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Machine Learning Based Metal Object Detection for Wireless Power Transfer Using Differential Coils

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Abstract. This paper presents the machine learning-based detection of foreign metal object for the wireless power transfer device including differential coils. To test the proposed method, the differential voltages are computed using finite element method for about 1500 cases with and without an aluminum cylinder at driving frequency of 85 kHz considering misalignment between the primal and secondary coils. It has been shown that gradient boosting decision tree and random forests classifier have the accuracy over 90% when input voltages and differential voltages are inputted together.

Keywords: wireless power transfer, metal object detection, differential coils, machine learning

1. Introduction

Electric vehicles (EV) are expected to spread rapidly in the background of serious environmental concerns. Wireless power transfer (WPT) has attained attentions for stationary and moving charging of EVs. Until now, many studies have focused on the designs of coils and magnetic cores for WPT aiming at increase in its power transfer efficiency [1, 2]. There is yet another important aspect for WPT, that is safety.

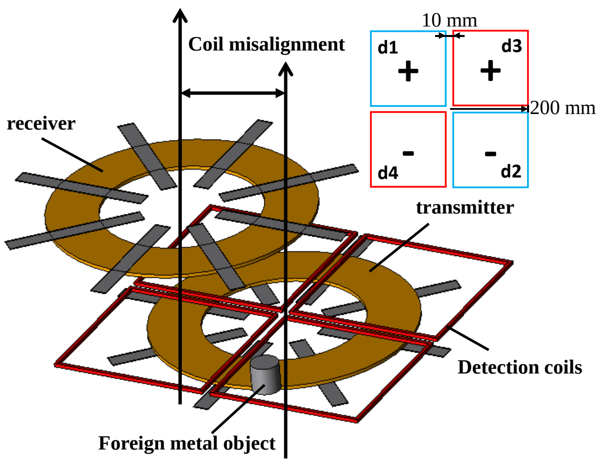
Many researchers have made effort in reducing the leakage flux generated by WPT exposed to persons [3]. Besides, it has been pointed out that the potential risk caused by foreign metal objects is also important. If any metallic objects such as can and key are exposed in the strong magnetic field generated by the WPT system, we would have dangerous electric discharge and fire accidents. For this reason, there have been the studies to realize metal object detection (MOD). Typically, additional detection sensors [4] or differential detection coils [5] are introduced to know the existence of the metallic objects. On the other hand, the authors have shown that MOD is feasible without using the detection coils if we introduce machine learning for classification of the frequency loci of the input impedance of the primary coil [6].

However, in [6], the effect of the magnetic core, which is used to increases the power transfer efficiency, on the detection system has not been considered. Moreover, the method proposed in [6] has been shown to be inaccurate for the loaded cases.

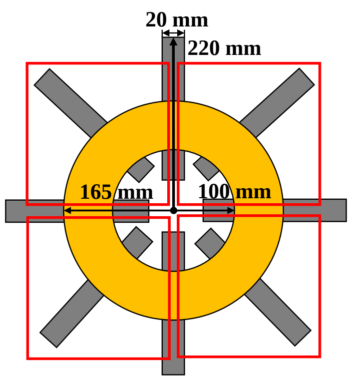
In this paper, we propose a new MOD based on machine learning, which judges if there are foreign metallic objects or not from the signals of the differential detection coils and input impedance of the primary coil. We consider the misalignment between the primary and secondary coil which would cause confusion signals to the detection coils and changes to the input impedance. We expect that this difficulty can be overcome by introducing machine learning that would identify the existence of the metallic objects from the input data. We compare the performance of support vector machine (SVM), naive Bayes classifier (NBC), gradient boosting decision tree (GBDT), and random forests classifier (RFC).

2. Simulation model

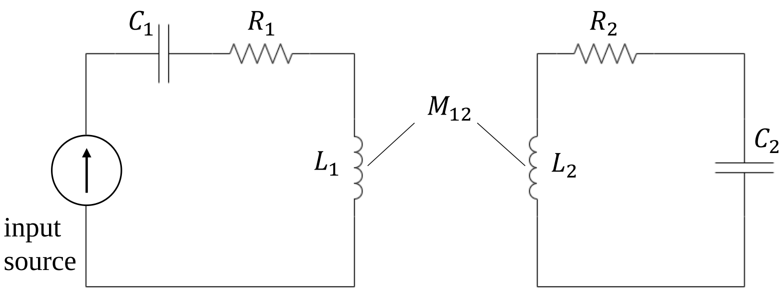
A WPT system that has resonance at 85kHz, driven by 1 A current source, is considered in the analysis. We consider the WPT device consists of the transfer coils shown in Figure 1.



(a) Structure of WPT and detection coils



(b) Size



(c) circuit model

Figure 1: WPT model

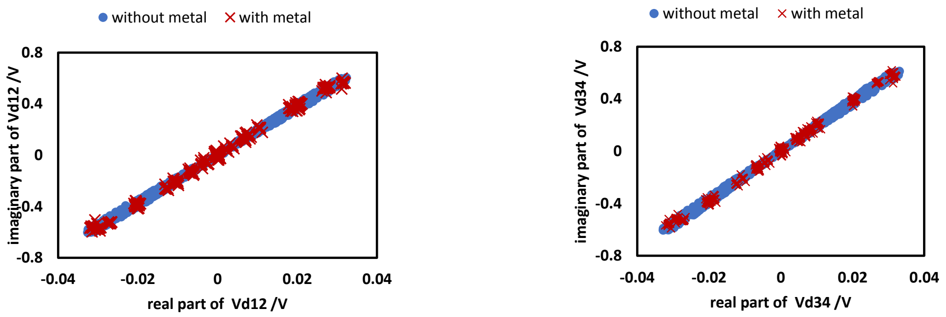
This system includes 1 mm-thick bar-shaped magnetic cores, relative permeability 3300, which increase the magnetic coupling between the primary and secondary coils. The gap between transmitter and receiver is 100 mm. We assume that two pairs of one-turn square detection coils shown in Figure 1 (a) are placed upon the transmitter. As illustrated in Figure 1 (a), two detection coils with opposite winding directions in diagonal position are connected to form pairs d1-d2 and d3-d4. All the coils in the model are assumed to have resistance of 1 Ω. The foreign metal object is assumed to be an aluminum cylinder of diameter 35 mm and height 35 mm. The load on receiver is set as short or 20Ω.

The idea of detecting metal object using differential coils is simple. When there is no misalignment on transmission coils and no metal object, the magnetic flux in each detection coil in a pair should be equal so that the induced voltages are totally canceled. In contrast, if there is a metal object in WPT system, it largely changes the magnetic flux of the closest coil, making the induced voltages in this coils pair different so that the induced voltage is not canceled. Moreover, misalignment between the transmission coils would also cause the net induced voltage. This makes the situation complicated because the induced voltage is affected from the foreign metallic objects and also the misalignment. To distinguish these effects, we introduce the machine learning methods.

3. Simulation results

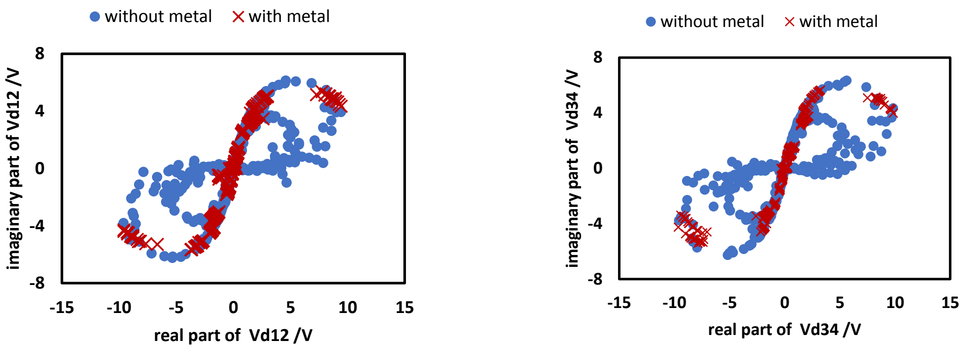
We assume that the coil-misalignment ranges from 0 to 80 mm in any direction, while the metal object is placed randomly within the space covered by the detection coils. In total, for the no-load condition where the receiver coil is shorted, we consider 901 cases with different coil misalignment and different position of the metal object, and 677 cases without the metal object to compute the induced voltage in the detection coils. Similarly, for load condition where 20Ω is connected to the receiver coil, 677 cases without metal and 625 cases with metal are simulated. We use JMAG® for the field computation, where the coil is modeled as a pancake instead of discretizing into the wires, under the assumption that the wire radius is sufficiently smaller than the skin depth. The eddy currents in conductors are considered in the field computation.

The differential induced voltage V_{d12} at 75, 85 and 100 kHz in the pair d1- d2 for the no-load condition are plotted in (a) of Figure 2, 3 and 4, where the horizonal and vertical axes represent the real and imaginary part of V_{d12}, respectively. The differential voltages V_{d34} for the pair d3-d4 is found to have the similar tendency as that for V_{d12}, as shown in (b) of Figure 2, 3 and 4. At 85 kHz that is the resonant frequency, when coil-misalignment is smaller than about 30 mm, the imaginary part of the differential induced voltages is relatively small, while the real part still changes obviously. At other frequencies, the differential voltages become smaller than those at the resonance. Moreover, the loci are linear in contrast to those at the resonance. It would difficult for humans to judge if there is a metallic object or not from the differential voltages. We employ the machine learning to which the differential voltages as well as the existence of the metallic object are input as the training data.



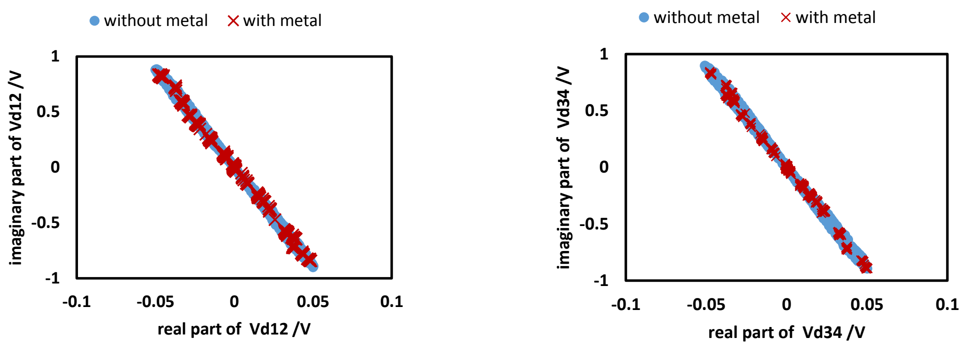
(a). pair d1-d2 (b). pair d3-d4

Figure 2: Differential induced voltages at 75 kHz for different cases



(a). pair d1-d2 (b). pair d3-d4

Figure 3: Differential induced voltages at 85 kHz for different cases



(a). pair d1-d2 (b). pair d3-d4

Figure 4: Differential induced voltages at 100 kHz for different cases

4. Proposed method based on machine learning

The proposed method judges the existence of foreign metallic objects through solving the classification problem with machine learning as shown in Figure 5. To construct the training data for machine learning, we compute the input voltage of the primary coil, which is equivalent to the input impedance since the system is driven by the current source, as well as the differential voltages of the detection coils pairs using finite element method. We train the classifier so that it makes correct judge of existence of metallic object from the input data. The data preparation and machine learning methods are described in detail below.

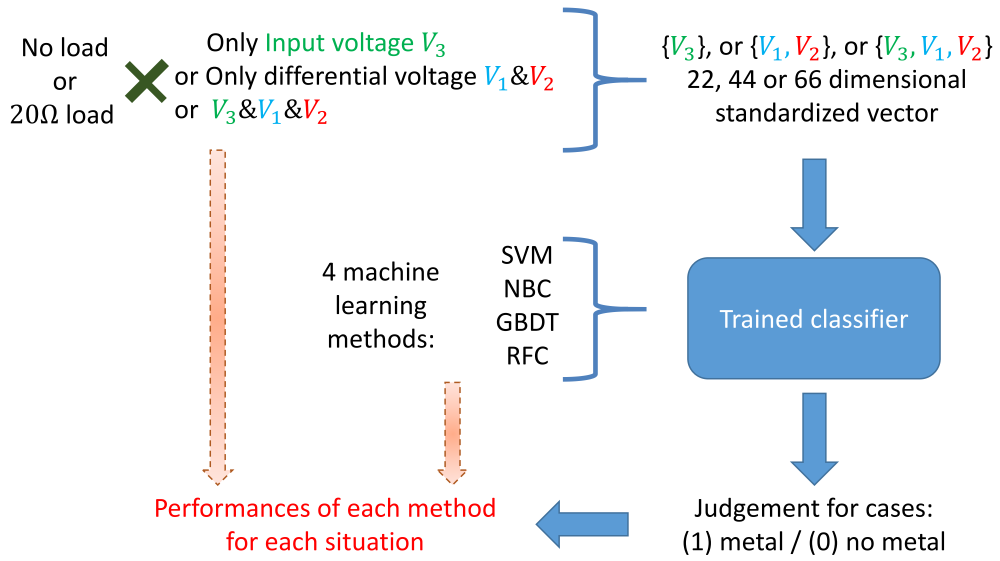


Figure 5: Process of proposed method

4.1. Data preparation

We compute the input voltage of WPT system, and differential voltages of two coil pairs at frequencies ranging from 75 to 100 kHz in equal 11 increments. Using this data, we construct three 22-dimensional vectors as followings:

$$\boldsymbol{V_1} = [u(1,1), \dots, u(1,11), v(1,1), \dots, v(1,11)\,] \tag{1}$$

$$\boldsymbol{V_2} = [u(2,1), \dots, u(2,11), v(2,1), \dots, v(2,11)\,] \tag{2}$$

$$\boldsymbol{V_3} = [u_{in}(1), \dots, u_{in}(11), v_{in}(1), \dots, v_{in}(11)] \tag{3}$$

where $\boldsymbol{V_1}$ and $\boldsymbol{V_2}$ consist of the real $u(i,j)$ and imaginary part $v(i,j)$ of the differential voltage of pair i at sampling frequencies identified by $j = 1,2, \dots, 11$. Moreover, $\boldsymbol{V_3}$ is composed of the real and imaginary part of the input voltage of the primary coil.

The classifiers are trained by these three vectors. For the machine learning methods, we employ here SVM, NBC, GBDT and RFC, described below, which are implemented by scikit-learn® [7] in Python.

4.2. Support vector machine (SVM)

To solve the classification problem, SVM searches for a (n-1)-dimensional hyperplane which divide the n-dimensional vectors into different classes with the widest gap [8]. In addition, for non-linear classification, a kernel function is usually used to project the input vectors into higher dimensional spaces, where the classification can be turned to linear. In this work, radial basis function kernel (RBF kernel) is used for the projection, which is defined as

$$K(\boldsymbol{x}, \boldsymbol{x}') = \exp(-\gamma \|\boldsymbol{x} - \boldsymbol{x}'\|^2) \tag{4}$$

where $\boldsymbol{x}$ and $\boldsymbol{x}'$ denote the feature vectors. It is assumed that $\gamma = 1/(n\sigma^2)$, where σ^2 represent the variance of the vectors. After standardization, the variance of the input vector become nearly 1 so that we have $\gamma \approx 1/n$.

4.3. Naive Bayes classifier (NBC)

The naive Bayes classifier is based on the Bayes's theorem which state that the posterior probability is given by

$$P(y_i|\boldsymbol{x}) = \frac{P(\boldsymbol{x}|y_i)P(y_i)}{\sum_1^N P(\boldsymbol{x}|y_i)P(y_i)} \tag{5}$$

where y_i and $\boldsymbol{x}$ denote the label of classification $\{0,1\}$, where 0 (1) corresponds to non-existence (existence) of metallic objects, and feature vector. We assume that likelihood $P(\boldsymbol{x}|y_i)$ obeys the normal distribution, and the prior probability $P(y_i)$ and $P(\boldsymbol{x}|y_i)$ are determined from the training data. N represents the number of labels of classification.

4.4. Gradient boosting decision tree (GBDT)

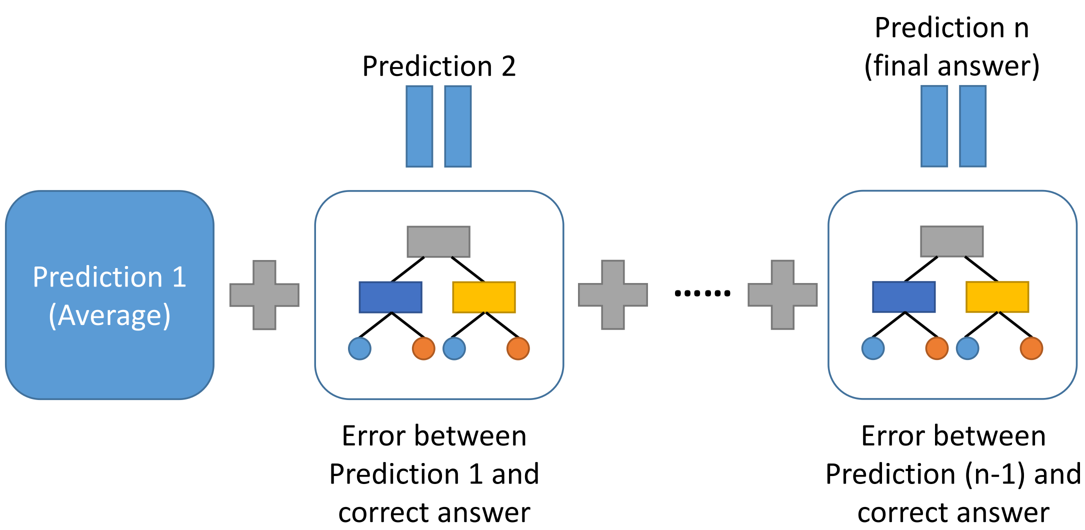


Figure 6: Gradient boosting decision tree

Gradient boosting decision tree (GBDT) is a machine learning method based on gradient boosting technique and decision tree [9]. Figure 6 schematically shows GBDT. Starting from the first prediction which is set as the average value of all the labels, decision trees are trained in each step to minimize the mean squared error between the correct answer and the prediction obtained in previous step. The sum of all the trees and prediction 1 provides the final answer of GBDT.

In scikit-learn®, softmax function given by

$$\sigma(\boldsymbol{z})_j = \frac{e^{z_j}}{\sum_{n=1}^{N} e^{z_n}}, \qquad for\ j = 1, \dots, N. \tag{6}$$

is used to transform the continuous predicted value to discrete label, when GBDT is applied in classification problem, where N denotes the number of class, which is 2 in this work. The hyper parameters and settings of GBDT are determined by default of scikit-learn®, and some important items of them are listed as Table 1.

Table 1: Hyper parameters and setting of GBDT

Loss function	Logistic regression	Number of boosting stages	100
Learning rate	0.1	Maximum depth of estimators	3
Function to evaluate split	mean squared error with improved by Friedman [10]	Minimum Number of samples to split a node	2

4.5. Random forest classifier (RFC)

Random forest (RFC) is an ensemble learning method based on bagging and decision tree [11]. To train each decision tree, the training data is selected randomly with replacement. The split of each tree is found from a random subset of the features, whose size is set as square root of the number of features. By repeating this, we construct many decision trees to compose a random forest. For classification, each tree in the forest gives their own prediction based on the input. The final prediction of the forest is decided by majority vote.

We set the hyper parameters and settings of RFC by default of scikit-learn® as well. The important items are summarized in Table 2.

Table 2: Hyper parameters and setting of RFC

Number of trees	100	Number of features for finding split	Square root of the dimension of input
Maximum depth of the tree	None	Minimum Number of samples to split a node	2
Function to evaluate split	Gini impurity	minimum number of samples required to be at a leaf node	1

5. Training and validation

5.1. K-fold cross validation

To eliminate the influence of division between training and validation data on the performance of classifiers, K-fold cross validation is used in this work. All the data are divided into 10 subsets while the proportion of each class in the subsets remain same as that in the entire dataset. Classifiers obtained by each machine learning methods will be trained for 10 times, while each subset will be used as validation data in order and the others as training data at the same time. Finally, the average accuracy of the 10 times training is treated as the final accuracy of the methods.

5.2. Classification results

We consider the different combinations of the input vectors $\boldsymbol{V_1}, \boldsymbol{V_2}$ and $\boldsymbol{V_3}$ and load conditions for the secondary (receive) coil in this work, which are summarized in Table 3. Under these conditions, the training and validation datasets are constructed with the procedure shown in Figure 5. We employ K-fold cross validation to measure the accuracy of the classifier. The resultant average accuracy of each method for validation datasets, which are not exposed to the classifiers, are listed in Table 3.

Table 3: Accuracy of trained classifiers

Load conditions	20Ω load	No load (short)
Case I: $\{\boldsymbol{V_3}\}$ (22 dimensions)	SVM=60.5%	SVM=77.9%
	NBC=60.5%	NBC=56.5%
	GBDT=82.5%	GBDT=93.5%
	RFC=84.0%	RFC=94.2%
Case II: $\{\boldsymbol{V_1}, \boldsymbol{V_2}\}$ (44 dimensions)	SVM=51.2%	SVM=57.1%
	NBC=50.8%	NBC=48.4%
	GBDT=93.4%	GBDT=89.2%
	RFC=97.2%	RCF=95.0%
Case III: $\{\boldsymbol{V_1}, \boldsymbol{V_2}, \boldsymbol{V_3}\}$ (66 dimensions)	SVM=63.4%	SVM=68.2%
	NBC=56.3%	NBC=54.8%
	GBDT=93.8%	GBDT=94.1%
	RFC=97.9%	RFC=95.8%

Comparing the three cases, Case III where we use all the input voltages results in the best performance, where GBDT and RF achieves accuracy over 90% regardless of the load conditions. Note that this accuracy is obtained even if there is misalignment between the primary and secondary coils. In Case I, the classification accuracy is below 85% for all the methods for the load condition, whose tendency has been reported in [6]. The reason for this is due to the fact that there are little differences in $\boldsymbol{V_3}$ because of the off-resonant states. By introducing the differential voltages into the input data, we can perform accurate classification.

Under all the situations, GBDT and RFC have relatively higher accuracy than SVM and NBC. The tree-based methods are concluded to be adequate for this classification problem. It is also found that RFC always performs best for all the situations, and it is the only method whose accuracy is higher than 95%. We conclude that the recognition of the foreign metallic objects is possible at about 95% accuracy by training RFC by $\{\boldsymbol{V_1}, \boldsymbol{V_2}, \boldsymbol{V_3}\}$. The proposed method would have difficulty in detecting small metallic objects. We plan to study the limit of the proposed method in future. Moreover, the experimental verification of the proposed method is remained for future work.

6. Conclusion

In this paper, a new metal object detection method for WPT including magnetic core using differential coils and machine learning has been proposed. Considering different misalignment between the coils and different positions of metal objects, the training and validation are computed using FEM. The input voltages of the primary coil and differential voltages of the detection coils are exposed to the classifier. We have trained four different classifiers which is tested by K-fold cross validation. It has been shown that GBDT and RFC have the accuracy over 90%, when input voltages and differential voltages are inputted together. In future, we will bring out experimental validation of the proposed method.

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