근전도를 이용한 근력 추정에 있어서 SVM 과 ANN의 성능 비교 평가

A Comparison of the ANN & SVM in prediction of muscle forces from EMG

Key words: ANN, SVM, Electromyography, Muscle force

1. Introduction

It is very important and is a methodologically interesting subject to determine muscle force generated by muscle in a dynamic state. The determination of muscle force of each muscle in the area of biomechanics essentially requires the accurate interpretation of kinetic mechanism. In addition, accurate prediction of internal muscle force is required in research on hightech assist equipment adopting biomechatronics in the area of silver and rehabilitation engineering.

The prediction of muscle force has usually used direct muscle force measuring and electromyogram-based estimation. First, the method of direct muscle force measuring measured tensile force generated in muscles using an implanted sensor. The method was researched by Herzog et al. and Xu et al. and is applied to animals and the human body. On the other hand, Guimaraes et al.³ tried to predict muscle force by defining the relationship between directly measured muscle force signals and electromyogram. The prediction of muscle force based on electromyogram can replace invasive muscle force measuring, and can be used effectively in areas such as rehabilitation engineering. However, the relationship between muscle force and electromyogram in a dynamic state is quite nonlinear and time-dependent. In addition, various elements including the condition of the subject and the type of exercise cause large differences.

Developing previous researches Herzog et al. Xu et al. 2 Guimaraes et al.3, recent researches predicted the relationship between electromyogram and muscle force using TDNN (Time Delayed Neural Network) in consideration of the temporal history of electromyogram. However, ANN has to expect a good result with an arbitrarily chosen number of hidden layers. That is, because optimized learning is not available, it is time-consuming and the result may be inaccurate. In order to solve the problems, this research used an intelligent learning method using SVC (Support Vector Classification) derived form SVM. SVC learning method is a kind of artificial neural network that is commonly used in computer science for data mining, image/voice recognition, etc.

On the other hand, an important task that must precede the prediction of muscle force is electromyogram signal processing. If the amplitude of electromyogram varies dynamically different from static states, existing filters of fixed length cause amplitude errors, which lower the performance of muscle force prediction. Thus, the present implemented a soft filter using moving average and SVR (function approximation). Amplitude data obtained through filtering EMG raw data were used as training input data of SVM.

2. SVM and ANN

SVMs can also be applied to regression problems by the introduction of an alternative loss function, (Smola, 1996). The loss function must be modified to include a distance measure. The loss function corresponds to the conventional least squares error criterion. The Laplacian loss function that is less sensitive to outliers than the quadratic loss function. Huber proposed the loss function as a robust loss function that has optimal properties when the underlying Linear Regression. Consider the problem of approximating the set of data,

$$D = \{(x^1, y^1), \dots, (x^l, y^l)\}, x \in \mathbb{R}^n, y \in \mathbb{R}, \text{ with a linear function,}$$

$$f(x) = \langle w, x \rangle + b.$$
 (2)

the optimal regression function is given by the minimum of the functional,

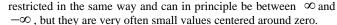
$$\Phi(w,\xi) = \frac{1}{2} \|w\|^2 + c \sum_{i} (\xi_i^- + \xi_i^+)$$
(3)

where C is a pre-specified value, and ξ^- , ξ^+ are slack liables representing ξ^- . variables representing upper and lower constraints on the outputs of the system. The human brain is a highly complicated machine capable of solving very complex problems. Although we have a good understanding of some of the basic operations that drive the brain, we are still far from understanding everything there is to know about the brain. A single artificial neuron can be implemented in many different ways. The general mathematic definition is as showed in equation (4).

$$y(x) = g\left(\sum_{i=0}^{n} w_i x_i\right) \tag{4}$$

 \boldsymbol{x} is a neuron with \boldsymbol{n} input dendrites $(\boldsymbol{x}_0 \ \dots \ \boldsymbol{x}_n)$ and one

output axon v(x) and where are weights determining how much the inputs should be weighted. g is an activation function that weights how powerful the output (if any) should be from the neuron, based on the sum of the input. If the artificial neuron should mimic a real neuron, the activation function g should be a simple threshold function returning 0 or 1. This is however, not the way artificial neurons are usually implemented. For many different reasons it is smarter to have a smooth (preferably differentiable) activation function. The output from the activation function is either between 0 and 1, or between -1 and 1, depending on which activation function is used. This is not entirely true, since e.g. the identity function, which is also sometimes used as activation function, does not have these limitations, but most other activation



functions use these limitations. The inputs and the weights are not

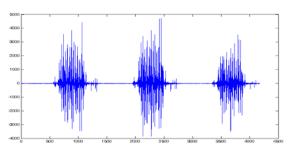


Fig. 1 Raw EMG

Fig. 2 Muscle force data

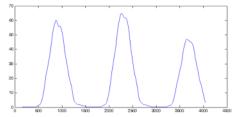


Fig. 3 Moving average data of EMG

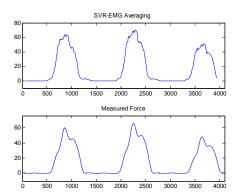


Fig. 4 Force (Down) & EMG Prediction (Up)

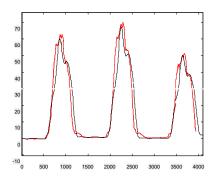


Fig. 5 Force (Solid line) & SVM EMG Prediction (Dotted line)

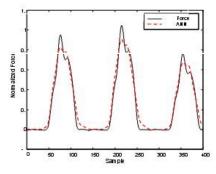


Fig. 6 Force (Solid line) & ANN EMG Prediction (Dotted line)

Table 1 SVM & ANN Correct Comparison

Correct (%)	SVM	ANN
Signal 1	82.21 ± 0.85	77.85 ± 0.54
Signal 2	83.02 ± 0.09	76.78 ± 0.27
Signal 3	83.07 ± 0.07	79.45 ± 0.65

3. Result

data used as training input data were obtained from a dog's calf muscle(Fig. 1). The laboratory animal exercised in a treadmill at a speed of 0.8m/s. The muscle force of calf muscle was measured from the tensile force of the muscle using an implantable sensor (Fig. 2), and electromyogram signal was measured through surface electrode at a limited bandwidth of 10-600Hz. Both of the two signals were obtained at sampling frequency of 1200Hz simultaneously. Measured raw EMG data were processed with the soft filter mentioned earlier in order to consider only amplitude. The result of regression by applying SVR as in Fig. 3 was used as the training input data of SVM. The result Fig. 5, 6 are prediction result and real data force. Fig. 4 separate EMG Moving-averaging (up) and Force (down) data. It can't know well that they are how much the same. So Fig. 5 is potted the same window. Fig. 5 is solid line is real date as Force and dotted line is result data SVM of EMG. Fig. 6 is solid line is real date as Force and dotted line is result data ANN of EMG. We can not know well which is better than another. Table 1 show that SVM prediction is better than ANN prediction. The errors are both SVM and ANN similar. The Correct percent is real data subtraction to result data. Y axe is predicted and X axe is Actual. SVM training resulted in models showing slightly higher prediction accuracy than the ANN systems (Table 1).

4. Conclusion

There can be several methods of predicting the relationship between EMG and muscle force. However, it is not easy to find a method of optimized processing time and prediction capability. When patients go through rehab, nobody knows how much patients better than before. Then we use EMG, we can know their rehabilitation state from Muscle force prediction data. The present study predicted the relationship between EMG and muscle force by applying SVM and ANN, which is spotlighted in the area of intelligent learning. The result of learning shows that the peaks and the patterns of muscle force were predicted successfully. SVM training resulted in models showing slightly higher prediction accuracy than the ANN systems.

In conclusion, we can say that SVM prediction is better than ANN prediction. In order to obtain better results of learning and prediction, it needs the experiences of many times do over again.

REFERENCES

- Herzog, A. Stano, and T.R.Leonard, "Telemetry system to record force and EMG from cat ankle extensor and tibialis anterior muscles," J.Biomechanics, Vol.26, NO.12, pp. 1463-1471,1993.
- W. S. Xu, D. L. Butler, D. C. Stouffer, E. S. Grood, and D. L. Glos, "Theoretical analysis of an implantable force transducer for tendon and ligament structures," Journal of Biomechanical Engineering, Vol. 114, pp. 170-177, 1992
- A.C.Guimaraes, W.Herzog, T.L.Allinger, and Y. T. Zang, "The EMG-force relationship of the cat soleus muscle and its association with contractile conditions during locomotion," Journal of Experimental Biology Vol.198, pp. 975 – 987, 1995.
- 4. V. N. Vapnik and A. Y. Chervonenkis, Theory of Pattern Recognition (in Russian). Moscow, Russia: Nauka, 1974.
- J. Schürmann, Pattern Classification: A Unified View of Statistical and Neural Approaches. New York: Wiley, 1996.
- O. L. Mangasarian and D. R. Musicant, "Lagrangian support vector machines," J. Machine Learning Res., 2000, to be published.
- B. Schölkopf, A. Smola, R. C. Williamson, and P. L. Bartlett, "New support vector algorithms," Neural Comput., vol. 12, pp. 1207–1245, 2000.
- 8. C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," Knowledge Discovery and Data Mining, vol. 2, no. 2, pp. 121–167, 1998.
- A. Smola and B. Schölkopf, "A tutorial on support vector regression," Statistics and Computing, 2001.