Exoskeletons for medical applications: design study and EMG signal classification

K. Mianowski, T. Zielińska and J. Wang

Warsaw University of Technology,

Faculty of Power and Aeronautical Engineering,

Division of the Theory of Machines and Robots,

Nowowiejska str. 24, 00-665 Warsaw, Poland

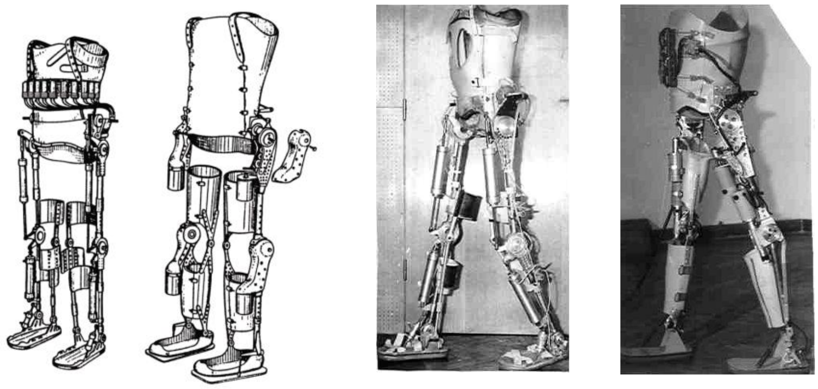
e-mail: kmianowski@meil.pw.edu.pl, wjikun@meil.pw.edu.pl

Abstract: The design study of exoskeletons for medical applications and the method of EMG signals processing are presented. Two versions of electro-mechanically driven robotic device are proposed. Exoskeleton for lower part of the body supports standing and walking persons with motion imparements. The control system will be using EMG signals registered by sensors integrated in the mechanical structure.

Key words: Exoskeleton, EMG signals, robotic device, sensors.

1 Introduction

The powered robotic exoskeletons are developed mainly for military, medical and domestic purposes. The concept comes from nature world where they are creatures owned an external shell to protect themselves and to support their displacement like crabs, lobsters, beetles. Research on artificial exoskeletons started in 1960s. In the medical field the powered-exoskeleton help persons with motion disorders to perform their daily activity. One of the first exoskeleton was invented by M. Vukobratovic and his co-workers, it is shown in Fig. 1. Fig.1a illustrates the basic concept, Fig.1b presents the version of active exoskeleton driven pneumatically, and Fig.1c - exoskeleton driven electro-mechanically. Those structures consist of two external legs, each with three degrees of freedom.



a) b) c)

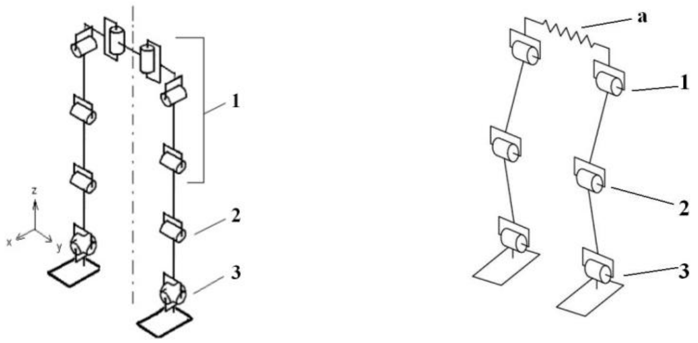
Fig. 1. Exoskeletons invented by M. Vukobratovic and his co-workers [9,10] from Michailo Pupin Institute/Belgrad: a) basic concept, b) active exoskeleton driven pneumatically, c) active exoskeleton driven electro-mechanically.

The electromyographical signal (EMG) is the bio-signal indicating the muscles activation. Using EMG signals the intended human movements or gestures can be recognized [1,2,3]. Supplied by those signals exoskeleton can produce the required motions together with increasing the motion speed or increasing the exerted forces.

EMG controlled exoskeletons are considered as reliable devices. The EMG signals are registered and applied to drive the exoskeleton motion in real time with good accuracy. The EMG registration and processing is an important field of research [4,5]. When developing the control system for lower body exoskeletons or for the active prosthesis it is important to relate properly the different walking activities with the properties of the EMG signals. Knowing such relation, gathered on-line EMG signals can be used in control system for concluding what kind of gait the patient would like to perform and for generating it. By this way activelly powered exoskeletons can speed up or just to generate the proper movement for the persons with motion impariments.

2 Exoskeleton design

The development of robotic exoskeletons supporting the lower limbs movements is relatively new field of research. Orthotic devices for this applications with external power supply have been more widely used only over the last decade. Scientific interest focuses on portable and body-mounted exoskeletons. Basic assumptions for the designed exoskeleton should be formulated taking into account typical geometry of the human body, kinematic scheme (number of DOF), and basic/important kinematic and dynamic properties of the mechanism. Number of DOF in the leg are: three in the hip joint, one in the knee, three in the ankle, with possible additional degrees of freedom in the foot.



a) b)

Fig. 2. Kinematic scheme of the external exoskeleton: a) first version with 12 DOF, b) simplified second version with 6 DOF : 1 – hip joint, 2 – knee joint, 3 – ankle joint.

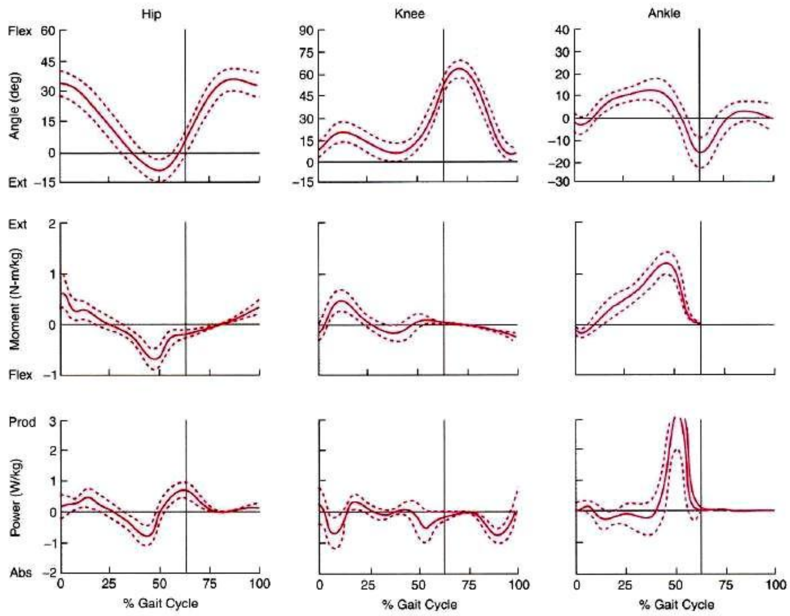


Fig. 3. Typical angular trajectories, moments and powers in hip, knee, and ankle joints during human gait cycle [8].

In the design of external electro-mechanically driven exoskeleton additional assumptions and simplifications should be considered. An example of kinematic scheme for the mechanical design is shown in Fig. 2a with 12 DOF, in which hip joint (1) consists of three revolute joints with axes intersecteding in one point. Assuming that the upper part (a) of the system attached to the trunk is made of elastic composite spatial frame and the ankle joint has only 1 DOF, the solution can be simplified to the version shown in Fig. 2b with total number of DOF's equal to 6.

In Fig. 3 the angular trajectories, the moments (torques) and power during gait cycle for typical human walking are presented [8].

Using the anatomical data and taking into account ranges of joints movements together with moments and power ranges, the parameters of active exoskeleton were specified. Table 1 gives the needed motion ranges for hip, knee and ankle joints together with torques and power requirements [8]. Table 2 presentes the peak values for motors power and torque [8]. Such data were considered in our design.

Table 1. Maximum values of power and torque for driving system of an exoskeleton for joints: hip, knee and ankle. [8].

Joint	Angle (deg)	Torque (Nm/kg)	Power (W/kg)
Hip	–20° ÷ 60°	–1 ÷ 1	–1 ÷ 0.8
Knee	0° ÷ 60°	–0.5 ÷ 0.6	–1 ÷ 1
Ankle	–15° ÷ 10°	–0.5 ÷ 2	–0.5 ÷ 3

Table 2. Maximum values of power and torque for driving system of an exoskeleton for joints: hip, knee and ankle. [8].

Joint	Power (W)	Torque (Nm)
Hip	120	100
Knee	140	75
Ankle	300	150

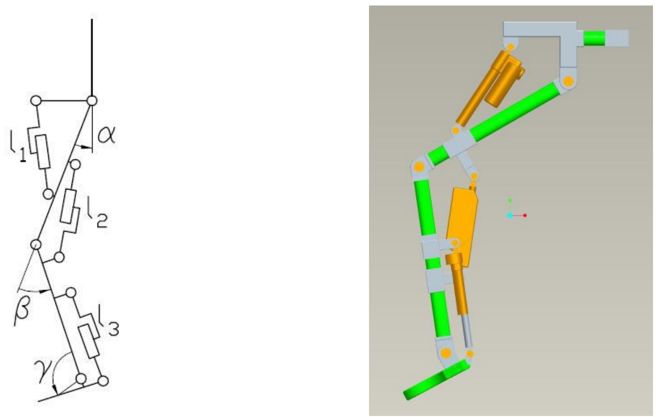
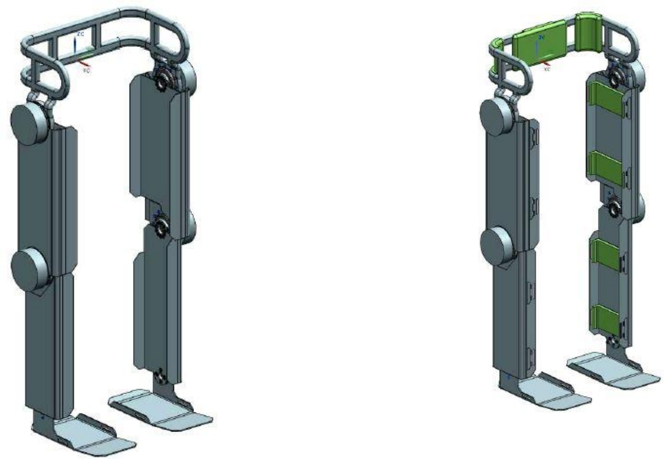


Fig. 4. Driving system of the leg I first version:: a) kinematic scheme, b) CAD model (our works).

Mechanical parts were designed using the computer-aided design (CAD) and engineering (CAE) software as the basic tools. For the final design of the whole exoskeleton CREO program was used. The CAD software ensured fast and accurate modelling of the structure details, whereas CAE software allowed to check the system structural properties (e.g. the stress distribution under various load) of the design for improve its strength and geometrical properties. The driving system of the first version of exoskeleton was equipped with linear actuators with ball-screw drives. In Fig. 4a kinematic scheme shows actuator location, and Fig.4b illustrates the CAD model together with actuators, angles α, β, γ are joint angles in the leg, and l_1, l_2, l_3 are marking the lengths of actuators.

Finally linear actuators were replaced by special high-torque electric motors with gears as it is shown in Fig. 5.



a) b)

Fig. 5. CAD design of exoskeleton for lower limbs – second version: (our works): a) general view of exoskeleton, b) exoskeleton equipped with special inner linning.

2 EMG analysis using classifying neural network

Our objective was to prove the method for automatic analysis of the electromyography (EMG) signals which will allow to conclude about the motion activitity. With such aim the experimental data collected over several walking tests for one person were analyzed. There are not commonly used tools which will enable to analyse the time signals for indicating its similarities and detecting its differences during different motions. Such information is needed for development of control methods for exoskeletons where the control systems must recognise what movement must be generated basis on the gathereed EMG signals.

Typical muscle groups in each leg (8 in each leg, totally 16 groups) were selected for EMG data gathering (Fig.6). We had no permission for working with the patients therefore for the primary invesitigation if our method is sufficient for recognising the differences in muscles activity we considered the EMG signals for the walk with different footwear [7]. Considered footwear was as following: bare foot, sneakers with 1cm high heel and with soft soles, and high heel shoes with 10 cm high heel and with hard soles.

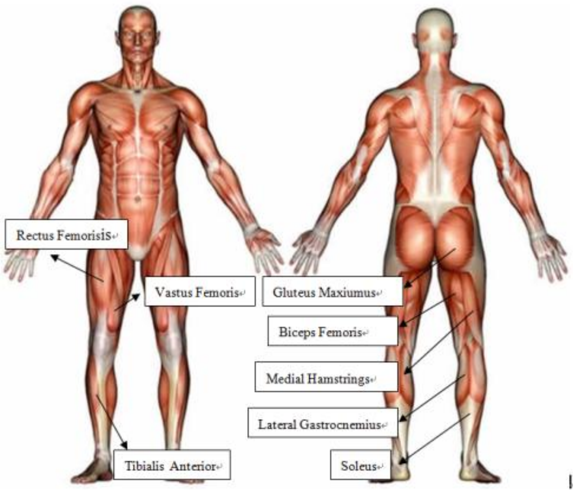


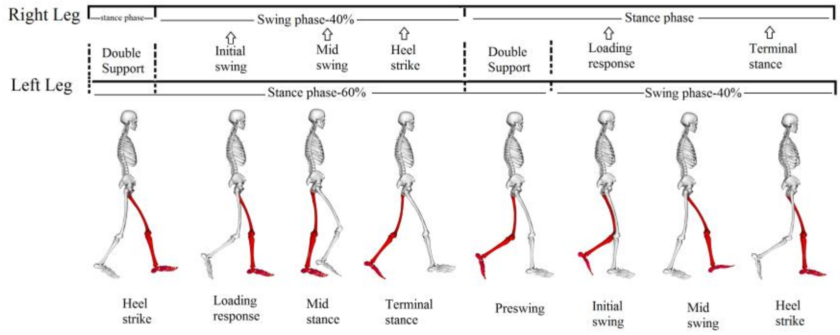
Fig. 6. Considered muscles (derived from http://www.shapesense.com/fitness-exercise/muscleanatomy/)

Typical muscle groups in each leg (8 in each leg, totally 16 in groups) were selected for EMG data gathering. They were: Rectus Femoris, Biceps Femoris, Lateral Gastrocnemius, Tibialis Anterior, Gluteus Maxiumus, Medial Hamstrings , Vastus Medialis, Soleus (Fig.6) for both legs .Using the 12 VICON T40 system the marker trajectories were registered, and the system MA 300 D. T. U was used for EMG recording when walking with different footwear.

The full walking step lasting 1.15s was divided into 33 equal intervals and the data were collected. The applied neural network was the classifier with learning vector quantization (LVQ) invented by Teuvo Kohonen [5,6].
Obtained EMG data were processed with rectified low pass filter 25 HZ of the 4^{th} order; all together it was collected samples 1151 for EMG signal. After that the RMS - root mean square - the typical statistical measures (1) was evaluated for each EMG signal.

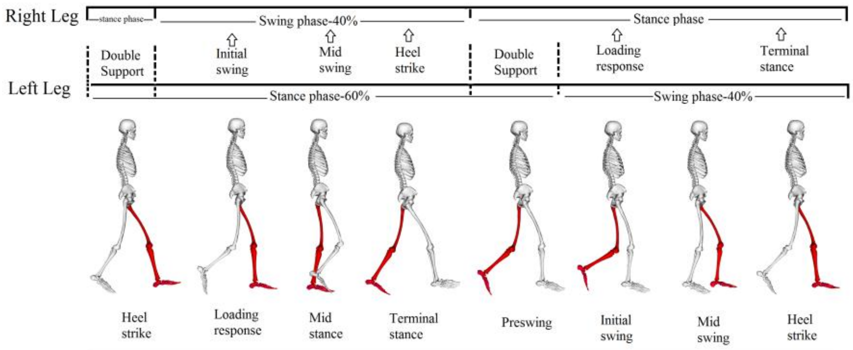
We tested how much the EMG data differs depends on the foot-wear. During LVQ training the data for each time instant for specific footwear were included to the same class (for each foot wear it was the different class). After network training the classification was tested applying to LVQ another sets of EMG data. By that way it was investigated how much the classification differs from the classification indicated during the training. The results are presented in Table 3 (sneakers - class 1 in training), Table 4 (bare foot – class 2 in training), Table 5 (high heels – class 3 in training). In the first line are numbered time intervals, second line represents the output indicated in training. The next five lines are giving the classification results.

Table 3. Sneakers



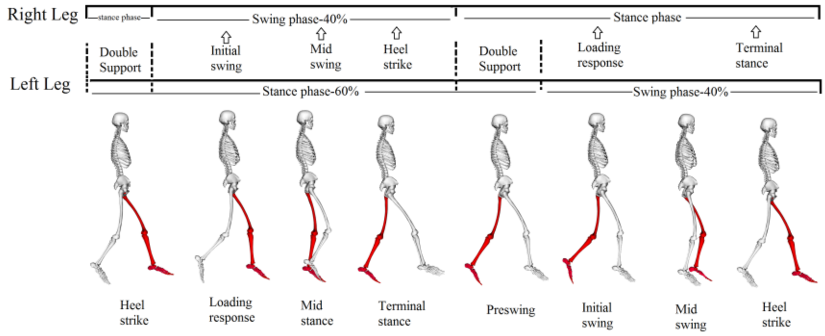
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	**3**	**3**	**3**	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**
1	1	1	1	1	1	1	1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

Table 4. Bare foot



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
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**3**	**3**	**3**	**1**	**1**	**1**	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1	**1**	**3**	**3**	**3**	**3**	**3**	**1**	**1**	**1**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1	**3**	**3**	**3**	**3**	**3**	**3**	**1**	**1**	**1**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1	**1**	**1**	**3**	**3**	**3**	**3**	**1**	**1**	**1**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1	**1**	**1**	**3**	**3**	**1**	**1**	**1**	**1**	**1**	**1**	**3**	**3**	**3**	**1**	**1**	**1**	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

Table 5. High heels



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
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
2	**2**	**2**	3	3	3	3	3	3	3	3	3	3	3	3	3	3	**1**	**1**	**2**	**2**	**2**	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	**1**	**1**	**1**	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	**1**	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	**1**	3	3	3	3	3	3	3	**1**	3	3	3	3	3	3
3	3	**1**	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	**1**	**2**	3	3	3	3	3	**1**	**1**	3	3	3	3	3	3
3	3	**1**	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	**1**	**2**	3	3	3	3	3	**1**	**1**	3	3	3	3	3	3

In all tables classification results different than that indicated in the training are marked by bold font. As it can be seen the high heels walking in majority of cases was classified to class 3 which was the class assigned in training for this footwear. It means that high heels EMG signals are most particular with less similarities to the others. In Table 3 only for several cases the EMG results were included to the class 1 or 2. Contrary the bare foot and sneakers EMG properties are showing many similarities - in Table 1 and Table 2 are mainly the classes 1 and 2. As we can see in the tables, the neural network classified sneakers to the same class as a bare foot for the second part of walking step which is the support phase but in the swing phase there are the differences in classification. Taking into account that in the exoskeletons the EMG signals in both legs are monitored such differences are enough to distinguish both situations.

For validation of the results delivered by neural networks, the EMG trajectories were deeply investigated (Fig.7) and good coincidence of the results with the classifications obtained in testing was observed. It was also justified that there is good similarity between the clustering delivered by artificial neural network and the trends in the joint trajectories including the velocities and accelerations. It is known that the features of EMG signals are directly related to the propeties of joint trajectories [4], therefore it was proper to make such comparison. Basis on the above summarized reasearch we proved that the EMG signals can be used for motion prediction in short-term horizons and therefore they can be applied for exoskeleton control. Using the EMG signals as the inputs the classyfying neural network is able to indicate what motion must be generated.

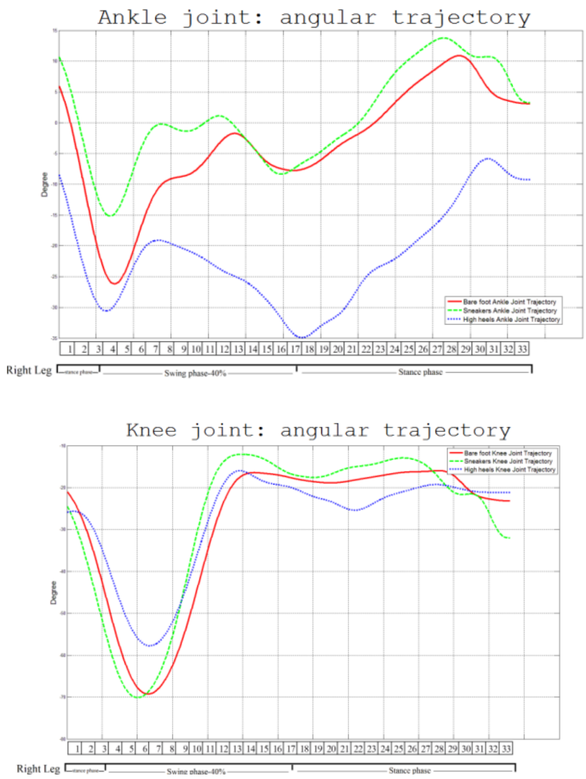


Fig.7. Angular trajectories of ankle and knee joints. (the time intervals considered in clustering are indicated)

3 Conclusions

The aim of this work was to elaborate the concept of portable robotic exoskeleton for the lower limbs. It consists of the part which is mounted to the lower part of the torso with the parts covering both legs. The device is maintaining kinematic functions of human legs but with reduced (comparing tu human) degrees of freedom. The preliminarly research on the EMG based motion control of proposed device was presented. It was confirmed that LVQ neural network can classify the EMG signals with distinguishing the diferences which are coincident with differences in the gait. Therefore it is concluded that the clustering neural network is the promising tool for development of control methods dedicated to intelligent exoskeletons. The serious problem in EMG control synthesis is that, that the feature patterns in different motions overlap, and it is troublesome to discriminate clearly between them. Basis on real-time EMG signals registration the network is able to produce the clusters which, after proper processing, are informing what kind of joint trajectories, velocities and accelerations must be developed by the joint actuators. Such conclusion matches the approach presented in [12] where the clustering method dedicated for the control of myoelectric hand was presented. The choice of two quite similar fotwear (bare foot, training shoes) versus very different (high heels) was intentional for tesing the network discrimination sensitivity. It should be added that the EMG signals (after preprocessing) are typcal for motion situations and they are not much personally affected. The differences can be caused mainly by the measurement conditions (weak fixing of sensors, thick skin etc.), there are available a software packages which are allowing to obtain the EMG from motions simulations. Such signals are very clean and easy to process, hovewer we decided to use the experimental data for being closer to real life conditions.

Acknowledgments Special thanks are expressed to Prof. Syczewska from Children's Memorial Health Institute (in polish Centrum Zdrowia Dziecka) in Warsaw who helped us to record the data. All of the equipments and laboratory tests had been supported by Warsaw children hospital. Also the gratitude is expressed to M.Sc. Magdalena Zurawska and B.Eng.. Maximilian Szumowski for their help with the whole EMG experiment.

References

1. Al-Mashhadany Y. I.: *Measurement of human leg joint angle through motion based on ectromygraphy (EMG) signal*, J.Comp.Comm.Control&Systems Eng., 2011,11(2), 10 pgs
2. Abel E. W., Zelacharia P. C., Forster A., Farrow T. L.: *Neural network analysis of the EMG interference pattern*, Med. Eng. Phys., 1996, Vol. 18, No. 1, pp.12-17.
3. Dollar A. M., Herr H.: *Lower extremity exoskeletons and active orthoses: challenges and state-of-the-art*, Robotics, 2008, vol. 24, No. 1, pp.144 - 158.
4. Erfanian A., Chizeck H. J., Hashemil R. M.: *The relationship between joint angle and evoked EMG in electrically stimulated muscle*, Eng. in Medicine&Biol.Society, 1994, pp,345 -346.
5. Kohonen T.: *Self-organizing maps*. Springer, Berlin, 1997.
6. Kohonen T.: *Learning vector quantization*, The Handbook of Brain Theory and Neural Networks, Arbib M.A., ed., MIT Press, Cambridge, MA, 1995, pp.537–540.
7. Su X., Gu Y.: *EMG in people with different heel height condition*, Applications of EMG in Clinical and Sports Medicine, 2012, DOI: 10.5772/25672.
8. Luksch T.: *Human-like Control of Dynamically Walking Bipedal Robots RRLab* Dissertations, Verlag, 2010, ISBN: 978-3-86853-607-2,
9. Vukobratović M., Borovac B., Surla D., and Stokic D.: *Biped Locomotion: Dynamics, Stability, Control, and Application*; Springer-Verlag, 1990,
10. Vukobratović M.: *When were acitve exoskeletons actually born?,* Int.J. Humanoid Robotics 4.03, 2007, pp.459-486,
11 Dudus A.: *Mechanical design of Exoskeleton to supporting human walk*, M.Sc. diploma thesis, supervisor K. Mianowski, Warsaw 2013,
12. Kahori Kita, Ryu Kato, and Hiroshi Yokoi: *Self-Organized Clustering Approach for Motion Discrimination using EMG Signal*. 31st Conf. of the IEEE EMBS, 2009, pp. 2587-2590.