Emotion-aroused human behaviors Perception Using RNNPB

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Abstract—**This paper proposes a novel framework to recognize emotions using the algorithm of a recurrent neural network with parameter bias (RNNPB). For this purpose, we performed three simulation experiments aim to explore the relationship between the perception and action. Three types of emotion-driven sequences are fed into the network for training. The training of RNNPB utilizes back-propagation through time (BPTT) method and the parametric bias unit (PB unit) updates in a self-organizing way. The results of the experiments show that the merged sequences can distinguish the emotion better compared to the other two kinds of information.**

Index Terms—**Emotion Recognition, RNNPB, BPTT.**

I. Introduction

It is important to endow a robot with intelligent ability of learning and reasoning about how to behave in response to the dynamical changing environment. For instance, for an intelligent service robot, how to perceive the intention behind human behaviors timely and accurately has become a charming challenge. Many researchers have studied the relationship between emotion and motor behaviors. Complex body behaviors are comprised of a series of the basic actions which are so-called "primitive behaviors", and we can find that these primitive behaviors have been found that clear signals about affective expression also was provided in them [1]. As a result, the critical feature of different body posture can express specific emotion. For instance, the action of lifting up the head may be linked with happy and pride. Thus people can distinguish emotions from these key features of human behaviors. Furthermore, some researchers consider that emotion states can modulate human action. As mentioned in [2], Zhong, J et. al propose a hierarchical perception-action model focus on that internal state regulates the sensorimotor behaviors, since sensory information that people received from the surrounding environment is determined by the motor actions.

Most of recent researchers [3]–[7] mainly focus on the expression for different modalities and perception for emotional information which can obtain from face, language voices and etc. However, the body sensorimotor behaviors recognition was rarely analyzed. Some researchers combined the sensory and motor process dynamically to classify objects of different shapes and weights [8].

A novel framework is proposed to recognize emotions from multiple sensorimotor sequences which is used to represents sentiment in the paper. Then the experiments of computer simulations are performed with three types of emotion-driven sequences. These sequences are utilized to train the RNNPB network, proposed by Tani and his colleagues [9]. The results of these experiments obviously show that the proposed framework can recognize emotion more efficiently.

The remaining article is structured as follows: the section II introduces the construction of the RNNPB. To research the relationship between the human behaviors and emotions, several simulations are carried out. And different types of emotion-driven behaviors are fed into the network to explore various input sequences how to effect the recognition results in these experiments in section III. Finally, section IV demonstrates the discussions and concluding remark.

II. Recurrent Neural Model

A. RNNPB

The recurrent neural network with parametric bias (RNNPB) is essentially a Jordan-type or an Elman-type recurrent neural network. It owns an additional PB unit which is connected to the hidden layer [10]. The PB units with adjustable internal values are updated through back-propagation in a self-organizing way. In contrast with the common RNN, the RNNPB network owns the the additional PB values. As bifurcation parameters for the nonlinear dynamical systems, the additional PB units endow the network to have generalization capability to the untrained data. Due to the PB units, we can regarded the RNNPB network as a multiple-layer hierarchical architecture. Based on the aboved features, the network can also be further utilized to imitate the processes of cognition such as sensorimotor regulation[10], object categorization [11].

In this article, we employ the model proposed by Cuijpers [12] which is used the Elman-type as its core to learn the multiple behaviour sequences from emotions. The PB units are applied to express emotion information and to recognize emotion. Also, the trained PB values can be used as emotional behaviors regeneration. Since the generalization ability of the network novel behaviour patterns can be generated except the learned ones.

Fig. 1 demonstrates the construction of the Elman-type RNNPB network [11].

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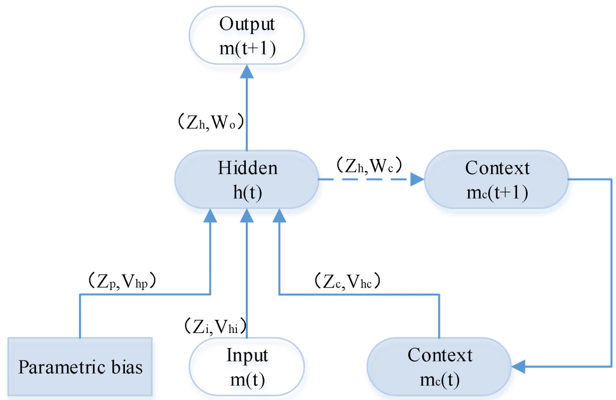

Fig. 1. The architecture of Elmam-type RNNPB

In the figure, the current emotion-driven behaviors state m(t) is the input and prediction state m(t+1) is the output of the RNNPB network. Three internal layers which expressed by the four blue block in the network are hidden layer, parametric bias layer and context layer. The black arrow lines represent the weights between different layers. We use the sigmoid function proposed by LeCun and his colleagues as the transfer functions for the hidden layer, PB units and output layer.

$$f(y)=\frac{1}{1+e^{-y}} \tag{1}$$

where y represents the input of the function.

Thus, the input of the hidden neurons Y_h are as follows:

$$Y_h = Z_i V_{hi} + Z_p V_{hp} + Z_c V_{hc} \tag{2}$$

where $Z_i = m(t)$, Z_p and Z_c are the output of input layer , PB units and context layer respectively. V_{hi} represents the connection weight between hidden layer and input layer. V_{hp} is the weight between the PB layer and the hidden layer , and V_{hc} is the weight matrices between the context layers and the hidden layer.

The input for the output and context neurons Y_o and Y_c are as follows:

$$m(t+1) = Y_o = Z_h W_o \tag{3}$$

$$Y_c = Z_h W_c \tag{4}$$

where $Z_h = f(Y_h)$ is the output of the hidden layer, and W_c , W_o represent the weights between the hidden layer and the context layer, output layer, respectively.

There are three different processes (learning, recognition and generation) of the network.

B. *Learning Process*

The learning process (Fig. 2) is executed off-line and PB values are learned in an unsupervised way when the training happens. The modification of all the synaptic weights in RNNPB are performed with back-propagation through time (BPTT) [13]–[15]. In other words, the errors between the desired outputs and the real outputs are not only used to update the internal values of the parametric bias units in a self-organizing way. In addition, if an epoch *e* is defined as an iteration of the whole sequences, the accumulated errors of back-propagation through time are also adopted to update the PB values after each epoch.

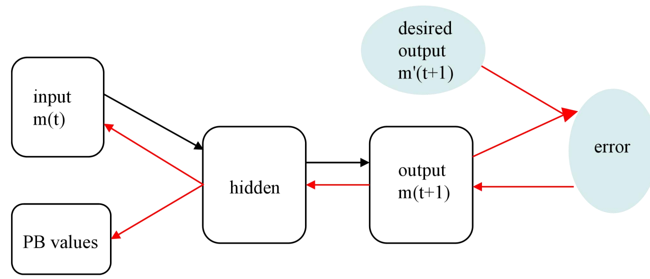

Fig. 2. The learning process of RNNPB

The update equation for the PB vector of the *k*-th unit during a period of T is given as [2]:

$$\rho_k(e+1) = \rho_k(e) + \eta_l \sum_{t_l=1}^{T} \delta_{k,t_l}^{pb} \tag{5}$$

where δ_{k,t_l}^{pb} is the back-propagation error of the PB nodes. η_l represents the learning rate of PB nodes which is scaled proportionally to the absolute mean value of summation errors being the back-propagated to the *k*-th PB node over time T[2]:

$$\eta_l \propto \frac{1}{T}\left\| \sum_{t=1}^{T} \delta_{k,j}^{pb} \right\| \tag{6}$$

Since it is difficult to converge for PB units in a steady way, we employed a small learning rate to guarantee the convergence of the network.

The cost function in the training process is given by[10]:

$$C = \frac{1}{2}\sum_{t}^{T}\sum_{k}^{N}(f_k(Z_o^{t+1}) - f_k(Z_o^{t}))^2 \tag{7}$$

where $f(Z^{t+1}{}_o)$ is the target output and $f_k(Z^{t}{}_o)$ is the prediction output. The updating of all weights in the network follows the gradient descent rule. The specific weight updates as follows [10]:

$$\Delta w_{ij} = -\eta_{ij}\frac{\partial C}{\partial w_{ij}} \tag{8}$$

η_{ij} the learning rate of the weights which is adjustable [9]. To acquire the changes trend of the weight, we can compute its sign by the following equation [11]:

$$\beta_{i,j} = \frac{\partial C}{\partial w_{i,j}}(t-1)\frac{\partial C}{\partial w_{i,j}}(t) \tag{9}$$

The learning rate η_{ij} updates [11]:

$$\eta_{i,j}(t) = \begin{cases} min(\eta_{i,j}(t-1)\cdot\xi^{+}, \eta_{max}) & if\ \beta_{i,j} > 0, \\ max(\eta_{i,j}(t-1)\cdot\xi^{-}, \eta_{min}) & if\ \beta_{i,j} < 0, \\ \eta_{i,j}(t-1) & \text{else .} \end{cases} \tag{10}$$

where $\xi^{+} > 1$ and $\xi^{-} < 1$ are the factors to control the change of learning rate. The maximum and minimum threshold values are η_{max} and η_{min}. If $\beta_{i,j} < 0$, the learning rate η_{ij} should be multiplied by $\xi^- < 1$ to decrease its value and prevent to miss the local minimum, vice versa.

C. Behaviour Recognition Process

In this process the different types of emotion-driven behaviour sequences are recognized via updating the PB units. Like the previous learning process, the updating of PB values is computed by back-propagation. The difference is that, the fixed synaptic weights which were obtained from the training process are used in this recognition process. Only the internal PB values are updated by [11]:

$$\rho_k(t+1) = \rho_k(t) + \eta_r \sum_{t_r = T-a}^{T} \delta_{k,t_r}^{pb} \tag{11}$$

η_r is a constant learning rate of PB values, and δ_{k,t_r}^{pb} represents the error back-propagation to the PB units.

D. Behaviour Generation Process

The RNNPB network has the ability of generalization because its substantial architecture. As [9] mentioned, the network also can acquire the substantial connections between a certain time-series sequence and its corresponding PB values. Hence the RNNPB network can generate novel sequences in a closed loop and the synaptic weights are confirmed in learning process. Additionally, the outputs prediction for the next time step should be provided as the current step inputs of the network and the PB values are manually set arbitrarily.

III. Experiments

This section three computer simulations focus on the learning process of the network, behaviour recognition and different patterns of behaviour sequences are implemented. Three different types of sequences are provided as the inputs of the network. Diverse parameters of the network are used in these simulation experiments.

In the experiments, we will address the following problems.

1）How can different behaviors can be learned in the network?

2）What results will emergent if the different patterns of emotion-driven behaviors are fed into the network?

Based the target, with respect to the five emotions, two sequences of data for the same emotion are used for the RNNPB network to eliminate the tiny distinction between different behaviors. The data that utilized for the network is acquired from one person by the Kinect. The sampling rate of the Kinect is 6Hz. Five kinds of emotion-driven behaviors are captured from the one person in order to eliminate the effects caused by different person. For each emotion we collect two types of data. One is a 27-dimention coordinate sequence and the other is a 14-dimention angle of joints. Then we merge the two types of data sequences into a 41-dimention sequence as a new input of the network. The data set of each training network is the same behaviour with five basic emotions. The capture system of the experiments is demonstrated in Fig. 3.

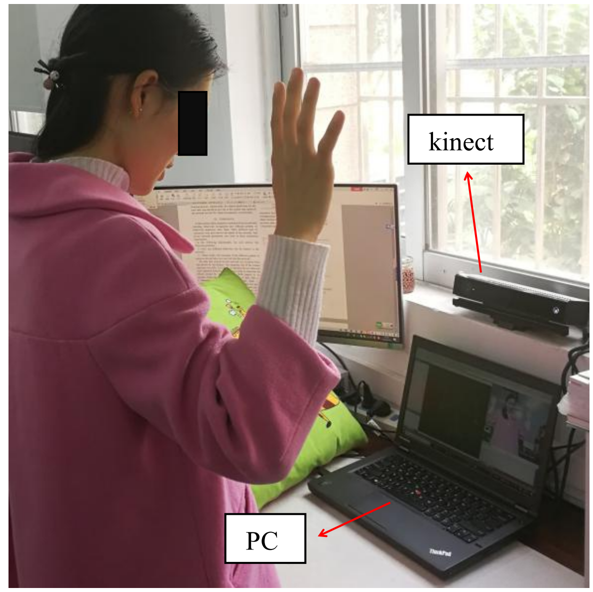

Fig. 3. The movement capture system of the experiment

A. Multiple action sequences of coordinates

In the simulation experiment, we choose ten sequences with three-dimensional coordinates of 9 parts of human upper body which include head, torso, neck, right shoulder, left shoulder, right hand, left hand, right elbow and left elbow to express human emotion. The parameters of the RNNPB we used to learn the multiple behaviors sequences are shown in Tabs. I.

Ten sequences expressed five different emotions are served as the network input, since we capture two sequences for each emotion. Fig. 4 shows the PB values corresponding to this experiment. In the figure, it is obviously that PB values of the same emotion fall in a similar position after training.

TABLE I
Parameters Using in The Network

Symbol	Description	Value
N_i	the number of nodes in input layer	27
N_o	the number of nodes in output layer	27
N_h	size of hidden layer	40
N_c	size of context layer	40
N_{pb}	size of PB units	2
Lr	adaptive learning rate of BP	0.001
Lpb	learning rate of PB units	0.2
ξ^+	increasing late of Lr	0.99999
ξ^-	decreasing late of Lr	1.00001
$\eta_{\max}$	the upper bound of the adaptive learning rate	1×10^{-4}
$\eta_{\min}$	the lower bound of the adaptive learning rate	1×10^{-8}

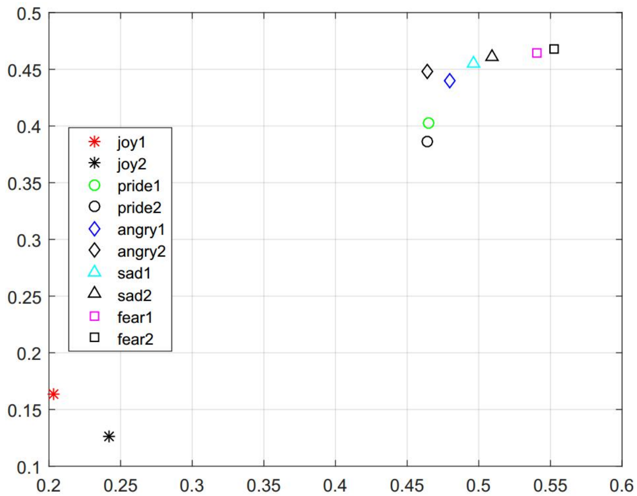

Fig. 4. Coordinates of the PB Vectors of the first experiment. In the figure, the same color implied the same emotion.

B. *Multiple action sequences of angle of joints*

In this simulation experiment, 14-dimensional angle of joints of human body behaviors which include seven angels of left arm and seven angles of right arm are fed into the network. Compared to the first experiment, we use the same 10 sequences which represents five emotions as the input of the network except the form of the emotion expression.

The parameters which are used to train the network are shown in Tabs. II. The parameters of $\eta_{\min}$ *and* $\eta_{\max}$ are the same with the first experiment. Fig. 5 shows the simulation result of the experiment.

TABLE II
PARAMETERS USING IN THE NETWORK

Symbol	Description	Value
N_i	the number of neurons in input layer	14
N_o	the number of neurons in output layer	14
N_h	size of hidden layer	55
N_c	size of context layer	55
N_{pb}	size of PB units	2
Lr	adaptive learning rate of BP	0.001
Lpb	learning rate of PB units	0.1
ξ^+	increasing late of Lr	0.99999
ξ^-	decreasing late of Lr	1.00001

C. *Multiple action sequences of angle-coordinate merged*

The last simulation experiment, we merge the coordinates and angles into a sequence with 41-dimension for each emotion as the input of the RNNPB. In other words, 41 numbers are located in each row of the sequence for one emotion. In this experiment, different parameters are chosen to distinguish fives emotions for training. The specific parameters are shown in Tabs. III. The parameters of $\eta_{\min}$ and $\eta_{\max}$ in this simulation are also same with the former experiment we have performed. The emotion classify results can be observed in Fig. 6.

TABLE III
PARAMETERS USING IN THE NETWORK

Symbol	Description	Value
N_i	the number of neurons in input layer	41
N_o	the number of neurons in output layer	41
N_h	size of hidden layer	80
N_c	size of context layer	80
N_{pb}	size of PB units	2
Lr	adaptive learning rate of BP	0.001
Lpb	learning rate of PB units	0.3
ξ^+	increasing late of Lr	0.99999
ξ^-	decreasing late of Lr	1.00001

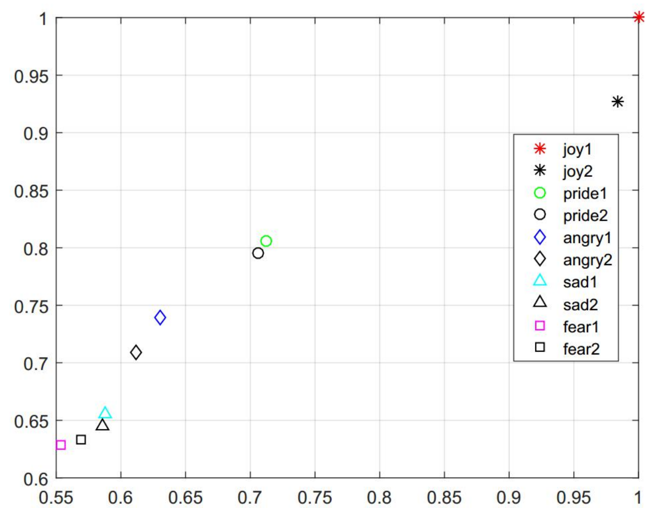

Fig. 5. Coordinates of the PB Vectors of the first experiment. In the figure, the same color implied the same emotion.

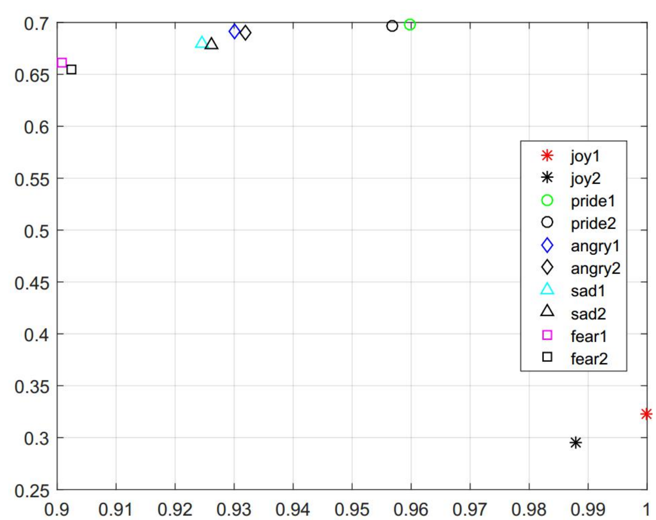

Fig. 6. Coordinates of the PB Vectors of the first experiment. In the figure, the same color implied the same emotion.

TABLE IV
THE DISTANCE BETWEEN DIFFERENT EMOTIONS FOR PB VALUES OF EXPERIMENT 1

PB values	joy1	joy2	pride1	pride2	angry1	angry2	sad1	sad2	fear1	fear2
joy1	0	***0.0536***	0.3552	0.3433	0.3910	0.3866	0.4132	0.4266	0.4530	0.4637
joy2	***0.0536***	0	0.3557	0.3421	0.3934	0.3914	0.4153	0.4280	0.4519	0.4619
pride1	0.3552	0.3557	0	***0.0170***	0.0392	0.0454	0.0600	0.0723	0.0979	0.1089
pride2	0.3433	0.3421	***0.0170***	0	0.0555	0.0624	0.0754	0.0868	0.1100	0.1204
anger1	0.3910	0.3934	0.0392	0.0555	0	***0.0184***	0.0221	0.0360	0.0662	0.0780
angry2	0.3866	0.3914	0.0454	0.0624	***0.0184***	0	0.0328	0.0468	0.0788	0.0907
sad1	0.4132	0.4153	0.0600	0.0754	0.0221	0.0328	0	***0.0143***	0.0461	0.0579
sad2	0.4266	0.4280	0.0723	0.0868	0.0360	0.0468	***0.0143***	0	0.0322	0.0440
fear1	0.4530	0.4519	0.0979	0.1100	0.0662	0.0788	0.0461	0.0322	0	***0.0119***
fear2	0.4637	0.4619	0.1089	0.1204	0.0780	0.0907	0.0579	0.0440	***0.0119***	0

TABLE V
THE DISTANCE BETWEEN DIFFERENT EMOTIONS FOR PB VALUES OF EXPERIMENT 2

PB values	joy1	joy2	pride1	pride2	angry1	angry2	sad1	sad2	fear1	fear2
joy1	0	***0.0742***	0.3473	0.3583	0.4528	0.4853	0.5372	0.5452	0.5805	0.5653
joy2	***0.0742***	0	0.2982	0.3081	0.4013	0.4320	0.4807	0.4882	0.5241	0.5083
pride1	0.3473	0.2982	0	***0.0123***	0.1057	0.1395	0.1950	0.2041	0.2374	0.2235
pride2	0.3583	0.3081	***0.0123***	0	0.0945	0.1278	0.1829	0.1920	0.2255	0.2115
anger1	0.4528	0.4013	0.1057	0.0945	0	***0.0354***	0.0939	0.1037	0.1341	0.1217
angry2	0.4853	0.4320	0.1395	0.1278	***0.0354***	0	0.0587	0.0686	0.0988	0.0864
sad1	0.5372	0.4807	0.1950	0.1829	0.0939	0.0587	0	***0.0101***	0.0434	0.0285
sad2	0.5452	0.4882	0.2041	0.1920	0.1037	0.0686	***0.0101***	0	0.0363	0.0201
fear1	0.5805	0.5241	0.2374	0.2255	0.1341	0.0988	0.0434	0.0363	0	***0.0167***
fear2	0.5653	0.5083	0.2235	0.2115	0.1217	0.0864	0.0285	0.0201	***0.0167***	0

TABLE VI
THE DISTANCE BETWEEN DIFFERENT EMOTIONS FOR PB VALUES OF EXPERIMENT 3

PB values	joy1	joy2	pride1	pride2	angry1	angry2	sad1	sad2	fear1	fear2
joy1	0	***0.0300***	0.3769	0.3767	0.3748	0.3734	0.3651	0.3624	0.3520	0.3452
joy2	***0.0300***	0	0.4033	0.4029	0.4000	0.3986	0.3900	0.3873	0.3755	0.3687
pride1	0.3769	0.4033	0	***0.0032***	0.0305	0.0289	0.0395	0.0393	0.0696	0.0721
pride2	0.3767	0.4029	***0.0032***	0	0.0273	0.0258	0.0365	0.0363	0.0667	0.0693
anger1	0.3748	0.4000	0.0305	0.0273	0	***0.0022***	0.0123	0.0141	0.0422	0.0462
angry2	0.3734	0.3986	0.0289	0.0258	***0.0022***	0	0.0124	0.0137	0.0428	0.0465
sad1	0.3651	0.3900	0.0395	0.0365	0.0123	0.0124	0	***0.0030***	0.0306	0.0341
sad2	0.3624	0.3873	0.0393	0.0363	0.0141	0.0137	***0.0030***	0	0.0304	0.0334
fear1	0.3520	0.3755	0.0696	0.0667	0.0422	0.0428	0.0306	0.0304	0	***0.0068***
fear2	0.3452	0.3687	0.0721	0.0693	0.0462	0.0465	0.0341	0.0334	***0.0068***	0

D. Data Analysis

The simulation results of these experiments reveal that the PB values with the same emotion are clustered together. The difference is that the PB values of the third experiment for the same emotions are much closer than the other twos in Fig. 3, Fig. 4 and Fig. 5. Then we contrast the distance of PB values between each emotions in three simulations to measure the performance of learning quantitatively. Tabs. IV, V and VI shows the distance of each PB values in experiment I, II and III respectively. From these tables, we can notice that the emotions of pride, angry, sad and fear are quite nearer. This means that there are some internal inherent connections in the four emotions with the similar sensory-motor. In addition, we plot the trend of root mean squared error (RMSE) in continuous 100 epochs to evaluate the learning performance for three different training sequences. And the RMSE curves of three entire training sets are shown in Fig. 7-9.

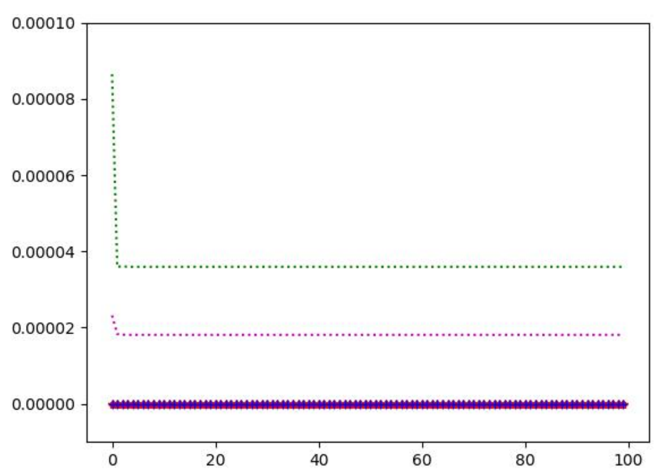

Fig. 7. RMSE curves of the first experiment. In the figure, seven different colors and three different shapes represent errors of ten disparate sequences corresponding to five emotions.

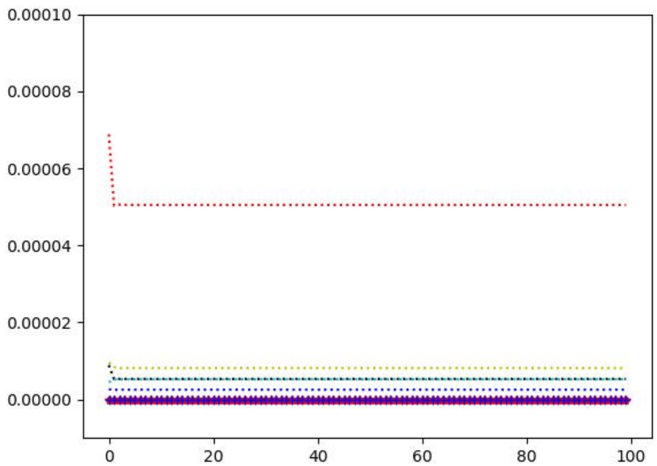

Fig. 8. RMSE curves of the second experiment. In the figure, seven different colors and three different shapes represent errors of ten disparate sequences corresponding to five emotions.

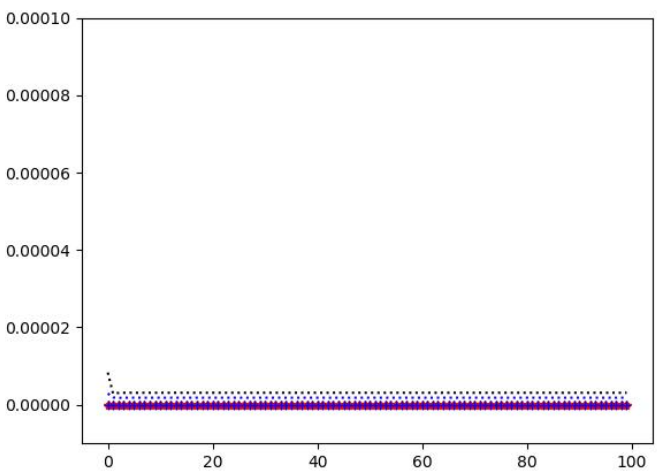

Fig. 9. RMSE curves of the third experiment. In the figure, seven different colors and three different shapes represent errors of ten disparate sequences corresponding to five emotions.

The RMSE errors for each training data are less than 10^{-4} (Fig. 7-9). We can observed that the RMSE errors of three training data converge quickly in the first, and then decrease slowly in a jarless way. In other words, the fluctuations of the learned PB values are minished, indicating that a steady PB vectors are reached.

IV. Conclusion

Compared to the general RNN, the RNNPB network has an addition layer to indicate the internal links in manifold cognitive process. It can be applied to classify various features by the low dimension PB vector since the PB space is changing for different characteristics and multiple categories. For instance, [16] proposes a three-layer, horizontal product RNNPB to recognize the visual perception. As we know, behaviors should not be driven by the internal states of emotion isolatedly. Actually, numerous factors yield the behaviors, such as personal interests and weather. Whereas, the instantly-short tiny action, such as the fold of finger, are caused by the internal emotion states.

In this article, a novel framework of the recurrent neural network with parametric bias is proposed. The behaviors data sets are captured by the Kinect. The PB internal values with respect to the same emotion are updated in a self-organized way. In term of the number of dimensions, PB vectors are more lower than the input data. In the next step, three experiments will be carried out:

1) The velocity of the linked joint will be acquired from the motion capture system and the corresponding data will be utilized to train the network.

2) Online training and recognition will be executed to explore the human perception to emotions.

3) The subtle action of facial expression will be captured by the special equipment to recognize human emotions compared to other recognition way, such as facial image.

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