

Simulating FES Gait: Radial Basis Function Networks vs. Neuro-Fuzzy Inference and Recurrent Neural Networks with Plant Wear Factors

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Abstract. Introduction: *Radial Basis Function Networks (RBFNs) and an Adaptive Network-Based Fuzzy Inference System (ANFIS) were used for simulating the neuromuscular system during FES-induced gait swing. These methods were compared to previous research with recurrent neural networks that included indexes related to muscle fatigue and reflex habituation. Real clinical data were used both for training and for evaluating the various models.*
Methods: *Two RBFN structures were developed for simulating FES-based gait. The simplest structure was to map frame by frame input-output relationships, while for the other structure each input-output vector pair included angular data from one entire gait swing cycle. The model's inputs were pulse width values applied to the common peroneal and femoral nerves, respectively, while the outputs were predicted knee and ankle flexion/extension angles. Also, two independent Sugeno-type ANFIS models were trained for making frame-by-frame predictions of knee and ankle angles, respectively.*
Results and Discussion: *The worst results were obtained with the RBFN structure based on gait cycle to gait cycle predictions (as opposed to a structure dealing with intra-cycle, frame by frame predictions). The results for both RBFNs were also significantly worse than for the previously studied recurrent networks with wear factors. Poor performance (both in training and in testing modes) was also obtained with the ANFIS model. These observations differ from those of other groups, which may stem from the fact that in this study real, noisy data were used both for training and for testing the various models. The superiority of the recurrent networks probably comes from their ability to map dynamic data structures. Thus, it is suggested that data representative of input delays be used with the RBFN and ANFIS structures in the future.*

Keywords – Radial basis function networks, Neuro-fuzzy inference, FES, human gait, recurrent neural networks.

1. Introduction

Simulation and control of FES-based gait must often be adaptive and include a model of the neuromuscular system's non-linear, time-varying, and

seemingly redundant characteristics. For control and simulation purposes, the models do not have to be descriptive of the systems internal elements. Thus, expanding on a previous effort [1][2], a simple approach is presented whereby Radial Basis Function Networks (RBFNs), and an Adaptive Network-Based Fuzzy Inference System (ANFIS) were used for simulating the neuromuscular system during FES-induced gait swing. These methods were compared to previous research with recurrent neural networks that included indexes related to muscle fatigue and reflex habituation. Real clinical data were used both for training and for evaluating the various techniques (obtained as described in [3]). A similar approach has been taken recently by another group [4], but the latter used data from a model to train and evaluate various networks.

This effort is a step towards a flexible platform based on machine-learning for simulated testing of FES regimes to restore locomotion. Further, the developed machine-learning structures can be easily incorporated into model-based control of FES for gait generation.

2. Methods

A. The RBFN Models

Two radial basis function network (RBFN) structures were developed for simulating FES-gait (Fig. 1). The RBFNs used Gaussian-Bar hidden layer transfer functions, which tend to work better with noisy data than regular Gaussian basis functions. Initially, learning was applied by increasing the size of the hidden layer based on the network's performance [5]. This procedure usually helps to reduce the RBFN dimensions and gives it better generalization properties. However, the observed generated networks always had the same size as a network with one RBF neuron for each training input, the so called exact-design network. Thus, exact RBFN design was used for the rest of the study as this approach always leads to the fastest training possible. As such, best results were found when the support for each RBF neuron was set at 0.1.

The simplest structure was to map frame by frame input-output relationships (Fig. 1a), while for the other structure each input-output vector pair included angular

data from one entire swing cycle (Figure 1b). The model's inputs were pulse width values applied to the common peroneal and femoral nerves, respectively, while the outputs were predicted knee and ankle flexion/extension angles. Data from 13 strides were used for training the models while data from another 16 strides (following the above 13) were used for testing. The input and output data were scaled to the (0,1) range for training and testing.

B. The ANFIS Model

Two independent Sugeno-type ANFIS models with linear output functions [6] were used for making frame-by-frame predictions of knee and ankle angles, respectively.

One separate ANFIS structure had to be used for predicting each of the two joint angles as the package used for the simulations allowed only single outputs (MatLab™ was used for the ANFIS simulations while C++ routines were written for the RBFNs and for the recurrent networks in [1] and [2]).

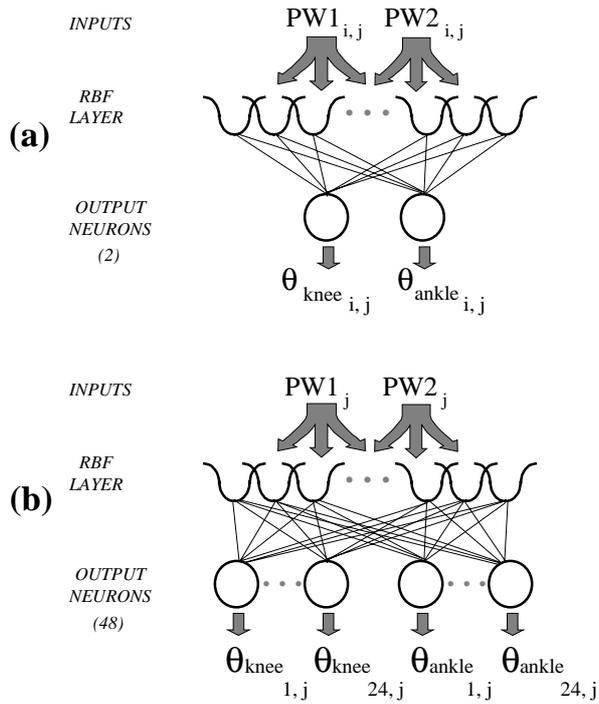


Figure 1 - RBFN structures used for modeling FES-induced gait swing trajectories based on stimulation pulse width (PW). **PW1**: PW applied to the common peroneal nerve. **PW2**: PW applied to the femoral nerve [3]. **i**: frame number within a gait cycle. **j**: gait cycle number. **(a)** Frame by frame, intra-cycle angle predictions. **(b)** Gait cycle to gait cycle angle predictions. Note the differences between (a) and (b) in the input indexes and in the number of output neurons.

The simplified ANFIS model structure is shown in Fig.2. Frame by frame pulse width values were used as inputs for both ANFIS structures. ANFIS 1 was

trained to yield knee angle predictions, while ANFIS 2 was trained to predict ankle angles. Training of the networks was done by applying the hybrid learning technique described in [6] along with a C-means clustering algorithm to minimize the model's size [7].

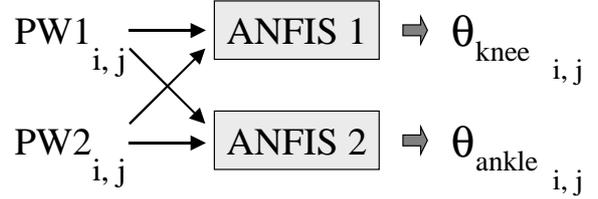


Figure 2 - ANFIS model structure for frame by frame prediction of joint angles. To setup the Gaussian membership function characteristics, a 1.25 squashing factor was used along with a 0.5 range of influence. See Fig. 1 for an explanation of the input and output indexes *i* and *j*.

3. Results and Discussion

The worst results were obtained with the RBFN structure based on gait cycle to gait cycle predictions, RBFN 1b (as opposed to a structure dealing with intra-cycle, frame by frame predictions, RBFN 1a). The results for both RBFNs were also significantly worse than for the previously studied recurrent networks with and without wear factors (RNN 2 and RNN 1, respectively) [1, 2].

Table 1 - Overall evaluation of the various models described here. **RBFN 1a**: frame by frame RBFN structure shown in Fig 1a. **RBFN 1b**: gait cycle to gait cycle RBFN shown in Fig 1b. **ANFIS**: combined results from the frame by frame ANFIS models 1 and 2 shown in Fig. 2. **RNN 1**: gait cycle to gait cycle, recursive network without wear factors. **RNN 2**: frame by frame recursive network with a wear factor analogous to neuroreflexive habituation. RNNs 1 and 2 were chosen for comparison as they yielded the best performance in [1] and [2]. **MCRC**: mean correlation coefficient between predicted and real trajectories. **MAE**: mean absolute error, *i.e.*, mean absolute difference between predictions and real data. **MTE**: mean training epochs to convergence (at a maximum absolute error of 0.050).

Model Type	MCRC	MAE	MTE
RBFN 1a	0.40	0.09	1
RBFN 1b	0.33	0.28	1
ANFIS**	0.48	0.09	**
RNN 1	0.79	0.07	91301
RNN 2	0.78	0.07	65650

** : The ANFIS model did not converge to the above maximum allowed error even after 10^5 training epochs (more than 30 hours in a dedicated 350MHz computer) at which point the maximum training error was at 0.27 for ANFIS 1 and 0.14 for ANFIS 2 (for all three training trials including initialization with synaptic weight randomization).

Poor performance, both in training and in testing modes, was also obtained with the ANFIS model. Model training was particularly long (see ** under Table 1).

The above observations differ drastically from those of other groups (*e.g.*, [4]), which may stem from the fact that in the present study real, noisy data were used both for training and for testing the various models. Also, portions of the training and test data contained pulse width saturation, a situation which may be encountered in a real control setting.

The poor ANFIS performance may also have resulted from the single-output, limited training approach taken, which was not the case for the RBFNs. However, in spite of the limited training in the ANFIS models, they were used for testing. This was done because ANFIS models are known to have good generalization properties even if poorly trained. Also (not shown in Table 1) the mean absolute error when training was stopped (at 10^5 epochs) was below 0.05 for both ANFIS 1 and 2, which is an acceptable mean error for most applications. However, the large difference between the maximum (see ** captions below Table 1) and the mean training errors results from using real, noisy clinical data, which illustrates why training and evaluation of a model based only on data from yet another model [4] does not allow for a realistic assessment of a system's capabilities.

Finally, the superiority of the recurrent networks in [1, 2] probably comes from their ability to map dynamic data structures. Thus, it is suggested that data representative of input delays be used with the RBFN and ANFIS structures in the future.

4. Conclusion

RBFNs, ANFISs, and recurrent networks were compared in an effort to produce a model for FES-induced gait swing. RBFNs were found to yield the worst predictions, especially when the chosen network structure's single output vector contained angular data for an entire gait cycle. Also, serious limitations were found in the ANFIS technique, at least as applied here.

It is suggested that data structures representative of input delays be used with the RBFN and ANFIS models in the future.

References

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