NEURAL NETWORK METHODS FOR ERROR CANCELING IN HUMAN-MACHINE MANIPULATION

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Abstract – **A neural network technique is employed to cancel hand motion error during microsurgery. A cascade-correlation neural network trained via extended Kalman filtering was tested on 15 recordings of hand movement collected from 4 surgeons. The neural network was trained to output the surgeon's desired motion, suppressing erroneous components. In experiments this technique reduced the root mean square error (rmse) of the erroneous motion by an average of 39.5%. This was 9.6% greater than the reduction achieved in earlier work, which followed the complementary approach of estimating the error rather than the desired component. Preliminary results are also presented from tests in which training and testing data were taken from different surgeons.**
Keywords –**Microsurgery, accuracy, tremor, robotics**

I. INTRODUCTION

The human ability to perform micromanipulation is hampered by inherent erroneous hand motion. This manual imprecision affects the performance of microsurgery [1]. It complicates many procedures and makes certain delicate procedures impractical and often impossible [2].

The most familiar type of involuntary or erroneous movement affecting microsurgery is physiological tremor [3]. Tremor is defined as any involuntary, approximately rhythmic, and roughly sinusoidal movement [4]. Physiological tremor is inherent in the movement of healthy subjects. The resulting tool tip oscillation can be 50 μm peak-to-peak (p-p) or greater [5]. Besides physiological tremor, measurements of the hand motion of surgeons have shown that non-tremorous components of erroneous or undesired motion such as jerk (i.e., normal myoclonus) and drift are often larger than physiological tremor [3,5].

For some time there has been research interest in enhancing human positioning accuracy during microsurgery. A number of efforts have followed a telerobotic approach [6,7], involving a robotic arm in place of the shaky human arm. Taylor et al. have used a "steady hand" approach, in which a robot and a surgeon directly manipulate the same tool, the robot having high stiffness and complying with only those components of the manual input force that are deemed desirable [8].

In order to further reduce cost, and to maximize ease of use, user acceptance, and compatibility with current surgical practice, the present authors are implementing active error compensation within a completely hand-held tool, seeking to keep the instrument size and weight as close as possible to those of existing passive instruments. This device, known as *Micron*, must sense its own motion, estimate the undesired component of the sensed motion, and manipulate its own tip to nullify the erroneous motion in real-time as shown in Fig. 1.

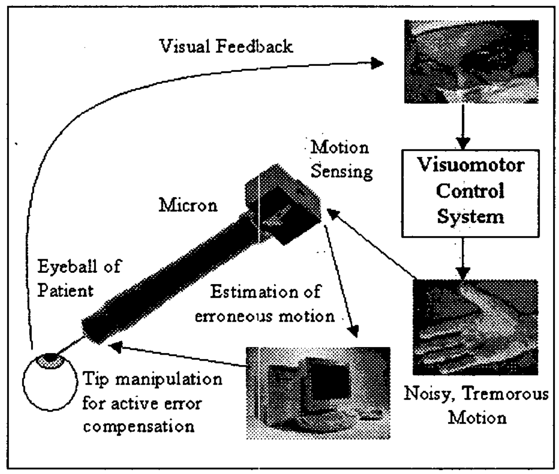

Fig. 1. Active hand-held instrument for error compensation in microsurgery

For this approach to work, it is of paramount importance to accurately model and predict both tremor and various types of non-tremorous involuntary movement, so as to enable online canceling without time delay. Several techniques have been developed for tremor modeling and suppression. Riley and Rosen [9], among others, have investigated lowpass filtering. Gonzalez *et al.* [10] proposed an equalizer to suppress pathological tremor. Riviere *et al.* [11] 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, e.g., myoclonic jerk, have yet to be substantially suppressed. Since little is known about these components, and since practical reference signals for adaptive noise canceling are unavailable, suppression is difficult.

The mapping from human intention to human movement output is nonlinear [12]. Neural networks model nonlinear processes well, and have been used in modeling of human control strategies [12]. The complexity and multiplicity of involuntary hand motion components, and the paucity of

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knowledge about many of them, makes a neural network approach well suited to modeling them. Riviere and Khosla [13] used a cascade-correlation neural network for noise canceling in human hand motion. Their experiments showed that the neural network successfully modeled and reduced the errors in recorded hand movement of four surgeons. This paper presents a different approach, employing the same neural network to model a different quantity (the desired part instead of the erroneous part) for the same set of data. We might call this the *direct* approach to suppressing positioning error. We then compare our results with those obtained by Riviere and Khosla using the *indirect* approach, i.e., modeling the erroneous component. We also go a step further and cross-test the networks, investigating the effectiveness of the trained networks on surgeons other than those on which they were trained.

Though the experiments presented here focus on surgery, the concepts demonstrated are directly relevant to a variety of manipulation applications with low signal-to-noise ratio, e.g., assistive computer and powered-wheelchair interfaces, and manual accuracy enhancement for cell micromanipulation in the biomedical laboratory.

II. METHODS

A. Neural Network Architecture

Instead of the traditional fixed architecture network with backpropagation, we used a technique introduced by Nechyba and Xu [12]. The technique combines (i) flexible cascade-correlation neural networks, which dynamically adjust the size of the neural network as part of the learning process, and (ii) node-decoupled extended Kalman filtering (NDEKF) [14], a fast-converging alternative to backpropagation.

When training starts, the network has no hidden nodes, only linear connections between the input and the output nodes. This enables the network to capture any linear relationship between the inputs and outputs (Fig. 2).

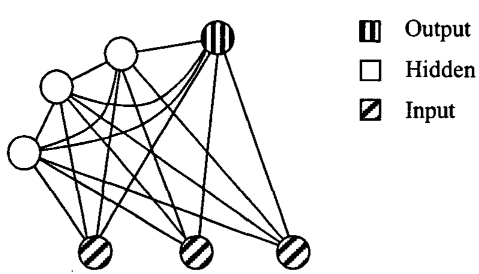


Fig.2. Diagram of the cascade-correlation neural network architecture. The diagram shows a network with three hidden nodes. As each hidden node is added, it is connected to the input and output nodes, as well as each of the preceding hidden nodes

During training, each time the error performance stagnates, a new hidden node is added to the network from a pool of candidate units (transfer functions). In our experiments, these candidates include sigmoid, Gaussian, sine, and Bessel functions. The best candidate unit is selected after all candidates have been trained independently and in parallel with different random initial weights. Once a new hidden unit is installed, the hidden-unit input weights are frozen, while weights to the output units are retrained. The process is repeated until the algorithm succeeds in reducing the root mean square error (rmse) sufficiently for the training set or the number of hidden units reaches a specified maximum number.

Extended Kalman filtering (EKF) is an extension of Kalman filter to deal with non-linear systems via linearization about the current parameter estimates. In neural network training, learning is cast as an identification problem for a nonlinear dynamic system. The neural network weights represent the state of the non-linear system. The EKF theory is then used to derive a recursion for the weight updates. This work uses NDEKF, in which the network weights are grouped such that each group contains the input nodes, the output nodes and one hidden node. For each group, elements of the error covariance matrix estimate corresponding to other groups can be ignored, greatly reducing the computational complexity.

B. Experimental Methods

The hand movement of surgeons was recorded at Wilmer Eye Institute of Johns Hopkins University. Each surgeon held a microsurgical instrument with the tip inserted in a sclerotomy in the eye of a vitreoretinal microsurgical simulator. A Hall effect sensor mounted inside the mannequin eye detected the position, in one dimension, of a 0.26g permanent magnet mounted on the tip of the instrument. Data were recorded for 16s at a sampling rate of 250Hz. 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. A total of 15 files were obtained from four surgeons (5, 5, 3, and 2 files, respectively).

To ease differentiation of erroneous movement from desired movement for purposes of evaluation, surgeons were given fixed targets at which to point, and tried to keep the instrument motionless, thus ensuring that all recorded motion is error. To make the experiments more realistic we generate low frequency pseudo-voluntary motions by lowpass filtering Gaussian white noise with a cutoff frequency of 1 Hz. This signal is then added to the recorded still hand error movement. The pseudo-voluntary motion serves as the target or desired motion in these experiments. The magnitude of the randomly generated pseudo-voluntary motions has a ratio of roughly 1:1 to the mean rmse of the 15 data recordings. Two different pseudo-voluntary motions are generated in this manner, one for the training the network and the other for testing.

A separate neural network was trained and tested for each of the four surgeons. In each case, one data recording was used for training, and the remaining data sets from that surgeon were used for testing of the trained network. The rmse with respect to the pseudo-voluntary motion was calculated for each file, both before and after processing by the neural network.

The input to the neural network was a window of data in the time series, i.e. the number of input nodes depended on the length of the window. The output of the neural network was the error-compensated motion, and since the data are one-dimensional, there is only one output node. Different numbers of input nodes and hidden nodes were tested to obtain the best net architecture for each surgeon. Riviere and Khosla [13] used the same set of data but chose the error estimate as the network output, so that the output of the neural network could be used directly as a compensation command to cancel the error. In addition, Riviere and Khosla fixed the number of input nodes at 100 and the maximum number of hidden nodes at 10.

Each neural network was also tested on one data file from each of the other surgeons.

III. RESULTS

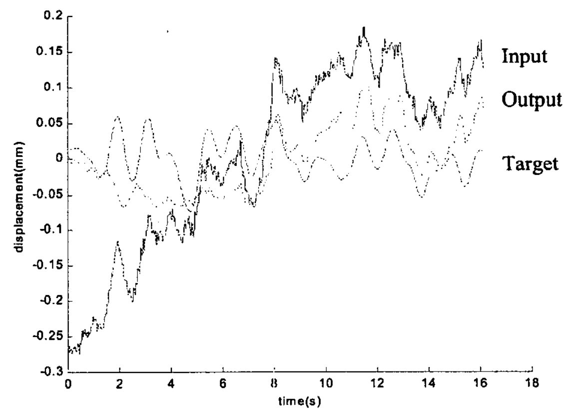
The neural network reduced the rmse with respect to the randomly generated pseudo-voluntary motion in all cases. For each surgeon, Table I shows the mean raw rmse of the data (with the number of testing data sets in parentheses), the mean and standard deviation of the rmse of the output of the neural network, and the architecture that yielded the best result. Table II demonstrates that the direct approach outperformed the indirect approach in these tests. Fig. 3 depicts sample results from the two approaches. Table III shows how well each network performed in filtering data from surgeons other than the one on which it was trained.

TABLE I
ERROR CANCELING PERFORMANCE

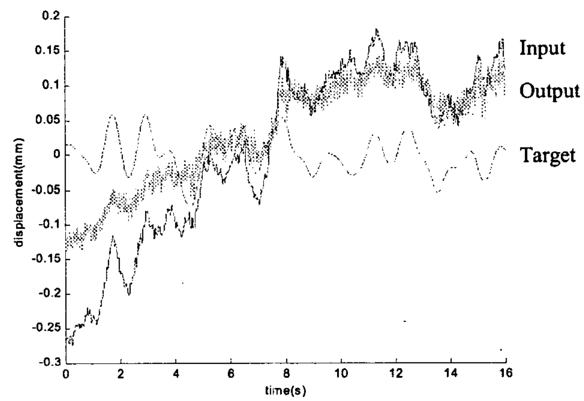
Surgeon # (no. of testing files)	Mean raw rmse (mm)	Mean rmse of neural network output (mm)	Standard deviation of output (mm)	Best Network Architecture
1 (4)	0.112	0.055	0.005	75 input, 3 hidden
2 (4)	0.046	0.033	0.002	60 input, 6 hidden
3 (2)	0.048	0.037	0.001	100 input, 3 hidden
4 (1)	0.127	0.056	-	50 input, 6 hidden

TABLE II
COMPARISON OF MODELING APPROACHES

Surgeon #	Rmse reduction, direct approach (%)	Rmse reduction, indirect approach (%)
1	50.9	44.6
2	28.3	26.1
3	22.9	18.8
4	55.9	29.9
Average	39.5	29.9



(a)



(b)

Fig.3. Comparison of direct and indirect approaches to error suppression. 'Target' is the pseudo-voluntary motion, generated by lowpass filtering white noise at 1 Hz cutoff frequency. 'Input' represents the network input, obtained by adding recorded erroneous hand motion error to the target motion. 'Output' indicates the filtered version of the data. (a) Sample result from the direct approach, in which the network estimates the pseudo-voluntary motion. (b) Sample result from the indirect approach, in which the network estimates the erroneous motion.

TABLE III
CROSS-TESTING
Parentheses indicate rmse for the surgeon the network was trained on. Boldface means performance equaled or surpassed what the network achieved on its own surgeon. Italics indicate performance worse than raw rmse.

NN trained on Surgeon #	NN test on Surgeon #	% rmse reduction
1	2	**26.2** (23.1)
	3	**38.1** (28.6)
	4	45.1 (56)
2	1	*-85.5*
	3	**28.6** (28.6)
	4	*-243.1*
3	1	0
	2	15.4 (23.1)
	4	*-0.9*
4	1	32.7 (54.5)
	2	*-30.8*
	3	22.7 (28.6)

IV. Discussion

The results show the feasibility of neural network-based error canceling in human-machine control. The neural network reduced the rmse of the surgeons' erroneous motion by an average of 39.5%.

The direct approach outperformed the indirect by 9.6% in reduction of rmse. During training, both methods terminated at the specified maximum allowable number of hidden nodes. The tests of the indirect approach used 100 input nodes in each case [13], whereas the present work explored the effect of different input-hidden node combinations on network performance. It is not yet clear whether the superior performance of the direct approach in these tests is due to an inherent superiority in the method, or is due simply to the fact that the network architecture was optimized for the direct approach.

The motion profiles produced by the direct and indirect approaches are distinctly different, as is clearly visible in Fig. 3. The direct approach produces much less high frequency noise than the indirect, and seems to preserve the general shape of the voluntary motion much better. In future work, appropriate performance metrics will be used in order to quantify this effect.

The cross-testing experiments yielded inconclusive results. Of twelve tests, three produced equal or better filtering than the network trained on data from the same surgeon, and nine produced worse results. Of those nine, four yielded results even worse than the raw rmse for the testing data set, i.e., the error was increased rather than decreased by the filtering process. Further study is necessary in order to determine whether a network can be successfully trained for general application to more than one subject. Additional work in the near future will involve training the networks using data from dynamic tasks, rather than static "pointing" tasks, so that the networks can be trained using real desired movement rather than pseudo-voluntary signals.

V. Conclusion

The use of cascade-correlation neural networks to suppress undesired components of microsurgical instrument motion has been demonstrated using 15 hand movement recordings collected from 4 surgeons. The neural network reduced the rmse of the surgeons' erroneous motion by an average of 39.5%. The networks performed better when trained to estimate the desired component than when trained to estimate the undesired component of motion.

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