Fuzzy Proximity Two-Dimension Inductance Gesture Recognition System Analysis and Implement

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Abstract. This paper presents a proximity inductance gesture recognition system with fuzzy identification. The field of smart home security has been the subject of extensive research in the Internet of Things domain, with security algorithms implemented in real-time processors to facilitate user identification. Recently, inductance sensor technologies have been developed for proximity-based detection of electronic variations around sensor detection points. The growing trend of low-priced devices in the smart home market is an important element in this context. To implement proximity inductance gesture recognition, we have leveraged a microcontroller with fuzzy expert knowledge identification algorithms. In our experimental results, we demonstrate the recognition of different gesture signals and patterns by the fuzzy expert knowledge system. Overall, this paper contributes to the advancement of proximity inductance gesture recognition systems and paves the way for more innovative solutions to be developed in the future.

Keywords: Microcontroller, Proximity capacitive, Gesture recognition, Fuzzy.

1 Introduction

Recently, there has been increased interest in smart home fields [1-2], which enable the combination of various algorithmic approaches to analyze user body signals. Health care research has been combined with smart home applications [3-5] through the management of home sensors. Wong et al. [3] have shown wearable sensing for solid biomechanics that analyze different sport postures based on a biomechanical view. Kafi et al. [4] have presented congestion control protocols in wireless sensor networks and discussed future trends in wireless sensor technology. Han et al. [5] have developed a smart home energy management system that includes renewable energy based on ZigBee and PLC for different transfer protocols. ZigBee utilizes mesh network technology, while PLC uses the electricity network to improve home network transmission quality. In constructing different device relations to obtain system patterns, fuzzy classification algorithms [6-8] have become increasingly difficult to ignore. Nguyen et al. [6] proposed a classification of multi-class BCI data by common spatial pattern and a fuzzy system, which demonstrated that fuzzy classification systems have favorable output performance. Yan et al. [7] showed scene capture and selected codebook-based refined fuzzy classification of large high-resolution images, in which the image noise problem was greatly improved by using a fuzzy classification system. Jafarifarmand et al. [8] presented a new self-regulated neuro-fuzzy framework for the classification of EEG signals in motor imagery BCI, and the neuro-fuzzy framework classification of EEG signals showed a satisfactory response in experimental results.

In sensor detection fields, one of the most significant current discussions pertains to inductance sensing methods [9-11], which utilize electromagnetic coil frequency analysis to detect the position of a user object. Ramesh et al. [9] presented a deployment of inductance-based pulsating sensor towards the development of a measurement technique for ovality in pipes, in which the inductance sensors demonstrated a satisfactory response in experimental results. Bist et al. [10] showed a reduced sensor configuration of a power factor correction-based single-ended primary inductance converter-fed brushless DC motor drive; the inductance converter feedback motor rotor position to control the correct switch. Ha et al. [11] presented a modeling and design of "smart braid" inductance sensors for fiber-reinforced elastomeric enclosures, in which the inductance sensors demonstrated a satisfactory response in experimental results.

According to different sensors, user gestures [12-14] have varying eigenvalues. Yan et al. [12] presented alpha-numeric hand gesture recognition based on the fusion of spatial feature modelling and temporal feature modelling. The methods of fusion of spatial feature modelling and temporal feature modelling have a better output response than traditional methods. Megalingam et al. [13] presented an IR sensor-based gesture control wheelchair for stroke and spinal cord injury patients, in which the IR sensor helped spinal cord injury patients control their wheelchair. In [14], Chang et al. published a nonparametric feature matching-based conditional random fields for gesture recognition from multi-modal video, which demonstrated that real-time image processor detection of gestures had a satisfactory response in experimental results.

This paper proposes a proximity inductance gesture recognition system that incorporates a fuzzy identification approach. The fuzzy identification system employs expert knowledge to process the inductance signals obtained from hand gestures, and we utilize fuzzy identification algorithms on a microcontroller to take advantage of the low-cost technology. The fuzzy identification system employs an energy function to converge and optimize the expert knowledge for identification performance. In the experimental results, the fuzzy identification system effectively identifies different gesture signals, demonstrating satisfactory output response.

2 Inductance device system construct

Fig. 1 shows the setup of the inductance sensors, where three PCB coils are placed to detect changes in the magnetic field and the inductance collector provides feedback on the magnetic field values to the computing unit for identification. Fig. 2 displays the functional diagram of the inductance sensor system. When a user performs a gesture in the vicinity of the PCB coils, the sensors detect the corresponding magnetic field changes and use rotation memory neural network algorithms to identify the user's gesture.

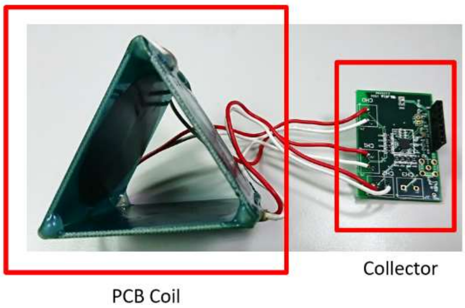


Fig. 1. Inductance sensor setting situation

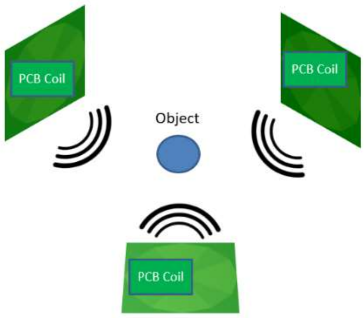


Fig. 2 Inductance sensor function diagram

3 Identification of fuzzy expert knowledge

Fig. 3 demonstrates the fuzzy identification system, which employs fuzzy expert knowledge to identify user gesture signals. Capacitance signals are used as inputs to the fuzzy expert knowledge to train identification eigenvalues. The user capacitance signal is derived from the electric field situation in the sensor pad. The gesture vector equation is defined as follows

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

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

The fuzzy membership function used Gaussian function which equation shows as

$$\varphi_a(t) = \exp\left(\frac{-(\mu(t) - d_a)^2}{2w_a^2}\right) \tag{2}$$

where d_a is the Gaussian function vertex. w_a is the Gaussian function width, a is the fuzzy expert knowledge number. We used the weight average methods normalization membership function output as

$$\phi_a = \frac{\varphi_a}{\sum_{i=1}^{n} \varphi_i} \tag{3}$$

Hence, we obtain output of fuzzy identify system as

$$\xi = \sum_{r=1}^{a} \phi_r \sigma_r \tag{4}$$

where σ_r is the expert rule.

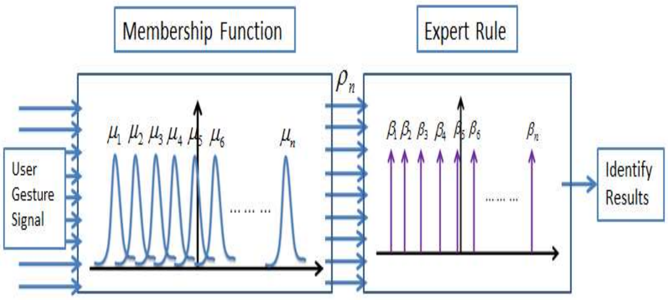


Fig. 3. fuzzy identify system

The fuzzy identify system used Energy function to trained and convergent expert knowledge rule base. The Energy function define as

$$E = \frac{1}{2} e^2 \tag{5}$$

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

$$\Delta \sigma_r(t) = -\eta_1 \frac{\partial E}{\partial \sigma_r} = \eta_1 e \phi_r \tag{6}$$

$$\Delta d_{na}(t) = -\eta_2 \frac{\partial E}{\partial d_a} = \eta_2 e \sigma_r \left(\frac{(\mu(t) - d_a)}{w_a^2} \right) \exp\left(\frac{-(\mu(t) - d_a)^2}{2w_a^2} \right) \tag{7}$$

$$\Delta w_{na}(t) = -\eta_3 \frac{\partial E}{\partial w_a} = \eta_3 e \sigma_a \left(\frac{(\mu(t) - d_a)^2}{w_a^3} \right) \exp\left(\frac{-(\mu(t) - d_a)^2}{2w_a^2} \right) \tag{8}$$

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

For the experimental results, we choose performance index as

$$\ell = \frac{1}{\left((x_d - \xi)^p + 1\right)} \tag{9}$$

where p is the choose square.

4 Experimental results

The experimental results of the user gesture signals are displayed on the remote PC. Fig. 4 illustrates the circular path of the gesture signals with the X and Y coordinates, as well as the 3D X-Y coordinate representation. Fig. 5 displays the fuzzy training error and the identification output response for a mixed sample signal.

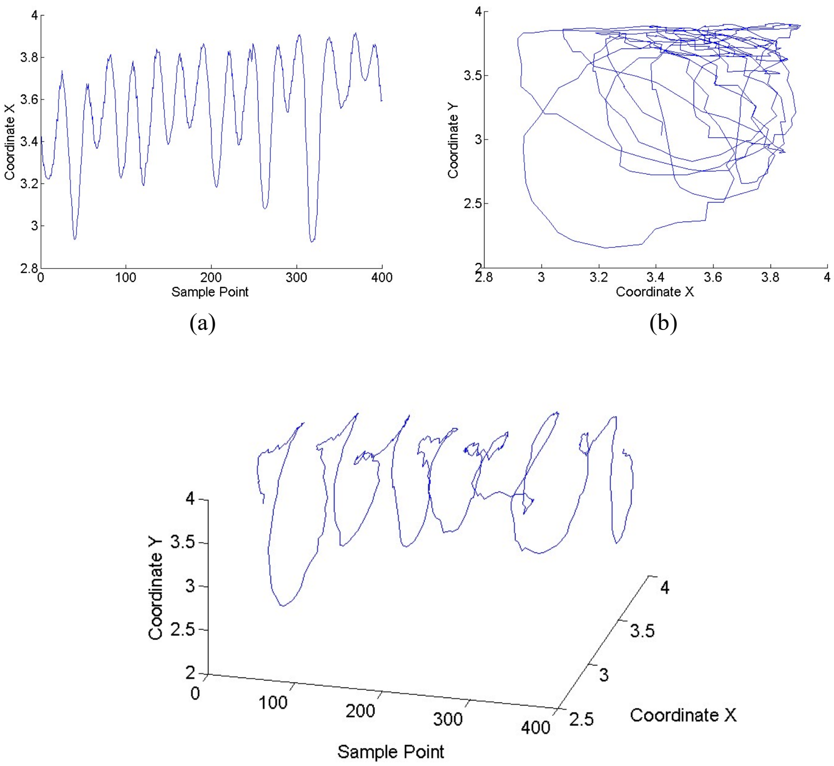
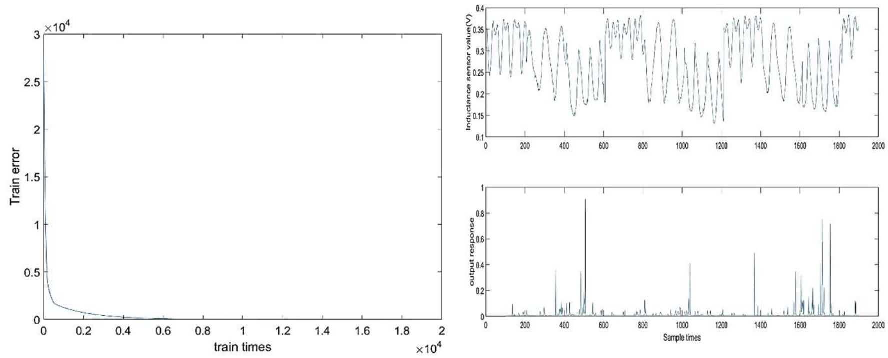


Fig. 4. Circular track from inductance sensor (a) X coordinate, (b) Y coordinate, (c) 3D space X-Y coordinate.



(a) (b)

Fig. 5. Fuzzy identification situation (a) train error, (b) mix signal and identification performance.

5 Conclusion

This paper presents an important research topic in the field of access control systems, which aims to assist in discriminating user access for home safety purposes. Specifically, we propose a successful approach using fuzzy model algorithms implemented in an inductance sensor, which has demonstrated high-performance in detecting user gesture signals and providing feedback to a remote PC. Our experimental results show that the rotation memory neural network model algorithms can effectively identify user gesture signals.

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