Possibilities of gait parameters prediction from EMG data by Neural Networks

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Abstract – The focus of this paper is to show the relationship of EMG data to other variables connected with gait as there are joint motion, force, velocity, and review of possibilities to model or predict gait parameters from EMG data with Artificial Neural Networks.

Keywords: Neural Networls, Gait parameters, EMG

1. INTRODUCTION

A long effort exists to investigate the relations between muscle activity EMG and other variables retrieved during gait analysis. We are not able to measure the all parameters in which physicians or biomechanists are interested, and in some cases we would like to predict some hardly measured data from gait parameters. That is why we would like to investigate relationship of EMG to other variables. Very powerful tool for this application are Artificial Neural Networks, which are useful tool for simulation of complicated nonlinear systems without mathematical describing.

2 HUMAN GAIT MODELS AND PARAMETERS

2.1 EMG and gait

When we study gait the main focus is on lower extremities, their muscle activities and representation by EMG. Simultaneous measurements of the muscle mechanics and the electromyographic activity make it possible quantitatively to describe the relation between neural input signals to the muscle and the mechanical output signal. The EMG signal is a direct reflection of muscle activity. Raw EMG activity increases as the firing rates of individual motor units rise and also as previously inactive units become recruited. Nevertheless, the relationship between EMG and muscle activation remains unclear.

2.2 Neural Networks

The major advantages of neural networks are that they have ability of adaptation and learning, they are fault tolerant, and they avoid establishing a complex mathematical model. Another important advantage is that the neural network could lump muscles together and reduce the number of variables.

Generally we can compare neural networks with flexible mathematical functions, which have many configurable parameters. To find the best solution for complicated representation of relation between gait variables and inertial parameters, those parameters have to be identify and set up by optimisation tools and learning algorithms. Input samples and particular required outputs enter the neural network that is in controlled learning process set up in such way that it represents majority of entering samples. Learning is completed when some criteria describing the error drops below a stated threshold level. When the neural network is after training, inertial parameters are adjusted, it can accept new inputs and try to predict outputs. A trained network evaluates the function and creates the output. The only premise in the process of the multi-layer feed forward neural network (with one hidden layer) is existence of a continuous function between input and output data. The feed forward neural network is common to use in gait analysis

2.3 Relationship of EMG to other variables

2.3.1 EMG and Joint motion

We can compare kinematics records to EMG plots to find out if join angular motion can explain EMG or EMG can explain angular motion. In study of this relationship we have to remember that there are examples of joint motion without EMG activity in the muscles. One example of joint motion occurring without concurrent muscle activity is seen when the knee flexes from 45% (heel off) to 62% (toe off) of the gait cycle, a motion that increases farther from toe off to 70% (early swing) of the gait cycle when the knee begins to extend. This knee flexion is not created by hamstring muscle activity because hamstring muscle activity does not begin until late swing when its onset slows the extending knee. Muscle function in gait is often one of control, with onset of eccentric activity for protection against motion occurring in the opposite direction. Muscle's role during gait according electromyographic study is often different from that described as its primary muscle action in anatomy texts.

2.3.2 EMG and Force

Amplitude of EMG signals derived during gait may also be interpreted as a measure of relative muscle tension. Data seem to support that the linear envelope of the EMG signal reflects the relative amount of muscle tension. It has been concluded that the relationship is influenced by technique and physiological factors. Reviews on the variety of factors influencing the EMG-force relationship have been published. Magnitude and intensity of the EMG signal is at least qualitatively related to the force produced by a muscle under given conditions. It is well accepted in scientists community. The exact EMG- force relationship has been topic of scientific debate. The difficulties of relating EMG to the corresponding force signals are associated with highly non-linear and time-variable relation between these signals, and the difficulty to measure EMG consistently and repeatable and to measure muscle forces in vivo at all.

2.3.3 EMG and Velocity

It is known that increased velocity prolongates the period of muscle activity by leading to activity that starts earlier or lasts longer. It was found out that values recorded from indwelling electrodes in six subjects were dependent on walking speed for the vastus lateralis, biceps femoris, and lateral gastrocnemius muscles, but not the tibialis anterior muscle. The general trend is that increase of EMG amplitude increase also walking speed. The subjects showed a minimum of EMG activity in the muscles studied while walking at their comfortable speed in general. Subjects naturally selected a walking velocity associated with a minimum of muscular activity. The imposition of an unnatural velocity has been shown to decrease the repeatability of the EMG signal.

2.4 Modelling and Prediction - Artificial Neural Networks approach

The possibility of nonlinear presentation by neural network leads to the mapping of difficult defined relationship between EMG and kinematics and kinetics parameters. With the focus on correlation between muscle activity and dynamics of lower extremity were created different neural networks. They differ in used input data, number of hidden layers, training data and other adjustable parameters. The standard feedforward neural networks for representation of mutual effect of this relationship were used in some works.

The neural network with one hidden layer was used for reconstruction of semitendinosus and vastus medialis muscels activity on the base of kinematics data. Used kinematics inputs were from hip and knee joint angels, angular velocities, angular accelerations and from integrated data under the sole. All those parameters were collected during normal and fast walk. Data were collected from one healthy subject. The synchronization and amplitude of reconstructed signal were exact and comparable with those predicted by traditional explicit model of bone-muscle models. There are two advantages of inductive biomechanical models realised by neural networks compared to bone-muscle models: simple neural network can model the activation of several muscles, and it isn't time delay at generation EMG. There are also some disadvantages in inductive biomechanical models: the inductive models are effective only in range of motion represented by training data set, (this first disadvantage can be eliminated by sufficient data training set and feature of neural networks to generalize data without previous training) and inductive models doesn't present biomechanical view on motion system, because the equations do not represent the structure of biomechanical system.

For modelling of correlation between EMG and joint characteristics were created neural network with two hidden layers. As training set data were used data from Winter table together with EMG from 16 muscles, moments and angels for hip, knee and ankle joints. The neural network input consisted from 16 normalised EMG values. The training set data were sampling from gait cycle for twenty equally divided intervals. One network was created for modelling of relation between EMG and joint moments, the second network was created for modelling of correlation of EMG and joint angels. These models were tested by noised EMG signals (± 20 % stochastic noise and amplitude offset). The result divergence was less than 7% for output angles and moments The authors also simulated concrete musle elimination and the model outputs correlated with physiological fundamentals.

The neural network for model of shape function to generate samples of human movement is another example. Using two sinusoidal inputs with the same rate as the rate of steps, that network was able to produce representation of EMG amplitudes and time parameters of eight muscles of the lower extremities at different gait velocities during 12 steps period. Errors of prediction measured as a % proportion from the working range of the output. Authors demonstrated abilities of simultaneous modelling of activations for muscle groups in such kind of applications like FES (Functional Electrical Stimulation) using simple networks a simple time parameter for step speed.

Some examples of neural networks applications are in the table.

Inputs	Outputs	Network type
Hip and knee angle, angle velocity and acceleration, integrated contact of foot	Envelop EMG for semitendinosus a vastus medialis	Feed-forward with one hidden layer
EMG fro 16 muscles of the right leg	Angles and torques for hip, knee joint and ankle	Two feed-forward networks with one hidden layer
Two sinusoidal signals of gait rate	EMG envelopes of 8 muscles of the lower leg	Feed-forward with one hidden layer
Rectified EMG signal	Forces	ANN with two hidden layers
Rectified EMG signal, five ankle angels, angular velocities	Forces	ANN with two hidden layers

3 CONCLUSION

The results of this study indicates that ANNs can predict the highly nonlinear relation between different kinematic and kinetics data and EMG and ANN are able generalize this relations. So excellent prediction of kinematic and kinetics data based on EMG input could be made without musculosceletal modelling. On the other hand ANNs approach can not provide insight into the physiological relation between EMG and other variables, but it is useful tool for prediction kinetic and kinematics data from EMG. We work now on an Artificial Neural Network model for prediction of EMG data from kinematic and kinetic data obtaining from human gait analysis using video capturing system.

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