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Shape Creation by Application of Support Vector Machine Discrimination Hyperplane

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Abstract: We examined support for shape creation by use of a support vector machine (SVM), which is one type of machine learning utilized as a solution in various fields. In the present study, we conducted basic research on SVM, applied discrimination hyperplane generation by SVM learning, and described a method leading to shape creation. We clarified how box constraint parameters in SVM shape derivation using Gaussian kernel affect the discrimination hyperplane.

Keywords: Support Vector Machine (SVM), Computer Aided Design (CAD), Mechanical Engineering

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I. INTRODUCTION

In the field of manufacturing, while improving quality and responding to the demands of customers, product development in a short period by lowering cost sis required. With this background, various design support systems have been developed as the result of advances in technology. In conventional machine design, while keeping in mind the needs and product concept, there is a series of processes such as proposal of ideas, creation of drawings of these ideas using software, etc. and performing strength analysis and operation verification using analysis software. However, although CAD/CAE, etc. exist as design and analysis systems, there are few systems for design creation at the initial stage of machine design.

Therefore, in the present study, we examined support for shape creation by use of a support vector machine (SVM), which is one type of machine learning utilized as a solution in various fields. In the present study, we conducted basic research on SVM, applied discrimination hyperplane generation by SVM learning, and described a method leading to shape creation.

II. SUPPORT VECTOR MACHINE

Although SVM proposed in the 1990s was originally a linear classification learning algorithm to solve two-class classification problems, many theoretical studies were conducted in the early 2000s and it has since been widely used as a general-purpose data analysis method (Vapnic, 1998).

In addition, SVM has been extended to multi-class classification problems(Cristianini et al., 2000) regression problems, unsupervised learning problems, etc. for use in data analysis tasks other than two-class classification problems. In addition, in this development, SVM became able to handle nonlinear classification by utilizing kernel function (Npser et al.,1992). In the present study, we handled the shaped in the design drawing as training data and performed data classification using nonlinear identification by incorporating the kernel function of SVM. The discrimination hyperplane of the classification criteria that could be derived as a result was used as the shape.

2.1 KERNEL FUNCTION

One of the characteristics of SVM is that it shows the positional relationship between input data by utilizing the inner product of vectors representing input data. A kernel function is used to perform learning and classification in a higher dimensional feature space than the space where data exists through calculation of the inner product. As a result of the kernel function, SVM can change the complexity of the model to be learned and embed the complex characteristics of the data.

To date, various kernel functions have been proposed (Muller et al., 2001) in accordance with the development of SVM, the research of the authors has shown that the kernel functions used for the purpose of deriving the nonlinear shape are Gaussian kernels or polynomial kernels. Therefore, in the simulation later described, a Gaussian kernel as shown in equation (2.1) is used. Here, (x, y) represents the input data, and γ is a parameter requiring presetting for the targets of learning.

$$K(x, y) = \exp(-\gamma \|x - y\|^2) \quad (2.1)$$

2.2 BOX CONSTRAINTS

Although SVM learning is a method of determining a hyperplane that separates a data point set mapped to a feature space, the data point set is not always separable. Therefore, in order to allow misclassification, the hyperplane optimization problem is defined as equation (2.2) by introducing the non-negative variable ξ(Cortes et al., 1995).

$$\min_{w,b,\xi} \frac{1}{2}(\|w\|^2) + C \sum_i \xi_i \quad (2.2)$$

In equation (2.2),w is a real number vector corresponding to the slope of the hyperplane, and the first term determines the margin for separating the data. The second term determines the suppression of misclassification. It is the role of the coefficient C to determine the extent of this suppression, which is referred to as a box constraint in the present study and is a parameter that determines the degree to which misclassification is allowed.

2.3 CROSS-VALIDATION

In statistics, the sample set is divided into n items, one of which is analyzed first, the remaining parts are tested for analysis as a method to examine the validation/confirmation of the validity of the analysis itself. It is possible to verify and confirm how well the data analysis and statistical prediction can actually handle the population with a good approximation. In machine learning, because the given original data set is divided into n items, one of which is used as evaluation data, and evaluation is performed after classification learning using the remaining training data, it is possible to estimate the generalization error for unknown data without it being affected by over learning.

The cross-validation method (Ron, 1995) with the partition function k is referred to as the k-fold cross-validation method. Suppose there is a data set consisting of n_{all} training examples at hand and this is denoted as D_{all}. In the k-fold cross-validation method, D_{all} is equally divided into k overlapping subsets D_1, ..., D_k at random. For simplicity, assuming that n_{all} is a multiple of k, in the k-fold cross-validation method, k number of times of learning and evaluation are performed. When a classifier learned as a training set other than cases contained in D_k is expressed as g(-D_k), the estimated value of generalization error by k division intersection verification method is:

$$\frac{1}{n_{all}} \sum_{k \in [k]} \sum_{i \in D_k} I(y_i \neq g(-D_k)(x_i)) \quad (2.3)$$

In the model selection on the box constraint parameter, equation (2.3) is calculated for various cases of C, and the one that minimizes this value is selected.

III. SHAPEDERIVATION SIMULATIONUSINGCROSS-VALIDATION METHOD

The authors' research has revealed that for shape derivation by SVM, it is necessary to set box constraints and parameters in the kernel function for each shape each time. In the present study, as basic research on shape creation system by SVM, the shape of the bottom and the foot of the shoes actually used by people were plotted as sample data, and the shape of the shoes against the foot were derived using learning and classification by SVM. Furthermore, by utilizing the cross-validation method, parameters of the box constraint that maximize utilization of the data classification function by SVM were calculated, the effectiveness of the box constraint parameters by cross-validation were examined by determining whether the discrimination hyperplane, when regarded as a shape, was appropriate as compared with the actual shape.

3.1 SIMULATION PROCEDURE

We input the sample point data on the foot and shoe contour using the numerical analysis software MATLAB, standardize the data, performed learning by SVM, and visualize the derived discrimination hyperplane to confirm the shape. Next, by performing cross-validation on the learned classification model, box constraints that were considered to be optimal for data classification were derived, the shape of the discrimination hyperplane was drawn by adjusting SVM using said values and allowing it to relearn the sampling data.

IV. SIMULATION RESULTS AND DISCUSSION

Figure 1(a) shows the support vector and discrimination hyperplane when the SVM box constraint is manually adjusted to 100 in the case of learning from sample data. Figure 1(b) shows the discrimination hyperplane when adjusting the box constraints of SVM using cross-validation when learning based on the sample data.

It has been revealed that for shape derivation by SVM, box constraints and parameters in kernel functions need to be set for each shape each time. This appears to discrimination hyperplane formation resulting from overlearning of SVM by setting the value of the box constraint too large and classification of the data more strictly regarding the red and blue data.

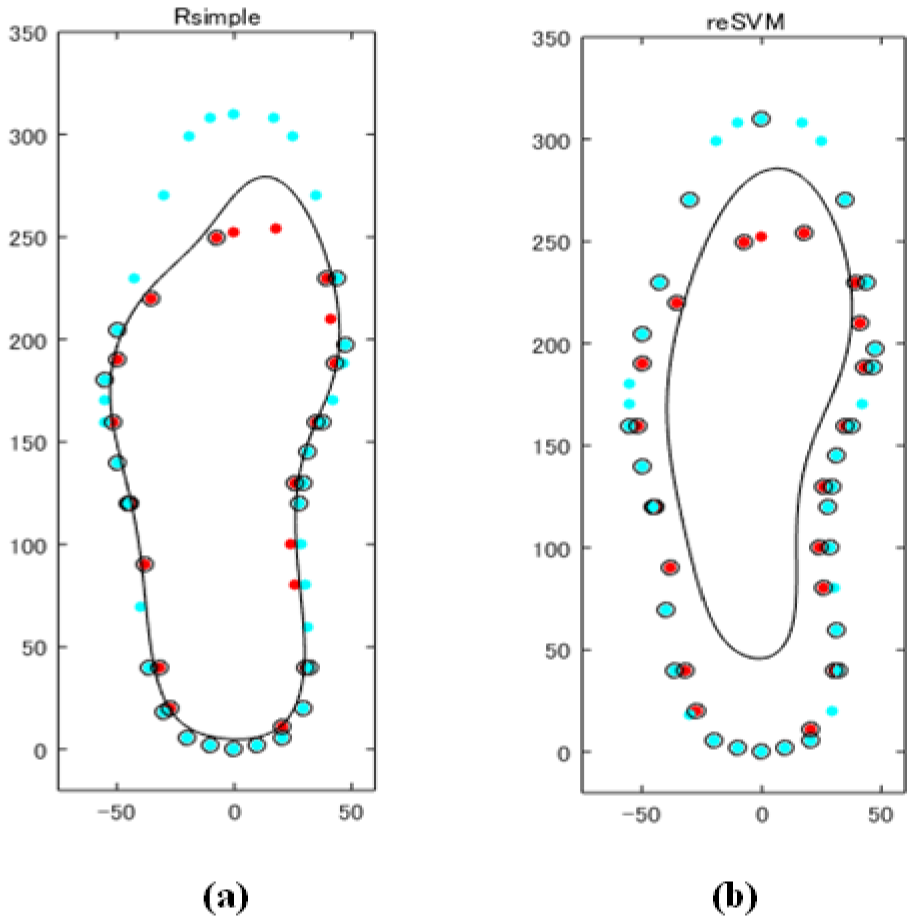

Figure 1: Use of cross-validation method and discrimination hyperplane

It can be seen that Fig. 1(b) is smaller than the original shape of the foot and shoe and has become smaller in comparison with Fig. 1(a), but because the values of the box constraints derived by cross-validation became smaller than 100, this appears to be due to the fact that SVM allowed more red points inside the margin. It can be inferred that only the red points near the toes could be properly classified because the margin distance by the support vectors of each shoe and foot in the toe region was large. Although the simulation results of the present study cannot be said to be favorable result for shape of the foot with respect to the original sample data, there was no large deviation of the shape of shoes and feet, it appears that the error falls within a range that allows the shape of a new shoe to be understood.

V. CONCLUSION

We clarified how box constraint parameters in SVM shape derivation using Gaussian kernel affect the discrimination hyperplane. In addition, we demonstrated that by deriving the discrimination hyperplane by box constraint using cross validation, it is effective for design support of shape creation by exhibiting a new shape while being influenced to some extent by the original shape.

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