Proximity Capacitive Gesture Recognition for Recursive Neighbor Memory Neural Network

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Abstract. This paper presented the proximity capacitive sensor using recursive Neighbor memory neural network (RNMNN) to detect user gesture. The human interactive gesture signal analyses have been a research topic smart home fields that algorithms build in local device to recognize real time. The neural network has been used in many fields that including identification, control and classification. The features of RNMNN have multi-recursive weight to communicate neurons that record neighbor neurons state to reach global train performance.
In addition, the utilization of RNMNN-based proximity capacitive sensors has several advantages, including high accuracy and robustness in detecting user gestures. The real-time detection capabilities of the sensor, coupled with its ability to adapt and learn from previous signals, make it a promising solution for enhancing human-computer interaction and user experience in smart home environments. The integration of this approach into various smart home devices holds significant potential for advancing the field of human-computer interaction and improving the overall functionality of smart homes.

Keywords: Neighbor memory; neural network; recursive; proximity capacitive.

1 Introduction

Recent, researchers have shown an increased interest in IOT fields [1-2] which advance is easy portable to combined different algorithms analysis user body signal. A considerable amount of literature has been published on smart care [3-5], These studies proposed home care research and application. A operations management applied to home care services have been proposed by Lee et al. [3] that experimental results shows the home care problem of assigning human resources to patients. Li et al. [4] proposed design and implementation of smart home control systems based on wireless sensor networks and power line communications, in which the power line communications system communicated different smart home wireless sensor real time. Han et al. [5] presented a smart home energy management system using IEEE 802.15.4 and zigbee. The 2.4G standard wireless zigbee linked different smart home sensor and feedback service control. In addition, research of wearable device fields has been combined sport [6-8] analysis to monitor body situation. Salvo et al. [6] proposed a wearable sensor for measuring sweat rate that monitor person sport water consumption and feedback person sport information. Wong et al. [7] shows a wearable sensing for solid biomechanics which analysis body different sport posture base on biomechanics view. A detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions have been proposed by Ermes et al. [8]; there are detected daily activities sports situation and return signal to remote monitor analysis.

More recently, literature has published that offers satisfactory classify performance about different type neural network for Hermite function [9-11]. The neural network approaches also used in noisy language modeling, in which Li et al. [9] shows neural network improve noisy environment to identification language. Xie et al. [10] developed accelerometer based hand gesture recognition by neural network and similarity matching. The proposed algorithms recognized different hand gesture have satisfactory performance. Martin et al. [11] proposed a detection and classification of single and combined power quality disturbances using neural networks that are shown neural networks applied power quality disturbances to detection and classification. According to a definition provided by different sensor, user gesture [12-14] eigenvalues also differently. Megalingam et al. [12] presented IR sensor-based gesture control wheelchair for stroke and SCI patients, in which the IR sensor help spinal cord injury patient to control wheelchair. In [13], a static and dynamic hand gesture recognition in depth data using dynamic time warping have been published by Plouffe et al. that shows depth data using dynamic time warping algorithms have satisfactory response in experimental results. Wang et al. [14] used variable Markov oracle algorithms to identify human gesture applications which Markov model train results identify user gesture immediately.

The purpose of this paper is construct RTMNN methods on the to detect user gesture, and combined proximity capacitive sensor to obtain hand signal. The feature of RTMNN used recursive weight to identify body motion signal, and proximity capacitive sensor detected 3D user gesture state real time. The RTMNN also used memory neural construct to obtain neighbor neurons state signal. Moreover, we implement proximity capacitive sensor with BLE (Bluetooth low energy) feedback body signal for remote PC. In the experimental results shows the RTMNN algorithms have distinguish different user gesture signal that have satisfactory output response.

2 Wearable device system construct

Fig. 1 is the capacitive sensor board. We used capacitive proximity mode sensing methods to obtain user gesture capacitive varies, and the microcontroller used RNMNN train and learn user gesture. Fig 2 is the capacitive sensor board function diagram. Firstly, the sensor pad obtained capacitive varies signal. Secondly, capacitive sensor controller collected user gesture signal and used identify system identify user gesture. Finally, we used Bluetooth module to transmit identification signal to remote PC which shows experimental results and notice.

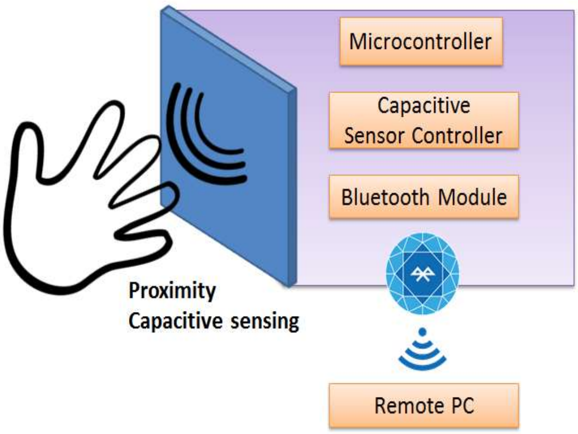


Fig. 1. Inductance sensor setting situation

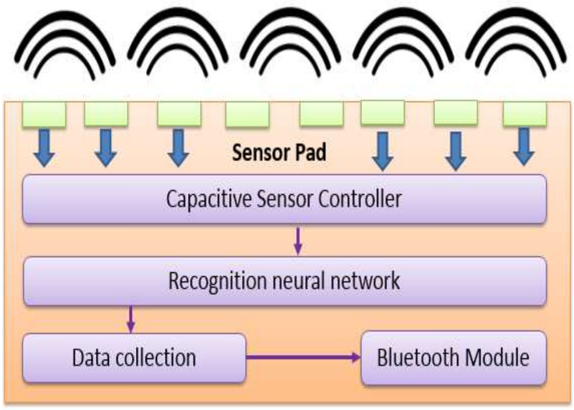


Fig. 2. Inductance sensor function diagram

3 Identification of RNMNN

The RNMNN identify system is shown in Fig 3 which used Neighbor neural construct to identify user gesture signal. We used capacitance signal input to RNMNN and train identification eigenvalues. The user capacitance signal used electric field situation in sensor pad. Define gesture vector equation as

$$\tau(t) = \sum_{i=1}^{n} G_i(t) \tag{1}$$

where n is the sensor pad number. G_i is the capacitance sensing signal from sensor pad. t is the sample times.

The RNMNN activation function equation shows as

$$\lambda_j = \exp\left(-\frac{(\tau_j - v_j)^2}{2d_j^2} \right) + \lambda_j^{L1}\alpha_j^{L1} + \lambda_j^{L2}\beta_j^{L2} \tag{2}$$

where v_j is the vertex of activation function. d_j is the width of activation function. j RNMNN node. λ_j^{L1} is the last time neighbor activation function output. λ_j^{L2} is the second last time neighbor activation function output. α_j^{L1} and β_j^{L1} are the recursive weight.

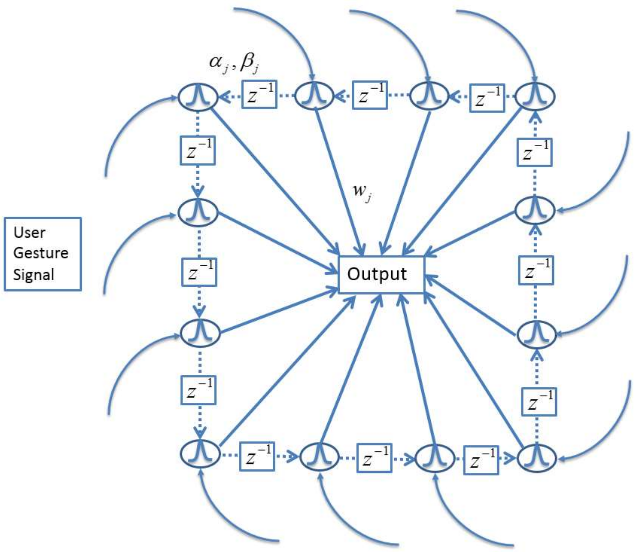


Fig. 3. RTMNN structure

Hence, we obtain output of RNMNN as

$$\xi = \sum_{i=1}^{j} (\lambda_i \cdot w_i) \tag{3}$$

where w_j is the output weight. The RNMNN used energy function to trained and convergent identifier parameters, and RNMNN function define as

$$E = \frac{1}{2} e^2 \tag{4}$$

where $e = x_d - \xi$, x_d is the target identify results.

Therefore, we have

$$\Delta w_j(t) = -\eta_1 \frac{\partial E}{\partial w_j} = \eta_1 e \lambda_j \tag{5}$$

$$\Delta v_j(t) = -\eta_2 \frac{\partial E}{\partial v_j} = \eta_2 e w_j \frac{(\tau_j - v_j)}{d_j^2} \tag{6}$$

$$\Delta d_j(t) = -\eta_3 \frac{\partial E}{\partial d_j} = \eta_3 e w_j \frac{(\tau_j - v_j)^2}{d_j^3} \tag{7}$$

where $\eta_1, \eta_2, \eta_3 > 0$.

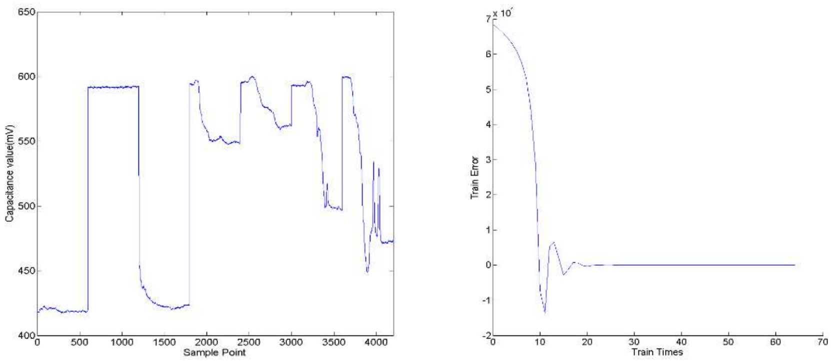
For the experimental results, we choose performance index as

$$\ell = \frac{1}{\left((x_d - \xi)^p + 1\right)} \tag{10}$$

where p is the choose square.

4 Experimental results

The remote PC shows person gesture signal experimental results. Fig 4 shows the input gesture signal of RNMNN and train error state. Fig 5 show the RNMNN gesture results. The have been obtained gesture single for different gesture state.



(a) (b)

Fig. 4. (a) Input gesture signal of RTMNN, (b) RTMNN train error.

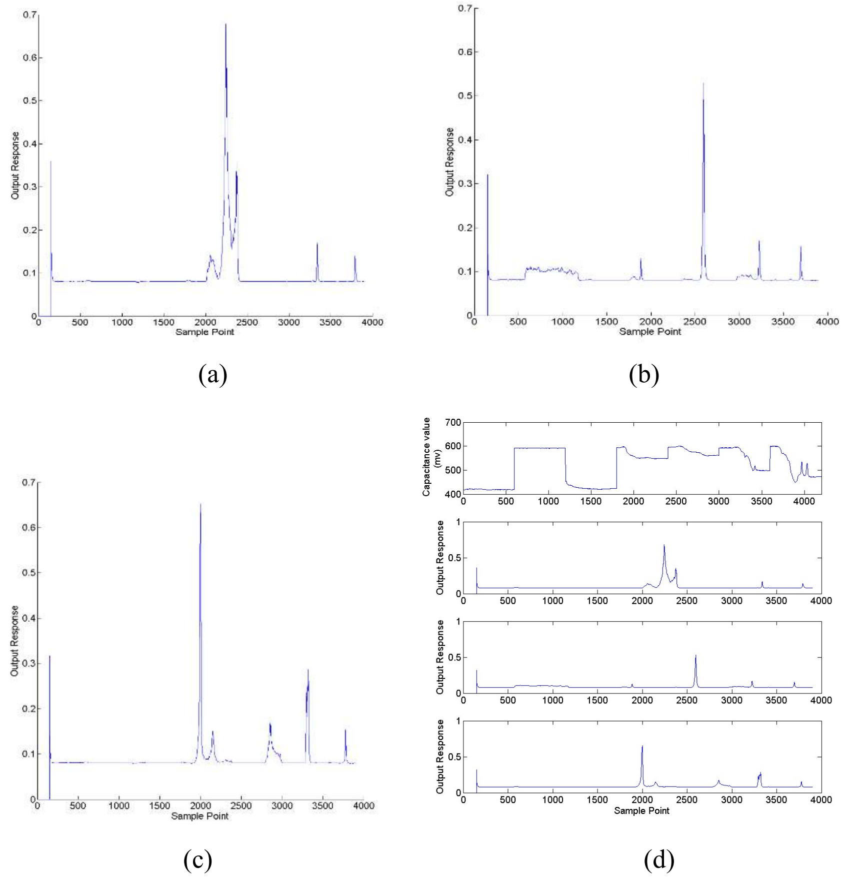


Fig. 5. RTMNN gesture results (a) gesture 1, (b) gesture 2, (b) gesture 3, (d) Compare of gesture and input gesture signal, respectively.

5 Conclusion

The gesture recognition is an important research topic in smart home security fields which identify user rank to protection different information. This paper successful used RNMNN algorithms implemented in proximity capacitive sensor that has high performance detection 3D user gesture signal and feedback remote PC. The experimental results show RNMNN algorithms have satisfactory output response to identify gesture signal situation.

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