

Gait features analysis using artificial neural networks – testing the footwear effect

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Purpose: The aim of this paper is to provide the methods for automatic detection of the difference in gait features depending on a footwear. *Methods:* Artificial neural networks were applied in the study. The gait data were recorded during the walk with different footwear for testing and validation of the proposed method. The gait properties were analyzed considering EMG (electromyography) signals and using two types of artificial neural networks: the learning vector quantization (LVQ) classifying network, and the clustering competitive network. *Results:* Obtained classification and clustering results were discussed. For comparative studies, velocities of the leg joint trajectories, and accelerations were used. The features indicated by neural networks were compared with the conclusions formulated analyzing the above mentioned trajectories for ankle and knee joints. *Conclusions:* The matching between experimentally recorded joint trajectories and the results given by neural networks was studied. It was indicated what muscles are most influenced by the footwear, the relation between the footwear type and the muscles work was concluded.

Key words: neural network, footwear, gait, EMG

1. Introduction

Walking barefoot is referred to as the most natural way [17], [3], but, on the other hand, the proper footwear reduces the dynamical impact during foot landing, increases the walking comfort and prevents gait disorders and foot injuries. In this work, we examined the relationship between the footwear and the muscles work using artificial neural networks. Gait data for sneakers and shoes with high heels were compared with the barefoot walk. According to Mika et al. studies [17], wearing high heels affects the trunk positioning and the work of hip extensor muscle, thus increasing the risk of abnormal spine loading and musculoskeletal injuries. Blanchette et al. [3] suggested that wearing high heels increases the chance of slips and falls. Barkema et al. [4] proved that the increase of the angle in the ankle joint due to high heel may contribute to larger medial loads at the knee and may put individuals at greater risk of joint degenera-

tion with developing medial compartment knee osteoarthritis. Ho et al. [10] showed that increasing the height of high heels causes an increase of patello femoral joint stress. According to Li and Lee [15], Ho et al. [10], knee joint and ankle joint motion ranges clearly depend on the footwear. Su and Gu [19] focused on the dependence of EMG (electromyography) signals on heel height; they found that increased heel height causes an increase of lower limb muscles EMG activity. Analyzing the dancing they found that the activity of tibialis anterior was the most vulnerable part, which means that dancing in high heels causes tiredness of tibialis anterior, therefore producing its disorders. Often the artificial neural networks are utilized to such kind of research. Abel et al. [2] applied neural network to classify the EMG signals for both healthy subjects and patients with neural disorders. The improved back-propagation (BP) artificial neural network with learning vector quantization (LVQ) network was applied here; the results were reliable but a large database was required. Subasi et al. [20] ap-

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plied the wavelet neural network to classify the EMG signals for healthy persons and the persons suffering from neurotic disease, obtaining good recognition rate. Kaczmarczyk et al. [11] applied neural networks for gait classification in post stroke patients, getting satisfactory results. The LVQ networks are also used for diagnosing the myopathy [9]. Liu and Luo [16] and Caetano et al. [5] used LVQ network to classify the hand motions and upper limbs prosthesis actuation patterns obtaining good results. Moslem et al. [18] used competitive network to examine EMG for recognizing the patterns of the muscles activity of pregnant patients.

Our main aim is to prove the method for neural network analysis of the EMG signals for the purpose of recognizing the walking step similarities and differences caused by some external factors. For this purpose we considered the data obtained for different footwear.

2. Materials and methods

2.1. Available data

The main aim of the work was to provide and validate the tool for automatic analysis of the gait features. Validation of the results was made considering the different physical data describing the gait (EMG signals versus joint trajectories), therefore the data from one person tested were enough.

The subject was a volunteered female, 27 years old, 168 cm tall with body mass equal to 55.3 kg; the subject was healthy and without muscles disorder history. For the purpose of motion recording, 39 markers were fixed on the subject's body (Fig. 1) and 16 EMG sensors were attached to the legs (Fig. 2).

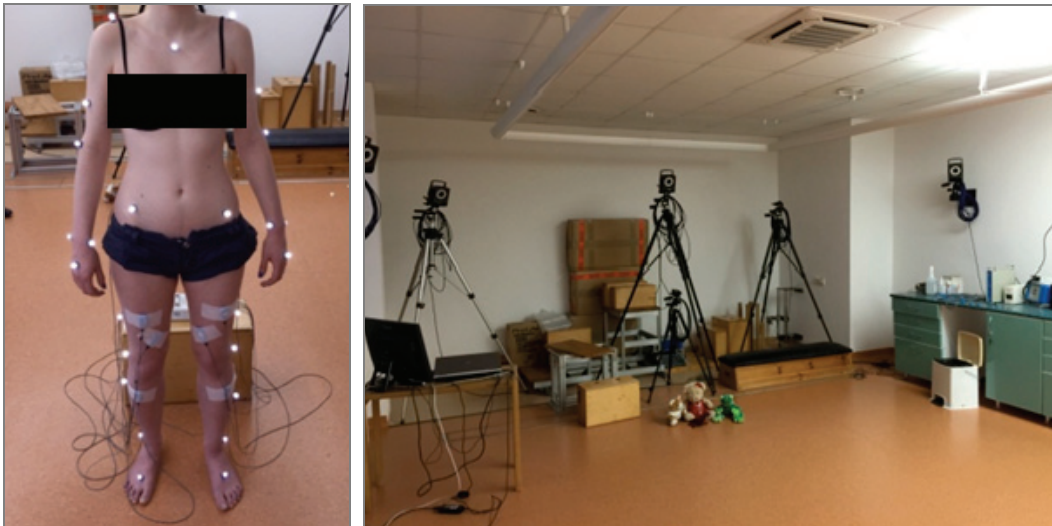


Fig. 1. Marker placement on subjects' body (right) and VICON camera system in the lab (left)

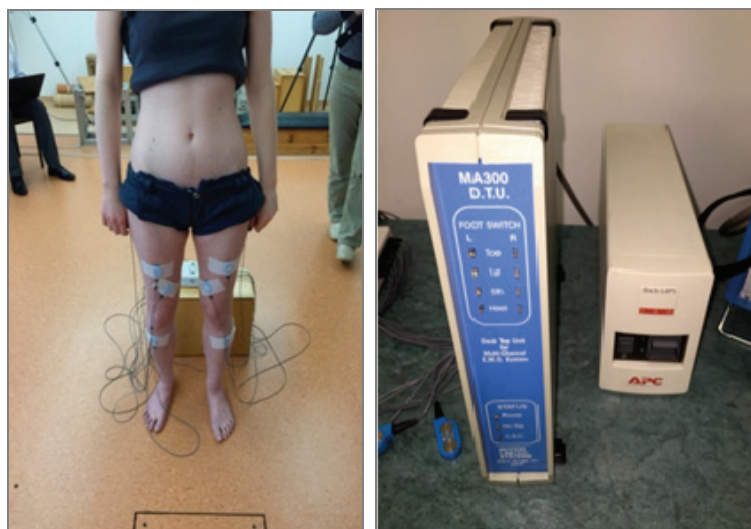


Fig. 2. The electrodes placement (left) and MA 300 DTU system for EMG registration (right)

Typical muscle groups in each leg (8 in each leg, totally 16 in groups) were selected for EMG data gathering. They were: rectus femoris (channels 1, 2), biceps femoris (channels 3, 4), lateral gastrocnemius (channels 5, 6), tibialis anterior (channels 7, 8), gluteus maxiumus (channels 9, 10), medial hamstrings (channels 11, 12), vastus medialis (channels 13, 14), soleus (channels 15, 16) (Fig. 3), where odd number

stands for left leg and even number stands for right leg. Using the 12 VICON T40 (Fig. 2, left) system the marker trajectories were registered, and the system MA 300 DTU was used for EMG recording when walking with different footwear. The footwear considered was (Fig. 4): barefoot, 1 cm high sneakers with soft soles, and hard sole shoes with 10 cm high heels.

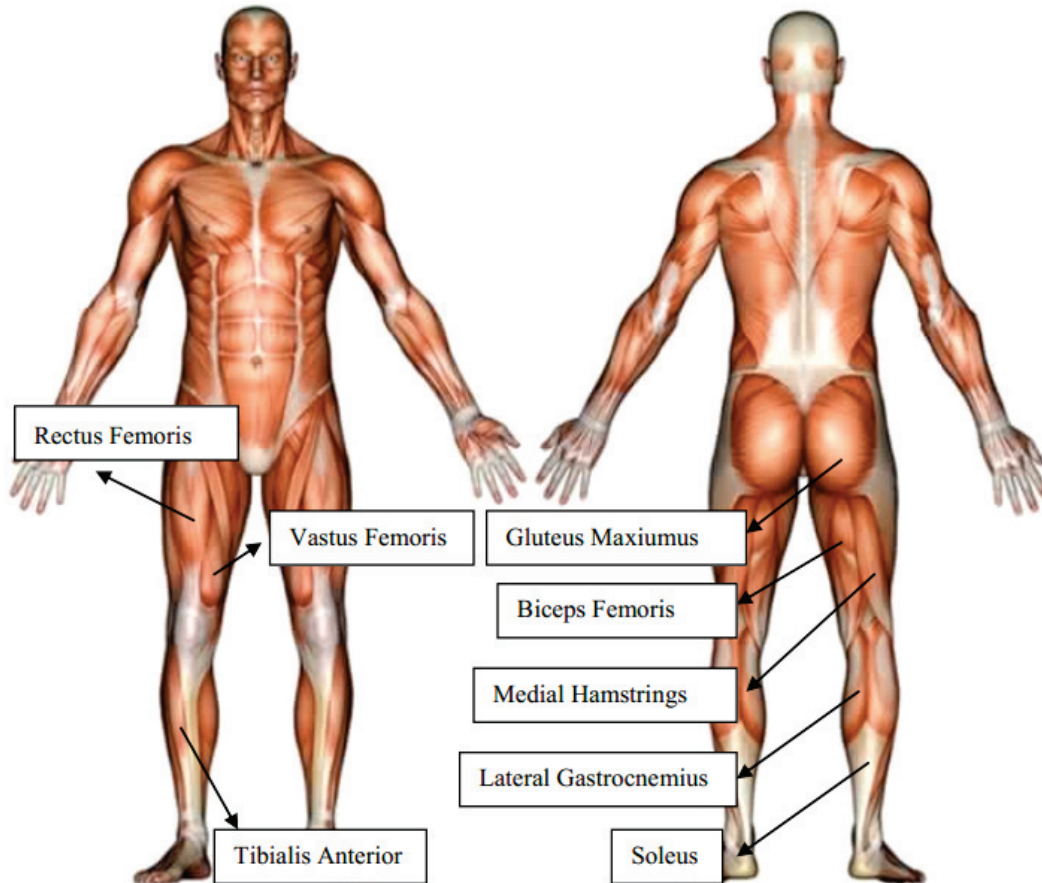


Fig. 3. The muscles under study (derived from <http://www.shapesense.com/fitness-exercise/muscle-anatomy/>)



Fig. 4. Footwear applied in experiment: 1 – sneakers, 2 – barefoot, 3 – high heels

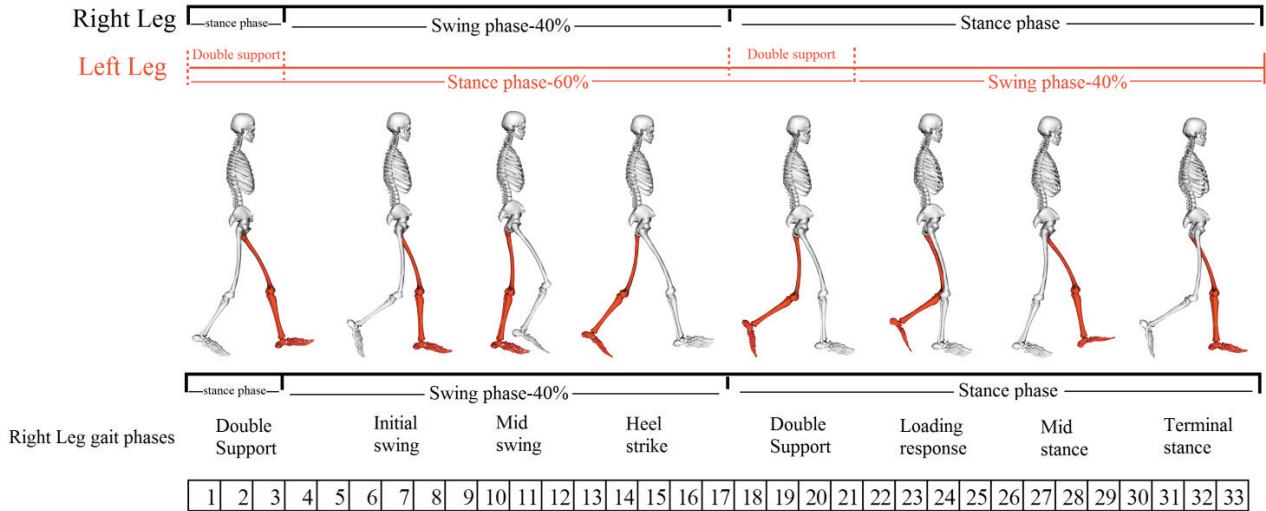


Fig. 5. Recorded walking step

For data gathering the walking step lasting 1.15 s was divided into 33 equal intervals (Fig. 5).

The EMG data obtained were processed with rectified low pass filter 25 HZ of the 4th order; there were collected 1151 samples altogether for EMG signal. After that the RMS (root mean square) a typical statistical measure (1), was evaluated for each EMG signal. The whole EMG signal was divided into several windows, for each window one RMS was evaluated. The results were stored in the form of data matrix. Such data were considered as the inputs to the neural networks.

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + x_3^2 \dots x_n^2)}. \quad (1)$$

2.2. Data analysis using neural networks

Two types of artificial neural networks were applied: the classifier with learning vector quantization (LVQ) invented by Kohonen [12], and the competitive network [6].

2.2.1. LVQ network applied

Learning vector quantization (LVQ) network applies “winner-take-all” training algorithm. During the training phase which is performed at the beginning, the weights of the connections from input neurons to the neurons of hidden layers are adjusted accordingly to the patterns data applied to the input

neurons [18]. After training, the weights between input and hidden layer are fixed, this way “storing” the information about patterns used in training. In the application phase another data sets are delivered to the inputs and the network indicates to what training pattern the actually applied vector is most similar. The LVQ network is composed of three layers, the input layer, the hidden layer – called also the competitive layer, and the output layer – called also the linear layer (Fig. 6). The competitive layer classifies the input vectors into subclasses. In both competitive and linear layer each neuron is associated with each subclass or with each target class. The competitive layer can produce up to S^1 subclasses and then in the output with linear transfer function there are formed S^2 target classes (Fig. 7).

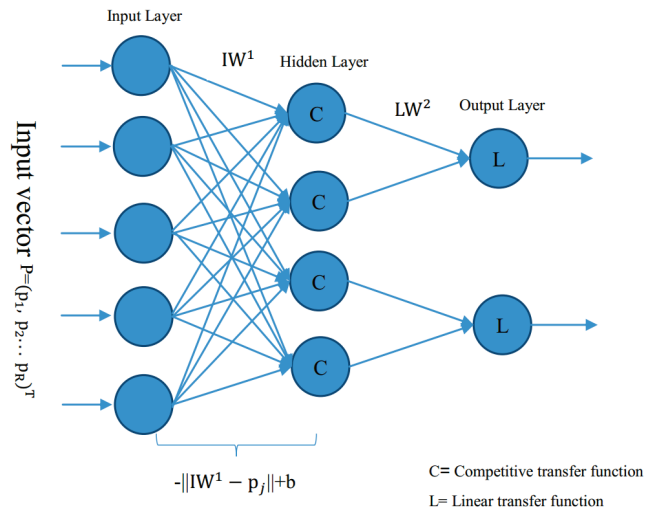


Fig. 6. Schematic diagram of learning vector quantization (LVQ) network which can classify up to 2 classes

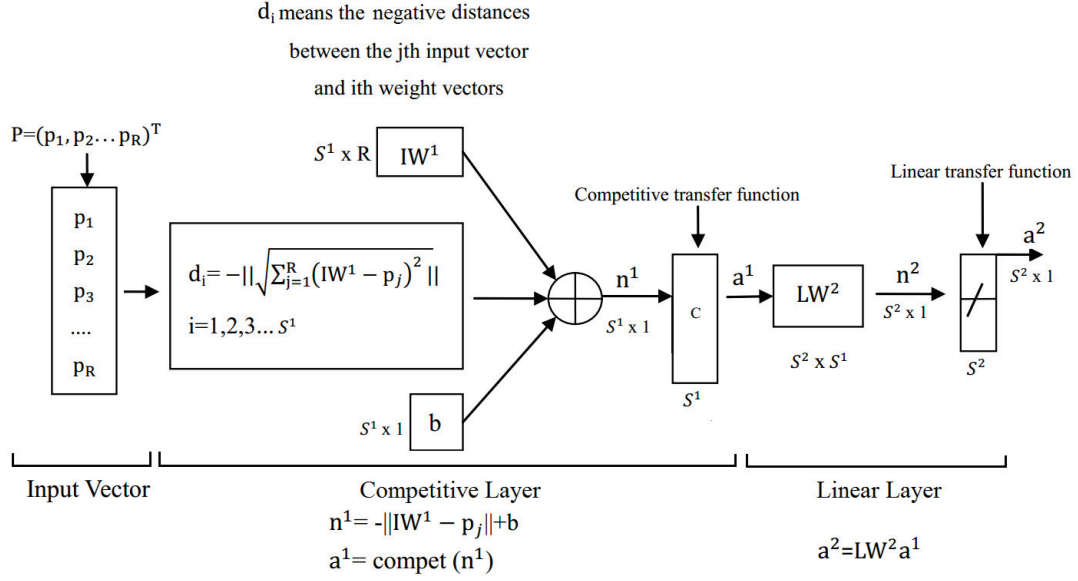


Fig. 7. The schematics of the computational diagram of learning vector quantization (LVQ) network

In the architecture of LVQ network, Fig. 7, R is the number of elements in input vector, S^1 denotes the number of neurons in competitive layer, S^2 is the number of linear neurons, IW^1 are the weights of the connections between input layer and competitive layer; b is the bias which usually equals 1; d_i means the negative of the distances between the input vector $\mathbf{P} = (p_1, p_2, \dots, p_R)^T$ and weight vectors IW^1 which produces a vector having S^1 elements (2); n^1 represents the net input from the competitive layer, which is the negative distance between input vector and weight vectors adding b . The transfer function of competitive layer is used to preliminarily classify the input data. Here, the biggest positive or the smallest negative value of measure considers the input and the bias vectors (3), a^1 is the output vector of competitive layer; LW^2 are the weights of connections between competitive layer and the output layer, n^2 is the input vector to output layer which equals $LW^2 a^1$, a^2 represents the output vector of output layer and also equals $n^2 = LW^2 a^1$ for linear transfer function there holds $y = x$.

Firstly, the weights between input layer and competitive layer are initialized using random generator and learning rate is set $\eta(0 < \eta < 1)$. Next, the distance between input vector $\mathbf{P} = (p_1, p_2, \dots, p_R)^T$ and competitive neurons (2) is calculated. The way of adjusting the IW^1 is to try to move one row of the weight closer to input vector \mathbf{P} when the assignment is correct (4), or move the row away from input vector \mathbf{P} when the assignment is incorrect (5).

$$d_i = -\left\| \sqrt{\sum_{j=1}^R (IW^1 - p_j)^2} \right\| \quad i = 1, 2, 3, \dots, S^1, \quad (2)$$

$$n^1 = -\|IW^1 - p_j\| + b, \quad (3)$$

where IW^1 is the weight between input layer neurons and competitive neuron.

$$IW_{\text{new}}^1 = IW_{\text{old}}^1 + \eta(p - IW_{\text{old}}^1), \quad (4)$$

$$IW_{\text{new}}^1 = IW_{\text{old}}^1 - \eta(p - IW_{\text{old}}^1). \quad (5)$$

2.2.2. Competitive network

Another neural network applied by us was a pure competitive network. Competitive network consists only of two layers: the input layer and the competitive layer. This is clustering neural network which does not need training. In general, the clustering (classification) mechanism is similar to the competitive part of LVQ network. The similarity measure (distance) between the set of input data and the weight vector of each neuron in hidden layer is calculated. The winner neuron indicates the class to which belongs the current vector of input data (Figs. 8, 9). The number of possible classes (clusters) is equal to the number of the output neurons. Therefore, changing the number of output neurons, the number of clusters to which the input data should be classified is modified. In the competitive layer, neurons compete with each other and only one of them wins adapting the current input. The winning neuron marks the classification result of the input. The output from competitive layer can be only 1 or 0, it is obtained as follows.

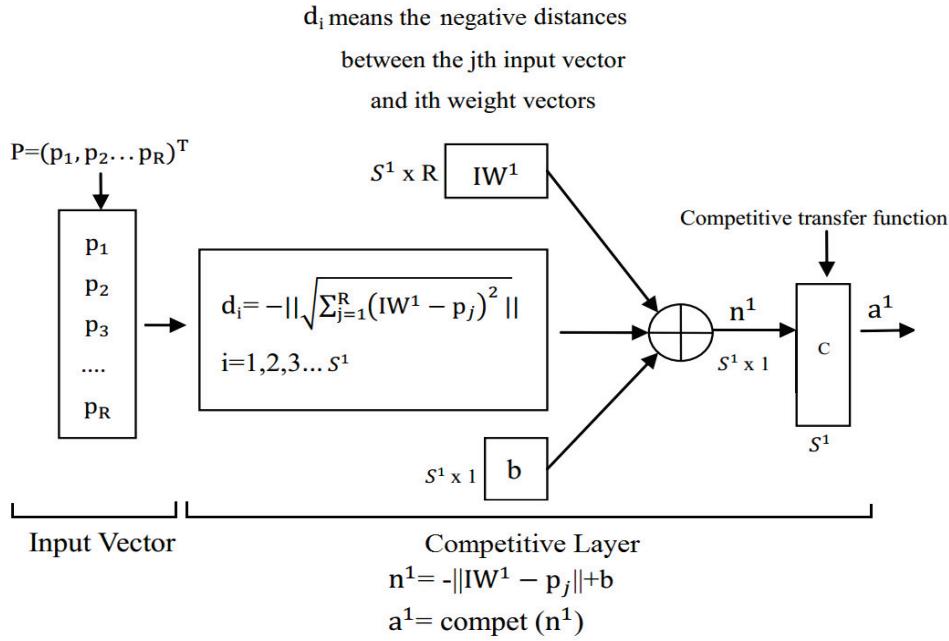


Fig. 8. The schematics of the computational diagram of competitive network;
 R is the number of the elements in input vector, S^1 is the number of competitive neurons

The net input n^1 to the layer with competitive transfer function is evaluated as the distance between input vector p and the weight vectors IW^1 with added biases b (which usually equals 1) (3). The competitive transfer function (C) uses the net inputs n^1 and sets the competitive neuron outputs as 0 for all the neurons except one winner neuron whose output is equal to 1. It is such neuron for which n^1 is the smallest. The weights of the winning neuron will be adjusted (4).

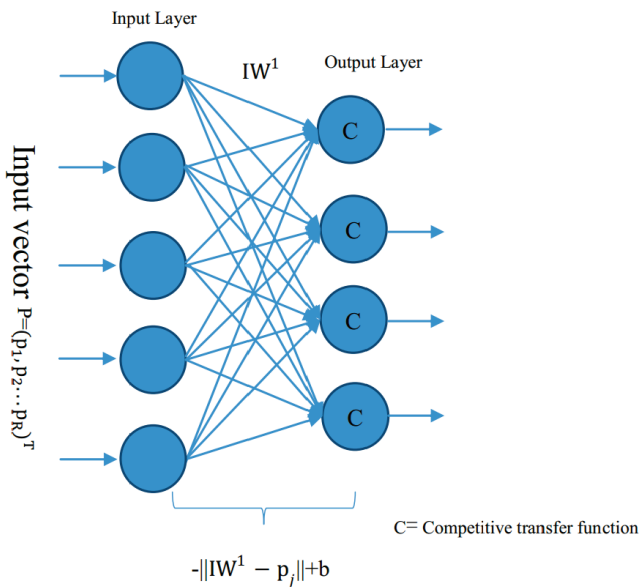


Fig. 9. Competitive network

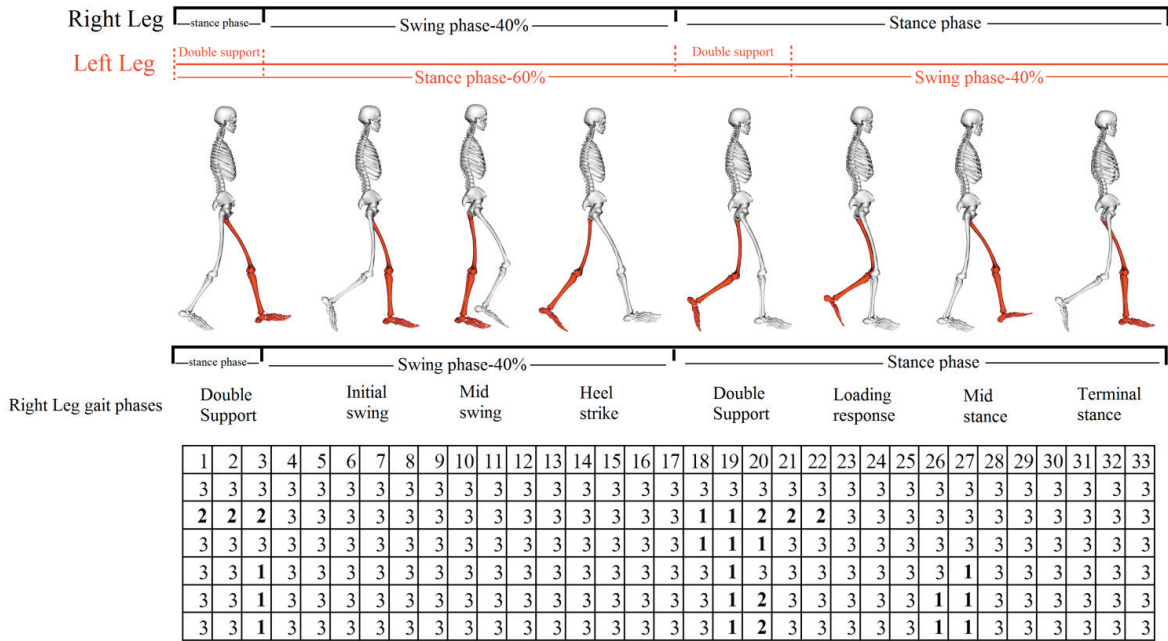
3. Results

3.1. LVQ classification results

First, it was tested if the neural network is able to distinguish the EMG data depending on the footwear. For this purpose, the LVQ network was applied. The inputs were the averaged data from several experimental records. The LVQ training was completed applying as each input the data for one walking step with each footwear. The whole data set for one walking step with each footwear was assigned to one pre-specified class. After training with pre-defined class for each footwear, other sets of recorded data for footwear considered were applied for testing how the EMG signals at each time instant will be classified.

As was already mentioned, the collected EMG data include processed signals for 16 muscles in both legs. Performing classification with neural networks we utilized the data for complete step of one leg that means the data for 8 muscles. The right leg was considered (marked by lighter color in Fig. 5). Each input set consisted of 33 EMG data samples (for 33 time instants), 8 muscles each. During the LVQ training, for each footwear the output classes were pre-defined in the following ways: class 1 – for the sneakers, class 2 – for barefoot, and class 3 – for high heels.

Table 3. High heels



cases the EMG signals were assigned to class 1 or 2. On the contrary the EMG signals for barefoot and sneakers show many similarities; in Tables 1 and 2 classes 1 and 2 are often indicated.

3.2. Competitive network clustering results

For more detailed analysis the competitive network was used with the possible number of clusters set to 6, 8 and 10, respectively (that is, the number of outputs). The results are presented in Figs. 10–12.

The networks with 6 classes and 8 classes for sneakers and barefoot clustered the first part of gait in a similar way; the differences are more obvious in the latter half of the gait. Sneakers and barefoot data were clustered into one group for periods 17–22 (first part from support for the right leg). For periods 23–33 (second part of support), sneakers, barefoot and high heels were clustered differently. This means that the influence of footwear is more significant in the second part of the stance phase. This is confirmed by clustering (classification) using 10 groups (Fig. 12).

10 classes offer higher “resolution” in analysis. As we can notice (Fig. 12), during the swing phase (4–17)

6 classes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
sneakers	4	2	6	6	6	6	6	6	3	3	3	3	3	3	3	6	4	4	4	4	4	5	5	1	1	1	1	6	6	6	6	6	6
bare foot	4	2	2	2	2	6	6	6	6	3	3	3	3	3	3	6	4	4	4	4	4	4	5	5	5	1	1	1	1	1	5	5	5
high heels	6	6	6	2	2	2	2	2	6	6	6	3	3	3	3	6	6	2	4	5	5	5	5	1	1	1	6	6	6	6	6	6	6

Fig. 10. Clustering results with 6 classes

8 classes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
sneakers	7	8	4	4	4	6	6	6	6	6	1	1	1	1	1	4	8	7	7	7	7	3	3	2	2	2	2	2	4	4	4	4	4
bare foot	8	8	8	4	4	4	4	6	6	6	6	1	1	1	1	6	8	7	7	7	7	3	3	3	2	5	5	5	5	2	2	2	2
high heels	4	4	4	8	8	8	8	4	4	4	4	6	6	1	1	1	6	4	4	3	3	2	2	2	2	2	2	4	4	4	4	4	4

Fig. 11. Clustering results with 8 classes

10 classes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
sneakers	2	2	8	9	9	9	9	6	6	6	6	6	6	6	6	8	2	4	4	4	4	5	5	5	5	5	5	6	6	9	9	9	8
bare foot	2	2	2	8	8	8	9	9	9	6	6	6	6	6	6	6	2	4	4	4	4	1	1	5	5	5	5	3	3	5	7	7	7
high heels	8	8	8	2	2	2	2	8	8	8	6	6	6	6	6	6	6	8	1	5	5	5	7	7	7	6	6	6	6	6	6	6	6

Fig. 12. Clustering results with 10 classes

there are more similarities in clustering than during the support. Especially, the sneakers and barefoot data are included to the same classes but with some time shift. More obvious differences are indicated for the high heels during the beginning of transfer phase (time intervals: 1–10), and in support (from interval no. 17). During late loading response (18–21) and terminal stance (24–27) the barefoot and sneakers EMG data were classified similarly, but the second part of the support (from interval 28) is different for the barefoot and for the sneakers. Such results confirm that the high heel affects the EMG during the whole support phase, and the sneakers influence is especially visible during the leg take-off.

In general, clustering with 10 classes gives the result which is most coherent with the gait phases (Figs. 5 and 12) when comparing to smaller number of classes. Therefore, the clustering network can be concluded as a good tool for indicating the gait phases based on EMG signals. This makes it useful for EMG based control of the prosthesis.

hibit oscillatory behavior during the whole gait. In Fig. 13 (sneakers), for periods 3–7 (initial swing) the signals for tibialis anterior and soleus are increasing, while the signals for the rest of the muscles are rather stable. In periods 8–15 (mid swing phase), the lateral gastrocnemius and soleus reach the maxima and next decrease sharply to minimum. In double support phase (periods 18–21), EMG for tibialis anterior stays at the high level, next in load response EMG for rectus femoris raises very fast, the signals for biceps femoris and medial hamstring increase, too. At terminal stance EMG signal for rectus femoris, biceps femoris and medial hamstring starts decreasing.

Based on Fig. 14 (barefoot) it can be noticed that double support (periods 1–3) is characterized by decreasing activity of all muscles, in initial swing (4–9) EMG signals stay mainly steady, except for lateral gastrocnemius and soleus for which the EMG increases, the activity of tibialis anterior and vastus medialis starts decreasing. Then, EMG signals for lateral gastrocnemius and soleus reach the peak and

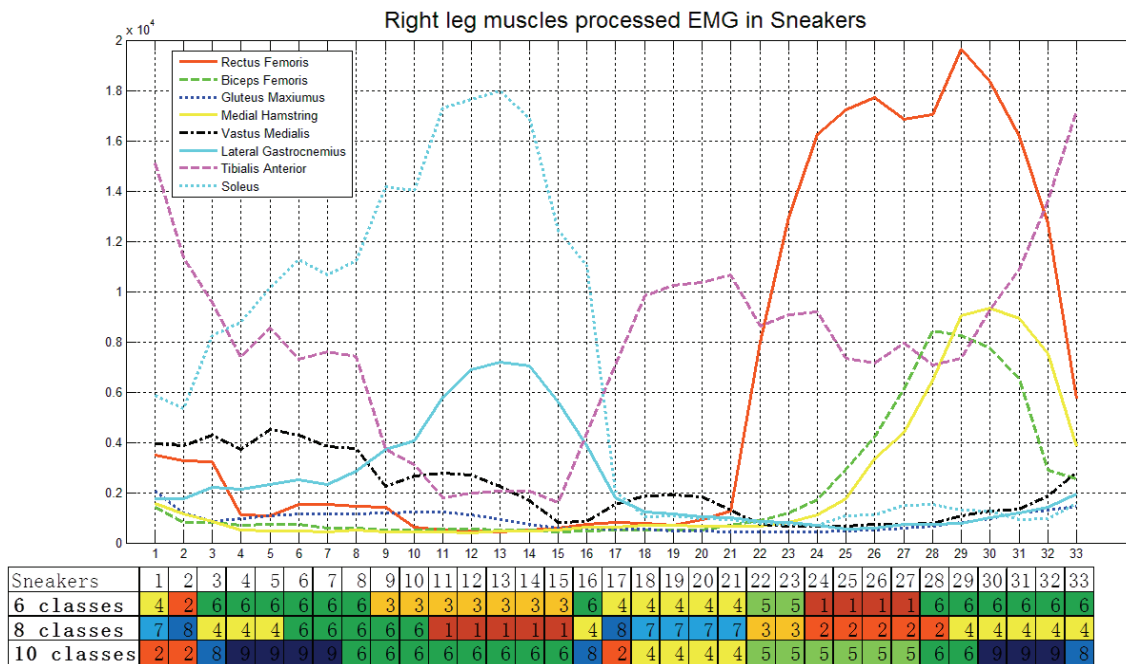


Fig. 13. EMG signals and classification results – sneakers

3.3. Comparison of clustering results with EMG data validation

For validation of the results delivered by neural networks, the EMG trajectories were analyzed (Figs. 13–15). It was noticed that the EMG signals for soleus, lateral gastrocnemius and tibialis anterior muscles ex-

then reduce to minimum during the end of swing till heel strike (10–16). Next, (double support till landing response) activity of tibialis anterior raises to the highest value, while activity of rectus femoris begins increasing in the second part of double support phase (18–22). Afterwards, rectus femoris increases its activity to maximum and slowly goes down during loading response phase (periods 23–25). In terminal

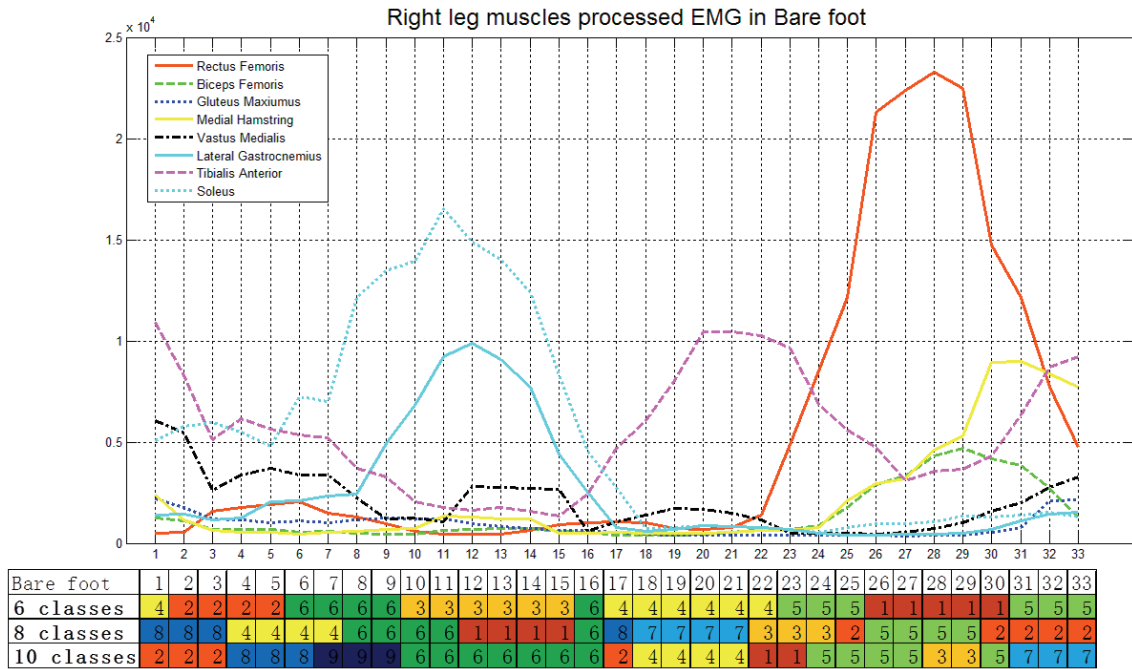


Fig. 14. EMG signals and classification results – barefoot

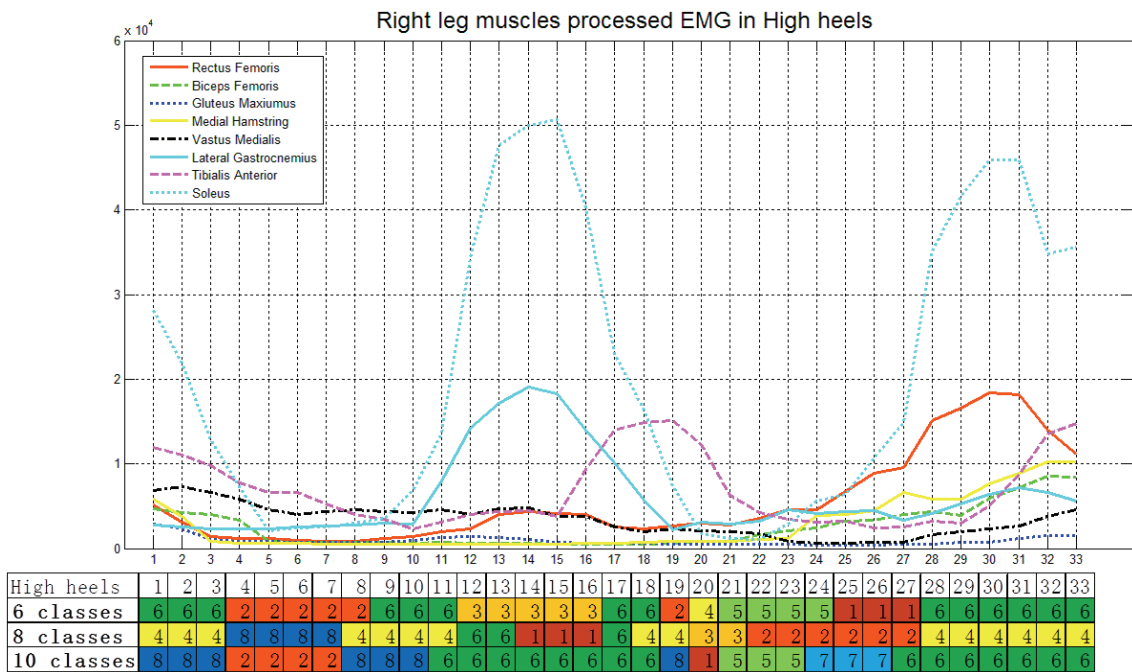


Fig. 15. EMG signals and classification results – high heels

stance, all the EMG signals decrease except for tibialis anterior.

Figure 15 (high heels) shows that all EMG signals decrease and especially the EMG for soleus decreases sharply and goes down in periods 1–3 (double support). During initial swing, all the signals stay stable while in mid swing the signals for lateral gastrocnemius and soleus begin to increase. Then, EMG for lateral gastrocnemius, soleus and tibialis

anterior increases to maximum and next decreases to minimum during heel strike (12–20). In terminal stance, EMG for rectus femoris and soleus reaches the second peak and rest of the signals are raising, too.

For more detailed analysis the EMG signals and classification results were compared (Figs. 13–15). For all footwear the EMG signals for soleus, lateral gastrocnemius and tibialis anterior muscles fluctuate

sharply during the whole gait. During periods 1–8, the EMG data for barefoot and sneakers show similar trends – competitive network clustered them in similar ways. Between periods 9–17, the EMG signals for lateral gastrocnemius and soleus are similar except for the high heels for which the EMG signals are smaller. During periods 18–21, tibialis anterior and vastus medialis dominate in barefoot and sneakers walking, and they are similar – the clustered results indicated this appearance. Afterwards, signals for barefoot and sneakers are still similar till interval 30. For intervals 31–33, competitive networks with 6 classes and 8 classes clustered sneakers and high heels data into one class, while 10 clusters network did not. The influence of high heels is mostly visible on soleus which puts much bigger effort during the second part of swing phase (10–19) reaching the magnitude of up to $5 \times 10^4 \mu\text{V}$, compared to $1.5\text{--}1.85 \times 10^4 \mu\text{V}$, and especially, during the second part of stance phase with the magnitude of about $4.6 \times 10^4 \mu\text{V}$, compared to $0.2 \times 10^4 \mu\text{V}$ for another footwear. This is a very drastic difference. As the second, the lateral gastrocnemius (12–17 – late swing, heel strike) and tibialis anterior (16–21 – double support) give more effort during high heel walking. Comparing to barefoot, the sneakers seem to reduce effort of rectus femoris during the middle of stance phase (26–30) and the effort of lateral gastrocnemius during the second part of swing – till the heel strike (10–16).

3.4. Clustering results and joint angle properties comparison

In [1], the joint trajectories were estimated for a human leg during flexion-extension during slow and high speed movements; neural network was used to predict the joint angles using the EMG data. Erfanian et al. [8] used EMG signals obtained from quadriceps muscle to determine the knee joint angle in paraplegic subjects and the EMG–joint angle relationship in both time domain and frequency domain was obtained. Such research confirmed that joint angles uniformly depend on EMG signals. Therefore, for validating the EMG clustering results we also considered the hip and knee joint trajectories. Figure 16 illustrates the notation applied for representing the human body data, 3 planes: coronal, sagittal and transverse. The joint trajectories recorded in sagittal plane were considered with the standing posture setting 0° in all joints.

As we can see (Fig. 17) the ankle joint trajectory is mostly affected by high heels while sneakers and barefoot trajectories are staying closer to each other, and are almost overlapping by the end of stance phase. The ankle trajectories for the swing phase and the first part of double support show more differences, and next, in the stance phase (periods 21–33), for sneakers and barefoot the trajectories are overlapping. It can

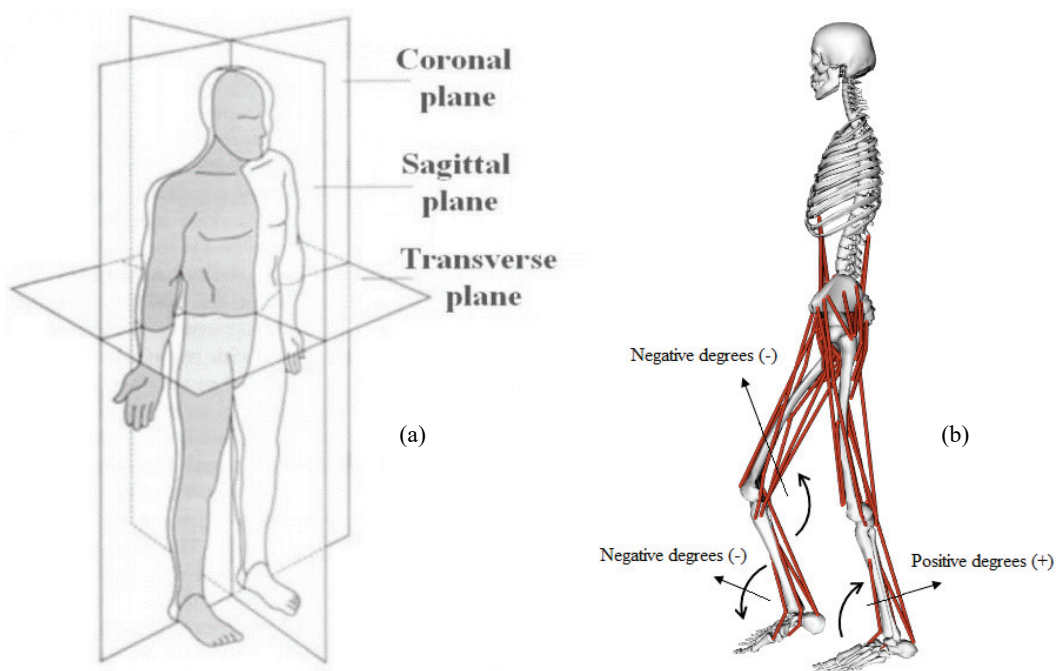


Fig. 16. (a) The anatomical planes of human body, adapted from [19]; (b) the graphics of the leg shown in the rest position with the positive and negative direction indicated

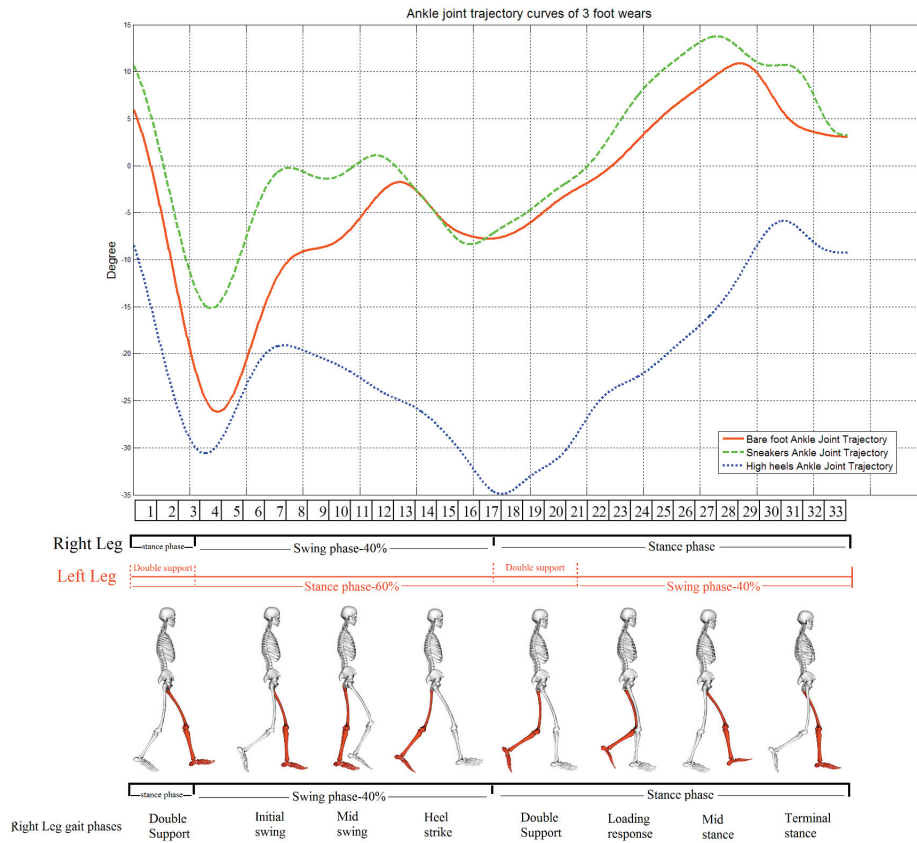


Fig. 17a. Ankle joint trajectories for different footwear

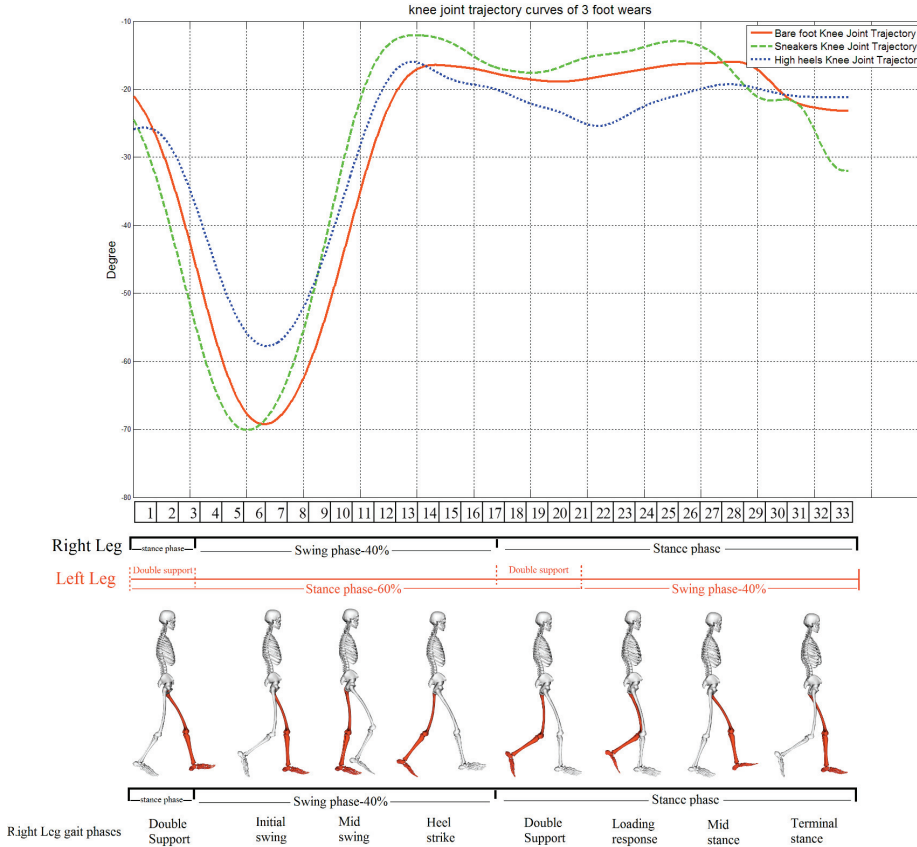


Fig. 17b. Knee joint trajectories for different footwear

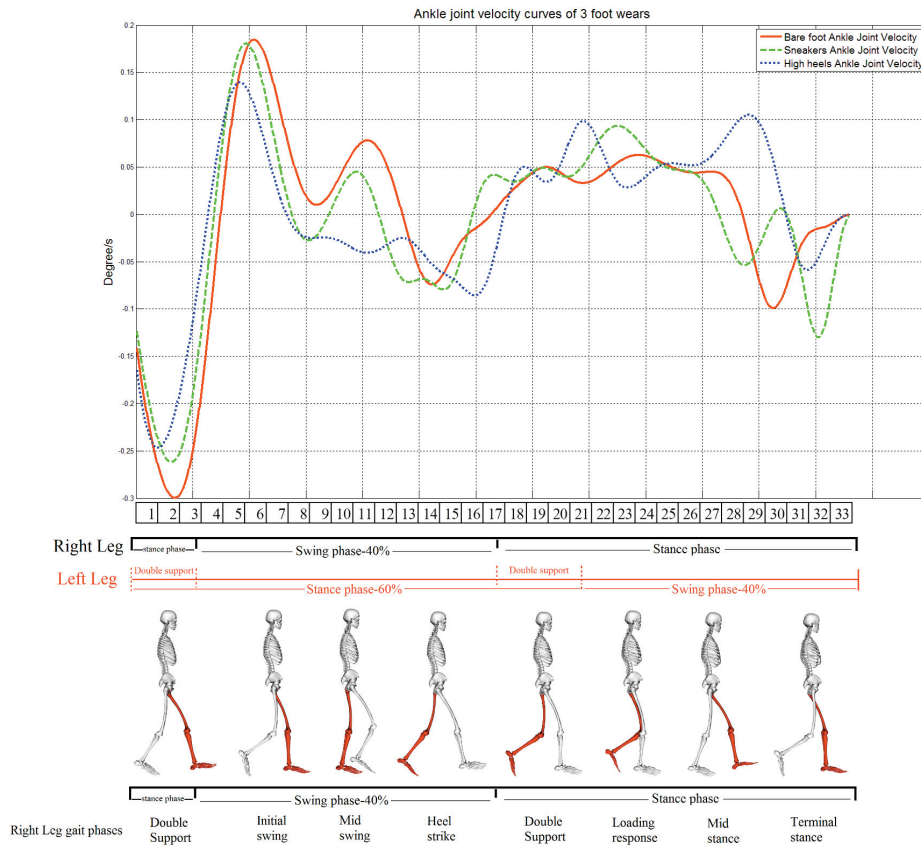


Fig. 18a. Ankle joint velocities for different footwear

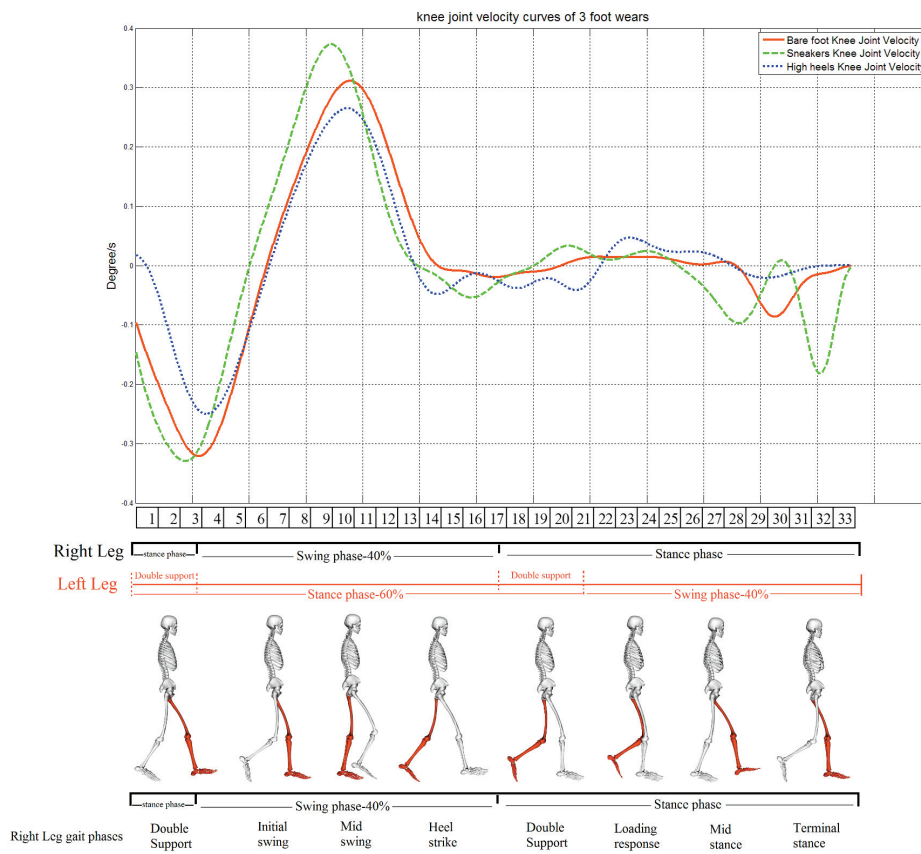


Fig. 18b. Knee joint velocities for different footwear

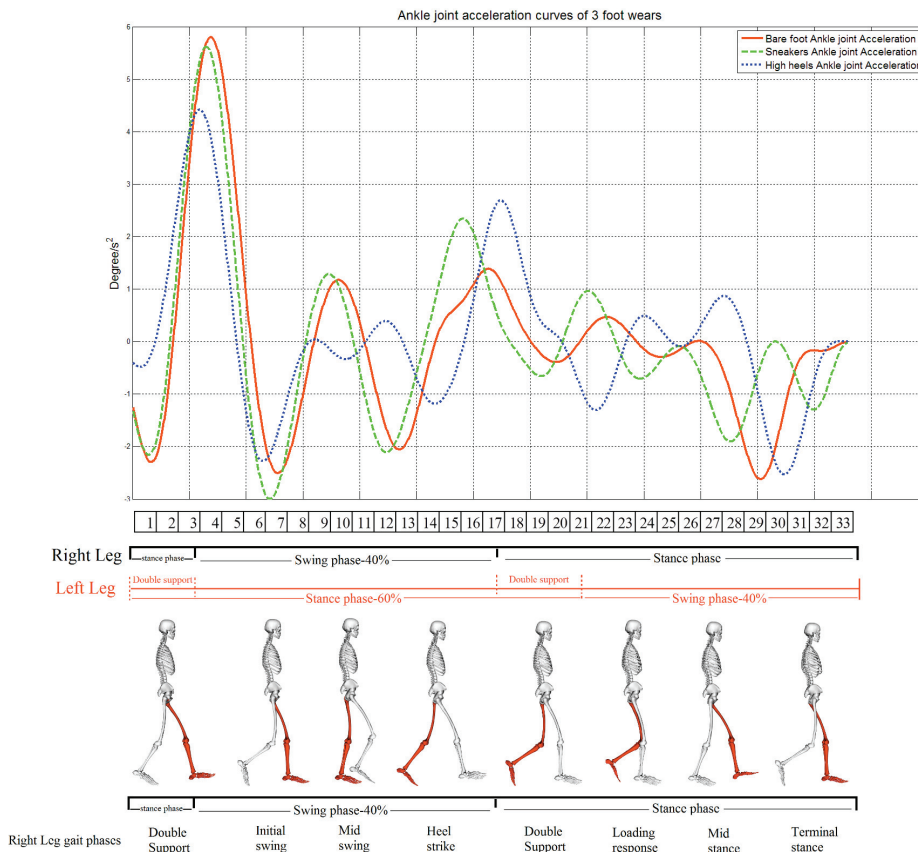


Fig. 19a. Ankle joint accelerations for different footwear

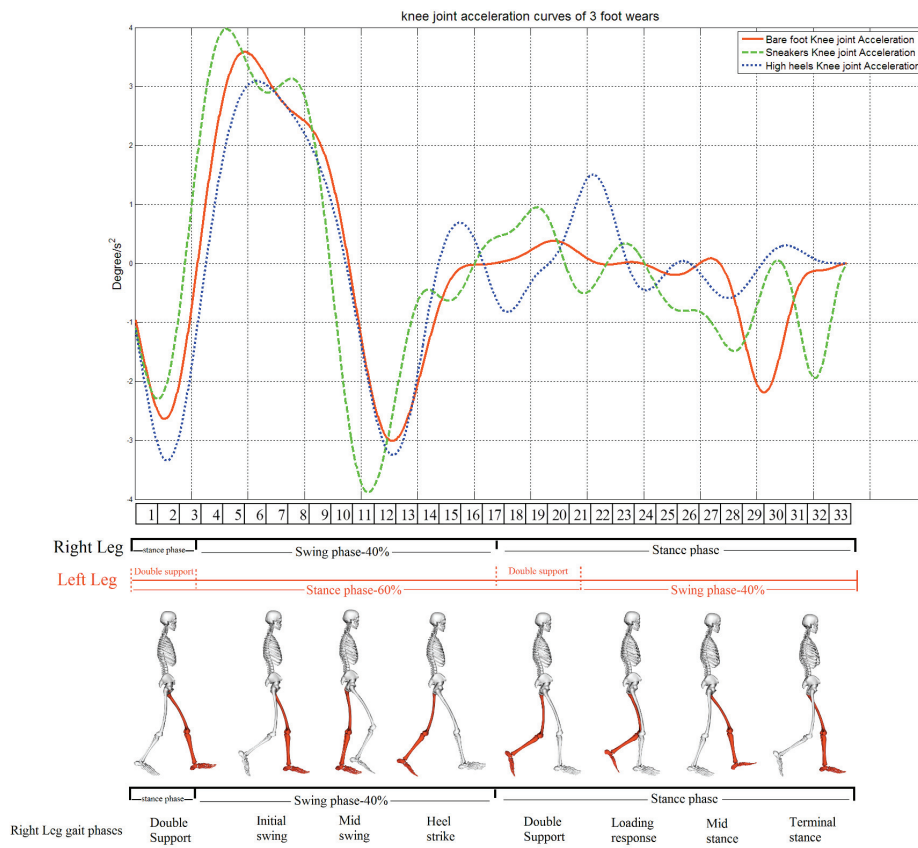


Fig. 19b. Knee joint accelerations for different footwear

also be noticed that knee joint trajectories are very similar for barefoot and sneakers; the knee joint trajectory for high heel is 20° smaller during the swing phase but finally overlaps with the other trajectories during the heel strike.

Comparing the angular velocities in ankle joints (Fig. 18a) one can notice their similarity in the first half of swing phase, in the rest of the walking step they are varying in different way, finally converting to similar range. The range of knee angular velocities for barefoot and sneakers is similar (Fig. 18b), but when walking on heels the knee joints velocity is reduced from initial to mid swing.

Similar tendency is visible in accelerations (Fig. 19), ankle accelerations for barefoot and sneakers are similar to each other and greater than those for the high heels, which is especially visible for the toe-off (around interval 4). For the single stance the velocities and accelerations are changing in different way but during the double support and the swing phases the trajectories show similar trends. This concerns the test footwear.

The joint trajectories and clustering results of EMG signals were compared, too. This brings the following observation: the class covering intervals 3–8 (Fig. 13, sneakers) responds to the rising trend of both ankle and knee trajectories (Fig. 17a, b), the class covering intervals 11–15 (Fig. 13) responds to the decrease of the ankle trajectory (Fig. 17a) and small variations of knee trajectory (Fig. 17b).

The coincidence between the trends in joint trajectories and the clusters is also visible for another footwear. For example, analyzing the joint velocities (Fig. 17) for clusters 1–3, 4–7, 18–21, 28–33 for barefoot and high heels (Fig. 14 and Fig. 15) we see the following: cluster 1–3 – the velocities are increasing, cluster 4–7 – ankle velocity reached passes local maximum, knee joint velocity increases, cluster 18–21 – small variation of velocities, cluster 28–33 – velocities are passing local minimum. Similar discussion can be provided when analyzing the clustering and joint accelerations.

Comparing the classification results by LVQ (Tables 1–3) and the joint trajectories, velocities and accelerations (Figs. 17–19) it can be concluded that the classification results are consistent with the features observed in trajectories.

In Table 1, later half of the sneakers gait was assigned into barefoot class, which matches the tendency illustrated in Fig. 17a,b, where the knee trajectories almost overlap and their other parts are similar. In Table 2, neural network classified periods 4–7 and periods 1–17 for barefoot (class 2) to class 3 (high

heels), which can find confirmation looking to ankle and knee joint velocities (Fig. 17).

Clustering results delivered by competitive network indicate also similar phenomenon as those observed in joint trajectories. The knee joint velocity and acceleration for barefoot and sneakers (Figs. 18b and 19b) at the beginning of step are similar, competitive network clustered the EMG for this part of the step to one group, the high heels data were included to another cluster. During the stance the knee velocity and acceleration for three types of footwear joint are more similar, the clustering (Fig. 10) included the data for this part of walking step to the same cluster. It can also be noticed that for the intervals where the trajectories in Figs. 18b and 19b are crossing each other, the clustering network assigned the EMG data to the same group.

4. Discussion

Based on the validation, it is concluded that LVQ competitive neural network and clustering network properly recognize the differences in the EMG signals. The barefoot, high heels and sneakers data were classified or clustered properly. The classification by LVQ network was not drastically different than clustering obtained by competitive network. For the parts of gait classified to the other footwear than that currently used, the properties of joint trajectories were similar to those observed for that footwear. As was shown, there is a good coincidence between the clustering delivered by artificial neural network and the trends in the joint trajectories including the velocities and accelerations. This proves that the clustering neural network can be considered as the promising tool for future works on intelligent exoskeletons. Based on real-time EMG registration the network can produce the clusters informing what kind of joint trajectories, velocities and accelerations must be developed by the joint actuators. Such conclusion matches the approach presented in [14] where the clustering method dedicated to the control of myoelectric hand was described.

One more result of our work is the conclusion about the foot impact on the gait properties. Comparisons between joint angles of each footwear emphasize the risk of falling and overloading the leg joints when wearing high heels. The joint angles showed a significant difference when walking in high heels. Being properly classified (with class indicating the footwear used when gathering the data) the gait phases indi-

cated that the data for those phases are most specific for the footwear, which means that such part of gait is most influenced by the footwear. The clustering results are especially valuable indicating the gait phases in which the EMG signals are similar to each other.

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