Proceedings of the IEEE International Conference on Robotics and Automation, Albuquerque, New Mexico, 20-25 April 1997.

Augmenting the human-machine interface: improving manual accuracy

Cameron N. Riviere and Pradeep K. Khosla

The Robotics Institute
Carnegie Mellon University
Pittsburgh PA 15213 USA

Abstract

We present a novel application of a neural network to augment manual precision by canceling involuntary motion. This method may be applied in microsurgery, using either a telerobotic approach or active compensation in a handheld instrument. A feedforward neural network is trained to input the measured trajectory of a handheld tool tip and output the intended trajectory. Use of the neural network decreases rms error in recordings from four subjects by an average of 43.9%.

1 Introduction

Various error components are inherent in human hand motion. Involuntary hand motion hampers microsurgery, particularly in the ophthalmological field [1]. Suppression of involuntary movement would improve microsurgical practice and enable manipulation of smaller tissue sites [2]. The two approaches available for this application are teleoperation and active noise control. In the teleoperative scenario, the human operates a master interface. Input signals from this master are processed to drive a slave manipulator, which performs the surgery. If error can somehow be distinguished from intended motion, it can be removed from the drive signal sent to the slave. Telerobotic microsurgical systems currently under development include those of Hunter *et al*. [3] and Schenker *et al*. [1]. In the active noise control approach, actuation is built into the handheld surgical instrument to perform error compensation, as in the development work of Bose *et al*. [4] and the experimental investigations of Riviere *et al*. [5]. In both cases, error must be distinguished from intended motion before error canceling can occur. This requires real-time error estimation.

The most frequently discussed component of involuntary motion is tremor. Tremor is any involuntary, roughly sinusoidal movement [6]. Though pathological tremor due to disease is more widely known, there is inherent in all human hand motion a small component known as *physiological* tremor. Physiological tremor contains both a component dependent on limb mechanical properties, and a neurogenic component that is roughly 8-12 Hz regardless of limb inertia. Its detrimental effect on microsurgery has been known for many years [2, 7]. Several techniques have been developed for tremor suppression, though most have focused on pathological tremor. Riley and Rosen [8], among others, have investigated lowpass filtering. Gonzalez *et al*. [9] proposed an equalizer to suppress pathological tremor. Riviere *et al.* [5] developed an adaptive filter to cancel physiological tremor during surgery, using an artificial frequency-modulated sinusoid as a reference. However, other significant sources of error, including jerk [1] and drift, or low-frequency error [10], have yet to be substantially suppressed. Since little is known about these components, and since reference signals, e.g., for adaptive noise canceling, are unavailable, suppression is difficult.

Neural networks model nonlinear processes well, and much research in nonlinear control has focused on their use [11]. Though little is known about the mapping from sensory input to human control output, it is known to be nonlinear [12]. Neural networks have therefore recently seen use in modeling of human control strategies [13, 14]. No explicit system model is available, but none is required, since neural networks learn their own mappings by observing input and output.

The multiplicity of involuntary hand motion components, and the paucity of knowledge about components such as drift [10], make a neural network approach well suited also to modeling of human movement error processes. Since unnecessary complexity can increase modeling error, it is desirable to use the simplest feasible neural network for a given task. This makes constructive methods ideal. The cascade learning architecture is one such method [15]. Nechyba and Xu [14] have observed that since the cascade architecture allows automatic selection not only of parameters within a model but also of the model functional form itself, it is ideal for modeling of human control strategies, with their unknown underlying structure. Much the same may be said of the motion error processes that accompany these human systems. We therefore present a study of the use of a cascade neural network for noise canceling in human hand motion.

Though the experiments presented here focus on surgery, the concepts demonstrated are directly relevant to a wide range of applications, including piloting of aircraft, human-guided weapon delivery systems, and manipulation and assembly of small parts and devices.

2 Neural network technique

The cascade learning architecture is a constructive neural network algorithm [15]. The basic cascade network structure is presented in Fig. 1. When training begins, the network has no hidden nodes, only linear connections between input and output nodes. During training, each time the error performance stagnates, according to a predetermined threshold, a new hidden node is added, subject to a preset maximum number of hidden nodes. As each new hidden node is generated, multiple parallel transfer functions are temporarily implemented, including sigmoids, sinusoids, and Bessel functions, and their performance is monitored in order to select one for permanent use. Each hidden node has connections with each previous hidden node, and with all input and output nodes. The total number of connections is [14]:

$n_c = n_i n_o + n_h(n_i + n_o) + (n_h - 1)n_h/2.$

The number of input and output nodes and the maximum allowable number of hidden nodes are fixed before training begins. The neural network used for this experiment had one output node, ten hidden nodes, and 100 input nodes in a tapped delay line configuration, with 250 Hz sampling.

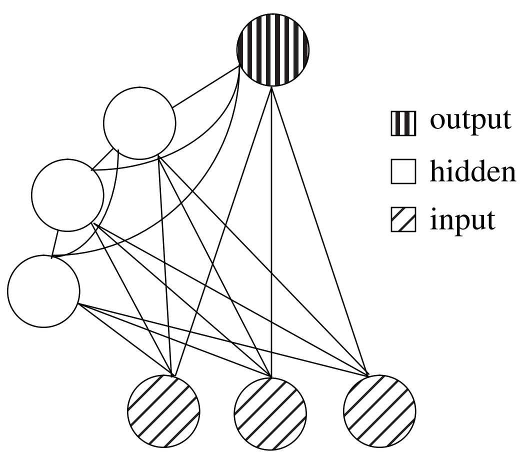

Figure 1: Diagram of the cascade neural network architecture. The diagram shows a network with three hidden nodes. As each hidden node is added, it is connected to the input and output nodes, as well as each of the preceding hidden nodes. The transfer function of each hidden node is determined by temporary competition among a set of candidate functions, such as sigmoid, sinusoidal, and Bessel functions.

Extended Kalman filtering (EKF) was used for learning in the neural network. EKF is an extension of the familiar Kalman filter [16] to deal with nonlinear systems via linearization about the current parameter estimates [17]. When EKF is used to train a neural network, learning is viewed as an identification problem for a nonlinear dynamic system [17]. The neural network weights represent the state of the nonlinear system. The EKF theory is then used to derive a recursion for the weight updates [17]. This method offers greatly improved convergence results over backpropagation, but the computational load is considerable. The variation of EKF used here is the node-decoupled EKF (NDEKF) of Puskorius and Feldkamp [18], who demonstrated that the network weights can be grouped such that for each group, elements of the error covariance matrix estimate corresponding to different groups can be ignored. This allows weights to be grouped and trained by node, greatly reducing the computational complexity. Full details regarding the algorithm may be found in [18].

3 Experimental methods

Recordings of the hand motion of ophthalmologic surgeons [19] were made available by Prof. R. S. Rader of The Johns Hopkins University. Each surgeon held a microsurgical instrument with the tip inserted in a sclerotomy in the eye of a mannequin face. A Hall effect sensor mounted inside the mannequin eye detected the position, in one dimension, of a 0.26 g permanent magnet mounted on the tip of the instrument. Data were recorded for 16 s. The original sampling frequency of 1 kHz was downsampled to 250 Hz for this study. A total of 15 files were obtained from four surgeons (5, 5, 3, and 2 files, respectively). The surgeons attempted to hold the instrument motionless for the duration of each test, therefore any motion in these recordings is considered to be error.

To evaluate the ability of the cascade neural network to perform error canceling with these data, pseudo-voluntary motions were generated, to be added to the recorded error data. Gaussian white noise sequences were generated and then lowpass filtered with a 1 Hz cutoff frequency, using a sixth-order Butterworth filter. Two such data sets were created, one for neural network training and one for testing. The training pseudo-voluntary motion was added to one file from each surgeon, and the testing pseudo-voluntary motion to each of the remaining files.

Separate neural networks were used for each of the four surgeons. For each surgeon, a cascade-architecture neural network, using extended Kalman filtering for learning, was trained using the training data file described above. The remaining data files from each surgeon were used for testing of the trained network. The root-mean-square error (rmse) with respect to the pseudo-voluntary motion was calculated for each file, both before and after processing by the neural network.

The cascade network trained for each surgeon was also tested a second time on the same data but with zero pseudo-voluntary motion. This was done to provide an indication of network performance during extremely slow voluntary motions, such as are common during microsurgery.

4 Results

The neural network decreased the rmse with respect to the pseudo-voluntary motion for all the testing data files. The average raw rmse of the testing data files was 0.076 mm. Table 1 presents the raw rmse for the files of each surgeon.

Table 1: Testing data files

Surgeon	*No. of testing files*	*Average raw rmse (mm)*
1	4	.112
2	4	.046
3	2	.048
4	1	.127

Table 2: Reduction in rmse

Surgeon	*mean (mm)*	*std. dev. (mm)*
1	.053	.013
2	.020	.005
3	.015	.005
4	.066	-

Table 3: Percent reduction in rmse

Surgeon	*mean (%)*	*std. dev. (%)*
1	48.5	2.8
2	42.9	3.6
3	32.8	4.8
4	51.6	-

Error canceling via cascade neural network decreased the rmse of the testing data files by the mean amounts shown in Table 2. Since surgeon 4 had only one testing file, no standard deviation was calculated. Table 3 displays the mean percentage reductions in rmse, where the rmse reduction for each test file is taken as a percentage of the raw rmse for that file. The average rmse after error canceling of all testing files was 0.041 mm.

Figure 2 displays a sample test result. The solid line shows the pseudo-voluntary motion. The dashed line shows the sum of the pseudo-voluntary and recorded hand motion error files. This represents the input to the trained neural network. The neural network output, estimating the human error component, is subtracted from the input signal to obtain the filtered output, shown by the dotted line. The filtered output is visibly closer than the raw input to the pseudo-voluntary motion.

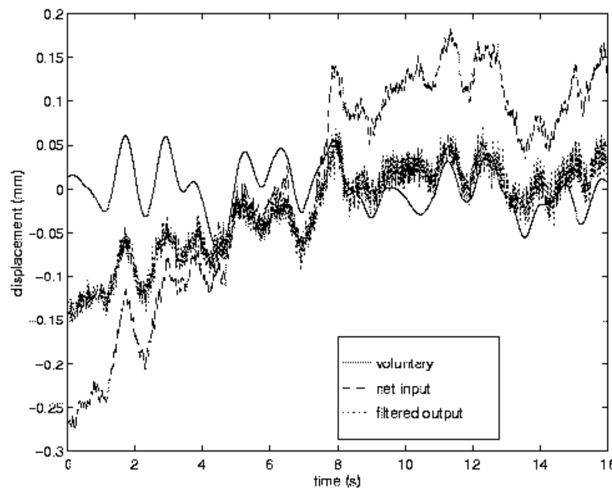

Figure 2: Results from one testing data file. The solid line shows the pseudo-voluntary motion, generated by lowpass filtering white noise at 1 Hz cutoff frequency. The dashed line represents the network input for the test, obtained by adding one of the recorded hand motion error files to the pseudo-voluntary motion. The dotted line indicates the filtered version of the data. The network estimates the human error component from the input data, and this is subtracted from the network input signal to obtain the filtered signal.

Table 4: Reduction in rmse, zero voluntary motion

Surgeon	*mean (mm)*	*std. dev. (mm)*
1	.053	.013
2	.020	.005
3	.010	0
4	.069	-

The neural network also decreased the rmse of the raw error testing files, i.e., the testing data with no pseudo-voluntary motion added, as shown in Table 4. Table 5 presents the mean percentage reductions in rmse for each surgeon in this zero-voluntary-motion case. The rmse reduction for each test file is taken as a percentage of the raw rmse for that file. The average rmse of all testing files after filtering in the zero-voluntary case was 0.043 mm.

Table 5: Percent reduction in rmse, zero voluntary motion

Surgeon	*mean (%)*	*std. dev. (%)*
1	48.7	1.3
2	48.6	9.3
3	21.3	3.2
4	54.0	-

5 Discussion

The results show the feasibility of the basic approach of neural network error canceling in human-machine control. The results in Tables 4 and 5, for the case of zero voluntary motion, demonstrate that the method used to train the cascade neural network is also effective in the commonly encountered situation of very slow voluntary motion. Performance in this case would likely improve with additional training of the network on a wider variety of input data. Further study of the nature of voluntary motion is warranted in order to determine the best way to represent it for the purpose of training the neural network.

Among the strengths of this method is its generality. It is not limited as to the type or number of error sources (tremor, low-frequency error, etc.) it can cancel. One of its primary drawbacks is that it is not adaptive, i.e., training must be done off-line. How much this detracts from the practicality of the approach remains to be seen. One-time training for permanent use may be feasible, if subjects' error patterns are found to be stationary. A more likely option is retraining the network for a short duration at regular intervals, e.g., monthly, using new data recorded from the user.

Recent studies of physiological tremor have characterized it as a linear stochastic process [20]. Long-term canceling of tremor based on one-time training of a neural network may therefore still be possible, as opposed to indefinite canceling of, say, a nonlinear deterministic process, which would clearly be infeasible due to the inevitable estimation error in training and the propensity for initially close trajectories to diverge [21]. Further study of other components of hand motion error, such as jerk and low-frequency error, is needed in order to better characterize these entities and determine whether long-term canceling based on one-time training is realistic.

As trained in this experiment, the neural network generated a certain amount of high-frequency noise, in the vicinity of 10 Hz. This is visible in the filtered output results in Fig. 2. This noise created a lower bound on rmse, limiting the attainable performance. All files used in these experiments had a raw rmse of greater than 0.025 mm. The system was also tested on several files with raw rmse of 0.025 mm or less, and in each case the final rmse was greater than the initial, owing to this high-frequency noise. Improving this behavior of the trained network is an aim of ongoing research.

Another option for error canceling is the development of a hybrid system combining of the neural network with the weighted-frequency Fourier linear combiner (WFLC) of Riviere and Thakor [22]. The WFLC is an adaptive filter designed for suppression of physiological tremor during microsurgery. It successfully cancels tremor, but by its nature does not account for lower-frequency components of error. A hybrid system potentially could suppress tremor using the WFLC, and other, mostly lower-frequency, components of error using a cascade neural network as presented here. Such a hybrid would likely be capable of a degree of surgical accuracy unattainable by either system operating alone.

6 Conclusion

The feasibility of hand motion error canceling using a cascade neural network trained via EKF has been demonstrated. Using a small training data set, the network learns to discriminate between error and other components in human hand motion. Position accuracy in microsurgery can be improved by the incorporation of such a technique. The method presented may be implemented either for signal filtering within a telerobotic microsurgical system or for active noise control with an active handheld surgical instrument.

Acknowledgments

Thanks to R. S. Rader for providing data and Y. Xu and M. Nechyba for software.

This paper is a corrected version. The results in the published version were in inches, but were erroneously labeled as mm.

References

[1] P. S. Schenker, E. C. Barlow, C. D. Boswell, H. Das, S. Lee, T. R. Ohm, E. D. Paljug, G. Rodriguez, and S. T. Charles, "Development of a telemanipulator for dexterity enhanced microsurgery," *Proc. 2nd Intl. Symp. Med. Robot. Comput. Assist. Surg.*, pp. 81-88, 1995.

[2] M. Patkin, “Ergonomics applied to the practice of microsurgery,” *Aust. N. Z. J. Surg.*, vol. 47, pp. 320-329, June 1977.

[3] I. W. Hunter, T. D. Tilemachos, S. R. Lafontaine, P. G. Charette, L. A. Jones, M. A. Sagar, G. D. Mallinson, and P. J. Hunter, “A teleoperated microsurgical robot and associated virtual environment for eye surgery,” *Presence*, vol. 2, pp. 265-280, Fall 1993.

[4] B. Bose, A. K. Kalra, S. Thukral, A. Sood, S. K. Guha, and S. Anand, “Tremor compensation for robotics assisted microsurgery,” *Proc. 14th Intl. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 3, pp. 1067-1068, 1992.

[5] C. N. Riviere, R. S. Rader, and N. V. Thakor, “Adaptive real-time canceling of physiological tremor for microsurgery,” *Proc. 2nd Intl. Symp. Med. Robot. Comput. Assist. Surg.*, pp. 89-96, 1995.

[6] R. J. Elble, W. C. Koller, *Tremor.* Baltimore: Johns Hopkins University Press, 1990.

[7] R. C. Harwell and R. L. Ferguson, “Physiologic tremor and microsurgery,” *Microsurg.*, vol. 4, pp. 187-192, 1983.

[8] P. O. Riley and M. Rosen, “Evaluating manual control devices for those with tremor disability,” *J. Rehabil. Res. Dev.*, vol. 24, pp. 99-110, 1987.

[9] J. G. Gonzalez, E. A. Heredia, T. Rahman, K. E. Barner, S. K. Basu, and G. R. Arce, “A new approach to suppressing abnormal tremor through signal equalization,” *Proc. RESNA Annu. Conf.*, pp. 707-709, 1995.

[10] C. N. Riviere and P. K. Khosla, “Accuracy in positioning of handheld instruments,” *Proc. 18th Annu. Conf. IEEE Eng. Med. Biol. Soc.*, 1996.

[11] K. J. Hunt, D. Sbarbaro, R. Zbikowski, P. J. Gawthrop, “Neural networks for control systems--a survey,” *Automatica*, vol. 28, pp. 1083-1112, November 1992.

[12] C. R. Kelley, “The measurement of tracking proficiency,” *Hum. Factors*, vol. 11, pp. 43-64, 1969.

[13] H. Asada and S. Liu, “Transfer of human skills to neural net robot controllers,” *Proc. IEEE Intl. Conf. Robot. Autom.*, vol. 3, pp. 2442-2447, 1991.

[14] M. Nechyba, and Y. Xu, “Human skill transfer: neural networks as learners and teachers,” *Proc. IEEE Intl. Conf. Intell. Robots Syst.*, vol. 3, pp. 314-319, 1995.

[15] S. E. Fahlman and C. Lebiere, “The cascade-correlation learning algorithm,” in D. S. Touretzky, ed., *Advances in Neural Information Processing Systems 2*, Los Altos, Ca.: Morgan Kauffman, pp. 524-532, 1990.

[16] R. E. Kalman, “A new approach to linear filtering and prediction problems,” *J. Basic Eng.*, vol. 82, pp. 35-45, 1960.

[17] S. Singhal and L. Wu, “Training multilayer perceptrons with the extended Kalman algorithm,” in D. S. Touretzky, ed., Advances in Neural Information Processing Systems 1, Los Altos, Ca.: Morgan Kauffman, pp. 133-140, 1989.

[18] G. V. Puskorius and L. A. Feldkamp, “Decoupled extended Kalman filter training of feedforward layered networks,” Proc. Intl. Joint Conf. Neural Networks, vol. 1, pp. 771-777, 1991.

[19] R. S. Rader, A. C. Walsh, C. C. Awh, and E. de Juan, Jr., “MADSAM: the objective evaluation of microsurgical tools and techniques,” to be submitted, 1997.

[20] C. Gantert, J. Honerkamp, and J. Timmer, “Analyzing the dynamics of hand tremor time series,” *Biol. Cybern.*, vol. 66, pp. 479-484, 1992.

[21] J. B. Elsner, “Predicting time series using a neural network as a method of distinguishing chaos from noise,” *J. Phys. A: Math. Gen.*, vol. 25, pp. 843-850, 1992.

[22] C. N. Riviere and N. V. Thakor, “Modeling and canceling tremor in human-machine interfaces,” *IEEE Eng. Med. Biol. Mag.*, vol. 15(3), pp. 29-36, 1996.