Multi-recursive Wavelet Neural Network for Proximity Capacitive Gesture Recognition Analysis and Implementation

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Abstract. This paper presents a multi-recursive wavelet neural network (MRWNN) with proximity capacitive gesture recognition. Recently, the capacitive sensor technologies have been developed for proximity methods that sensing electronic varies around sensor detection point, but the user gesture signals are time-variant. The MRWNN have multi layers recursive weight to record last signal variation, and we utilize microcontroller with MRWNN to identify algorithms and implement proximity capacitive gesture recognition. Moreover, we show MRWNN weight convergence analysis of the MRWNN signal identifier. In the experimental results, we show MRWNN can recognize patterns of different gesture signal accurately and reliably. In addition, we use wearable device combined with BLE (Bluetooth Low Energy) feedback output response immediately.

Keywords: Microcontroller · Proximity capacitive · Gesture recognition · Wavelet

1 Introduction

Recently, researchers have shown increasing interest in IOT fields [1, 2] which detect different sensor situation and feedback users. The health care with sensor control system has been developed which make some researchers [3–5] to propose researches in different applications. Semnani et al. [3] proposed a semi-flocking algorithm for motion control of mobile sensors in large-scale surveillance systems that the proposed semi-flocking algorithm monitor motion situation immediately. Usman et al. [4] presented a mobile agent-based cross-layer anomaly detection in smart home sensor networks using fuzzy logic, in which fuzzy logic used expert knowledge methods anomaly detection smart home sensor networks. Kafi et al. [5] shows a congestion control protocols in wireless sensor networks, in which the researches discussed wireless sensor technical future trends. It is becoming increasingly difficult to ignore the user biological signal [6–8] analysis that fall detection alarm to help older users to avoid danger situation. Inertial sensing-based pre-impact detection of falls involving near-fall scenarios has been proposed by Lee et al. [6] which predicted human falls alert

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before near-fall scenarios. In [7], a development and evaluation of a prior-to-impact fall event detection algorithm has been published by Liu et al. There are shown prior-to-impact algorithm detection fall event real time and feedback to backstage processed. Yu et al. [8] presented an online one class support vector machine-based person-specific fall detection system for monitoring an elderly individual in a room environment. The experimental results show person-specific fall detection system estimation fall signal real time.

A considerable amount of literature has been published on neural network. These studies used neural network [9–12] applied to classification fields. In [9], Deshpande et al. showed the research about fully connected cascade artificial neural network architecture for attention deficit hyperactivity disorder classification from functional magnetic resonance imaging data, in which the functional magnetic resonance complex imaging data used neural network classification has contentment output performance. In [10], a Hermite functional link neural network for solving the van der pol–duffing oscillator equation have been proposed by Mall et al., in which the Hermite functional link neural network have multivariate input layer to improve complex van der pol–duffing oscillator equation. Ma et al. [11] developed a constructive feedforward neural networks using Hermite polynomial activation functions that experimental results have satisfactory output response. A recent study by wavelet and neural network involve in control and identify [12–14] fields. Devi et al. [12] shows diagnosis and classification of stator winding insulation faults on a three-phase induction motor using wavelet and MNN, in which wavelet neural network classify stator winding insulation faults have satisfactory response in experimental results. Duan et al. [13] proposed EMG-Based identification of hand motion commands using wavelet neural network combined with discrete wavelet transform. The wavelet neural network detected hand sway of EMG signal and identified user motion state. For the control fields, a squirrel-cage induction generator system using wavelet petri fuzzy neural network control for wind power applications have been presented by Tan et al. [14] that shows proposed algorithms control induction generator system track command speed precisely.

The smart home securities have been a research topic in internet of things fields that securities algorithms build in real-time processor to recognize user identification. This paper proposes proximity capacitive gesture recognition with MRWNN. The features of MRWNN have multi layers recursive weight to record last signal vary, and the wavelet activation function classify user input signal. The Sect. 4 shows the MRWNN weight convergence prove to identify user gesture situation. Finally, we implement proximity capacitive sensor with BLE (Bluetooth low energy) module feedback user hand signal. In the experimental results shows the MRWNN algorithms identify different gesture signal that have satisfactory output response.

2 Wearable Device System Architecture

Figure 1 is the capacitive sensor board. We use capacitive proximity mode sensing methods to obtain user gesture capacitive variation, and the microcontroller uses MRWNN train and learn user gesture. Finally, the Bluetooth module transmits identification results and user gesture capacitive variation to remote PC.

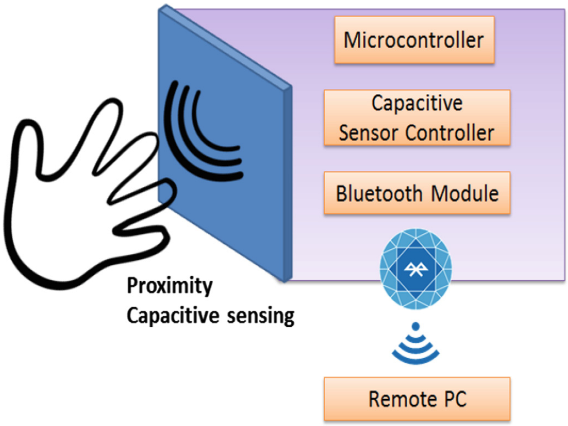

Fig. 1. Capacitive sensor board

Figure 2 is the capacitive sensor board function diagram. Firstly, the sensor pad obtains capacitive varying signal. Secondly, capacitive sensor controller collects user gesture signal and uses identify system to identify user gesture. Finally, we use Bluetooth module to transmit identification signal to remote PC which shows experimental results and notice.

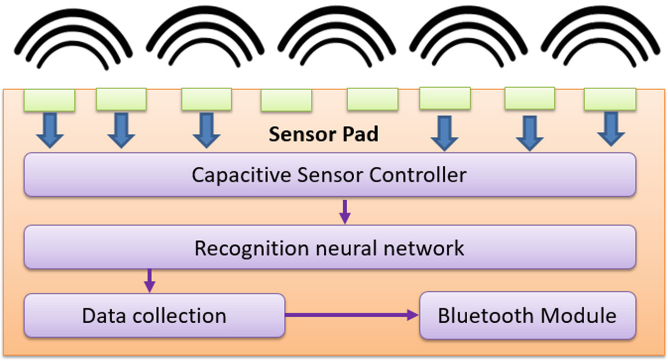

Fig. 2. Capacitive sensor board function diagram

3 Identification of MRWNN

The MRWNN construct is shown in Fig. 3 which uses multi-recursive weight to identify user gesture signal. We use capacitance signal input to MRWNN 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. A MRWNN has an input layer, a membership layer, a rule layer and an output layer. The input signal of MRWNN is user gesture signal, in which equation can be express as

$$u_i(N) = \tau(N) + O_i^{(1)}(N-1) \tag{2}$$

$$O_i^{(1)}(N) = u_i^{(1)}(N) \tag{3}$$

where u_i is the input of input layer. O_i^1 is the output of input layer. N is the $N-th$ iteration.

The membership layer can be express as

$$h(x) = -x\exp\left(-\frac{x^2}{2}\right) \tag{4}$$

$$u_{ij}^{(2)} = \frac{O_i^{(1)} - n_{ij}}{\gamma_{ij}} \tag{5}$$

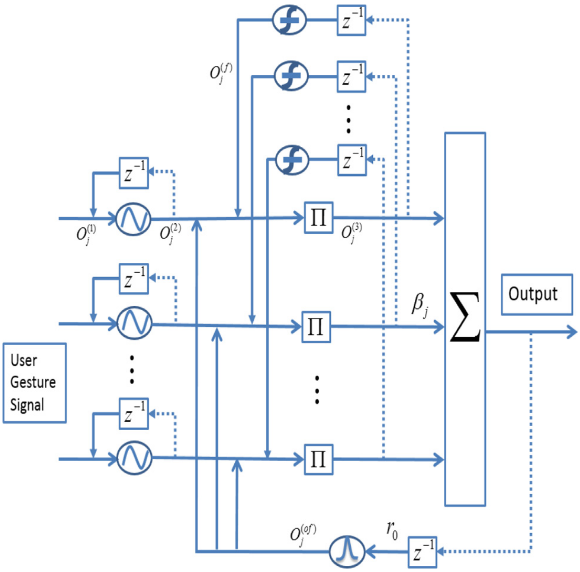

Fig. 3. MRWNN architecture

$$O_{ij}^{(2)} = h\left(u_{ij}^{(2)}\right) \tag{6}$$

Where $j = 1, 2, \ldots,$ n. n_{ij} and γ_{ij} is the translation and dilation, respectively. u_i^2 is the input of membership layer. O_j^2 is the output of membership layer. The superscript (2) represents membership layer. The subscript j is the neurons numbers of the membership layer.

The recursive rule layer can be express as

$$u_j^f(N) = O_j^{(3)}(N-1) \tag{7}$$

$$O_j^f(N) = f\left(u_j^f(N)\right) \tag{8}$$

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{9}$$

where exp is exponential function. u_i^f is the input of recursive rule layers. O_j^f is the output of recursive rule layers. Superscript f represents recursive rule layer. Superscript (3) represents the rule layer.

The rule layer can be express as

$$u_j^{(3)} = O^{of} \cdot O_j^f \cdot O_{1j}^{(2)} \cdot O_{2j}^{(2)} \tag{10}$$

$$O_j^{(3)} = u_j^{(3)} \tag{11}$$

where $u_j^{(3)}$ is the input of rule layer. $O_j^{(3)}$ is the output of rule layer.

The recursive of output layer can be express as

$$u^{of}(N) = r_o \cdot y(N-1) \tag{12}$$

$$O^{of}(N) = \exp\left(-\left(u^{of}(N)\right)^2\right) \tag{13}$$

where r_o is a not adjust recursive weight of output layer. u^{of} is the recursive input of output layer. O^{of} is the recursive output of output layer. Superscript of is the output layer.

Finally, the output layer is

$$u^{(4)} = \sum_{j=1}^{5} \beta_j \cdot O_j^{(3)} \tag{14}$$

$$U = y(N) = O^{(4)} = u^{(4)} \tag{15}$$

where β_j is the weight between rule layer and output layer. $u^{(4)}$ is the input of output layers. U is the output of output layers. Superscript (4) represents the output layer.

4 Training Algorithm of the MRWNN Identification System

The MRWNN system is trained using the back-propagation learning algorithm, where a gradient vector is calculated recursively. The energy function is defined as

$$E = \frac{1}{2}e^2 \tag{16}$$

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

The error of the output layer is defined as Eq. (17).

$$\delta^{(4)} = -\frac{\partial E}{\partial y(N)} = -\frac{\partial E}{\partial e} \cdot \frac{\partial e}{\partial y(N)} \approx e \tag{17}$$

The weights between output and wavelet layers are updated as Eqs. (18)–(19).

$$\Delta\beta_j = -\frac{\partial E}{\partial \beta_j} = -\frac{\partial E}{\partial y(N)} \cdot \frac{\partial y(N)}{\partial u^{(4)}} \cdot \frac{\partial u^{(4)}}{\partial \beta_j} = \eta_\beta \delta^{(4)} O_j^{(3)} \tag{18}$$

$$\beta_j(N+1) = \beta_j(N) + \Delta\beta_j \tag{19}$$

where η_β is the learning rate of output layer.

Let the rule layer and membership layer error as

$$\delta_j^{(3)} = -\frac{\partial E}{\partial O_j^{(3)}} = -\frac{\partial E}{\partial y(N)} \cdot \frac{\partial y(N)}{\partial u^{(4)}} \cdot \frac{\partial u^{(4)}}{\partial O_j^{(3)}} = \delta^{(4)} \beta_j(N) \tag{20}$$

$$\delta_{1j}^{(2)} = -\frac{\partial E}{\partial O_{1j}^{(2)}} = -\frac{\partial E}{\partial y(N)} \cdot \frac{\partial y(N)}{\partial u^{(4)}} \cdot \frac{\partial u^{(4)}}{\partial O_j^{(3)}} \cdot \frac{\partial O_j^{(3)}}{\partial u_j^{(3)}} \cdot \frac{\partial u_j^{(3)}}{\partial O_{1j}^{(2)}} = \delta_j^{(3)} O^{of} O_j^f O_{2j}^{(2)} \tag{21}$$

$$\delta_{2j}^{(2)} = -\frac{\partial E}{\partial O_{2j}^{(2)}} = -\frac{\partial E}{\partial y(N)} \cdot \frac{\partial y(N)}{\partial u^{(4)}} \cdot \frac{\partial u^{(4)}}{\partial O_j^{(3)}} \cdot \frac{\partial O_j^{(3)}}{\partial u_j^{(3)}} \cdot \frac{\partial u_j^{(3)}}{\partial O_{2j}^{(2)}} = \delta_j^{(3)} O^{of} O_j^f O_{1j}^{(2)} \tag{22}$$

Therefore, the updated data of translation and dilation, we get

$$\begin{aligned}\Delta n_{ij} &= -\eta_n \frac{\partial E}{\partial n_{ij}} \\ &= -\eta_n \frac{\partial E}{\partial y(N)} \cdot \frac{\partial y(N)}{\partial u^{(4)}} \cdot \frac{\partial u^{(4)}}{\partial O_j^{(3)}} \cdot \frac{\partial O_j^{(3)}}{\partial u_j^{(3)}} \cdot \frac{\partial u_j^{(3)}}{\partial O_{ij}^{(2)}} \cdot \frac{\partial O_{ij}^{(2)}}{\partial u_{ij}^{(2)}} \cdot \frac{\partial u_{ij}^{(2)}}{\partial n_{ij}} \\ &= \eta_n \frac{\delta_{ij}^{(2)}}{\gamma_{ij}} \left[1 - \left(u_{ij}^{(2)}\right)^2\right] \exp\left[-\frac{\left(u_{ij}^{(2)}\right)^2}{2}\right]\end{aligned} \tag{23}$$

$$\begin{aligned}\Delta \gamma_{ij} &= -\eta_\gamma \frac{\partial E}{\partial \gamma_{ij}} \\ &= -\eta_\gamma \frac{\partial E}{\partial y(N)} \cdot \frac{\partial y(N)}{\partial u^{(4)}} \cdot \frac{\partial u^{(4)}}{\partial O_j^{(3)}} \cdot \frac{\partial O_j^{(3)}}{\partial u_j^{(3)}} \cdot \frac{\partial u_j^{(3)}}{\partial O_{ij}^{(2)}} \cdot \frac{\partial O_{ij}^{(2)}}{\partial u_{ij}^{(2)}} \cdot \frac{\partial u_{ij}^{(2)}}{\partial \gamma_{ij}} \\ &= \eta_\gamma \frac{\delta_{ij}^{(2)} u_{ij}^{(2)}}{\gamma_{ij}} \left[1 - \left(u_{ij}^{(2)}\right)^2\right] \exp\left[-\frac{\left(u_{ij}^{(2)}\right)^2}{2}\right]\end{aligned} \tag{24}$$

where η_m is the learning rates for the translation of wavelet function. η_σ is the learning rates for the dilation of wavelet function.

Hence,

$$n_{ij}(N+1) = n_{ij}(N) + \Delta n_{ij} \tag{25}$$

$$\gamma_{ij}(N+1) = \gamma_{ij}(N) + \Delta \gamma_{ij} \tag{26}$$

For the experimental results, we choose performance index as

$$\Psi = \frac{\sigma}{((x_d - \xi)^p + 1)} \tag{27}$$

where x_d is the target result,p is the choose square, σ is the constant.

5 Experimental Results

The remote PC shows person gesture capacitive varies signal experimental results. Figure 4 shows the MRWNN identify system train error state and identify results which used error train about 400 times. In addition, the recognition results are show close to 1 that MRWNN identify results have clear recognition different user gesture in Fig. 5.

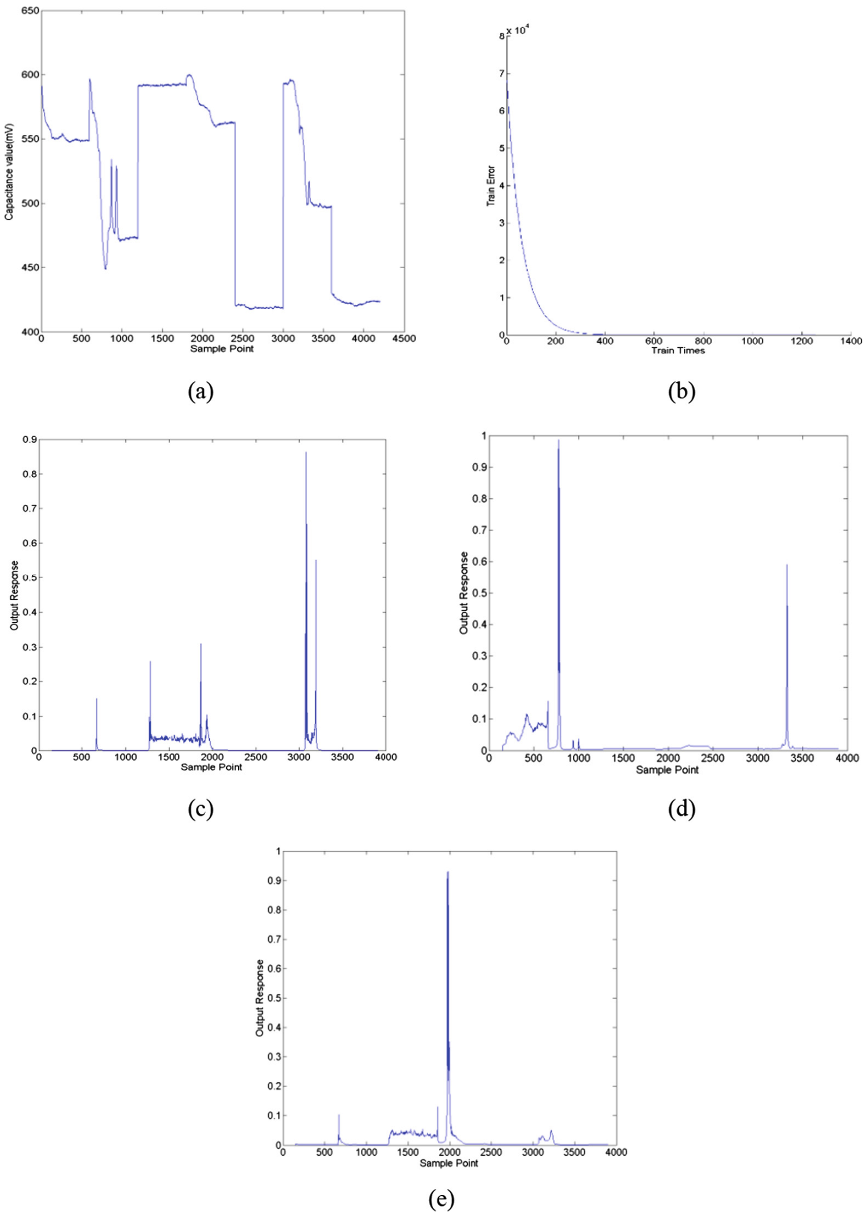

Fig. 4. MRWNN identify situation (a) capacitive sensing data, (b) train error, (c) identify results of user first gesture, (d) identify results of user second gesture, (e) identify results of user third gesture.

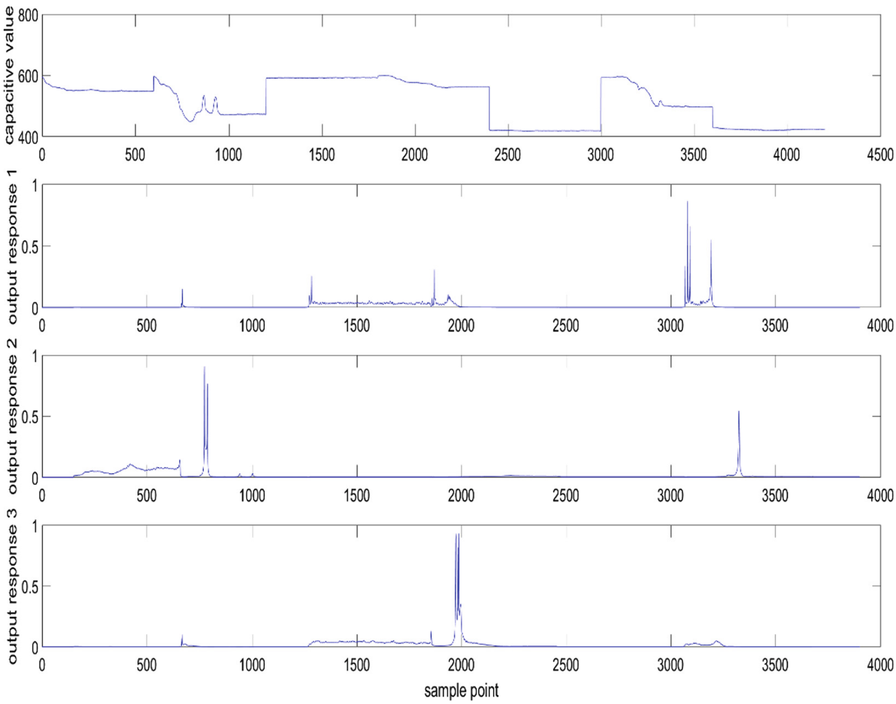

Fig. 5. MRWNN identify situation

6 Conclusion

The user gesture detection is an important research topic in smart home application that different gesture combined security identification and intelligent interaction in home life. This paper successful used MRWNN algorithms implemented in microcontroller that has high performance detection user gesture and feedback remote PC. The experimental results show MRWNN algorithms analysis different user gesture and clear to identify the true user gesture.

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References

1. Lin, X., Adhikary, A., Wang, Y.P.E.: Random access preamble design and detection for 3GPP narrowband IoT systems. IEEE Wirel. Commun. Lett. **5**(6), 640–643 (2016)
2. Chu, C.T., Chiang, H.K., Hung, J.J.: Dynamic heart rate monitors algorithm for reflection green light wearable device. In: International Conference on Intelligent Informatics and Biomedical Sciences, vol. 62, no. 8, pp. 438–445 (2015)

3. Ha, U., Lee, Y., Kim, H.T., Roh, J., Kim, B.C., Yoo, H.J.: A Wearable EEG-HEG-HRV multimodal system with simultaneous monitoring of tES for mental health management. IEEE Trans. Biomed. Circuits Syst. **9**(6), 758–766 (2015)
4. Brugarolas, R., et al.: Wearable heart rate sensor systems for wireless canine health monitoring. IEEE Sens. J. **16**(10), 3454–3464 (2016)
5. Wiens, A.D., Etemadi, M., Roy, S., Klein, L., Inan, O.T.: Toward continuous, noninvasive assessment of ventricular function and hemodynamics: wearable ballistocardiography. IEEE J. Biomed. Health Inform. **22**(1), 1435–1442 (2015)
6. Semnani, S.H., Basir, O.A.: Semi-flocking algorithm for motion control of mobile sensors in large-scale surveillance systems. IEEE Trans. Cybern. **45**(1), 129–137 (2015)
7. Fazio, M., Puliafito, A.: Cloud4sens: a cloud-based architecture for sensor controlling and monitoring. IEEE Commun. Mag. **41**(47), 4–8 (2015)
8. Kafi, M.A., Djenouri, D., Othman, J.B., Badache, N.: Congestion control protocols in wireless sensor networks: a survey, and future trends. IEEE Commun. Surv. Tutor. **16**(3), 1369–1390 (2014)
9. Giles, C.L., Miller, C.B., Chen, D., Chen, H.H., Sun, G.Z., Lee, Y.C.: Learning and extracting finite state automata with second-order recurrent neural networks. Neural Comput. **4**(3), 518–527 (1992)
10. Kim, Y., Moon, T.: Human detection and activity classification based on micro-doppler signatures using deep convolutional neural networks. IEEE Trans. Ind. Electron. **13**(1), 8–12 (2016)
11. Bu, N., Okamoto, M., Tsuji, T.: A hybrid motion classification approach for EMG-based human–robot interfaces using bayesian and neural networks. IEEE Trans. Rob. **25**(3), 502–511 (2009)
12. Gupta, H.P., Chudgar, H.S., Mukherjee, S., Dutta, T.: A continuous hand gestures recognition technique for human-machine interaction using accelerometer and gyroscope sensors. IEEE Sens. J. **16**(16), 6425–6432 (2016)
13. Chang, J.Y.: Nonparametric feature matching based conditional random fields for gesture recognition from multi-modal video. IEEE Trans. Pattern Anal. Mach. Intell. **38**(8), 1612–1625 (2016)
14. Lefter, I., Burghouts, G.J., Rothkrantz, L.J.M.: Recognizing stress using semantics and modulation of speech and gestures. IEEE Trans. Affect. Comput. **38**(8), 162–175 (2017)