Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 20, No 5, 1998

DETERMINING SYNERGY BETWEEN JOINT ANGLES DURING LOCOMOTION BY RADIAL BASIS FUNCTION NEURAL NETWORKS

Dejan Popović, Slavica Jonić
Faculty of Electrical Engineering, University of Belgrade
Bulevar revolucije 73, 11000 Belgrade, Yugoslavia
E-mail: DBP@EL.ETF.BG.AC.YU

Abstract - *This paper shows that the radial basis function neural networks are suitable tools for determining the synergies between the leg joint angles for cyclic activities. The study was motivated by earlier studies showing the following: 1) cyclic functional movements (e.g., walking) are synergistic [1]; and 2) machine learning techniques for recognizing gait events perform similar when a training set includes one or more joint angles [2]. The results of this study prove that the only one joint angle sensor is sufficient to describe a cyclic motor pattern, and that the second joint angle sensor is redundant for cyclic activities, but very useful to detect the change of the mode of locomotion or hazard [3]. The results of the study will be implemented for restoring walking of humans with disabilities using a functional electrical stimulation system*

Keywords: synergy, walking, radial basis function neural networks, control, functional electrical stimulation

1. INTRODUCTION

It was demonstrated that walking can be restored with multi channel functional electrical stimulation (FES) systems [4], and that performances of the gait will be improved if a rule-based controller (RBC) is implemented [5]. RBC is a sensory driven controller requiring "If-Then" model of the process. RBC eliminates the dynamical model and operates even if the parameters are not known with adequate accuracy [6]. Studies determining if-then model [e.g., 6,7,8,9,10] used a-priori selected sensors, but did not analyze the minimal number of sensors required [7,10].

Synergies are time sequences of central motor commands to groups of muscles that lead to simple coordinated motor acts [1,11]. Existence of synergies, i.e. invariant features, in the execution of motor tasks can be explained by the existence of inherent optimization laws governing the acquisition of motor skills. Bernstein [1] considered maintenance of vertical posture during a voluntary movement an illustration of the concept of synergies. Presence of synergies is assumed to simplify the control of the vertical posture thus solving (at least partially) a problem of mechanical redundancy. The question: How does the central nervous system (CNS) choose a certain sequence of motor commands to execute a motor task from an infinite number of possibilities is known as the Bernstein problem. According to equilibrium-point hypothesis, that is, λ-model [12], the CNS can use only one independently controlled variable λ for each muscle, thus avoiding the Bernstein problem at the single-muscle level.

For multijoint movements we have not a central language similar to the λ-language for single-joint movements, that is, we cannot suggest even a hypothetical independently controlled central variable that would be analogous to λ for single-joint movements [11]. Therefore, the Bernstein problem overcoming excessive degrees of freedom at a control level is frequently substituted by a different problem of overcoming this redundancy at the level of performance. This problem, termed as the pseudo-Bernstein problem [11], can be formulated as finding a combination of joint angles (known as the problem of inverse kinematics) or muscle forces (the problem of inverse dynamics) required for executing a motor task when the number of mechanical degrees of freedom for the effectors exceeds the number of parameters defining the task. Both problems belong to the class of ill-posed problems.

The usage of a sensory driven FES system is a direct implementation of the synergistic control found in biology. This study follows our earlier work, which was dedicated to determine the timings and levels of muscle activities by using artificial neural networks (ANN) [2]. The study showed that machine learning (ML) predictions of timings and levels of muscle activations (outputs) when using the knee joint angle and ground reaction forces (inputs) are similar to the predicted activations when the hip, knee, and ankle joint angle and ground reaction forces were used as inputs. This finding imposed that we prove that by knowing one joint angle (e.g., the knee joint angle) other joint angles are determined for a given locomotor pattern. The ML technique used is a radial basis function (RBF) type of ANN [2,13]. RBF network with a supervised learning, that is, with orthogonal least squares (OLS) learning algorithm [13] is characterized by fast training, tuning and ability for good generalization [2,14]. The examples presented are for level walking.

2. RADIAL BASIS FUNCTION TYPE OF ARTIFICIAL NEURAL NETWORK

RBF neural network [2,13] is a feed-forward type of ANN. RBF network used here has a single output node and a single hidden layer which contains as many neurons as are required to fit the function within the specifications of error goal. The transformation from the input space to the hidden-unit space is nonlinear, whereas the transformation from the hidden-unit space to the output space is linear. The output of this network can be described by:

$$f(\omega)=\xi_0+\sum_{q=1}^{N}\xi_q\zeta(\| v-c_q \|)$$

where v is the input vector, N is the number of the hidden nodes, and $\zeta(\bullet)$ is the activation function (known as the radial basis function for a RBF network). Theoretical investigations and practical results show that the type of nonlinearity $\zeta(\bullet)$ is not crucial to the performance of RBF network [15], and it is usually taken to be bell-shaped function as in this case. The $\|\bullet\|$ denotes a norm that is usually taken to be Euclidean. The c_q are known as vectors of radial basis function centers, ξ_q and ξ_0 are the q-th weight and the bias for output linear node.

A common learning algorithm for RBF networks is based on first choosing randomly some data points as radial basis function centers and then using singular value decomposition to solve for the weights of the network. An arbitrary selection of centers may not satisfy the requirement that centers should suitably sample the input domain. Furthermore, in order to achieve a given performance, an unnecessarily large RBF network may be required. Since performance of an RBF network critically depends upon the chosen centers, we used an alternative learning procedure based on the OLS learning algorithm [13]. By providing a set of inputs and corresponding outputs, the values of weights ζ_q, bias ζ_0, and radial basis function centers (parameters for RBF network) can be determined using the OLS algorithm in one pass of the learning data so that a network of an adequate size can be constructed.

When an input vector v is presented to such a network, each neuron in the hidden layer will output a value according to how close the input vector is to the centers vector of each neuron. The result is that neurons with centers vector are very different from the input vector will have outputs near zero. These small outputs will have a negligible effect on the linear output neurons. In contrast, any neuron whose centers vector is very close to the input vector will output a value near 1. If a neuron has an output of 1, its output weights in the second layer pass their values to the neuron in the second layer. The width of an area in the input space to which each radial basis neuron responds can be set by defining a spread constant for each neuron. This constant should be big enough to enable neurons to respond strongly to overlapping regions of the input space. The same spread constant is usually selected for each neuron.

3. TASK FORMULATION AND PREPARATION OF DATA FOR MACHINE LEARNING

Examples presented in this paper illustrate the method for determining the synergies between the leg joint angles.

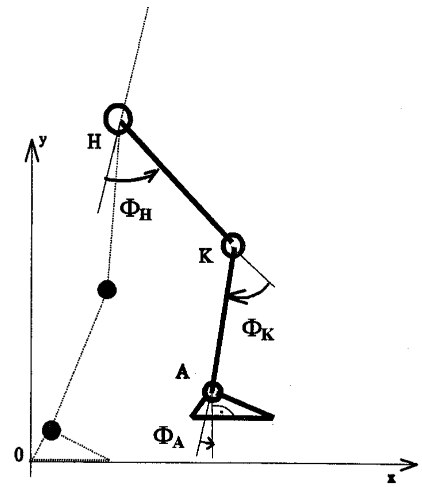

Figure 1: Model of a human body showing the ankle, knee and hip joint angles used for pattern matching

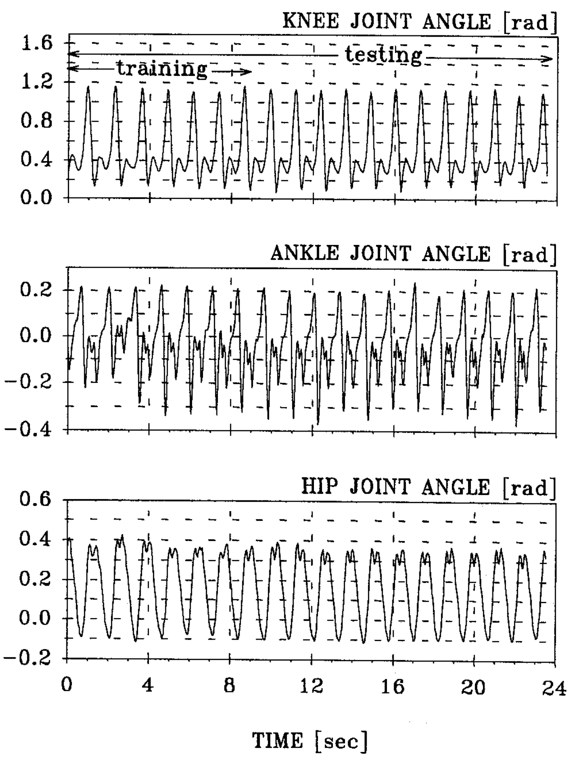

Figure 2: Data recorded during a level walking of an able-bodied human and used as input and output data for ML.

The results show that by measuring the knee joint angle it is possible to determine the ankle and hip joint angle using ML. Nineteen consecutive strides during level walking of an able-bodied human are included in the results, but the study analyzed synergies between those three angles for level walking with various velocities, and climbing up and down the stairs. The geometry that was analyzed, that is the ankle, knee and hip joint angles are shown in Fig. 1.

Fig. 2 shows the recorded data used for ML. The top panel shows the knee angle, the middle panel shows the ankle angle, and the bottom panel shows the angle at the hip joint. The sampling rate for all data was 100 per second. The input to the ANN was the knee joint angle, while the output was either the ankle or the hip joint angle. Since the determination of synergies by the ML was not good enough when using only one input signal, and because of a plausible future implementation for real-time control, the training set for ML was generated by using two data series: the knee joint angle data time shifted (preceding values) for 50 ms and for 100 ms. It was shown that those intervals allow sufficient time for turning on the stimulation, and for a muscle to contract [8].

During the training phase the number of the nodes and the parameters of the network were tuned using the OLS learning algorithm on the basis of the provided inputs and desired outputs of the system, called the examples in the supervised learning. The spread constant of the network was selected to secure as good as possible matching. For testing of the obtained network only inputs were provided, and the goal was to generate outputs. The quality of matching was evaluated by comparing the desired outputs with the estimated ones. The testing was done for two cases: 1) using data used for the training (the first seven strides), and 2) using data that was not used for training (the last twelve strides), being somewhat different from the one used for training.

The correlation can be graphically observed, but the cross-correlation between the desired outputs and the estimated outputs by the network was selected as a measure of the generalization.

4. RESULTS OF MACHINE LEARNING

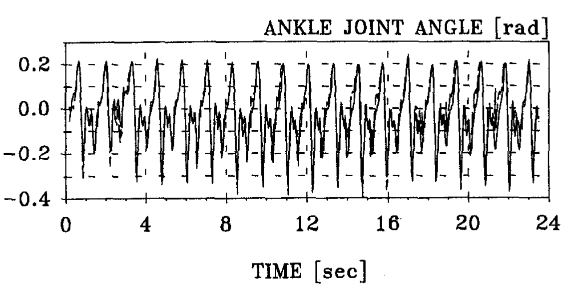

Figure 3: Matching of the desired (full line) and the estimated value of the ankle joint angle (dashed line) obtained by applying the RBF neural network with OLS learning algorithm.

The ML algorithm was implemented using MatLab 5.1 on a PC platform. Fig. 3 shows the results of the pattern matching between the desired and estimated ankle joint angles. The desired ankle joint angle (full line) is superimposed over the estimated angle (dashed line).

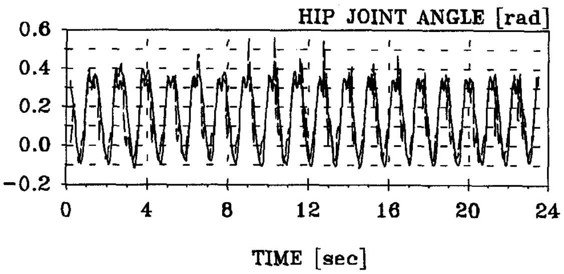

Figure 4: Matching of the desired (full line) and the estimated value of the hip joint angle (dashed line) obtained by applying the RBF neural network with OLS learning algorithm

The spread constant for this pattern matching was selected at 1.6, and the obtained network had 440 nodes in the hidden layer. The cross-correlation between the desired and the estimated value of ankle joint angle was 0.94.

Fig. 4 shows the results of pattern matching between the desired and the estimated hip joint angles. The desired hip joint angle (full line) is superimposed over and the estimated angle (dashed line).

The spread constant in this case was selected at 2, and the obtained network had also 440 nodes in the hidden layer. The cross-correlation between the desired and estimated value of hip joint angle was 0.95. The number of training epochs for pattern matching was one for both examples presented.

It is noticeable that the results of estimating the ankle joint angle are somewhat better than the results for estimating the hip joint angle. The results obtained are acceptable for the purpose of this study, because the step to step variability found in normal walking is comparable to the differences generated by the ML.

5. DISCUSSION

At present most clinically applied FES systems for restoration of locomotion use manually triggered open-loop control methods. Other FES systems use open-loop control based on the concept of "stored" sequences of muscle activation associated with the phases in the gait cycle. Regardless of the technology or control principle utilized, the achievements, including practicality, gait speed and endurance, efficiency etc. in spinal cord injured (SCI) patients are not substantially different. Having in mind that it is necessary to integrate machine control with biological control, and even more recent findings on the role of synergies RBC seems to be a promising control technique.

RBC is a sensory driven system; hence, the complexity of FES based rehabilitation device system rises with the incorporation of sensors mounted on the body. Minimizing the number of sensors is also desirable for other reasons such as: simplifying donning the system, tuning it for every day usage, minimizing the need for filtering out drifts and noise, etc. Since the walking is a process which may lead to dangerous situations (e.g., falling, overloading joints, non-physiological stresses, etc.) it is of great importance to use some redundant sensors to increase the reliability.

The ML technique for searching of a synergy between the ankle, knee and hip joint angles during cyclic, locomotor activity of an able-bodied human is described in this paper. The ML used is a RBF neural network with OLS learning algorithm because fast training and ability for good generalization characterize it. The tuning of this network is not too complicated because it requires only that the spread constant be chosen, while the remaining elements in the network are determined automatically. However, a large number of the rules, which are not explicit and not easily comprehensible, are obtained by using this type of ANN. Yet, there are methods that extract approximate rules from a trained ANN, thus helping in evaluating the knowledge [16].

We analyzed several types of cyclic activity: level and slope walking with various speeds, stairs climbing and descending, starting and stopping walking, standing up from a wheelchair and sitting down to a wheelchair that are not presented in this paper. The experiments included eight volunteer, able-bodied subjects. We found that a mapping found for one type of locomotor activity is applicable to other subjects, but in this case the correlation was about 80 percent. We found that each locomotor activity requires separate mapping. When analyzing level walking, the conclusion was that the same RBF ANN mapping is to be used if the difference in speed of progression is within 15 percent.

We found that the difference from day to day in the same subject is neglectable viewed from the point of sensory mapping. It became evident that the second sensor, positioned at the neighboring joint, can be used for detecting the mode of locomotion but the ANN with RBF were not the most suitable tool for this task.

By using this ML the existence of synergies between joint angles was affirmed. These synergies obtained in a form of rules can be used for control of FES-assisted human walking [4,9,17]. The importance of the findings presented here is the reduction of the number of sensors that are required, and increasing of error tolerance because of the potential malfunctioning of sensors.

REFERENCES

[1] N.A. Bernstein, *The co-ordination and regulation of movements*, Pergamon Press, Oxford, 1967.

[2] S. Jonić, T. Janković, V. Gajić and D.Popović, Three machine learning techniques for automatic determination of rules to control locomotion, *IEEE Trans. BME*, subm., 1997.

[3] D. Popović, R. Tomović, D. Tepavac and L. Schwirtlich, Control aspects of active above-knee prosthesis, *Intern. J. Man-Machine Studies*, vol. 35, pp. 751-767, 1991.

[4] R.B. Stein, P.H. Peckham and D.B. Popović (Eds.), *Neural Prostheses: Replacing motor function after disease or disability*, Oxford University Press, pp. 162-190, 1992.

[5] R. Tomović, D. Popović and R.B.Stein, *Nonanalytic Methods for Motor Control*, World Sci, Singapore, 1995.

[6] S.K. Ng and H.J. Chizeck, Fuzzy model identification for classification of gait events in paraplegics, *IEEE Trans on Fuzzy Systems*, Vol TFS-5, pp. 536-544, 1997.

[7] B.J. Andrews, R.W. Barnett, G.F. Phillips, C.A. Kirkwood, N. Donaldson, D. Rushton and T.A. Perkins, Rule-based control of a hybrid FES orthosis for assisting locomotion, *Automedica*, vol. 11, pp. 175-199, 1989.

[8] B.W. Heller, P.H. Veltink, N.J.M. Rijkhoff, W.L.C.Rutten and B.J. Andrews, Reconstructing muscle activation during normal walking: a comparison of symbolic and connectionist machine learning techniques, *Biolog. Cybern.*, vol. 69, pp. 327-335, 1993.

[9] A. Kostov, B. Andrews, D.Popović, R.B. Stein and W.W. Armstrong, Machine learning in control of functional electrical stimulation (FES) for locomotion, *IEEE Trans Biomed Eng*, Vol BME-42, 541-551, 1995.

[10] D. Popović, Finite state model of locomotion for functional electrical stimulation systems, *Progr. Brain Res.*, vol. 97, pp. 397-407, 1993.

[11] M.L. Latash, *Control of human movement*, Human Kinetics Publishers, 1993.

[12] A.G. Feldman, Once more on the equilibrium-point hypothesis (λ-model) for motor control, *J. Mot. Behav.*, No. 18, pp. 17-54, 1986.

[13] S. Chen, C.F.N. Cowan and P.M. Grant, Orthogonal least squares learning algorithm for radial basis function networks, *IEEE Trans. Neu. Net.*, NN-2, pp.302-309, 1991.

[14] S. Haykin, *Neural networks, a comprehensive foundation*, Macmillan Publ.Company, New York, 1993.

[15] M.J. Powell, Radial basis functions for multivariable interpolation: a review, in *Algorithms for Approximation*, J.C. Mason and M.G. Cox, Eds. Oxford, pp. 143-167, 1987.

[16] H. Narazaki, T. Watanabe and M. Yamamoto, Reorganizing knowledge in neural networks: an explanatory mechanism for neural networks in data classification problems, *IEEE Trans. Sys. Man and Cybern.*, SMC-26, pp. 107-117, 1996.

[17] Z. Nikolić and D. Popović, Control of locomotion: minimum entropy algorithm for capturing knowledge, *J Autom Control*, Vol. 6, pp 1-14, 1996.

ACKNOWLEDGMENT: The work on this project was partly funded by the grant from the Ministry of Science and Technology of Serbia, Belgrade, Yugoslavia.