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Effective method for screening discharged battery using support vector machine and high-resolution acoustic analysis

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Abstract

Alkaline dry batteries and nickel-metal hydride (NiMH) rechargeable batteries are used worldwide for various portable devices that require continuous current. Nevertheless, visual verifying such a battery as discharged or not remains as difficult checking a watermelon for ripeness. Although one can detect a dead battery using a battery indicator, such a useful tool is not always available. Therefore, a simple and intuitive means of ascertaining whether a battery is dead or not must be found to avoid problems such as battery leakage. In our previous work, we proposed an acoustic analysis based method for estimating the discharge state of an alkaline dry battery: a hammering test method can screen dead batteries by analyzing the tone color of the tapping sound. In this report, we propose a more effective method and apply it to NiMH rechargeable batteries. To improve the decision accuracy, we also employ a support vector machine (SVM) and super high-resolution recording system, which can obtain sound up to 100 kHz. Our experimentally obtained results suggest that the proposed method can provide effective screening.

Keywords: Battery, Nondestructive inspection, Hammering sound, inaudible sound, Support vector machine

1 INTRODUCTION

In recent years, demands for alkaline dry batteries and rechargeable batteries has increased especially in emerging countries. It is generally difficult, however, to check whether they are dead (less than about 1.0V) or not. Although we can surely infer their residual quantity if we use a battery indicator, it is an unusual device in daily life. If a dead battery is misapplied, it sometimes causes safety problems such as breakdown of equipment. Therefore, it was necessary to find the simple and intuition way to screen whether present battery is dead or not to avoid these problems.

To overcome these problems, in our previous study, we proved that the alkaline dry batteries can be screened just by tapping them and listening to its sound[1]. However, despite the fact that rechargeable batteries are widely used all over the world, the method we proposed was not enough effective to screen rechargeable batteries. Thanks to the development information and communication technology in recent years, more devices can analyze high tone which is hard or impossible for human to hear (it is called “inaudible sound” in this research; generally higher than 20kHz) at a high resolution. For example, some smart phones can record and play sounds on the 192kHz/24bits system.

In our previous studies, it was found that the more improved sampling rates the less noise floor level, therefore it is worth analyzing acoustic architecture in high-frequency band that is generally small amplitude with high resolution.

Therefore, we research and analyze hammering sound of rechargeable batteries including inaudible sound to screen them for finding out dead one by a new procedure. To estimate the possibility of classifying remain of rechargeable batteries using hammering sound, in this study, we evaluated the accuracy of SVM trained by hammering sound of them including inaudible sound.

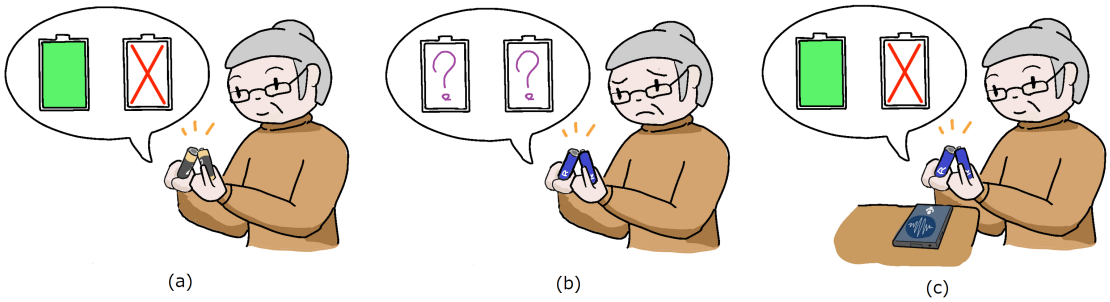

Figure 1. (a) Remains of alkaline dry battery can be discriminated by listening its tapping sound; (b) Remains of NiMH rechargeable battery can not be discriminated by only listening its tapping sounds; (c) It can be discriminated by classifier which can analyze its tapping sound

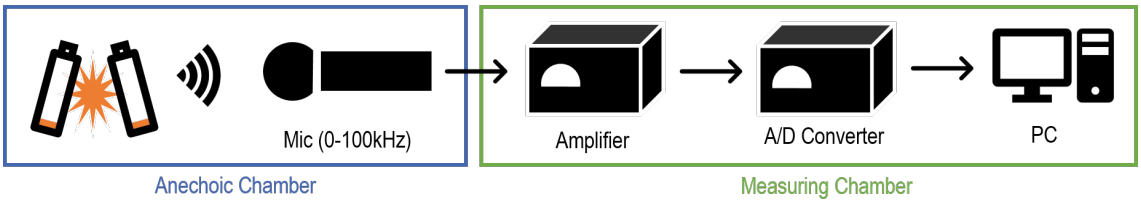

Figure 2. Details of 768kHz/32bit super-high-resolution recording system

2 EXPERIMENTAL METHODS

2.1 Support vector machine

SVM) is the one of the classifier which has high classification ability [2, 3, 4, 5]. Define $(\boldsymbol{x}_i, y_i)_{i\in[n]}$ as n train data, where $\boldsymbol{x}_i \in \mathbb{R}^d$ is d-dimensional real vector and $y_i \in \{-1,1\}$ is label for $\boldsymbol{x}_i$, and decision function as $f(\boldsymbol{x}) = \boldsymbol{w}^{\mathsf{T}}\boldsymbol{x} + b$. The optimization problem to evaluate classification boundary which is given by $f(\boldsymbol{x}) = 0$ is expressed as:

$$\begin{aligned} &\min_{\boldsymbol{w},b,\boldsymbol{\xi}} \|\boldsymbol{w}\|^2 + C\sum_{i\in[n]} \xi_i \\ &\text{s.t.} y_i(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{x} + b) \geq 1 - \xi_i, i \in [n] \\ &\quad \xi_i \geq 0, i \in [n] \end{aligned} \tag{1}$$

where ξ indicates the slack variables and C shows regularization parameter which is one of the hyper parameters of this model. Larger C means less classification error and less computational complexity. In case the data has a complex distribution, data need to be mapped to higher dimensions by kernel function to solve the optimization problem. To generate simpler model, in this research, homogeneous polynomial function was used as kernel function which is expressed as:

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \gamma(\boldsymbol{x}_i \cdot \boldsymbol{x}_j) \tag{2}$$

where γ indicates kernel parameter and polynomial order [6]. This is another hyper parameters of this model. The performance of this model is determined by these two hyper parameters. To find the best hyper parameters, there are two searching methods: grid search and Bayesian optimization. Grid search is the full search while Bayesian optimization is the searching method by maximization acquisition function [7]. The model which is

trained on each combination of hyper parameters are evaluated by k-fold cross validation. The performance of the model which is trained on best combination ow hyper parameters is evaluated by how test data set is classified correctly by this model.

2.2 The super-high-resolution recording system

The details of super-high-resolution recording system are as follows: the system is in the radio/acoustic anechoic room and there is equipment such as the microphone, the amplifier, the A/D converter and the computers as shown in the figure 2 [8]. The wall of the radio/acoustic anechoic room consist of radio wave absorber and sound wave absorber. These architectures contribute for reducing level of reflections on the wall and avoid multi-path phasing. Hence purer sound is able to be collected there. The noise floor in this room and indicates that there is about -12 dB at the lowest in analyzable band thanks to the noise shaping. The analyzable frequency band is from about 20 Hz to about 100kHz because of the nominal value of the microphone in this system. Therefore, the system is enough to analyze acoustic structure in inaudible range and high dynamic range.

2.3 Hammering methods

The hammering test method is one of the non-destructive inspections to judge internal condition by the response generated by hitting with something such as a hummer. In Japan, for example, this method is used for maintaining concrete structure. As a similar example in daily life, whether a watermelon is ripe or not [9] and whether a clam is dead or not [10] are able to be discriminated by this method.

In our previous works, it was proved that also whether an alkaline dry battery is dead or not can be estimated by this method because of the fact that physical organization of discharged alkaline dry battery is denser than not discharged one while they are about same appearance and weight. To avoid mixing excessive sounds when they are hit each other and to consider practical using, in this study, we compared with the sounds generated by hitting discharged or not batteries each other.

2.4 Learning and evaluation

We analyzed ten rechargeable batteries as samples. Five of them are fully charged rechargeable batteries (group F: F0 to F4) and the others are completely discharged ones (group E: E0 to E4). “eneloop (Panasonic)” was used as sample rechargeable batteries in this research. The hammering sounds of F0 vs. F1 to F4 and E0 vs. E1 to E4 were collected for each fifteen times for each combination by hand. The reason why the hammering sounds were collected by hand is to package the classifier as an application in the future. They were standardized to have same energy; then amplitude frequency characteristics were gotten by FFT. Audible band (0 to 20 kHz) and inaudible-included band (0 to 100kHz) of these frequency characteristics was separated by each ΔF kHz, $\boldsymbol{x}^i_{20}$ and $\boldsymbol{x}^i_{100}$ $i \in [n]$ were defined as attribute vectors, or train data, given by energy of each band, where ΔF was shown in Table. The objective SVM model was trained by ten of training data-set of each battery (F1 to F4, and E1 to E4) as in the previous section, where both of C and γ were from 10^{-3} to 10^3 and were equally divided into 30×30 logarithmic mesh grid, and the model of each point were evaluated by 5-fold cross validation; then the accuracy of obtained model was calculated by using the other five test data-set. Mean square error (MSE) was chosen as loss function in the optimization as $\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2$, where x_i is true value and $\hat{x}_i$ is observed value.

Table 1. The relationship between ΔF and $\boldsymbol{x}^i$

ΔF (kHz)	0.1	0.2	0.25	0.5	1	2	4	5	10	20	50
Dimension of $\boldsymbol{x}^i_{20}$	200	100	80	40	20	10	5	4	2	1	*
Dimension of $\boldsymbol{x}^i_{100}$	1000	500	400	200	100	50	25	20	10	5	2

3 RESULT AND DISCUSSION

3.1 Analysis of hammering sound in each state

Figure 3 shows features of examples of hammering sound. It is assumed that it is hard to differentiate their remain by their hammering sound because frequency-amplitude characteristics of discharged one resembled fully charged one.

3.2 Relationship between attribute and model's accuracy

The results of grid search, Bayesian optimization search and confusion matrix which shows the performance of each optimized model given by classification of test data-set are shown as figure 4, figure 5 and 6. The following about how to train SVM model which has high generalization ability for screening rechargeable batteries were found from these figures. First, it was shown in comparing each b-5 and b-9 of figure 4 to 6 that higher frequency resolution benefits higher generalization ability. Second, it was shown in comparing a-6 and b-6 of each figure that training with wider frequency analyzing including inaudible sound benefits higher generalization ability in condition under the same frequency resolution. Third, it was shown in comparing a-5 and b-5 of each figure that if the same dimension attribute vectors were used, high accuracy can be obtained only trained in the audible range.

4 CONCLUSION

In this study, we proved that the residual quantity of rechargeable battery is able to be almost correctly determined by SVM model which is trained by their hammering sound. That is, it was concluded that the classifier which has high accuracy can be obtained by training the sounds in wide frequency band and high frequency resolution. Thanks to the development of the information and communication technology, studies of machine learning for any sound have prospered nowadays. Because of the same reason, the frequency band of recording and playing devices become wider and wider.

Furthermore, in recent years, the demand for rechargeable batteries has increased in developed countries to solve environmental problems. Therefore, we believe that this research will be the basis of further research for the classification method employing high resolution sound and machine learning in the future.

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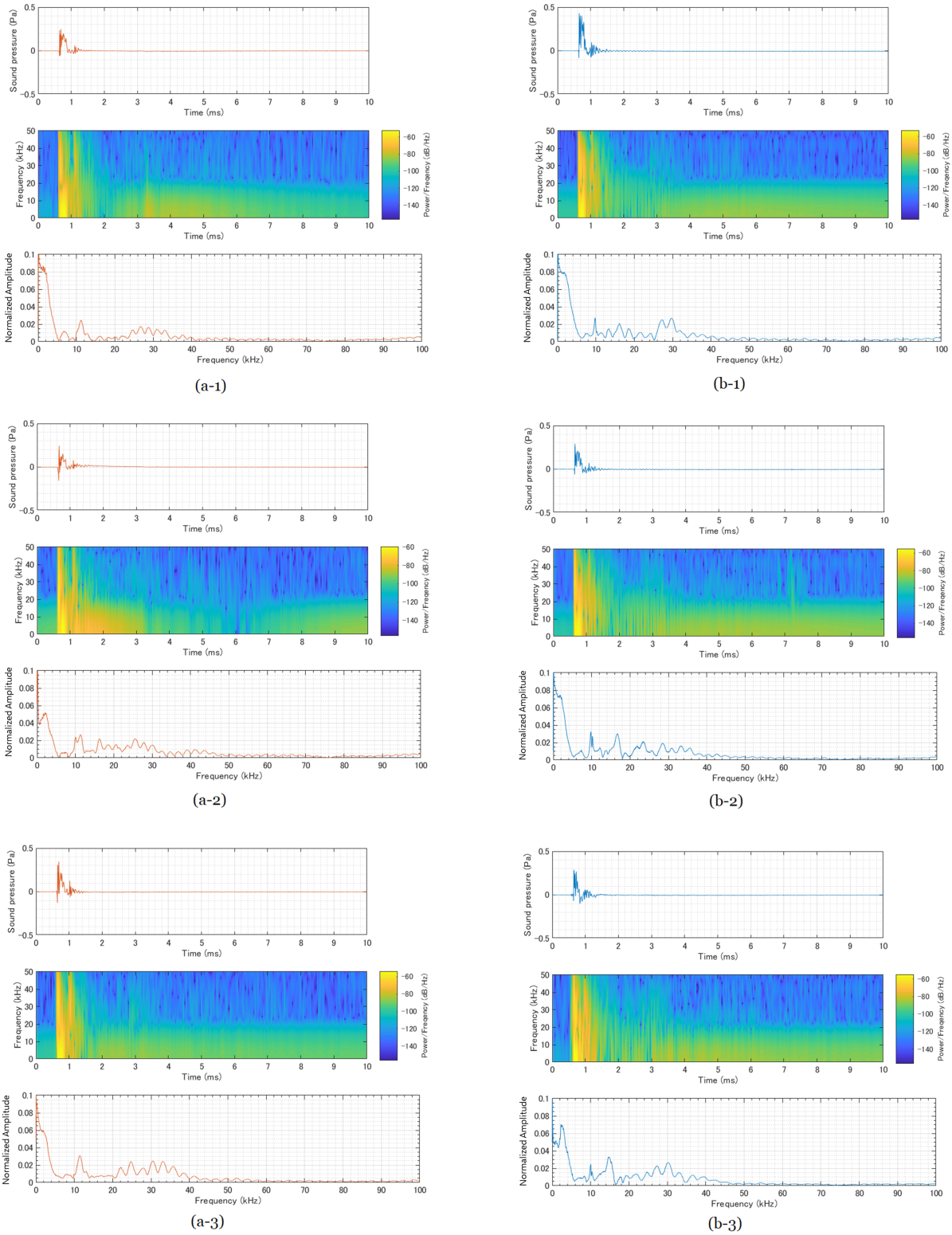


Figure 3. Details of examples of hammering sound: sound pressure signal (top), spectrogram (middle), and amplitude frequency characteristic (bottom). (a-1,2,3) and (b-1,2,3) in the figure show that the result of analysis of the hammering sound of discharged one and charged one

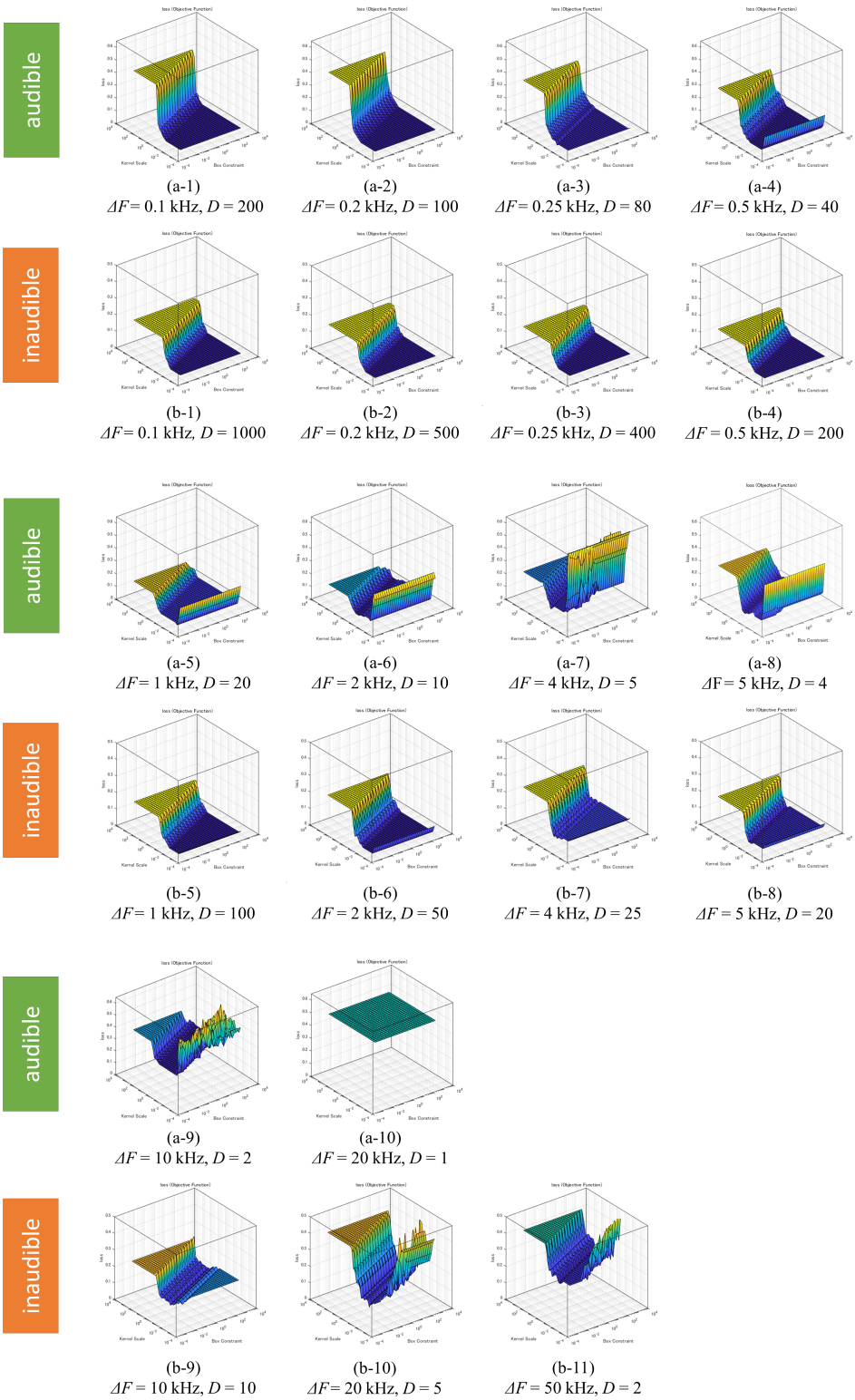
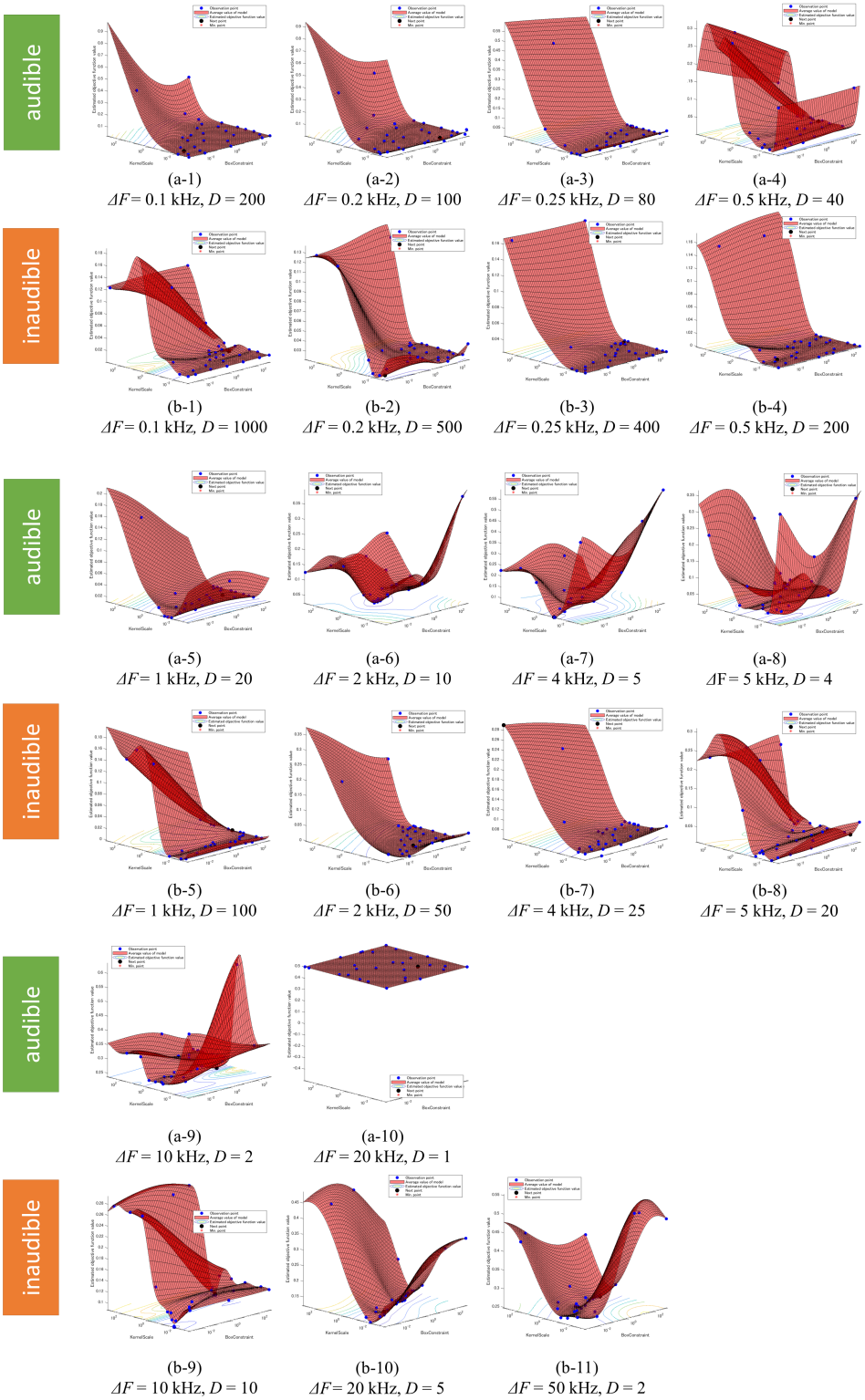


Figure 4. The result of grid search of each model. ΔF and D means band width for separating frequency amplitude characteristics and dimension of attribute vector, $\boldsymbol{x}^i_{20}$ and $\boldsymbol{x}^i_{100}$ $i \in [n]$



(a-1) $\Delta F = 0.1$ kHz, $D = 200$
(a-2) $\Delta F = 0.2$ kHz, $D = 100$
(a-3) $\Delta F = 0.25$ kHz, $D = 80$
(a-4) $\Delta F = 0.5$ kHz, $D = 40$
(b-1) $\Delta F = 0.1$ kHz, $D = 1000$
(b-2) $\Delta F = 0.2$ kHz, $D = 500$
(b-3) $\Delta F = 0.25$ kHz, $D = 400$
(b-4) $\Delta F = 0.5$ kHz, $D = 200$
(a-5) $\Delta F = 1$ kHz, $D = 20$
(a-6) $\Delta F = 2$ kHz, $D = 10$
(a-7) $\Delta F = 4$ kHz, $D = 5$
(a-8) $\Delta F = 5$ kHz, $D = 4$
(b-5) $\Delta F = 1$ kHz, $D = 100$
(b-6) $\Delta F = 2$ kHz, $D = 50$
(b-7) $\Delta F = 4$ kHz, $D = 25$
(b-8) $\Delta F = 5$ kHz, $D = 20$
(a-9) $\Delta F = 10$ kHz, $D = 2$
(a-10) $\Delta F = 20$ kHz, $D = 1$
(b-9) $\Delta F = 10$ kHz, $D = 10$
(b-10) $\Delta F = 20$ kHz, $D = 5$
(b-11) $\Delta F = 50$ kHz, $D = 2$

Figure 5. The result of bayesian optimizatio of each model. ΔF and D means band width for separating frequency amplitude characteristics and dimension of attribute vector, $\boldsymbol{x}^i_{20}$ and $\boldsymbol{x}^i_{100}$ $i \in [n]$

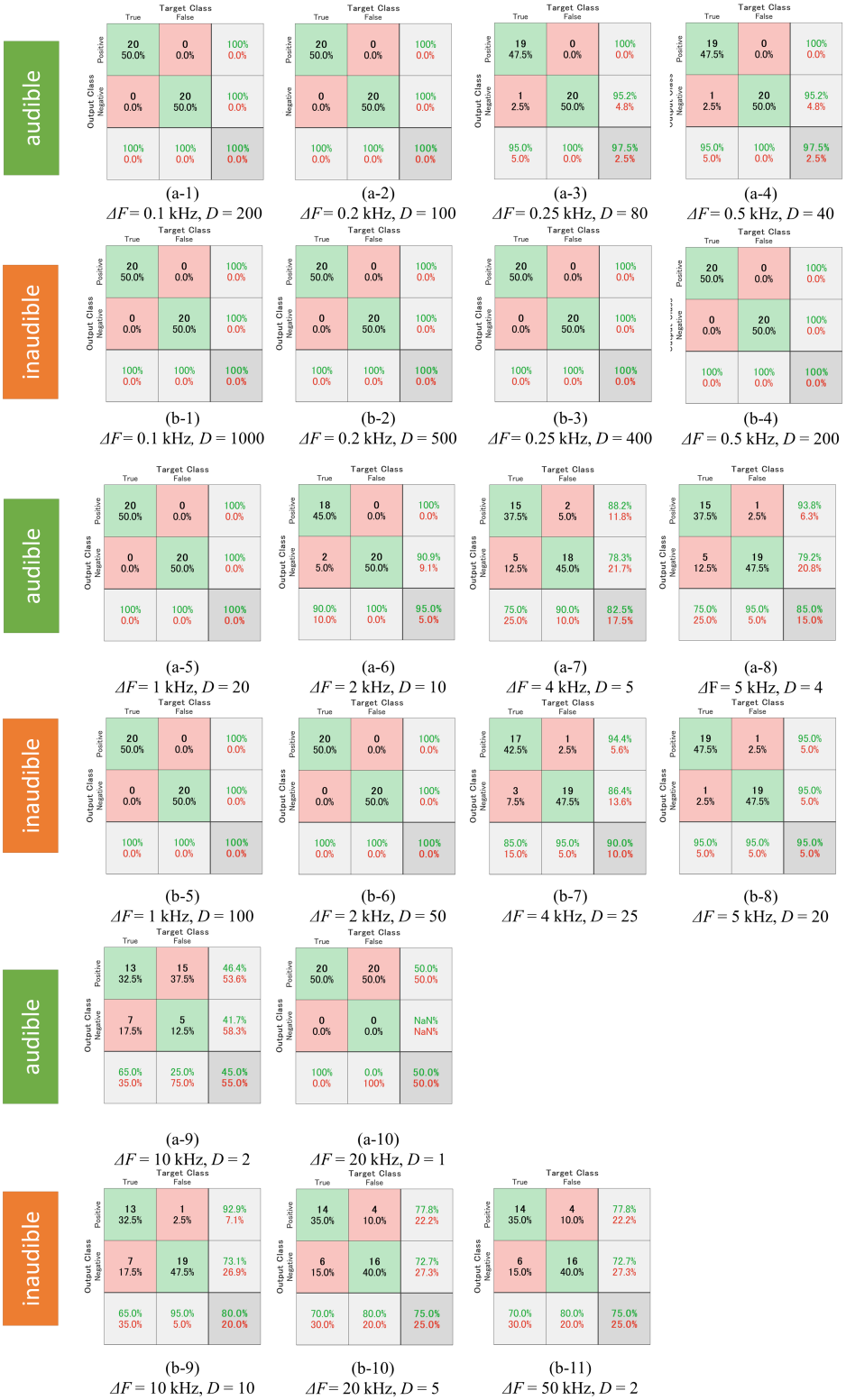


Figure 6. The confusion matrix of each model. ΔF and D means band width for separating frequency amplitude characteristics and dimension of attribute vector, $\boldsymbol{x}^i_{20}$ and $\boldsymbol{x}^i_{100}$ $i \in [n]$