Failure Prediction Method for Long Life Photoconductor Based on Statistical Machine Learning

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Abstract

In the production printing market, the electrophotography system is asked for high durability, and long-life photoconductors are usually implemented in it. Ordinary method of periodic maintenance uses print volume counter and preset limitation value to alert an operator. But damage processes depend on various phenomena and there are difficulties to predict the exact lifespan of each photoconductor. We examined the methodology for developing new risk decision rule by using the logged data of the field machines. In this method, we focused on photoconductor's three basic parameters and used one of the machine learning method "AdaBoost" to find failure signal pattern. These basic parameters were pre-calculated to the physical and statistical characteristic value to estimate abnormality of these value. We selected learning data from the typical fatigue log data and "AdaBoost" algorithm generated the risk decision rule that consist with the weak learners. The field tests showed enough result for practical use. Additionally it was confirmed that this risk decision rule was almost coincident with the photoconductor deterioration model knowledge by "Score plots". We obtained the calculation method to determine the risk of image defect from monitoring signal data log and it can be predicted whether photoconductor should be replaced or not.

This failure prediction method can reduce urgent imaging trouble and the loss of photoconductor's lifespan that occurred in the ordinary method.

Introduction

In the production printing market, the electrophotography system is asked for high durability, and long-life photoconductor is usually installed in it [1,2]. The photoconductor should be replaced to new one before image quality decreasing by degradation of photoconductor's performance. However, it is not easy to predict it because the deterioration factors are associated with diversity of usage environment, such as operation style or installation environment. Ordinary, we use periodic maintenance method of photoconductor which alerts replace necessity by using the print volume counter and preset limitation value. To eliminate print quality trouble, the preset limitation value should be set shorter than each real lifespan of the photoconductor. And that causes loss of productivity and running cost increases.

On the other hand, almost product printing machines have implemented a remote monitoring system connected with the internet [3,4]. If we have some suitable signal for prediction of photoconductor's deterioration, we will be able to find more accurate decision rule from remote monitoring data. And we examined a methodology to obtain a new decision rule with remote monitoring data.

Monitoring Data

There are many reasons why photoconductor must be replaced. But we think the main reasons of replacement could be mapped out as follows.

(A) Deterioration-causing factors
- i) Mechanical (Abrasion, etc.)
- ii) Electrical (Charge fatigue, etc.)

(B) Breakages
- iii) Pollution (Toner filming, etc.)
- iv) Physical (Human error, etc.)

It is known that the abrasion on the surface of photoconductor causes the reduction of photosensitivity [5]. The long-life photoconductor has hard over-coated layer on its surface for the reduction of the abrasion rate. Even if we choose such reinforced photoconductor, it is necessary to take into account. Additionally "Charge fatigue" is well known phenomenon of photoconductor deterioration. Along with using photoconductor, charge-trapping spots have grown inside of the charge transfer layer and they interferes charge transportation smoothness. This phenomenon causes decreasing of charge ability or increasing of residual potential. We have to take attention that charge fatigue is a reversible phenomenon and it effected by the temperature. Figure 1 shows simple model of deterioration of photoconductor include abrasion effect and charge fatigue effect to surface potential.

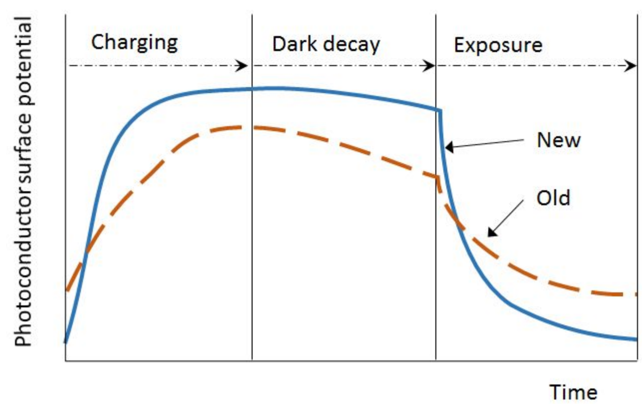

***Figure 1**. Deterioration Model of the photoconductor.*

We focused on "(A) Deterioration-causing factors" and selected simple three monitoring signals as follows.

- Vh: Charging Potential
- Vm: Exposure Potential
- Vl: Residual Potential

Figure 2 is a typical sample data of these surface potentials. That measurement results can be seen long-term deterioration trend, but a fairly large variation is included in the short-term. We think the short-term variation is caused by the effects of fatigue-recovery and temperature mainly, but there may be a hidden factor of the others. In order to avoid trial and error to determine subjective criteria which do not leave the realm of hypothesis, we used the actual data and machine learning algorithms to determine accurate timing of the photoconductors replace timing.

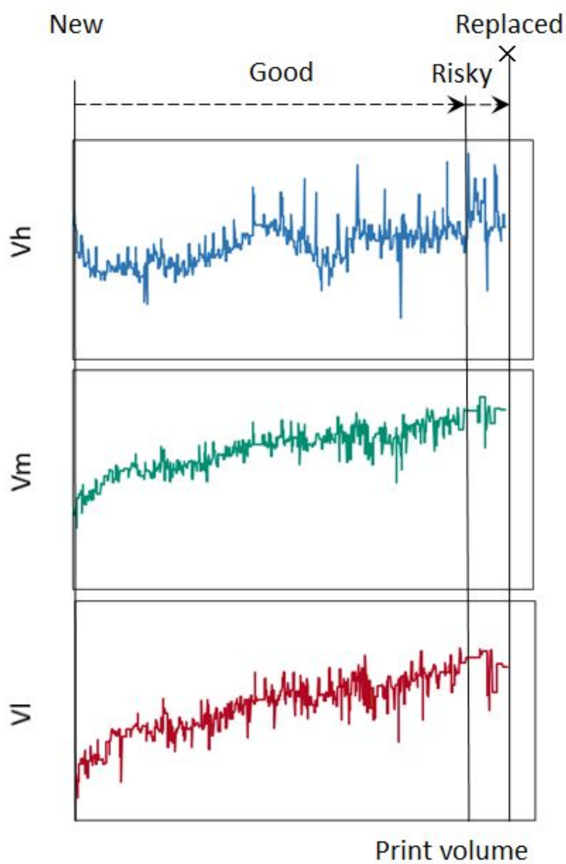

***Figure 2**. Sample data profiles of Vh, Vm, and Vl.*

Applying Machine Learning Method

Machine learning method could be categorized for three types. "Unsupervised Learning" is to classify data without label. "Supervised Learning" is to make decision rule from labeled learning data. "Reinforcement Learning" makes action rule to obtain maximum profit.

We applied the supervised learning algorithm with the labeled learning data set in this study and figure 2 is one of them. We chose to use one of supervised machine learning method named "AdaBoost" [6]. This method generates simple decision rule from many "Weak learners" that have each weight of decision.

We chose "Decision Stamp" as very simple weak learner. The equation (1) shows decision stamp. It comperes some data element "xi" to border value "bi" and multiplies "Sgni". "Sgni" takes value of 1 or -1 that concerned with decision polar. Totally decision will be determined by value "F" from equation (2). Value F is given by the sum of weak decision's results with weight "α". If the value F is less than zero, we decide that photoconductor should be replaced.

We can understand the decision rule meanings without mathematical complex space transfer processes.

$$S_i = \begin{cases} 1 & : Sgn_i \times (x_i - b_i) \geqq 0 \\ -1 & : Sgn_i \times (x_i - b_i) < 0 \end{cases} \tag{1}$$

$$F = \sum_{i=1}^{N} \alpha_i \times S_i \tag{2}$$

Data preparation

AdaBoost is one of the searching algorithm. It learns the suitable rule from the given labeled data set of "Good" term and data set of "Risky" term. Before starting the learning, we should prepare the adequate characterized data from three monitoring signals, Vh, Vm and Vl.

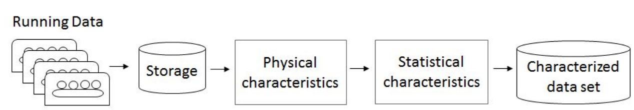

***Figure 3**. Data preparation steps.*

As Figure 3, large size monitoring data should be transform characteristic values to use by physical calculation and statistical calculation steps. Physical calculation is to make physical meaning value like "Vh-Vl" that means the dynamic range of potential. Also it should be included temperature correction calculation. Statistical calculation is to make statistical meaning value like "moving average" for the reduction of short-term variation. Also it could be included recent standard deviation calculation.

Modeling

After data preparation, we must separate prepared data to training and testing data set as figure 4. Using only training data that labeled "Good" or "Risky", AdaBoost learning process should do with them. After learning process, the decision rule is obtained from training data. This decision rule must be tested carefully by using testing data. It is very important step because the decision rule should be tested for its broad utility.

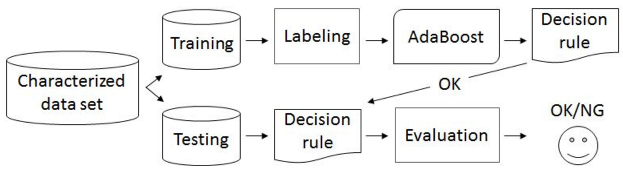

***Figure 4**. Modeling steps.*

Score plots

The decision rule is given as the matrix object which consists of characteristic quantity ***x*** of interest, the threshold value ***b***, the polarity ***Sgn***, and the weight ***α***. But it is difficult to determine the meaning of rule by the matrix object. There is the convenience method named score plots which can visualize that rule graphically. Score plots are described by each characteristic value on the horizontal axis and the weighted evaluation value ***F***j on the vertical axis. It is possible to understand the weak learner's behavior as the evaluation functions that has step-like shape for each characteristic values.

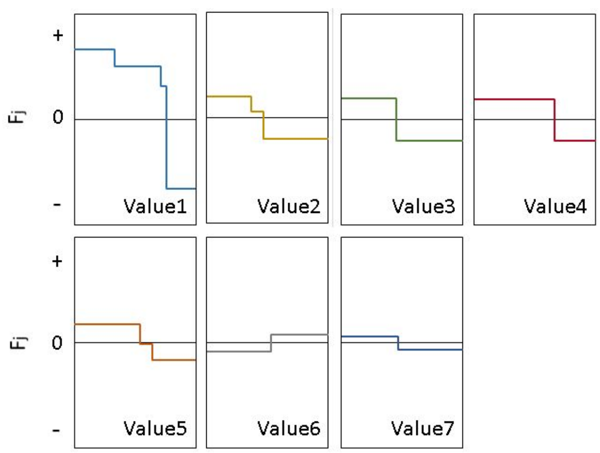

***Figure 5**. Score plots.*

We show the score plots of decision rules that can be derived from this study in Figure 5. Seven characteristic values that were derived from surface potential measurement result Vh,Vm,Vl, were chosen and eleven weak learners were processed. Every characteristic value has three, two or one weak learners.

It is possible to examine the coincidence between score plots and physical interpretation.

Value 1 indicates the level of Vm. It seems reasonable evaluation because it given better point with low value.

Value 2 indicates the deviation of Vl. It seems reasonable evaluation because it given better point with low value.

Value 3 indicates the deviation of Vh-Vl. It seems reasonable evaluation because it given better point with low value.

Value 4 indicates the ration of Vl/Vm. It seems reasonable evaluation because it given better point with low value.

Value 5 indicates the moving average of Vl. It seems reasonable evaluation because it given better point with low value.

Value 6 indicates the moving average of Vh-Vl. It seems reasonable evaluation because it given better point with high value.

Value 7 indicates the moving average of Vh. It doesn't seem reasonable evaluation because it given better point with low value. But that weight is not large and we decide to keep this factor as it be.

Figure 6 shows F value calculated the whole data of Figure 2. The correspondence between the label and the F value seems fit well together because they used as training data.

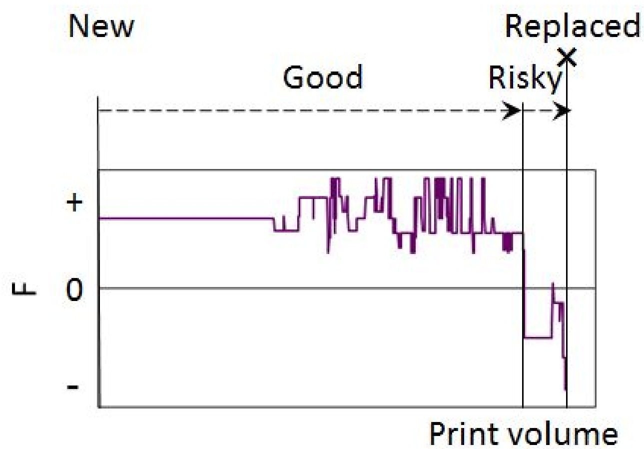

***Figure 6**. F value.*

Result

We evaluated the validness of the decision rule using a lot of field machine monitoring data and these machine's maintenance records as Table 1. These machines are maintained by conventional method not to stop due to photoconductor's problems. Evaluation method was done by comparing relationship between the photoconductor replacement record and alert timing that generated by the decision rule. For the term of good condition of photoconductors, we found no false-positive decision (0.00). From the view of maintenance cost, it is important result to start to use such a new maintenance method like this.

On the other hand, false-negative ratio (0.94) was high. This result comes from the conventional maintenance operation to refuse imaging troubles. But we found there were some cases (0.06) that photoconductor should be replaced earlier than the real replacement timing. We think our decision rule is useful for these cases to refuse print quality troubles.

In the future, if we will change maintenance method to new decision rule, we will be able to obtain better false-negative ratio and it will bring productive replacement operation that is consistent with real photoconductors lifespan.

Table 1: Field estimation result.

Photoconductor	Decision	
	Good	Risky
Good	1.00	0.00
Replaced	0.94	0.06

N = 313

Conclusions

By using the remote monitoring data of the field operation and applying the machine learning algorithm AdaBoost, it was able to create an appropriate decision rule for determining the replacement timing of the long-life photoconductor.

Additionally it was confirmed that this risk decision rule was almost coincident with the photoconductor deterioration model knowledge by drawing the score plots. We obtained the calculation method to determine the risk of image defect from monitoring signal data log and it can be predicted whether photoconductor should be replaced or not.

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Author Biography

Yasushi Nakazato received his ME in University of Electro-Communications (1985). After he worked as a technical developer of the electrophotography at Ricoh Company, Ltd. He is now studying the data mining of the machine monitoring data. He is a member of ISJ and SICE.