Motion Recognition in Wearable Sensor System Using an Ensemble Artificial Neuro-Molecular System

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Abstract. This paper proposes an ensemble artificial neuro-molecular system for motion recognition for a wearable sensor system with 3-axis accelerometers. Human motions can be distinguished through classification algorithms for the wearable sensor system of two 3-axis accelerometers attached to both forearms. Raw data from the accelerometers are pre-processed and forwarded to the classification algorithm designed using the proposed ensemble artificial neuro-molecular(ANM) system. The ANM system is a kind of bio-inspired algorithm like neural network. It is composed of many artificial neurons that are linked together according to a specific network architecture. For comparison purpose, other algorithms such as artificial neuro-molecular system, artificial neural networks support vector machine, k-nearest neighbor algorithm and k-means clustering, are tested. In experiments, eight kinds of motions are randomly selected in a daily life to test the performance of the proposed system and to compare its performance with that of existing algorithms.

Keywords: Artificial neoro-molecular system (ANM), Motion recognition, Wearable sensor system, Ensemble network.

1 Introduction

A rapid development in computer technology has imposed a new computing environment. A computer is combined with an intelligent human-friendly interface and will appear a new computing environment. This concept is represented by a ubiquitous computing. Most of all, wearable computing leads a next generation computing based on ubiquitous computing. Wearable computing includes not only intelligent computer that is worn to the body, but also just sensors attached to the body. Nowadays, wearable computing technology has been used in a variety of fields including sports, medical care, the game, etc. There are also many researches about wearable computing, and exist two big issues about wearable computing. One is a new computer environment that is combined with human-friendly interface. Another is a wearable health care system that can help patients and senior man at long distance.

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This paper proposes an ensemble artificial neuro-molecular (ANM) system for motion recognition for a wearable sensor system with 3-axis accelerometers considering a human-friendly interface. Many researches related to wearable computing based on human-friendly interface have been conducted. In particular, human motion recognition using sensor systems is widely used. Hardware platforms based on accelerometers are most popular. Other kinds of sensors such as gyro sensors, pressure sensors and cameras can also be used for the hardware platforms [1]. The sensors are attached to various locations such as forearms, wrists, head, waist, legs, etc [2]. As for the classification, algorithms such as classifier including neural network, support vector machine, k-means clustering, k-nearest neighbor, etc., can be used [3]–[7].

For comparison purpose, the performance of the proposed ensemble ANM system is compared with that of those algorithms. To demonstrate the effectiveness of the proposed system, experiments are carried out for eight kinds of motions that are randomly selected in a daily life. Also, its performance is compared with that of existing algorithms including neural network, k-nearest neighbor, support vector machine, and k-means clustering.

The rest of this paper is organized as follows. In Section 2, the ensemble artificial neuro-molecular system is proposed. Section 3 describes the wearable sensor system The experimental results are discussed in Section 4 and concluding remarks follow in Section 5.

2 Ensemble Artificial Neuro-Molecular System

2.1 Artificial Neuro-Molecular System (ANM)

Artificial neuro-molecular system (ANM) is a biologically motivated system that captures the biological structure-function relationships, and it possesses several features that facilitate evolutionary learning [9].

Overall Structure: ANM mainly consists of four neurons, receptor neurons, cytoskeletal neurons, reference neurons, and effector neurons. Receptor neurons receive input data from outside and transform into an internal signal. Cytoskeletal neurons receive a signal from receptor neurons and fire an effector neuron. Then finally, an effector neuron determines a class of input data. Reference neurons play a role to supervise cytoskeletal neurons. The overall strucutre of ANM is depicted in Fig. 1.

Cytoskeletal Neuron: A cytoskeletal neuron is composed of 8×8 sized site array. Each site can have one of the three-types of components (C1, C2, or C3) or none. Each site can also have MAP, readout enzyme, and readin enzyme. A MAP links two neighboring components of different types together. Specific combinations of cytoskeletal signals will activate a readout enzyme, which causes the neuron to fire. A readin enzyme converts an external signal into a cytoskeletal signal. For the details of signal flow in a cytoskeletal neuron, the reader is referred to [8], [9].

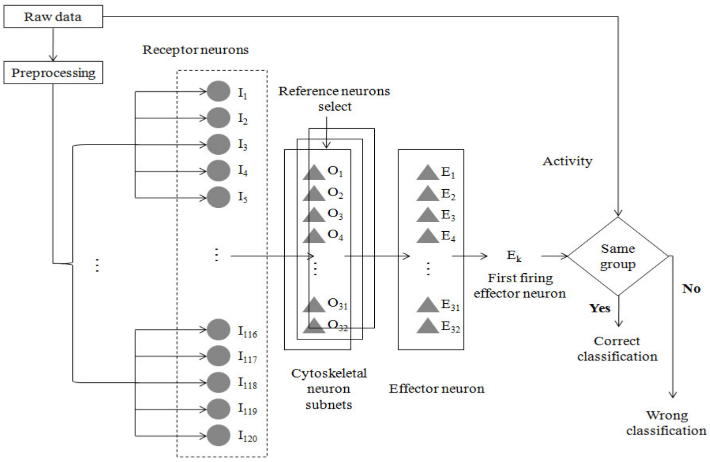

Fig. 1. Overall structure of ANM system

Reference Neuron: Two-layered reference neurons supervise cytoskeletal neurons. High-level reference neuron chooses a bunch of low-level reference neurons, while each low-level reference neuron chooses cytoskeletal neurons. Only selected cytoskeletal neurons receive a signal from receptor neurons. The structure of the reference neurons are described in Fig. 2.

Two-level Evolutionary Learning: In the ANM system, evolutionary learning is used as a learning method. It is progressed in two level, cytoskeletal neuron level and reference neuron level as follows.

I. Evolutionary learning at cytoskeletal neuron level

1) Calculate the fitness value of each subnet.
2) According to the fitness value, copy the best three subnets to other subnets.
3) Mutate some of neurons in other subnets.

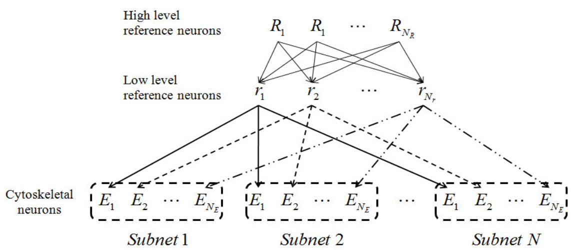

Fig. 2. Structure of reference neuron

II. Evolutionary learning at reference neuron level

1) Calculate the fitness value of each high level reference neuron.
2) According to the fitness value, copy the best reference neuron to other reference neurons.
3) Mutate some of neurons in other subnets.

2.2 Ensemble ANM System

A single ANM system has poor performance if the number of classfication categories increases. In this case, the performance can be improved by constructing ensemble network. There are several kinds of combination method which have been frequently used: voting, weighted sum, Bayesian, etc. The results from each independent network are integrated by a combination method which yields a new single result. In this paper, th voting combination method is used. The key of the voting combination is a majority vote. The final result is decided as the one that most of individuals choose. In this paper, ensemble network is constructed, which is composed of eight individual networks, as shown in Fig. 3.

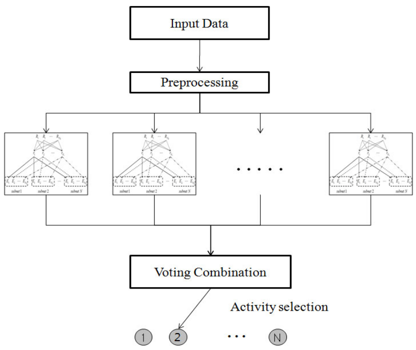

Fig. 3. Ensemble ANM system

3 Wearable Sensor System

3.1 Hardware Structure

Hardware platform of the wearable sensor system mainly consists of accelerometers and a communication module. Freescale MMA7260Q triaxial accelerometer is selected as a measurement device, which has four different sensitivities, 1.5g, 2.0g, 4.0g, 6.0g. In this paper, 1.5g is used and two accelerometers, each of which needs 3.3V for battery power, are attached to forearms, respectively, and a communication module to a waist, as shown in Fig. Fig. 4. As for the micro-controller, ATmega128 is used, which needs 5V for battery power. Considering both of the accelerometer and micro-controller, a 5V dry cell type battery is used so that a battery is directly connected to an ATmega128 and connected

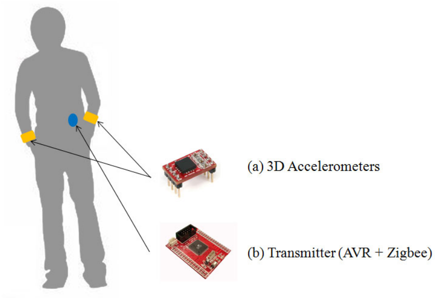

Fig. 4. Locations of sensors and a communication module

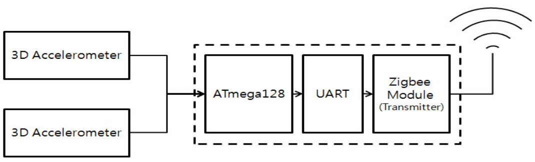

Fig. 5. Internal structure of the wearable sensor system

to the two accelerometers through a diode that drops electric pressure by 1.7V. For communication, Zigbee module is used, which is connected to UART in ATmega128 board. The internal structure of the wearable sensor system is shown in Fig. 5.

3.2 Data Collection

The output of the accelerometer is analog data, so ATmega128 converts it into 10-bit digital data. Also, acceleration data from the two accelerometers is collected for each sampling time of 100ms for 3 seconds. In other words, acceleration data of which length is 3 seconds will be an input data of classification algorithm. In this case, there are two drawbacks: over-fitting problem and heavy computational complexity. Thus, a series of pre-processing steps is needed to solve the problems. The steps are executed by data sampling, removal gravity acceleration and quantization in order.

3.3 Pre-processing

Data Sampling: Raw acceleration data is obtained at 50Hz, but the mean of every five acceleration data is used to reduce the complexity of the algorithm.

Removal Gravity Acceleration: Gravity acceleration is included to an acceleration data from the acceleromter. Because we are interested in a trajectory of the acceleration data, an initial reference value is subtracted from the accelration data. After this pre-processing, all initial values are set to 0 g.

Quantization: The ADC values are divided into five intervals and transformed into 5 bit data. The quantization rule used is as follows:

$$\text{Quantized data} = \begin{cases} 00001 & \text{if} \quad -300.0 < \text{actual value} < -180.0 \\ 00010 & \text{if} \quad -180.0 < \text{actual value} < -60.0 \\ 00100 & \text{if} \quad -60.0 < \text{actual value} < 60.0 \\ 01000 & \text{if} \quad 60.0 < \text{actual value} < 180.0 \\ 10000 & \text{if} \quad 180.0 < \text{actual value} < 300.0 \end{cases} .$$

4 Experiments

4.1 Experimental Setup

We randomly selected eight kinds of motions in a daily life. Each motion is defined in Table 1. A training set was obtained by repeating ten times for each motion, and a test set was obtained by repeating five times for each motion. One motion data was composed of six accelerometer values for 3 seconds.

Table 1. Motions

Motion No	Motion
1	Halt
2	Swing two arms
3	Shake two arms back and forth
4	Stretch two arms forward
5	Put the hands behind the head
6	Greeting
7	Raise a right arm
8	Intend to hit something with left arm

4.2 Experimental Results

In the ANM system, mutatin rate for neurons, the number of receptor neuron, the number of subnets, and cytoskeletal neurons in a subnet were set to 0.1, 120, 8, and 32, repectively. The termination condition was 800 generations. We used multi-layered perceptron (MLP) trained with backpropagation for neural networks. Three hidden layers were used, and each hidden layer contains 5 neurons. In the case of k-NN, we classifed motions based on closest training examples in the 8-dimensional euclidean space. Finally, a 3rd order polynomial kernel function was used for SVM because input data was non-linear.

Table 2a, 2b shows that k-NN and SVM performed best. However, there are drawbacks in k-NN and SVM. First, the performance of SVM is heavily influenced by kernel functions which transform support vector. Actually, SVM had the worst performance when inappropriate kernel functions were used. Second, the performance of k-NN is dependent on k and types of motions. In other words, k-NN might have poor performance for the classification problem of complex motions. Artificial neuro-molecular (ANM) system has a similar structure

Table 2. Accuracy for training and test data

(a) Training data

Classification Algorithm	Training Data Accuracy
ANM	61.25%
ANN	68.75%
k-NN	-
SVM	96.25%
K-Means Clustering	83.75%
Ensemble ANM	91.25%
Ensemble ANN	86.75%

(b) Test data

Classification Algorithm	Test Data Accuracy
ANM	53.75%
ANN	46.00%
k-NN	95.00%
SVM	85.00%
K-Means Clustering	47.50%
Ensemble ANM	72.50%
Ensemble ANN	75.00%

as artificial neural network. Both algorithms have randomness and we do not know how to classify data internally. In additions, both algorithms can classify the data without specific pre-processing like a kernel. It means that performances of classification is less affected by the input data. Therefore, it is reasonable to compare the performances of ANN and ANM system. In actual practice, ANN and ANM system have a similar performance and ANM system's performance is slightly better than ANN in accuracy for training data. It is also shown that the proposed ensemble ANM network improves classification accuracy.

5 Conclusions

This paper proposed a novel ensemble artificial neuro-molecular (ANM) system and applied it to motion classification in a wearable sensor system. The system classified human motions when she/he wearing the system did some different motions. Artificial neuro-molecular system employed two-level evolutionary learning. As the performance of a single ANM system was poor, the ensemble network of ANM systems was developed. As a result, classification accuracy was improved as much as general classification algorithms' accuracy. To test the performance of the proposed ensemble ANM system, eight motions were randomly selected in a dailtly life. The ANM system gave an accurate classification result for the eight motions. For comparison purpose, neural network, k-nearest neighbor, support vector machine and k-means clustering were tested for the same motions. As a result of the comparison, the performance of the proposed ensemble ANM system was similar as that of other algorithms. Other sensors such as gyro sensors, ECG sensors, image sensors as well as accelerometers could improve the performance, which is left for future work.

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