New Multi-expert System Based on LSSVM and FI

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Abstract: In order to make a diagnosis and obviate the fault more effectively, when complicated mechanical system goes wrong, combining the characteristics of support vector machine, fuzzy integral and expert system, this paper puts forward the integral structure and diagnosis model of multi-expert system based on LSSVM and FI. The model synthesizes the advantages of each algorithm. This method overcomes the insufficiency of traditional expert system such as lack of the mechanism of effective self-study and self-adapt, be difficult to resolve the nonlinear system fault problems. Therefore, it is a convenient way to resolve the multi-sign and multi-reason fault problems of complicated mechanical system.

1. Introduction
In the modern fault diagnosis field, as a symbol-based reasoning system, expert system is a very effective method, it has the function of explanation, but it takes a long time to solve complex problems, there are "bottleneck" problems of knowledge acquisition, "narrow step" problems of knowledge, it does not have the function of associative memory and has poor ability to deal with uncertain knowledge.

SVM is a new learning machine. It is based on the VC dimension theory of statistical learning theory and the structural risk minimization principle. According to the limited sample information, it seeks the best trade-off between the complexity of the model and the learning ability [1,2], in order to obtain the best generalization ability. Automatic Knowledge Acquisition from training samples, it breaks through the bottleneck of knowledge acquisition of expert system and overcomes many problems of machine learning, such as neural network over-learning, dimension disaster and local minimum.

Therefore, if the improved SVM is combined with a multi-expert system, and FI is used to improve the accuracy of multi-expert collaborative diagnosis, the efficiency of troubleshooting for complex systems can be improved.

2. LSSVM and FI

2.1. LSSVM
The basic idea and principle of Support vector machine, which is developed from the optimal classification surface in the case of linear separability, can be found in reference [3-5].

LSSVM is an improved algorithm based on SVM. The quadratic loss function is used to replace the insensitive loss function in SVM, and the quadratic optimization of the original SVM algorithm is changed to solve the linear equation [6] by constructing the loss function, which greatly simplifies the computational complexity.
For a standard SVM, the optimization problem with maximum classification interval is expressed as the following quadratic programming problem:

$$\min_{\omega, b, \xi} J(\omega, \xi) = \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{N} \xi_i$$  \hspace{1cm} (1)

subject to

$$y_i \left[ \omega^T \Phi(x_i) + b \right] \geq 1 - \xi_i$$  \hspace{1cm} (2)

$$\xi_i \geq 0, \quad i = 1, 2, \ldots, N.$$

Among them, $N$ is the number of samples $x_i$, its belonging to the category $y_i$, expressed as $\{(x_i, y_i)\}, \ x \in \mathbb{R}^d; \ y_i \in \{1, -1\}; i = 1, 2, \ldots, N$.

$d$ is the dimension of the input space, $\xi_i \geq 0 (i = 1, 2, \ldots, N)$ is the relaxation factor, $C$ is the penalty factor, $\Phi$ is the nonlinear transformation function.

Then the optimal objective function of LSSVM becomes lower.

$$\min_{\omega, b, \xi} J_{LSS}(\omega, \xi) = \frac{1}{2} \|\omega\|^2 + \frac{1}{2} \gamma \sum_{i=1}^{N} \xi_i^2$$  \hspace{1cm} (3)

subject to

$$y_i \left[ \omega^T \Phi(x_i) + b \right] = 1 - \xi_i$$  \hspace{1cm} (4)

$\gamma$ equivalent to the role of the parameters $C$.

The problem is solved as follows.

First, introduce the following Lagrangian

$$L_{LSS}(\alpha, b, \xi, \alpha) = J_{LSS}(\alpha, \xi) - \sum_{i=1}^{N} \alpha_i \left[ y_i \left[ \omega^T \Phi(x_i) + b \right] - 1 + \xi_i \right]$$  \hspace{1cm} (5)

Which is a Lagrangian multiplier. Transform (5) into (6)

$$\begin{bmatrix}
I & 0 & 0 & -Z^T \\
0 & 0 & 0 & -Y^T \\
0 & 0 & \gamma I & -I \\
Z & Y & I & 0
\end{bmatrix}
\begin{bmatrix}
\omega \\
b \\
\xi \\
\alpha
\end{bmatrix}
= \begin{bmatrix}
0 \\
0 \\
0 \\
\tilde{1}
\end{bmatrix}$$  \hspace{1cm} (6)

$I \in \mathbb{R}^{(N \times N)}$ is the identity Matrix.

$$Z = \begin{bmatrix}
\Phi(x_1) & \cdots & \Phi(x_N)
\end{bmatrix}^T$$

$$Y = \begin{bmatrix}
y_1 & \cdots & y_N
\end{bmatrix}^T, \quad \tilde{1} = [1, \cdots, 1]^T$$

$$\xi = [\xi_1, \cdots, \xi_N]^T, \quad \alpha = [\alpha_1, \cdots, \alpha_N]^T$$

After elimination $\omega$ and $\xi$, formula (6) is simplified to (7)

$$\begin{bmatrix}
0 & Y^T \\
Y & ZZ^T + \gamma^{-1}I
\end{bmatrix}
\begin{bmatrix}
b \\
\alpha
\end{bmatrix}
= \begin{bmatrix}
0 \\
\tilde{1}
\end{bmatrix}$$  \hspace{1cm} (7)

The equation can be solved by least squares.

### 2.2. Fuzzy estimate and fuzzy Integral

Fuzzy estimate is a generalization of classical measures. Suppose $X$ is a set, $\Omega$ is algebra $\sigma$—consisting of some subsets of the space $X$, $g : \Omega \to [0, 1]$ is a set function defined on $\Omega$. If it has the following characteristics, I. E,

$$(1) \quad g(\Phi) = 0, g(\{x\}) = 1;$$
(2) \( g(A) = g(B) \), if \( A \subseteq B \)

(3) If \( \{ A_i \}_{i=1}^{\infty} \) is an incremental sequence of measurable sets, then \( \lim_{i \to \infty} g(A) = g(\lim_{i \to \infty} A) \), and called it as ambiguity. Fuzzy estimate has no countable additivity, which measure of union set can not be calculated by directly adding the measures of two disjoint subsets.

Definition of the fuzzy integral based on the fuzzy estimate, Supposing \((X, \Omega)\) is a measurable space, make \( e = \max_{i=1}^{n} \left[ \min \left( h(x_i), g(A_i) \right) \right] \) as a measurable function on \( \Omega \), then the fuzzy integral of function \( h \) to the fuzzy estimate \( g \) on \( A \subseteq X \) is defined as:

\[
\int_A h(x) \cdot g() = \sup_{\alpha \in [0,1]} \left[ \min_{x \geq \alpha} \left( \min_{E} h(x), g(A \cap E) \right) \right] = \sup_{\alpha \in [0,1]} \left[ \min(\alpha, g(A \cap F_{\alpha})) \right]
\]

(8)

Among them, \( F_{\alpha} = \{ x : h(x) \geq \alpha \} \)

To \( h(x_1) \geq h(x_2) \geq \cdots \geq h(x_n) \),
the fuzzy integral \( e \) on the set \( X \) can be expressed as:

\[
e = \max_{i=1}^{n} \left[ \min \left( h(x_i), g(A_i) \right) \right]
\]

(9)

Among them, \( g(A_i) \) can be obtained from the following equation

\[
\begin{cases}
g(A_i) = g(\{x_i\}) = g^i & 1 \leq i \leq n \\
g(A_i) = g^i + g(A_{i-1}) + \lambda g^j g(A_{i-1})
\end{cases}
\]

(10)

And, \( A_i = \{x_1, x_2, \cdots, x_i\} \)

The theory of fuzzy integrals takes into account not only the objective effect of the objective evidence itself on the hypothesis, but also the subjective expectation of the evidence on the hypothesis. The values of the fuzzy integrals obtained under different fuzzy measures are also different.

3. Multi-expert Fault Diagnosis System Based on LSSVM and FI

3.1 system structure.
The structure of multi-expert intelligent fault diagnosis system based on Lssvm and FI is shown in figure. 1

![Fig.1 the system structure of multi-expert intelligent diagnosis](image)

That is, Lssvm, expert system as an independent module, respectively execute some functions of the system, and then after FI fusion, get the diagnosis results.
In the figure, FP represents the fault phenomenon information, TS represents the training sample information, HR represents the implicit knowledge base, AR represents the explicit knowledge base, and SM represents the knowledge base management. SS stands for sample stock. M1 is the LSSVM module, M2 is the knowledge acquisition module, M3 is the explanation module, the symbol "Ei" is the expert i, "FI" is the fuzzy integration, and "Fi" is the diagnosed fault i.

3.2 Module partition.

According to the system internal logical structure and operating mechanism, the system is divided into the following five major modules.

3.2.1 Knowledge Base Module

Knowledge Base Module stores two types of information: explicit knowledge and implicit knowledge.

An explicit knowledge base for domain experts, knowledge engineers and users represents the production rules about the fault symptom and the fault relation of the diagnostic objects, and stores the expert knowledge information based on the rules. Explicit knowledge is represented by traditional artificial intelligence methods, such as first-order predicate logic representation, Petri net representation, etc. The LSSVM-oriented implicit knowledge base represents the learning samples in the form of internal coding which are transformed from the production rules. The implicit knowledge is usually represented by weight Matrix. Explicit Knowledge Base is used for expert reasoning, and implicit knowledge base is used for updating rules.

3.2.2 Inference Module

The mechanism of the inference engine is essentially a numerical calculation process, that is, the forward calculation of the input vector. Under the guidance of this mechanism, according to the acquired symptom information, we use various rules synthetically, and make inference and judgment according to the knowledge in the knowledge base and the real-time data in the dynamic database, at the same time, some intermediate results are sent to the dynamic database as the reasoning process goes on.

3.2.3 Learning Machine Module

The function of learning machine module is to develop, enrich knowledge and correct knowledge base in time. Because LSSVM has the ability of self-adaptation, self-learning, memory and induction. The state of classification decision hyperplane in high dimensional feature space can be changed by training samples according to the change of surrounding environment. Therefore, the system uses Lssvm to improve the system diagnosis accuracy and learning efficiency. References

3.2.4 Multi-expert Diagnosis Module Based on FI

The establishment of this module is the further improvement of the diagnosis conclusion and the knowledge base. The function is to fuse the different diagnosis conclusions drawn by different experts, as follows.

Supposing \( X = \{x_1, x_2, \ldots, x_k\}, K \) is the number of diagnosticians;

- Measurable function \( \{h_j\}, j = \{1, 2, \ldots, N\}, N \) is the number of possible faults for the diagnostic object, the implementation of the improved FI algorithm is as follows.
  1. Computing measurable function \( h : x \rightarrow [0, 1] \)
  2. Determining the fuzzy density \( \{g'_i\}, i = 1, 2, \ldots, K \)

Where \( L \) is the group size, each individual sequence \( \{g'_i\} \) can be obtained according to the initial group.

3. Calculating parameter \( \lambda_{ij} \)
(4) Calculating $F_1 e_{jk}$

(5) Individual evaluation, calculation of fitness

(6) Cross calculation

(7) Mutation calculation, go to the step (3)

### 3.2.5 Man-machine Interface and Interpretation Module

The interface is the bridge of communication between man and system. It mainly completes the setting of system parameters, the input and output of data, etc. Interpretation Module makes the system work more transparent, easy for users to understand and enhance the trust of the system. The input and output information of LSSVM is analyzed by expert system, and the reasoning process is explained by extracting rules automatically.

### 4. Application example

The fault of some rotating machinery is analyzed as an example.

There were 420 fault samples, including 100 wear samples, 88 deformation samples, 79 pitting samples, 90 corrosion couplings, 63 crack samples, which were divided into training sample set and test sample set. Using wavelet packet analysis technology, the energy analysis of the common faults of the unit is carried out. Through a large number of experiments, some fault causes and fault phenomena corresponding to table [7]. Five of them are used as the output of the model, and the different peak energy of the five frequency bands of the vibration signal spectrum is used as the characteristic quantity to form the training sample. As shown in Table 1.

| $S$  | FB      | $0.01-0.39f$ | $0.40-0.49f$ | $0.50f$ | $0.51f-0.99f$ | $f$ |
|------|---------|--------------|--------------|--------|--------------|-----|
| 0    | wear    | 0.000        | 0.000        | 0.000  | 0.000        | 0.899 |
| 1    | deformation | 0.000     | 0.000        | 0.000  | 0.000        | 0.197 |
| 2    | pitting  | 0.103        | 0.858        | 0.101  | 0.100        | 0.000 |
| 3    | corrosion | 0.001      | 0.298        | 0.097  | 0.610        | 0.000 |
| 4    | crack    | 0.000        | 0.001        | 0.000  | 0.000        | 0.401 |

$S$——samples; $FB$——Frequency band

Firstly, the two models (the model of diagnosis system and the model of Neural Network [8,9] based on probability) are trained respectively with training samples, and then the trained models are used to diagnose the simulation faults in turn. In this method, the group size is 110, the crossover probability is 0.7, and the variance probability is 0.01. The obtained value of the mold density is shown in Table 2.

| $g_1$ | $g_2$ | $\lambda$ |
|-------|-------|-----------|
| 0.0601| 0.6973| 0.8789    |

$g_1$ is the modulus of the diagnosis method based on Lssvm, $g_2$ is the modulus of the neural network based on probability. According to the obtained value of the modulus, using the samples data of the test set, the diagnosis conclusions are fused by the FI-based multi-expert diagnosis fusion algorithm.

Finally, the diagnosis result is shown in Table 3.

| $\alpha$ | Intelligent model of this paper | Neural network model based on probability |
|---------|---------------------------------|----------------------------------------|
| 0       | 100                             | 100                                    |
| 0.17    | 98.9                            | 97.0                                   |
| 0.35    | 96.2                            | 92.5                                   |
| 0.67    | 91.9                            | 85.8                                   |
It can be seen that when the noise control coefficient is zero or very small, both the multi-expert model based on LSSVM and FI, and the neural network model based on probability have high accuracy. The diagnostic accuracy of both models will decrease as the noise increases, but the multi-expert model based on LSSVM and FI drops slower, which shows that it is robust, while the multi-expert model based on LSSVM and FI dynamically selects noise control parameters, it can improve the diagnostic accuracy.

In a word, under the condition of the same diagnosis object and the same noise control coefficient, the multi-expert model based on LSSVM and FI has higher accuracy than the neural network model based on probability.

5. Conclusion
New Multi-expert System Based on LSSVM and FI combines the features of SVM, FI, expert system and so on, the main advantages are:

First, a least squares algorithm is implemented to simplify the computational complexity. Secondly, the collaborative work of multiple sub-experts expands the overall ability of the expert system to solve problems, thus improving the accuracy of diagnosis. Thirdly, Each sub-expert has only one method to solve the problem, and can get different diagnosis conclusion. FI is used to fuse the sub-expert to get the conclusion with higher reliability.

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