Fault diagnosis of railway point machines using dynamic time warping

H. Kim, J. Sa, Y. Chung✉, D. Park and S. Yoon

A practical condition monitoring method is proposed for the fault diagnosis of railway point machines (RPMs) by considering the difficulty of obtaining in-field failure data. Failures in RPMs have a significant effect on railway train operations, and it is very crucial to detect abnormal conditions in RPMs. However, it is generally difficult to obtain in-field failure data for a classifier training step. A diagnosis method using dynamic time warping is proposed to manage the variation in durations of RPM movement without a training step. On the basis of the experimental results with RPMs operated in Korea, it is believed that the proposed method without a training step can detect abnormal electric-current shapes more accurately than previous training-based methods.

Introduction: Recently, computer analysis techniques such as neural network, fuzzy logic, and support vector machine (SVM) have been applied to fault diagnosis applications [1, 2]. In this Letter, we consider a fault diagnosis of railway point machines (RPMs), which are the key actuators used to provide a means for moving a switch blade from one position to another. Failures in RPMs have a significant effect on railway train operations, and it is very crucial to detect the early signs of the deteriorating condition of RPMs and thereby prevent failures [3, 4].

RPM condition monitoring systems often contain an alarm system based on a threshold technique [5]. For example, an alarm is created if the measured value of an RPM movement exceeds the predetermined threshold. However, this threshold technique can detect neither a subtle change in the measured shape nor a fault at its earliest stage [3, 4]. Furthermore, the variation in durations of the machine movement should be managed.

Previous studies of the duration-variation problem of RPM movements reported that SVM-based classifications, with discrete wavelet transform-based feature extraction [3] or uniform scaling [4], could be used to warn about a possible failure in RPMs. However, it is generally difficult to obtain in-field failure data for an SVM training step, and the uniform scaling solution cannot manage the phase-shifted shape accurately.

In this Letter, we proposed a dynamic time warping (DTW)-based method in order to manage the duration-variation problem of RPM movements, without the SVM training step. To the best of our knowledge, this is the first report on the RPM duration-variation problem that shows how to manage the phase-shifted shape accurately, without a classifier training step.

Method for managing the duration-variation problem: As in [3, 4], the electric-current values of an RPM movement are assumed to be measured and a subtle change in the electric-current shape needs to be detected. Especially, because each shape of electric-current measurements differs in length, the duration-variation problem of an RPM movement should be managed in order to detect abnormal electric-current shapes. To solve this problem, feature extraction with SVM [3] or uniform scaling with SVM [4] has been proposed.

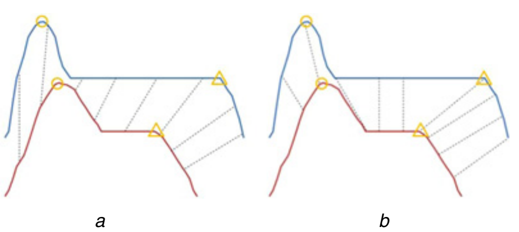

Fig. 1 *Illustration of phase-shifted shape with uniform scaling and DTW*
a Uniform scaling
b DTW

In practice, it is generally difficult to obtain 'in-field' failure data for a classifier training step, compared with fault-free data. For example, failures were introduced manually in a laboratory environment [3] in order to avoid this difficulty of obtaining in-field failure data. Vileiniskis *et al.* [4] interpreted the fault detection as a one-class classification (i.e. normal versus abnormal). However, the uniform scaling used by Vileiniskis *et al.* [4] cannot manage the phase-shifted shape, as shown in Fig. 1*a*.

In this Letter, we propose a DTW-based method that can manage the phase-shifted shape and that does not require a training step for a classifier such as SVM. The DTW is one of the widely used algorithms in speech recognition and speaker recognition for measuring the similarity between two temporal sequences that may vary in time [6]. Since the sequences are warped nonlinearly in the time dimension, to determine a measure of their similarity independent of certain nonlinear variations in the time dimension, DTW can be used to manage the phase-shifted shape, as shown in Fig. 1*b*.

For measuring the similarity between two temporal sequences, two sequences are denoted as $S(s_1, s_2, s_3, \ldots, s_n)$ and $T(t_1, t_2, t_3, \ldots, t_m)$, where the length of these sequences is denoted by n and m, respectively. The DTW calculates the shortest path between two sequences, and the distance between s_n and t_m is calculated to obtain an optimal warping path cost. If the result of the DTW algorithm (i.e. the optimal warping path cost between sequence S and sequence T) is smaller than δ, then two sequences are regarded as 'similar.'

$$\mathrm{DTW}(n,m) = D(n,m) + \mathrm{Min}\,(\mathrm{DTW}(n-1,m), \mathrm{DTW}(n,m-1), \mathrm{DTW}(n-1,\,m-1)) \text{ where } D(n,m) = |s_n - t_m| \qquad (1)$$

Note that, because DTW itself can manage the subtle change in the electric-current shape, it does not require a training-based classifier. On the contrary, a classifier with uniform scaling requires a training step in order to manage the subtle change in the electric-current shape [4].

Experimental result: In our experiments, in-field data of several RPMs (captured at a sampling rate of 100 Hz from 1 January 2015 to 30 October 2015) were obtained from the Youngdeungpo Station in Korea. Note that these RPMs were installed relatively recently (i.e. January 2013) by considering the average lifetime of an RPM (i.e. 10 years) and that there was no in-field failure case (i.e. all RPM movements were completed correctly, even with various electric-current shapes due to possible events such as the insertion of pebbles). However, we need to check each electric-current shape automatically because accumulated *abnormal* (i.e. the electric-current shape of an RPM movement is different from that of a typical RPM movement, with the phase-shifted shape consideration) movements will result in a failure eventually.

With the help of maintenance staffs, we labelled the entire data set as normal and abnormal and set δ to 200. From the half of the normal data set, we determined the normal 'sample' shape [i.e. S sequence in (1)] of the electric-current measurements by averaging them. Then, we validated the proposed method with the remaining half of the normal 'test' data set and the entire abnormal 'test' data set [i.e. T sequence in (1)].

Fig. 2 shows the validation result with various RPMs. If the accumulated difference between the input 'test' shape and the normal 'sample' shape exceeds δ(=200), we regard this input shape as abnormal. From the January RPM data shown in Fig. 2*a*, we determined 37 normal and 1 abnormal shapes correctly. In addition, from the March RPM data shown in Fig. 2*c*, we determined 33 normal and 1 abnormal shapes perfectly. Finally, from the October RPM data shown in Fig. 2*j*, we determined 47 normal and 1 abnormal shapes correctly.

Note that the shape of normal (2) shown in Fig. 2*j* looks different from that of normal (1) shown in Fig. 2*j* (i.e. the uniform scaling may regard those shapes as different). With the help of maintenance staffs, however, the normal (2) movement was determined as the phase-shifted case, and DTW regarded it as normal. That is, the proposed method without a training step could obtain better accuracy than the uniform scaling method with a training step [4].

Note again that those RPMs were installed relatively recently (i.e. January 2013) by considering the average lifetime of an RPM (i.e. 10 years). There were not many abnormal shapes from the measured RPMs, and there was not a significant variation between the normal shapes of each month. As explained in [4], however, we believe that the changes in the measurements of electric-current shapes due to worn-out RPMs can be detected before an actual fault is detected and that such early warnings enable deriving an efficient maintenance plan.

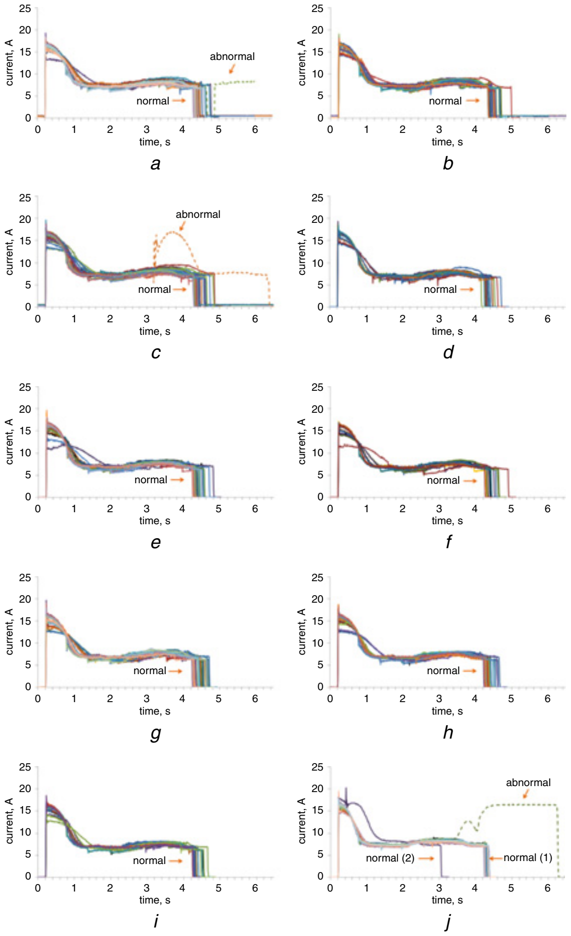

Fig. 2 *Validation results*

a RPM data in January
b RPM data in February
c RPM data in March
d RPM data in April
e RPM data in May
f RPM data in June
g RPM data in July
h RPM data in August
i RPM data in September
j RPM data in October

Conclusions: Failures of RPMs lead to hazardous situations, and thus an RPM condition monitoring system is required to detect the early signs of a deteriorating condition. Especially, the variation in durations of the machine movement should be managed efficiently, and it is generally difficult to obtain in-field failure data for a classifier training step.

In this Letter, we proposed a DTW-based method for managing the duration-variation problem of RPM movements without a classifier training step. Since it is a very flexible solution, it can manage the phase-shifted shape accurately. Furthermore, it can avoid the difficulty as well as the computational workload associated with the use of a classifier training step. On the basis of the experimental results with RPMs operated in Korea, we were able to determine 264 normal and 3 abnormal shapes perfectly and believe that the proposed method can detect abnormal electric-current shapes of RPMs practically (i.e. accurately and cost-effectively).

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One or more of the Figures in this Letter are available in colour online.

H. Kim, J. Sa, Y. Chung and D. Park (*Department of Computer and Information Science, Korea University, Sejong, Republic of Korea*)

✉ E-mail: ychungy@korea.ac.kr

S. Yoon (*Sehwa, Daejeon, Republic of Korea*)

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