Relationship between Muscle Activities and Different Movement Patterns on an Unstable Platform using Data Mining

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Abstract: - Association rule mining is widely used in the market-basket analysis. The association rule discovery can mine the rules that include more beneficial information by reflecting item importance for special products. Association rule mining could be a promising approach for clinical decision support system by discovering meaningful hidden rules and patterns from large volume of data obtained from the problem domain. The objective of this study was to analyze the muscle activities of different movement patterns on a training system for posture control using an unstable platform through association rule mining methodology. In this research, in order to find relational rules between posture training type and muscle activation pattern, we investigated an application of the association rule mining to the biomechanical data obtained mainly for evaluation of postural control ability. To investigate the relationship of the different movement patterns and muscle activities, fifteen healthy young subjects took part in a series of postural control training using a training system that we developed. The electromyography of the muscles in the lower limbs were recorded and analyzed under the different movement patterns. An improved association rule mining methodology was applied to analyze the relationship of the movement patterns and muscle activities. The results showed the significant differences in muscle activities for the different movement patterns. The experimental results suggested that, through the choice of different movement pattern, the training for lower extremity strength could be performed on specific muscles in different intensity. And, the ability of postural control could be improved by the training for lower extremity strength. Through the analysis results, we tried to find the best training method to improve the ability of postural control through improving the lower extremity muscular strength. The discovered rules could be used as a more useful knowledge for the rehabilitation and clinical expert's.

Key-Words: - Muscle activity, Association rule mining, Unstable platform, Postural control, Training

1 Introduction

Adequate postural control depends on the spatial and temporal integration of vestibular, visual, and somatosensory information about the motion of the head and body, and the generation of appropriate responses to that motion [1]. Age-related alterations in postural control strategies are also well known. Many studies have reported on the increase in postural sway with advancing age. The increased incidence of falls in the elderly population suggests that one or more of the components of vestibular, visual, and somatosensory degenerate with age. Diminished visual, vestibular, and somatosensory function and slowing of sensorimotor processing all occur with normal aging, and older people are also at higher risk for many diseases affecting the peripheral and central nervous system. Diminished balance ability has been identified as a multifactorial construct. It could be the result of degenerations in visual and vestibular sensory systems, degenerations of proprioception, and impairments in central processing, or combinations of these factors. In addition to decreases in muscle strength and slower neural processing, there are a number of sensory changes that may contribute to unsteadiness in the elderly adults. These include age-related decreases in the number of hair cells in both the canals and the otolith organs, and in the number of nerve fibers in the vestibular nerve, eventually resulting in reduced vestibular excitability [2, 3].

A considerable numbers of studies have reported on the training for postural control or improving the stability of standing balance for the elderly adults and patients. Various methods and instruments were performed for the improvement for postural control and balance abilities. The results of several studies have demonstrated that lower extremity muscular strength is a common factor associated with balance impairment in elderly fallers [4]. Lord et al. [5] determined that ankle dorsiflexion strength was one of the three variables that discriminated significantly between older adults who had not fallen or had fallen only once, and those with a history of multiple falls. A study of nursing home residents with a history of fallings showed that muscle forces (torque) and isokinetic power were significantly lower in the knee flexors (quadriceps) and extensors (hamstrings), and ankle dorsiflexors (tibialis anterior) and plantar flexors (gastrocnemius and soleus) [6]. These studies indicated a strong relationship between lower extremity strength and posture control ability. The association between weak leg muscles and falling has compelled researchers to conduct studies on strength training for the improvement of balance in balance-impaired older adults. These studies have evaluated the effects of strength training alone or in combination with other activities including tai chi, aerobic exercise, and balance training [7,8,9]. Hess and Woollacott [10] studied the effect of high-intensity strength-training on functional measures of balance ability in balance-impaired older adults. High-intensity strength training can safely and effectively strengthen lower extremity muscles in balance impaired older adults, resulting in significant improvements in functional balance ability and decreased fall risk. Morioka and Yagi [11] investigated the influence of perceptual learning training for hardness discrimination of sponge rubber by the soles on postural sway. Seidler and Martin [12] determined and contrast the effect of five weeks of balance training on the postural stability of elderly adults with a history of falls and those who have not previously fallen. There was the effectiveness of short term balance training for functionally independent elderly adults. Granacher et al. [13] examined the influence of postural and muscle responses of heavy resistance training and the sensorimotor training in elderly men and suggested that the sensorimotor training could be a well-suited method for fall preventive programs in elderly people. Page [14] described the scientific rationale for the program and the clinical progression of sensorimotor training.

Based on these studies, the training aimed at improving balance ability in elderly adults need to enhance strength of the muscles in the lower extremities, especially ankle plantar and dorsiflexors and improve the somatosensory through the sensorimotor training. A training system using an unstable platform was previously developed to improve the ability of postural control for the trainees. The muscle activities for the different movement patterns on the unstable platform were studied using association rule mining [15].

Classification is one of the key issues in the field of decision sciences, a field which plays an important role in supporting business and scientific decision-making. In recent years, it has also been one of the focal points in data mining and knowledge discovery [16,17]. Classification is finding a classifier that results from training datasets with predetermined targets, fine-tuning it with test datasets, and using it to classify other datasets of interest. A classification rule is of the form X→C, where X is a set of data items, and C is a class (label) and a predetermined target. With such a rule, a transaction or data record t in a given database could be classified into class C if t contains X. Apparently, a classification rule could be regarded as an association rule of a special kind. Roughly speaking, an association rule is a relationship between data items. Two measures, namely the Degree of Support (D_{supp}) and the Degree of Confidence (D_{conf}), are used to define a rule. For example, a rule like "Milk→Diaper with D_{supp}=20%, D_{conf}=80%" means that "20% of the customers bought both Milk and Diaper" and that "80% of the customers who bought Milk also bought Diaper". That is, D_{supp} corresponds to statistical significance, while D_{conf} is a measure of the rule's strength [18, 19].

Formally, let I ={I_i, i =1,. . ., s} be a set of items. A transaction database T is a set of transactions, where each transaction t is a set of items such that

$t \subseteq I$. An association rule is of the form $X \rightarrow Y$, where $X \subset I$, $Y \subset I$ are called itemsets, and $X \cap Y = \Phi$. A transaction t is called to contain X, if $X \subseteq t$. Let $D_{supp}(X)$ be the fraction of transactions that contain X in a database T, $D_{supp}(X) = \|X\|/|T|$. The degree of support and degree of confidence for a rule $X \rightarrow Y$ are defined as follows:

$$D_{supp}(X \rightarrow Y) = \|X \cup Y\|/|T| \tag{1}$$

$$D_{conf}(X \rightarrow Y) = \|X \cup Y\|/\|X\| \tag{2}$$

where X and Y are itemsets with $X \cap Y = \Phi$, T is the set of all the transactions contained in the database concerned, $\|X\|$ is the number of the transactions in T that contain X, $\|X \cup Y\|$ is the number of the transactions in T that contain X and Y, and $|T|$ is the number of the transactions in T. In other words, $D_{supp}(X \rightarrow Y)$ is the percentage of transactions containing both X and Y in the whole dataset, while $D_{conf}(X \rightarrow Y)$ is the ratio of the number of transactions that contain X and Y over the number of transactions that contain X. They are used to evaluate a rule against given thresholds, minimal support α and minimal confidence b, respectively. In particular, if Dsupp of an itemset X is no less than a (i.e., $D_{supp}(X \geq \alpha)$, then X is called a frequent itemset, otherwise called an excluded itemset. There have been many efforts proposed to discover association rules in various ways, among which the Apriori algorithm by Agrawal and Srikant is usually deemed as a classical algorithm [20,21,22,23].

Association rule mining is widely used in the market-basket analysis. The association rule discovery can mine the rules that include more beneficial information by reflecting item importance for special products. In the point-of sale database, each transaction is composed of items with similar properties. However, when items are divided into more than one group and the item importance must be measured independently for each group, traditional association rule discovery cannot be used. To solve this problem, we propose a new association rule mining methodology. The items should be first divided into subgroups according to their properties, and the item importance is defined or calculated only with the items included in the subgroup.

But this analysis method is not widely used in the biomedical data analysis. The objective of this study was to analyze on muscle activities of different movement patterns on an unstable platform using the improved association rule mining. We tried to find the association of the muscle activities and the movement patterns. Through the analysis results, the best training method to improve the ability of postural control through improving the lower extremity muscular strength could be used in the clinical rehabilitation training. The discovered rules could be used as a more qualitative and useful prioriknowledge for the rehabilitation and clinical expert's decision-making, and as a index for planning an optimal rehabilitation exercise model for patients.

2 Experimental method

2.1 Subjects

Fifteen healthy volunteers, 9 males and 6 females, whose age ranged from 23 to 33 years, participated in this study. The average age was 27.88±4.09 years. The average weight of the subjects was 64.13±9.39 kg. The average height of the subjects was 173±5.26 cm. Before the start of the examination, the volunteers were all informed of the experiment and signed a consent form.

2.2 Experimental device

Fig. 1 shows the training system for posture control that consists of an unstable platform, a monitoring device, a computer interface, a computer and a safety harness. This system provides the simultaneous excitations to visual sensory, somatic sensation and vestibular organs. The unstable platform is shown in Fig. 2. This unstable platform provides 360 degrees of movement allowing for training in various directions. The dimensions of the unstable platform are 550mm long, 390mm wide and 90mm high. The curvature radius of the unstable platform is 300mm. The maximum tilt angle in left-right direction is 18°; the maximum tilt angle in anterior-posterior direction is 28°. Two tilt sensors were installed inside of the unstable platform. Through the tilt sensors, we can compute the center of pressure (COP) of the subject on the unstable platform. The signals of the tilt sensors were input to a computer using a PCI-6024E card (National instruments, USA) by a SCB-68S (National instruments, USA) connecter.

2.3 Acquisition of EMG signals

We measured the EMG of the muscles in the lower limbs using a MP150 system (BIOPAC system, Inc., USA). The sampling rate is 1000 and the gain is 1000. A band pass filter was used to filter the EMG signal. The selected band was between 5 and 500 Hz. The surface electrodes were EL500. The surface electrode shape was discs. The diameter of the electrode was 20 mm. Alcohol was applied to cleanse skin. Eight muscles were measured in the right leg. They were rectus femoris (RF), biceps femoris (BF), tensor fasciae latae (TFL), vastus lateralis (VL), vastus medialis (VM), tibialis anterior (TA), gastrocnemius (Ga) and soleus (So) as shown in Fig. 3.

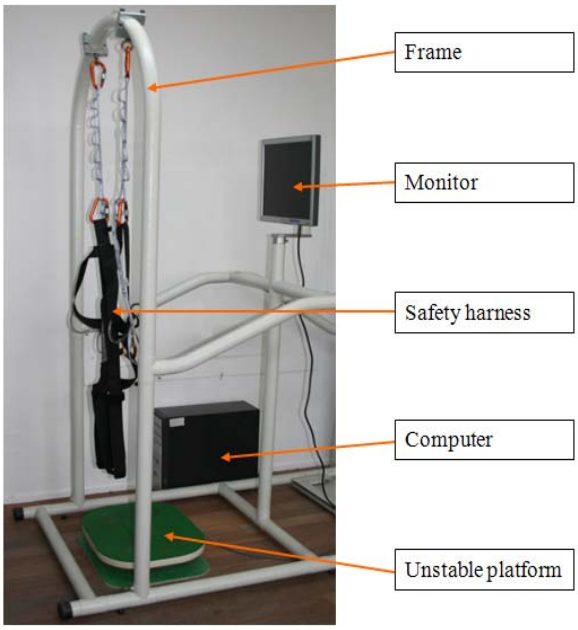
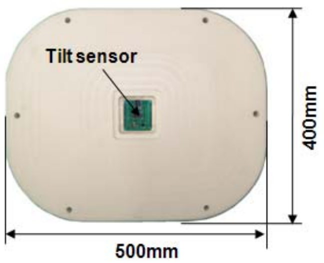


Fig. 1 Training system for postural control using an unstable platform



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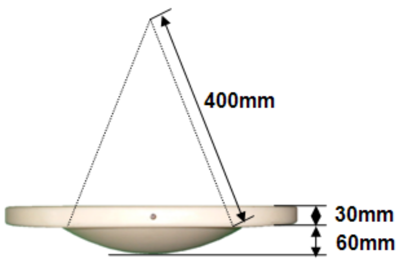


(b)

Fig. 2 The unstable platform: (a) Top view (b) Side view

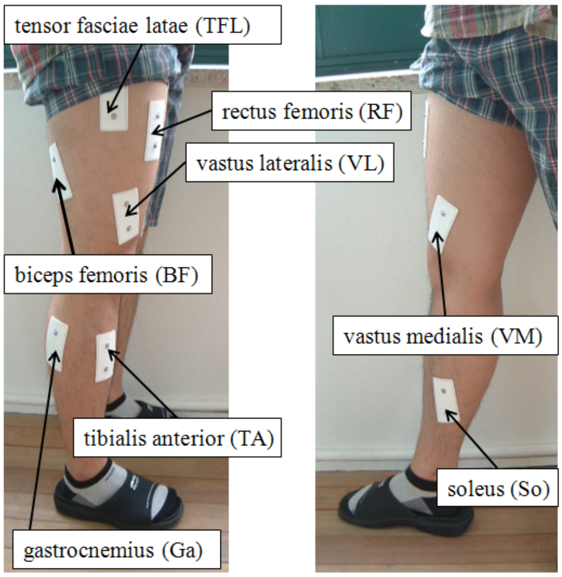


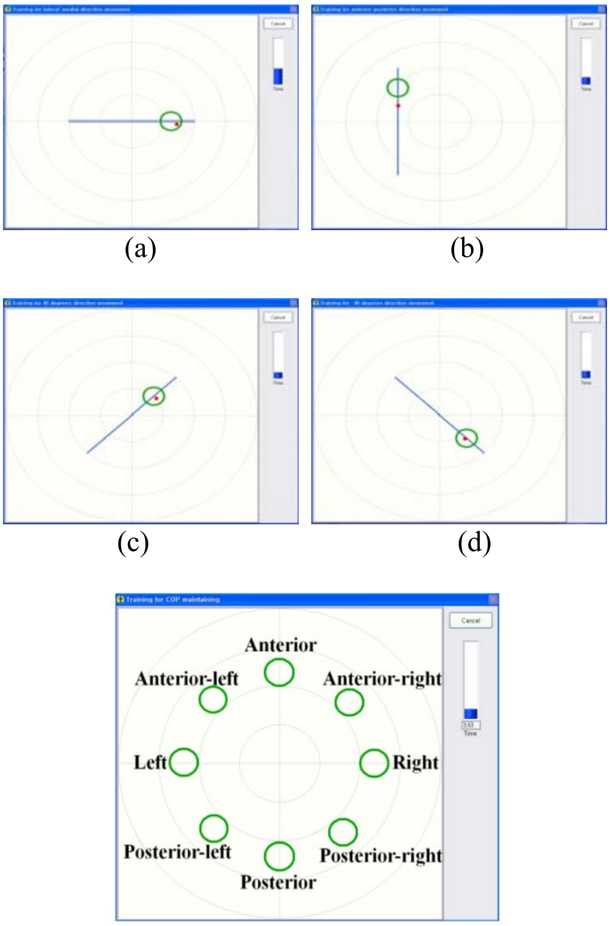
Fig. 3 Measured muscles

2.4 Movement patterns

The subjects were request to perform the movements following the appointed moving patterns on the unstable platform. The training programs were shown in Fig.4. Each movement pattern had five selectable levels (Level 1-5) (4, 5, 6, 7 and 8 cm) and five selectable speeds (Speed 1-5) (0.3, 0.45, 0.6, 0.75 and 0.9 cm/s). As shown in the figure, the line shows the moving direction, the circle shows the desired movement pattern and the point shows the COP of subject. The subject should try his best to move the COP following the circle. In the maintaining training, the maximum distance of the 8 directions from the center was 60 mm. In the movement training, the levels were level 1-5. The moving speed of the target circle was 6.25 mm/sec [15].

2.5 Experimental procedure

Before the experiments, the surface electrodes were put on specific muscles and were wired to the MP150 system. Then, the subjects were requested to stand and balance on the unstable platform. The distance of two feet is 200mm. After 5 minutes of free training, the actual test took place. The subject was request to move his COP by moving his posture following a desired movement pattern. The movement patterns include movements in the anterior-posterior direction, movements in the left-right direction, movements in the 45 degrees direction and movements in the -45 degrees direction. The directions of the COP maintaining training were anterior (A), posterior (P), left (L), right (R), anterior-left (AL), anterior-right (AR), posterior-left (PL) and posterior-right (PR). The experimental sequence was chosen in a random order. The rest time between each trial was 1 minute. All of the experiments were repeated twice. In this process, The EMG signals were recorded by a MP150 system.



(a) (b)

(c) (d)

(e)

Fig. 4 Training programs: (a) Movement in the anterior-posterior direction (b) Movement in the left-right direction (c) Movement in the 45° direction (d) Movement in the -45° direction (e) Maintaining training

2.6 Data analysis

2.6.1 Muscle activities

Muscle activity is typically studied using EMG. As a task is being performed, the muscle activity will generate signals that give valuable information about muscle fatigue, strength and movement patterns. EMG is a technique to measure muscle activity where surface electrodes are placed on the skin overlying a muscle or group of muscles. Since the magnitude of EMG activity is required to be estimated, a transformation procedure in the time domain can be used, such as rectification, linear envelope, integration, and root mean square. EMG force measurements seek to quantify the average number and firing rate of motor units contributing to a particular muscle contraction. This observation can relate the quantity to the actual force produced. The integrated EMG (IEMG) is quantity analogous to electrical work or energy that associated with the magnitude of EMG activity, frequency, and continuance time. In our research, IEMG was used to evaluate the muscle activities [9]. All of the IEMG were normalized for association rule mining. Table 1 showed the percentage of the muscle activities under the different movement patterns. The percentage of muscle activities were calculated by maximum voluntary contraction (MVC) of the muscles. The range in 20~60% was marked Low(L), 61~100% was marked High(H).

2.6.2 Improved association rule mining

The traditional association rule discovery can mine the rules that include more beneficial information by reflecting item importance for special products. In the point-of sale database, each transaction is composed of items with similar properties. However, when items are divided into more than one group and the item importance must be measured independently for each group, traditional association rule discovery cannot be used. To solve this problem, we propose a new association rule mining methodology. The items should be first divided into subgroups according to their properties, and the item importance is defined or calculated only with the items included in the subgroup [24].

Let $P(i)=\{p_1, p_2, \dots ,p_n\}$ $(1\le i\le n)$, $Q(j)=\{q_1, q_2, \dots ,q_j\}$ $(1\le j\le m)$, …are in the transaction database (T). $P(i)$, $Q(j)$, … have different properties. $P(i)$, $Q(j)$, … are the item spaces, which is a set of distinct items. D is a database which is a set of transactions and each transaction T_j be defined as a set of items (itemset) such that $T_j \subseteq T$.

Item frequency (ic) is the count of a item appears in the transaction database Item frequency (ic) is the count of a item appears in the transaction database. Item subgroup frequency (isc) is the count of all the items of a subgroup appears in the transaction database. Item support (isp) is defined as equation (3).

$$\text{Item support(isp)} = \frac{\text{Item frequency}}{\text{Item subgroup frequency}} \quad (3)$$

Transaction support (tsp) is measured by summing the item supports each of which is calculated from its subgroup, as defined in the equation (4).

$$\text{Transaction support(tsp)} = \sum_{k} \frac{\sum(\text{Item support})_k}{n_k} \quad (4)$$

where, k is the number of subgroups, n represents the number of items in the subgroup k.
A set of transactions T_j respects a rule R in the form of $X \rightarrow Y$ where X and Y are finite sub-items of the item space and they share no item in common. The support is computed as the fraction of the transaction support, where the transaction contains the candidate items. It is used as statistic value for pruning large items. The support can be formulated as the equation (5).

$$\text{Support(XY)} = \frac{\sum_{k=1}^{s_t \& (X \cup Y) \subseteq t_k} \text{transaction support}(t_k)}{\sum_{k=1}^{S_T} \text{Transaction support}(t_k)} \quad (5)$$

3 Results and Discussions

3.1 Generated rule numbers

In this study, the relationship of the muscle activities and the movement patterns was investigated using a new association rule mining methodology. Fig. 5 showed the generated rule numbers according the different minimum support. The minimum support was set to larger than 0.025. The generated rule number was decreased following the increased minimum support. According to the minimum support, the generated rules could be selected for the data mining. Table 2 showed the generated rules sample of the movement patterns and muscle activities. For the different movement patterns and the different levels and speed, the different muscles and the grade of muscle activity were found using the improved association rule mining.

3.2 Muscle activity of different movement patterns

According to the different movement pattern, the generated rules were grouped to processing the data mining. Fig. 6 showed the generated rule numbers of the different movement patterns (minimum support=0.025).

The generated rule numbers of the movement in AP direction and movement in 45 degrees direction were more than the other movement patterns. The lager rule numbers indicated that the muscles were more activated. Therefore, the movement in AP direction and movement in 45 degrees direction were more effective in the muscle activity training than the other patterns.

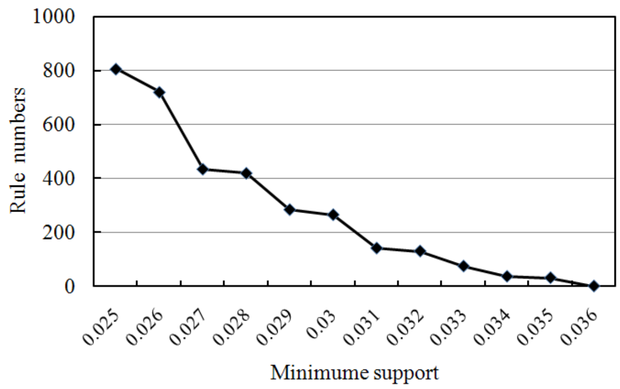


Fig. 5 Generated rule numbers according to the different minimum supports

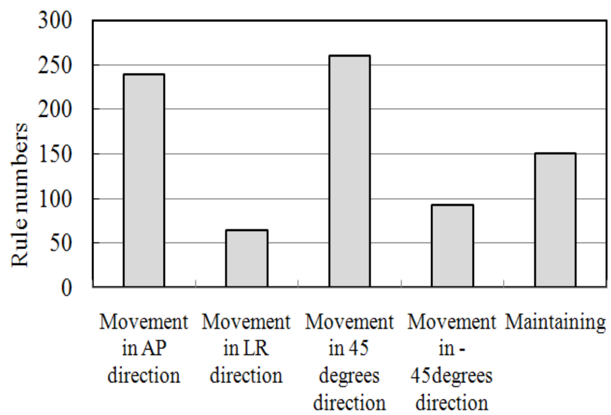


Fig. 6 Generated rule numbers of the different movement pattern.

Fig. 7 showed the count of generated rules of different muscles in the different movement patterns. According to the generated rule numbers, the activated muscles of the different movement patterns could be identified. As shown in the figure, BF, RF, TFL, VL, VM, Ga and So were more activated in the movement in AP direction and movement in 45 degrees direction. TA was more activated in movement in 45 degrees direction. In our study, the measured muscles were in the right leg. The BF, RF, TFL, VL, VM, Ga and TA of the right leg were more activated in the 45° direction more than the -45° direction. On the other side, BF, RF, TFL, VL, VM, Ga and TA of the left leg were more activated in the -45° direction more than the 45° direction. Compared with the other movement patterns, there was no significantly effect for the training of muscle activity in the movement in the LR direction. It was due to the movement in LR direction was easier than the other movement patterns on the unstable platform.

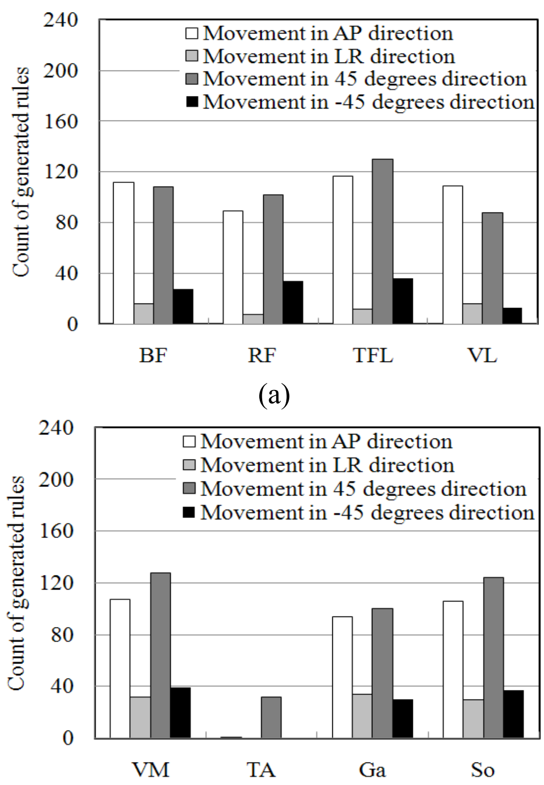
Table 1 Movement patterns and activated muscles

Movement pattern	Activated muscles							
45 degrees(Level 1; Speed 3)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	Ga(L)	TA(L)	So(L)
45 degrees(Level 3; Speed 3)	RF(L)	BF(H)	TFL(L	VL(L)	VM(L)	Ga(L)	TA(L)	So(L)
45 degrees(Level 2; Speed 1)	RF(H)	BF(L)	TFL(H	VL(H)	VM(H)	Ga(L)	TA(L)	So(H)
AP(Level 3; Speed 3)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	Ga(L)	So(H)	
AP(Level 2; Speed 3)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	Ga(H)	TA(L)	So(L)
AP(Level 2; Speed 1)	RF(H)	BF(H)	TFL(H	VL(H)	VM(H)	Ga(H)	TA(L)	So(H)
LR(Level 2; Speed 3)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	Ga(L)	So(L)	
-45 degrees(Level 3; Speed 3)	RF(L)	BF(H)	TFL(L	VL(L)	VM(L)	Ga(L)	TA(L)	So(L)
-45 degrees(Level 3; Speed 3)	RF(L)	BF(L)	TFL(L	VL(L)	Ga(L)	So(L)		
Maintaining(AR)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	Ga(L)	So(L)	
Maintaining(PL)	RF(L)	BF(H)	TFL(L	VL(H)	VM(L)	TA(L)	So(L)	
Maintaining(PR)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	So(L)		
Maintaining(R)	RF(L)	TFL(L	VL(L)	VM(L)	So(L)			
Maintaining(L)	VM(L)	Ga(H)	TA(L)	So(L)				
Maintaining(AL)	RF(L)	BF(L)	TFL(L	VL(L)	VM(L)	Ga(H)	TA(L)	So(L)
. . .	. . .							
AP(Level 1; Speed 3)	RF(L)	TFL(L	VL(L)	VM(L)	Ga(L)	So(L)		
LR(Level 5; Speed 3)	RF(L)	BF(L)	TFL(H	VL(L)	VM(L)	Ga(L)	TA(L)	So(H)
-45 degrees(Level 2; Speed 5)	BF(L)	VM(L)	Ga(L)	So(L)				
Maintaining(AL)	RF(L)	BF(L)	VM(L)	Ga(H)	So(L)			
Maintaining(P)	RF(H)	BF(L)	TFL(H	VL(H)	VM(L)	Ga(L)	TA(H)	So(L)

patterns, there was no significantly effect for the training of muscle activity in the movement in the LR direction. It was due to the movement in LR direction was easier than the other movement patterns on the unstable platform.

Fig. 8 showed the count of generated rules of different muscles in the different maintaining directions. The maintaining training in the different directions was very important for the training of postural control. Compared with the other directions, maintain in AR direction was effectively activated the RF, TFL, VL, TA and So. Different directions could activate the different muscles for the maintaining of postural control.

Therefore, according to the different subjects, the different movement patterns could be applied for improving the lower extremity strength for the appointed muscles and improving the ability of postural control. The movement in the left-right direction could be applied in the training for lower extremity strength in lower intensity the movement in the anterior-posterior direction and 45 degrees direction could be applied in the training in higher intensity. Through the choice of the different movement patterns, the training for postural control could be processed in the different intensities, and aimed to the appointed muscles to enhance the



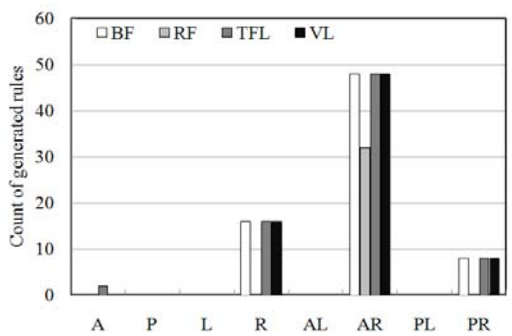
(a)

(b)

Fig. 7 Count of generated rules of different muscles in the different movement patterns

Table 2 Generated rules of movement pattern and muscle activity

Movement pattern	Muscle activity							Minimum support
Maintaining(AL)	So(L)	Ga(H)						0.02799
Maintaining(AL)	Ga(H)							0.028
45 degrees(Level 1; Speed 3)	RF(L)	BF(L)	TFL(L)	VL(L)	VM(L)			0.026433
45 degrees(Level 1; Speed 3)	TFL(L)	VL(L)	VM(L)					0.03083
45 degrees(Level 1; Speed 3)	RF(L)	BF(L)	VM(L)					0.026433
LR(Level 1; Speed 3)	VM(L)	Ga(L)	So(L)					0.028733
LR(Level 2; Speed 3)	RF(L)	VL(L)	VM(L)	Ga(L)				0.02655
LR(Level 3; Speed 3)	VM(L)	Ga(L)						0.02865
AP(Level 1; Speed 3)	RF(L)	TFL(L)	Ga(L)					0.026484
AP(Level 2; Speed 3)	RF(L)	TFL(L)	VL(L)					0.030574
AP(Level 2; Speed 3)	RF(L)	BF(L)	TFL(L)	VM(L)	Ga(L)			0.026248
-45 degrees(Level 1; Speed 3)	VM(L)	Ga(L)	So(L)					0.028641
-45 degrees(Level 2; Speed 3)	TFL(L)	VM(L)	Ga(L)					0.03086
45 degrees(Level 2; Speed 5)	VM(L)	Ga(L)	So(L)					0.030638
45 degrees(Level 2; Speed 5)	TFL(L)	So(L)						0.026251
. . .	. . .							. . .
Maintaining(AL)	So(L)							0.03241
Maintaining(AR)	RF(L)	BF(L)	TFL(L)	VL(L)				0.02667
Maintaining(PR)	RF(L)	TFL(L)	VL(L)	So(L)				0.030841



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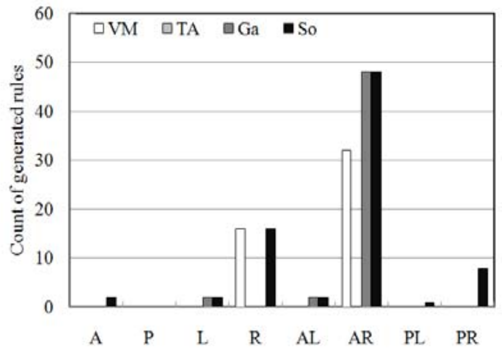

(b)

Fig. 8 Count of generated rules of different muscles in the different maintaining directions

aimed muscle voluntary contraction strength. Also, the ability of postural control could be improved through the training.

4 Conclusions

In this study, the muscle activities of different movement patterns on a training system for posture control using an unstable platform through an improved association rule mining methodology was investigated. The results showed the significant differences in muscle activities for the different movement patterns. The experimental results suggest that, through the choice of different movement pattern, the training for lower extremity strength could be performed on specific muscles in different intensity. And, the ability of postural control could be improved by the training for lower extremity strength. Through the study of the muscle activities in the different movement patterns on the unstable platform, an appropriate training scheme for lower extremity strength could be applied for the specific muscles, and improve the ability of postural control.

Acknowledgement

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