Prediction of lower extremities' movement
by angle–angle diagrams and neural networks

Patrik Kutilek[1]*, Barbora Farkasova[2]

[1] Faculty of Biomedical Engineering, Czech Technical University in Prague, Czech Republic.
[2] Department of Biomedical Engineering, Motol University Hospital in Prague, Czech Republic.

In contemporary science, the analysis of human walking is extensively used. The prediction of leg motion, as well as rehabilitation, can be usable for orthosis and prosthesis programing. Our work is focused on predicting of human walking by angle–angle diagrams, also called *cyclograms*. The applications of cyclograms in conjunction with artificial intelligence offers wide area of applications in medicine. But until now, this approach has not been studied or applied in practice.

Key words: *simulation, walking, artificial intelligence, gait angles, cyclograms, artificial neural networks*

1. Introduction

In medical practice, there is no appropriate and widely used application of the system based on artificial intelligence (AI) for identifying defects in the movement of human legs, or for the control the actuators of prosthesis or rehabilitation facilities. Above all, the evaluation of the walking quality is difficult and often based only on the subjective views of physicians who do not use appropriate or accurate methods in their clinical practice.

In medical practice or physiotherapy research, we can use several methods for identifying defects in the movement of a human body. The commonest method for studying gait behaviour in clinical practice is the analysis of gait phases by the time phase cycles of gait [1], [2]. The time phase cycles of gait were used to analyze gait by means of artificial intelligence methods in the past [3]–[9], but without subsequent application in medical practice. The research into predicting the leg movement by artificial intelligence and measured EMG signal is very extensive [10]–[12],

mainly due their prospective application in the myoelectrical prostheses' control systems.

In our study of gait, we apply new methods that are based on the analysis of gait angles by cyclograms (also called *angle–angle diagrams* or *cyclokinograms*) and artificial intelligence and allow us to predict the motion of human legs/prosthesis. The concept of angle–angle diagrams, although known to the biomechanics' community, has not been found very frequently in contemporary literature. The first information about the cyclogram [13] argued that a cyclic process such as walking is better understood if studied with a cyclic plot such as an angle–angle diagram and described some methods for observing the deviations of gait characteristics in diagrams called *cyclograms*. The creation of cyclograms is based on gait angles which are objective, reliable and well suit to statistical study [14]. Furthermore, the technique is strongly rooted in geometry and the quantities are intuitively understandable [15]. Depending on the cyclicity of the gait, cyclograms are closed trajectories generated by a simultaneous plotting two (or more) joint quantities. In gait study, the easily identifiable planar knee–hip cy-

clograms have traditionally received the most attention. In order to quantify the symmetry of human walking, we obtained and studied the cyclogram for the same joint and two sides of the body [16].

The cyclograms in conjunction with artificial intelligence can offer a wide area of applications in medicine, but until now this approach has not been studied or put into practice.

2. Methods

In order to draw and study the angle–angle diagrams we use a model of the human body created respectively in MatLab Simulink and SimMechanic software. The movement of the model of a body is controlled by the data measured by motion capture system which identifies the position of points/markers in the Cartesian coordinate system. To measure the movement in two/three-dimensional space we can generally use several methods, for example, infrared (IR) camera with active markers or only cheaper web camera. We used the medical IR camera with active markers (Lukotronic AS 200 system) and LED diode markers placed on the person examined at the following points: malleolus lateralis, epicondylus lateralis, trochanter major and spina iliaca anterior superior (figure 1).

By this method we can record the movement in a three-dimensional space, though we study primarily the movement in a two-dimensional sagittal plane. Commonly human gait data consist of the recorded positions of markers on the skin/dress at the extremities of the limb segments (the thigh, the shank, etc.) of a subject. If we have information on the movement of points/markers in space and the points characterizing the parts of human body, then we can use these points to define the vectors of the positions of body parts. The difference in coordinates of two points in space defines a vector. The angles between each two segments are calculated by assuming the segments to be idealized rigid bodies. For computing angles we use the following formula:

$$\beta = \arccos \frac{u \cdot v}{|u| \cdot |v|}, 0 \leq \varphi \leq \pi \ \text{(rad)} \qquad (1)$$

for a two-dimensional system, because we assume that such a knee or elbow joint has only one rotational degree of freedom in the case of simplified assumptions [17]. The u and v are the vectors of body segments (thigh, shin, foot, etc.) represented by two points (markers) at a minimum. Equivalently, the calculation is performed for three-dimensional space. If we are interesting in an angle between body segment and physical horizontal we determine the angle between horizontal vector (1,0) and vector that is defined by the coordinates of points on the body segments evaluated in the Cartesian coordinate system. Markers, i.e. points, are moving in space together with body segments and the individual segments of the
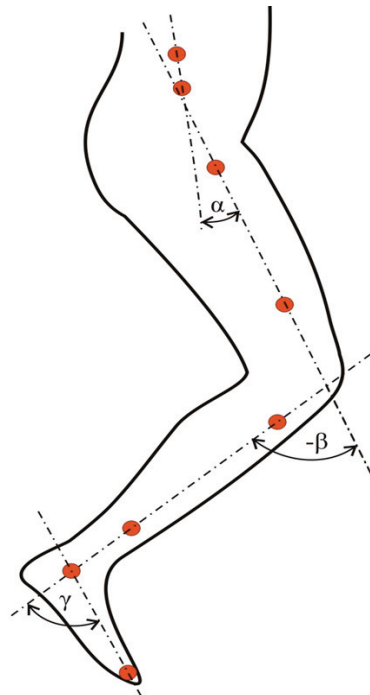

Fig. 1. Location of IR markers and angles measured during examination

body are moving by means of the translational or angular movement per unit time. Therefore, in order to determine translational and rotational speed and acceleration of the individual segments, i.e., markers, we use numerical derivations.

The aim of this study is not to evaluate a joint center of rotation, because even in practice, in the case of motor control system of prosthetics, we do not expect complete conformity with the anatomical characteristics, and the deviations are negligible for our needs to verify the methods of the movement prediction. For this reason we used for calculation the vectors based on coordinates of markers, and the vectors u and v in equation (1) do not necessarily correspond to the directional unit vectors of body parts.

During the clinical measurement the measuring data are grouped according to ages of subjects and can be grouped according to diagnoses of subjects. We create the cyclograms of angles, angular velocities and angular acceleration: left knee – left hip, right knee – right hip, left hip – right hip, left knee – right knee, right shoulder – right hip, left shoulder – left hip. Furthermore, we could study these characteristics of cyclograms: the length of trajectory, frequency of loops, slope of loops, maximum range, average speed, total circumscribed area of loops.

The most important aim of our work was to design the methods for applying the cyclograms in practice to identify the defects in the movement and for applying the cyclograms in the control system of the actuators of prosthesis or rehabilitation facilities. This is why we use artificial intelligence methods which are implemented in MatLab toolboxes [18], [19]. We can use, for example, the artificial neural networks (ANN) for the prediction of angles in joints, i.e., for the prediction of cyclograms.

Artificial neural networks are based on the neural structure of brain [20], [21]. They process records one at a time, and "learn" by comparing their prediction of the record with the known actual record [22], [23]. The input to the first layer consists of the values in a data record. The final layer is the output layer, where there is one node for each physical quantity. The prediction of time series using neural network consists in teaching the net history of the variable in a selected limited time and applying the taught information to the future. Data from the past are provided to the inputs of neural network and we expect data on the future from the outputs of the network.

Our learning method is based on the premise that the table consists of $m + 1$ columns of states, we assume that five columns of the previous states plus one columns for the prediction will be sufficient (table 1).

In the first row of table 1, the first five angles computed from the measuring data are set, and the sixth column indicates the next calculated value of the angle as a target to which the artificial neural network learns by example. In the second row, there are recorded the second to sixth calculated values of the angle, and into the sixth column in the same row we insert the seventh value of the angle as a target. This cascading method is presented in a table of $n - 4$ rows, where $n + 1$ is the number of the known values of angles in the joint, which we decided to use for a learning process (table 1). So the method is generally based on the information about a human walking. This walking is described in the cyclogram, and the curve of the cyclogram allows neural networks to be learned. For neural networks' learning we use this segment of the cyclogram which represents a set of states for learning being divided into past states and prospective states.

Table 1. Learning basic artificial neural network
to the angles calculated in joint

Input data					Target data
Angle in joint					Angle in joint
x_1	x_2	x_3	x_4	x_5	x_6
x_2	x_3	x_4	x_5	x_6	x_7
x_3	x_4	x_5	x_6	x_7	x_8
x_4	x_5	x_6	x_7	x_8	x_9
...	...	...	...	...	...
x_{n-4}	x_{n-3}	x_{n-2}	x_{n-1}	x_n	x_{n+1}

We used the Neural Network Toolbox in MatLab for the prediction of the angles in joints, as revealing the value of human movement. As an approach to selecting data for training artificial neural network learning, we chose the calculated values of angles in the joints. With each presentation the output of the neural network was compared to the desired output and an error was computed. This error was then fed back (backpropagated) to the neural network and used to adjust the weights in such a way that the error decreased with each iteration and the neural model got closer to producing the desired output.

The table of input and target data can be extended to other parameters which are also very important in predicting the movement of lower limbs. An appropriate parameter is, for example, the angular acceleration (i.e., four states of acceleration), but also the subject's weight in kilograms and the subject's age in years (table 2). We tested several modifications of ANNs. The first ANNs predict an angle only in one joint of the left leg (hip, knee and ankle). We also designed

Table 2. Learning artificial neural networks to the angles
and angular accelerations calculated in joint, subject's weight and subject's age

Input data											Target data	
Angle in joint					Angular accelerations				Patient's weight	Patient's age	First joint angle	Second joint angle
x_1	x_2	x_3	x_4	x_5	ε_1	ε_2	ε_3	ε_4	m	N	x_6	y_6
x_2	x_3	x_4	x_5	x_6	ε_2	ε_3	ε_4	ε_5	m	N	x_7	y_7
x_3	x_4	x_5	x_6	x_7	ε_3	ε_4	ε_5	ε_6	m	N	x_8	y_8
x_4	x_5	x_6	x_7	x_8	ε_4	ε_5	ε_6	ε_7	m	N	x_9	y_9
...	...	...	...	...	...	...	...	...	...	...	...	...
x_{n-4}	x_{n-3}	x_{n-2}	x_{n-1}	x_n	ε_{n-4}	ε_{n-3}	ε_{n-2}	ε_{n-1}	m	N	x_{n+1}	y_{n+1}

ANNs for the prediction of complete knee-hip cyclogram or ankle–knee cyclogram, i.e., for the prediction of two angles. One of the structures of ANN designed for predicting the angles of the hip–knee curve of cyclogram show in figure 2.
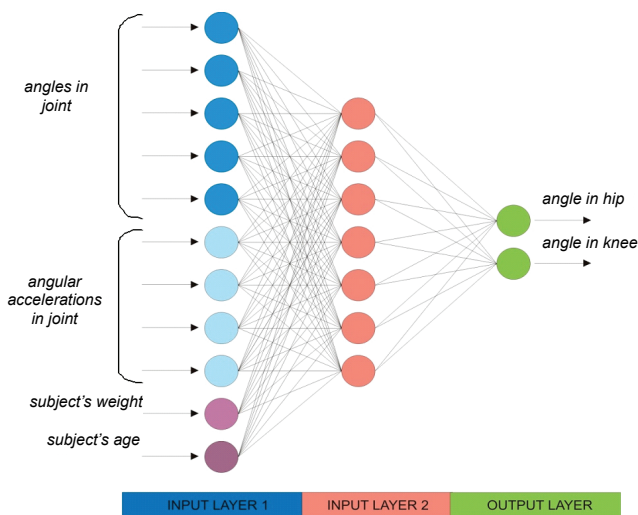

Fig. 2. Designed artificial neural network 11–7–2
for predicting the movement of lower limb

We can also add for learning the NN the height of the subject in meters, or other additional parameters, for example, a predefined code for an illness, operation of musculoskeletal apparatus, etc. For training the neural networks designed the backpropagation algorithm is used. With backpropagation, the input data was repeatedly presented to the neural network.

The above methods for predicting a motion using the learned neural networks reflect only a short segment of the curve of the angle–angle diagram of a gait cycle. The values by which the neural network is learned reflect only the information on a limited number of states in a short period of time. Such a method may not always adequately describe the stereotypes of human walking. The main problem is that the method does not describe either the whole one gait cycle or the transition from the current gait cycle to a new gait cycle. It is theoretically possible to design a number of input neurons of a neural network to describe the whole gait cycle, but the structure of the neural network is then very complex and therefore the calculation is difficult and slow. For this reason, we proposed new ways to describe the gait cycle using the linear regression analysis and principal component analysis.

The two-dimensional angle–angle diagram represents a set of states. In linear regression analysis, the mean-square value of the residual distance between the data samples and the regression line in the direction of the dependent variable is minimized to find the best-fit regression line [24], [25]. This leads to a biased estimate of the principal axis of the distribution, an effect known in statistics as regression to the mean. When y is considered first the dependent variable and then the independent variable, the direction of the principal axis, i.e., the inclination angle of angle–angle diagram, is obtained from the data samples as follows

$$\tan\theta_{y,x} = \frac{\sigma_{x,y}^2}{\sigma_{x,x}^2} \tag{2}$$

and

$$\tan\theta_{x,y} = \frac{\sigma_{y,y}^2}{\sigma_{x,y}^2}, \tag{3}$$

where covariance

$$\sigma_{x,y}^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y}), \tag{4}$$

$\bar{x}$ and $\bar{y}$ are the mean values of angles and the summation is done over all N measured points, i.e., states. The variances $\sigma_{x,x}^2$ and $\sigma_{y,y}^2$ are defined equivalently.

The second method proposed is based on principal component analysis (PCA) [25], [26]. The inclination angle of angle–angle diagram is defined by inclining the ellipse which is found by means of PCA. Principal component analysis finds the direction of maximum

and minimum dispersion of the distribution in the *x–y* plane. In mathematical terms, PCA defines the direction of the principal axis as that of the first eigenvector of the covariance matrix

$$R = \begin{bmatrix} \sigma_{x,x}^2 & \sigma_{x,y}^2 \\ \sigma_{x,y}^2 & \sigma_{y,y}^2 \end{bmatrix} \tag{5}$$

and the variance along this axis is then the corresponding (largest) eigenvalue. The second eigenvector and value define the direction of the minor axis (orthogonal to the first) and its variance, respectively. Eigenvalues σ_0^2 are calculated from the covariant matrix. The two eigenvalues are thus

$$\sigma_0^2 = \frac{\sigma_{x,x}^2 + \sigma_{y,y}^2 \pm \sqrt{(\sigma_{x,x}^2 - \sigma_{y,y}^2)^2 + 4(\sigma_{x,y}^2)^2}}{2} . \tag{6}$$

The sway area of the cyclogram could be reproduced by an ellipse with the two principal axes σ_0 at the inclination angle θ:

$$\tan\theta = \frac{\sigma_{x,y}^2}{\sigma_0^2 - \sigma_{y,y}^2} . \tag{7}$$

If the area covered with cyclogram of gait cycle is defined by an ellipse which is fitted to the data, then all the stereotypes of walking are characterized by their area of cyclogram and the inclination of the cyclogram. The values of the inclination angle and eventually the area of ellipse are then used for learning the neural network. The neural network will be extended to neurons with regard to the other input values such as the inclination angle of one cycle before the actual value of the joint angles. The neural network will also be extended to new output neurons, so that the neural network learns by target values, such as the inclination angle of a subsequent cycle after the actual value of the joint angles (table 3).

The learned neural networks prefer the typical changes from the previous cycle to subsequent cycle and prevent the use of atypical changes. In addition, NN is allowed to estimate the expected gait cycle based on a specified slope of the cyclogram of a gait cycle. The method based on PCA is proposed for training neural networks on the basis of individual data for a particular person. The method can however be modified to take into account the anthropometric data such as weight, height or age of the subject and the neural network can be expanded to include an appropriate number of input neurons, and thus to become universal.

The main goal of our study was to predict a curve of the cyclograms based on the current state of the lower extremities and the prediction by artificial intelligence. The set of data for learning artificial neural networks was measured on 10 volunteers recruited from the students of the Czech Technical University in Prague. The subjects tried to walk properly on the treadmill with variable speed. The main human walking speed was 1.5 m/s for studying and adjusting the method proposed.

In order to record the data, a very accurate motion capture system, Lukotronic AS200, we used. The manufacturer of the IR camera with active markers is Lutz Mechatronic Technology e.U. who declares, according to the CE-certification for medical products, EU-Directive 93/42/EEC, that the LUKOtronic motion analysis system can be used for the care of patients in hospitals and rehabilitation centers. One camera system mounted before or behind the subject moving on the treadmill allowed the 3D motion of the lower limbs to be recorded. Markers were placed in accordance with the manufacturer's recommendations for gait analysis by GaitLab software. The recommended model of marker set is the same as the set defined by Helen Hayes Hospital model [27] for Vicon Clinical Manager and sagittal plane. Only in the case of plac-

Table 3. Learning artificial neural networks to the joint angles and PCA angles of gain cycles

Input data									Target data		
First joint angle				Second joint angle				Inclination of the previous gait cycle	1st joint angle	2nd joint angle	Inclination of the subsequent gait cycle
x_1	x_2	x_3	x_4	y_1	y_2	y_3	y_4	θ_1	x_5	y_5	θ_1'
x_2	x_3	x_4	x_5	y_2	y_3	y_4	y_5	θ_2	x_6	y_6	θ_2'
x_3	x_4	x_5	x_6	y_3	y_4	y_5	y_6	θ_3	x_7	y_7	θ_3'
x_4	x_5	x_6	x_7	y_4	y_5	y_6	y_7	θ_4	x_8	y_8	θ_4'
…	…	…	…	…	…	…	…	...	...	...	...
x_{n-3}	x_{n-2}	x_{n-1}	x_n	y_{n-3}	y_{n-4}	y_{n-2}	y_n	θ_n	x_{n+1}	y_{n+1}	θ_n'

ing markers on a foot, a physician selected the location of the markers by Helen Hayes marker set model. The position of markers on a foot was chosen mainly according to the requirements for good record, because in practice the movement of feet is not usually measured, and the manufacturer does not mention the placing more than one marker on a foot.

After obtaining the measuring data we create the necessary cyclograms in the MATLAB software. By the way we get graphs of changes of angles per time in all main parts of lower part of human body and the sagittal plane. It was important for the subsequent computing of the curve of cyclograms and for the prediction of motion.

In the next most important step of the study, we used the cyclograms for predicting the motion of lower extremities. The cyclograms include the information about the relationship between the angles and their changes over time. We used cyclograms as models/patterns for learning artificial neural networks. After learning neural networks we used them for predicting the future states of angles in the joints of lower limbs.

3. Results

Our measuring data proves that the angle in knee is usually changing from 5° (stretched leg) to 70° (tucked up leg), in hip it usually ranges from 5° to 40° (figure 3), and in ankle – usually from 60° to 100° (figure 6). If we neglect an inaccurate placement of markers and make other simplifying assumptions, it can be inferred that the angles correspond to the angle between femur and tibia and the angle between tibia
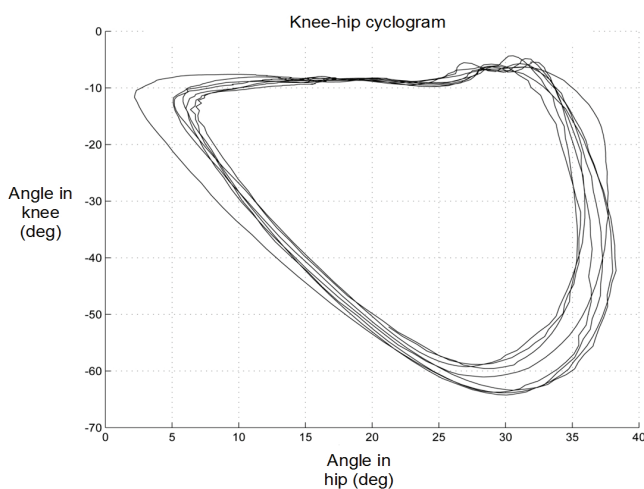
and metatarsus. From cyclogram (figure 3), we know that typically the swing phase starts at 0° angle of thigh extension and a knee flexion at the maximum of about 80%. The subject's weight and age were 65 kilograms and 23 years, respectively.

After learning the neural networks we used the segments of cyclograms for predicting the future states of angles in the joints. The result was that by using short segments of the cyclogram curve, which was loaded into a neural network, learned neural network predicted the subsequent behaviour of the gait by the predicted cyclogram curve. The two results of our method for predicting gait are shown in the form of predicted knee–hip cyclogram (figure 4) and predicted ankle–knee cyclogram (figure 7). For prediction
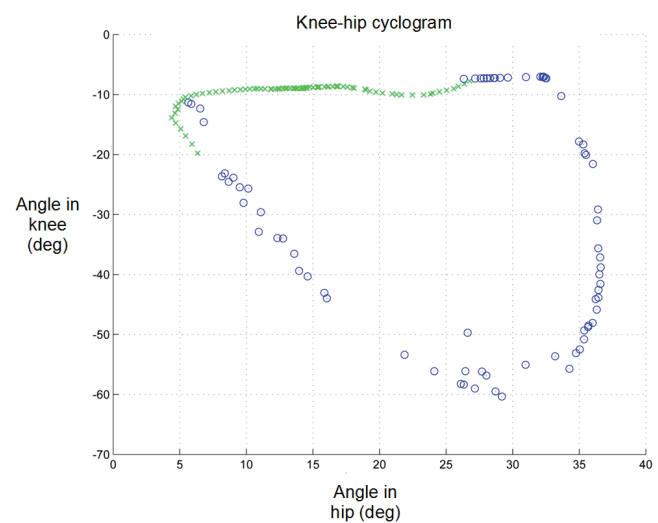

Fig. 4. Predicted knee–hip cyclogram (NN learning without taking account of the inclination angles of gain cycles): predicted values of angles – circles; measured known values – crosses
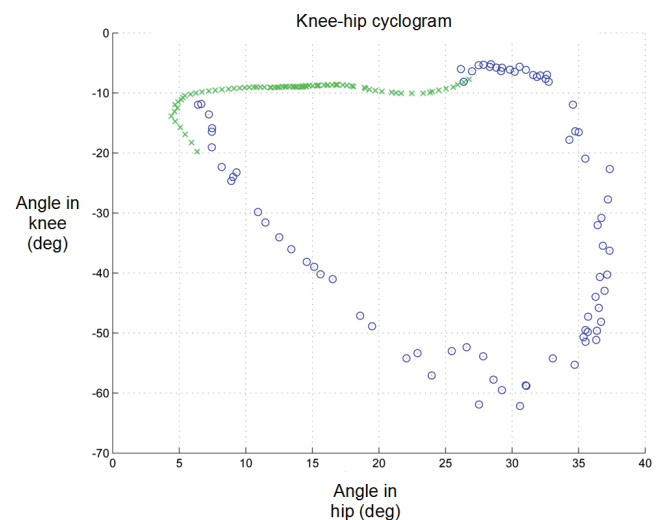

Fig. 5. Predicted knee–hip cyclogram (NN learning with taking into account the inclination angles of gain cycles): predicted values of angles – circles; measured known values – crosses

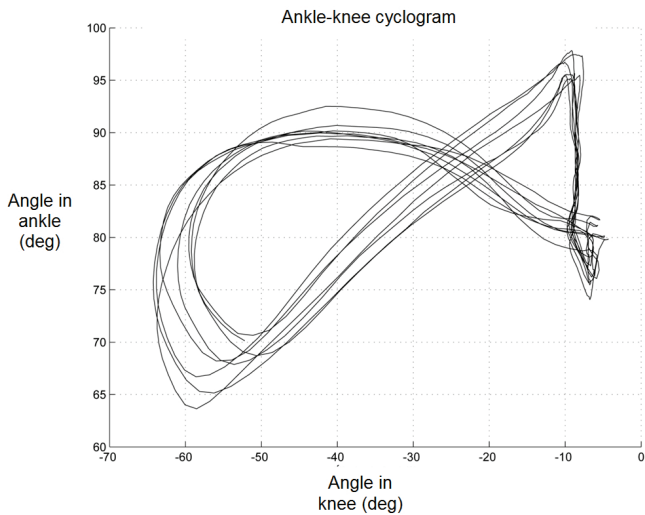Fig. 3. Knee–hip cyclogram
(treadmill, walking speed of 1.5 m/s)

Fig. 6. Ankle–knee cyclogram
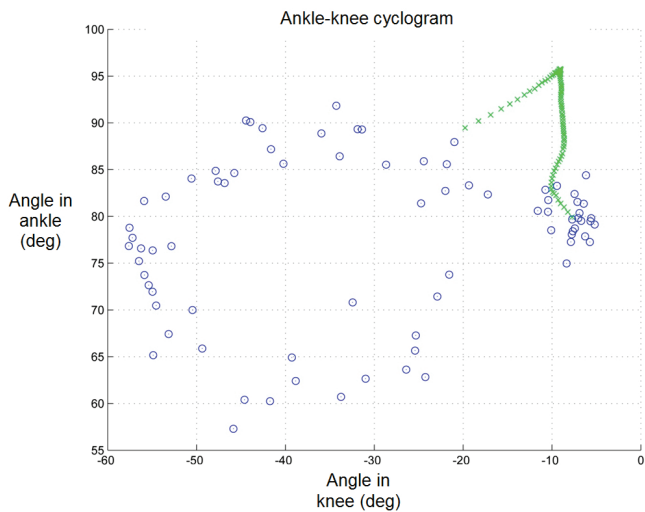(treadmill, walking speed of 1.5 m/s)

Fig. 7. Predicted ankle–knee cyclogram (NN learning
without taking into account the inclination angles of gain cycles):
predicted values of angles – circles;
measured known values – crosses

we used NN learning without taking into account the inclination angles of gain cycles. The two-dimensional knee–hip and ankle–knee cyclograms show the prediction cyclogram curves based only on measurements of past states, i.e., the remaining segment of the curve is predicted by assuming the knowledge of a short curve segment. We can see that the predicted curves correspond only partially to the usual form of cyclograms [13]–[16]. For the prediction of the cyclograms (figures 4 and 7) we used the artificial neural network 11–7–2 (figure 2) modified for knee–hip and ankle–knee cyclograms. The prediction results show that especially in the ankle–knee cyclogram the prediction is inaccurate because of its complicated shape. The

predicted knee–hip cyclogram is relatively accurate and similar to the pattern (figure 3).

We found out that the predictions of movement based only on the evaluation of a short segment of the cyclogram are particularly suitable only for the prediction of complex movements. In the case of walking, which is often changed, the prediction is not always appropriate and accurate.

Improved predictions are achieved by increasing the monitored segment of the cyclogram curve, but the complexity of the neural network also increases and the computing time increases as well. These aspects are inappropriate and we have to modify both neural networks and methods of learning. For ANN learning and prediction we use the variables identified by the methods of linear regression analysis and PCA. The predicted knee-hip cyclogram (figure 5) and the predicted ankle–knee cyclogram (figure 8) show that the prediction is very accurate. A low variability in prediction of angles is identified, but the variability is negligible because even in cases of typical gait, the variations in angles are small (figures 3 and 6). This way of prediction is suitable for situations where the movements often fit the stereotypes and typical gait changes between these stereotypes of human walking.
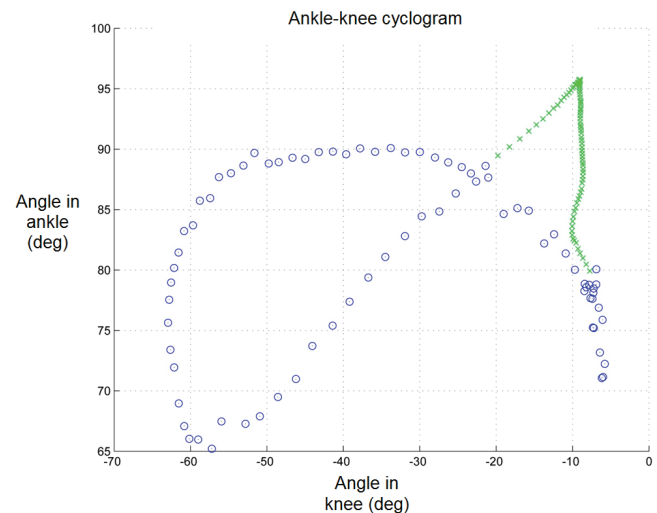

Fig. 8. Predicted ankle–knee cyclogram (NN learning with taking
into account the inclination angles of gain cycles): predicted
values of angles – circles; measured known values – crosses

According to the method described the cyclograms inform us about the previous position of the lower limbs and we can obtain the expected conditions, i.e., states during future predicted walking. Then these states are compared with the conditions in which the limb actually gets. This information is important in

rehabilitation medicine, or as an expected value of the angles used in the control algorithms of lower limb prosthesis.

4. Discussion

The angle–angle diagrams in conjunction with artificial intelligence can be widely applied in medicine. We described the method for predicting the motion of lower extremities and this predicted data may be used for the evaluation of human walking in physiotherapy practice based on the study of angle–angle diagrams. The prediction of angles in joints of leg is based on the principles of artificial intelligence and in our study we use the artificial backpropagation neural networks. The analytical system based on NNs for the study of a three-dimensional knee–hip–ankle cyclogram and of a leg movement as well is designed in the way identical to the one used for the study of two-dimensional cyclograms. The new methods can be applied in a clinical practice for the study of disorders or characteristics in motion function of human body [28] and we can use this method in advanced control systems of the prosthesis of lower extremities [29]. In the past, it was almost impossible to use the complex algorithms based on the artificial intelligence in slow control systems of prosthesis, but today we can consider the application of the methods described in the algorithms of new prosthetic knee control systems [30], [31]. It is an obvious opportunity to continue the development of these methods in order to design new hydraulic or pneumatics knee prosthesis.

A new robotics orthosis offers the second very important possibility of applying the above methods in rehabilitation medicine. We can use them in the algorithms of a robot-driven gait orthosis utilized in locomotion therapy [32], [33]. The therapy is based on simulating the movement of lower limbs of healthy people by sophisticated robotic devices. An example of such a system is the Hocoma's Lokomat system which supports the rehabilitation of patients suffering from neurological diseases (multiple sclerosis, post-stroke), patients after spinal cord injury or a traumatic brain injury resulting in a partial loss of ability to walk. The Lokomat has been on the market since 2001 and is considered to be a crucial improvement in the art and science of locomotion therapy in the Motol University Hospital in Prague. We assume that our method will be used in the control systems of such device because artificial intelligence applied in control systems can extend the possibilities of rehabilitation,

i.e., training possibilities. Furthermore, the identified and predicted gait pattern can be individually adjusted to the patient's needs [34], [35], because in our method of movement prediction the patient's weight and age are taken into account. Moreover, the new methods of identifying the technique of human walking, which are used for learning neural networks, can be modified and used in other areas of artificial intelligence, such as reinforcement learning [36], [37].

This work is not intended to describe all potential possibilities of applying cyclograms in conjunction with artificial intelligence. This article intends to show new methods which are subsequently proved by a number of simulations in MATLAB software because the methods designed based on cyclograms and ANNs could be useable and widely applied.

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