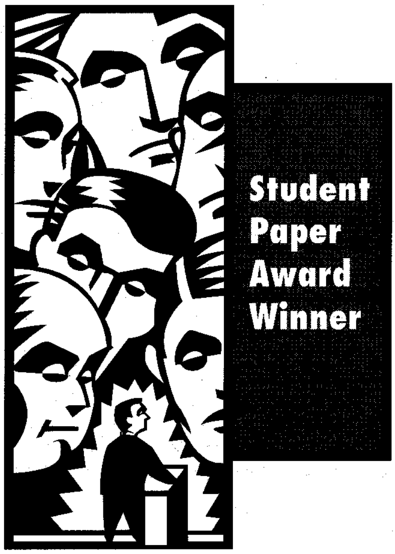
Modeling and Canceling Tremor in Human-Machine Interfaces

Zero-phase modeling and canceling of tremor can improve precision in human-machine control applications. Past methods of tremor suppression have been hindered by feedback delays due to phase lag and by the inability to track tremor frequency over time. The weighted-frequency Fourier linear combiner (WFLC) is an adaptive noise canceller that precisely models tremor with zero phase lag. This article briefly presents the WFLC algorithm and describes its application to computer input filtering, clinical tremor quantification, and active tremor canceling for microsurgery.

Overview

Tremor is any involuntary, roughly sinusoidal movement [1]. Pathological tremor is caused either by brain injury or diseases such as essential tremor, Parkinson's disease, and multiple sclerosis [1]. It is a persistent nuisance in mild cases, and in severe cases it can be completely debilitating [2]. Physiological tremor exists in all human motion [3]. Studies have shown that tremor corrupts voluntary motion with an additive oscillatory disturbance, or noise [2]. Therefore, during voluntary motion, tremor causes an unwanted oscillatory disturbance, or noise. An example of tremor disability is presented in Fig. 1, in which a subject with cerebellar tremor due to brain trauma is unsuccessful in attempting to draw an Archimedes spiral on a digitizing tablet.



The importance of tremor suppression during computer input is increasing as input interfaces that sense human motion become more widespread. Computer mice, joysticks, trac-balls, and digitizing tablets are used to control applications from word processing to computer-aided design (CAD). Palmtop computers such as the Newton (Apple Computer, Cupertino, CA) use pen input. Sensory gloves are used as input to virtual environments, which are being investigated for various design and analysis functions, as well as for educational and entertainment uses [4]. Use of these devices affects employability. For example, a vocational CAD training program for disabled clients at Maryland Rehabilitation Center is currently inaccessible to persons with severe pathological tremor, as they lack adequate control over the interfaces used. For these persons, effective tremor suppression during computer input would enhance quality of life, personal independence, and workplace competitiveness [5]. Pathological tremor is most commonly treated with medication [1], but this fails to suppress many tremors adequately—as many as 50% by some estimates [6]—necessitating development of assistive computer interfaces. Past approaches to assistive interfaces include viscous damping of a joystick [7] or mouse (The MouseTRAp, Michaelis Engineering, Southampton, UK) and lowpass filtering of input signals [2]. These techniques involve phase lag, which causes a time delay in the user's visual perception of motion via the computer monitor. Studies have shown that feedback delays result in decreased motion accuracy and degraded handwriting legibility [8]. Clearly, tremor canceling without time delay is needed during computer input.

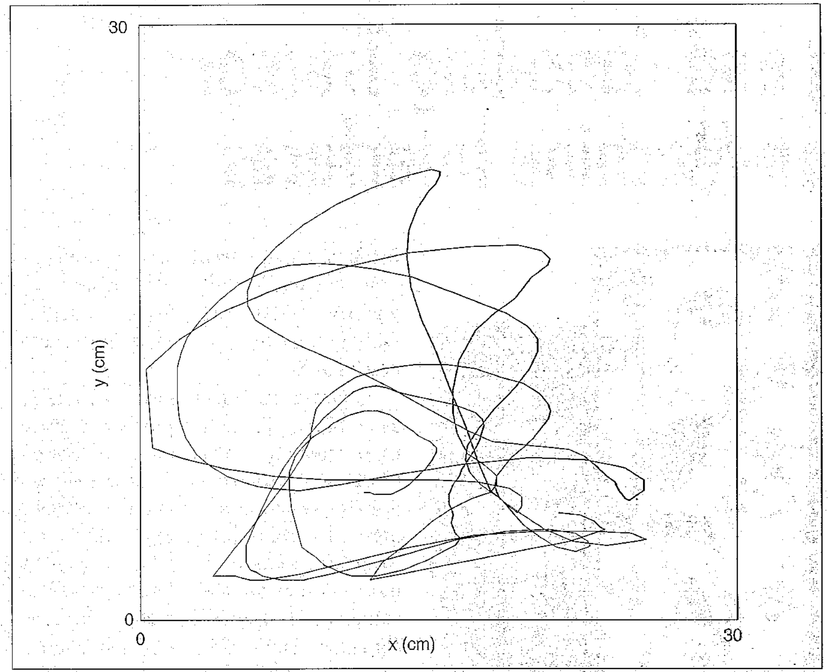
Cameron N. Riviere
The Robotics Institute, Carnegie Mellon University
Nitish V. Thakor
Department of Biomedical Engineering,
Johns Hopkins School of Medicine

Quantification of tremor is of interest as an aid to clinical diagnosis and objective evaluation of treatment [9]. Tremor is typically examined via handwriting and drawing specimens, often recorded using digitizing tablets [10]. Fast-Fourier transform (FFT)-based spectral analysis is the most popular method of tremor quantification [1,3]. The FFT models the input signal as a stationary periodic signal, i.e., one whose statistical characteristics do not change with time. Yet tremor amplitude and frequency are time-varying [1], often making power spectra difficult to interpret [11]. A method to track modulation in tremor frequency and amplitude over time would allow a better clinical understanding of individual cases of tremor.

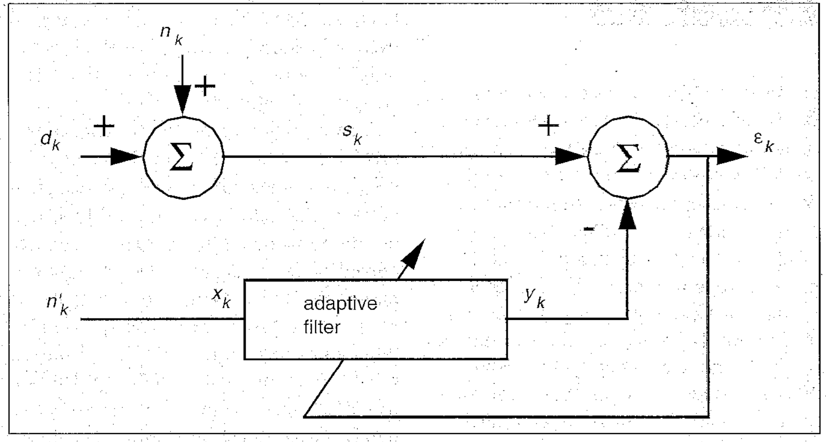
Physiological hand tremor causes imprecision in microsurgery [12]. Despite the development of teleoperated surgical systems that suppress tremor, direct, i.e., non-teleoperated, microsurgery retains its appeal for the surgeon, due to its more natural feel [13] and lower equipment cost [14]. Effective tremor suppression in handheld microsurgical instruments would result in greater precision, leading to better outcomes and lower costs. The ideal tremor-canceling system for direct microsurgery would have a natural, unobtrusive feel. One promising method is an active noise control approach. Rather than suppressing the actual hand tremor, the surgical instrument tip is actuated with an equal but opposite motion, effectively subtracting the tremor out of the tip motion. Since this compensating signal can only be effective in the absence of time delay, a zero-phase tremor estimation system is needed.

To model and cancel tremor during purposeful movement, we have developed the WFLC [15]. This algorithm is well suited in several ways to the applications listed above. It is based on a dynamic truncated Fourier series model of tremor,

0739-5175/96/$5.00©1996



1. Disturbance in motion due to pathological tremor. This figure shows the results of a subject with cerebellar tremor attempting to draw an Archimedes spiral on a digitizing tablet.



2. Adaptive noise canceling. A desired signal, d_k, is corrupted by a noise, n_k. The adaptive filter takes in a noise n'_k, correlated with n_k, and outputs an estimate y_k of n_k, which is subtracted from the primary input, s_k. This yields ε_k, which is an estimate of the desired signal, d_k.

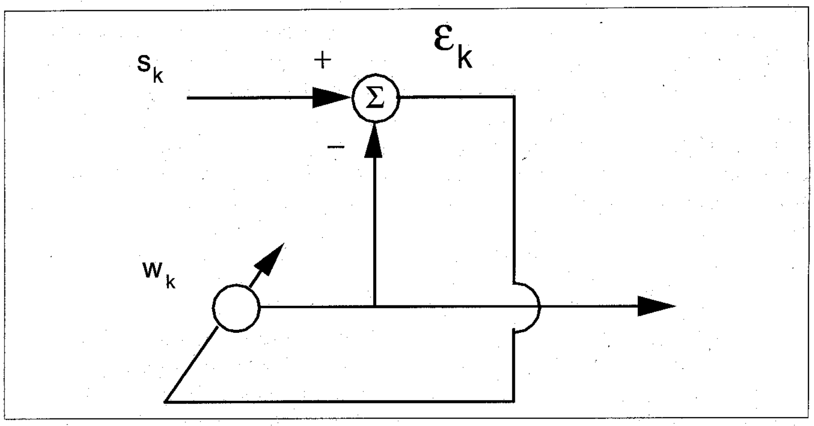
as is common in the literature [11], and can precisely model tremor, as it incorporates few simplifying assumptions. It generates a specific estimate of tremor, as necessary in both clinical tremor quantification and active compensation for microsurgery. The WFLC is an adaptive noise canceler. It therefore has zero phase lag and introduces no time delay into personal computer input filters or active compensation systems. Furthermore, it operates completely in the time domain, and its computational simplicity aids in on-line implementation. It adaptively tracks modulation in the frequency and amplitude of tremor.

Adaptive Canceling of Tremor

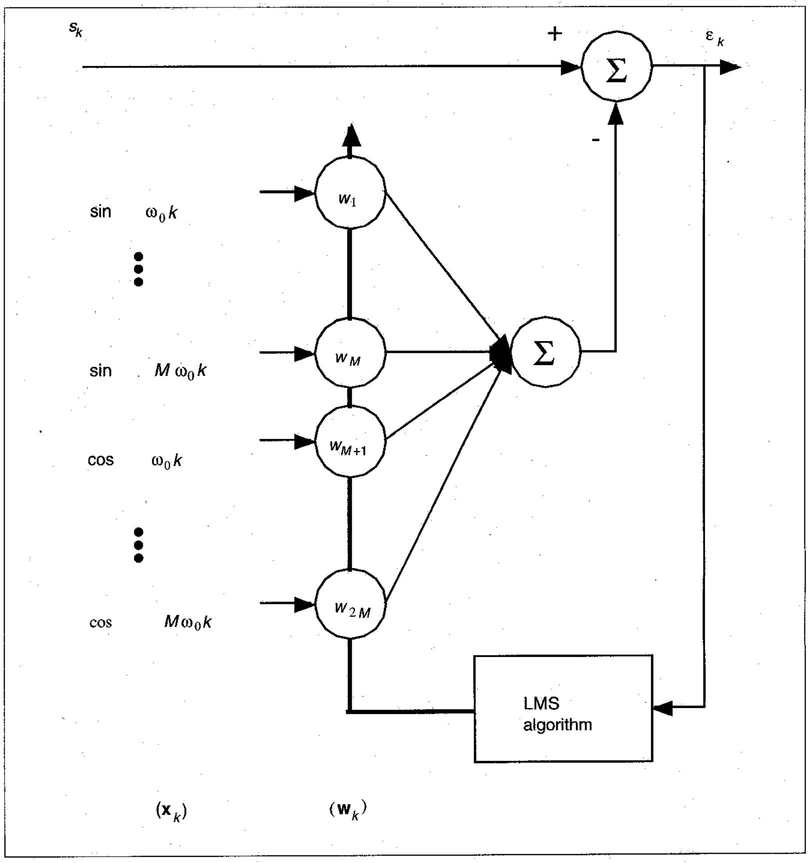
Adaptive Noise Canceling

Tremor is a nonstationary process exhibiting characteristic frequency and amplitude modulation [10]. Adaptive algorithms are particularly suited to tremor canceling since they adjust automatically to such signal changes over time. The most relevant technique is adaptive noise canceling [16]. An adaptive noise canceler is a noise filter that self-optimizes on-line as it encounters an input signal, adjusting its parameters according to a learning algorithm. The basic structure of an adaptive noise canceler is presented in Fig. 2. The system accepts two inputs: a primary input, s_k, containing a desired signal, d_k, and independent uncorrelated noise, n_k; and a reference input, $\mathbf{x}_k$, which contains a noise, n'_k, correlated with n_k. The reference input, $\mathbf{x}_k$, typically a vector, is often obtained via a tapped delay line from a single reference input channel [16]. The object of adaptive noise canceling is to filter the reference input, $\mathbf{x}_k$, via the adaptive weights to form y_k, an estimate of n_k. This noise estimate, y_k, is then subtracted from the primary input signal, s_k, to yield ε_k. The object of the filter is to minimize the mean square value of ε_k, thus also minimizing the mean square error between n_k and y_k, making ε_k an estimate of d_k. The time-varying, self-optimizing performance of the adaptive noise canceler is generated by updating the filter weights according to an adaptive algorithm, e.g., the least mean square (LMS) algorithm [16].

This adaptive noise canceling scheme requires a reference signal that is correlated with the tremor signal. In many human-machine control applications, obtaining a reference signal that contains tremor but little else is not convenient. At first glance, this would seem to make this approach impractical for tremor suppression during human-machine control. However, there are a number of ways to circumvent this difficulty. For periodic interference, one such method is to generate a reference input via a tapped delay line that receives the primary input, delayed by some amount, Δ [16]. In this case, d_k is assumed to be a broadband signal, and the delay, Δ, must be large enough to decorrelate the components of d_k in the reference input from those in the primary input. This adaptive filter structure therefore attempts a linear prediction of the current noise value based on past values, and is known as an adaptive predictor. Implementing this type of filter for tremor canceling in control applications is problematic for two reasons. Little is known about d_k, the human voluntary motion, so it is difficult to determine a suitable value for Δ. A more significant drawback is that the system models the interference as a linear autoregressive process. Gantert, *et al.* [17], have shown that essential and Parkinsonian tremors, for example, are nonlinear processes. The linear prediction is therefore unlikely to yield a satisfactory estimate of the tremor, particularly when delayed by a potentially large value Δ. In experiments with essential and rubral tremors, we have indeed found this approach to yield poor results. Another method for circumventing the lack of a true reference input containing the interference is to construct an artificial reference signal based on some knowledge or model of the interference. This can be done in various ways, as will be seen below.



3. Schematic of adaptive lowpass filter. s_k is the system input, ε_k is the filter error, and w_k is the adaptive weight, which provides the low frequency filter output.



4. The Fourier linear combiner. This adaptive algorithm forms a dynamic truncated Fourier series model of an input signal that can be used to cancel a quasi-periodic interference provided the fundamental frequency is known.

Adaptive Lowpass Filtering

Probably the simplest of all adaptive filters is one proposed by Widrow, *et al.*, in their seminal paper on adaptive noise canceling [16]. A brief look at this filter provides general insight into the use of lowpass filters for tremor cancellation during computer input. The filter is an adaptive highpass filter with a single adaptive weight. The interference is assumed to be of low frequency, and the reference signal is generated by modeling it as a constant value. The weight follows the input, but is limited in its capacity to do so by the size of the adaptive gain parameter. It is therefore able to cancel only low frequency components of the input, and high frequency components are preserved. Thus, it acts as a highpass filter. As with most adaptive noise cancelers, the filter error, ε_k, is also the filter output.

Using the adaptive weight, w_k, itself, rather than the error, ε_k, as the filter output converts this algorithm into a type of adaptive lowpass filter, shown in Fig. 3. The corner frequency, in radians, can be shown to be equal to 2μ [16]. This simple adaptive lowpass filter can be used to suppress tremor while preserving voluntary motion, presumed here to be at lower frequencies. Figure 5(b) presents the results of this filter on recorded data from target tracking with a computer mouse. While comparison of Figs. 5(a) and 5(b) shows that the filter visibly attenuates tremor, it also introduces a phase lag, causing a time delay. Studies have shown that time delays as small as 30 ms may degrade performance in human-machine control [18], and the phase lag inherent in lowpass filtering is therefore a drawback for this application. We wish to develop a technique that suppresses tremor but does not suffer from the drawback of phase shift.

The Fourier Linear Combiner

The roughly sinusoidal nature of tremor makes it well-suited to a Fourier representation [10]. The Fourier linear combiner (FLC) [19, 20] is an adaptive filter that forms a dynamic truncated Fourier series model of an input signal. The FLC operates by adaptively estimating the Fourier coefficients of the model according to the LMS algorithm. The FLC is presented in Fig. 6. The adaptive weight vector, $\mathbf{w}_k$, generates a linear combination of the harmonic orthogonal sinusoidal components of the reference input vector, $\mathbf{x}_k$. For a noiseless periodic input, s_k, with M harmonics and fundamental frequency ω_0, the FLC converges exponentially to zero mean square error. A detailed performance analysis of the FLC is presented in [20].

The FLC effectively estimates and cancels periodic interference of known frequency. It has been presented, for M=1, as an adaptive notch filter [16, 21], and in the general case as a multiple-notch filter [21]. Several features of the FLC are useful for canceling quasi-periodic interferences such as tremor. The FLC adapts to the amplitude and phase of an oscillation in the primary input and tracks their changes [20]. It is computationally inexpensive [20], inherently zero-phase [19], and has an infinite null [16]. However, cancellation of periodic interference with the FLC depends on determination of the proper reference frequency, ω_0. The FLC cannot estimate the proper ω_0 value online, and it is not possible to choose it off-line, because the tremor frequency is not known *a priori*. Making the FLC useful for tremor canceling during human-machine control requires a method to adapt the reference frequency to the primary input frequency.

The Weighted-frequency Fourier Linear Combiner

Since we hope to develop a system that rivals the low computational expense of the FLC, we seek a simple approach to direct frequency adaptation. This can be done by replacing the fixed frequency, ω_0, of the FLC with another adaptive weight, w_{0_k}, that learns the input frequency via the LMS algorithm, much as the FLC weights learn the input amplitudes. The modulating harmonic reference sinusoids maintain a running sum of w_{0_k} so that phase information is not lost. This yields the WFLC [22]:

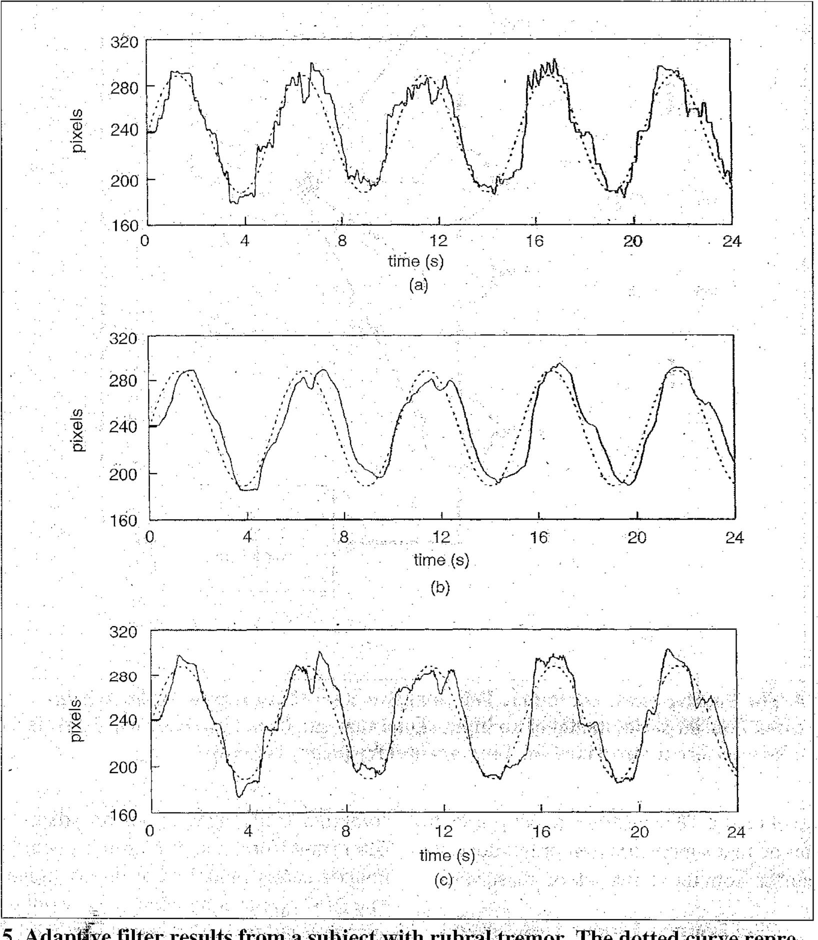
$$x_{r_k} = \begin{cases} \sin\left(r\sum_{t=1}^{k} w_{0_t}\right), & 1 \le r \le M \\ \cos\left((r-M)\sum_{t=1}^{k} w_{0_t}\right), & M+1 \le r \le 2M \end{cases} \tag{1a}$$

$$\varepsilon_k = s_k - \mathbf{w}_k^T \mathbf{x}_k \tag{1b}$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu \mathbf{x}_k \varepsilon_k, \tag{1c}$$

$$w_{0_{k+1}} = w_{0_k} + 2\mu_0 \varepsilon_k \sum_{r=1}^{M} r(w_{r_k} x_{M+R_k} - w_{M+r_k} x_{r_k}) \tag{1d}$$

where, $\mathbf{w}_k = [w_{1_k} \ldots w_{2M_k}]^T$ and $\mathbf{x}_k = [x_{1_k} \ldots x_{2M_k}]^T$. Figure 6 presents the WFLC as an adaptive noise canceler. The WFLC adapts to a periodic input with number of harmonics M, with $\mathbf{w}_k$ learning its amplitudes and phases as in the FLC, and w_{0_k} learning its fundamental frequency. The WFLC is stable for sufficiently small adaptive gains [22]. An analysis of the algorithm is presented in [22].



5. Adaptive filter results from a subject with rubral tremor. The dotted curve represents the target motion. The solid line is the human tracking signal. (a) Raw tracking signal. (b) Tracking signal filtered by adaptive lowpass (Fig. 3). (c) Tracking signal filtered by WFLC/FLC (Fig. 6).

The WFLC is designed to adapt to the dominant frequency component in a signal, provided that component is of sufficient duration relative to the time required for adaptation. Since the voluntary motion is unknown, it is not guaranteed that the WFLC will not in some cases converge to it rather than the tremor, distorting the desired signal. To address this potential problem, the WFLC is augmented with a second set of amplitude weights, $\hat{\mathbf{w}}_k$, or "secondary FLC," with adaptive gain, $\hat{\mu}$. The WFLC operates on an input signal, s'_k, highpass prefiltered with cutoff frequency between 1 and 2 Hz (pathological tremor frequency tends to be higher than 2 Hz [1]). This filtering suppresses most voluntary motion, minimizing its effect on the tremor frequency estimate. The secondary FLC operates on the raw input, s_k. Both weight vectors, $\mathbf{w}_k$ and $\hat{\mathbf{w}}_k$, use the reference vector, $\mathbf{x}_k$, of the WFLC algorithm, which contains the tremor frequency information. Input prefiltering allows the main WFLC system to adapt more robustly to the weights w_{0_k} and $\mathbf{w}_k$ to the correct values for tremor frequency estimation, while operation on the raw input, s_k, allows $\hat{\mathbf{w}}_k$ to perform zero-phase amplitude estimation and adaptive tremor canceling. Although the amplitude estimation is zero-phase, prefiltering does introduce a phase lag into the frequency estimation, but since proper WFLC performance requires $\mu_0 << \mu$ [22], w_{0_k} is already constrained to adapt slowly, and the effect is minimal. A bias weight [16], with adaptive gain, μ_b, is often added to minimize the effect of constant bias and very low frequency signal components on the FLC [16]. Figure 5(c) shows that, unlike the adaptive lowpass filter, the WFLC/FLC combination provides zero-phase tremor canceling. Unlike the FLC, it does not require *a priori* knowledge of the tremor frequency.

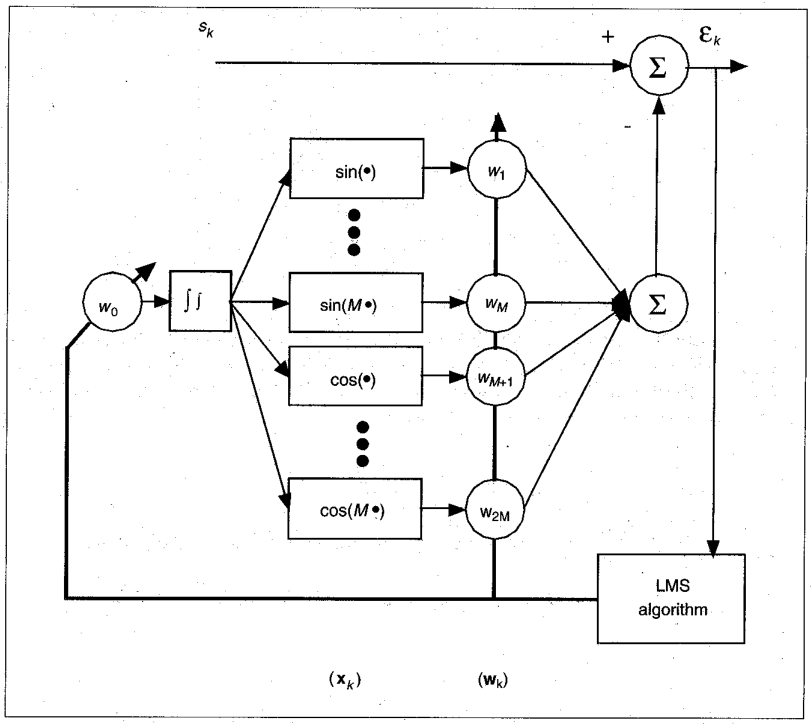
The WFLC/FLC filter combination can be implemented on-line to suppress pathological tremor in input signals from a mouse, electronic pen, sensory glove, or any other motion interface. Its zero-phase estimate of tremor is suitable as a compensating command signal in an active tremor suppression system for microsurgery. The system's dynamic Fourier model can also be used off-line to quantify tremor from recorded data for clinical use. Although only the first harmonic (M=1) is used in the experiments shown here, the method is a general one that can handle any desired number of harmonics.

Applications

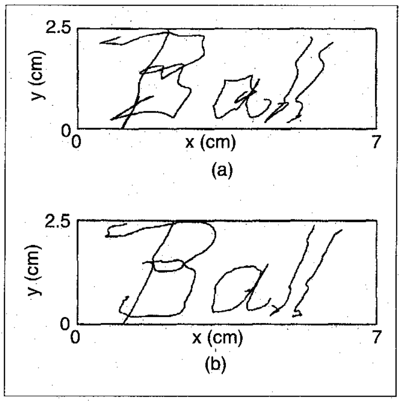
Canceling Pathological Tremor for Computer Input

The WFLC/FLC can be used to cancel pathological tremor in graphical user interfaces, providing smooth cursor control for mice, joysticks, and pens. WFLC adaptive tremor canceling during pen input improves not only the qualitative legibility of handwriting, but also the success rate of character recognition methods frequently used to convert the writing into type. The system also assists in target acquisition or point-and-click tasks. Because the WFLC/FLC system is inherently zero-phase, performance increases due to filtering are not offset by decreases due to time delay in visual feedback [22].

Figure 7 shows the results of the WFLC/FLC processing of computer pen input from a male subject, age 84, with essential tremor. These data are recorded with a SummaSketch (Summagraphics, Seymour, CT) digitizing tablet at 116 Hz and are filtered off-line. The parameters are $\mu=0.005$, $\mu_0=2\times10^{-7}$, $\mu_b=0.02$, $\hat{\mu}=0.1$, M=1. The filtering suppresses the pathological tremor, improving the handwriting output.



6. The weighted-frequency Fourier linear combiner as an adaptive noise canceler. The system maintains a running sum of the frequency weight, w_0. Harmonic sines and cosines of this quantity are taken (the vector x), weighted by the Fourier coefficient vector, w, and summed to provide a truncated Fourier series model of the input s. This Fourier estimate is subtracted from the input to obtain canceling.



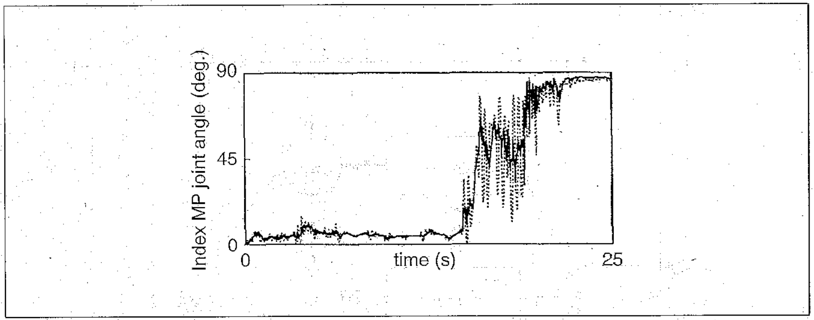
7. Handwriting sample from a subject with essential tremor. (a) Unfiltered. (b) Filtered.

The WFLC similarly suppresses pathological tremor in dextrous glove input, allowing persons with tremor to take advantage of a variety of applications expected to incorporate such interfaces in the near future. Figure 8 presents input and output results for the index metacarpophalangeal (MP) joint from a flexion experiment. In this experiment, a subject with cerebellar tremor wears a VPL data glove, sampled at 200 Hz. He attempts to hold the hand steady in a cylindrical-grasp position, then flexes until the hand is almost closed, and attempts to hold steady again. Parameters used are $\mu_0=10^{-8}$, $\mu=0.007$, $\hat{\mu}=0.1$, $\mu_b=0.006$, M=1. Here and in the section below, the subject provides written consent to a protocol approved by the Johns Hopkins Joint Committee on Clinical Investigation.

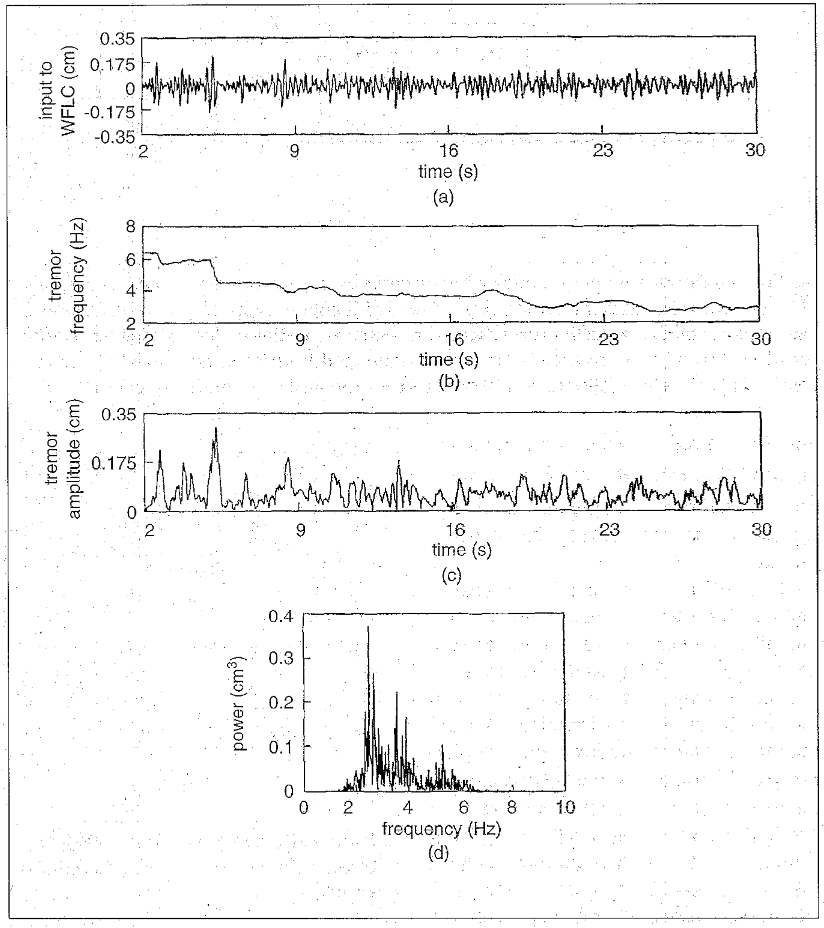
The performance of the WFLC is demonstrated here, off-line, using recorded pen and glove input data to allow direct comparison of filtered and unfiltered results. Work is currently underway to demonstrate the on-line performance of the WFLC/FLC in further testing of subjects with pathological tremor.

Modeling Pathological Tremor for Clinical Use

Used off-line in the neurological clinic, the WFLC provides a quantification of tremor that takes into account its nonstationarity, or time-varying nature.



8. Raw (dotted) and filtered (solid) flexion data from index metacarpophalangeal joint of VPL DataGlove, from a subject with cerebellar tremor. The subject first attempted to hold steady posture with hand half-closed, then changed to a closed-grip position, and again attempted to hold steady.



9. Sample from subject with essential tremor. Subject drew an Archimedes spiral. μ_b=0.001, $\hat{\mu}$ =0.3; μ_0 and μ calculated as functions of input signal power. (a) High-pass filtered input to WFLC. (b) Frequency. (c) Amplitude. (d) Power spectral density via FFT.

Spectral analysis of pathological tremor sometimes exhibits multiple peaks. Since a power spectrum does not indicate the timing of the various frequency components, interpreting such cases is difficult [11]. For example, what appears to be multiple simultaneous oscillations may in fact be frequency modulation of a single tremor oscillation during a recording [23]. Analysis with the WFLC helps to clarify the situation in that when frequency modulation is present, it is visible in the time history of the WFLC frequency weight, w_{0_k}.

Figure 9 presents an example of the use of the WFLC algorithm for off-line tremor quantification. A subject with essential tremor draws an Archimedes spiral on the tablet. The following formula is used:

$$\mu = \frac{0.004}{\sqrt{p}}$$

where p is the average signal power in cm^2. The other system parameters are $\frac{\mu_0}{\mu} = 7\text{x}10^{-6}$, $\hat{\mu} = 0.2$, M=1. The tremor frequency and amplitude modulation can be seen in Figs. 8(b) and 8(c). Tremor frequency is estimated directly by w_{0_k}. Figure 9(c) presents the effective amplitude at each step, obtained from the WFLC amplitude weights:

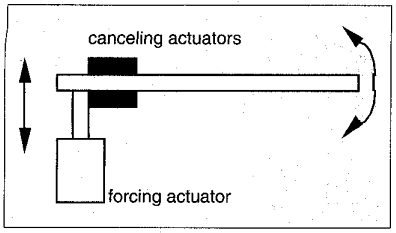
$$a_k = \sqrt{\hat{w}_{1_k}^2 + \hat{w}_{2_k}^2} \qquad (2)$$

Modulation in frequency during the test is reflected in the fundamental frequency history in Fig. 9(b). The adaptive tracking capability of the WFLC facilitates investigation of the pathophysiology behind certain cases of tremor, such as the spontaneous changes in frequency sometimes observed in severe cases of essential tremor [10]. The WFLC is well suited to processing long-term recordings of tremor [24], since it continually tracks tremor frequency and amplitude and compactly represents the results, following one dominant frequency of interest rather than an entire spectrum.

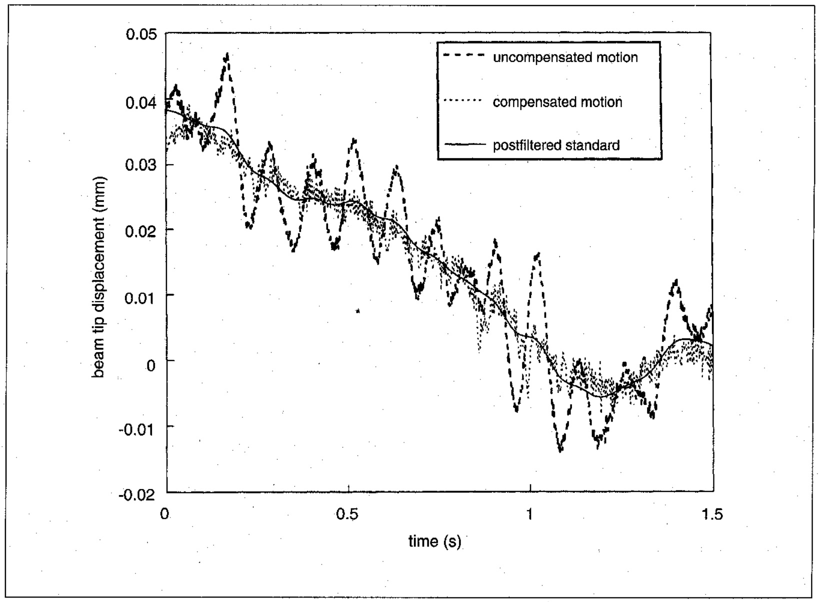
Canceling Physiological Tremor for Manual Microsurgery

The WFLC/FLC has been designed to generate a specific model of tremor, with zero phase lag, to make a practical drive signal for an active tremor canceling system for handheld microsurgical instruments. The narrow intraocular probe of a handheld ophthalmological microsurgical instrument was viewed as a cantilever beam. Piezoelectric ceramic actuator elements, widely used in the field of intelligent structures for active vibration control [25], could be used to create a bending moment in the probe, generating a transverse deflection to counteract the physiological hand tremor oscillation at the probe tip.

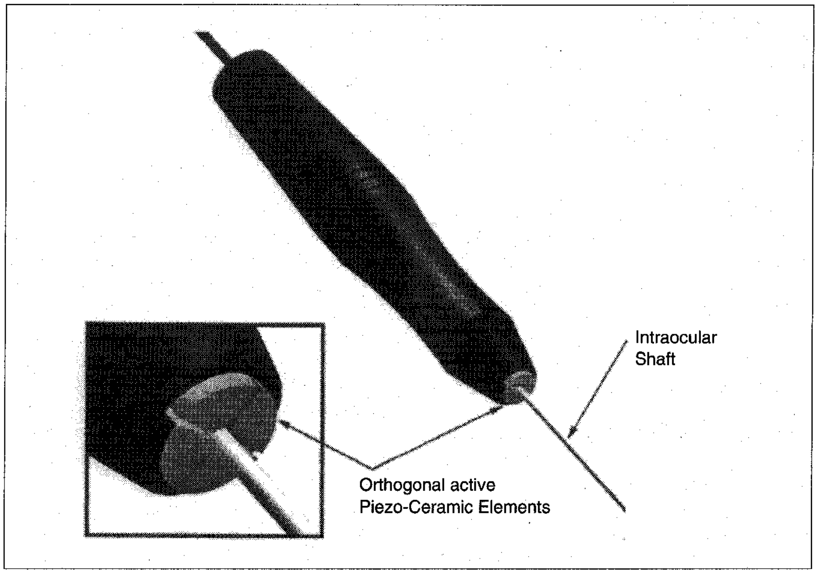
To simulate human hand motion and active tremor canceling during microsurgery, we constructed a testbed, shown in Fig. 10. The testbed consisted of a cantilever beam mounted on an electromag-



10. Illustration of the simulation hardware for active physiological tremor suppression during microsurgery. The forcing actuator translates the beam back and forth, as the surgeon's hand would move the surgical instrument probe. The canceling actuators flex the beam in the opposite direction from hand tremor, in order to suppress the tremor oscillation at the tip of the beam.



11. Adaptive active control of physiological tremor using the test setup. The WFLC generates a command to the piezoelectric actuators, flexing the beam to counteract the tremor. The solid line shows the zero-phase lowpass postfiltered version of the uncompensated motion, which is an estimate of the true voluntary motion. The fine dotted line shows the motion during WFLC compensation, which is visibly closer to the off-line voluntary motion approximation than is the uncompensated motion.



12. Proposed design of handheld ophthalmological microsurgical instrument with active tremor control. The piezoelectric ceramic actuators cancel tremor by flexing the intraocular shaft, opposing the tremor oscillation.

netic actuator, used as a forcer to introduce raw human hand motion into the system. The base of the beam was sandwiched between two piezoelectric elements (12.7 mm x 18.3 mm x 0.2 mm), used for tremor canceling. Recordings of human hand motion during simulated surgical procedures [26], containing both physiological tremor and voluntary motion components, were used to drive the forcer. A noncontact Hall effect displacement sensor [27] detected the location of the beam tip in the direction of actuation. The sensor output was used as input to the WFLC/FLC, which estimated the physiological tremor on-line. This tremor estimate was the command signal for the piezoelectric canceling actuators. The sampling rate of the control system was 1000 Hz. The parameter values were μ=0.01, μ_0=7x10^{-7}, μ_b=0.007, M=1. The secondary FLC used $\hat{\mu}$ =0.3 and M=1.

Figure 11 presents the results of a test with this apparatus. A recorded hand motion signal was fed to the system, once with active tremor compensation, and once without it. These results are shown by the coarsely dotted line and the finely dotted line, respectively. For comparison, the thin solid line shows an *a posteriori* estimate of the voluntary motion. The voluntary motion could not, of course, be measured directly from the raw data, but was lower in frequency than the physiological tremor. Therefore, a simple estimate was generated by lowpass filtering the uncompensated beam motion at 2.25 Hz using a forward-backward filtering technique that preserves phase. The compensated beam tip motion was visibly closer to this trajectory than the uncompensated motion, as shown in Fig. 11. The active compensation canceled physiological tremor from the tip motion, without causing time delay in the voluntary motion.

This technique can be implemented in an active handheld surgical instrument, such as the proposed design shown in Fig. 12. Probe tip oscillations due to tremor can be actively compensated in the two orthogonal directions perpendicular to the probe by transverse deflection, generated as described above. If needed, additional actuators can be incorporated into the design for axial tremor compensation in the probe. Active tremor control in such an instrument will increase precision in microsurgery, allowing smaller incisions, less tissue damage, and improved surgical outcomes. Furthermore, it may open the way to new microsurgical procedures not possible today because of manual accuracy limitations.

Research into active orthotics to suppress pathological tremor has been seen in recent years [28, 29]. The goal is to develop more general devices whose usefulness is not restricted to computer input. The active tremor suppression approach described here for microsurgery can also be applied to rehabilitative orthotics. Future research will include investigation in this area.

References

1. **Elble R, Koller W:** *Tremor.* Johns Hopkins, Baltimore, 1990.
2. **Riley P, Rosen M:** Evaluating manual control devices for those with tremor disability. *J Rehabil Res Dev* 24:99-110, 1987.
3. **Wade P, Gresty M, Findley L:** A normative study of postural tremor of the hand. *Arch Neurol* 39:358-362, 1982.
4. **Burdea G, Coiffet P:** *Virtual Reality Technology.* Wiley & Sons, New York, 1994.
5. **Riviere CN, Thakor NV:** Effects of age and disability on tracking tasks with a computer mouse: accuracy and linearity. *J Rehabil Res Dev* 33, to appear, 1996.
6. **Weiner W, Lang A:** Tremor. In: Weiner W, Lang A (Eds): *Movement Disorders: A Comprehensive Survey.* Futura, New York, pp. 221-256, 1989.
7. **Beringhause S, Rosen MJ, Huang S:** Evaluation of a damped joystick for people disabled by intention tremor. *Proc 12th Annu RESNA Conf,* New Orleans, LA, vol. 40-41, 1989.
8. **Kalmus H, Fry DB, Denes P:** Effects of delayed visual control on writing, drawing and tracing. *Language and Speech* 3:96-108, 1960.
9. **Elble RJ:** Physiologic and essential tremor. *Neurol* 36:225-231, 1986.
10. **Elble RJ, Sinha R, Higgins C:** Quantification of tremor with a digitizing tablet. *J Neurosci Methods* 32:193-198, 1990.
11. **Gresty M, Buckwell D:** Spectral analysis of tremor: understanding the results. *Electroencephalogr Clin Neurophysiol* 53:976-981, 1990.
12. **Patkin M:** Ergonomics applied to the practice of microsurgery. *Austr N Z J Surg* 47:320-329, 1977.
13. **Bose B, Kalra AK, Thukral S, Sood A, Guha SK, et al:** Tremor compensation for robotics assisted microsurgery. *Proc 14th Intl Conf IEEE Eng Med Biol Soc,* Paris, 3:1067-1068, 1992.
14. **Riviere CN, Rader RS, Thakor NV:** Adaptive real-time canceling of physiological tremor for microsurgery. *2nd Intl Symp Med Robot Comput Assist Surg,* Baltimore, Md., pp. 89-96, 1995.
15. **Riviere CN, Thakor NV:** Adaptive human-machine interface for persons with tremor. *Proc 17th Annu Conf IEEE Eng Med Biol Soc,* Montréal, 1995.
16. **Widrow B, Glover J, McCool J, Kaunitz J, Williams C, et al:** Adaptive noise cancelling: principles and applications. *Proc IEEE* 63:1692-1716, 1975.
17. **Gantert C, Honerkamp J, Timmer J:** Analyzing the dynamics of hand tremor time series. *Biol Cybern* 66:479-484, 1992.
18. **Jacobus HN, Riggs AJ, Jacobus CJ, Weinstein Y:** Implementation issues for telerobotic handcontrollers: human-robot ergonomics. In: Rahimi M, Karwowski W, (Eds): *Human-Robot Interaction.* Taylor and Francis, London, pp. 284-314, 1992.
19. **Vaz C, Thakor N:** Adaptive Fourier estimation of time-varying evoked potentials. *IEEE Trans Biomed Eng* 36:448-455, 1989.
20. **Vaz C, Kong X, Thakor N:** An adaptive estimation of periodic signals using a Fourier Linear Combiner. *IEEE Trans Signal Proc* 42:1-10, 1994.
21. **Glover J:** Adaptive noise canceling applied to sinusoidal interferences. *IEEE Trans Acoust Speech Signal Proc* ASSP-25:484-491, 1977.
22. **Riviere CN:** Adaptive suppression of tremor for improved human-machine control, Ph. D. dissertation, Johns Hopkins University, Baltimore, Md., 1995.
23. **Riviere CN, Reich SG, Thakor NV:** Adaptive Fourier modeling for quantification of tremor. *J Neurosci Methods,* submitted for publication, 1995.
24. **Tyrer PJ, Bond AJ:** Diurnal variation in physiological tremor. *Electroencephalogr Clin Neurophysiol* 37:35-40, 1974.
25. **Crawley EF, de Luis J:** Use of piezoelectric actuators as elements of intelligent structures. *AIAA J* 25:1373-1385, 1987.
26. **Humayun MU, Rader RS, Walsh AC, Awh CC, Schallen EH, et al:** The objective analysis of vitreoretinal surgical instruments. *Investigative Ophthalmol Visual Sci* 35:1261, 1994.
27. **Geddes LA, Baker LE:** *Principles of Applied Biomedical Instrumentation.* Wiley-Interscience, New York, 1989.
28. **Prochazka A, Elek J, Javidan M:** Attenuation of pathological tremors by functional electrical stimulation I: method. *Ann Biomed Eng* 20:205-224, 1992.
29. **Rosen MJ, Arnold AS, Baiges IJ, Aisen ML, Eglowstein SR:** Design of a controlled-energy-dissipation orthosis (CEDO) for functional suppression of intention tremors. *J Rehabil Res Dev* 32:1-16, 1995.

Acknowledgments

This research was supported by the National Institute on Disability and Rehabilitation Research (grant H133G30064). The authors thank Dr. S. Reich for access to test subjects; Dr. R.S. Rader for assistance in the surgical experiments; and D. Hsu, M. Kim, S. Yichun, W. Huang, M. Fung, and K. Ng for data analysi.

Cameron N. Riviere (S'94-M'96) received the B.S. in aerospace engineering and the B.S. in ocean engineering from Virginia Polytechnic Institute and State University in 1989, and the Ph.D. in mechanical engineering from Johns Hopkins University in 1995. Since September 1995 he has been a Research Associate in the Robotics Institute at Carnegie Mellon University. His research interests include adaptive signal processing, neural networks, nonlinear control systems, human-machine interaction, and medical robotics. He received second place in the 1995 EMBS Whitaker Student Paper Competition.

Dr. Riviere may be reached at The Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, 15213-3890; e-mail: Cam.Riviere@cs.cmu.edu.

Nitish V. Thakor (S'78-M'81-SM'89) received the B. Tech. degree in electrical engineering from the Indian Institute of Technology, Bombay, in 1974, and the Ph.D. degree in electrical and computer engineering from the University of Wisconsin, Madison, in 1981. He previously served on the faculty of Electrical Engineering and Computer Science at Northwestern University between 1981 and 1983, and since then he has been with the Johns Hopkins University School of Medicine, where he is currently serving as a Professor of Biomedical Engineering. He teaches and conducts research on cardiovascular and neurological instrumentation, signal processing, and large-scale computer applications, and is an author or more than 70 peer-reviewed publications on these subjects. He serves on the editorial boards of several journals, including the IEEE Transactions on Biomedical Engineering, and is actively interested in developing international scientific programs, collaborative exchanges, tutorials, and books on the topics of Biomedical Signal Processing, Neuroengineering, and High Performance Computers in Biomedical Engineering. Dr. Thakor is a recipient of a Research Career Development Award from the National Institutes of Health and a Presidential Young Investigator Award from the National Science Foundation, and he is a fellow of the American Institute of Medical and Biological Engineering.