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Applying Machine Learning Methods to the Shooting Accuracy Prediction: A Case Study of T-75 Pistol Shooting

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Abstract: In this study, we investigate the quantitative correlation between human factors and the shooting accuracy of the T75 assault pistol. We carry out live pistol firing. Eleven shooters are selected to fire 30 rounds each. We obtain 330 data successfully. Interest factors are assigned to three human factors, whereas performance evaluation methods are assigned to three parameters of impact points; these experiment datasets are measured using an I-CubeX glove force sensor system. Three prediction models (for shooting score, shooting precision and shooting trueness) are established by using a Least Squares Support Vector Machine (LS-SVM), Back-Propagation Neural Network (BPNN) and Response Surface Methodology (RSM); the results of present study indicate that the model developed by using an LS-SVM exhibits excellent prediction ability. The force of the shooter's right index finger abdomen for pulling the pistol trigger and the force of the shooter's left palm for gripping the pistol significantly influence shooting performance. An inexperienced shooter can use the results of this study as a reference for improving his or her shooting skills. Furthermore, this study will greatly assist efforts to upgrade pistol design and performance.

Key words: Shooting accuracy, least squares support vector machine, back-propagation neural network, response surface methodology

INTRODUCTION

Pistols are important firearms for military and police applications. The shooting accuracy of a pistol depends on the correlation between the shooter and the pistol. This correlation comprises three human factors: gripping the pistol stably, aiming at the target correctly and pulling the trigger steadily. These factors are strongly correlated with the correctness of the pistol holding position and pulling the trigger (USMC, 2003). However, the quantitative correlation between a shooter and a pistol has not yet been extensively investigated. The objective of present study is to investigate the quantitative correlation between grip pistol force and shooting accuracy.

Certain factors that affect the shooting accuracy-such as pistol parameters, shooting distance, geography and weather-are listed as control items; they lie beyond the scope of this study and hence are not discussed herein (Yuan and Lee, 1997). In this study, we investigate the effects of only three human factors (Wang, 1992). Live ammunition is employed and sensors are used to detect the variables associated with the human factors. The shooting performances are predicted on the basis of prediction models developed using a Least Squares Support Vector Machine (LS-SVM). Further, we fit correctness function and correctness index to verify the shooter's grip position. To develop the prediction models and the correctness index, we identify three relevant factors and three response parameters:

Factors

- **Factor 1:** The force with which the shooter pulls the pistol trigger using his or her right index finger
- **Factor 2:** The force with which the shooter grips the pistol in his or her left palm
- **Factor 3:** The force with which the shooter grips the pistol in his or her right palm

Response parameters

- **Response parameter 1:** The score of the shot impact point

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- **Response parameter 2:** The angle between the shot impact point and the horizontal
- **Response parameter 3:** The distance between the shot impact point and the bulls eye

SHOOTING PERFORMANCE AND PREDICTION METHODS

Definition of statistical accuracy: In the field of statistics, the term "accuracy" is typically used to denote the degree of correctness of a measurement. According to ISO 5725-1 (ISO 5725-1, 1994), accuracy comprises "precision" and "trueness." Precision refers to the degree of similarity between each measurement. In other words, precision denotes the variation in measurement-the smaller the variation, the higher is the accuracy. Trueness refers to the difference between the mean and actual values of the measurement. In other words, trueness denotes the bias of each measurement-the smaller the bias, the higher is the accuracy (ISO 5725-2, 1994).

Definition of shooting accuracy: A high-variation and high-bias scenario of shot group which represents low precision and low trueness of shooting accuracy; a low-variation and low-bias scenario of shot group which represents high precision and high trueness of shooting accuracy (Berenson *et al*., 2006).

Evaluation of shooting performance

Analysis of shot impact points: Shooting performance can be evaluated by carrying out analysis of impact points, as shown in Fig. 1. Shot performance analysis can be divided into the analysis of score, precision and trueness. Score can be evaluated according to the impact point position in the target sheet. Precision can be evaluated according to the angle between the shot impact point and the horizontal. Trueness can be evaluated according to the distance between the shot impact point and the bulls eye. Score denotes the level of the shooter, precision denotes the stability of the shooter and trueness denotes the correlation between the shooter and the pistol.

Performance evaluation: The T75 assault pistol was used in our study; it was operated in the semi-automatic mode (one round at a time). The target sheet was analyzed to identify the impact points. Table 1 lists the independent and dependent variables used in present study.

Prediction methods

Support Vector Machines: The Support Vector Machine (SVM) is a supervised learning method that analyses data and recognizes patterns (Liejun *et al*., 2009); SVM are

Fig. 1: Shot results measurement

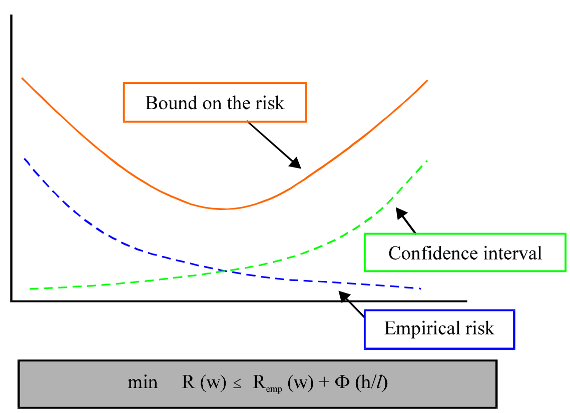

Fig. 2: Structural risk minimization

used for classification and regression analysis. The SVM algorithm is based on Statistical Learning Theory (SLT) and follows the Structural Risk Minimization (SRM) principle. The SVM was developed by Vapnik (1995) and followed the VC Dimension (Vapnik Chervonenkis dimension). The VC dimension measures the capacity of a hypothesis space. Capacity is a measure of complexity, and it also measures the expressive power, richness, or flexibility of a set of functions by assessing how wiggly its members can be. The SVM is based on approaching the upper bound of the minimum prediction error

Table 1: Independent variables and dependent variables

Independent variables (experiment code number)	Dependent variables (experiment code number)
The force with which the shooter pulls the pistol trigger using his or her right index finger (X_1)	The score of the shot impact point (Y_1)
The force with which the shooter grips the pistol in his or her left palm (X_2)	The angle between the shot impact point and the horizontal (Y_2)
The force with which the shooter grips the pistol in his or her right palm (X_3)	The distance between the shot impact point and the bulls eye (Y_3)

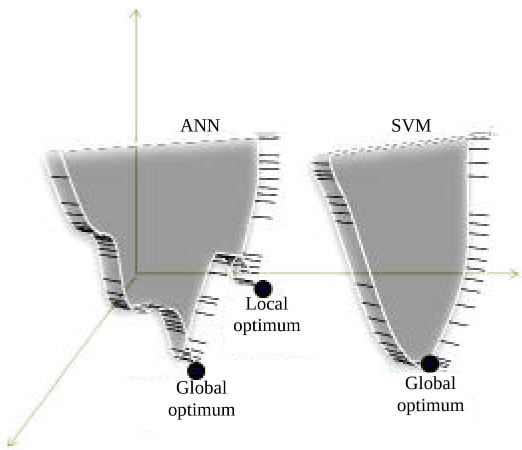

Fig. 3: Comparison of ANN and SVM solutions

(structural risk) and it differs from ANN in its approach to minimum training error (empirical risk), as shown in Fig. 2 (Pugazhenthi and Rajagopalan, 2007). The most important feature is that the SVM approach is based on a constrained quadratic programming optimal problem (Shafri and Ramle, 2009). Therefore, SVMs can avoid a local optimal solution (ANN algorithm) and achieve a global optimal solution, as shown in Fig. 3.

Vapnik *et al.* (1997) developed Support Vector Regression (SVR) which introduced the ε-loss function concept into the SVM and thus extended the SVM to solving function prediction problems. Traditional regression procedures are often stated as the processes that derive a function that has the least deviation between predicted and experimentally observed responses. One of the main characteristics of SVR is that, instead of minimizing the observed training error, SVR attempts to minimize the generalized error bound so as to achieve generalized performance. This generalization error bound is the combination of the training error and a regularization term that controls the complexity of the hypothesis space. SVR has been applied to such problems as time series financial forecasting (Tay and Cao, 2001), establishing the bankruptcy prediction model (Shin *et al.*, 2005) , making forecasts regarding corporate financial distress (Hua *et al.*, 2007), forecasting tourism demand (by combining SVR and genetic algorithms) (Chen and Wang, 2007) and forecasting control of HVAC plants (Xi *et al.*, 2007).

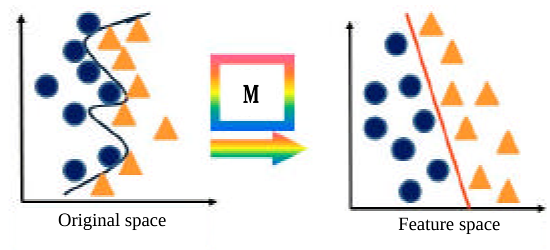

Fig. 4: Nonlinear transfer function

Least squares support vector machines (LS-SVM): The Least Squares Support Vector Machine (LS-SVM) which is a least squares version of SVM, was proposed by Suykens *et al.* (2002). LS-SVM is based on equality constraints and a sum square error cost function, as opposed to earlier approaches that utilized inequality constraints and solved complex convex optimization problems (Hung and Liao, 2008).

The LS-SVM reformulation simplifies the problem and solution by adopting a linear system (Liejun *et al.*, 2008). Also, LS-SVM is easier to optimize and it requires less computing time because it follows a linear KKT system, which is a calculating process that considers the training errors of all training samples (Wu and Zhao, 2006). LS-SVM is useful for applications in which most or all of the training samples can affect the training phases. The LS-SVM theory is based on the assumption that the dataset $S = \{(x_1, y_1)\ldots(x_n, y_n)\}$ which processes a nonlinear function and a decision function, can be written as shown in (1). In (1), w denotes the weight vector; Φ represents the nonlinear function that maps the input space to a high-dimension feature space and performs linear regression (Fig. 4) and b is the bias term (Suykens *et al.*, 2002).

$$f(x) = \Phi(x) \cdot w + b \qquad (1)$$

For the function prediction problem, the SRM principle is introduced and the optimization problem is used to formulate the R function (2), where C denotes the regularization constant and e_i represents the training data error.

Minimize:

$$R\,(w,e,b)=\frac{1}{2}\|w\|^2+\frac{1}{2}C\sum_{i=1}^{n}e_i^2 \tag{2}$$

Subject to:

$$y_i=[\Phi(x_i)\cdot w]+b+e_i\; i=1,....n$$

To derive solutions w and e, the Lagrange Multiplier optimal programming method is applied to solve (Eq. 2); the method considers objective and constraint terms simultaneously. The Lagrange function L is shown in Eq. 3:

$$L\,(w,e,b;\alpha)=\frac{1}{2}\|w\|^2+\frac{1}{2}C\sum_{i=1}^{n}e_i^2-\sum_{i=1}^{n}\alpha_i\{(\Phi(x_i)\cdot w)+b+e_i-y_i\} \tag{3}$$

In Eq. 2, $\alpha_i \geq 0$ called Lagrange multipliers which can be either positive or negative due to the following equality constraints, from based on the Karush Kuhn-Tucher's (KKT) conditions (Fletcher, 1987) and which may obtain the extreme value in the saddle point, the conditions for optimality are given by Eq. 4. Equation 4 Can be expressed as the solution to the following set of linear Eq. 5:

$$\begin{aligned}&\partial_w L=w-\sum_{i=1}^{n}\alpha_i\Phi(x_i)=0\\&\partial_b L=\sum_{i=1}^{n}\alpha_i=0\\&\partial_{e_i} L=C\cdot e_i-\alpha_i=0\\&\partial_{\alpha_i} L=(\Phi(x_i)\cdot w)+b+e_i-y_i=0\end{aligned} \tag{4}$$

$$\begin{bmatrix}I&0&0&-Z^T\\0&0&0&-1_v^T\\0&0&CI&-I\\Z&1_v&I&0\end{bmatrix}\begin{bmatrix}w\\b\\e\\\alpha\end{bmatrix}=\begin{bmatrix}0\\0\\0\\y\end{bmatrix} \tag{5}$$

In Eq. 10, $Z=[\Phi(x_1)^T;\ldots;\Phi(x_n)^T]$, $y=[y_1;\ldots;y_n]$, $1_v=[1;\ldots;1]$, $\alpha=[\alpha_1;\ldots;\alpha_n]$ and $e=[e_1;\ldots;e_n]$. The solution is also given by Eq. 6:

$$\begin{bmatrix}0&1_v^T\\1_v&ZZ^T+C^{-1}I\end{bmatrix}\begin{bmatrix}b\\\alpha\end{bmatrix}=\begin{bmatrix}0\\y\end{bmatrix} \tag{6}$$

In order to simplify the solving process, let $\Omega=ZZ^T+C^{-1}I$, where α and b are the solution to Eq. 7 and 8:

$$\alpha=(y-b1_v)\Omega^{-1} \tag{7}$$

$$b=(1_v^T\,\Omega^{-1}1_v)^{-1}1_v^T\,\Omega_y^{-1} \tag{8}$$

The resulting LS-SVM model for function prediction is represented as Eq. 9:

$$f(x)=\sum_{i=1}^{n}\alpha_i K(x,x_i)+b \tag{9}$$

In Eq. 9, the dot product $K\,(x\cdot x_i)$ is known as the kernel function. Kernel functions enable the dot product to be computed in a high-dimension feature space using low-dimension space data input without the transfer function Φ and must satisfy the condition specified by Mercer (Vapnik, 1995). Some common kernel functions are represented in (10-12), where T, d and γ denote the kernel function parameters (Gunn, 1998) this study employed the Radial Basis Function (RBF), a common function that is useful in nonlinear regression problems (Smola and Scholkopf, 2002).

Linear function:

$$k(x_i,x_j)=x_i\cdot x_j^T \tag{10}$$

Polynomial function:

$$k(x_i,x_j)=(1+x_i\cdot x_j)^d \tag{11}$$

Radial basis function:

$$k(x_i,x_j)=\exp\left(-\gamma\|x_i-x_j\|^2\right) \tag{12}$$

When adopting LS-SVM with the RBF kernel function, the parameter combinations (C, γ) should be established. C denotes the regularization parameter which corresponds to the trade-off between minimizing the training error and minimizing the complexity of the LS-SVM model and γ denotes the RBF kernel parameter, which represents the change in the RBF kernel function. Different parameter combinations can significantly affect prediction performance. Therefore, selecting parameters is one of the most important steps in establishing LS-SVM prediction models. The grid search algorithm and the k-fold cross-validation method were generally applied to obtain the optimal parameter combination (Duan *et al*., 2003).

Back propagation neural network (BPNN): The neural networks method is based on imitating the neuron transfer frameworks present in the human brain, especially those involved in the training and learning phases and is also known as the Artificial Neural Networks (ANN) method. The most popular networks are the Back-Propagation Neural Network (BPNN) which are based on constant error feedback and modification of the weighted parameter approach to establish a minimum error prediction model (Lippmann, 1987).

BPNN networks compare the training samples with the desired output and minimize errors using the gradient steepest descent method. The BPNN framework is a Multi Layer Perceptron (MLP) that applies an error back-propagation algorithm to continuously operate the error feedback process, modify the network weight and approach the minimum error between the desired output and the network prediction output. The main components of BPNN include the input layer, hidden layer and output layer (Haykin, 1999).

Prediction using statistical parameters: Prediction techniques using statistical parameters have been widely applied in many fields. These techniques predict responses by employing independent variables and determining errors in dependent variables. By using the least squares method, a first-order regression model can be fit to the data. A first-order regression model can be employed only for simple prediction problems; for complex problems, we have to employ a second-order regression model by incorporating square and interaction terms of the variables as follows Eq. 13 (Montgomery, 2001).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_{12} + \varepsilon \quad (13)$$

In Eq. 13, X_i denotes the independent variables; y, the dependent variables; β, the coefficients of regression and ε, the error in estimation. Second-order regression analysis is also known as Response Surface Methodology (RSM). Prediction models using statistical parameters provide accurate results because the parameters exhibit little or no variation. However, the accuracy of such models is easily affected by the external environment. In other words, such models are unsuitable for computing complex variables. Thus, several experts have recommended the use of neural networks to solve prediction problems.

EXPERIMENTAL SETUP OF T-75 PISTOL FIRING

The experimental parameters and their units of measurement are as follows: Independent variables 1, 2, and 3 denote physical strength (kilograms). Dependent variables 1, 2 and 3 denote the level (score), precession (angle) and trueness (distance). Table 2 lists the instruments and contents used to measure the independent and dependent variables.

Instruments in the experimental setup: An I-CubeX sensor system (http://www.infusionsystems.com/support/editor-25x-ref.pdf) is used to measure independent variables 1, 2 and 3; this system is advantageous in that it is compact and lightweight. The flexibility of the glove system contributes to a reduction in measurement interference while shooting. The glove is a six-channel pressure-sensing device. When connected to the I-CubeX digitizer, the glove becomes a fingertip controller. Each glove has six pressure sensors (one on each fingertip and one on the palm). The I-CubeX system can display data in numerical form, as shown in Fig. 5.

Prediction performance criteria: The purpose of performance criteria is to estimate prediction abilities for LS-SVM. We use R^2 (Coefficient of determination), MSE (Mean Squared Error) and P (p-value) to evaluate 3 models. About above 3criteria, we make introduction as follows (Walpore *et al*., 2007).

Table 2: Instruments and contents to measure variables

Variables type	No.	Contents	Instrument
Independent variables	1	The force with which the shooter pulls the pistol trigger using his or her right index finger	I-CubeX glove sensors and multiple handle systems
	2	The force with which the shooter grips the pistol in his or her left palm	
	3	The force with which the shooter grips the pistol in his or her right palm	
Dependent variables	1	The score of the shot impact point	Target sheet
	2	The angle between shot impact point and the horizontal	Protractor
	3	The distance between shot impact point and the bulls eye	Rubber ruler

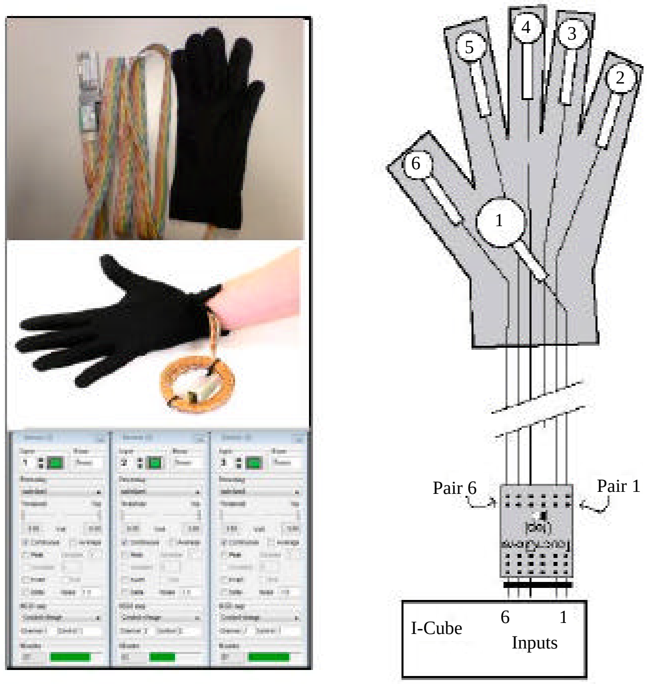

Fig. 5: I-CubeX glove sensors and multiple handle systems

R^2 is used in the context of statistical models whose main purpose is the prediction of future outcomes on the basis of other related information. It is the proportion of variability in a data set that is accounted for by the statistical model. It provides a measure of how well future outcomes are likely to be predicted by the model. R^2 values vary from 0 to 1. The R^2 value more neared 1, the model prediction ability more strong.

MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the square of the "error". The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. The MSE value lower, the prediction value more neared actual value.

P is the probability of obtaining a test statistic at least as extreme as the one that was actually observed, assuming that the null hypothesis is true. The lower the p-value, the less likely the result is if the null hypothesis is true and consequently the more "significant" the result is, in the sense of statistical significance. The regression p-value lower, the model prediction ability more strong.

The formulas about R^2 and MSE are listed in Eq. 14 and 15. Some abbreviation meanings as follows: SS_R: Sum Square of Regression; SS_T: Sum Square of Total; SS_E: Sum Square of Error; n: numbers of sample; y_i: actual value; y_i': prediction value.

$$R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T} \tag{14}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i'\right)^2 \tag{15}$$

LS-SVM modeling procedure: The LS-SVM modeling procedure is presented in Fig. 6. The modeling procedure is summarized as follows (Deng and Yeh, 2010):

- Divide the entire dataset into the training dataset and the test dataset. The training dataset is used to build the LS-SVM model and the test dataset is used to verify the model's performance
- Use the grid search algorithm with the cross-validation method to find the optimal parameter combination (C, γ). Separate the training data into grid training data and test data. Present research applied a ten-fold cross-validation method, dividing the training into ten aliquot parts. The grid training data comprises nine aliquot parts and the other part is the grid test data. Train the LS-SVM model with the grid training data and the initial parameter combination (C, γ). Test the LS-SVM model with the

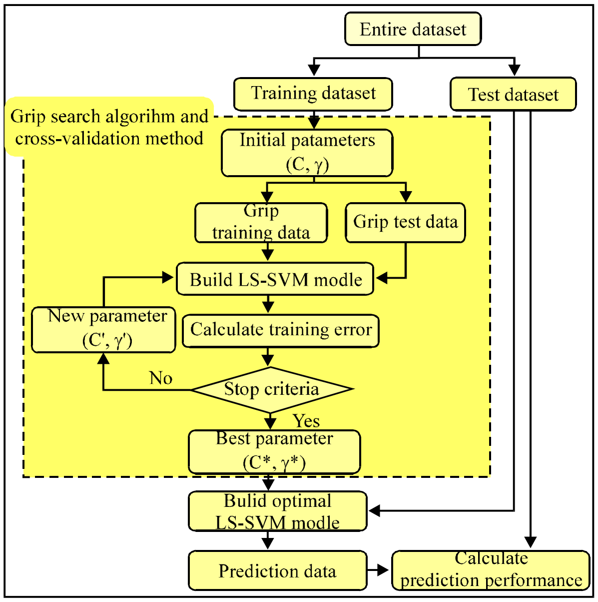

Fig. 6: LS-SVM modeling procedure

Table 3: Analysis of datasets

Grade	Y_1 (score)	Y_2 (degree)	Y_3 (cm)	X_1 (kg)	X_2 (kg)	X_3 (kg)
1st	9.0	54.3	3.3	2.2	2.8	4.2
2nd	8.9	64.6	3.4	2.2	2.8	4.2
3rd	7.3	117.9	8.0	1.9	2.5	4.2
4th	7.1	125.4	8.8	1.9	2.5	4.2
5th	5.4	182.1	13.0	1.6	2.3	4.2
6th	5.3	186.9	13.4	1.6	2.3	4.2
7th	4.8	204.2	14.8	1.5	2.2	4.2
8th	3.9	230.7	17.2	1.4	2.0	4.2
9th	1.2	325.3	25.9	0.9	1.6	4.2
10th	1.1	327.2	26.3	0.8	1.6	4.2
11th	1.0	329.8	26.8	0.8	1.5	4.1

grid test data and iterate the process ten times. The average training error is collected and calculated afterwards. Insert the new parameter combination (C', γ) and repeat the process until the stop criteria are approached. This process can successfully obtain the optimal parameter combination (C^*, γ^*) with the minimized error:

- Adopt the optimal parameter combination (C^*, γ^*) to build the LS-SVM prediction model. Substitute the test dataset into the LS-SVM model and the prediction data can now be obtained successfully. Finally, use three criteria to calculate the prediction performance

Analysis of experimental data: Eleven shooters were selected to fire 30 rounds each and 330 datasets were obtained successfully. The average values of the 30 rounds for each shooter are listed in Table 3. After deleting 89 outlier datasets, 241 datasets remained. These 241 datasets involved three independent variables (X_1, X_2 and X_3) and three dependent variables (Y_1, Y_2 and Y_3). Analysis of variance (ANOVA) indicated that the independent variable X_3 had a non-significant influence on the three dependent variables (Y1, Y_2 and Y_3), as shown in Table 4. Thus, we used only two independent variables (X_1 and X_2) to establish the models. These 241 datasets were randomly grouped into 161 datasets for model training and 80 datasets for model testing.

Model 1: Prediction of shooting score (the position of shot impact point): This model discusses correlation between two independent variables (X_1 and X_2) and dependent variables (Y_1).

Model 1: Modeling by LS-SVM: A Radial Basis Function (RBF) was selected as the kernel for nonlinear mapping and searching the best parameter sets ($C = 35.035$, $\gamma = 2.648$) by using the grid search and cross-validation method. We successfully obtain all the prediction performance criteria (R^2: 0.977, MSE: 0.002 and P: 1.20e-12) for Model 1.

Model 1: Modeling by BPNN: Our objective was to search for the best parameter sets that would yield minimum training error in the BPNN training phase. We obtained different permutations and combinations using seven training functions (SDBP, MOBP, VLBP, RPROP, CGBP, QN and LM) and 11 sets of neurons (containing 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12 neurons). Finally, it is observed that the minimum training error can be attained only by adopting a combination of the LM training function and 12 neurons; therefore, this combination is chosen as the parameter set for Model 1, 2 and 3. The parameters of BPNN training model as follows: Epoch: 723; Time: 72 sec; Gradient: 4.21; Mu: 1.00. We successfully obtained all the prediction performance criteria (R^2: 0.891, MSE: 0.007 and P: 1.20e-08).

Model 1: Modeling by RSM: By using the professional software, we found that the best regression Model 1 as follows. We successfully obtained all the prediction performance criteria (R^2: 0.733, MSE: 0.018 and P: 2.30e-05).

$$Y_1 = -7.84 + 9.87X_1 - 0.91X_1^2 - 0.91X_2 + 1.23X_2^2 - 1.19X_1X_2$$

Model 2: Prediction of shooting precision (the angle between impact point and horizontal): This model discusses correlation between two independent variables (X_1 and X_2) and dependent variables (Y_2).The source way of datasets the same as Model 1.

Table 4: Analysis of variance

X	Y	Source	SS	df	MS	F	p	Significant (95% CI)
X_1	Y_1	SS_{Tr}	88.03	6	14.67	1676.67	0.00	Yes
		SS_E	0.04	4	0.01			
		SS_T	88.06	10				
	Y_2	SS_{Tr}	101709.22	6	16951.54	705.80	0.00	Yes
		SS_E	96.07	4	24.02			
		SS_T	101805.29	10				
	Y_3	SS_{Tr}	754.01	6	125.67	948.44	0.00	Yes
		SS_E	0.53	4	0.13			
		SS_T	754.54	10				
X_2	Y_1	SS_{Tr}	88.03	6	14.67	1676.67	0.00	Yes
		SS_E	0.04	4	0.01			
		SS_T	88.06	10				
	Y_2	SS_{Tr}	101710.79	6	16951.80	717.57	0.00	Yes
		SS_E	94.50	4	23.62			
		SS_T	101805.29	10				
	Y_3	SS_{Tr}	754.06	6	125.68	1036.50	0.00	Yes
		SS_E	0.49	4	0.12			
		SS_T	754.54	10				
X_3	Y_1	SS_{Tr}	17.60	1	17.60	2.25	0.17	No
		SS_E	70.46	9	7.83			
		SS_T	88.06	10				
	Y_2	SS_{Tr}	19896.59	1	19896.59	2.19	0.17	No
		SS_E	81908.70	9	9100.97			
		SS_T	101805.29	10				
	Y_3	SS_{Tr}	162.99	1	162.99	2.48	0.15	No
		SS_E	591.55	9	65.73			
		SS_T	754.54	10				

Table 5: Prediction performance of 3 models

	R^2			MSE			P		
Prediction method	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
LS-SVM	0.975	0.961	0.971	0.003	0.005	0.004	1.31e-11	4.11e-16	3.12e-15
BPNN	0.882	0.841	0.824	0.009	0.010	0.016	1.51e-05	4.51e-06	3.11e-05
SM	0.641	0.618	0.608	0.021	0.031	0.043	3.71e-03	5.12e-02	2.51e-02

Model 2: Modeling by LS-SVM: A radial basis function (RBF) was selected as the kernel for nonlinear mapping and searching the best parameter sets (C = 56.452, γ = 1.351) by using the grid search and cross-validation method. We successfully obtain all the prediction performance criteria (R^2: 0.964, MSE: 0.004 and P: 2.30e-18) for Model 2.

Model 2: Modeling by BPNN: Adopting a combination of the LM training function and 12 neurons as the parameter set for Model 2. Other parameters of BPNN training model as follows: Epoch: 717; Time: 68 sec; Gradient: 3.11; Mu: 0.10.We successfully obtained all the prediction performance criteria (R^2: 0.883, MSE: 0.008 and P: 2.10e-08).

Model 2: Modeling by RSM: By using the professional software, we found that the best regression Model 1 as follows. We successfully obtained all the prediction performance criteria (R^2: 0.733, MSE: 0.019 and P: 2.33e-05).

$$Y_2 = -3.49 + 9.12X_1 - 7.14X_1^2 - 0.56X_2 + 1.41X_2^2 - 2.17X_1X_2$$

Model 3: Prediction of shooting trueness (the distance between impact point and bull's-eye: This model discusses correlation between five independent variables (X_1 and X_2) and dependent variables (Y_3). The source way of datasets the same as Model 1.

Model 3: Modeling by LS-SVM: A Radial Basis Function (RBF) was selected as the kernel for nonlinear mapping and searching the best parameter sets (C =92.753, γ = 1.418) by using the grid search and cross-validation method. We successfully obtain all the prediction performance criteria (R^2: 0.973, MSE: 0.003 and P: 1.25e-17) for Model 3.

Model 3: Modeling by BPNN: Adopting a combination of the LM training function and 12 neurons as the parameter set for Model 3. Other parameters of BPNN training model as follows: Epoch: 754; Time: 81 sec; Gradient: 4.35; Mu: 0.10.We successfully obtained all the prediction performance criteria (R^2: 0.843, MSE: 0.011 and P: 2.32e-07).

Model 3: Modeling by RSM: By using the professional software, we found that the best regression Model 1 as follows. We successfully obtained all the prediction performance criteria (R^2: 0.718, MSE: 0.038 and P: 1.40e-04).

Prediction performance of three models: Random sampling of 80 datasets was carried out for model testing. Regarding the prediction performance of three models, the results are summarized in Table 5. The LS-SVM and BPNN models were established by using the best parameter sets, whereas the RSM model was established by using regression methodology. The boldfaced content in Table 5 clearly indicates that R^2 of the LS-SVM model have the highest values, whereas MSE and P have the lowest values among the three models. On the basis of the description in Section 3.2 (Prediction performance criteria), it can be shown that the LS-SVM model outperforms both the BPNN and RSM models in terms of prediction ability.

CONCLUSIONS

Compared with RSM, LS-SVM can deal with high-level nonlinear problems without knowing the original prediction model. Compared with BPNN, LS-SVM uses quadratic programming and the solution obtained is a global optimal solution. And LS-SVM requires fewer parameters than BPNN and RSM in establishing model. Therefore, LS-SVM can save much time in parameter selection. The results of Model 1, 2 and 3 have indicated that LS-SVM has excellent prediction ability than BPNN and RSM.

Gripping a pistol stably, aiming at a target correctly, and pulling the trigger steadily are strongly correlated with the correctness of the pistol holding position. The force of the shooter's right index finger abdomen for pulling the pistol trigger and the force of the shooter's left palm for gripping the pistol significantly influence shooting performance. An inexperienced shooter can use the results of this study as a reference for improving his or her shooting skills. With regard to the management of the T75 pistol configuration, these results can be used as a reference for improving the pistol design and, accordingly, for enhancing the pistol's performance. In addition, these results can contribute to the development of a T75 pistol simulator.

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