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Gesture Recognition Using Data Glove: An Extreme Learning Machine Method

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Abstract— **In recent years, the use of human movements, especially hand gestures, serves as a motivating force for research in gesture modeling, analyzing and recognition. Hand gesture recognition provides an intelligent, natural, and convenient way of human–robot interaction (HRI). According to the way of the input of gestures, the current gesture recognition techniques can be divided into two categories: based on the vision and based on the data gloves. In order to cope with some problems existed in currently data glove. In this paper, we use a novel data glove called YoBu to collect data for gesture recognition. And we attempt to use extreme learning machine (ELM) for gesture recognition which has not yet found in the relevant application. In addition, we analyzed which features play an important role in classification and collect data of static gestures as well as establish a gesture dataset.**

I. Introduction

In current Virtual Environment (VE) applications, keyboards, mice, wands and joysticks are still the most popular devices. In recent years, the use of human movements, especially hand gestures, serves as a motivating force for research in gesture modeling, analysis and recognition. Although hand gestures are complicated to model since the meanings of hand gestures depend on people and cultures, a set of specific hand gesture vocabulary can be always predefined in many applications, such as Virtual Environment (VE) applications, so that the ambiguity can be limited. Generally, these hand gestures can be either static hand postures or temporal hand gestures. Hand postures express some concepts by hand configurations and hand shapes, while temporal hand gestures represent some actions by hand movements. Sometimes, hand postures act as special transition states in temporal gestures, and supply a cue to segment and recognize temporal hand gestures. Some research results show that static hand signs and temporal hand gestures seldom present simultaneously, which suggests us study static hand gestures and temporal gestures separately.

Hand gesture recognition provides an intelligent, natural, and convenient way of human–robot interaction (HRI) [1]. Sign language recognition (SLR) and gesture-based control are two major applications for hand gesture recognition technologies. Recognizing human gestures is an important research area in the field of human-machine interfaces. Especially, utilization of inertial sensors (mostly accelerometers or angular rate sensors) is gathering more and more interest in various applications [2,3,4].

According to the way of the input of gestures, the current gesture recognition techniques can be divided into two categories [5]. The first method of gesture recognition is based on vision [6,7]. To begin with, the camera captures the user's gestures, and transfers gesture information into the computer, then computer makes the analysis of the gesture information, and guides the virtual interactive system to accomplish interaction tasks [8,9,10,11]. However, there are still some problems with this method, it is well-known that recognition system based on vision is sensitive to the environment, so object shelter or illumination may lead to the poor recognition accuracy of algorithm analysis with high probability. Furthermore, the recognition system based on vision are constrained to the volume space in which the cameras are placed.

Secondly, though the wearable data gloves [12,13,14]. Data glove is composed of multiple sensor devices, through these sensors, the location, position and rotation of the user's hand and finger can be provided in the computer system. In addition, some gloves can detect high precision bending fingers, or even provide tactile feedback to the user, this is a simulation of the sense of touch. The best advantage of data gloves is that it available for all degrees of freedom of a human hand [15]. The past several years has witnessed a sharp increase in the number of researchers attach more importance to data gloves. But there are still some problems with this method, most of currently data gloves [16] are expensive (such as CyberGlove [17,18], humanglove [19], 5DT Data Glove [20]), accuracy of calculation is limited and short in service life.

In order to cope with the problem of data gloves which I have just outlined. In this paper, we use a novel data glove called YoBu [21] to collect data for gesture recognition. The characteristics of YoBu are low-cost and a relatively high accuracy.

Aim to address one crucial issue in such a framework is in the light of the high variability of the input data, in terms of different people do the same action of diverse habits, classic machine learning techniques such as k-Nearest Neighbor(k-NN) [22], ANNs (artificial neural networks) [23,24], and SVM (Support Vector Machine) [22,25] has been applied to the field of hand gesture recognition. Nonetheless, it is known that both them face some challenging issues as follows:(1) slow training speed (2) trivial human intervene (3) large computational quantity (4) poor generalization ability [26].

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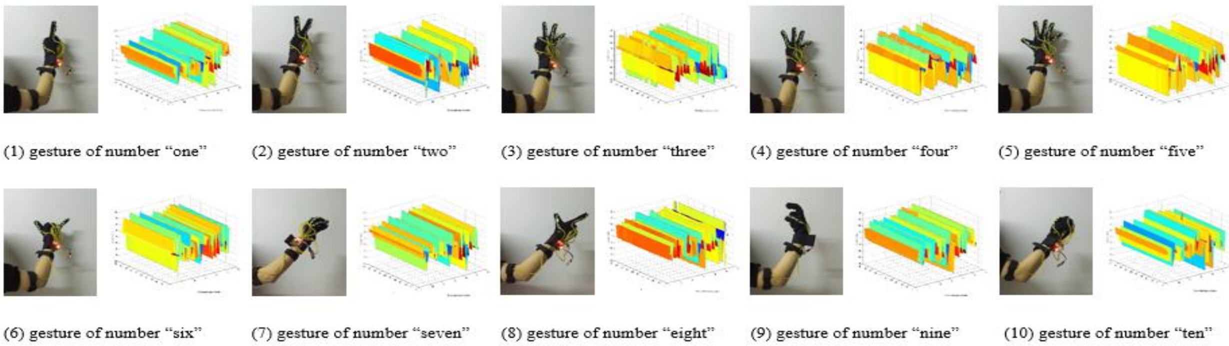

Figure 1. feature-image pair information of the gesture dataset.

In this paper, we attempt to use extreme learning machine for gesture recognition. On the one hand, compare to those compared with those Machine learning algorithm, Elm [27,28] has better generalization performance at a much faster learning speed. On the other hand, ELM [29] is insensitive to parameters. Elm has not been applied in the field of gesture recognition based on data glove.

In this work, we use Elm as a method for gesture recognition based on data glove. In order to compare, we also use SVM. The main contributions are listed as follows:

(1) Extract 54-dimensional features from a novel low-cost data glove, and analyses which features play an important role in classification.

(2) In this work, we prefer to choose ELM as a machine learning algorithm based on gesture recognition

(3) We collect data of static gestures and establish a gesture dataset which includes 10 kinds of static gestures.

The remainder of this paper is organized as follows: In Section 2 we brief an architecture of this problem. Section 3 give a description of feature design. Section 4 introduces the theories of ELM. Section 6 Section 4 presents the experimental results; while Section 6 concludes this paper.

II. Architecture

The framework of the gesture recognition based on data glove using ELM can be divided into three stages.

The first stage is establishing a gesture database. In this part, we collect the movement data of different gestures through the YoBu [21]. Then, we establish a gesture dataset which includes 10 kinds of static gestures.

The second stage is training classifier. Firstly, on the basis of the gesture dataset, we extract the 54-Dimension hand feature of each hand gesture and express it. The part of feature-image pair information of each gesture is shown in Figure.1. Secondly, we extract three 15- Dimension features: (1) The yaw angle of the five fingers; (2) The pitch angle of the five fingers; (3) The roll angle of the five fingers, and the 45-Dimension feature which include the yaw angle, the pitch angle and the roll angle from the 54-Dimension hand feature. Finally, we train the ELM classifier.

The third stage is experiment and analysis. We collect the movement data from different participants of various gestures, and use the trained classifiers for gesture recognition, then we will obtain the accuracy and analysis which feature plays an important role in gesture recognition.

The architecture of this system is shown in Figure.2.

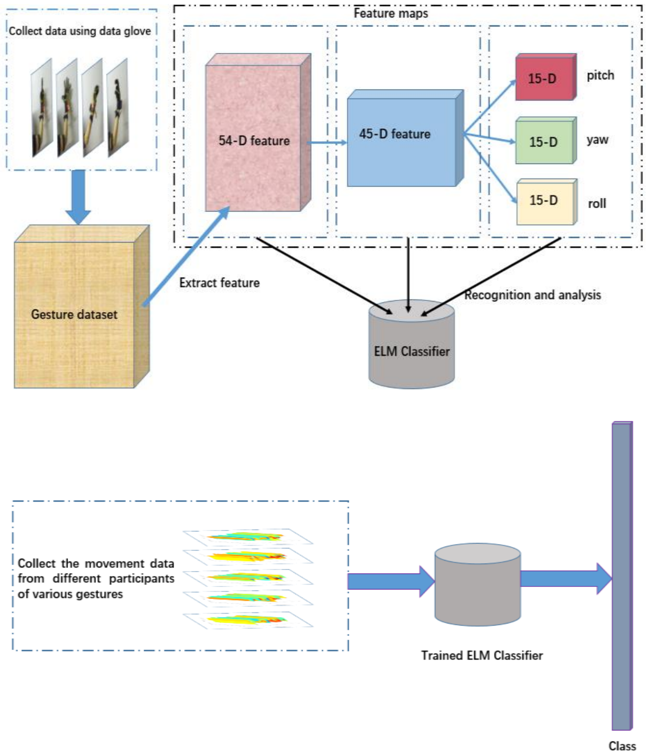

Figure 2. Architecture of the gesture recognition based on data glove using ELM.

III. FEATURE DESIGN

A. A brief description of YoBu

A glove instrumented with multiple IMMUs' for arm and hand motion capture has never been proposed to our knowledge. We proposed a low-cost data glove that uses inertial and magnetic measurement units placed on various arm, hand and finger segments which is able to accurately capture full 3D arm, hand and finger motion. The data glove is designed based on the low-cost IMMU, which can capture more information of motion than the traditional sensors. The traditional sensors of data glove like fiber or hall-effect sensor are frail. Nevertheless, the board of inertial and magnetic sensor that is an independent unit. It is more compact, more durable and more robust. Commercial data gloves are too costly for the consumer market, but the proposed data glove in the paper is low-cost. Moreover, the proposed data glove can not only capture the motion of hand but also capture the motion of arm, and the estimated results of motion are outputting real time.

Based on the measured 3D angular velocity, acceleration and magnetic field of one single IMU, it is possible to stably estimate its orientation with respect to a global (gravity and magnetic north aligned) coordinate system. For this, angular velocity is integrated to obtain absolute orientation. Due to noise and offsets present in the sensor measurements, the resulting orientation exhibits strong drift. Accelerometer and magnetometer measurements are therefore used to counteract this drift. By assuming negligible body acceleration, the accelerometers can be modeled as inclinometers (measuring only acceleration due to gravity) providing absolute information about two angles, i.e. pitch and roll. By assuming local static magnetic field homogeneous throughout the whole arm, the magnetic field measurements, projected into the horizontal plane, provide absolute information about the heading direction. By fusing all the measurements, a drift-free and long-term stable orientation estimate can be obtained. The above assumptions and principles have been formalized in a nonlinear state-space model for estimating the IMU orientation and kinematics within an extended Kalman filter. Hence, the stable orientations of gestures are estimated by the data glove.

B. Features of data gloves

We extract the 54-Dimension feature of each hand gesture through data glove. The sketch of hand joints of the data glove YoBu is shown in Figure.3. Then we extract three 15-Dimension features: (1) The yaw angle of the five fingers; (2) The pitch angle of the five fingers; (3) The roll angle of the five fingers, and the 45-Dimension feature which includes the yaw angle, the pitch angle and the roll angle from the 54-Dimension hand feature. The 54-Dimension feature include the 45-Dimension, the feature of palm, the feature of forearm and the feature of upper arm. What are the 54-dimention feature of the data glove YoBu represent are shown in Table. I.

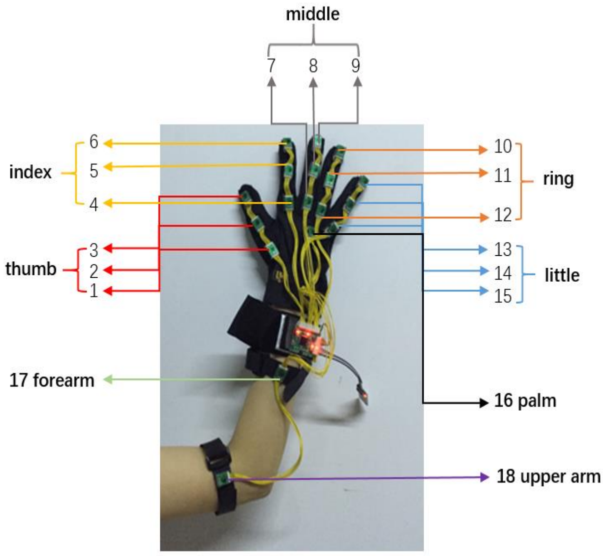

Figure 3. Sketch of hand joints of data glove

TABLE I. 54-DIMENTION FEATURE OF THE YOBU

Data glove	**Distribution of feature**			
	No.	***features***		
thumb	1	yaw	pitch	roll
	2	yaw	pitch	roll
	3	yaw	pitch	roll
index	4	yaw	pitch	roll
	5	yaw	pitch	roll
	6	yaw	pitch	roll
middle	7	yaw	pitch	roll
	8	yaw	pitch	roll
	9	yaw	pitch	roll
ring	10	yaw	pitch	roll
	11	yaw	pitch	roll
	12	yaw	pitch	roll
little	13	yaw	pitch	roll
	14	yaw	pitch	roll
	15	yaw	pitch	roll
palm	16	yaw	pitch	roll
forearm	17	yaw	pitch	roll
upper arm	18	yaw	pitch	roll

IV. CLASSIFIER DESIGN

A. Kernel-based Extreme Learning Machine

ELM was first proposed by Huang et al., which randomly generates the input weights and hidden layer biases of SLFNs and then determines the output weights analytically. And ELM can be biologically inspired, provide significant advantages such as fast learning speed, independent from implementation, and minimal human intervention.

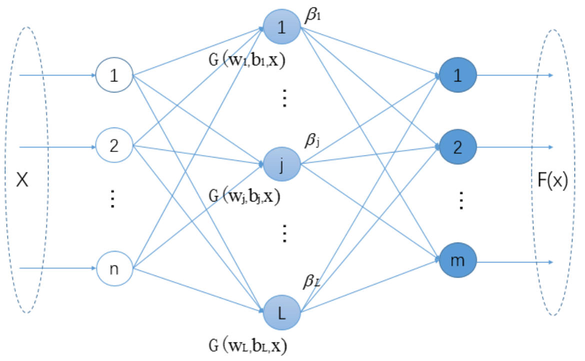

Figure 4. The model of ELM.

If the input data is $\boldsymbol{x}$, then we can obtain the output function of the L hidden layer node as:

$$\begin{cases} f_L(\boldsymbol{x}) = \sum_{i=1}^{L} \beta_i g_i(\boldsymbol{x}) = \sum_{i=1}^{L} \beta_i G_i(\boldsymbol{w}_i, \boldsymbol{b}_i, \boldsymbol{x}) \\ w_i \in C^d, x_i \in C^d, \beta_i \in C. \end{cases} , \quad (1)$$

where β_i is the output weight vector of the node of the i_{th} hidden layer, $g_i(x)$ denotes hidden nodes nonlinear piecewise continuous activation functions.

According to the theory of Bartlett [30], the method based on the least weight is used to calculate the output weights, and the ELM can obtain the minimum error solution through the minimum norm, which will achieve a great general performance. Given N training samples $(\boldsymbol{x}_i, \boldsymbol{t}_i)$, the output of L hidden layer nodes is:

$$f(\boldsymbol{x}) = \sum_{i=1}^{L} \beta_i \mathbf{G}(\boldsymbol{w}_i, \boldsymbol{b}_i, \boldsymbol{x}) = \beta \cdot h(\boldsymbol{x}), \quad (2)$$

where $h(x)$ is the output vector of the hidden layer, the parameters of the hidden layer nodes are randomly assigned, βi is the weight vector connecting the i-th hidden neuron and output neurons.

Thus, the matrix expression of this linear system is:

$$\mathbf{H} \cdot \beta = \mathbf{T}, \quad (3)$$

$$\mathbf{H} = \begin{pmatrix} \mathbf{G}(\boldsymbol{w}_1, \boldsymbol{b}_1, \boldsymbol{x}_1) & \cdots & \mathbf{G}(\boldsymbol{w}_L, \boldsymbol{b}_L, \boldsymbol{x}_1) \\ \vdots & \cdots & \vdots \\ \mathbf{G}(\boldsymbol{w}_1, \boldsymbol{c}_1, \boldsymbol{x}_N) & \cdots & \mathbf{G}(\boldsymbol{w}_L, \boldsymbol{b}_L, \boldsymbol{x}_N) \end{pmatrix}_{N \times L}, \quad (4)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times d}, \quad \mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_L^T \end{bmatrix}_{N \times d}. \quad (5)$$

Based on the input $\boldsymbol{x}_i$, the network matrix H is outputs of hidden layers, in which the i-th line represent the output vector of hidden layer. According to all input $(\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N)$, the i-th column represents the output of the i-th hidden layer neuron. The minimum norm the least-square solution to the linear system is:

$$\left|\mathbf{H} \cdot \hat{\beta} - \mathbf{T}\right| = \min_{\beta} \left|\mathbf{H} \cdot \beta - \mathbf{T}\right| \quad (6)$$

Therefore,

$$\hat{\beta} = \mathbf{H}^{\dagger}\mathbf{T} \quad (7)$$

where $\mathbf{H}^{\dagger}$ is the Moore-Penrose generalized inverse of matrix H.

In order to improve the ELM with better generalization capabilities in comparison with the least square solution-based ELM, which requires randomly generated input weights, Huang et al. proposed the use of kernel methods in the design of ELM and suggested adding a positive value $\frac{1}{C}$ (where C is a user-defined parameter) for the calculation of the output weights such that:

$$\beta = \mathbf{H}^T (\frac{I}{C} + \mathbf{H}\mathbf{H}^T)^{-1} \mathbf{T}. \quad (8)$$

Kernel-based ELM can be represented as follows:

$$\begin{aligned} &\mathrm{K}_{ELM}(x_i, x_j) = h(x_i) \cdot h(x_j) \\ &= [\mathrm{G}(w_1, b_1, x_i), \ldots, \mathrm{G}(w_L, b_L, x_i)]^T \cdot [\mathrm{G}(w_1, b_1, x_j), \ldots, \mathrm{G}(w_L, b_L, x_j)]^T. \end{aligned} \quad (9)$$

Because of the parameter of $(\boldsymbol{w}, \boldsymbol{b})$ is randomly assigned, the $h(\cdot)$ is also randomly generated, so the dual kernel optimization function is:

$$\begin{aligned} &\text{minimize} : \mathbf{L}_D = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} t_i t_j \mathbf{K}_{ELM}(\boldsymbol{x}_i, \boldsymbol{x}_j) \alpha_i \alpha_j - \sum_{i=1}^{N} \alpha_i \\ &\text{subject to} : 0 \le \alpha_i \le C, i = 1, \ldots, N \end{aligned}, \quad (10)$$

which can be seen from the above, the kernel ELM is a combination of the optimization method of nuclear learning and standard to find the optimal solution. Due to the relatively weak optimization constraints, the kernel ELM has better generalization ability.

V. Experimental Result

A. *Classification Result*

We use the 54-dimention feature of the data glove for gesture recognition classification. Table. II summarizes that compared with other methods, ELM-kernel can achieve better performance. And we can see from the Table. III the time which is spent on the ELM is i far less than one spend on SVM.

TABLE II. GESTURE RECOGNITION ACCURACY FOR DIFFERENT APPROACHES

Feature	method		
	ELM	*ELM-kernel*	*SVM*
54-dimention	68.05%	**89.59%**	83.65%

TABLE III. TRAIN TIME OF DIFFERENT APPROACHES

Feature	Train time (s)		
	ELM	*ELM-kernel*	*SVM*
54-dimention	**1.6094**	12.5456	1886.5

To analyze the roles of the parameters, we perform the sensitivity analysis. The most important parameters in the ELM-kernel include the penalty coefficient C and kernel parameter sigma. Therefore, we vary the value of C and the value of sigma within the set $\{10^{-3}, 10^{-2}, \ldots 10^{3}, 10^{4}\}$ to analyze the performance variations. The results are shown in Figure. 5.

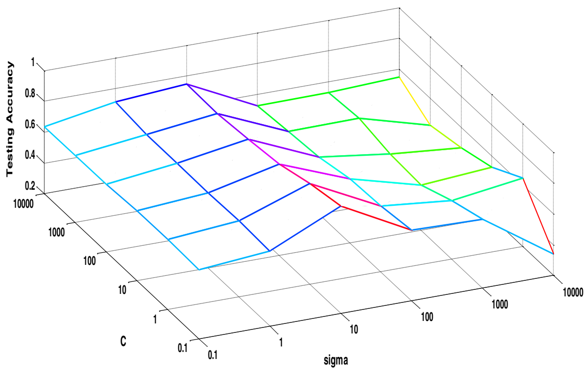

Figure 5. Testing accuracy of ELM-kernel in terms of C and sigma

We also analyze the overall performances of ELM, ELM-Kernel and SVM depicted in Figure.6. The average gesture recognition classification accuracy of ELM-Kernel is higher than that of ELM and SVM.

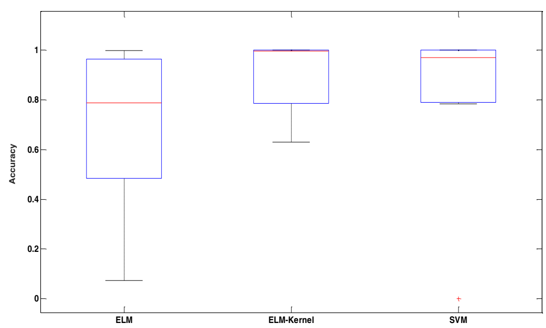

Figure 6. The comparison of the overall classification performance

Figure.7 shows the confusion matrix across all 10 classes. Most model confusions are evidently showing that the ELM kernel method has a better gesture recognition accuracy compared with the ELM and SVM.

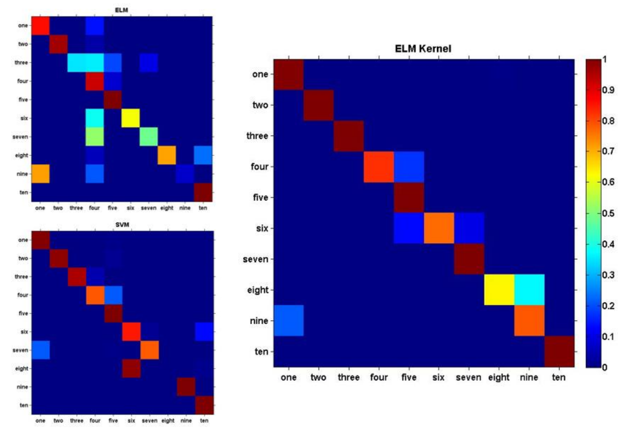

Figure 7. The confusion matrix of ELM,ELM Kernel,SVM.

In order to analyze which features play an important role in classification. We extract three 15- Dimension features: (1) The yaw angle of the five fingers; (2) The pitch angle of the five fingers; (3) The roll angle of the five fingers, and the 45-Dimension feature which include the yaw angle, the pitch angle and the roll angle from the 54-Dimension hand feature. Then we use these features for gesture recognition through different approaches. From Table. IV we can see the gesture recognition accuracy for different approaches.

TABLE IV. GESTURE RECOGNITION ACCURACY FOR DIFFERENT APPROACHES

Feature	method		
	ELM	*ELM-kernel*	*SVM*
yaw(15-D)	43.24%	**50.13%**	29.24%
pitch(15-D)	88.91%	**91.15%**	86.14%
roll(15-D)	**52.44%**	49.45%	35.78%
45-dimention	84.40%	**85.51%**	81.09%

From Figure.8, we can find out that the feature of the pitch is of importance for gesture recognition. But if we only use the feature of the pitch for gesture recognition classification, we will most likely to be confused with the gesture of number one and the gesture of number seven. In addition, the 45-dimention of feature is also essential to gesture recognition. However, if we only use the feature of 45-dimention for gesture recognition, we will most likely to be confused with the gesture of number eight and the gesture of number nine.

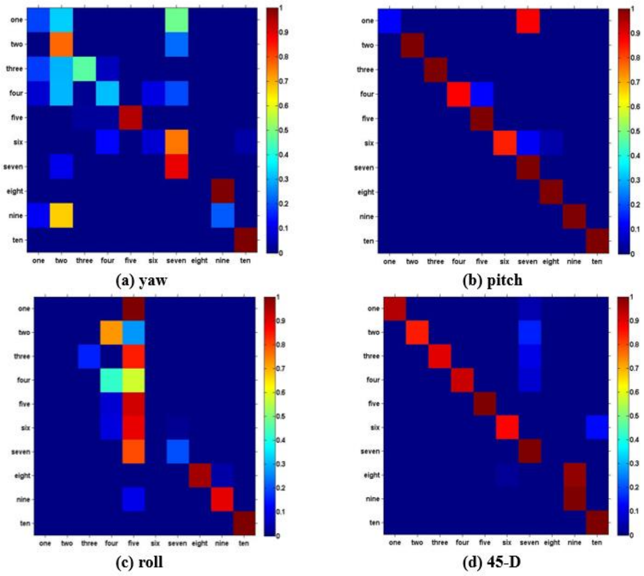

Figure 8. The confusion matrix of ELM Kernel for different features.

VI. CONCLUSION

In this paper, we attempt to use Elm as a method for gesture recognition based on data glove. Through experiments, we can get the conclusion that in view of overall, using ELM Kernel as a method for gesture recognition based on 54-dimention of data glove can achieve better performance. And the feature of the pitch is of importance for gesture recognition. This work can be applied to the robotic teleoperation based on gesture recognition in the future.

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