POSTURE ACTIVITY CATEGORIZATION AND FEATURE ANALYSIS USING AN ARTIFICIAL NEUROMOLECULAR SYSTEM

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Abstract:
Monitoring of posture activities enables accurate differentiation of human behavior. In this paper, an artificial neuromolecular system (ANM), a self-organizing system movtivated from brain information processing, was used to separate human behavior patterns. We also looked into the biometric features of each activity acted by each individual. Five healthy adults were invited to participate in this study. Each individual was asked to perform walking, racewalking, stair ascent/descent and jogging activities ten times. A smart phone was tied up with the left heel of each individual for data collection. Experimental results show that the patterns of heel acceleration uniquely characterize differences for each person's behavior patterns, and the proposed system could be used to analyze and estimate as a classification tool by characteristic differences.

Keywords: artificial neural network, evolutionary learning, data mining

1. INTRODUCTION

Successful monitoring of postural activities not only allows us to identify human behaviors, but also may provide an aid in reducing the degree of injury caused by an accident. Instruments that quantitatively monitor levels of physical activity (e.g., accelerometers) have been shown to viable outcomes. Drosou et al.[1] presented a multimodal image analysis system that can identify subjects and monitor human behavior through spatiotemporal analysis of human activities. Even though the system demonstrated satisfactory results in human activity recognition; however, the constraint on indoor activities is its major weakness.

To assess both indoor and outdoor daily physical activity, Bouten et al. [2] proposed using a triaxial accelerometer. Similary, Mathie et al.[3] used a triaxial accelerometer to categorize different types of human activities, including walking, leaning backward, leaning forward, falls, sitting, and standing. Karantonis et al.[4] presented a real-time classification system for the types of human movement associated with the data acquired from a single, waist-mounted triaxial accelerometer unit. Allen et al. [5] used a single, waist-mounted 3-D accelerometer to classify static postures (lying, sitting, standing) and five transitions between postures (e.g., sit-to-stand). It was reported that not all activities were recognized equally well by the current devices. For example, Pärkkä et al.[6] did not successfully differentiate between sitting and standing, grouping these postures together; Ermes et al. [7] faced challenges in recognizing such activities as cycling and ascending and descending stairs. Overall, as stated by Sazonov et al.[8], reliable recognition of static postures and typical daily activities from a single location of the body remains a challenge.

Most of the aforementioned studies emphasized how to improve recognition accuracy, but little was discssued about the significant features of each individual activity that allowed us to separate one from another (e.g., biometric authentification). Here, we assumed that some features were more comparatively important than others, and that some features might be strictly personal, or even activity-dependent. However, how to determine significant and insignificant features of each activity was absolutely not an easy job. The ANM system originated from brain information processing possessed a feature of self-organizing learning capability, based on a presupposition that the system captured the gradual structure/function transformability feature of an artificial organism. With this feature, the system was capable of determining significant and insignificant features, based on each individual behavior, in a self-organizing manner.

To collect time-domain signals of each individual activity, an acceleromoeter embedded in a smart phone was used. To link with the ANM system, some preprocessing of the data (i.e., the time-domain signals collected) was needed. First, the data were converted into patterns of frequency and amplitude features by using fast Fourier transform. Finally, the ANM system was applied to perform pattern categorization. Evolutionary learning mechanisms were used to determining significant and insignificant features.

This paper is organized as follows. Section II reviews the ANM system constructed earlier. Section III describes the data collection system and data preprocessing, classification methods. Section IV illustrates the input/output interface that links to the problem domain. Section V summarizes the results of the experiments, and Section VI provides a discussion of the results. The final conclusions are drawn in Section VII.

2. THE ANM SYSTEM

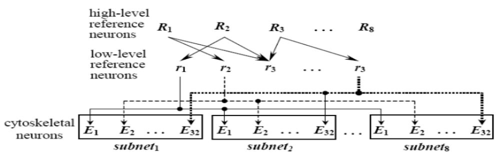
The establishment of an ANM system is based on two presumptions. Firstly, intra-neuron information processing in the brain is extremely vital since it may directly or indirectly affect the triggering actions of these neurons. Such neurons, called cytoskeletal neurons or enzymatic neurons, may combine together in a self-organization way and accept input information from different times and spaces to generate a series of output information for the control of outputs from other neurons or organisms. Secondly, some neurons, called reference neurons, have a capability to control other neurons. By integrating these two types of neurons, the ANM system becomes a multi-layered artificial neural structure, which may generate effective operation and interdependent learning [9]. Furthermore, the adaptability and learning capability of an ANM system may be enhanced according to the increased variety of components inside the cytoskeletal neurons or enzymatic neurons [10].

The main architecture of an ANM system, comprising one group of reference neurons and cytoskeletal neurons (Picture 1), could be divided into 3 layers: high-level reference neurons, low-level reference neurons and cytoskeletal neurons. The main function of reference neurons is the control or assembly of other neurons. Each cytoskeletal neuron may be seen as a specific input/output converter while the conversion of input information to output information is dependent on the intra-neuron dynamics. For early ANM systems, cytoskeletal information processing occurred like cellular automation, based on a presumption that the cytoskeleton may integrate information. The transmission of extracellular information into the cytoskeleton will induce the circulating of various cytoskeletal signals, which then may gather at a certain place to compose signal combinations. Eventually, this signal combination may affect one cellular enzyme, such as the enzyme controlling the ion channel switch, to enhance the intra-neuron potential and lead to a firing action.

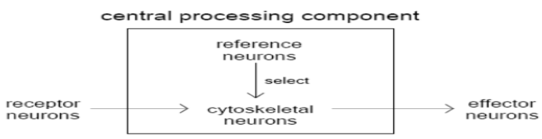
A total of 256 cytoskeletal neurons were divided into 8 subnets with 32 neurons in each subnet. The connection of input/output interface of central processing component in ANM system is shown in Picture 2. The input/output interface is composed of receptor neurons and effector neurons. Cytoskeletal neurons and receptor neurons are connected in the same way in each subnet to ensure that each subnet may receive the same input signal from the same receptor neuron transmission. Similarly, cytoskeletal neurons and effector neurons are connected in the same way to ensure that organisms may act in the same way in response to the same output from each subnet.

The detailed subnet input/output interface consists of 64 receptor neurons and 32 effector neurons (Picture 3). During the system configuration, each receptor neuron was connected to a cytoskeletal neuron in a different and randomized way; therefore, each cytoskeletal neuron may receive information from different receptor neurons to become different input/output information processors. Along with learning process, these connections will be appropriately adjusted to fulfill the system requirements. The effector neurons are connected with cytoskeletal neurons in a fixed way, and then according to altered transmission of cytoskeletal neurons, the system output will be subsequently changed.

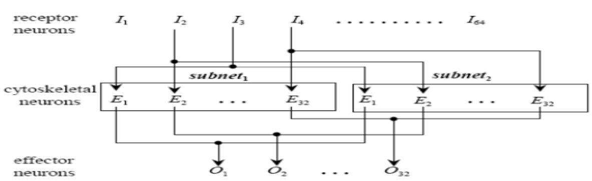
Picture 1: Architecture of the ANM system



Picture 2: The input/output interface of central processing component

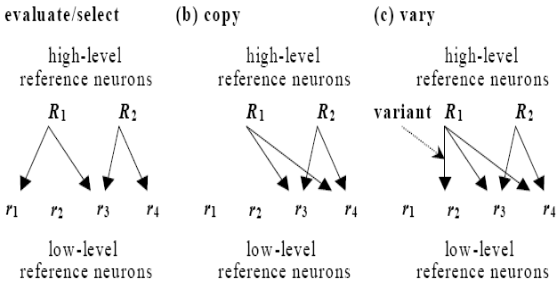


Picture 3: The subnet input/output interface of information processing neurons

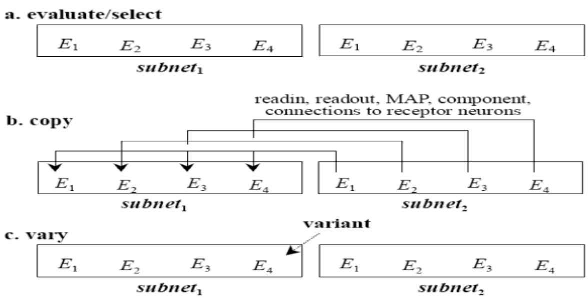


As described above, the cytoskeletal neurons in the ANM system are divided into 8 subnets. In response to the same input, these 8 subnets will be initialized and evaluated sequentially. Several region networks with superior performance will be duplicated into those with inferior performance. With a variation-selection evolutionary search, evolutionary learning will consist of 3 steps: evaluation and selection of subsystems with better performance, duplication of superior subsystems into inferior subsystems and varied performance of inferior subsystems (Picures 4 & 5).

Picture 4: The evolutionary learning process of reference neurons



Picture 5: The evolutionary learning process of cytoskeletal neurons



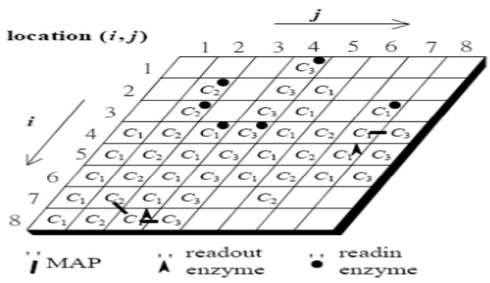
The following description is on how to use two dimensional cellular automata to simulate the cytoskeletal information processing. In Picure 6, each grid presents a basic unit of cytoskeletal component and is indicated as C1, C2 or C3, based on the presumption that intra-neuron information transmission is conducted by 3 various components (microtubules, microfilaments and neurofilaments). The transmission features of these 3 components are different; the transmission speed of C1 is the slowest but the transmission energy is the strongest; the transmission speed and energy of C2 are both intermediate; and C3 has the weakest transmission energy but the fastest transmission speed.

Each unit could be a point for information input or output while an input point is called a readin enzyme and an output point is named as a readout enzyme. A readin enzyme is responsible for receiving the extracellular signals transmitted to the cellular membrane and transferring these signals into molecular structure signals. When a signal combination arrives, the readout enzyme is responsible for the firing of that neuron; however, there are some limitations to the conPicuration of readin and readout enzymes. A readin enzyme could be deployed on any component while a readout enzyme could be only deployed on a C1 component since it is believed that the firing of a neuron is caused by one certain type of component.

Signals could be transmitted between the same types of components. While extracellular signals are transmitted to cellular membrane to open a readin enzyme, this readin enzyme simultaneously opens components at the same position. These opened components again affect neighboring similar components and the continuous effect leads to a signal circulation of the cytoskeleton. As shown in Picure 6, the readin enzyme at (2, 2) receives a signal and then activates the C2 component to generate a signal moving along the column starting from the C2 component at (2, 2) to the C2 component at (8, 2). During this process, activated components enter into a transient refractory phase right after the signal transmission in order to form a directional signal flow. During this refractory phase, this component cannot be activated again until the end of refractory phase to ensure one directional transmission.

Signals could also be transmitted between different types of neurons. On the cytoskeleton, one type of connection protein (microtubule associated protein, MAP) is especially responsible for the connection between different components. Upon contact with a connection protein, the signal of a certain component will be transmitted by this connection protein to a different component at the other end to induce an energy level change. Such an energy change may produce a new signal circulating among components. For example, the readin enzyme at (4, 3) receives a signal to activate the C1 component and then moves to (8, 3) along the C1 component. Two connection proteins at (8, 3) respectively connect to C2 at (7, 2) and C3 at (8, 4), to affect the energy levels at these 2 positions. Since the energy of C1 is greater than that of C2 and C3, new transmission signals are generated individually on C2 and C3 components. However, if the signal is transmitted from C2 at (7, 2) to C1 at (8, 3), a new transmission signal is not necessarily generated to the C1 component due to the difference in transmission energy levels of various components.

Picture 6: Cytoskeleton of cytoskeletal neurons



In the ANM system, to ensure the capability of the cytoskeleton to integrate signals from various times and spaces, it is presumed that various components possess different energy impacts. Energy association decides the difficulty level for a component activation (components with higher energy levels are easier to be activated), as well as the signal transmission time between components and signal combination required by neuron firing. For each component, the energy has to reach S (Strong) level to be activated to generate a signal movement. For the precedent example, the signal was transmitted from C2 at (7, 2) to C1 at (8, 3) without generating any new transmission signal since the energy level is under S. However, the energy level of C1 is raised to I (intermediate), indicating a nearly activated state. With a timely signal from C3 at (8, 3), the energy level of C1 may possibly be raised to S and then signal movement of C1 will be activated. On the other hand, without any timely signal, the energy of C1 will gradually dissipate in time.

Furthermore, transmission energy levels among the same components are all S, like C1 to C1, C2 to C2, and C3 to C3, which could be due to the particular relationship between the same components; they easily open each other despite the different energy levels of C1, C2 and C3. This is the reason why this type of energy level is defined as S and accounts for the signal transmission between the same types of components.

As described above, once a signal combination reaches the readout enzyme, that particular neuron will fire. The cytoskeleton has the capability to integrate signals from various times and positions. For example, C1 at (8, 3) may simultaneously connect to C2 and C3 through two connection proteins to generate 3 different sets of signal combinations at C1 to induce the neuron firing, including C2 signal activated by (2, 2) or (3, 2), C1 signal activated by (4, 3), and C3 signal activated by (1, 4) or (4, 4). Among C1, C2, and C3, the moving speed is different and the required time for signal integration is different; subsequently, the time required for neuron firing is also different.

For the adjustment of neuron transmission behavior and the assembly of neuron groups, the evolutionary learning of ANM system takes place at 5 levels:

1) at the readin enzyme: controlling the activation point of the initial signal,
2) at the readout enzyme: controlling the point of integration of response signals (indirectly controlling the neuron firing),
3) at the cytoskeletal components: controlling the signal pattern on the cytoskeleton,
4) at the connection protein: controlling the impact of signals between various components,
5) at the reference neurons: controlling or combining various neurons to accomplish one particular assignment.

The first 4 levels are intra-neuron evolutionary learning (internal dynamics) and the fifth level is inter-neuron evolutionary learning. For the current system variation, only one level is altered in one variation cycle, and another level will only be altered after several cycles of learning. With such cycling procedure, learning at each level may sequentially conducted.

3. DATA

GYROSCOPIC SENSOR

The user behavior data were collected from the accelerometer of a smart phone tied up with the left heel of each subject. Our preliminary result showed that such positioning allowed for differentiation of the most critical parts of the gait cycle, such as heel strike, stance phase, and toe-off as well as accounting for differences in loading of anterior and posterior areas of the foot in ascending/descending stairs.

A. *Data Collection Procedure*

In the present study, data were collected at a frequency of 16.66 frames per second (fps). Five healthy male subjects were invited to participate in the study. Those who had impairments that prevented physical activity were excluded. Only one of these five subjects was smoker (a heavy smoker). For each of the following class activity, each subject was asked to perform 20 times. The data collection protocol is:

1) Class “walking” (100~120 steps/min);
2) Class “race-walking” (140~160 steps/min);
3) Class “jogging” (80~200 steps per minute);
4) Class “stair ascending stair”; and
5) Class “stair descending”.

B. *Data Preprocessing*

In the present implementation, the ANM system only accepted binary patterns. The following described how to covert the time series signals into binary patterns for the ANM system. First, an FFT (Fast Fourier Transform) algorithm was used to convert each time-series signal collected into components of different frequencies and their maginitudes. Noted that in the present study only the signals in x-axis were taken into account (though all the signals in the other two axes could also be used).

Next, the data in frequency domain were divided into 16 equal groups, ranging from frequency 0 to frequency 6. (Our experimental result showed that significant frequencies only falled within the range of frequency 0 and 6.). The first group covered the data of the range of frequency (0, 0.375], the second the range of frequency (0.75, 1.125], and so on (see Table 1). For each group, the maximum magnitude falling within that range of frequencies was chosen to represent the significant data of that group. (Here, we assumed that the greater the magnitude of a specific frequency, the more significant feature of an activity induced.)

The final step was to binirize the data after step 2 into 64-bit patterns for the ANM system (noted that each bit of a pattern corresponded to the firing activity of a receptor neuron). For each range of frequency, the minimal and maximal numbers for these training patterns were determined (to be denoted by MIN and MAX, respectively), and the difference between these two numbers was divided by 5 (to be denoted by INCR). The encoding of each actual parameter value (to be denoted by ACTUAL) into the corresponding 4-bit pattern was shown in Eq. (1). All the data collected were combined in a pattern matrix Fs,c. Subject s represented one of these five distinct subject classes: A, B, C, D, and E, whereas class c represented one of these five distinct activity classes: walking, race-walking, jogging, stair ascending, and stair descending. Table 1 gave an example of the feature vectors of two subjects.

$$= \begin{cases} \text{"....", if} & \text{MIN} \le \text{ACTUAL} < (\text{MIN}+\text{INCR}) \\ \text{"...*", if} & (\text{MIN}+\text{INCR}) \le \text{ACTUAL} < (\text{MIN}+\text{INCR}\times 2) \\ \text{"..**", if} & (\text{MIN}+\text{INCR}\times 2) \le \text{ACTUAL} < (\text{MIN}+\text{INCR}\times 3) \\ \text{".***", if} & (\text{MIN}+\text{INCR}\times 3) \le \text{ACTUAL} < (\text{MIN}+\text{INCR}\times 4) \\ \text{"****", if} & (\text{MIN}+\text{INCR}\times 4) \le \text{ACTUAL} \le \text{MAX} \end{cases} \tag{1}$$

4. INPUT/OUTPUT INTERFACE

The ANM system as currently implemented has 64 receptor neurons and 32 effector neurons. The connections between the cytoskeletal neurons of each competing subnet and its I/O interface are the same. This ensures that corresponding cytoskeletal neurons in each subnet (neurons with similar intraneuronal structures) will receive the same input from receptor neurons, and that the outputs of the system are the same when the firing patterns of each subnet are the same. Each effector neuron is controlled by eight corresponding cytoskeletal neurons (i.e., one from each competing subnet). An effector neuron fires when any one of its controlling neurons fires.

Effector neurons are divided into four groups, representing four different overall behaviors of the system (they can also be used to represent component behaviors that combined to yield an overall behavior). In the present study, for each input pattern, the first 8 pulses (temporal sequence of firings) of the effector neurons were taken as its corresponding output. To measure the degree of similarity (DS) of two outputs, the longest common subsequence algorithm (LCS) was used.

For the same activity acted by an individual, our goal was to group them together, as closely as possible. However, as we knew, the time series signals collected at different times would not be exactly the same. This meant that the feature patterns (through the data preprocess procedure) provided for the ANM system would be different, and presumably the outputs generated from the system would not be the same. Given the same activity acted by an individual, the assignment of the system was to transform these different feature patterns into the same outputs (or similar outputs) through evolutionary learning acted on the system’s structure. Cohesion, a term in computer programming, was used to measure how strongly-related of these outputs. (The greater the degree of cohesion was, the better the fitness the system possessed.)

For the different activities acted by an individual (or the same actvitiy acted by different people), our goal was to separate them as clearly as possible. That is, different outputs should be generated for the different activities acted by an individual (or for the same actvitiy acted by different people). Coupling, a term in computer programming, was used to measure the similarity of two outputs. (The smaller the degree of coupling was, the better the fitness the system possessed.)

When taking the above-mentioned two factors into account, our goal was to maximize the degree of cohesion but to minimize the degree of coupling. The performance level (or fitness) of the system was determined by the degree of cohesion subtracted by the degree of coupling.

5. RESULTS

As mentioned above, there were five healthy male subjects invited to participate in the study, and each of them was asked to perform a specific ctivity twenty times. The goal of the experiment was to test whether the system could differeniate subjects, based on the same activity they performed. All the feature vectors (patterns) belonged to the same activity were grouped together as a set. In total, there were five activity sets, one for each activity class. The ANM system was trained and tested in turn for each activity set, with one half of the patterns for training and the other half for validation. That is, for each activity set, we trained the system with one half of the data until fully differentiating five different subjects was completed, and then tested it with the other half of the data.

Then, for each activity set, the ANM system after substantial training was tested with the other half of data. The experimental result showed that, among these five activity sets, the system achieved the highest accuracy (4.53) and the second highest accuracy (4.37) when it was tested on the stair-ascending set and the walking set, respectively. That is, the features of their stair-ascending and walking activities were comparatively more distinct than those of the other three activities. As shown in Table 2, the system was able to almost 100% identify the ascending activities of subjects B, C, D, and E. By contrast, the accuracy was comparatively low (2.32) when we tried to differentiate them from their stair-descending activity. A previous study [7] has shown that recognizing ascending and descending stairs was a challenging job. Our result was interesting, as the ANM system was able to differentiate these subjects from their stair-ascending activity but not from their stair-descending activity. A possible reason might be due to the fact that those who participated in this study were healthy and comparatively young, and most importantly, they had less experience of accidental fall. Unlike the elderly, stair-descending appeared to be a pleasant and mild activity for them, when compared with stair-ascending. Our intuition, but definitely not a conclusive remark, was that they tended to perform stair-descending activity in a comparatively more casual way than stair-ascending. Quite possibly, the results might be different if the subjects investigated were the elderly people. Indeed, this would be an interesting issue worth for advanced study.

Unlike the other three activities, race-walking and jogging were not necessarily the daily activities for most people. Hardly a consistent pattern of activity could be formed for those activities peole did not perform regularly, as they tended to act differently at various times. This might explain why the recognization accuracy was comparatively low when we tried to differentiate them from their jogging activity. An interesting result was found on the jogging set that all these five subjects were identified as subject D. Except the race-walking activity, the recognition accuracy of subject D was 100% correct for the other four activities. That is, when they all performed the same activity, it was more easily for us to separate subject D from the others four subjects.

Our summary was that it was comparatively more difficult to differentiate them from their non-daily activities than from their daily activities (except the stair-descending activity). On very rare occasion, these five individual selected ever engaged in race-walking activity. Hardly form specific patterns when one rarely engaged a particular activity. Among the five activity classes, from their walking and stair-ascending activities, we were able to differentiate different subjects but faced a challenge in differentiating them from their descending activity.

The goal of the above experiment was to identify subjects by their behavioral characteristics or traits (to be referred to as biometric identifiers). In the following, our goal was to find out these biometric identifiers. More specifically, our aim was to investigate the contribution of each frequency made to recognition accuracy and to determine the best conPicuration of frequencies used for identifying different subjects. Here, we assumed that certain frequencies were much more significant than others. By significant frequencies, we meant that they were utilized by the system to identify subjects and altering them would greatly affect recognition accuracy. By contrast, insignificant frequencies were those whose changes had not noticeable effect on recognition accuracy.

The system after substantial learning with the activity set was tested, but with an altered set of patterns on which it was trained. As stated earlier, the training set was comprised of 64-bit patterns (or 16-frequency patterns). The alteration was made by altering a specific frequency position of every pattern on the training set (i.e., the activity set). (The modified set was used as a test set to the system.). That is, the test set was exactly the same as the training set, apart from the altered frequency position. The entire test sets were generated by systematically altering a specific frequency position of every pattern on the training set from frequency f1 to frequency f16. That is, a first test set was generated by altering frequency f1 of each training pattern, a second test set by altering frequency f2, and so forth. In total, this yielded 16 test sets.

The experimental result showed that some frequencies were comparatively more important than others in differentiating subjects. As shown in Table 2, significant frequencies were different for each activity class, and each frequency more or less played some roles in pattern categorization. For example, in differentiating subjects from their walking activity, frequencies f4, f6, f10, and f12 played a vital role, whereas frequencies f1, f2, f5, f7, f11, f13, f14, and f16 were comparatively insignificant. By contrast, in differentiating their jogging activity, f5 was the only frequency shown significant.

Table 1: Average recognition accuracy in five-subject recognition for each activity

1. Ascending

Stair-Ascending (%)	Subject tested				
Subjects trained	A	B	C	D	E
A	53	0	57	0	54
B	12	100	0	44	62
C	100	72	100	91	29
D	0	21	28	100	0
E	59	44	0	41	100

2. Walking

Walking (%)	Subject tested				
Subjects trained	A	B	C	D	E
A	52	0	19	53	0
B	100	100	81	50	84
C	74	60	100	0	43
D	0	48	0	100	100
E	34	74	56	85	85

3. Race-walking

Racewalking (%)	Subject tested				
Subjects trained	A	B	C	D	E
A	100	0	40	0	47
B	28	100	100	100	67
C	15	0	7	78	3
D	7	45	73	64	0
E	0	82	0	59	100

4. Jogging

Jogging (%)	Subject tested				
Subjects trained	A	B	C	D	E
A	8	0	64	35	78
B	85	36	64	71	0
C	0	7	93	0	17
D	100	100	100	100	100
E	54	64	0	35	61

5. Descending (2.32, 46.4%)

Stair-Descending (%)	Subject tested				
Subjects trained	A	B	C	D	E
A	0	100	38	32	9
B	75	7	100	58	45
C	32	0	25	0	0
D	43	96	0	100	36
E	100	21	0	99	100

Unless these subjects had distinct features at this frequency, otherwise it was insufficient to differentiate subjects with a single parameter. This confirmed the above-mentioned result that differentiating subjects from their jogging activity was not very successfully. In the case of differentiating them from their descending activity, except f7, all frequencies played some role in pattern categorization. From the other viewpoint, the specificity was lost, as all frequencies were treated equally important. This explained why the accuracy was comparatively low among the five activity classes.

Table 2: Frequencies used in differentiating activities

Motion	Parameter															
Activity	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}
walking	–	–	○	●	–	●	–	○	○	●	–	●	–	–	○	–
jogging	–	○	–	○	●	○	–	○	–	–	–	–	–	○	○	C
race-walking	–	–	●	○	–	–	●	–	○	○	–	●	–	–	–	–
ascending	–	–	–	–	–	●	○	○	○	–	–	○	–	○	–	–
descending	○	○	○	●	○	●	–	●	○	○	○	●	○	○	○	○

(“●”: most significant, “○”: moderately significant, “–”: insignificant)

6. DISCUSSION & CONCLUSION

The proposed methodology, a self-organizing learning system, demonstrated satisfactory results in pattern categorization, allowing for accurate recognition without individual calibration. Even though in some cases the performances of our proposed methodology matched or outperformed those of some previous studies; however, a fair comparison was hard to be made. This was due to the fact that not only different type and conPicuration of sensors had been used for different studies, but also the types of behaviors investigated were distinct. We believe that the actual accuracy may be even higher as more different types or numbers of sensors were used. However, it should be noted that it is not goal to build the state-of-art classification system for monitoring posture activities, but to construct a self-organizing system that can differentiate different posture activities in an autonomous and also look into what biometric features possessed by the activity of each individual.

This paper presents a self-organizing methodology for automatic recognition of five different activities (walking, jogging, race-walking, ascending stairs, descending stairs) and also for automatic identification of five different subjects, based on the same activity class. The design of using a mobile phone as an input sensor requires minimal additional effort for everyday use. The proposed methodology requires only minimal processing of the sensor data. Overall, the low intrusiveness and high accuracy of the proposed device should enable long-term studies of human mobility in free-living conditions given further improvement and durability of the sensor design.

ACKNOWLEDGEMENT

This research was supported in part by the R.O.C. National Science Council (Grant NSC 102-2221-E-224 -038 -MY2).

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