or other approach. This feature-extraction use of image data is the most straightforward and should be used when the focus is on known features, such as dimensional variables. This approach has been used for roughly 20 years in the automotive industry, e.g., with Perceptron® measurement systems (www.perceptron.com). A concern with extracting known features from images is that some unknown features or other ignored information in the images could be important because images allow for the detection of localized faults (e.g., the presence of an extra punched hole) that do not necessarily affect the extracted features.

In some applications, however, uniformity of the image is the ideal situation, as when checking a metal surface for flaws. In this case, some measure of the number and size of flaws must be obtained and monitored. In other cases, such as in fabric monitoring, the ideal image has a specified pattern and any variations from this pattern are to be detected and located within the image. Spatial control charts are designed for this purpose. If the image is not expected to be uniform or with a particular specified regular pattern, there may still be requirements on the overall pattern, as in the monitoring of cultured marble countertops. In this case, MIA may be most useful. Finally, in some cases, it is not the images that are monitored over time so much as the image-capturing device. In medical applications, for example, one obviously does not expect images to be consistent over time when different patients are being imaged. The overall image quality and consistency, however, can be measured and monitored.

Practitioners should be aware that many of the papers on image monitoring are rather difficult to understand. In a number of cases, no careful justification is given for the monitoring approach. In our view, a considerable amount of work is needed in image monitoring to give it a more coherent structure and to provide guidelines for implementation. MIA is an exception in this regard, but it is applicable only under certain conditions and for certain purposes. We devote a section to MIA later in our paper.

Univariate Control Charts for Industrial Image Data

We first consider some univariate methods that were designed for use with successive binary or grayscale images.

Horst and Negin (1992) were among the first to discuss the advantages of using control charts with industrial image data, although we expect that control charts were used with image data in industry prior to the publication of their article. Horst and Negin (1992) argued that the use of Shewhart charts and histograms with machine vision data could lead to significant productivity improvements in web process applications, e.g., with paper, textiles, and plastic films. Emphasis was given to processes for which the in-process and post-process manufacturing steps need to be accomplished "in register" with a visual feature such as a watermark. Their paper gave an overview of how control charts could be used with web production processes and included an example related to dimensional control.

Tan et al. (1996) used an MVS to sample and measure the quality characteristics (length, width, and area) of an extruded food product, specifically corn puffs, as a part of total statistical process control system. An X-bar control chart was used to monitor the size of the product. Corrective actions were determined using a proportional and integral (PI) control scheme to minimize the product size variations arising from variations in the moisture content of the corn. Considerable improvement was thereby achieved in product size uniformity.

Armingol et al. (2003) combined machine vision inspection techniques and control charts in developing an online inspection system for manufactured metallic parts. In their approach, they first accounted for illumination changes through a transformation of the pixel values of the image. Illumination changes can be due to problems in the positioning of the camera or changes in the light source. Then M (equal to number of pixels) individual-moving range (I-MR) control charts were constructed for each of the pixel locations to detect any abnormal changes in the image at each of the pixel locations. In their example, they constructed 439,296 control charts for the pixel values using control limits at plus and minus six standard deviations (estimated based on 20 images representing Phase I Data) to decrease the number of false alarms. In the case of a signal, the size and the location of the defect was based on the control charts that signaled. The construction of a control chart for every pixel location, however, does not account for the inter-pixel redundancy of neighboring pixels. In addition, this resulting huge number of control charts can require an excessive amount of computational time that may not allow for online monitoring in real time.

Nembhard et al. (2003) developed a MVS for monitoring color transitions in plastic extrusion processes using a forecasting algorithm. They transformed the original RGB data into grayscale using the hue as the metric, where the hue was calculated as the average of the red, green, and blue intensities. Their methodology integrates traditional SPC tools for variable data with a forecasting system based on the exponentially weighted moving average (EWMA) statistic. Their algorithm utilizes process knowledge of whether a new color has been added to the extruder or not. In the absence of a color addition, their algorithm captures an image, eliminates the background, applies the hue transformation, and calculates the error between the actual image intensity values and the forecasted intensity values. The forecast errors are then plotted on a Shewhart control chart. On the other hand, if a new color has been added to the extrusion process, then their MVS would identify the end of the color transition stage so that the color of the produced product would be acceptable.

Liang and Chiou (2008) designed a MVS to automatically monitor the tool wear of coated drills. Their tool measurement system consisted of a macro lens and a ring light-bulb in addition to the camera and suitable computer software. The authors segmented (separated) the cutting tool from the background using a suitable threshold pixel intensity value that was based on their Taguchi method experimentation. This was followed by a number of digital image processing steps where they used edge detection techniques. Then they used an X-bar chart with three sigma limits to automatically select the upper and lower curvature threshold values which were needed to identify the vertices that represent the current profile of the cutting tool. Afterwards, the crater wear width, which reflects the amount of tool wear, was calculated using commercially available software.

Multivariate Control Charts for Industrial Image Data

Typically manufacturing processes are characterized by more than one quality characteristic. In these situations, the simultaneous monitoring of these quality characteristics often yields better results than monitoring each of these characteristics separately. This joint monitoring can be accomplished using multivariate control charts. A thorough review of multivariate control charting was provided by Bersimis et al. (2007), although these authors did not include any papers on the monitoring of image data. In this section, we will review some of the literature available on the use of multivariate control charts for industrial image monitoring.

Tong et al. (2005) used Hotelling T^2 control charts to monitor integrated circuit (IC) defects on a wafer map. It should be noted that a wafer is the building block of semiconductor manufacturing, where several hundred integrated circuits (ICs) are simultaneously fabricated on one wafer. A wafer map is a visual display used in semiconductor manufacturing to show the locations of the defective IC chips on the wafer. Even though the wafer map is not based on an image, we include the approach by Tong et al. (2005) among our discussion of the literature because wafer maps possess many of the same spatiotemporal characteristics as industrial image data. Thus, some of the methods of analysis for wafer maps may be modified for use with image data.

The rationale behind the adoption of the Hotelling T^2 control chart by Tong et al. (2005) to monitor integrated circuit defects instead of a traditional defects control chart (C chart) is based on previous research in the field of semiconductor manufacturing. Hansen et al. (1997) showed that IC defect positions on a wafer map are highly correlated since defective chips often occur in clusters or display systematic patterns. The defect clustering pattern can reflect the causes of the IC defects and therefore clustering indices (CIs) have been developed to accurately represent the clustering phenomenon (e.g., Jun et al. (1999)). The defect counts often cannot be modeled by a Poisson distribution and the corresponding traditional C charts can have high false alarm rates, as shown by Friedman and Albin (1991).

The method proposed by Tong et al. (2005) is based on the number of defects and the CI as the two quality characteristics to be monitored. Tong et al. (2005) monitored these two quality characteristics using a Hotelling T^2 control chart. In the case of a signal in the T^2 control chart, Tong et al. (2005) suggested the decomposition of the T^2 statistic based on the method by Mason et al. (1997) to identify the cause of the signal. It must be determined whether a control chart signal is associated with an increased number of defects, due to the clustering of the defects, or associated with both.

Liu and MacGregor (2006) developed an MVS for monitoring the appearance and aesthetics of manufactured products with engineered stone countertops used as an example. A primary purpose of their paper was to extend the use of MVSs to the appearance of items that contain "visible patterns such as stripes, swirls, and ripples with varying characteristics in their shapes, sizes, and intensities." Their methodology is composed of the following three major steps: extraction of textural features from product images using wavelet transformations, quantitative estimation of the product appearance using principal component analysis (PCA), and monitoring the product appearance based on the most significant principal components. They used control charts in the last two stages of their methodology. In the second stage, a squared prediction error (SPE) plot was used to ensure that the variability of the countertop slabs was well modeled by the PCA model. In the last stage Hotelling T^2 and SPE control charts were used to detect off-specification countertops.

In another application, Lin (2007a, b) used wavelets and multivariate statistical approaches, including the Hotelling T^2 control charts, to detect ripple and other types of defects in electronic components, in particular surface barrier layer (SBL) chips of ceramic capacitors. The wavelet characteristics were used to describe the surface texture properties and then the author proposed a Hotelling T^2 control chart to judge the existence of a defect based on combining the different texture properties. In a later paper, Lin et al. (2008) conducted a comparison between the capabilities of a wavelet-Hotelling T^2 control chart approach and a wavelet-PCA-based approach in detecting surface defects in light-emitting diode (LED) chips. Their results showed that the wavelet-PCA based approach was more effective for their application.

Recently, Lyu and Chen (2009) integrated image processing technologies and multivariate statistical process control charts to design an automated visual inspection expert system, which could be used in mass production manufacturing systems as a part of the inspection process. As in many of the papers on this topic, their approach could be divided into a digital image processing step and a step where the control charts are applied. In the digital image processing stage, they suggested transforming the grayscale image into a binary image and then applying edge detection methods to further reduce the dimensionality of the data. Afterwards, the binary image was analyzed and the required dimensional quality characteristics were obtained and plotted on a multivariate control chart. They suggested the use of the chi-square control chart, Hotelling T^2 control chart, or a multivariate exponentially weighted moving average (MEWMA) control chart with the necessary control limits calculated based on Phase I data. In their application, they inspected the inner and outer diameters of concentric circles using image processing techniques and used multivariate control charts for detecting special cause variations in the sample mean vector. In their illustrative example they used 20 samples as Phase I data and then applied their Phase II method on the remaining 15 samples.

Profile Monitoring for Industrial Image Data

Profile monitoring is the use of control charts for cases in which the quality of a process or product can be characterized by a functional relationship between a response variable and one or more explanatory variables. For detailed reviews on the subject, readers are referred to Woodall et al. (2004) and Woodall (2007). Image monitoring could be considered as a natural extension of profile monitoring methods to cases where the explanatory variables indicate the location of the intensity measurement(s) within the image. In general it is worth noting that the papers written on image monitoring can be considerably more difficult to understand than the papers on monitoring profiles involving only one explanatory variable. One tends to have much more data with image applications, a complicating spatial component, more complex analysis methods, and more wide-ranging potential purposes of the monitoring.

In profile monitoring one also has to decide if a particular feature of the profile is to be monitored, e.g., the maximum value, or whether the entire profile function should be monitored. If one chooses to monitor specific features, then standard control charting methods can be used directly. To monitor the entire profile function, one has to first model the function and take different approaches depending on whether parametric or nonparametric methods are used.

Wang and Tsung (2005) used profile monitoring techniques to detect changes in grayscale images using a Q-Q plot, which reflected the relationship between a current image sample and a baseline conforming image sample. The authors used their method in a case study to detect defects in mobile-phone liquid crystal display (LCD) panels. Their technique, however, can serve only as a fault detection tool since the pixel locations were ignored, thus removing any information on the type, size, or location of any defect(s).

Woodall (2007) suggested that the monitoring of product shapes is a very promising area of profile monitoring research since the shape of manufactured items is very often an important aspect of quality. Profile monitoring approaches using shape data can be more efficient than standard engineering methods for monitoring shape data because in many cases the engineering approaches do not use all of the information in the data. Colosimo et al. (2010) and Colosimo and Pacella (2011) extended the application of profile monitoring techniques to three dimensional surfaces using coordinate measuring machine data. For example, Colosimo et al. (2010) dealt with a more complex dataset than those traditionally considered in profile monitoring approaches in their application to monitor the surface quality of metallic surfaces. Their proposed approach combined a regression model with spatially correlated noise with univariate and multivariate control charts. They successfully tested their approach on metallic cylindrical items produced by turning on a lathe.

Spatial Control Charts for Industrial Image Data

The authors of the papers discussed in this section proposed control charting methods in a nonstandard way since the horizontal axis of each control chart represents a position in the image, not time. The control charts are used spatially by moving a mask (or window) across the image and then calculating and plotting a statistic each time the mask is moved. Typically the mask positions do not overlap and there is an implicit assumption that defects are just as likely to occur in one region of the image as in any other region of the same size. The size of the mask depends on the expected size of the defects to be detected, with smaller defective regions requiring smaller mask sizes.

Jiang and Jiang (1998) used a digital image processing system to inspect oil seals for conformance to size specifications and used modified I-MR charts to detect surface defects and their locations on the oil seals. They based their I-MR control charts on the gray level of pixels along analyzed circles superimposed on images of the oil seal.

In another application, Jiang et al. (2005) developed a method for the inspection of the uniformity of high-grade LCD monitors that involves analysis of variance (ANOVA) and spatial control charts to detect the type, size, and location of any defects. Their approach did not utilize image processing techniques per se, but instead used a luminance meter, a light sensitive device, to collect the needed data for analysis. Their measurement process was to divide the LCD panel into a number of different blocks, each with an area of 1000 pixels. Data collection was done in a darkroom with the panel switched to a white background. ANOVA methods were used to identify areas significantly different from other areas in a panel. The EWMA chart was used to detect small differences in various panel areas and to detect the position and size of any defects. Since this method could have easily been implemented using image processing techniques where each block's intensity would be calculated through the mean intensity values of the pixels within that block, this paper falls within the image-based control chart literature. An illustration of an EWMA chart presented by Jiang et al. (2005) is shown in Figure 2. Despite the capability of their method to identify the defect type, location, and size, there are two limitations in this research. First, it would be difficult to detect a defective area partially overlapping two or more of the testing blocks. Also, there were no general guidelines for determining the value of the EWMA parameter λ. The authors determined their smoothing parameter value of 0.80 by trial and error.

In a similar application, Lu and Tsai (2005) used machine vision and a spatial X-bar chart to tackle the problem of detecting defects in LCD panels. Their approach first removed the repetitive background texture of LCD panels by transforming the image matrix into the eigenvector space and removing the larger eigenvectors that captured the textural structure. Then the image was reconstructed from the resulting eigenvector space to check for defects. The defect detection scheme was based on a spatial X-bar chart, which can be applied to their reconstructed image since the variation in the intensity of the pixels was small. Thus the spatial control chart was used in distinguishing defects from the uniform background region. They used Chebyshev's theorem to determine the limits for their control chart with 4-sigma limits so that their false classification percentage was around 6%.

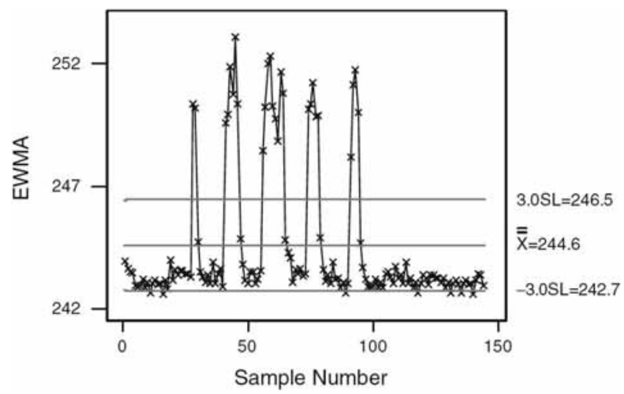
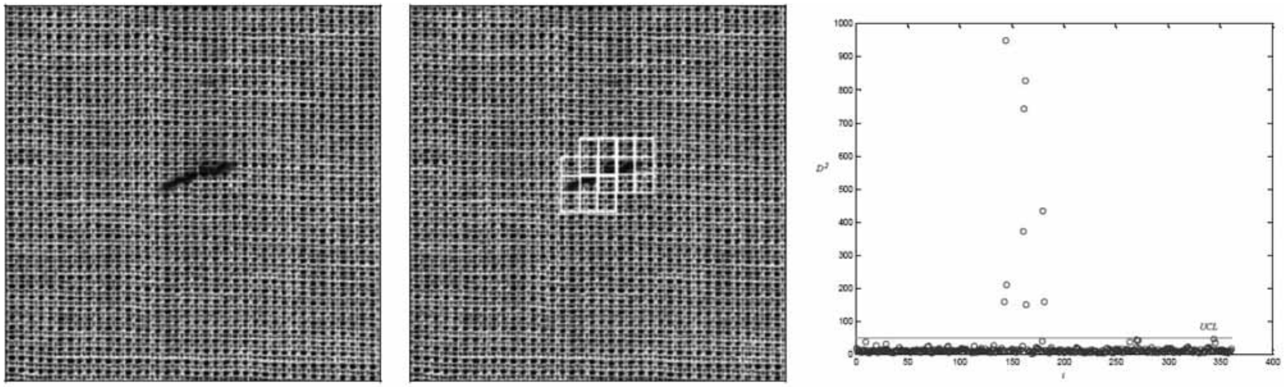


FIGURE 2. EWMA Chart for Detecting LCD defects. (Adapted from Jiang et al. (2005).) Reprinted with permission from *Taylor & Francis Group*. Copyright 2005 International Journal of Production Research.

Lin and Chiu (2006) recommended the use of the Hotelling T^2 control chart, among other methods, to detect MURA defects in LCD monitors. MURA defects are lighting variations on what should be uniform luminance over a surface. More specifically, they used the multivariate Hotelling T^2 statistic to combine the various coordinates of the color models to detect small color variations in the LCD panels. This was a spatial control chart procedure in the sense that the images of size 256×256 pixels were divided into 5×5 pixel subregions with a T^2 statistic calculated and plotted for each subregion.

Defects on thin film transistor (TFT) panels are classified into two categories, macro and micro defects. Lu and Tsai (2005) provided examples for each of the two defect categories. They defined the appearance of macro defects as regions of high contrast with irregular shapes and sizes such as MURA (unevenness in the TFT panels), SIMI (stains on TFT pan-



(a) (b) (c)

FIGURE 3. (a) Foreign Body Defect, (b) the Marking of Out-of-Control Windows Based on T^2 Control Chart, (c) Plotting the Quality Characteristics on the T^2 Control Chart. (Adapted from Tunák and Linka (2008). Reprinted with permission from *Hong Kong Institution of Textile and Apparel (HKITA)*. Copyright 2008 Research Journal of Textile and Apparel.

els) and ZURE (misalignment of TFT panels). On the other hand, micro defects include pinholes, fingerprints, particles and scratches, which are generally very small and hard to detect using human inspectors. Accordingly, an effective machine-vision system should be able to detect both defect categories. This goal has yet to be achieved and the available literature for image-based control charts has initially focused more on detecting the macro defects. It should be noted, however, that detecting macro, especially MURA, faults is not an easy task as they often have no clear contour or contrast. (Taniguchi et al. (2006))

Tunák and Linka (2008) provided a robust technique for detecting the occurrence and location of defects in woven fabrics with a plain weave structure using grey system theory, which has been proposed as an alternative to the use of probability and fuzzy methods. For information on grey system theory, see Deng (1989). By observing that any woven image is periodic in nature and therefore can be considered to have directional texture, Tunák and Linka (2008) used second-order texture statistics because they allow for maintaining both brightness and spatial information. Specifically they used the grey level co-occurrence matrix, GLCM, of grey system theory first introduced for fabric monitoring by Haralick et al. (1973). Tunák and Linka (2008) used classification and regression tree techniques to extract the following five significant features from their matrix: energy, correlation, homogeneity, cluster shade, and cluster prominence. Since the presence of a texture defect causes regular structural changes and, consequently, statistical changes, the authors used a spatial Hotelling T^2 chart to combine multiple texture features and detect defects. Their approach is illustrated in Figure 3. The spatial Hotelling T^2 charts involved ten quality characteristics, each of the five features in both the warp and weft directions. Weft is the yarn which is drawn under and over perpendicular to the warp yarns to create a fabric, as illustrated in Figure 4.

Tunák et al. (2009) improved the defect detection capability on plain weave structures by relaxing some of the earlier assumptions and adding more features to the SPC algorithm. Their proposed algorithm can account for the misplacement of the yarn on the image, e.g., possible rotation of the image. In addition, it can be used not only to detect defects associated with the change of weaving density of weft yarns, but also to monitor weaving density in the direction of the length of the fabric. Fabrics could also have different patterns, such as plain, twill, and satin. In order to achieve this flexibility, the authors followed a different approach than that of Tunák and Linka (2008). In particular, after the image is captured Tunák et al. (2009) performed contrast enhancement to increase the distinction between the woven fabric and the background. Then the authors applied a two-dimensional discrete Fourier transformation (2-D DFT) on the image matrix since this representation was found to be well-suited in representing the directionality of the periodic patterns. Through some manipulation of the parameters involving the 2-D DFT and its inverse, the resulting images can be made to contain only warp or weft set of yarns. Therefore, the restored images can be used for the au-

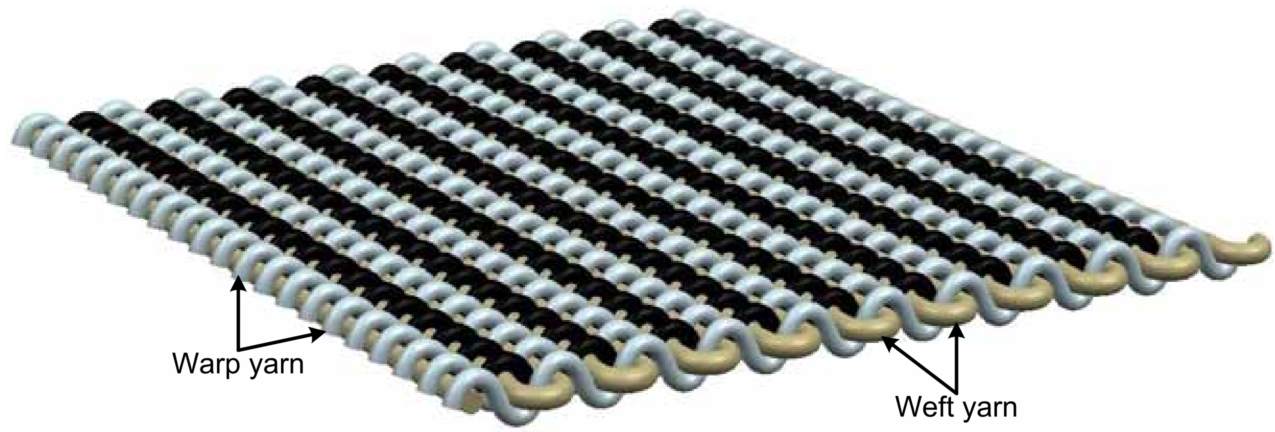


FIGURE 4. A Schematic of the Warp and Weft Directions for Fabric.

tomatic assessment of weaving density. The authors then used a spatial X-bar control chart on the weaving density as a tool to find sites of potential defects. A sample of their results is illustrated in Figure 5.

Anagnostopoulos et al. (2001) showed that one of the main difficulties with computer-based fabrics quality monitoring is the huge diversity in the types of fabrics and their defects. They provided a detailed list of fifteen different textile faults and their causes. Fabric monitoring methods based on more standard approaches, as opposed to the use of grey system theory, remain to be developed.

MIA-Based Control Charts

In MIA the images involve measurements taken for at least three different wavelengths. Before any monitoring is done, there is usually a dimension reduction step based on principal component analysis (PCA) or partial least squares regression.

Bharati and MacGregor (1998) proposed an online approach for extracting information from multivariate spectral images collected over time. The methods can be used for measurements with three or more measured wavelengths where one receives a sequence of images over time and wants to detect and isolate specific features from the images. In their approach, they aggregated the data over pixel locations and used PCA to identify the two principal components that explained most of the variation in the vectors of wavelength intensities. Then they monitored the pixel frequencies corresponding to certain specified features in the score space of the first two

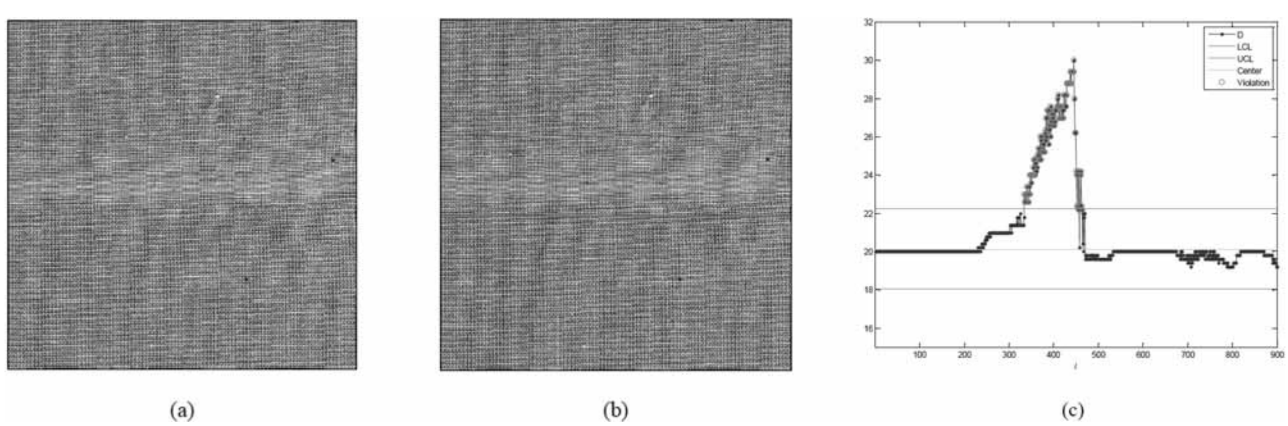


FIGURE 5. (a) Image of Woven Fabric in a Plain Weave with Defective Weft Stripe, (b) Defective Region, (c) Control Charts for Weaving Density of Weft Yarns (Adapted from Tunák et al. (2009)). Reprinted with permission from *Springer Science and Business Media*. Copyright 2009 Polymers and Fibers.

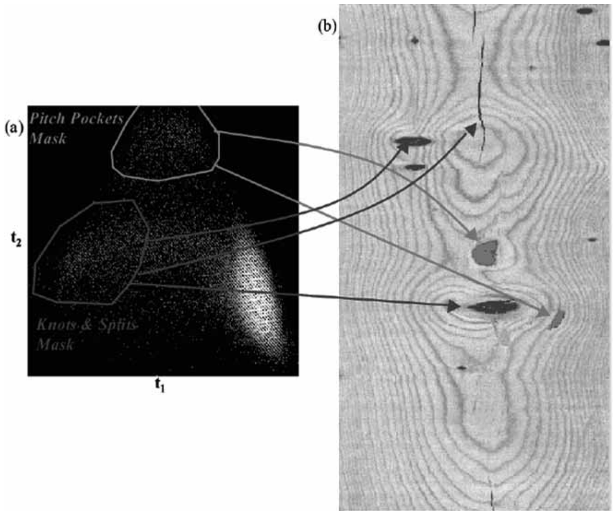


FIGURE 6. (a) Principal Component $t_2 - t_1$ Score Plot of Lumber Image with Polygon Masks of the Upper and Lower Left Point Clusters. (b) Original image (converted from color) with overlay of highlighted pixels from the two classes outlined in part a. (From Bharati et al. (2003).) Reprinted with permission from *Industrial and Chemistry Research*. Copyright 1998 American Chemical Society.

principal components. Image masks were developed in the score space to correspond to each feature of interest in the original image space to be monitored. When any of the pixel frequencies in any specified mask area exceeded a predefined threshold, there would be a signal to allow the operator to look for assignable causes for this change. In order to illustrate the fault diagnosis aspect, the authors showed how these changes could be traced back to show their spatial locations on the original image. Thus, the operator/engineer would know the change in the pixel frequency and location, which would facilitate the root-cause analysis aspect of fault diagnosis. Standard control charting methods can be applied to the pixel frequencies over time corresponding to each feature being monitored.

An example of the use of principal component image masks and how they relate to the original image is illustrated in Figure 6. The pixels in each of the two masks in Figure 6(a) correspond to flaws of the type shown in Figure 6(b).

MacGregor et al. (2001) provided additional discussion of the approach of Bharati and MacGregor (1998). They mentioned several industrial applications, which included texture/roughness analysis and monitoring of sheet and film products, monitoring of different gels and faults in polymer films, and the quality category classification of wood products. Bharati et al. (2003) applied the method of Bharati and MacGregor (1998) to the automatic quality grading of softwood lumber boards. In this application, they constructed three frequency-based one-sided (individual sample) control charts, where the control limits were based subjectively on unacceptable quality levels. For example, the control limit of their control chart shown in Figure 7(a) has been set at 4912 pixels (which is 2% of the total number of pixels in each lumber image). The authors stated that the control limits must be selected in practice to balance the consequences of classification errors. Two other control charts are shown in Figure 7(b) and Figure 7(c). The authors recommended always plotting the squared prediction error (SPE) of each image on a control chart to check to see whether or not the model is valid for that image.

In two interesting applications of monitoring industrial processes with MIA methods, Yu et al. (2003) developed an online MVS for monitoring and controlling industrial snack food quality and Yu and MacGregor (2004) monitored flames in an industrial steam boiler system. Even though control charts were not employed in these papers, they are useful in better understanding the MIA on-line monitoring methods. In addition, Kourti (2006) provided an excellent review paper on the role of multivariate analysis in process analysis, which included a review of some MIA surveillance methods and mentioned applications not only of electronic vision, but also electronic versions of taste, hearing, and smell. MIA monitoring approaches were also briefly discussed by Kourti (2005).

Liu et al. (2005) developed a MIA-based MVS to monitor the froth of a flotation process, which is one of the most widely used separation processes in mineral processing to separate valuable metals from ore. Their approach involved MIA methods based on PCA analysis with a residuals control chart used to check the validity of the model over time. The residuals control chart was used to prevent the operators from taking corrective actions based on abnormal images resulting from camera problems, lighting problems, or other unusual conditions. This is beneficial because the problem would then be in the images rather than in the process.

Graham et al. (2007) used MIA based on principal component analysis to measure and predict the ladle eye phenomenon in metallurgy with the "eye"

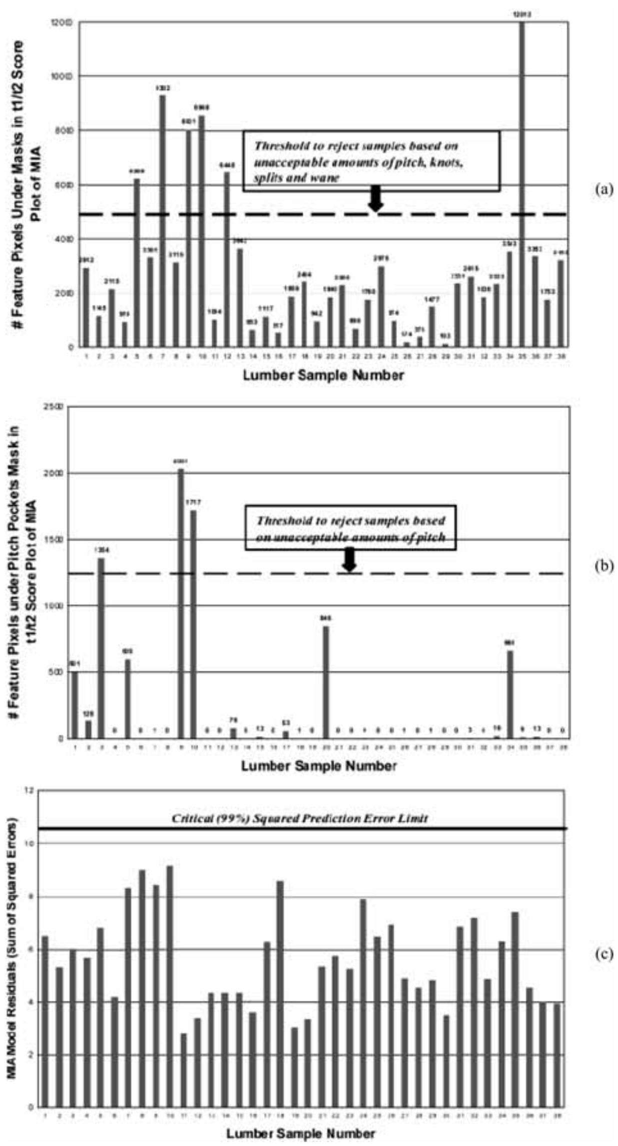


FIGURE 7. (a) Control Chart of Total Number of Pixels Belonging to all Modeled Lumber Defects (Pitch, Knots, Splits, Wane, and Bark) in 38 Lumber Sample Images, (b) Control Chart of Pixels Belonging to the Pitch Pocket Lumber Defect in 38 Lumber Sample Images, (c) Residual (Sum-of-Squared Prediction Errors) Plot of MIA Model Used on 38 Lumber Sample Images. (Adapted from Bharati et al. (2003).) Reprinted with permission from *Industrial and Chemistry Research*. Copyright 1998 American Chemical Society.

referring to the region where liquid metal is exposed to the atmosphere. Their MIA approach is similar to the approach by Bharati and MacGregor (1998). After the MIA stage, they used a Hotelling T^2 control chart to monitor the validity of their ladle eye area predictions and to test for outliers and/or poor image preprocessing.

Facco et al. (2008) developed a MIA method that is based on a two-level nested PCA model for monitoring the surface quality of photolithographed devices in semiconductor manufacturing. In their paper, they recommended the use of control charts (such as the Hotelling T^2 control chart and a residuals chart) to characterize the quality features of the image after it has been transformed into the principal component subspace. They applied two spatial residuals control charts (the horizontal axis was the pixel number) to monitor the surface roughness on different locations on the semiconductor since roughness on the edges of the produced parts was much smaller than in the associated valleys. Two different schemes were required to monitor each of these features separately.

Control Charts for Medical Image Devices

In this section we review the use of control charts with medical image data. These control charts are usually employed to ensure that medical imaging devices are functioning properly, as opposed to detecting changes in the items or processes being imaged, as done in the industrial applications. Readers are referred to Pearson and Lawson (2007) for a more comprehensive discussion on the topic of quality assurance for medical imaging devices. We did not find any papers on the use of control charting methods to monitor successive images taken of a single patient to detect changes in health status.

Knight and Williams (1992) used V-mask CUSUM charts and conventional Shewhart charts to monitor the performance of gamma-cameras based on quantitative measures of uniformity of the produced images under a uniform (flood) source. A gamma camera is a device used to image gamma radiation-emitting radioisotopes. The applications include early drug development and nuclear medical imaging to view and analyze images of the human body or the distribution of medically injected, inhaled, or ingested radionuclides emitting gamma rays. In their analysis, they calculated nine uniformity statistics and plotted Shewhart charts and the V-mask CUSUM charts for each of these statistics.

Orwoll et al. (1993) suggested a multi-rule Shewhart control chart to be used in monitoring the long-term precision of the dual-energy X-ray absorptiometry (DXA) scanners from bone measurement density (BMD) measurements obtained from the DXA scans. More specifically, they applied three run rules to the traditional Shewhart chart with BMD as their quality characteristic. The rules used were four consecutive measurements more than one standard deviation on one side of the mean; two consecutive measurements more than two standard deviations on one side of the mean; and ten consecutive measurements on the same side of the mean. Their approach was able to detect small changes in the performance of the machines under consideration. Accordingly, their quality control protocol provided the ability to detect changes objectively and to adjust for variations in performance over the long-term.

Lu et al. (1996) compared five different quality control procedures for ensuring the functionality of DXA scanners. These five procedures were 1) visual inspection; 2) a Shewhart control chart with sensitizing rules; 3) a Shewhart chart with sensitizing rules with a filter for clinically insignificant mean changes; 4) a moving average chart and standard deviation chart; and 5) a CUSUM control chart. Their measurements were based on scan data and on simulated data. From their analysis, they found that the CUSUM approach was the best because it had good sensitivity for detecting changes with a low false alarm rate. In their conclusion, they suggested that the use of the more intuitive (for medical personnel) Shewhart charts can be acceptable at the individual testing sites if their scanner performance is followed up by CUSUM charting monitoring at a central quality assurance center.

Similarly, Garland et al. (1997) compared the scanner's built-in quality assurance system, visual inspection, a multi-rule Shewhart chart, and CUSUM control charts in establishing the best procedure for the quality assurance of DXA scanners. They utilized three criteria for analysis, the number of faults detected out of eight non-mechanical faults, the true positive fraction, and the Type I error rate. Their analysis was based on simulated (phantom) image data. Based on their criteria, they found that visual inspection, the multi-rule Shewhart chart, and the CUSUM control chart performed much better than the scanner's built-in quality assurance system. In another comparison for DXA machines, Pearson and Cawte (1997) found that the multi-rule Shewhart control chart performed as well as or better than the CUSUM control chart based on their simulated data set and their operating characteristic curve criteria.

Simmons et al. (1999) developed a quality assurance protocol that can be used in evaluating the functional Magnetic Resonance Imaging (fMRI) system performance. The evaluation of the fMRI system performance is achieved through monitoring the quality characteristics of the fMRI, mainly a signal-to-noise ratio (SNR) and a signal-to-ghost ratio (SGR), through two separate X-bar charts with run rules. A ghost image is a fainter second image of an object being viewed. The control charts allowed for the detection of trends reflecting deterioration in the performance of the fMRI machine that were undetected using other quality assurance methods. Stöcker et al. (2005) also discussed the quality assurance of fMRI systems, but did not discuss control charting.

Chiu et al. (2004) developed a quality assurance protocol for detecting system malfunctioning and assessing the comparability of four image cytometers in a multicenter clinical trial. A cytometer is a device for counting and measuring the number of cells within a specified amount of fluid, such as blood, urine, or cerebrospinal fluid. They constructed an X-bar and R control chart for each of the four quality characteristics that they measured at each of the four clinical centers involved in the study. They also recommended the use of a Hotelling T^2 control chart to combine the four quality characteristics into one statistic for plotting.

Conclusions and Recommendations

We view image-based analysis and control charting as a very promising area of application within statistical quality control. Image monitoring is a natural extension of profile monitoring, an application and research area of increasing importance. Image-based monitoring adds the capability of monitoring a wide variety of quality characteristics, such as dimensional data, product geometry, surface defect patterns, and surface finish, in real-time. There are also applications of control charting in monitoring the performance of the imaging devices themselves. As the use of imaging increases, there will be an increasing number of practical applications where the concepts of statistical quality control can play an important role.

Some research opportunities in the analysis of image data for quality improvement include the study of the statistical properties and performance of many of the control charting methods. The justifications for many of the proposed methods are not clear. Work is needed to improve the performance of existing methods as well as understand the differences between competing approaches. Spatial control charts, for example, might be designed to provide greater sensitivity to locations in images where flaws are more likely to occur. In addition, some of spatiotemporal monitoring ideas in public health surveillance for cluster detection and other purposes, such as those discussed by Sonesson (2007), Rogerson and Yamada (2009), and Jiang et al. (2010), may have applications in image monitoring.

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