

## Article

# Aging Detection of Electrical Point Machines Based on Support Vector Data Description

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**Abstract:** Electrical point machines (EPM) must be replaced at an appropriate time to prevent the occurrence of operational safety or stability problems in trains resulting from aging or budget constraints. However, it is difficult to replace EPMs effectively because the aging conditions of EPMs depend on the operating environments, and thus, a guideline is typically not suitable for replacing EPMs at the most timely moment. In this study, we propose a method of classification for the detection of an aging effect to facilitate the timely replacement of EPMs. We employ support vector data description to segregate data of “aged” and “not-yet-aged” equipment by analyzing the subtle differences in normalized electrical signals resulting from aging. Based on the before and after-replacement data that was obtained from experimental studies that were conducted on EPMs, we confirmed that the proposed method was capable of classifying machines based on exhibited aging effects with adequate accuracy.

**Keywords:** aging effect diagnosis; electrical point machines; electric current signal processing

## 1. Introduction

Recently, the importance of condition monitoring [1–6] has been receiving attention in Industry 4.0 [7]. For example, fault diagnosis for railway components was reported in [8–10] because the maintenance of component health ensures safety on the railway. The electrical point machine (EPM) is a significant railway component that safely switches train direction. If a failure of an EPM is not quickly repaired, trains could experience serious accidents, such as derailments, which could lead to human casualties [11]. The electric motor used in EPMs generates electric current signals in specific patterns that can be used for health monitoring of the EPMs. One approach to EPM fault diagnosis involves the classification of machines based on health using support vector machines (SVM) and a discrete wavelet transform (DWT)-based strategy [11]. Further, a fault detection and diagnosis approach for EPMs has been reported using audio signals regarding different abnormal situations [12].

In this study, we focus on the aging effect in existing EPMs with a view to developing a strategy that facilitates their replacement at an appropriate time. From the perspective of safety in railway transportation, the monitoring of significant components such as EPMs is necessary and should be mandated. Regarding the aging of EPMs that progresses slowly, however, it is difficult to determine when to replace them. In the majority of cases, EPMs are replaced based on guiding factors, such as the operating period (e.g., more than ten years) or the number of moving switch blades (e.g., more than 100,000 movements). However, these guidelines are frequently poorly followed and the relatively long operating period of EPMs makes it difficult to obtain in-field electric current signals. Moreover, environmental factors in locations where EPMs are installed, such as severe weather conditions and heavy loads from passing trains [13], are the main cause of aging.

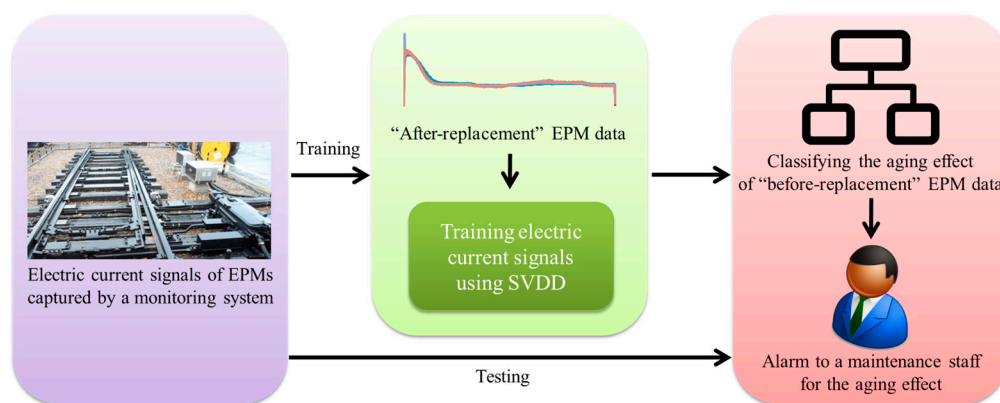
In this study, we propose a method for detecting aging in EPMs using the electric current signals obtained from the machine. The aging decision for EPMs can be regarded as a binary-class classification

problem that determines if the current generated from the motor in the EPMs belongs to the aging category, unlike the previous decision problem of the abnormal condition of the EPMs. To detect the aging effect of EPMs, however, it is important to monitor if the current signals are identified to be in the aging category in real time. That is, it is rational to consider this problem as a one-class classification problem because it is a process of identifying only the aging effect of the current signals monitored in real time. Therefore, we exploit the support vector data description (SVDD) [14] approach, which is a one-class classifier that can detect the aging effect of EPMs by only training “not-yet-aged” current data. To the best of our knowledge, this is the first report on the detection of aging in EPMs by SVDD-based analysis of after-replacement (i.e., “not-yet-aged”) data only.

The remainder of the paper is as follows. In Section 2, we describe the proposed method using SVDD to detect the aging effect of EPMs. In Section 3, we present the experimental results using the proposed method for both in-field before and after-replacement data. Then, we discuss the results comparing the previous method and present future work. Section 4 presents the conclusions.

## 2. Method for Diagnosis of Aging in EPMs

Figure 1 displays the system structure of the detection method for the aging effect of EPMs. First, current signals that are generated from a motor when an EPM is operated are captured by a monitoring system. The current signals are stored in a database in the monitoring system and can be used to manage EPMs in preparation for abnormal situations, such as failures. After gathering both before and after-replacement data using the monitoring system, which monitors the electrical current signals that are generated from the EPMs, both the before and after-replacement data are labelled with the assistance of maintenance staff. Then, only the after-replacement data among all of the labelled current signals is trained through SVDD to produce a hypersphere for classifying the aging effect regarding the EPMs. Using the hypersphere, the before-replacement data can be classified as to whether the data is aging. Finally, the results from this method are directed (as an alarm) to a maintenance staff to consider the aging effect of the EPMs.



**Figure 1.** Overall structure of aging detection system of electrical point machine (EPMs).

Although the EPMs are provided by different manufacturers, we determined that after-replacement (i.e., “not-yet-aged”) data obtained from each replaced EPM exhibited normal electric current patterns. Further, some electric current patterns in the before-replacement data were nearly identical to the patterns from the after-replacement data. However, the majority of the before-replacement (i.e., “aged”) data exhibited subtle differences from the patterns from after-replacement data resulting from the aging effect. Based on these patterns, we classified the electric current patterns in the before- and after-replacement data as “not-yet-aged” and “aged”. Using this approach, an automated decision strategy can be developed to classify before-replacement data into “not-yet-aged” and “aged” categories.

We assume that the machines from which the before-replacement data was measured were not faulty. In fact, because EPMs are the most critical components in a railway system, maintenance staffs check every EPM every night, when trains are non-operational. If an EPM starts exhibiting faulty behavior in the daytime, the maintenance staffs check it immediately. If the fault is a one-time fault caused by noise, such as ballast obstruction [12], then the EPM resumes its operation after the ballast has been removed. Otherwise, the EPM is repaired or replaced the same night. Furthermore, as indicated in Figure 2, the electric current shape of a faulty (i.e., abnormal) EPM is totally different from that of a not-faulty (i.e., normal) EPM, and the faulty EPM can be easily detected by the dynamic time warping (DTW) method [15] for quick repair. However, the subtle difference caused by aging may not be detected by the previous method.

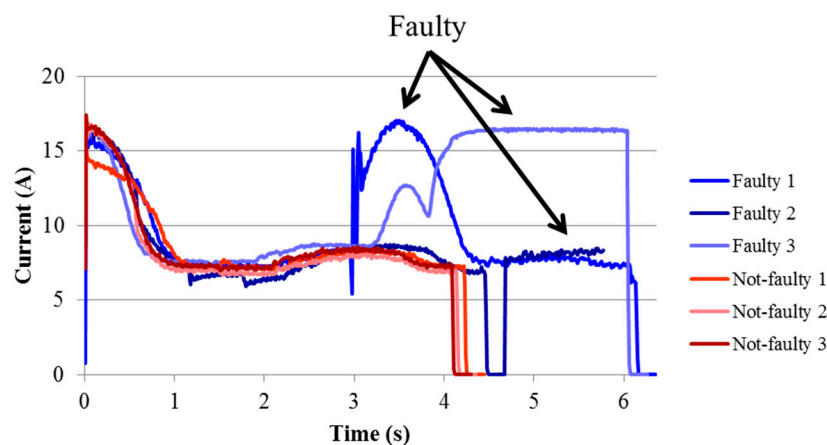


Figure 2. Comparison between faulty and not-faulty data.

### 2.1. Data Preprocessing

For practical issues, we also assume that the operating environments of the EPMs for measuring electric current signals differ. Parameters measured, such as length, peak, or average value, in the before-replacement data differ from the values constituting after-replacement data because of environmental factors. That is, the parameters gained from the operating EPMs have a wide range of attributes. Figure 3 describes the different attributes in the current signals according to the operating environments of each EPM, and indicates the differences between the before-replacement data and the relatively constant after-replacement data.

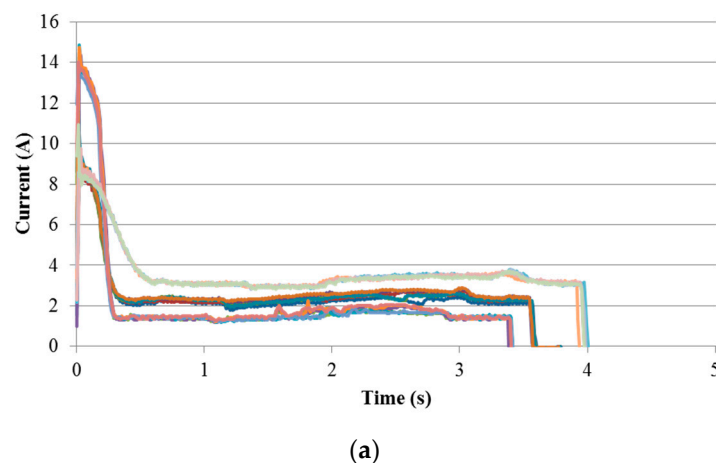
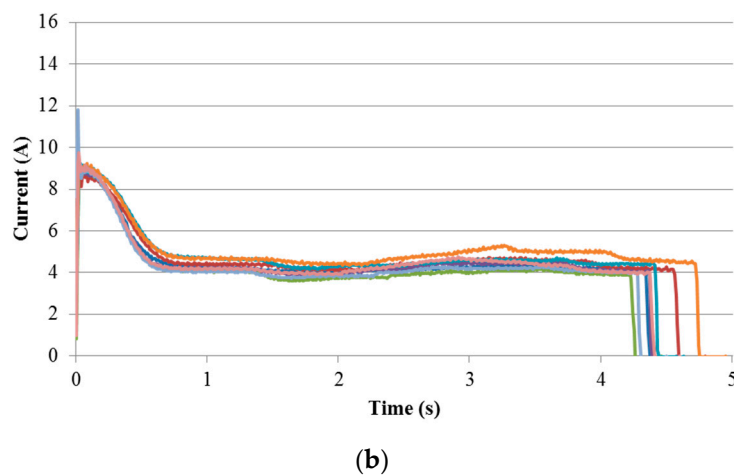
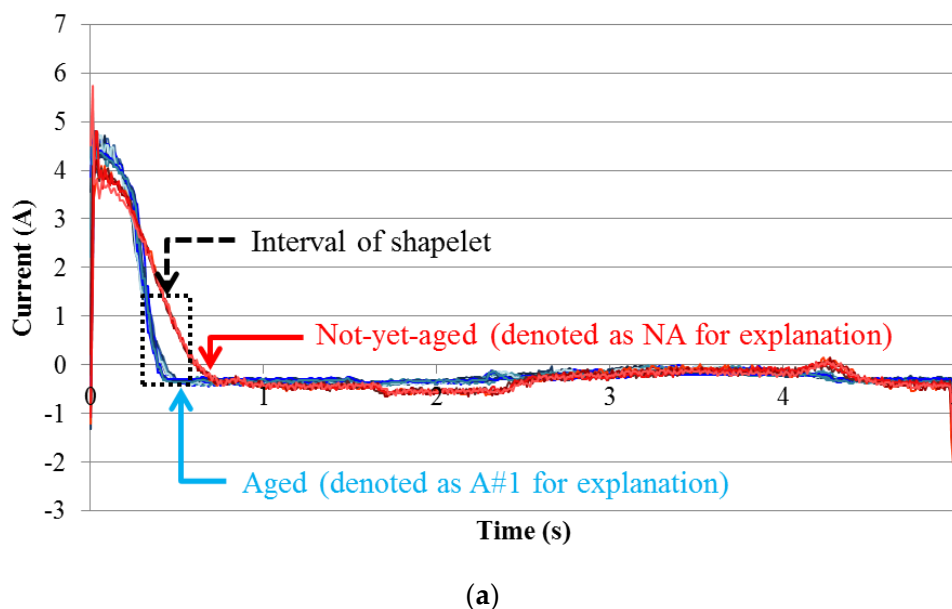


Figure 3. Cont.

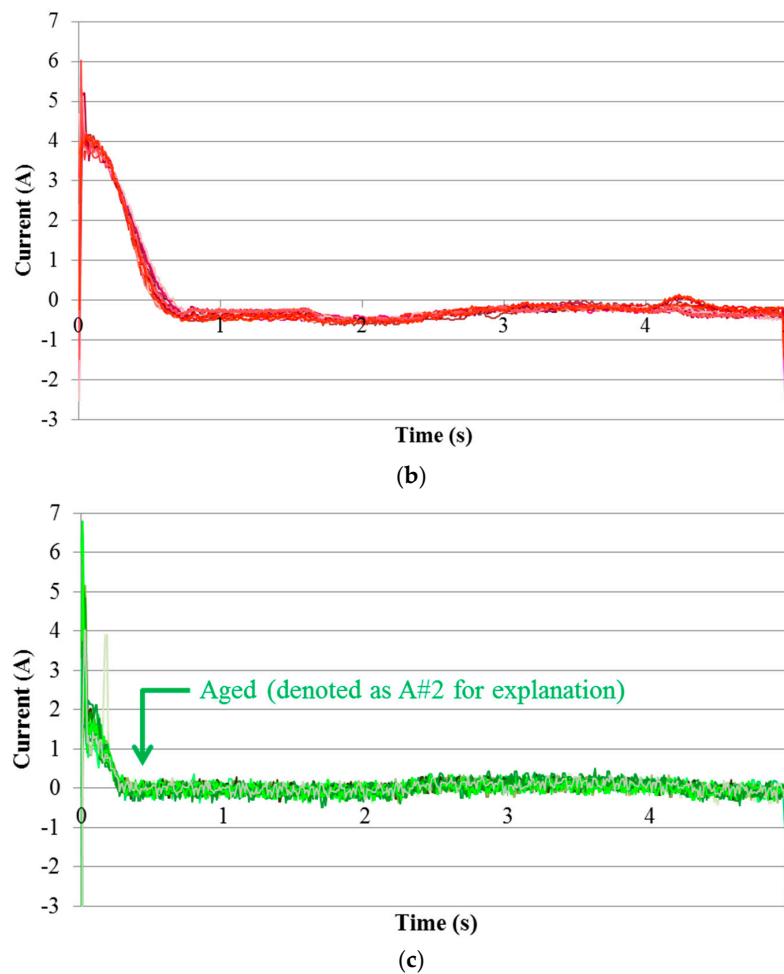


**Figure 3.** Comparison between before and after-replacement data: (a) different attributes in before-replacement data caused by operating environment; (b) relatively constant attributes in after-replacement data.

These properties can result in misclassification in detecting aging in EPMs. To ensure that the properties for both sets of data are uniform, we applied length-normalization and Z-normalization to them. Note that this normalization is typical of time-series analysis [16]. Figure 4 depicts some of the “normalized” before and after-replacement data. As indicated in Figure 4a, the normalization allows for the before-replacement data to represent subtle differences in the data due to the aging effect. These subtle differences are likely to be clues to detect the aging effect for the EPMs. Furthermore, similar current shapes are displayed between the “not-yet-aged” before-replacement and after-replacement data in Figure 4a,b, respectively. Thus, a two-class classifier can be used to classify them.



**Figure 4.** Cont.



**Figure 4.** Comparison between “normalized” before and after-replacement data: (a) Normalized before-replacement data operating more than ten years; (b) Normalized after-replacement data; and, (c) Another normalized aged pattern in before-replacement data.

For example, our previous study employed a shapelet method [16] and achieved an acceptable accuracy [17]. The Shapelet method is a machine learning approach that is used to classify data by analyzing time-series shapes. A subsequence called a shapelet is extracted by determining the intervals separating two classes in the training dataset. The shapelet can be used to classify the data into two classes by measuring the Euclidean distance between the subsequence and electric current in the test dataset. In other words, the shapelet method classifies the electric current as “not-yet-aged” or “aged” through the similarity between the shapelet and the time-series shapes. Owing to the fact that the shapelet method could provide a domain expert “visual interpretability” of the criteria that is used for the time-series classification (as compared to typical classification methods), the domain experts agreed that the shapelet method could improve the reliability of each EPM. Note that, in safety- or mission-critical applications such as railway transportation, domain experts are very conservative, and providing the visual interpretability of the proposed technique is important in order for it to be accepted by a domain expert.

However, if we have multiple aged patterns, then the shapelet method has a limitation in distinguishing the aged patterns from not-yet-aged patterns. For example, from a specific infrequently operated EPM, we found that a different pattern occurred repeatedly (see Figure 4c), and maintenance staffs regarded it as a result of aging. As explain in Section 1, each EPM has been affected by different environmental factors in locations where EPMs are installed. Furthermore, collecting a large amount of

not-aged data is easy, whereas collecting a large number of various aged patterns is very difficult in real applications. Because another aged pattern can be observed in a specific EPM later, the aging effect of EPMs can be detected accurately using a one-class classifier (e.g., SVDD) trained with after-replacement (i.e., not-aged) data only. That is, we expect that “aged” EPMs can be efficiently replaced with new units when compared to the current replacement guideline (e.g., more than 100,000 movements or ten years).

## 2.2. SVDD for Detecting the Aging Effect of EPMs

The normalized before and after-replacement data is suitable for SVDD-based analysis, which involves one-class classification of machines based on the aging effect. In this study, we use SVDD for classifying before and after-replacement from EPMs based on the aging effect.

SVDD [14] facilitates the definition of a hypersphere of the least possible volume, such that it contains all data within it. A sphere that meets these criteria can be obtained by solving the minimization problem:

$$\begin{aligned} \min(r^2, a, \xi) &= r^2 + C \sum_{i=1}^n \xi_i, \\ \text{s.t. } \|x_i - a\|^2 &\leq r^2 + \xi_i, \xi_i \geq 0, \forall i. \end{aligned} \quad (1)$$

The slack variable  $\xi_i$  is represented as the penalty factor for acceptable error ranges with the deviation of training patterns out of the sphere. The constant  $C$  controls the trade-off that is made based on the relative importance of each term;  $a$  and  $r$  are the center and the radius of the sphere, respectively. Because it is difficult to solve Equation (1), a Lagrange function is constructed by transforming the dual problem to Equation (2):

$$\begin{aligned} \min_{\alpha_i} \sum_{i=1}^n k(x_i \cdot x_i) - \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j k(x_i \cdot x_j), \\ \text{s.t. } \sum_{i=1}^n \alpha_i = 1, 0 \leq \alpha_i \leq C, \forall i. \end{aligned} \quad (2)$$

where,  $\alpha_i$  is a Lagrange multiplier, and  $k(x_i \cdot x_j)$  is a kernel function represented as  $\phi(x_i) \cdot \phi(x_j)$ , which calculates the inner product in a feature space.

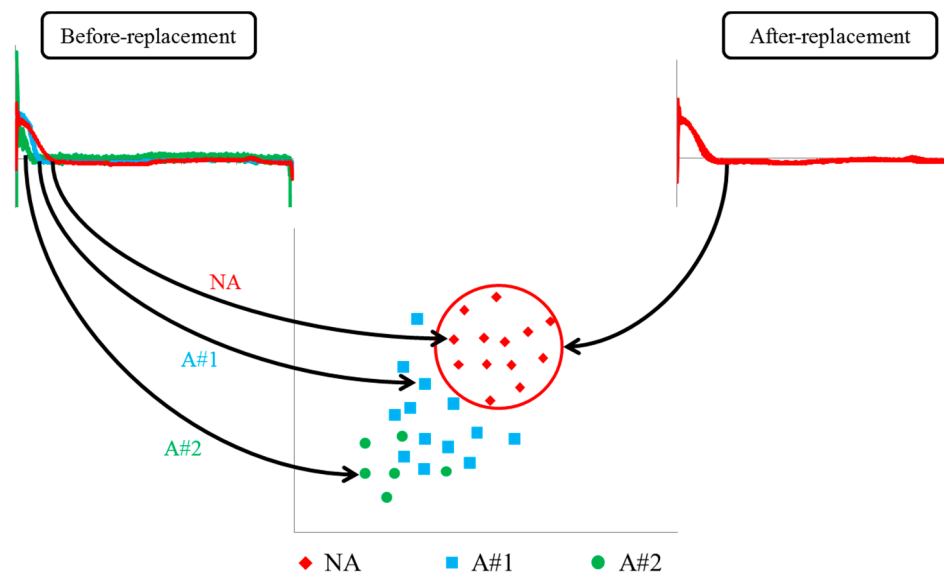
Then, the radius of the sphere can be calculated with the selected support vector  $x_u$ :

$$r = \sqrt{1 - 2 \sum_{j=1}^n \alpha_j k(x_u \cdot x_j) + \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j k(x_i \cdot x_j)}. \quad (3)$$

By definition,  $r$  represents the distance from the center of the sphere to its boundary. Then, the distance  $D$  between current sample  $x$  and the center is calculated as:

$$D = \sqrt{1 - 2 \sum_{j=1}^n \alpha_j k(x_u \cdot x) + \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j k(x_i \cdot x_j)}. \quad (4)$$

Based on Equation (4), the current sample  $x$  is determined to be the aging effect if the distance between the sample and the center is outside the radius. Figure 5 indicates that the electric current signals are classified as “not-yet-aged” and “aged” using SVDD. Thus, after the hypersphere is produced through SVDD using only the after-replacement data, “not-yet-aged” and “aged” before-replacement data can be classified based on internal or external on the hypersphere.



**Figure 5.** Classification as “not-yet-aged” and “aged” from electric current signals using support vector data description (SVDD).

### 3. Experimental Results

#### 3.1. In-Field Current Signals

The proposed method was executed using the following environment: Intel Core® i5-4670 3.40 GHz, 8GB RAM, and MATLAB R2015a (MathWorks, Massachusetts, MA, USA). We obtained in-field measurement data at a sampling rate of 100 Hz from 48 EPMs installed and having been operated for 14 years on average in nine stations in Korea. Table 1 shows properties of the current data that was measured from some before-replacement EPMs at the seven stations. As indicated in Table 1, each EPM from the A to G stations exhibited “replacement in a timely manner” challenges that were based on the guideline because of environmental factors. For example, even though EPM “52” in “E” station had been in operation for over 12 years and the number of switch movements was approximately 390,000, the EPM had been assigned a “not-yet-aged” condition. Conversely, EPM “51 A” in “G” station had been in operation for over 17 years and had a relatively small number of switch movements, however, the aging of the EPM had advanced and not been replaced at an appropriate time. Thus, we performed the proposed method for detecting the aging effect of EPMs at the proper time.

The obtained in-field data was of two types: before-replacement (data from EPMs that had been in operation for more than ten years) and after-replacement (data from EPMs that had been in operation for less than ten years). As indicated in Figure 3b, the after-replacement data exhibited certain normal electric current patterns despite each EPM being produced by different manufacturers. With the assistance of the maintenance staff, before-replacement data was categorized into two classes: “normal” and “abnormal.” As indicated in Figure 3a, the differences between the two classes resulting from aging and variations in the classes were subtle (especially when compared with the differences resulting from faulty machinery [15] displayed in Figure 1). By performing length-normalization and Z-normalization on the data, variations within each class were reduced, meaning that the effect of aging on electric current signals could be clearly understood.



**Table 1.** Properties of before-replacement current data of some EPMs.

Station	Name of EPM	Operating Period	Total Movements	Aging Status
A	22B	2002.09–2014.12	4654	Aging
	23A	2002.05–2014.12	2059	Aging
	23B	2002.05–2014.12	1284	Aging
	24A	2002.09–2014.12	8968	Aging
	24B	2002.09–2014.12	2596	Aging
	25	2002.05–2014.11	2981	Aging
	26B	2002.05–2014.11	9388	Aging
	27B	2002.09–2014.11	5367	Aging
	28	2002.09–2014.11	33,272	Aging
	52B	2002.11–2014.11	3193	Aging
	54A	2002.10–2014.11	8624	Aging
	54B	2002.10–2014.11	8260	Aging
	57B	2002.10–2014.11	13,674	Aging
	58	2002.10–2014.11	22,953	Aging
B	21A	2002.04–2014.12	4376	Aging
	22A	2002.04–2014.12	8245	Aging
	55	2000.12–2014.03	653	Aging
C	22B	2001.01–2014.05	107,927	Aging
	23	2001.01–2014.05	70,022	Aging
	25B	2002.01–2014.05	83,276	Not aging
	51A	2002.01–2014.12	22,304	Aging
	54B	2001.01–2014.12	12,875	Aging
	58A	2001.01–2014.12	66,050	Aging
	59	2001.01–2014.12	77,214	Aging
D	32	2004.04–2014.12	11,442	Aging
E	21B	2000.12–2014.03	23,517	Not aging
	22	1998.05–2014.03	113,811	Aging
	51A	2002.04–2014.12	5778	Not aging
	52	2002.04–2014.12	391,141	Not aging
	55A	2002.04–2014.12	52,906	Not aging
F	51A	2000.12–2014.03	6303	Aging
	51B	2001.12–2014.11	5209	Aging
	52	2000.12–2014.03	82,795	Aging
	53	2000.12–2014.11	12,195	Aging
G	22	2000.01–2014.12	108,600	Aging
	23A	1997.01–2014.12	11,269	Aging
	23B	1997.01–2014.12	11,282	Aging
	51A	1997.01–2014.11	436	Aging
	53	1997.01–2014.12	62,658	Aging

### 3.2. Results and Analysis

Before evaluating the performance of the proposed method, we obtained a total of 2401 data items, which comprised 1080 before-replacement data and 1321 after-replacement data, respectively. Then, with the help of a domain expert, we labeled the before-replacement data and the after-replacement data as “not-yet-aged” and “aged.” In the before-replacement data, three patterns (i.e., not-yet-aged, aged #1, and aged #2) were identified, as shown in Figure 4a,c. There were 158, 894, and 28 instances of not-yet-aged, aged #1, and aged #2 patterns, respectively, in the before-replacement data. The 2401 data items were labeled as normal (i.e., 1479 of not-yet-aged) and abnormal (i.e., 922 of aged), along with the after-replacement data. The labeled data was divided into the training and test set at a ratio of 8:2 to perform  $5 \times 5$ -fold cross validation. The training set consisted of 1183 normal and 737 abnormal data, and the test set consisted of 296 normal and 185 abnormal data. Note that because SVDD is a one-class classifier, the training set for SVDD consisted of normal data only. Setting the parameters



$\sigma = 5.40$  and  $C = 0.001$ , we then trained the SVDD classifier using the training dataset and subsequently classified the testing dataset into normal (i.e., “not-yet-aged”) and abnormal (i.e., “aged”) categories.

To evaluate the performance of the proposed method, we compared it with the shapelet method [16], support vector machine (SVM) [18], and random forest [19]. Then, we measured the performance of the classification with the Matthews correlation coefficient (MCC) [20]. MCC is a metric to evaluate the classifier performance, which has been recently acknowledged as an elective measure in the machine learning community. MCC returns a value between  $-1$  and  $+1$ . If the coefficient is equal to  $+1$ , then it indicates a perfect prediction. By contrast, if the coefficient is equal to  $-1$ , it represents a total disagreement between the prediction and observation. In addition, MCC leads to a good generalization of results regardless of the ratio between the two classes, contrary to other measurements of classification performance. Thus, we derived the MCC results for each method following Equation (5):

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FN})(\text{TP} + \text{FP})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}}, \quad (5)$$

where True Positive (TP) is “not-yet-aged” data identified as “not-yet-aged”, True Negative (TN) is “aged” data identified as “aged”, False Positive (FP) is “aged” data identified as “not-yet-aged”, and False Negative (FN) is “not-yet-aged” data identified as “aged”, respectively. Table 2 shows the MCC results of each method with regards to the  $5 \times 5$ -fold cross validation.

**Table 2.** Comparison of the Matthews correlation coefficient (MCC) results of each method.

# of Repetitions	# of Folds	MCC			
		Proposed Method	Shapelet [16]	SVM [18]	Random Forest [19]
Repetition 1	1	0.94	0.86	0.89	0.88
	2	0.93	0.87	0.86	0.90
	3	0.95	0.83	0.87	0.92
	4	0.94	0.85	0.87	0.96
	5	0.95	0.86	0.94	0.89
Repetition 2	1	0.94	0.86	0.91	0.91
	2	0.96	0.77	0.96	0.87
	3	0.93	0.79	0.86	0.91
	4	0.94	0.84	0.88	0.71
	5	0.96	0.83	0.87	0.90
Repetition 3	1	0.95	0.81	0.97	0.91
	2	0.90	0.83	0.85	0.95
	3	0.96	0.76	0.86	0.94
	4	0.97	0.84	0.91	0.92
	5	0.93	0.81	0.91	0.91
Repetition 4	1	0.94	0.92	0.98	0.91
	2	0.93	0.85	0.85	0.89
	3	0.96	0.78	0.86	0.94
	4	0.95	0.84	0.92	0.86
	5	0.96	0.82	0.92	0.92
Repetition 5	1	0.89	0.81	0.88	0.93
	2	0.96	0.91	0.85	0.95
	3	0.97	0.87	0.97	0.96
	4	0.95	0.81	0.98	0.88
	5	0.94	0.84	0.88	0.86
Average	–	0.94	0.83	0.90	0.90

As indicated in Table 2, the classification performance of the proposed method was the best when compared with other classification methods. Of course, the performance of both the SVM and random forest methods outperformed the proposed method in some datasets, but the classification methods could not yield as consistent a performance as the proposed method. Furthermore, although

the shapelet method achieved a good classification performance for the two (i.e., one aged and one not-yet-aged) patterns in [17], it had a limitation in distinguishing multiple aged patterns from the not-yet-aged pattern. Given that the EPM environment undergoes many variations in each location, the possibility of unpredictable or various aging patterns should not be ignored. Comparison methods should be re-learned whenever the various aging patterns occur, and this may not be practical in railway applications. By contrast, the proposed method is only trained with the not-yet-aged pattern, and thus, it is practically suitable for detecting the aging effect for EPMs. Finally, the computation time for the classification using the proposed method was 0.67 msec (measured without executing other user programs) per each test data, on average. Therefore, the proposed method can detect the aging effect of EPMs in real-time.

#### 4. Conclusions

Managing EPMs is crucial to the prevention of severe accidents, such as derailments. Aging detection of EPMs is particularly important for avoiding future accidents in advance. However, replacing EPMs based on a replacement guideline is not appropriate because of the environmental variations of the installed location. Thus, EPMs must be analyzed for the aging effect and replaced in a timely manner by considering such factors.

In this study, we proposed a classification system to detect the aging effect in EPMs based on their electric current signals. The proposed method trained after-replacement data from EPMs using SVDD and then classified tested EPMs as “not-yet-aged” and “aged” using before-replacement data. On in-field replacement data, the proposed method based on one-class classification exhibited improved accuracy in terms of experimental results on the detection of EPM aging than the typical methods based on a two-class classification such as shapelet, SVM, and random forest.

In fact, the performance of a data-driven method depends on the quality of the training data. However, for the aging detection problem, it is very difficult to acquire an adequate number of diverse types of “in-field” aged data, not “laboratory-simulated” aged data. Given that EPMs are the most critical components in a railway system and are affected by the environmental variations of the installed location, a low probability of an unknown aged pattern occurring later cannot be ignored. Even with the unbalanced data of the aged patterns, or unknown aged patterns, the one-class classifier-based method trained only with the not-aged pattern can practically solve the aging detection problem. We are continuously collecting more data, and we will report further results to compare the SVDD method with deep learning methods [21,22].

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**Author Contributions:** Yongwha Chung and Daihee Park conceived and designed the experimental method; Yongwha Chung, Daihee Park, and Jonguk Lee described the SVDD; Jaewon Sa and Yunchang Choi analyzed the before and after-replacement data obtained from the EPMs; Jaewon Sa conducted the experiment using SVDD to detect the aging effect in the current data; Jaewon Sa and Yunchang Choi conducted three classification methods for comparison with our proposed method; Jaewon Sa, Yunchang Choi, and Yongwha Chung wrote the paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

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