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NOISE CONTROL FOR A BETTER ENVIRONMENT

Noise-based pavement condition inspection method with dynamic time warping

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ABSTRACT

Traditionally, pavement condition inspections have been dependent on visual-based information, but there are disadvantages that it requires a lot of manpower, equipment and budget. Especially, very expensive automated inspection vehicles are essential for network level pavement inspection. This is considered as a major obstacle to the introduction of the pavement management system of road agencies in poor management environment. This study proposes a method determining the pavement service level using the pavement-tire friction noise. Noise measurement specification is according to the ISO11819-2, and judging the service ratings for noise profiles is conducted by the K-nearest neighbor with Dynamic Time Warping (DTW), a pattern recognition algorithm categorized in the machine learning. This simple idea and technique could present a new paradigm that replaces traditional visual-based inspection methods.

Keywords: Pavement Management, Pavement condition monitoring, Tire-surface friction noise, Dynamic time warping

I-INCE Classification of Subject Number: 75

1. INTRODUCTION

Condition monitoring is essential for pavement asset management. It takes a lot of manpower, time, equipment and budget. These have been considered as major obstacles to introduction of the Pavement Management System (PMS). In Korea, only 17% of road networks managed by the (rich) central government are monitored and maintained by the PMS using automated inspection cars[1].

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Of course, the (poor) local governments managing small road network also want to implement the management process, but a problem is that the monitoring system is too expensive, and requires relevant experts. In addition, the inspection car requires additional costs for operating and maintenance, and even data analysis. Simply put, introducing the expensive monitoring system is not matched with their reality, and they need for the cheaper, easier, and more convenient solution. This study seek to the solution from acoustic property of pavement, much precisely friction noise between tire and road surface when vehicle is running. Noise measurement specification is according to the ISO11819-2,3[2-3], and determining the condition ratings for noise profiles is conducted by the K-nearest neighbor dynamic time warping algorithm categorized in the machine learning. This simple idea and technique could present a new paradigm that replaces the traditional visual-based inspection methods.

2. METHODOLOGY

2.1 Suggestion of noise-based pavement condition monitoring method

Key ideas of this novel approach are very simple; 1) Vehicles make friction noise between road surface and tire when driving, and 2) old pavement texture or deteriorated parts (e.g. potholes, and alligator crack) generate higher or abnormal sound profiles. 3) These acoustic characteristics can be quantitatively recorded in time-series noise profiles, and artificial intelligence (AI) may useful for determining pavement condition rating. Research process in order to realize the approach is presented in Fig. 1.

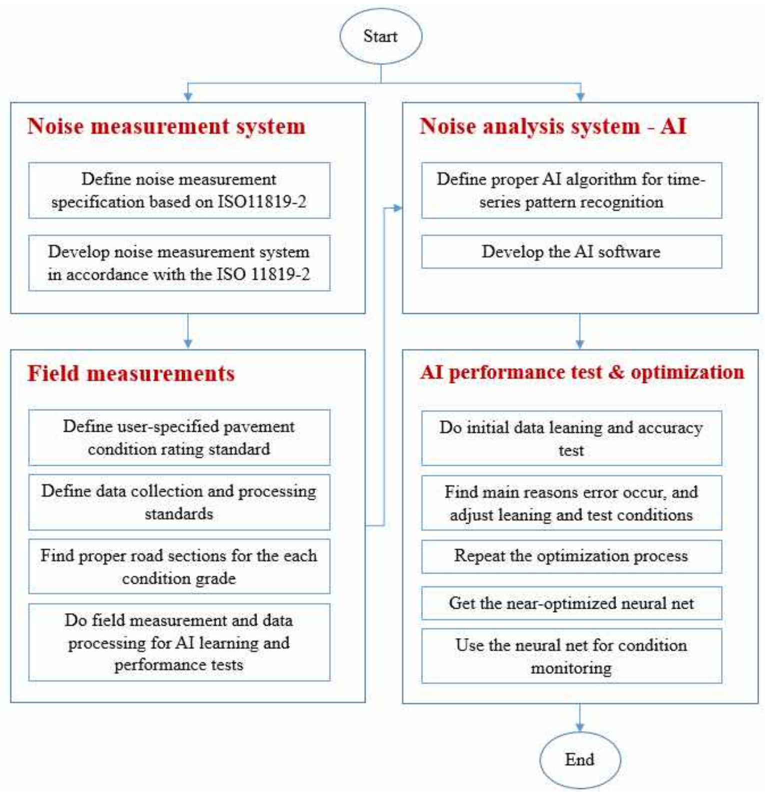


Figure 1. Research process for Noise-AI based pavement monitoring system

Function of the AI was limited to only determining pavement condition rating. Although general pavement condition indices in the PMS are crack, rutting and IRI (International Roughness Index), this study focused on determination of the condition ratings as a basic research. Further research, such as building neural networks finding specific deteriorated conditions, will be next challenge.

2.2 Building noise measurement system with ISO 11819-2

Because acoustic properties are very sensitive to measurement conditions, it is very important to define specifications of noise measurement system and preconditions. The International Standard, the ISO11819-2 proposes the detail specifications on tire, noise measurement equipment and standards, microphone position, data calibration, analysis method and so on. This study complied with all the criteria given in ISO11819-2 to take into account the reliability of the collected data. Although the measurement methods described in ISO allow both vehicle on-board type and trailer-type, this study choose the former one since it is easier to implement and operate in practical viewpoint. Since there is no commercialized on-board microphone zig, we got to develop the zig based on the ISO standard. Figure 2 shows development process of the measurement system.

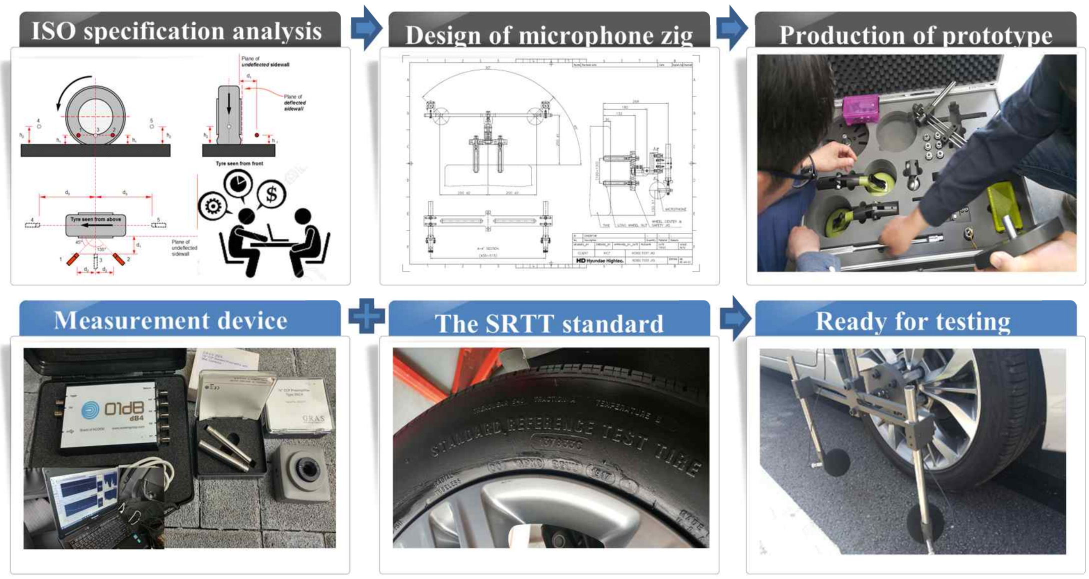
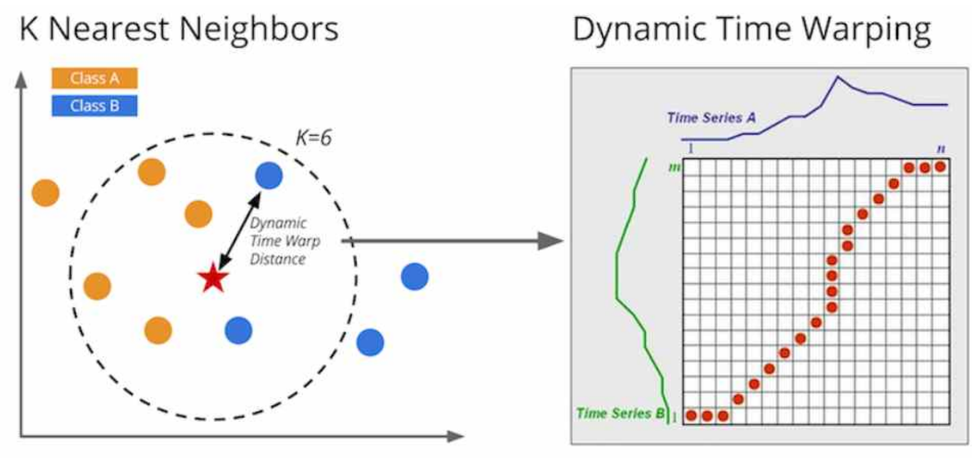


Figure 2. The self-designed on-board type measurement system

2.3 K-nearest neighbor with dynamic time warping for pattern recognition

In this study, artificial intelligence was introduced as a means to exclude the subjective determination of condition ratings. The method of statistical processing of noise data was also considered, but there was a limitation that simple statistical methods are difficult to reflect various movements and figures of time-series data in determining condition rating. Although artificial intelligence with various functions has been developed, pattern recognition artificial intelligence algorithm is required to determine the condition rating of time series data. Based on the relevant literature review, K-nearest neighbor with dynamic time warning algorithm, which is a family of Machine learning, was considered to be most suitable. This method is reported to be concise in implementation and robust in estimation accuracy[4]. Especially the characteristic of solving problems that occur when learning and testing data have different sequence lengths is a strong strength in practical application. The concept of K-nearest Neighbor, which determines the most approximate pattern, and the concept diagram of dynamic time warning, which resolves the 1:1 correspondence problem between time series data, are briefly presented in Figure 3. Refer to Xi et al.[4] and Hsu et al.[5] for more detail theoretical background.



Source : https://github.com/markdregan/K-Nearest-Neighbors-with-Dynamic-Time-Warping

Figure 3. A concept of the K-nearest neighbor with dynamic time warping method

3. EMPIRICAL RESEARCH

3.1 Field measurement for learning and testing data collection

In order to apply the suggested method, criteria for determining the condition rating must be established first because the criteria is referred for field investigation, learning, evaluation and optimization. In addition, each rating must have specific meaning or interpretation related to maintenance actions or evaluation of road service level in practical viewpoints. The literature on pavement deterioration modeling, condition index, service rating system shows that most of them are classified into 5 ratings[6-7]. This study also introduced 5 rating system (best – good – fair – bad – poor) as an initial alternative, and the criterion may be incorporated or further subdivided depending on initial learning results of artificial intelligence. The applied definition of each rating is summarized in Table 2.

Table 2. Description of pavement condition rating criteria

Condition rating	Description	Note
A – Best	New or almost new condition usual	Tolerable level (Maintenance is not required)
B – Good	Good condition without any deterioration but discolored	
C – Fair	General condition but minor cracks occur	
D – Bad	Old and deterioration progressed without pothole or alligator crack	Maintenance review is required based on budget level
E – Poor	Potholes and alligator crack happened or worse	Maintenance required in urgent

Once the criteria are established, learning data should be obtained by finding the sections that correspond to each rating. Naturally, it is convenient to find road sections remain as uniform as possible. In this study, leaning data were obtained by selecting five sections that can represent the characteristics of each rating. The reference vehicle speed was determined to be 40 km/h, taking into account the speed limit in the urban area, and the suggest lowest speed limit indicated by the ISO standard. The frequency of data acquisition was determined to be 10 Hz. Given these two criteria, it is considered that 1 raw data represents a pavement condition of about 1 meter, and is sufficient to reflect local deterioration such as portholes.

3.2 Performance evaluation of the AI

The number of obtained data set processed in 20m was more than 500. We select 500 sets, and divided the sets into learning data 80% and test data 20% randomly. As an application option of the KNN-DTW, the hyper-parameter "K" was defined 5, which means 5NN-DTW model applied for rating determination. Initial performance test result are represented by a confusion matrix, and its numerical interpretation with Precision, Recall, F1-score index are shown in Figure 1 and Table 1 respectively.

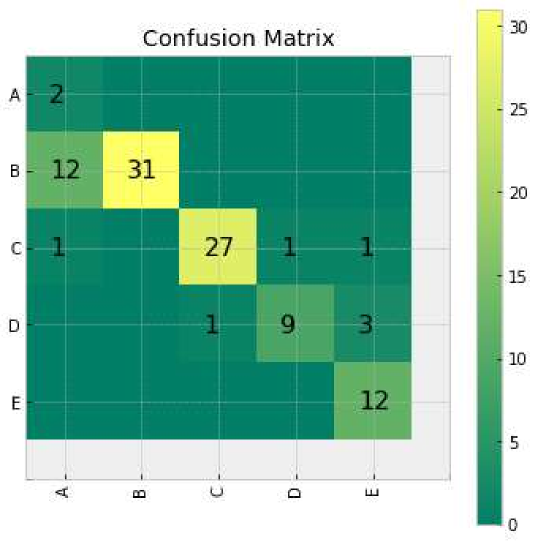


Figure 1. Confusion matrix for 5 condition ratings

Table 2. Performance evaluation of the 5NN-DTW model

Rating	KNN-DTW estimation result (Learning 80%, Testing 20%)					
	True	Predict	Correct estimation	precision	recall	f1-score
A	15	2	2	0.13	1.00	0.24
B	31	43	31	1.00	0.72	0.84
C	28	30	27	0.96	0.90	0.93
D	10	13	9	0.90	0.69	0.78
E	16	12	12	0.75	1.00	0.86
Total / Avg.	100	100	81	92.9%	81.0%	84.9%

The Figure 1 and Table 1 tell that condition ratings B, C and D are very positive in term of precision over 90%. However, ratings A and E was relatively negative, especially in the rating A. In order to find the reasons, we compared noise profiles by ratings used for learning. Refer to the graphs showed in Figure ?

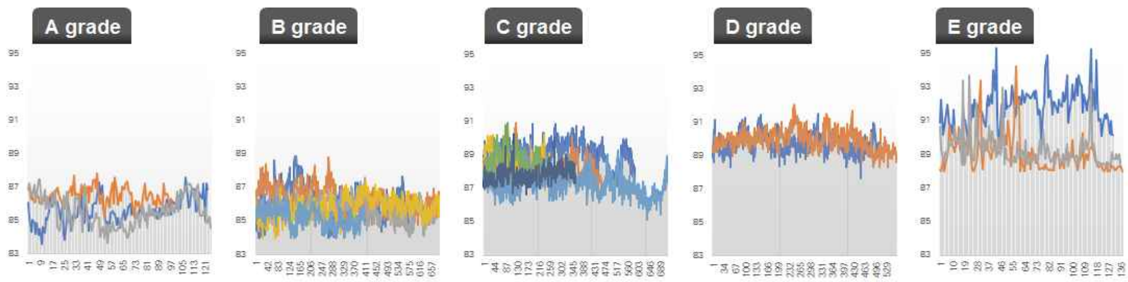


Figure 2. Comparison noise profiles of each condition rating

From the Figure 2 we can see the reason intuitively. First, characteristics of noise profiles between the A and B rating are very similar in absolute noise level and range. That is, we can anticipate that the precision of the rating A can be dramatically improved by merging A and B rating into one. In case of the E rating, it is confirmed that some parts in the profiles are similar with the ratings D. The reason was readily apparent through field inspection. As shown in some profiles in the E rating, pavement condition is not continuously damaged. In other words, it is the result of giving false answers to artificial intelligence.

4. CONCLUSIONS

This study proposed a method determining the pavement condition rating based on acoustic property using the tire-surface friction noise to overcome visual-based inspection method. Noise measurement specification is according to the ISO11819-2, and determining the condition ratings for noise profiles is conducted by the K-nearest neighbor dynamic time warping algorithm categorized in the machine learning. The most remarkable finding is that the noise characteristics vary with pavement conditions sensitively. We believe that it would be the significant first step opening a new paradigm in pavement condition monitoring sector.

5. ACKNOWLEDGEMENTS

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