Quantitative Evaluation of Non-Uniform Coating

Abstract

Evaluation of subtle irregularities in coatings has historically been a job for the human eye. Unfortunately, this can be very subjective. To become more quantitative, Carestream sought to utilize hardware and software to augment manual inspection.

Using an off-the-shelf film scanner, a high-resolution digital copy of each sheet was created. This digital copy was processed using ImageJ software and run through an algorithm in Excel to return a flow mottle grade. The entire process takes less than two minutes. This improvement to the detection of subtle defects has created the opportunity for engineers to make very subtle changes to the process and quantify visually indistinguishable differences in the product.

Article

Evaluation of subtle irregularities in roll-to-roll coatings has historically been a job for the human eye, which has an exceptional ability to distinguish abnormalities in solid colors. Unfortunately, with modern manufacturing being a 24/7 operation, the repeatability and reproducibility of grading is heavily impacted by different operators on different shifts and fatigue caused by long hours. To help eliminate this variability, we looked to technology to conduct a study that augmented a manual inspection system with a digital system. The study tracked the impact of subtle process variations on the product to determine if pursuing larger changes in that direction could potentially be beneficial.

The primary defect used for this study was flow mottle on x-ray film. Flow mottle is a visual defect caused by slight differences in surface tension or airflow of a coating during drying which causes a "blotchy or streaky" appearance. Currently to evaluate the quality, film samples are printed with various levels of mottle which are then used to subjectively grade production material. These printed film samples are called Visual Comparison Standards (VCS).

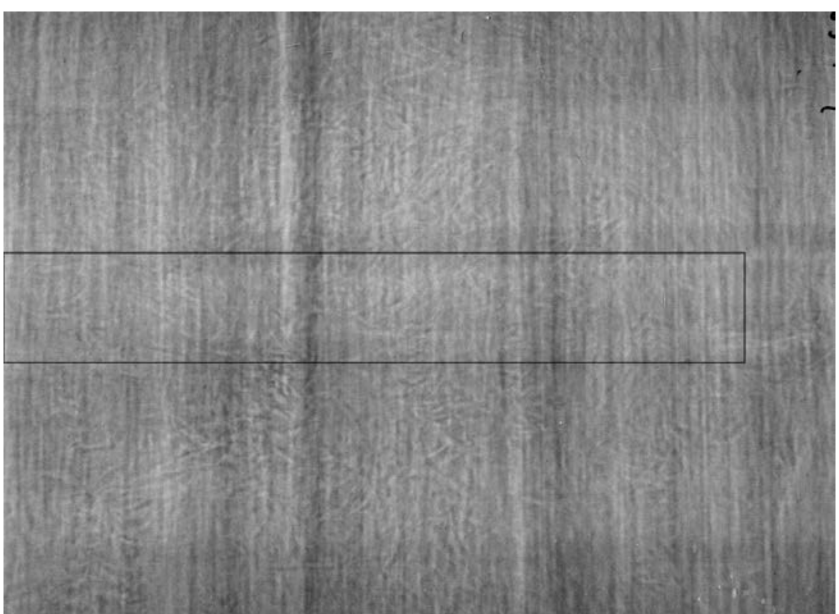

Figure 1 Contrast Enhanced Image of X-ray Flow Mottle with Region of Interest denoted

Figure 2 Level 6 Flow Mottle VCS (reject)

Figure 3 Level 7F low Mottle VCS (minimum accept)

To gain an understanding of how well the inspectors were performing, 44 samples ranging from very good to very bad mottle were evaluated by 6 different certified technicians. The average standard deviation was 0.30 flow mottle units (FMU) for these samples, which was OK, but the average spread from worst to best grading per sample was 0.73 FMU. For this product, a rating of six was terrible and eight was perfect, so the average spread from worst to best grading presented a large area for improvement.

The first challenge was creating a digital copy of the physical films. Initial attempts to scan these films were done with materials on hand. A lightbox was placed on top of a flatbed scanner that the light source was removed from. This transformed the captured image from reflected to transmitted light. Unfortunately, there were problems with light bleeding in from the edges and the resolution was not sufficient. Eventually, a readily available film scanner was purchased from eBay®. The film scanner was capable of producing high-resolution (570 DPI) digital copies of up to 25 sheets at a time.

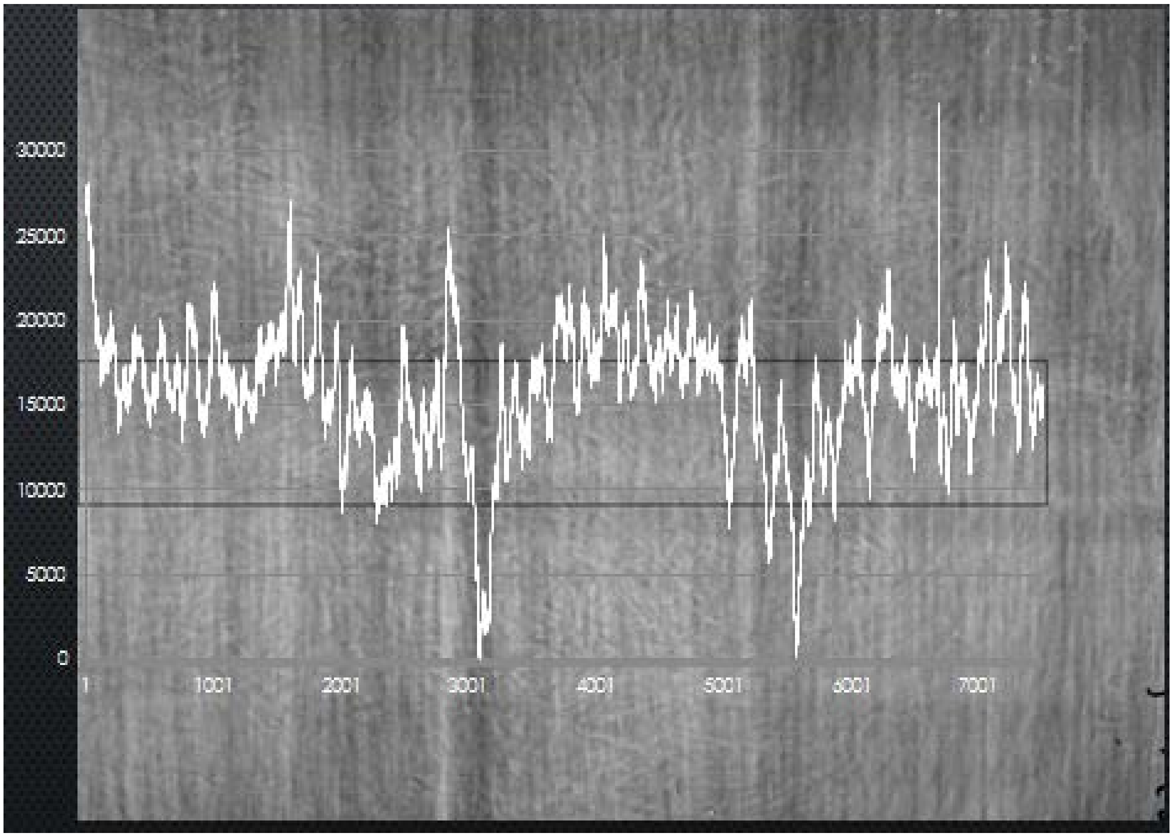

Figure 4 Plot of optical density values overlaid on the image of Mottle

Carestream worked to develop a model to quantify mottle. First, the image was captured and pixel intensity averaged in the downweb direction over a two-inch region across the width of the film. This gives us numerical values for the optical density of the film in each location. If the region selected is too wide, it averages out the intensity variations. In contrast, if the region selected is too short of a distance, it results in excessive noise. This process provided a series of crossweb optical density values for the sheet in question.

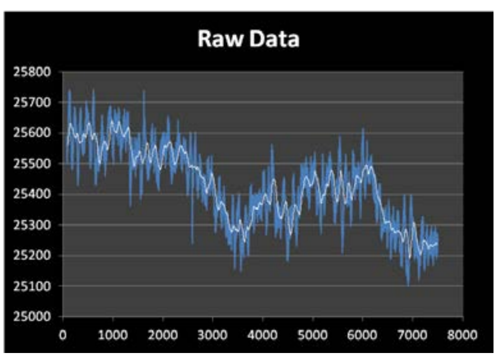

Figure 6 Image density across the sample with overlaid moving average

From this series of data, a long distance moving average was subtracted to remove baseline drift in intensity over the sheet. This was done because there were very subtle differences in the optical density of the film over large distances (2%). While these variations could pose a problem to the visual inspection of the film, it is not a feature of the defects that were being examined. As a result, subtracting a long-term moving average that follows the baseline density of the sheet leaves behind a flat dataset with localized variations caused primarily by mottle.

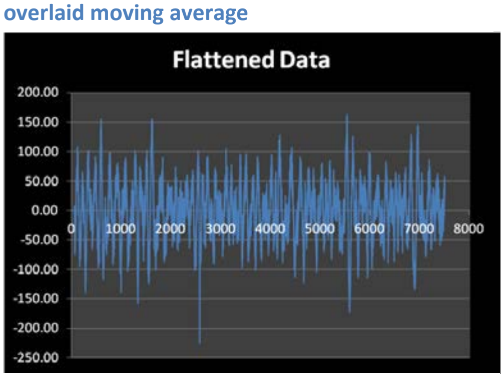

Figure 5 Density values after the moving average was subtracted

Initial thoughts on how to solve the problem of quantifying mottle proved to be overly simplistic. It seemed like since the defect was characterized by random variations in transparency that a simple standard deviation would correlate to that variability; however, the individual outlier points caused a large portion of the standard deviation and not the mottle itself.

The next theory was that the eye was picking out the rapid change in optical density over a short distance, which would be seen as a steep slope for the quantitative data. Although this model showed promise, it did not perform as well as our next attempt.

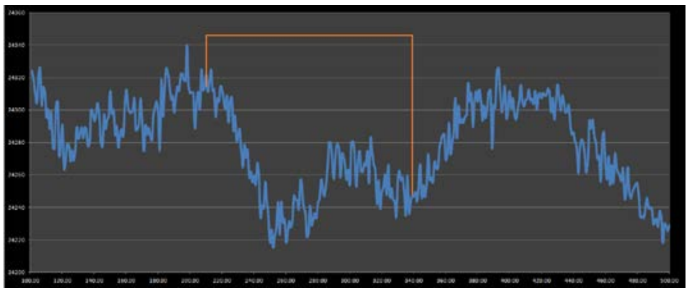

Figure 7 Step height model for evaluating flow mottle

Finally, working on the same concept of the eye seeing areas with high contrast ratios, a height threshold model was created. Every time the localized optical density of the film changed by a certain amplitude over a fixed width, a tally is taken. For our test, the optimal criteria were a change in intensity of 60 density units in a 1/5" span. The number of these intensity variations per sheet was counted and run through a linear fit to positively correlate to the human-graded mottle. Using this model, we attained r^2 values of 0.91 and a correct disposition of 98% of samples. The one failed sample grading 7.06 by the algorithm and 6.98 by the inspectors versus a minimum acceptable grade of 7. Additionally, the model was on average only 0.13 FMU's different than the inspector average.

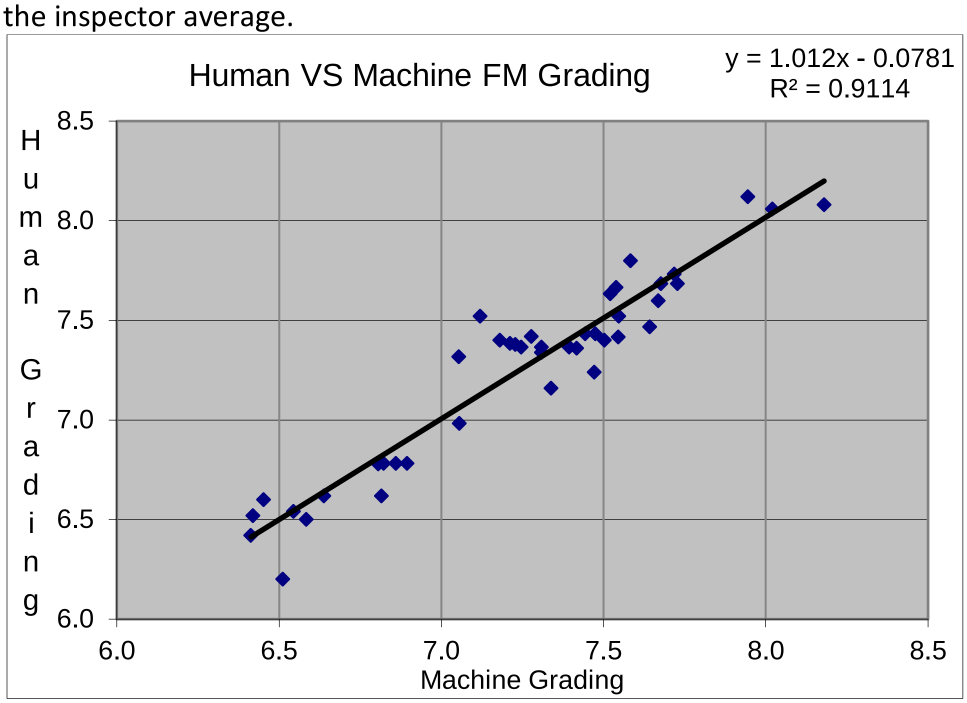

Figure 8 X-Y Plot of Human grading vs Machine Grading

Following this success, an attempt was made to examine using FFT (Fast Fourier Transform) analysis. We achieved some initial progress performing this in Matlab; however, the possibility of a vast improvement was unlikely and the complexity of the system was much greater, leading us to eventually abandon further research into the modeling.

The end result was a process using image analysis software (ImageJ) to quantify the image and run the output data through an algorithm in Excel to return a graded value for mottle. This entire process takes less than two minutes. To finalize the interface, a macro was written for ImageJ and Excel, which took all of the images in a given folder, processed them one at a time and saved them in a new folder. The process quantified dozens of samples with the pressing of just two buttons – allowing the engineer to walk away to be productive else ware.

While the general concept for this project is somewhat straightforward, the implementations proved to be fairly challenging. Each sample was scanned and processed to create 7,500 data points which was later reduced to 4200. To optimize the process for those sheets, each dataset needed to be averaged across a certain number of data points (Variable 1), and then multiple amplitude thresholds (Variable 2) were tested across a varying distances (Variable 3). This turns out to be 8,600 calculations per sample per condition. To validate this method, 42 samples were scanned twice each. This is 84 datasets to perform 8,600 calculations on each. We also needed to optimize the variables to maximize the R^2 values between the algorithm and the human grading.

These calculations were all being performed in Excel utilizing its built-in features. While these were useful, they all had their shortcomings. Goal seek only optimizes one variable at a time, which created an endless loop of optimizing for sequential variables only to get caught in a local maxima. Solver, on the other hand, works for multiple variables, but does not support the complexity of the equations and arrays in our algorithm. We also attempted to use a third-party add on for Excel; however, it was unsuccessful at handling the large quantity of data.

Alternatively, the brute force approach was taken. A macro was created to test >74,000 combinations of our three variables. The macro would change the value of a single variable at a time, then reprocess 84 samples, evaluate the correlation to the manual inspected data and save the variables values and fit in a table before going to the next value. The standard desktop computer did not take kindly to this, so we moved the processing to an 8-core processor computer. The ~54 billion calculations took just about a week to finish.

In the end, this method of augmenting the manual inspection system with a digital system proved to be more accurate, precise and robust than the system of multiple lab technicians, operators and engineers taking turns subjectively comparing the samples to visual guides at multiple levels. The effects of small process changes, within the operating window, were also discerned – allowing us to quickly explore many different paths without risk to our final product. Some of the conditions we were able to explore were fan speeds, laydown, oven temperatures, and line speed.

Summary

In today's corporate environment, there is always a push to keep costs down to maintain the bottom line. That is one of the main reasons this project was able to proceed. Identifying the contributing factors to mottle would allow the coater to run at an increased linespeed and reduce the cost per square meter. The scanner was purchased for ~2% of the price of a new scanner, while ImageJ was free and Excel was already on the computers. The cost of this project was virtually free.

While this is just the start of Carestream's exploration into augmenting the manual inspection system with a digital system, the implications are promising. In addition to delivering improved consistency and avoiding human error caused by fatigue or multiple technicians, there is potential for this technique to also apply to quantifying many other defects such as white spots, black spots, streaks, scratches, cleanliness and more.

Quantifying visual defects can have many challenges, but in the current environment of virtually free processing power, reliable free software, an abundance of used equipment for sale and a continual drive to improve processes, many obstacles can be overcome. This is just one example of one defect, but this technology will continue to be leveraged for additional testing in the future.

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Derek Hammill is an analytical chemist with Carestream Health. He received a Bachelor's in Advanced Chemistry from Oregon State University in 2002. He spent several years in the pharmaceutical industry before transitioning into medical devices. He has been with Carestream for the last 10 years working on products in fields ranging from medical devices, to touchscreen, energy storage, paint protection and electro active polymers.

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