

Defect state and Severity Analysis Using the Discretized State Vectors

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ABSTRACT

The time series of sensor data for condition monitoring of a system is often characterized as very-short, intermittent, transient, highly nonlinear and non-stationary random signals, which hinders the straightforward pattern analysis. For discovering meaningful features from original sensor data, we transform continuous time series data into a set of contiguous discretized state vectors using a multivariate discretization approach. We then search for important patterns that are found only in the case of defective systems. We discuss how to measure the level of importance of each defect pattern and further how to assess the severity degree of a defective state. We consider that a defective state is more severe if various defect patterns are observed in the state. Likewise, if a particular defect pattern describes as many as defective states, the pattern will be treated as significant. The proposed procedure is applied to detecting defective car door trims that have the potential to generate small but irritating noises. We analyzed the datasets obtained from two different monitoring methods using a typical acoustic sensor array and acoustic emission sensors. Defective car door trims were efficiently identified with their severity degrees.

1. INTRODUCTION

Defect detection has been extensively studied in defect detection from various industries such as power plants (Marhadi & Skrimpas, 2015), (Du et al., 2016), batteries (Acuña, Orchard, Silva, & Pérez, 2015), (Yin, Xie, Lam, Cheung, & Gao, 2015), and various mechanical parts (Zhang & Dong, 2012), (Georgoulas, Karvelis, Loutas, & Stylios, 2015) (Jaber & Bicker, 2016). Defect detection using time series of sensor data is the procedure to investigate whether the product is normally operated or not.

In the literature, statistical distance-based binary clustering/classification methods have been extensively used for defect detection. Mishra, Vanli, and Park (2015) developed a cumulative sum chart using Hotelling's T^2 statistics for considering correlations among multivariate data. This cumulative sum chart provides a higher result in

detecting relatively small, gradual changes as well as large, and sustained behaviors.

Multiple classification methods also have received much attention to investigate defect types which are already known. Jaber and Bicker (2016) used Artificial Neural Network (ANN) of which input data is standard deviations from discrete wavelet analysis of x, y, and z axis movement. ANN finally provided detection results as a bearing's defect detection (i.e., healthy or not), and classifying discernible detection results into three defect types (i.e., inner race bearing defect, 1 and 2 mm hole in outer race defects).

For more accurate multiple classification, defect information from every possible defect phenomenon are necessary to be obtained in advance. However, it is not simple since defects can arise from unexpected root causes which are not be considered at the product's design stage (Haldar & Mahadevan, 1999). Instead of multiple classification on pre-defined defect types, there are extensive studies devoted to defect detection with statistical evidences on defect occurrences.

For example, Chetouani (2014) applied ANN based Bayes classifier to detecting and isolating defects compared to normal states. He defined a residual between normal and defect states of the process as a symptomatic indicator. After the residual is calculated by nonlinear auto-regressive model, Bayes classifier generates a probability whether it is normally operated and it is considered as an evidence of defect occurrences at a specific time point.

In case of Al-Atat, Siegel, and Lee (2011), they constructed a classifier which provides the probability of defect occurrences based on the modified Euclidean distance compare to the normal baseline. They focused on how to select most representative data from the whole healthy sample data. Another research for predicting the disk drive's defects (Hamerly & Elkan, 2001), a normal model was also developed based on Naïve Bayes theory using only normal dataset. Like anomaly detection, they defined that as a data point is far from the developed normal model, it is more likely to be determined as a defect.

Like above studies, a dense unimodal distribution (or its mean value) is usually employed for representing normal states with regard to a specific defect type and experimental condition. However, it is not always reasonable to build a normal model with unimodality when sensor data are scattered and randomly mixed without clear distinction between normal or defect states, like in-tolerance defect analysis.

Therefore, we need to propose a statistical evidence on defect occurrence which is not fully based on geometric similarity measure from a normal state. To do this, in this paper, we first extract defect patterns which are only found in defect state, then we propose two indicators for analyzing extracted defect patterns and defect states with regard to defect occurrences and various root causes.

In particularly, for extracting defect patterns from multivariate time series data, our previous method (multivariate discretization based pattern extraction) is employed because the extraction performance of this method was proven when sensor signals are not clearly discernible between normal and defect states (Baek & Kim, 2016). In addition, symbolic time series data are used to investigate significant defect patterns (Georgoulas et al., 2015), (Park & Kwon, 2016), (Yiakopoulos, Gryllias, Chioua, Hollender, & Antoniadis, 2016), since they usually provide excellent performance in preserving signals' significant features while

reducing the amount of original dataset.

This paper is organized as follows. Section 2 details about the defect state's severity degree and the defect pattern's importance level with defect pattern extraction. The proposed approach will be experimentally verified and validated using two datasets which are collected for in-process Buzz, Squeak, and Rattle (BSR) noise detection in Section III. Finally, the last section presents summarized results and further researches.

2. DEFECT STATE AND SEVERITY ANALYSIS

2.1. Defect Pattern Extraction from multivariate time series data

Defect pattern extraction will be conducted from original time series as a prerequisite for defect state and severity analysis. When signals' change points which are relevant to defect occurrences are not significantly investigated, statistical-distance based defect detection methods do not usually provide quite accurate outcomes. Therefore, for searching informative defect pattern, multivariate discretization based pattern analysis is adopted from our previous study (Baek & Kim, 2016) as Figure 1 is illustrated. This analysis approach can be summarized as three main steps: (1) label definition, (2) label specification, (3) defect pattern extraction.

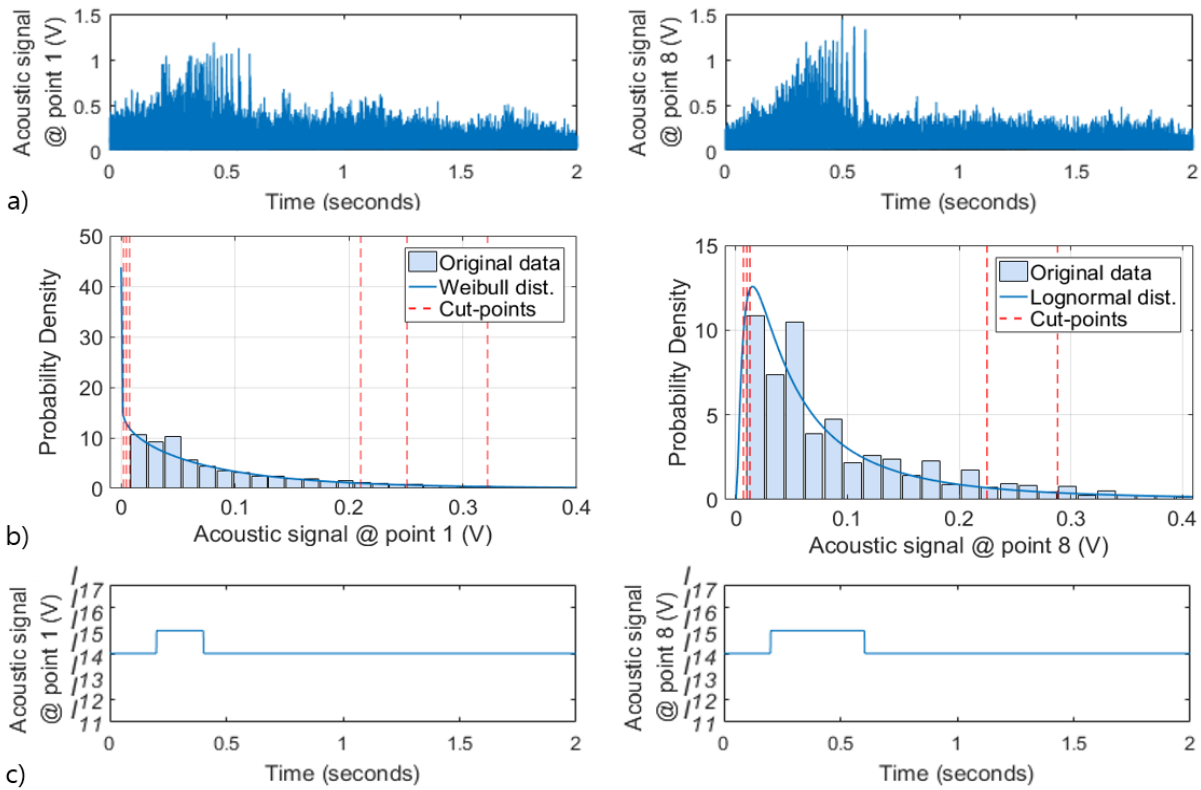


Figure 1. Label definition and label specification: (a) original data, (b) Cut-points generation based on estimated distribution, and (c) a set of discretized state vectors for each acoustic sensor data collected from pre-defined point 1 and 8.

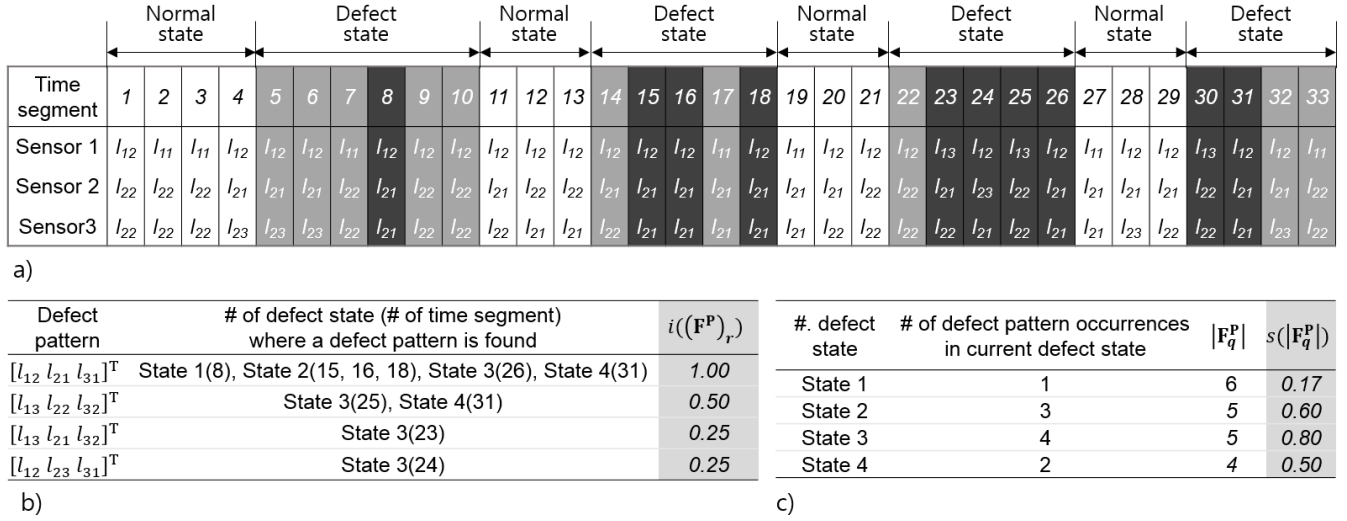


Figure 2. Examples of computing the severity degree of defect states and the importance level of defect pattern: (a) a series of discretized state vectors where the number of sensor is 3 and recording time period it 1 to 33, (b) the procedure for the severity degree of each defect state, and (c) the computation of the importance level of each defect pattern.

Assume there is a multivariate time series dataset which are collected from 1 to n time points and m sensors as m -by- n matrix. In order to describe sensor data's relevant behaviors effectively, many features can be utilized for label definition. In this study, we choose a feature in time series: a relative location of mean value within a time segment. First, we estimate histogram of original sensor data as parametric probability density function (*i.e.*, estimated distribution) by maximum likelihood estimation. Based on discretization parameters (*i.e.*, the number of bins and bin width threshold), the estimated distribution is divided into a set of contiguous bins (*e.g.*, cut-points). This procedure is conducted for each individual sensor data, and then a label is defined as bin index depending on which bin a mean value within a time segment belongs to. Label is represented as l_{ij} where i is the number of sensor and j is the bin index.

After label definition, we assign a relevant label to each time segment to symbolize system's states. There are two approaches to divide a continuous time series into a finite number of time segments (*i.e.*, exclusive point and nested points), exclusive point is adopted for simple time segmentation. We specify a relevant label $D(X)_{ik}$ to each time series data $\mathbf{X}_{i,(k-1)*w+1:k*w}$ within a time segment regarding predefined label, where w is the length of time segment, and k is the number of time segment. Finally, original multivariate time series data is converted into discretized multivariate time series denoted as following Eq. (2).

$$\mathbf{D}(\mathbf{X}) = \begin{bmatrix} D(X)_{11} & D(X)_{12} & \cdots & D(X)_{1s} \\ D(X)_{21} & \ddots & \ddots & D(X)_{ms} \\ \vdots & \ddots & \ddots & \vdots \\ D(X)_{m1} & D(X)_{m2} & \cdots & D(X)_{ms} \end{bmatrix} \quad (2)$$

where s is the number of time segment, $= \lfloor \frac{n}{w} \rfloor$

Each column vector is defined as a "discretized state vector", since it can represent the system's state within a specific time segment. Using the information of fault state, we extract defect patterns \mathbf{F}^P which are only discovered during the defective systems, not found from normal system, in order to prevent annoying false alarms to system. For detail explanations about defect pattern extraction, you can refer our previous works (Baek & Kim, 2016).

2.2. The Importance Level of a Defect Pattern

If a specific defect pattern is discovered in every state, it is reasonable to employ it as the strongest reference for defect monitoring. On the other hands, if a certain defect pattern is extracted from only a fault state, it is not reasonable to employ it as a reference defect patterns solely for every defect state. But we should not neglect it since defect can occur by various root causes and this defect pattern can represent a root cause of minor defect. Therefore, it is reasonable to employ a set of the whole extracted defect patterns for defect deflection, but give a commensurate with its frequency of occurrence as a weight.

The importance level of a defect pattern is devised as the above weight, in order to estimate the effect of defect patterns quantitatively. Algorithm 1 is the procedure to compute the importance level for each defect pattern. Because it is measured in proportional to the number of defect pattern occurrence in every state, the higher value means a particular defect pattern is discovered in as many as defect state, it consequently can be interpreted as a significant pattern. In case of a recurring same defect patterns repetitively in a defect state, it is counted as once because they describe same defect states. In addition, for effective compression among defect pattern, the importance level is also normalized by

dividing the number of defect pattern occurrences in a set of defect states into the total number of defect states.

Figure 2 illustrates the computing procedure of importance level of defect patterns. First defect pattern, $[l_{12} \ l_{21} \ l_{31}]^T$, has the highest importance level (= 1.00) than others, because it is found in every defect state. Last two defect patterns have the smallest importance level (= 0.25), but the value is larger than 0 because a defect pattern should be discovered at least one defect state.

Algorithm 1. Importance level of a defect pattern

Require: \mathbf{F}^P (a set of defect patterns), $\mathbf{D}(\mathbf{X})$ (multivariate discretized time series), \mathbf{F}_q^P (a set of defect patterns during q^{th} defect state), f_{sum} (the number of defect states)

- 1: **for** $r = 1 : |\mathbf{F}^P|$ **do**
- 2: $i((\mathbf{F}^P)_r) \leftarrow 0$ // Importance level of r^{th} defect pattern
- 3: **for** $q = 1 : f_{sum}$ **do**
- 5: **if** $(\mathbf{F}^P)_r \in \mathbf{F}_q^P$
- 6: $i(\mathbf{F}_q^P) + +$
- 7: **end if**
- 8: **end for**
- 9: $i((\mathbf{F}^P)_r) \leftarrow \text{Normalized}(i((\mathbf{F}^P)_r), f_{sum})$
- 10: **end for**

2.3. The Severity Degree of a Defect state

Although many defect states are given, each defective system will assign different severity level such as critical, major, minor, warning, and indeterminate. Assigning severity degree is also important for finding optimal maintenance action, scheduling repair procedure, and further root cause analysis (Goyal & Pabla, 2015). Therefore, we also introduce the severity level of a defect state.

If various defect patterns are discovered from a defect state, it is reasonable to consider the target system more hazardous. Similarly, if a defect pattern is constantly found during a defect state, the defect state can be treated as more severe one. Considering both characteristics, the severity degree is calculated by dividing the number of occurrence of defect patterns in a defect state into the number of discretized state vectors in a defect state, and Algorithm 2 explains minutely how to measure the severity degree of each defect state.

For example, as Figure 2 also shows, the length of first defect state is quite longer than others, but only one defective pattern, $[l_{12} \ l_{21} \ l_{31}]^T$, is found. On the other hand, the largest number of defect patterns, 4 patterns (i.e., $[l_{13} \ l_{21} \ l_{32}]^T$, $[l_{12} \ l_{23} \ l_{31}]^T$, $[l_{13} \ l_{22} \ l_{32}]^T$ and $[l_{12} \ l_{21} \ l_{31}]^T$), is found from third defect state. According to

the number of defect pattern occurrences in each defect state, third state (= 0.80) gets a higher severity degree than first (= 0.17) state. In case of first and second state, an identical defect pattern $[l_{12} \ l_{21} \ l_{31}]^T$, is only extracted respectively. Since the defect pattern occurs three times consecutively at second state, whereas it appears once at first state, the severity of second state (= 0.60) is much higher than first one. From now, discretized state vector is written as last number of each element ($[l_{12} \ l_{21} \ l_{31}]^T$ is written as [2 1 1])

Algorithm 2. Severity degree of a defect state

Require: \mathbf{F}^P (a set of defect patterns), $\mathbf{D}(\mathbf{X})$ (multivariate discretized time series), \mathbf{F}_{time} (the information of defect states' length), f_{sum} (the number of defect states)

- 1: **for** $q = 1 : f_{sum}$ **do**
- 2: $\mathbf{F}_q^P \leftarrow \text{dsv_in_a_fault_state}(\mathbf{D}(\mathbf{X}), \mathbf{F}_{time}^q)$ // separate discretized state vector in a specific defect state from multivariate discretized time series
- 3: $s(\mathbf{F}_q^P) \leftarrow 0$ // Severity degree of q^{th} defect states
- 4: **for** $r = 1 : |\mathbf{F}_q^P|$ **do**
- 5: **if** $(\mathbf{F}_q^P)_r \in \mathbf{F}^P$ // $(\mathbf{F}_q^P)_r$ is r^{th} defect pattern in \mathbf{F}_q^P
- 6: $s(\mathbf{F}_q^P) + +$
- 7: **end if**
- 8: **end for**
- 9: $s(\mathbf{F}_q^P) \leftarrow \text{Normalized}(s(\mathbf{F}_q^P), |\mathbf{F}_q^P|)$
- 10: **end for**

3. EXPERIMENTAL RESULTS

The introduced analysis is conducted to detect defective car trims which have the potential to generate negligibly weak noise, but noticeably annoying noise (Cook & Ali, 2012). It is defined as Buzz, Squeak, and Rattle (BSR) noise and it usually caused by the unexpected contacts between car parts because of incomplete assembly or poor geometrical design according to Chen and Trapp (2012). These noises are characterized by intermittent, very short and small change, and non-stationary random signals. Therefore, we apply the proposed approach to two different monitoring datasets, for in-process BSR-noise detection, and conduct further defect states' severity degree and defect patterns' importance level.

3.1. Dataset Collected from a Typical Acoustic Sensor Array (Data set #1: Acoustic Sensor Array)

The entire sensor signals are collected from the experimental system which Baek et al. (2017) developed for the in-process

BSR-noise detection adopted from general fixed noise evaluation test as Figure 3. A pneumatic pusher applied pressure to a car door trim lying on the system, and 13 acoustic signals are recorded by microphones. 9 sensors are mounted inside of the system for the sake of inside noise, whereas 4 sensors are located at four outside of the system to obtain outside environmental noises such as shop floor noises.

If the pusher gives pressure to the target car door trim and a noticeable sound occurs that are loud enough to experimental hear, then the target is treated as defect state. On the other hands, the dataset for the door trim is considered as normal state. From when the pusher’s pressurization begins, Sensor signals are recording for about 2 second at a sampling rate of 32,768 Hz. Total 60 normal states and 40 defect states are obtained respectively. Since sound signal oscillates up and down quite symmetrically, it is not easy to catch the change of mean value in original signals. Thus, absolute values of original sensor signals are applied to defect pattern extraction.

According to Figure 4, there are various sensor signals’ behaviors from normal states. Whereas weak stationary signals are discovered from 11th car door trim, impulsive changes which are like defect states are also found from 14th car door trim. In case of defect sates, there are different background noise level between 21st and 39th car door trims. That is, the assumption, “The far the statistical or geometrical distance from the normal states, the more likely it is considered as a defect state” is not always reasonable in this dataset #1.

As Table 1 is described, total 47 defect patterns are extracted from 40 defect states, the set of defect patterns can explain every defect state. On the other hands, four discretized state

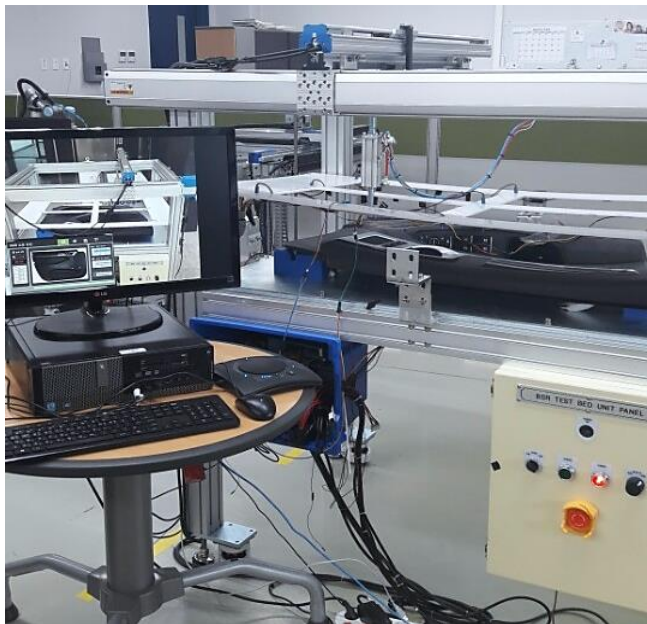


Figure 3. In-process BSR-noise detection system which constructed by Baek, Kim, and Ceglarek (2017)

Table 1. Summary of a set of extracted defect patterns and their importance level from data set #1

#. Defect pattern [A corresponding discretized state vector]	#. Discernible defect state	Importance level
Defect pattern 1 [4 3 3 4 4 3 4 3 4 4 4 4 4]	20, 22, 24, 27, 28, 29, 30, 32, 35, 38	0.25
Defect pattern 2 [4 3 4 4 4 3 4 4 4 4 4 4 4]	19, 23, 31, 36	0.10
Defect pattern 3 [4 3 4 4 4 4 4 4 4 4 4 4 4]	9, 12	0.05
Defect pattern 4 [4 3 4 4 4 4 4 4 3 4 2 2 4]	28, 35	0.05
Defect pattern 46 [3 2 2 3 3 3 4 3 4 4 3 4 4]	6	0.03
Defect pattern 47 [3 2 2 3 3 2 4 3 4 4 3 4 4]	2	0.03

vectors, which represents normal states (i.e., normal patterns), are extracted. It is interpreted that signals during normal states are relatively stationary than those during defect states.

Important levels of defect patterns are measured from 0.03 to 0.25. The strongest defect pattern can describe 10 defect states, whereas 33 weakest defect patterns are discovered at only one defect state. As Table 1 shows, relatively lower importance levels of all extracted patterns can be interpreted as consisting of root causes that have minor effects, not a single major root cause. That is, many defect patterns have been extracted means there are various root causes of BSR defect states. In fact, even a single BSR noise can be caused by various causes in a car door trim, because a certain part is attached to several parts, it can suffer multiple collisions. Also, the more we conduct experiment to the target, the more aging occur, thus it is also possible that every defect pattern can indicate different root causes.

Several defect and normal patterns are illustrated as Figure 5, to investigate their difference in terms of signal’s behaviors. We can know, from Table 1 and Figure 5, that the Euclidian distance between a specific defect pattern and normal patterns is not accurately corresponding to importance level of the defect pattern. For example, defect pattern 47 is more far (=3.87) from the mean of normal patterns than defect pattern 1 (=1.16), but the importance levels of two defect patterns are vice versa (i.e., 0.03 for defect pattern 47 whereas 0.25 for defection pattern 1).

In case of severity degree of defect states, as Table 2 shows, maximum severity degree is 0.2 and assigned to 31 defect states. Remaining 9 defect states have 0.1 severity degree.

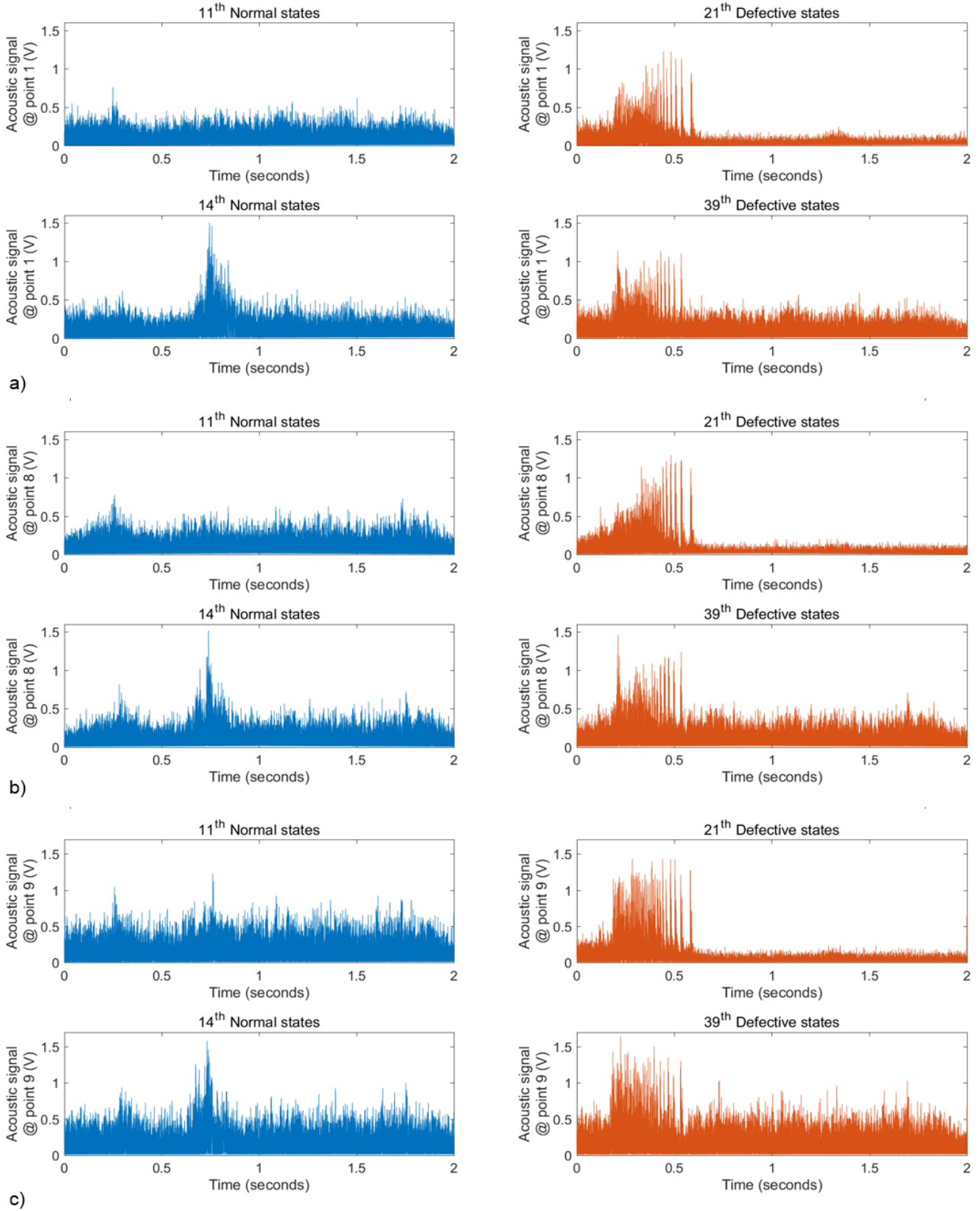


Figure 4. Acoustic sensor signals monitored at three positions from normal(blue) and defective (red) states: (a) at the inside bottom right corner (b) at the inside top center corner, and (c) at the left outside of the system.

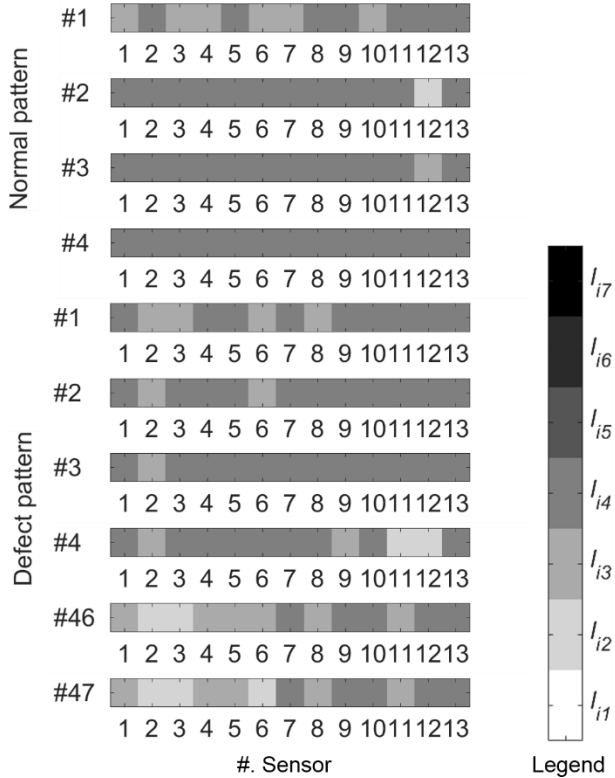


Figure 5. Examples of 6 defect and 4 normal patterns which are described as a shape of discretized state vector from dataset #1: a darker color means a value corresponding to each sensor is larger.

Table 2. Severity analysis of defect states for dataset #1.

#. defect state	Severity degree
State 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 19, 20, 22, 23, 24, 27, 28, 29, 30, 31, 32, 34, 35, 36, 37, 40	0.20
State 16, 17, 18, 21, 25, 26, 33, 37, 39	0.10

Since a BSR noise occurs only a specific short time period during recording time, not in an entire defect state, a lot of normal and defect patterns are mixed in a defect state. Therefore, all defect states show similar severity degree (from 0.1 to 0.2), since all defect states are collected from a single car door trim.

3.2. Dataset Collected from Acoustic Emission Sensors (Data set #2: Acoustic Emission Sensor)

According to Qu, Bechhoefer, He, and Zhu (2013), vibration-based signals, such as accelerometer or microphone, have a difficulty to detect incipient anomaly with low frequency

range. They suggested acoustic emission sensor signals which has a strength to investigate various cracks and closures, since it is used to measure the behaviors under internal stress (Niknam, Thomas, Hines, & Sawhney, 2013). In consideration of these characteristics, the environment setup for data collection is designed as follow; a target car door trim is laid on the test bench, and 4 acoustic emission sensors are attached on the target. Background noise is always played toward the target.

Defect was artificially caused by unscrewing a specific screw, because incomplete fastener assembly is one of major BSR root causes (Chen & Trapp, 2012). Then collected raw signals, at a sampling rate 100Hz, are converted into time-based features (*i.e.*, Average Signal Level (ASL), Root Mean Square (RMS), and absolute energy) to monitor defect states. That is, three signals from a sensor is obtained and the total number of monitored signal is 12 per a state. 24 normal states and 24 defect states from two type of car door trims and four unscrewing points are finally analyzed.

Despite the environmental noises, acoustic emission signals (Figure 6) shows quite clear behaviors than conventional sound signals (Figure 4). Every signal changes as if there seems to be a regular cycle, and behaviors of three signals are dynamic and nonstationary regardless of normal and defect states. That is, it is not straightforward to develop a statistical control limit for classifying normal and defect states.

As a result, 31 defect patterns are extracted, and a set of extracted defect patterns make every defect state discernible. That is, any defect state of dataset #2 is explained by a set of

Table 3. Summary of a set of extracted defect patterns and their importance level from data set #2

#. Defect pattern [A corresponding discretized state vector]	#. Discernible defect state	Importance level
Defect pattern 1 [4 4 3 4 4 3 4 4 4 4 4 1]	3, 11, 12, 20, 21	0.21
Defect pattern 2 [4 4 3 4 4 2 4 4 4 4 4 1]	1, 2, 4, 6, 14	0.21
Defect pattern 3 [4 4 2 4 4 2 4 4 4 4 4 1]	5, 13, 15	0.13
Defect pattern 4 [4 6 4 6 6 4 6 4 4 6 6 4]	23, 24	0.08
Defect pattern 30 [2 3 1 4 4 3 4 4 4 4 4 4]	13	0.04
Defect pattern 31 [2 3 1 4 4 2 4 4 4 4 4 4]	13	0.04

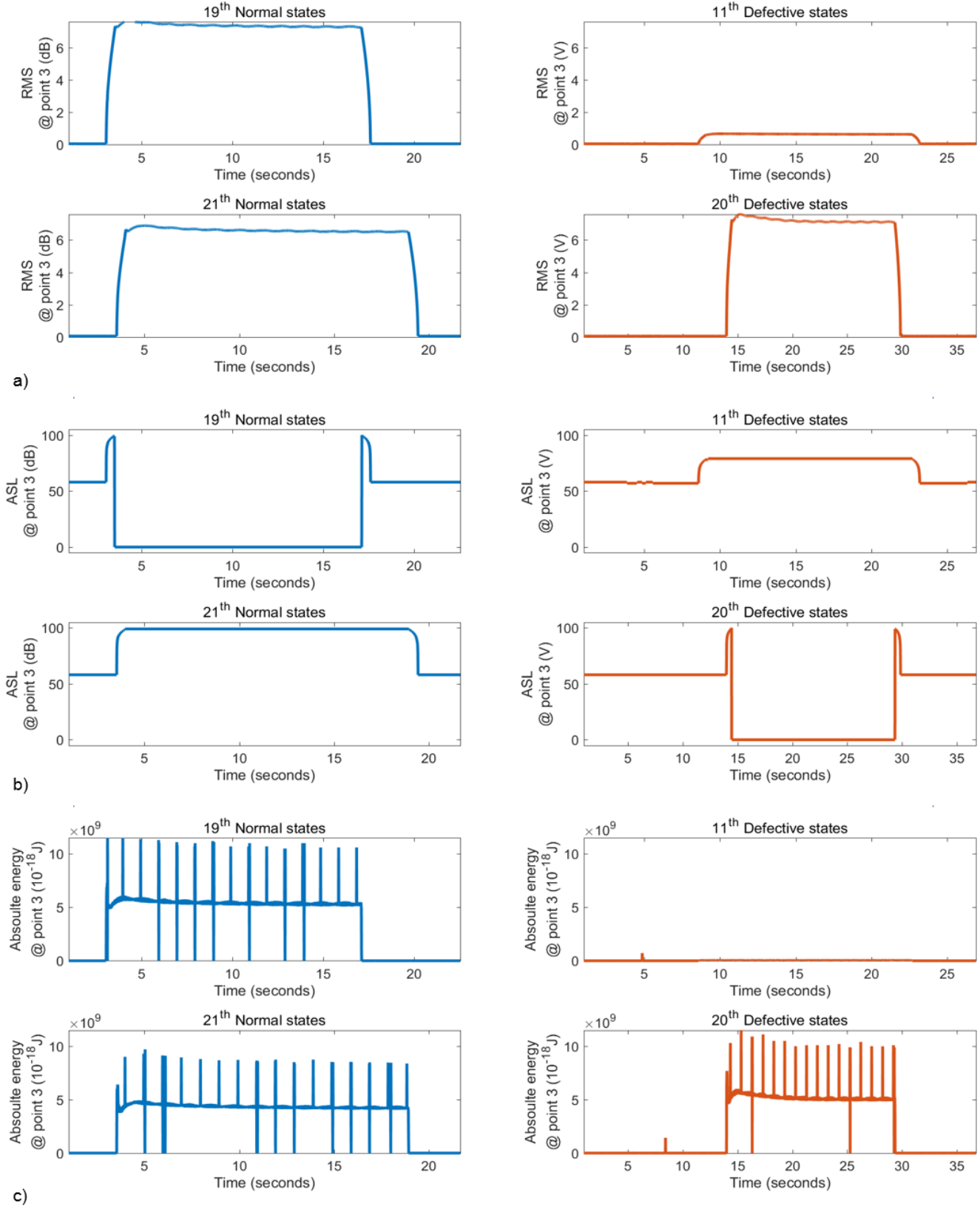


Figure 6. Three signals from acoustic emission sensor at 3rd point from normal (blue) and defective (red) states: (a) Root mean square, (b) Average signal level, and (c) absolute energy.

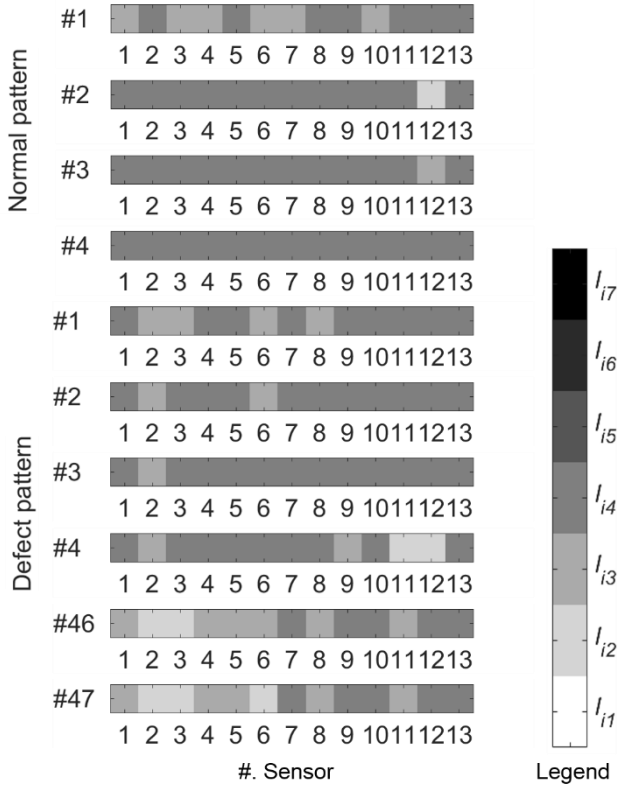


Figure 7. Examples of 6 defect and 4 normal patterns which are described as a shape of discretized state vector from dataset#2: a darker color means a value corresponding to each sensor is larger.

defect patterns. In case of normal states, 44 discretized state vectors are extracted. That is, sensor signals' shows time-variant and non-stationary behaviors in both normal and defect states, as Figure 7 is illustrated.

There are also powerful two defect patterns which has higher importance level (=0.21) than others (See Table 3). They are discovered in 5 defect state respectively. In addition to the small number of defect pattern than that of normal pattern, the set of extracted defect pattern shows relatively small. It is also investigated a mean and a maximum value of Euclidean distance between patterns in either normal (=4.18 and 9.00) and defect states (=4.47 and 8.49) respectively. Since the Euclidean distance between mean the values of normal and defect patterns (=1.34) is even smaller than maximum distances of each pattern group, that is many normal patterns appear in defect states.

In Table 4, Among 24 defect states, two states show much higher severity degrees (=0.63, and 0.57 respectively), and thus they are interpreted as more broken car door trim. On the other hands, the state 1 is considered as most powerless defect state (=0.08). Artificial defect generation, by four different unscrewing points and at two different car door trim, makes relatively large difference in severity degree.

Table 4. Severity analysis of defect states for dataset #2.

#. defect state	Severity degree
State 21	0.63
State 7	0.57
State 13, 16, 17, 18, 23	0.38
State 10, 11, 12, 22, 24	0.29
State 14	0.25
State 3, 20	0.20
State 6	0.18
State 4, 5, 8, 15, 19	0.13
State 2, 9	0.11
State 1	0.08

4. CONCLUSION

For effective defect detection, we analyze defect state in terms of state's severity. The severity degree of a defect states is computed by how many defect pattern makes a defect state discernible considering diverse broken degree of each defect states. That is, the more defect patterns are found, the more severe the defect state is determined as. Defect pattern is defined as the discretized state vectors which is found only in defect states, not in normal state. Discretized state vector is extracted from multivariate time series of sensor data by the previous proposed multivariate discretization method. Regarding various root causes, every extracted defect pattern is employed, and thus we estimate an importance level of each defect pattern in proportional to their occurrence in all defect states. If the defect pattern is discovered from as many as defect states, it has high availability to explain many defect states, finally it is interpreted as an informative indicator for defects.

In order to demonstrate the effectiveness of the proposed defect state and defect pattern analysis, two datasets are analyzed to detect defective car door trims which generate BSR-noises. The proposed method successfully discovered a set of defect patterns for each data sets which can be employed as references for defect detection of BSR-noises. Defect states' severity and defect patterns' importance are calculated, and they will be further used as the estimator of probability of defect occurrences for online detection.

There are several further studies for improving this works: 1) to investigate relationships among severity degree, importance level, and physical root causes of defects , 2) to develop a similarity measure with regard of characteristics of discretized state vectors for online monitoring, and 3) to discuss on relationships between the two proposed indicators

and the performance of sensor data in identical detection problem, for example which sensor data are more suitable for in-process BSR-noise detection either traditional microphone sensor array or acoustic emission sensor.

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