An Adaptive Model-based Approach to Reduce Calibration Frequency While Maintaining Tone Consistency for Color Electrophotography*

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Abstract

In electrophotography, color reproduction is susceptible to variations in operating conditions. Calibrations are performed to ensure consistent tone reproduction. The timing of calibration directly impacts color consistency. Calibration consumes time and toner. Frequent calibration is not desirable. It is important to determine appropriate calibration timing to maintain acceptable color consistency while minimizing consumable usage and print job interruption. This paper proposes an adaptive approach that uses a decision tree (DT) to determine calibration timing. In the approach, experiments are designed to collect tone measurements under various operating conditions. Decision trees are developed with these measurements using machine learning algorithms. The resulting DTs can be used to predict tone deviations and determine appropriate calibration action based on changes in operating conditions. Experimental results demonstrate that the proposed approach can reduce the overall calibration frequency by 30.9% while maintaining desired tone consistency.

Introduction

For electrophotography (EP), color reproduction quality is known to be affected by changes in operating conditions, such as temperature, humidity, OPC drum age, usage, and throughputs. Calibrations are performed to maintain tone consistency under changing operating conditions [1-5]. During a calibration, a number of color patches are printed on either transfer belts or output media and measured by on-board sensors. Based on these measurements, calibration algorithms generate appropriate adjustments to EP process parameters, such as developer bias voltages, and rendering algorithms, such as tone correction, to maintain consistent tone reproduction. Calibrations cause job interruption and consume toner. Although desirable for maintaining tone consistency, frequent calibration increases the cost of ownership and negatively impact the customer's bottom line.

Calibration results in additional toner use and process downtime and is regarded as a cost from a customer point of view. For most EP systems, calibration strategies are either reactive or preventive [6, 7]. Preventive calibrations are scheduled after a fixed number of printed pages while reactive calibrations are initiated when undesirable outputs are observed. Preventive calibration is inefficient when a scheduled calibration is performed while the tone deviation is still within specification. Reactive calibration is inadequate due to the fact that an out-of-specification tone deviation has been observed. A more efficient and accurate calibration timing can decrease operation cost by reducing downtime and toner usage associated with calibration while maintaining desired tone consistency.

This work formulates the calibration timing determination as a decision making problem (see Fig. 1). At a decision point in time, the appropriate calibration action for compensating tone deviation is estimated using decision trees (DT). To carry out the approach, experiments are conducted to collect tone measurements on paper under various operating conditions. Decision trees are developed with these measurements using machine learning algorithms. The inputs to DTs are operating conditions of the printer, such as temperature, humidity, cartridge age, usage, developer bias voltage, and changes in the operating conditions. The output from DTs is a binary calibration decision, to calibrate or not to calibrate, based on experimental tone deviation. During actual operation, the DTs can predict appropriate calibration actions with only measurable operating conditions and no tone measurements are needed.

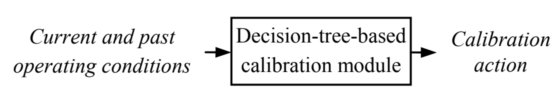

***Figure 1**. Scheme of decision-tree-based calibration approach.*

Decision Tree

Decision trees are empirical predictors that have been widely implemented. Decision trees can be used to determine appropriate maintenance actions of a device/process for given events. For example, they can be used to determine performing calibration or not for given changes in temperature, humidity, and/or cartridge life. Decision trees are constructed by machine learning algorithms. These algorithms iteratively create a sequence of if-then-else tests arranged as nodes in a tree structure. A decision

* Research supported by the Hewlett-Packard Company. Research partially conducted while Yan-Fu Kuo was a graduate student at Purdue University.

tree is composed of a root node, internal nodes, and final nodes (see Fig. 2). Each internal node (including the root node) of the tree represents a test associated with an input attribute, e.g., temperature. At a decision point in time, the input attribute values are measured and fed into the DT. Tests are performed in the tree nodes, starting from the root node and ending when the process reaches one of the final nodes. In each test, the current value of an input attribute specified by the test is compared with the node branching value to select the branch for advance. By branching forward throughout the tree until a final node is met, the best calibration action is asserted and applied. Note that, while proceeding along the tree branches, not all input attributes are necessarily checked throughout the process. For example, in the very right branch in Fig. 2, the input attribute temperature is not checked.

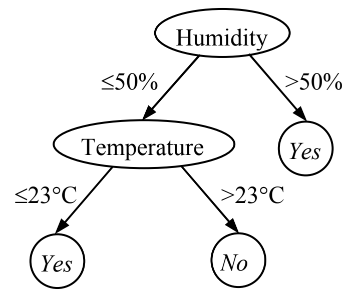

***Figure 2**. An example decision tree.*

Method

Let $\boldsymbol{x}(t) = [x_i(t)] \in \Re^m$ denote a set of operating conditions of an EP printer at a point in time $t \in \Re$, and $\boldsymbol{y}(t) = [y_i(t)] \in \Re^n$ denote the measured tone values at a set of pre-determined halftone levels. Suppose the EP system was calibrated at a previous time t_1. As time goes by, the operating condition varies from $\boldsymbol{x}(t_1)$ to $\boldsymbol{x}(t_2)$, where the t_2 is current time and $t_2 > t_1$. Consider that the change in operating condition results in tone deviation $\Delta\boldsymbol{y}(t_2, t_1) = [\Delta y_i(t_2, t_1)] \equiv \boldsymbol{y}(t_2) - \boldsymbol{y}(t_1) \in \Re^n$, where each Δy_i corresponds to a pre-determined halftone level. At the current time t_2, a calibration is necessary to bring the output tone value back to desired target if some metrics of the tone deviation $\Delta\boldsymbol{y}$ are larger than a threshold; otherwise, no action may be taken. The objective of this work is to develop a decision making module f in the form of a DT that determines appropriate calibration action at the current point in time t_2 when given the current and past operating conditions as inputs to the DT, i.e.,

$$c = f(\boldsymbol{x}(t_2), \boldsymbol{x}(t_1)), \tag{1}$$

where $c \in$ {calibration, no calibration} is a calibration action. Note that alternative DT inputs can be used. Denote $\Delta\boldsymbol{x}(t_2, t_1) = [\Delta x_i(t_2, t_1)] \equiv \boldsymbol{x}(t_2) - \boldsymbol{x}(t_1) \in \Re^m$ as the difference between the two operating conditions measured at the current time t_2 and the past time t_1. Equation (1) can be re-formulated as

$$c = f(\boldsymbol{x}(t_2), \Delta\boldsymbol{x}(t_2, t_1)). \tag{2}$$

In this work, a separate DT is developed for each primary color. Assuming interactions between primary colorants is minimal, the same procedure can be applied to all primary colors since each of them is reproduced independently on in-line color EP printers. The proposed DT development process comprises four steps – experiment design and data collection, training sample composition, DT growth, and DT pruning.

Experiment Design and Data Collection

Experiments are designed to collect data for DT development. Controllable EP variables, measurable environmental parameters, and consumable factors that are significant to EP process performance can be selected as control variables. Typical control variables can include developer bias voltage, temperature, humidity, usage duty cycle, or cartridge life. Note that on-board color patch measurements [3-5] are not included as control variables since they are only available during calibration. In the experiment design, the setup points of each control variable should cover a broad range of conditions encountered in typical customer usage.

The data collection procedure is as the follows. During an experiment, EP printers are operated under a controlled condition $\boldsymbol{x}$. Tone correction and calibration are bypassed. Once a steady operating condition is reached, primary color patches are printed on output media. The corresponding tone value $\boldsymbol{y}$ is measured off-line using a calibrated instrument, such as a spectrophotometer. The tone value $\boldsymbol{y}$ and its corresponding operating condition $\boldsymbol{x}$ is collected and recorded in a database.

Training Sample Composition

Training samples for DT development are composed from the data points collected under different conditions. Two data points $[\boldsymbol{x}(t_k)\ \boldsymbol{y}(t_k)]$ and $[\boldsymbol{x}(t_j)\ \boldsymbol{y}(t_j)]$, where $t_k > t_j$, are selected from the database. Here, we rewrite $\boldsymbol{x}(t_k)$ as $\boldsymbol{x}(k)$, and $\boldsymbol{y}(t_k)$ as $\boldsymbol{y}(k)$ for simplicity. The point $[\boldsymbol{x}(k)\ \boldsymbol{y}(k)]$ represents the current operating condition and tone value, and the point $[\boldsymbol{x}(j)\ \boldsymbol{y}(j)]$ represents the operating condition and tone value at a previous calibration. A training sample is composed of the current operating condition $\boldsymbol{x}(k)$, the difference between the two operating conditions $\Delta\boldsymbol{x}(k, j)$, and the calibration action $c(k, j)$. The calibration action $c(k, j)$ is determined by comparing the absolute weighted mean tone deviation $d_w(k, j)$ to a threshold $\delta \in \Re$, i.e.,

$$c(k, j) = \begin{cases} c_1, \ d_w(k, j) > \delta \\ c_2, \ d_w(k, j) \leq \delta \end{cases}, \tag{3}$$

where c_1 and c_2 represent the class labels “calibration” and “no calibration,” respectively. The absolute weighted mean tone deviation is defined as

$$d_w(k, j) \equiv \left| \frac{\sum_{i=1}^{n} w_i \Delta y_i}{\sum_{i=1}^{n} w_i} \right| \in \Re, \tag{4}$$

where $\boldsymbol{w} = [w_i] \in \Re^n$ is a weighting vector. Each entry in $\boldsymbol{w}$ corresponds to a unique halftone level. Larger entry values can be assigned in w_i to further penalize the tone deviation Δy_i at the corresponding halftone levels. The threshold δ is usually determined based on tone consistency requirement and the performance limitation of EP printers.

Restrictions may be applied to screen out training samples that are not applicable under normal operation. For example, in typical customer usage, cartridges are used until the end of their lives. Data points that are not from the same cartridge are not used to compose training samples. The training sample composition and selection proceed until all the possible combinations of data points have been examined.

Decision Tree Growth

Decision trees are developed starting from the root node with the training samples in a top-down manner. In each training sample, the entries of the current operating condition x_i, and the entries of the difference between the two operating conditions Δx_i are attributes. The calibration action c is the class label. The main task in the DT growth is to recursively find an appropriate attribute for each test (internal node) with which the training samples are split into subsets. This study uses the *C4.5* machine learning algorithm [8] for DT growth. *C4.5* evaluates attributes based on information entropy. Let $\boldsymbol{D}$ denote a set of training samples. Suppose there exist $q \in \boldsymbol{N}$ different possible (calibration action) classes c_i, where $i = 1,\dots, q$. The information entropy $h(\boldsymbol{D}) \in \Re$ of the set $\boldsymbol{D}$ is defined as

$$h(\boldsymbol{D}) \equiv -\sum_{i=1}^{q} p(\boldsymbol{D}, c_i) \cdot \log_2(p(\boldsymbol{D}, c_i)) \,, \tag{4}$$

where $p(\boldsymbol{D}, c_i) \in \Re$ denotes the proportion of samples in the set $\boldsymbol{D}$ that belong to the class c_i, and $\sum_i p(\boldsymbol{D}, c_i) = 1$. The information entropy is a measure of randomness of the sample class in a set. A smaller information entropy indicates that a larger majority of the samples in the set belong to the same class. Note that the information entropy is always larger or equal to zero. When all the samples in a set belong to a single class, there is no uncertainty and the information entropy is zero.

A test on an effective attribute should reduce the overall information entropy of the split subsets. *C4.5* evaluates all the attributes and chooses the one that gives the maximum reduction in information entropy. Let $\alpha \in \{x_i, \Delta x_i\}$ denote an attribute. Consider α as a discrete-valued attribute with $r \in \boldsymbol{N}$ different values, i.e., $\alpha = \alpha_1,\dots, \alpha_r \in \Re$. Usually r is a small number. A test on α partitions the set $\boldsymbol{D}$ into mutually excluded subsets $\boldsymbol{D}_1, ..., \boldsymbol{D}_r$, where $\boldsymbol{D}_i$ is the subset of training samples associated with attribute value α_i. The weighted sum of information entropies over the subsets for the attribute α is defined as

$$h(\boldsymbol{D}, \alpha) \equiv \sum_{i=1}^{r} \frac{d_i}{d} \cdot I(\boldsymbol{D}_i) \,, \tag{5}$$

where $d_i \in \boldsymbol{N}$ denotes the number of training samples in the subset $\boldsymbol{D}_i$, and $d = \sum_i d_i \in \boldsymbol{N}$ denotes the number of training sample in the set $\boldsymbol{D}$. Information gain $g(\boldsymbol{D}, \alpha) \in \Re$ for the test on the attribute α is defined as the reduction in information entropy, i.e.,

$$g(\boldsymbol{D}, \alpha) \equiv h(\boldsymbol{D}) - h(\boldsymbol{D}, \alpha) \in \Re \,. \tag{6}$$

Decision Tree Pruning

The DT built in the growth stage can be complex due to noise in the training data set. The goal of the prediction, however, is to determine appropriate calibration action for unseen cases. Pruning mechanism generalizes DTs to improve their accuracy by removing tests corresponding to noise that may be particularly only included in the training data set. Define a subtree as a branch of a fully developed DT associated with one internal node and some final nodes. Pruning algorithms check the DT from bottom to top to determine whether or not a subtree should be replaced with a final node.

Several pruning methods have been introduced in the literature. Some of them have been developed to minimize error rates of DTs. However, in some other applications, DT prediction errors are associated with different costs (or penalties). Define a false negative error as the mis-prediction of failing to perform a calibration when the tone deviation is actually larger than the specified threshold, and false positive error as the mis-prediction of failing to restrain a calibration when the tone deviation is actually smaller than the threshold (see Table I). From a color consistency point of view, the false negative error leads to undesired tone variation and should be prevented. On the other hand, if consumable economy is the top priority concern, the false positive error should be avoided. The cost of making a false negative error can be substantially higher or lower than that of making a false positive error, depending on different considerations. A cost-based pruning algorithm is applied in this work to provide a way for trading-off between different error costs.

Table I: Two types of calibration errors

Decision-tree-predicted state	True state	
	Need calibration	Do not need calibration
No calibration	False negative error	-
calibration	-	False positive error

EXPERIMENT

The proposed DT-based calibration timing determination approach is performed on an off-the-shelf in-line color EP printer. Calibration and tone correction are bypassed during the experiment to prevent the resulting tone variation. The operating condition $\boldsymbol{x}$ includes developer bias voltage (DBV), cartridge life remaining (CLR), relative humidity (RH), and temperature (T). The DBVs are denoted in percentage between 0 and 100%, where 0% represents the lowest admissible voltage and 100% represents the highest admissible voltage. The CLR ranges between 0 and 100%, where 0% represents an empty cartridge and 100% represents a new one.

The operating condition setup points are as the follows. The experiment is performed with four DBV setup points at 0%, 33%, 66%, and 100% of the admissible voltages. Eight different T and RH setup points that cover extensive environmental condition (15 to 30°C and 30 to 80% RH) in typical customer usage are chosen. The number of environmental conditions in the current design is subject to the cost of the experiment. More T and RH setup points may be included in the design to provide further comprehensive data for DT development when desirable. Figure 3 shows the eight T and RH setup points in a psychrometric chart.

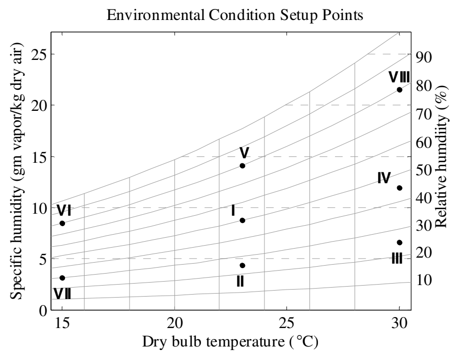

***Figure 3**. The eight temperature and humidity setup conditions in a psychrometric chart.*

Historic printer usage data from a print quality project [3] conducted at Purdue University is used to estimate the potential calibration frequency reduction when the proposed method is applied. In the project, printers were located under typical office environments. Their operating conditions were collected every few hours and were stored in a database. The simulation is conducted with the data collected on a printer between November 2005 and October 2006. The printer produced more than 180,000 pages with 15 sets of cartridges during this period.

The calibration criteria of the proposed and existing calibration timing determination algorithms are as the follows. The proposed algorithm triggers a calibration whenever a new cartridge is inserted, whenever the output of any primary color DT is “calibration”, or whenever any cartridge has its 20% CLR consumed. The last criterion for the proposed algorithm is given because the maximum CLR difference of the training samples is 20%. Any unseen cases with CLR difference larger than 20% are beyond the knowledge stored in the DTs; hence a calibration should be enforced. The existing algorithm triggers a calibration whenever a new cartridge is inserted or whenever any cartridge has 10% of its CLR consumed. Note that the existing algorithm does not consider tone variation due to changes in environmental condition.

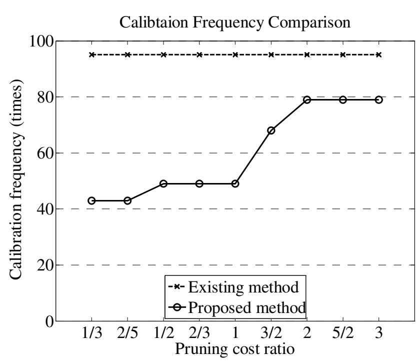

***Figure 4**. Calibration frequency versus different cost ratios.*

The calibration events from the simulation are categorized into two groups: new cartridge calibration and other types of calibration. This is because new cartridge calibration is necessary for purposes of color plane registration and should not be included in the comparison. Figure 4 shows the numbers of other types of calibration with the proposed and existing approaches. It shows that, with unity pruning cost ratio, the proposed approach can save 48.4% of the other types of calibration while the color consistency of the EP printer is guaranteed. The overall saving in calibration frequency is 30.9%.

CONCLUSION

Traditional preventive calibration strategy results in waste in consumables and interruption to print jobs. This motivates using a knowledge-based approach to reduce calibration frequency for color EP printers while maintaining desirable tone consistency. In the approach, experiments are designed to collect tone measurements under various operating conditions. Decision trees are developed with these measurements using machine learning algorithms. The effectiveness of the proposed calibration timing determination method is verified with historic data. Simulation shows that the proposed method can reduce the total calibration for an office printer by 30.9% while the color consistency is maintained.

Acknowledgements

We gratefully acknowledge the support from the Hewlett-Packard Company. We would like to especially thank Dennis A. Abramsohn for his valuable guidance in this research.

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