Application of SVM Optimization Based on GA in Electronic Sphygmomanometer Data Fusion

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Abstract

If the proper kernel function parameter σ is chosen, using of the multi-sensor data fusion method based on SVM, the influence of cross sensitive disturbance variables including the temperature T and the power supply current I , can be significantly suppressed and the stability of the pressure sensor can be improved in the electronic sphygmomanometer. While kernel function parameter σ is difficult to ascertain after repeated test. GA(Genetic Algorithm) with powerful global searching for optimal solutions is able to meet the requirement of optimization for kernel function parameter σ of SVM(Support Vector Machine).
Keywords: *SVM, GA, Kernel Function Parameter, Multi-sensor Data Fusion.*

1. Introduction

In regard to human body, blood pressure usually refers to the surface arterial pressure of brachial artery, medically known as noninvasive blood pressure [1]. Blood pressure is one of important comprehensive physiological medical parameters, of which non-invasive detection methods include Korotkoff souna method, oscillometric method, double-cuff method, ultra-sound method, tension location survey method ,constant volume method, etc. Electronic sphygmomanometer, which has been treated specially about collection and filtering signal, can achieve blood pressure measurement in those regions which is not limited to only the upper-arm, but also the lower-arm and the wrist, even the finger. Oscillometric method is preferred in most electronic sphygmomanometer designs, because of its insensitivity from subjective measurement factors, conventional treatment, small equipment investment and good murmur resistance [1], [2].

The blood pressure measurement precision of the electronic sphygmomanometer based on oscillometric method is heavily conditioned, because whose pressure sensor performance is mainly influenced by temperature and power supply changes.With the development of the informatization and communalization of medical institutions, the electronic sphygmomanometer based on the systematic platform should satisfy patients' self-measurement, the diversity of adapter interface and working environment, and so on. Multi-sensor data fusion is one of the effective methods for improving reliability and measurement accuracy of the electronic sphygmomanometer [3], [11].

With SVM (Support Vector Machine) approach, the inverse model can be built to eliminate the effect of cross sensitive disturbance variables on the pressure sensor from the ambient temperature and the constant current power supply current in the electronic sphygmomanometer, so that the stability of the pressure sensor can be improved using the multi-sensor data fusion method of suppressing cross sensitive disturbance variables [3], [4]. In the training process of SVM, lots of trial are often needed to select kernel function parameter because of the complexity and nonlinear level of systems, but it is exactly these results that are at risk.GA(Genetic Algorithm) with powerful global searching for optimal solutions is able to meet the requirement of optimization for kernel function parameter of SVM, in order to modify the inverse model used for offseting the disturbance of cross sensitive disturbance variables, and to improve the measuring precision of blood pressure [4], [7].

2. Suppressing Cross Sensitive Disturbance Variables by SVM

Unlike multiple regression analysis, this method using of the multi-sensor data fusion based on SVM to suppress cross sensitive disturbance variables and improve the stability of the pressure sensor, don't have to establish the analytic function which has the untargeted parameters to be eliminated, but turn it into a convex quadratic optimization problem which is used to get theoretically the global optimization result by researching the estimation and prediction to small sample size according to VC dimension and structural risk minimization in statistical learning theory. Using kernel function by SVM, the sample points $\{(\boldsymbol{x_i},\ y_i)\}_{i=1}^{N^+}$ in input space $\boldsymbol{X}$ are mapped to the training points $(\boldsymbol{\varphi}(\boldsymbol{x_i}),\ y_i)$ in the higher dimensional Hilbert space $\boldsymbol{F}$, and the mapped training set $D=\{(\boldsymbol{\varphi}(\boldsymbol{x_i}),\ y_i)\}_{i=1}^{N^+}$ can catch regressions that is adopted to propose linear discriminant function in the Hilbert space $\boldsymbol{F}$ [5], [6]. It is this property that guarantees tthe generalization of the inverse model, can avoid the curse of dimensionality, becomes an irrelevance between the complexity of algorithm and the sample dimension, therefore can be suitable for the multi-sensor data fusion.

Let sample set be $\{(\boldsymbol{x_i},\ y_i)\}_{i=1}^{N^+}$, where $\boldsymbol{x_i} \in \boldsymbol{R}^d$ is input vector, y_i is corresponding expected value. The dual problem that corresponds to the constrained convex quadratic optimization problem can be expressed as

$$\arg\max_{\boldsymbol{\alpha}} \boldsymbol{\omega}(\boldsymbol{\alpha}) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j K(\boldsymbol{x}_i, \boldsymbol{x}_j)$$
$$s.t. \sum_{i=1}^{N}\alpha_i y_i = 0\ ;\ 0 \le \alpha_i \le C,\ i = 1, 2, \cdots, N \quad (1)$$

Where α_i is the Largrange multiplier, $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is the kernel function.

Set $\boldsymbol{\alpha}^* = (\alpha_1^*, \alpha_2^*, \cdots, \alpha_{N^+}^*)$ be the solutions for formula (1), only some of which is in general nonzero. The corresponding sample input $\boldsymbol{x_i}$ of nonzero solutions is used as support vector which a decision boundary decisions depends on. The purpose of data fusion based on SVM is fitting the relationship between the input $\boldsymbol{x}$ and output y .The Relationship expression is as follows [7], [9].

$$y(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + b = \sum_{i=1}^{s}\alpha_i K(\boldsymbol{x}, \boldsymbol{x}_i) + b \quad (2)$$

In formula (2), $\boldsymbol{x_i}$ is support vector; s is the number of support vectors; $\boldsymbol{x}$ is the measured input; b is the offset of SVM; $\boldsymbol{\omega}$ is the weight coefficient of SVM,whose number is the same as the number of support vectors. The Gaussian radial basic function , which meets the Mercer criteria,is chosen and is as follows.

$$K(\boldsymbol{x}, \boldsymbol{x}_i) = \exp\left(-\frac{\| \boldsymbol{x} - \boldsymbol{x}_i \|}{2\sigma^2}\right) \quad (3)$$

Where σ is kernel function parameter, Adjustment of which can improve SVM predictive accuracy.

3. Measuring Blood Pressure Based on Oscillometric Method

3.1 Principle of Measurement

Blood pressure value parameters include systolic blood pressure and diastolic blood pressure during a heart pulsating cycle. To get blood pressure value, the oscillation envelope of pulses produced when blood flow strike vessel wall with oscillometric method, must be to detect and analyse [1], [3], [7]. Usually, oscillometric method can be divided into amplitude coefficient method and waveform feature method.

The measuring system of an electronic sphygmomanometer based on amplitude coefficient method is composed mainly of inflatable cuff, miniature electric air pump, electromagnetic gas valve, pressure sensor, temperature sensor, electric current sensor, microcontroller, etc. In many practical design based on oscillometric method, blood pressure can be measured in the course of inflation or deflation. Electromagnetic gas valve and miniature electric air pump under the control of microcontroller inject air into inflatable cuff at the rate of 5mmHg/s; The oscillation signal of surface arterial pressure pulses detected pressure sensor, is extracted alternating component through 0.8Hz second-order high-pass filtering and 300 times amplification, and gets A/D conversion through 38Hz second-order low-pass filtering to remove cuff frictional noise and power noise. The peak value $V_{\max}$ of oscillation envelope of pulses across the inflation cycle, and the concrete values of systolic blood pressure and diastolic blood pressure according to amplitude coefficient, are calculated by the microcontroller. As shown in Figure 1, the intersection V_{sp} of cuff pressure line and oscillation envelope of pulses is the amplitude value of systolic blood pressure, $V_{sp} / V_{\max} = k_{sp}$, k_{sp} always lies between 0.4～

0.65. In the process of an actual running, it is so critical to improve the stability of the pressure sensor for the accuracy of blood pressure measurement, because each pressure amplitude value of the sampling point obtained by pressure sensor will have an effect on the decision for the amplitude value of systolic blood pressure [1], [2].

In the process of blood pressure measurement, the ambient temperature and the constant current power supply current of pressure sensor is respectively under surveillance of temperature sensor and electric current sensor. This surveillance data willbe used to fuse the data of pressure sensor by the inverse model to eliminate the effect of cross sensitive disturbance variables.

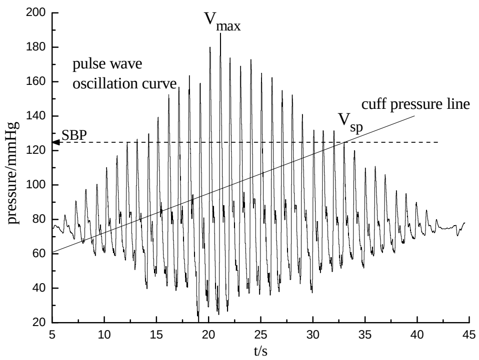

Fig. 1 Measuring systolic pressure based on oscillometric method.

3.2 Data sample preparation

For measuring systolic blood pressure, when SVM is trained to built the inverse model to eliminate the effect of cross sensitive disturbance variables, the three variables of pressure P , temperature T and electric current I are selected in three dimensional calibration experiment. In experimenting, the sensor choosing include the SC0073 dynamic micro pressure sensor, the JLB-11 electromagnetic balancing electric current sensor and the DS18B20 embedded miniature digital temperature sensor. The output voltage of temperature sensor used for detecting temperature disturbance variable T is U_T ; The output voltage of electric current sensor used for detecting electric current disturbance variable I is U_I ; The output voltage of pressure sensor used for detecting output variable P is U_P .

The number of total sample data pairs $(\boldsymbol{x}_i, \ y_i)$ $(i = 1,2,\cdots, \ N)$ is $N = N_p + N_t$ in calibration experimenting , where N_p is the number of training samples (N_p account for about 1/2～2/3 of the number of total sample), N_t is the number of testing samples [11], [14]. The three dimensional calibration experiment data of the SC0073 dynamic micro pressure sensor, as shown in Table 1.

Table 1: The three dimensional calibration experiment data of the SC0073 dynamic micro pressure sensor

SN	***P* /mmHg**	**I /mA**	**T /℃**	**U_I /V**	**U_T /V**	**U_P /V**
1	80	5	-5	5.32	0.5	0.296
2	81	5	-5	5.32	0.5	0.384
3	82	5	-5	5.32	0.5	0.483
4	83	5	-5	5.32	0.5	0.536
5	84	5	-5	5.32	0.5	0.608
6	85	5	-5	5.32	0.5	0.713
7	86	5	-5	5.32	0.5	0.771
8	87	5	-5	5.32	0.5	0.884
9	88	5	-5	5.32	0.5	0.996
10	89	5	-5	5.32	0.5	1.08
……	……	……	……	……	……	……
282	115	11	45	13.32	1.1	5.509
283	116	11	45	13.32	1.1	5.642
284	117	11	45	13.32	1.1	5.756
285	118	11	45	13.32	1.1	5.895
286	119	11	45	13.32	1.1	6.002
287	120	11	45	13.32	1.1	6.249

4. GA Optimization

GA is a kind of simulated evolutionary algorithm, which imitate biological evolution law and encode the parameters of a problem to be solved into chromosomes whose information across group will be exchanged by operation including selection, crossover, mutation, etc., and will finally be able to develop by iteratively a globally optimal chromosome [4], [7].

Trained SVM with training samples is tested, as measured by the standard deviation MSETD between predicted output values and the pressure calibration value of testing samples, to reduce reliance of parameter choices on training samples. It is found through experiments that, these learning parameters of SVM including boundary of lagrange multiplier C , the condition parameter of convex quadratic optimization λ and ε -neighborhood parameter around solutions ε , have little impact on the output, while kernel function parameter σ is difficult to ascertain after repeated test [5], [9], [10]. Taking the standard deviation MSETD between predicted output values and the pressure calibration value of testing samples as objective function, kernel function parameter σ is optimized with global search performance of GA for optimal solutions, and then the proper offset b and the proper weight coefficient ω are finded, so that output results are optimal or suboptimal to meet the precision and accuracy of system measurement.

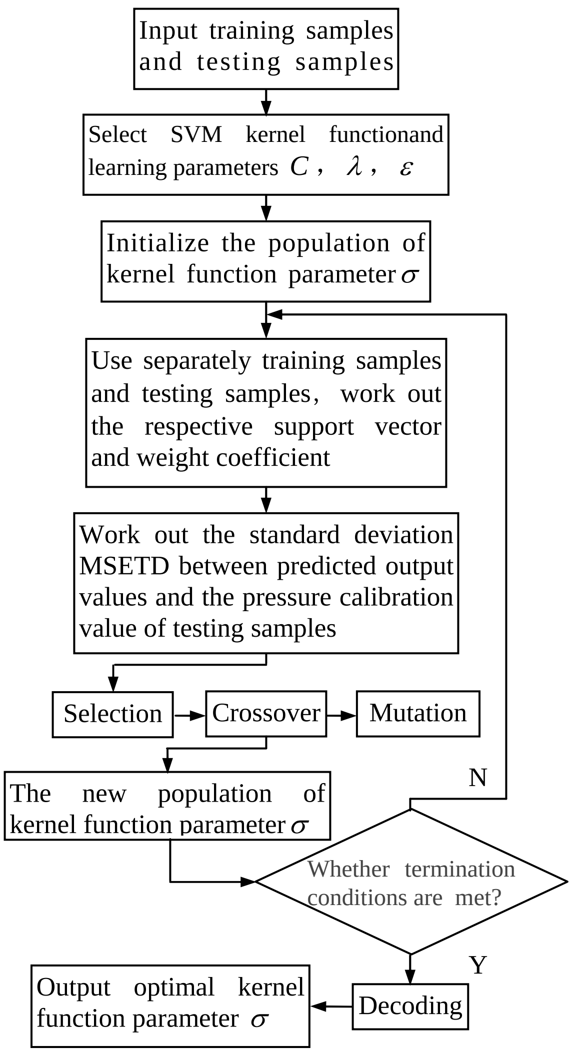

Fig. 2 GA optimizing kernel function parameter σ flow diagram.

GA optimizing kernel function parameter σ flow diagram , as shown in Figure 2.

4.1 Population Initialization

In the course of GA, the parameters in problem space aren't calculated directly, but the feasibility solutions of the problem to be solved are first expresses as Chromosomes or individuals in genetic space by encoding. Here, the population of kernel function parameter σ is initialized.

4.2 Fitness Function

Fitness function, which is used to distinguish the quality of individuals in population and is the only guide of natural selection, is usually derived from objective function. Here, the reciprocal of the standard deviation MSETD minimum between predicted output values and the pressure calibration value of testing samples is chosen as the fitness function value. The larger the fitness function value is, and the better the quality of individual is [3], [7].

4.3 Selection, Crossover and Mutation

Rely on selection , excellent individuals can be found from old population, and new population can be build to reproduce the next generation individual. The larger the fitness function value of individual is, the higher the probability of being selected is. Here, the roulette wheel method which is an selection method according to fitness Proportion, is used in selection, and the probability of being selected to the individual i is

$$p_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \tag{4}$$

In formula (4), F_i is the fitness function value of the individual i, n is population size.

Crossover is used to randomly find out two individuals from the present population, whose chromosome information is exchanged and combined for each other to pass outstanding characteristics of father string down to son string, in order to reproduce the new excellent individuals. The real crossing method is adopted in crossover because all individuals are encoded using of real.

$$\begin{aligned} a_{kj} &= a_{ij}(1-d) + a_{li} d \\ a_{lj} &= a_{lj}(1-d) + a_{ki} d \end{aligned} \tag{5}$$

In formula (5), d is a random number on interval $[0, 1]$.

Mutation is used to reproduce a better individual, which has been randomly found from the present population and mutated slightly. Mutation aims at maintaining the diversity of population [3], [7]. The operation of mutation to the jth gene of the ith individual is as follows.

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g), & r \geq 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g), & r < 0.5 \end{cases} \quad (6)$$

In formula (6), $a_{\max}$ and $a_{\min}$ are upper and lower bounds of gene a_{ij}. r is a random number on interval $[0, 1]$; $f(g) = r' * (1 - g/G_{\max})^2$, r' is a random number, g is the present number of iterations, $G_{\max}$ is the maximum evolutionary generation.

4.4 Operation Results of GA

Here, population size is set to 40, binary digit capacity of variable is set to 20. Crossover probability is set to 0.7, mutation probability is set to 0.01, the maximum evolutionary generation is set to 40. After these learning parameters of SVM are set: boundary of lagrange multiplier C is 500, the condition parameter of convex quadratic optimization λ is 1e-10, ε - neighborhood parameter around solutions ε is 1e-6, genetic manipulation is implemented to kernel function parameter σ on interval $[0, 10]$. Evolutionary process, as shown in Figure 3. Optimum value per generation, as shown in Figure 4.

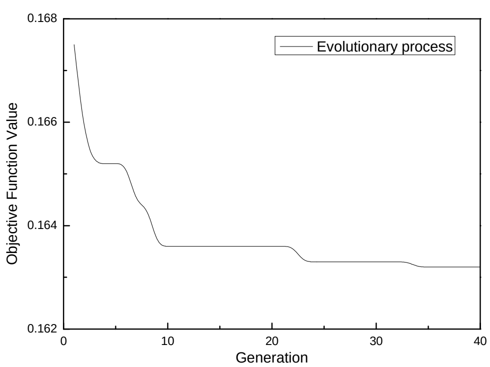

Fig. 3 Evolutionary process.

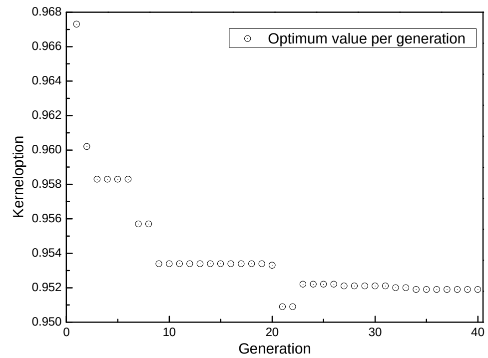

Fig. 3 Optimum value per generation.

According to the operation results of GA, kernel function parameter σ is 0.95187, the standard deviation MSETD between predicted output values and the pressure calibration value of testing samples is accordingly 0.16321.

5. Conclusions

When $\sigma = 0.95187$, over the range of $\Delta T = 50$ ℃ and $\Delta I = 6$mA, the maximum fusion deviation of initial point $|\Delta P'_{0m}| = 0.4016$ mmHg; The full scale pressure $P_{FS} = 120$ mmHg, of which the maximum fusion deviation $|\Delta P'_m| = 0.6691$ mmHg [12], [13]. So, the initial point temperature coefficient is

$$\alpha_0 = \frac{|\Delta P'_{0m}|}{P_{FS}} \cdot \frac{1}{\Delta T} \quad (7)$$

the sensitivity temperature coefficient is

$$\alpha_s = \frac{|\Delta P'_m|}{P_{FS} \cdot \Delta T} \quad (8)$$

the current impact coefficient is

$$\alpha_I = \frac{|\Delta P'_m|}{P_{FS} \cdot \Delta I}. \quad (9)$$

The parameters contrast between before and after the fusion, as shown in Table 2.

From this it can be derived that , the influence of cross sensitive disturbance variables, the temperature T and the power supply current I in the electronic sphygmomanometer, can be significantly suppressed and the stability of the pressure sensor can be improved, using of the multi-sensor data fusion method based on SVM if the proper kernel function parameter σ is chosen.

Table 2: The parameters contrast between before and after the fusion

Evaluation Parameters	α_0 /℃	α_s /℃	α_I /mA
Before the fusion	6.296e-3	9.991e-2	8.326e-1
$\sigma = 0.95187$, Gaussian RBF kernel fusion	6.693e-5	1.115e-4	9.293e-4

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