The Analysis of Inline Color Measurements for Package and Labels Printing Using Statistical Process Monitoring Techniques

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Abstract

Inline color measurement systems measure color on the press while the web is moving, allowing press operators to measure color continuously throughout a run. The amount of data generated by inline color measurement systems exceeds offline color measurement systems and must be analyzed using different methods than used for analyzing offline color measurement data. The statistical process monitoring (SPM) methods for analyzing inline color measurement data must take into account the units of measure, amount of data, and organization of the data.

Color difference data is best suited for monitoring printed color in relation to tolerances set by the printer or print buyer, but is less suited for statistical analysis because it relates little to the physical aspects of the printed color. Plots of CIE ΔL*Δa*Δb* and CIE ΔL*ΔC*Δh are best suited for informing the printer about how printed color is different from a Standard L*a*b* target, but cannot be used to monitor color relative to ΔE tolerances. Spectral reflectance is a direct physical measurement of the printed process, and using Principle Components Analysis, can be decomposed into two or three orthonormal eigenvectors that can be monitored independently using SPM techniques.

Regardless of the color measurement units, the SPM method must be carefully considered. Commonly used control charts, such as I/MR and $\overline{x}$/R, assume independence and normality the data, assumptions generally not valid for printing processes where features such as process drifting and process shifts are common, thus requiring the use of more advanced SPM methods.

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Introduction

A primary concern of printers is whether they are printing accurate color. Visual judgements are too unreliable to use in a standard test procedure. Color measurement technology and colorimetry provide a standardized, quantitative method for specifying and comparing colors. The base unit of measure for spectrophotometers is spectral reflectance. Any change in the color of the print is quantified by a change in reflectance. However, we interact with printed products in ways that cannot be described by direct physical measurements. The Commission Internationale de l'Eclairage (CIE) system of colorimetry, which includes the CIELAB (L*a*b*) color space and various color difference formulas, was developed to bridge the gap between physical measurements and perception and to estimate the visual experience of color (Berns, 2000, Chapter 2).

Individual color measurements are compared to a reference color measurement in most print process monitoring systems. Comparing measurements using L*a*b* units is not useful for describing whether the difference between two colors is perceivable. The color difference between a pair of L*a*b* values is called ΔE. A ΔE value of one is meant to represent the threshold of perceptibility. (Note, throughout this report, use of the notation ΔE represents a non-specific reference to color difference. Specific formulas in this article will be referred to using standard notation, such as ΔE_{00}, the formula recommended by the ISO and CIE (CIE/ISO 11664, 2014), and the formula used in this article. However, the concepts discussed in this article apply to all color difference formulas.)

Print buyers may specify a ΔE tolerance and printers may have an internal ΔE tolerance, but measuring ΔE is not trivial. Decisions must be made regarding the measurement procedure. In statistical process monitoring, acceptance sampling is a method used to accept or reject a product based on the outcome of each sample that is inspected. Acceptance sampling is appropriate when inspection costs are high (Borror, 2009, p. 194), such as the case where an offline color measurement system is used and the press must be stopped to pull samples.

The exact position and frequency of measurement in a run is partially determined by the measurement technology employed and the restraints of the printing process. Color measurement using a handheld spectrophotometer can only be performed when samples are pulled from the press. The most convenient time to pull samples during production on flexible packaging presses is usually at the end each roll. Color differences, then, can only be calculated from the set of samples pulled at the end of each roll. The printer must rely on this individual sample to represent the entire roll.

Inline color measurement systems measure color on the press while the web is moving, allowing measurement of color within each roll. Using this data to monitor the printing process would be preferable to acceptance sampling. However, the data, regardless of quantity, must be analyzed. Operators might wonder how they conclusively decide whether a run, or an individual roll, is in control and within the tolerance limits.

Having a small number of handheld color measurements or a large number of inline color measurements does not change the fact that printers still need to know how consistently color is printed within the ΔE tolerance limits and whether color is changing over time. The operator must know what action to take when color is outside of the ΔE tolerance limits. Using an offline color measurement system, one out-of-tolerance measurement at the end of a roll might cause alarm, but does a single out-of-tolerance inline measurement cause alarm and warrant a response? The operator must be careful when taking action because acting on a drifting process, or otherwise unstable process, by adjusting the color may not solve the problem if the color continues to change. In addition, there is always a delay between the time an action is initiated and the time the effect of that action is detected on the print. Some changes, such as changing pressure, often take effect within seconds, while changes to the ink require minutes to fully manifest themselves as the reformulated ink is circulated through the inking system. This delay between action and effect means that operators may not see, in real-time, the intended effect of their changes, which makes the work of adjusting color particularly dependent on individual judgement and process knowledge.

Deciding on an appropriate action requires more information than can be provided by color difference data alone. Color difference says nothing about how colors differ, but only by how much they differ. Analyzing a process in terms of lightness, chroma, and hue can reveal in which color dimensions the process varies and, if outside the ΔE tolerance limits, which components should be adjusted.

Ensuring sufficient quality at the level of reflectance will result in sufficient quality at the visual level because colorimetry is derived from reflectance. If accurate color is established during make-ready then reflectance can be monitored to determine if there is a significant change in the process mean or variance. However, the many complex ways in which reflectance data can vary are not readily assessed in a ‘live’ production environment. Investigations into the root causes of process changes are often more expeditiously done in the colorimetric domain, where rule-based monitoring of individual colorimetric parameters will often point to the more common process shifts.

If accurate color is never achieved during make-ready, or, if the operator is constantly trying to fine-tune the color during runtime, then variation in the process will be considered a result of special causes, such as operator intervention. In such cases, the process will never be in control. A process is considered to be "in-control" if it is "operating with only chance causes of variation" (Montgomery, 2013, p. 189). Traditional methods for statistical process monitoring (SPM) assume that processes are in control with the aim of identifying at what point they deviate from that assumption. For processes that are known a priori to be out-of-control, such as when the operator is making adjustments, traditional SPM methods will not be useful.

The following sections discuss how techniques of SPM can be applied to inline color measurement data. As mentioned above, the three primary units of measure for color—reflectance, L*a*b*, and color difference—serve different purposes and require different treatments when employed in an SPM workflow due to their unique natures. Methods for analyzing color difference, L*a*b*, and spectral reflectance data are discussed in the sections that follow. In addition, suggestions for the use of color data in SPM workflows, described in Table 1, are proposed. The reasons for those suggestions are also discussed in detail in the following sections.

Unit of Measure	When to Use	When Not to Use
Color Difference	Monitoring production relative to the tolerance limits set by the printer or print buyer.	Assessing whether the process is in statistical control.
L*a*b*/L*C*h	Informing the operator about how the process differs from the Standard.	Assessing whether the process is in statistical control.
Reflectance	Assessing whether the process is in statistical control.	Monitoring production relative to the tolerance limits set by the printer or print buyer.

Table 1. *Suggestion for the use of color measurement data in statistical process monitoring.*

Monitoring a Process Using Color Difference

Color difference is the metric nearly all flexographic packaging printers rely upon to establish how well they meet their customers' color reproduction expectations. Color measurements collected throughout a run for a specific color target are compared against the "Standard" color values for that target. Standard values, commonly specified in L*a*b* units, are provided by either the print buyer or established by the printer internally. Color difference data can also be used to determine how consistently a color is printed during a job. For example, color measurements collected throughout a job can be compared to the first L*a*b* measurement of the job to monitor change. Using the first measurement as a reference makes sense if it is assumed that accurate color was established during make-ready and is expected to be maintained.

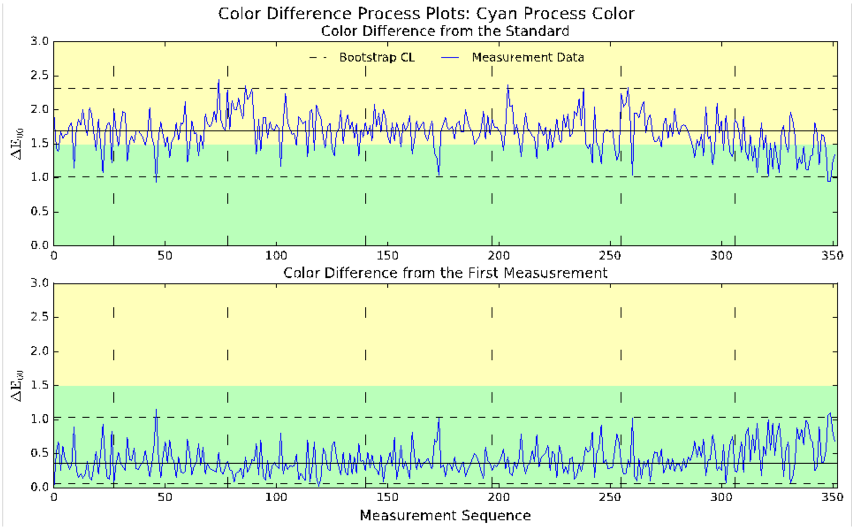

Figure 1. *Color difference data process data for a cyan process color. Top) Color difference from the standard, $\Delta E_{00(S)}$, and Bottom) Color difference from the first measurement, ΔE00(D). The upper and lower control limits were calculated using a bootstrap method proposed by Phaladiganon, et al. (2009).*

Color difference data from measurements made by an inline color measurement system for a cyan process color are plotted in Figure 1. The top plot of Figure 1 shows the ΔE_{00} color differences between individual measurements and the standard L*a*b* values, $\Delta E_{00(S)}$. The bottom plot of Figure 1 shows the ΔE_{00} color differences between individual measurements and the first L*a*b* values in the job, $\Delta E_{00(D)}$. Upper and lower control limits, computed using a bootstrap method discussed later, are designated by the dashed black lines. Note that, in both of these plots, there is a dimension of time along the x-axis. Gaps in time did occur during the actual job process, but for simplicity, measurements are shown in their relative sequence. In this paper, it is assumed that a printer has established a minor tolerance limit at 1.5 $\Delta E_{00(S)}$ and a major tolerance limit at 3.0 $\Delta E_{00(S)}$. This means that any value between 1.5 and 3.0 $\Delta E_{00(S)}$ is close to being out-of-tolerance and a $\Delta E_{00(S)}$ above 3.0 is out-of-tolerance. Tolerance limits will vary from printer-to-printer.

SPM control charts are used to identify where a process is out-of-control, where it is out-of-tolerance, and to help diagnose why it may be out-of-control or out-of-tolerance. Among the most commonly used control charts, the data can either be averages of small, rational subgroups, or individual values. Rational subgroups are samples of measurements grouped together such that changes in the process are easily identified, while changes within each subgroup are minimized (Montgomery, 2013, p. 201).

Figure 1. Color difference data process data for a cyan process color. Top) Color difference from the standard, $\Delta E_{00(S)}$, and Bottom) Color difference from the first measurement, $\Delta E_{00(D)}$. The upper and lower control limits were calculated using a bootstrap method proposed by Phaladiganon, et al. (2009).

In offline color measurement workflows, a group of impressions from the end of every roll is collected and measured. The average for each group is plotted in an $\overline{x}$/R chart. Inline color measurement systems measure individual impressions continuously throughout the run. There are no obvious ways to group inline color measurements because measurements are made continuously throughout the run. However, rational subgroups could be defined for an inline color measurement system as the average of some number of consecutive measurements. An advantage to using rational subgroups is that averages of individual values approximate a normal distribution, according to the central limit theorem, and an $\overline{x}$/R could be used to monitor color differences of inline color measurements. Employing classical control charts, which assume data is normally distributed, for data that is not normally distributed can lead to a prevalence of false-alarms, incorrectly classifying points as out-of-control, or false-positives, incorrectly classifying points as in control.

While a detailed discussion on the pros and cons of using rational subgroups in analyzing inline color measurement data is not the main point of the article, it is certainly an interesting topic for future research. Individual values are used in figures throughout the remainder of this article, but the discussion has relevance whether individual values or rational subgroups are used.

Color difference data is well understood to be non-normally distributed (Nadal, 2011; Seymour, 2016). In some cases, it is possible to run across a color difference process that appears to be normally distributed. The $\Delta E_{00(S)}$ and $\Delta E_{00(D)}$ data in Figure 1 were tested for normality using a test of kurtosis and skew (Jones, 2017). The $\Delta E_{00(S)}$ data had a p-value of 0.380, which could be interpreted as indicating the $\Delta E_{00(S)}$ data was normally distributed. In reality, it is the process noise that was normally distributed, not the color difference itself. The $\Delta E_{00(D)}$ data had a p-value of <0.000, indicating the process noise was not normally distributed. These two tests for normality demonstrate that, even if the distribution of an underlying metric is not normally distributed, the process noise could be normally distributed.

As stated above, one of the primary motivations for process monitoring is to identify when the process is out-of-control and/or out-of-tolerance. The idea of a tolerance limit in a color difference control chart is clear: it's an upper limit only and is predetermined by the printer or print buyer. Printers primarily care only if they are above of the major (red) ΔE tolerance limit. This is the difference between printing acceptable product and unacceptable product. However, a process could be out-of-control process without being out-of-tolerance. Identifying when a process is out-of-control can help the printer identify potential problems with a job before the process goes out-of-tolerance. Control limits for individual value ΔE charts must be established using methods that do not rely on normally distributed data, such as bootstrap methods (Nadal, 2011; Phaladiganon, 2011). Control limits were added to the color difference control charts in Figure 1 for the 99.9 percentile and 0.1 percentile using the bootstrap method proposed by Phaladiganon et al. (2011)

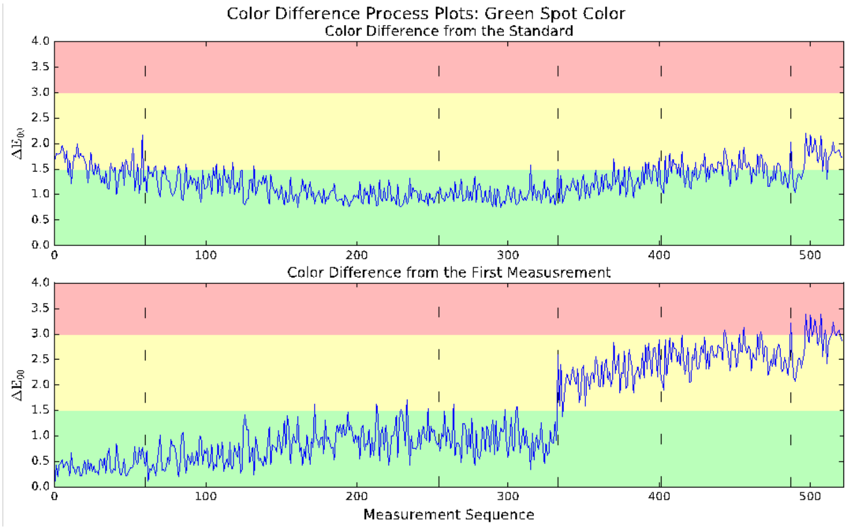

Figure 2. *Color difference data process data for a green spot color. Top) Color difference from the standard, $\Delta E_{00(S)}$, and Bottom) Color difference from the first measurement, $\Delta E_{00(D)}$.*

Ideally, control limits are first established with a representative in-control process. For example, one might consider the cyan $\Delta E_{00(S)}$ process plot in the top of Figure 1 to be in-control. Those control limits can be used to control the printing of that cyan color every time the job is run. If a printer is able to maintain consistent production across repeat jobs, then the bootstrap methods might be a useful tool for assessing whether the process is in control.

Despite the "well-behaved" cyan process in Figure 1, printers are more likely to see processes that are less well-behaved. The color difference process plots in Figure 2 show two important common characteristics of out-of-control processes: drifting and a process shift.

The upper plot decreases steadily from 2.0 $\Delta E_{00(S)}$ to 1.0 $\Delta E_{00(S)}$ during the first half of the run, then increases steadily from 1.0 $\Delta E_{00(S)}$ to 2.0 $\Delta E_{00(S)}$ in the second half of the run. Most printers would not be alarmed by this process because the $\Delta E_{00(S)}$ is less than the 3.0 $\Delta E_{00(S)}$ tolerance, drift or no drift. However, a process that is in control means that the printed color is not changing over time. The plot of $\Delta E_{00(D)}$ reveals not only a drifting process, but also a major shift in the process at measurement 330, where $\Delta E_{00(D)}$ shifted from around 1.0 $\Delta E_{00(D)}$ to around 2.5 $\Delta E_{00(D)}$. It should be emphasized that both the $\Delta E_{00(S)}$ and $\Delta E_{00(D)}$ processes shown in Figure 2 were calculated form the same measurement data, but were compared to difference reference points.

Figure 2. Color difference data process data for a green spot color. Top) Color difference from the standard, $\Delta E_{00(S)}$, and Bottom) Color difference from the first measurement, $\Delta E_{00(D)}$.

Monitoring a Process Using L*a*b*/L*C*h

It is not surprising that the shift in color was present in the plot of $\Delta E_{00(D)}$ but not present in the plot of $\Delta E_{00(S)}$. The L*a*b* values of the individual Green Spot Color measurements are shown in Figure 3. The left plot shows the a*b* projection and the right plot shows the C*L* projection. The standard L*a*b* is the red point and the first measurement is the yellow point. Two clusters of measurement points were determined using K-means clustering. The green points correspond to the first 330 measurements before the shift occurred. The blue points correspond to points occurring after the shift. Observing the L*a*b* points closely reveals why the plot of color difference to the standard did not reveal a shift. The standard is roughly equidistance from the two clusters in the a*b* projection, and also roughly

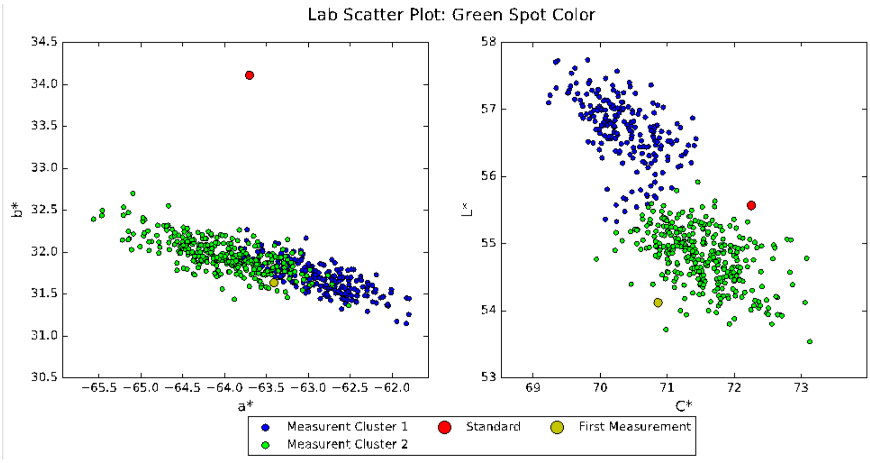

*Figure 3. The L*a*b* values of individual Green spot color measurements. Left) the a*b* projection and, Right) the C*L* projection. The standard L*a*b* is the red point and the first measurement is the yellow point. Two clusters of measurement points were determined using K-means clustering. The green points correspond to the first 330 measurements before the shift occurred. The blue points correspond to points occurring after the shift.*

the same distance from the two clusters in the C*L* projection. While the first measurement was also roughly the same distance from each cluster in the a*b* projection, the second cluster is clearly farther from the first measurement than the second cluster. Numerically, the median color difference between Cluster 1 and the standard was 1.1 $\Delta E_{00(S)}$ versus 1.4 $\Delta E_{00(S)}$ between Cluster 2 and the standard, a difference of only 0.3 $\Delta E_{00(S)}$. Yet, the median color difference between Cluster 1 and the first measurement was 0.7 $\Delta E_{00(D)}$ versus 2.5 $\Delta E_{00(D)}$ for Cluster 2.

Process shifts can occur for a number of reasons. They are often observed when the process is interrupted for some period of time. Although most packaging presses have the ability to continue running during a splice, many printers Figure 3. The L*a*b* values of individual Green spot color measurements. Left) the a*b* projection and, Right) the C*L* projection. The standard L*a*b* is the red point and the first measurement is the yellow point. Two clusters of measurement points were determined using K-means clustering. The green points correspond to the first 330 measurements before the shift occurred. The blue points correspond to points occurring after the shift.

choose to stop the press before splicing on a new roll at the unwind or splicing to a new core at the rewind. Interruptions to a run occasionally occur mid-roll, for reasons such as maintenance, troubleshooting defects, or web-breaks. However, the printer must be aware that a shift in color could, and often does, occur after a restart. Printers using an offline color measurement system may stop the press following every roll change to check color. It may be more cost effective to check color conformance for every roll than risk running the press with incorrect color. Use of an inline color measurement system allows the operator to monitor color throughout a roll and respond to changes in the process in real time.

Of the three commonly used types of color data—reflectance, L*a*b*/L*C*h, and ΔE—the most intuitive for monitoring color is L*a*b*/L*C*h. It is the relative difference of those value from the standard, ΔL*Δa*Δb* or ΔL*ΔC*ΔH (ΔH is calculated using Equation 1), that can best guide an operator in the control of color. For example, if the printed color is lighter than the reference (a large ΔL* value), that informs one action, perhaps adjusting ink film thickness. However, if the printed color is a different hue (a large Δh value), then the ink may need to be reformulated. These dimensions are easily described using common language, translated to phrases such as “too red” or “too light.”

$$\Delta \mathrm{H} = \sqrt{(\Delta \mathrm{E}^*_{ab})^2 - (\Delta \mathrm{L}^*)^2 - (\Delta \mathrm{C}^*)^2} \qquad \text{Eq. 1}$$

Unfortunately, ΔH is not an intuitive metric to monitor because the values cannot be negative. The operator cannot know from the ΔH data whether the hue error is due to a larger or smaller hue angle. Plotting Δh (hue angle in degrees) is not intuitive either because the units, degrees, are different from the unit-less ΔL* and ΔC*. A possible solution, shown in Figure 4 as ΔH′, is to use a representative sign for ΔH based on the sign of the Δh. If Δh is negative, ΔH′ is given a negative sign, and if Δh is positive, ΔH′ is given a positive sign. The operator is informed of both how the hue is different and of its contribution to color difference relative to lightness and chroma. The formula for calculating ΔH′ is shown in Equation 2.

$$\Delta \mathrm{H}' = \Delta \mathrm{H}\left(\frac{\Delta \mathrm{h}}{\mathrm{abs}(\Delta \mathrm{h})}\right) \qquad \text{Eq. 2}$$

The plots in Error! Reference source not found. show ΔL*, ΔC*, and ΔH′ process plots compared to the standard for the green spot color. The raw data is shown in red and the black line represents averages across each roll. Roll changes are marked by dotted black lines. All three axes are scaled equally. The ΔH′ suggests that, while there is a hue difference, hue is stable throughout the process relative to lightness

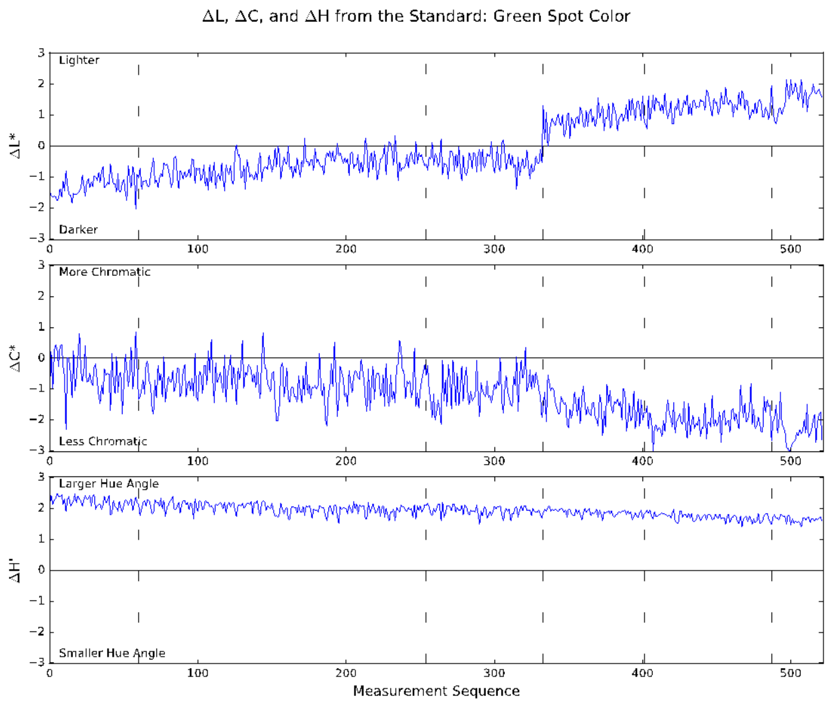

Figure 4. *ΔL*, ΔC*, and ΔH′ process plots compared to the standard for the green spot color.*

and chroma. Chroma is decreasing slightly and lightness appears to be approaching the standard value, as seen in the plot of color difference versus the standard in Figure 2. A process shift is observed after the transition from the third roll to the fourth roll.

Monitoring a Process Using Spectral Reflectance

Reflectance measurements of the same color target on different impressions often have the same basic shape. While the high dimensionality of reflectance vectors can make them difficult to monitor in their original form, a set of reflectance measurements can be decomposed into a small number of orthonormal eigenvectors using Principle Components Analysis (PCA) (Johnson and Wichern, 2007, Chapter 8). The shape of the first eigenvector describes how the set of reflectance curves vary the most. The shape of the second eigenvector describes how the set of reflectance curves vary the second most, and so forth. In most cases, a linear combination of two to three eigenvectors describes >95% of the variability in a given job. The dimensionality of reflectance can thus be reduced from 31 channels to 2 channels.
In PCA, the mean is subtracted from the data set before analysis is performed. The covariance of the mean-subtracted data is calculated and eigenvectors are calculated for the covariance matrix. A set of reflectances, **M**, can be Figure 4. ΔL*, ΔC*, and ΔH′ process plots compared to the standard for the green spot

color. reconstructed from a linear combination of the set of eigenvectors, β, and the mean reflectance $\overline{\mathrm{R}}$, shown in Equation 3, where *w* are the weights of each

$$\mathbf{M} = \boldsymbol{\beta}'\mathrm{w} + \overline{\mathrm{R}} \qquad \text{Eq. 3}$$

eigenvector used in the reconstruction. There are 31 possible eigenvectors for a set of reflectances. However, as mentioned above, most of variability can be explained by two or three eigenvectors. Therefore, while a perfect reflectance match to any reflectance vector in the set can be calculated using a linear combination of all 31 eigenvectors, plus the mean, a reasonable reflectance match can be calculated using a linear combination of two to three eigenvectors. The remaining eigenvectors describe noise.

The set of eigenvectors and the mean will be constant for a given measurement target in a job. The reflectances for that given measurement are mapped to a new space defined by the eigenvectors. The mapped values are called principal component scores. The scores for each reflectance curve, i, are calculated using Equation 4, where si is the score for measurement *i*.

$$\mathrm{s_i} = \boldsymbol{\beta}'(\mathrm{R_i} - \overline{\mathrm{R}}) \qquad \text{Eq. 4}$$

PCA was used to reduce the dimensionality of the reflectance data for the green spot color. The spectral reflectances are shown in Figure 5 (left) as a function of wavelength. It is difficult to glean much information about the process from reflectance as a function of wavelength because the curves look similar and don't represent changes in time. The plot of reflectance as a function of measurement sequences does show the shift in the mean at measurement 330, but the change is so small that it is hard to determine visually whether it is significant or not. Furthermore, there are many wavelengths that do not reflect the process shift because the signal is so low.

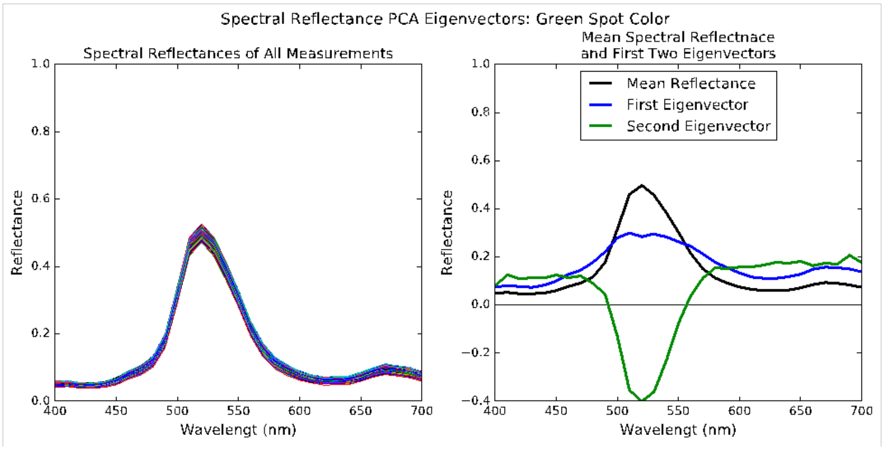

Figure 5. *Spectral reflectances for the green spot color, Left) as a function of wavelength and, Right) as a function of measurement sequence.*

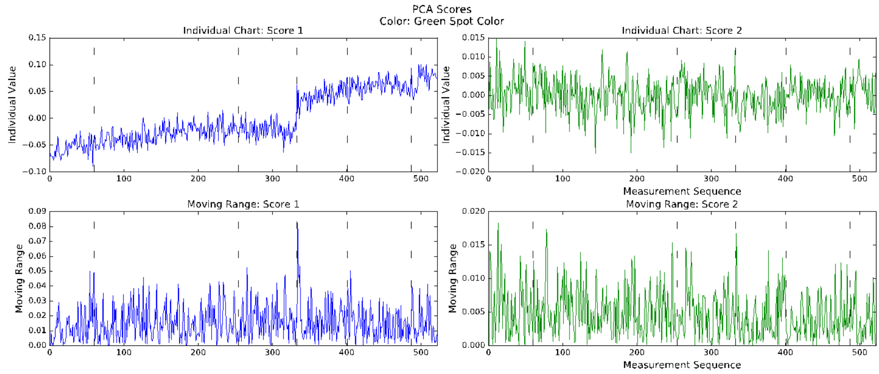

Figure 6. *I/MR charts for the green spot color PC scores.*

It was determined that two principle components were sufficient to describe 99.2% of the variability of reflectance throughout the job. The first PC described 98.2% of the variability and the second PC described 1% of the variability. The two eigenvectors, along with the mean reflectance, are show in Figure 5 (right).

Unfortunately, control limits are not appropriate for monitoring the quality of the Score 1 and Score 2 because Score 1 is not normally distributed. The shift in the process at measurement 330 is clearly visible in the Individual plot of Score 1 in Figure 6. The p-value of a normality test for Score 1 is < 0.000, meaning the assumption of normality is rejected, while the p-value of a normality test for Score 2 is 0.216, indicating the data is normally distributed.

One important advantage of inline color measurement is the ability to monitor color within a roll. Much has been said about how process shifts commonly occur at roll changes and at other interruptions to the process. In these cases, the process is out-of-control and the operator can choose to make an adjustment to the color

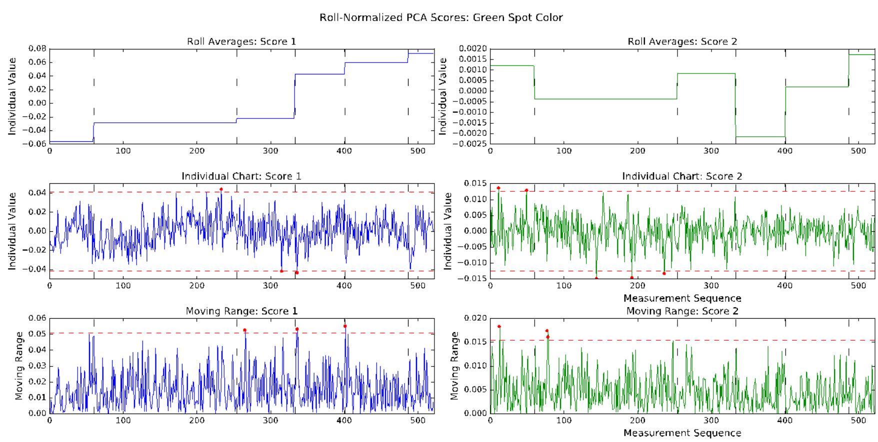

Figure 7. *Roll averages and I/MR charts for the roll-normalized green spot color PC scores.*

if they feel it necessary, usually if the shift results in the color moving outside the ΔE00(S) tolerance limits. However, it is also useful to know whether the process for individual rolls is in control. Rolls can run anywhere from 10 minutes to 40 minutes, and many measurements can be collected for individual rolls. A process behaving normally should have PC scores that vary randomly, at least within an individual roll. Assuming normal production within individual rolls, the PC scores can be analyzed relative to the mean scores of individual rolls. I/MR charts of scores with the mean scores of each roll subtracted are shown in Figure 7. The individual values of the roll-normalized scores were tested for normality. The resulting normality test p-values, 0.480 and 0.121, respective to roll-normalized Scores 1 and 2, suggest that the assumption of normality. The upper control limit for the MR chart was calculated using Equation 5.

$$\mathrm{UCL_{MR}} = 3.267 * \overline{\mathrm{MR}} \qquad \text{Eq. 5}$$

where $\overline{\mathrm{MR}}$ is the average of the moving range, and the upper and lower control limits for the I chart were calculated using Equation 6.

$$\mathrm{UCL_I} = \bar{\mathrm{I}} + 3\left(\frac{\overline{\mathrm{MR}}}{1.128}\right),\ \mathrm{LCL_I} = \bar{\mathrm{I}} - 3\left(\frac{\overline{\mathrm{MR}}}{1.128}\right) \qquad \text{Eq. 6}$$

I and MR outliers are indicated by red dots in Figure 7.

It is not always the case, however, that roll-normalizing scores results in normally distributed data. Process drifts or other non-random effects that occur within each roll will lead to cases in which the data might be autocorrelated, meaning measurements in the process are dependent upon previous measurements. Autocorrelation is discussed at length in Snoussi et al. (2005) and Snoussi (2011) and presence of autocorrelation in inline color measurement data will be a topic for future research.

While it may be inappropriate to use non-normal data to calculate control limits, a different, previously run job could be used to establish the control limits. In fact, it is common practice and recommended to establish control limits using an in-control data set, then apply those control limits to future jobs. If ink is formulated consistently, the reflectance curves are similarly shaped for all repeated jobs of a color, then eigenvectors can be calculated to describe reflectance variation across multiple jobs.

Concluding Remarks

The ultimate goal of inline color measurement data is to help streamline the printing process, providing operators with a tool to determine when the process is out of control and decide how it should be corrected. Colorimetric charts are useful for visual display while reflectance-based changes, whether using PCA or not, have the greatest utility for quality experts and for processing data behind the scenes. The major piece not discussed in this article is specifically how an operator should respond to various clues provided by control charts. ΔL*ΔC*Δh plots can provide some clue as to whether there is a problem with the ink or some other component on the press, but the data itself is no substitute for the operator's experience and color data only goes so far. Inline color data is best used in conjunction with data from an inline inspection system and a seasoned pair of eyes to ensure the printed product is of optimal quality.

The ability of an inline color measurement system to collect color measurements within a roll without stopping the press is an important advantage to these systems over offline color measurement systems. In addition, many printers are required to supply print quality data, including color measurements, to print buyers, via print quality reporting applications (Gamm, 2016). Viewing the data remotely, either during a job or after the job is complete will give print buyers a different perspective on the process than printers. Printers are trying to actively control the process and ensure consistent quality while print buyers do not have any direct control, but may be viewing data from across many presses and suppliers. Careful statistical assessment is needed to assure that the analyses chosen for one purpose are truly suited for the other. The differences between analytical methods employed on site and remotely may be completely different, and would be an interesting topic for further research.

While this paper focused on a few commonly-used analytical methods, it was acknowledged that they may not be appropriate for all data sets. A useful guide for selecting process monitoring methods is provided in Marques et al. (2015) and is a starting point from which to explore additional methods for the statistical analysis inline color measurement data.

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