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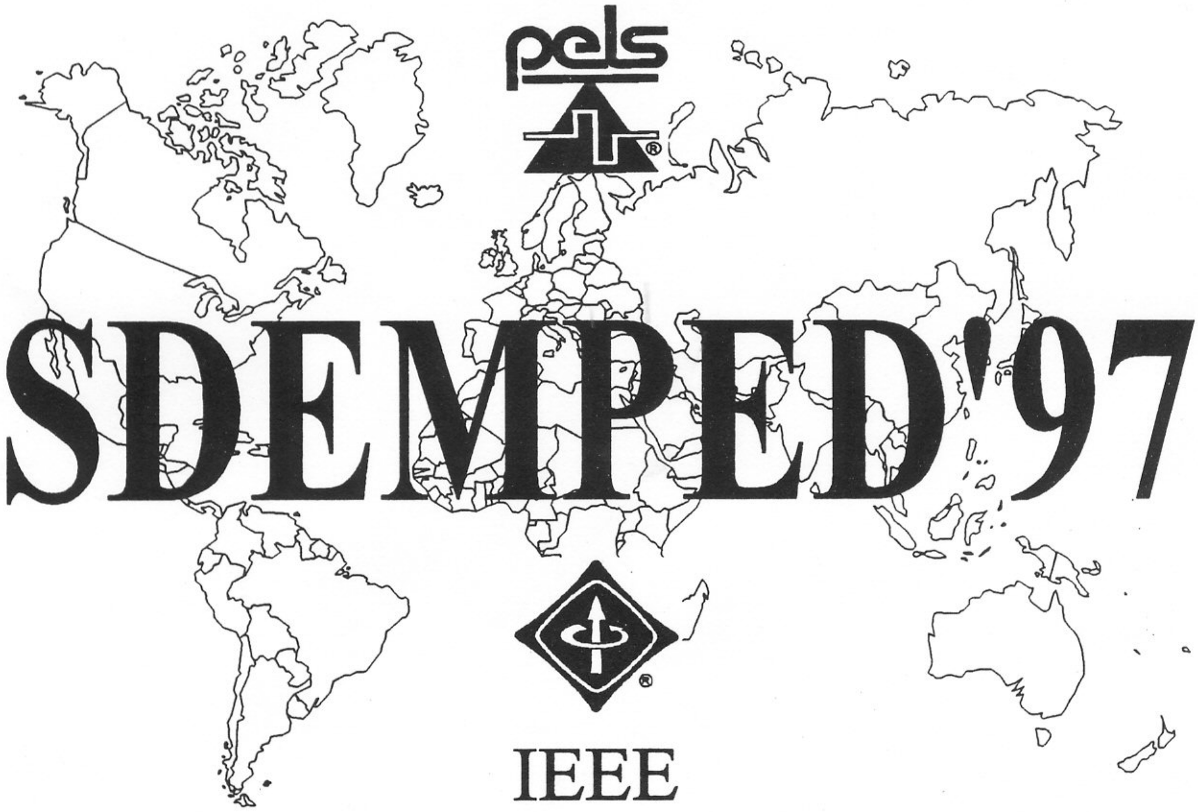

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Shorted Windings Sensing for Excited Electrical Machines

Robert J. Marks and Mohamed A. El-Sharkawi

Computational Intelligence Applications Laboratory
Department of Electrical Engineering
University of Washington
Seattle, WA 98195-2500

Abstract:

The twin signal sensing method for the detection and localization of winding shorts is reviewed. Pulses are injected into each terminal of the device with windings. The reflected signals are subtracted to produce a signature signal that contains information about the device's state. Using standard pattern recognition techniques, the method has been shown to be effective for detecting and/or localizing shorted windings in autotransformers and synchronous turbine-generators. The twin signal sensing method has been shown effective both in laboratory and field tests.

Key Words - Shorted-Turn Detection, Neural Networks, Feature Extraction, Novelty Detection, Autotransformers.

Introduction

Devices using windings include autotransformers and synchronous turbine-generators. Shorted turns in windings occur due to machine stress, aging and external transients. A winding short typically leads to deterioration of the efficiency and effective operation of the machines. This degeneration of machine performance may bring a high cost of repair.

Our purpose is to present an overview of *twin signal sensing* in the detection and subsequent localization of winding shorts. Details in the development can be found in earlier papers [1-5]. The methodology requires the taking of a fingerprint *signature signal*, generated from twin signals, of a healthy machine. No additional internal probes or electromechanical devices are required. If, during operation, the signature signal deviates significantly from that of a healthy system, a shorted winding is suspected. If the announcement of a short is deemed sufficiently serious, the rotor is taken off line for repair. When off line, a second signature signal can act as a stimulus to a trained neural network to announce the winding short location. The short location information greatly reduces required maintenance time. Since rotor down time can be economically expensive to the generation process, minimizing maintenance time is of critical importance. The procedure to find the location of a shorted winding a rotor can also be used for autotransformers, turbogenerators and other devices with windings.

Synopsis of Shorted Winding Detection & Localization Technology

Early detection and subsequent localization of shorted windings has remained elusive. Time domain reflectometry techniques do not work due to inductive leakage of the signal into surrounding windings making assessment of reflection of the signal from the impedance discontinuity intractable. A variety of other methods have been proposed for the detection of shorted windings in rotors of large turbine-generators. One method relies on the indirect measurement of the impedance of the rotor field-winding during operation [6]. This method, however, yields dubious results unless the number of shorted-turns is significantly high. One positive characteristic of this approach is the possible detection of a intermittent shorted-turns that disappear at a certain speed. Continuous monitoring of the field resistance during coast-down operation may reveal an abrupt change in value. This most certainly can be related to an intermittent shorted-turn. However, this method will not provide any help when a constant short is present.

Some methods of detecting shorted turns monitor flux asymmetry created by applying AC current to the field through the collectors and holding a C-shaped pick-up coil across the slot [7]. This approach is accurate but can only be performed after removing the rotor from the bore. Doing so is an expensive exercise. In addition, detection of all shorts that tend to disappear when the rotor is brought to stand-still is precluded.

Other methods for shorted turn detection rely on special design of the stator winding [7] Flux asymmetries generate circulating currents which can be measured. Although the method has the advantages of being applied to the machine under operation and not being intrusive, it also presents some serious disadvantages. For example, many machines presently in operation do not have a winding design which lends itself to the application of this method. Redesigning a machine for the sole purpose of detecting shorted-turns is not practical.

One of the most reliable methods for shorted turn detection requires direct measurement of the air-gap magnetic flux with the machine in operation [8]. The flux is measured by a pick-up coil installed in the gap. Unfortunately, the presence of these coils in existing machines (and new ones) is rare and installation requires excessive down-time.

Neural network models of machines have been proposed as a technique to detect shorted turns [9-13]. These methods, however, require a detailed mathematical model of the machine

Twin Signal Generation of the Signature Signal

A generic description of twin signal sensing is illustrated in Figure 1. The windings are connected from both ends to a high frequency pulse generator. Two identical signals are injected into the winding from both sides. The reflected waveforms are received and subtracted to form the *signature signal*. The frequency of the injected signal must be selected to ensure no interference between the falling edge of the injected signal and the reflected wave.

Ideally, if the windings are symmetric and there are no shorted windings, a signature signal identically zero is expected. Shorted windings introduce asymmetry into the reflected waveforms and the signature signals deviate from zero. In practice, however, the signature signal for healthy windings, although small in amplitude, is not identically zero. It does, however, serve as a reference to which subsequent signature signals can be compared.

The Signature Signal

The signature signal for the healthy windings provides the template to which subsequent signature signals are compared. For rotors, the signature signal can be relatively insensitive to rotation rate and load. This is illustrated in Figure 2 [1] where the signature signal is shown for the 60 MW generator at Southern California Edison's Highgrove Power Station. Four steam turbine generators are subsumed in the station. The station's design offers ready access to the machine. The generators are two-pole, hydrogen cooled machines. The DC rotor field windings are fed from rotary exciters attached to the shaft of the outboard end of the machine. Access to the generator's collector rings, and to the exciter's commutators are readily attainable through hatches on both sides of each machine. The four generators are almost identical units. This fact allows comparison tests to be performed between the different machines.

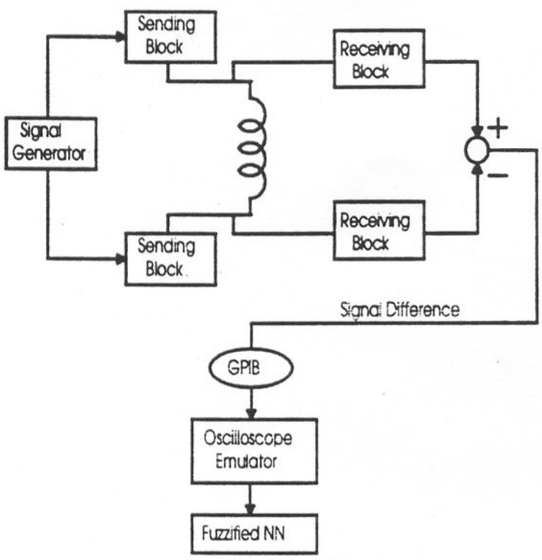

Figure 1: Generation of the signature signal using twin signal sensing.If the windings are totally symmetric and no winding shorts are present, the signature signal will be identically zero. If the signature signal deviates from zero, the presence of a shorted winding is suggested. In certain cases, the signature signal can be processed using a neural network to localize the short.

In several stages, the rotor of the first machine was brought up to full speed with the excitation connected and thus providing power to the rotor. The voltage applied to the rotor is proportional to rotation speed. Figure 2 shows plots of the signature signal at several different speeds. The solid line represents no rotation, the dotted line represents a very slow rolling rate, the dashed line represents 1800 rpm, and the dash-dot line represents 3600 rpm.

Winding Short Detection Using Novelty Detection

When a rotor is operating, shorted windings *detection* can be performed by a technique known as *novelty detection*. Novelty detection is a term used for finding a signal that differs from a given set of signals, or, equivalently, detecting change in otherwise status quo operation. Novelty detection can be conceptually viewed as a method of grouping a representative set of healthy signature signals and comparing future samples with this group. The underlying assumptions are

- the training set is statistically representative of all healthy status quo operating conditions, and
- the signal is not time variant..

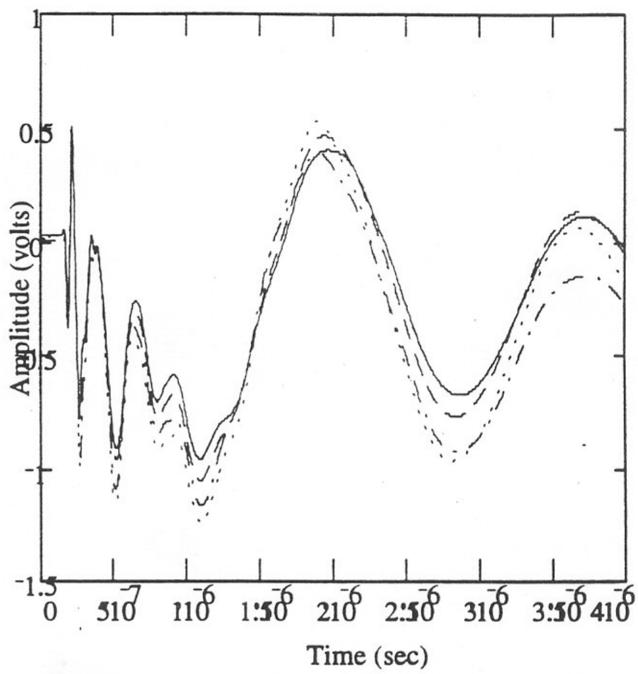

Figure 2: Signature signals of a rotor at different speeds [1].

A number of approaches to novelty detection have been suggested. A linear spanning method [13] (referred to as the *novelty filter*) is an approach where the orthogonal complement of the linear space spanned by the training set is measured and compared to a threshold. In geometrical terms, this method tries to fit a hyperplane to the data and ignores all distances in that plane. Only the orthogonal distance to the hyperplane is considered in making a decision concerning novelty. *Radial basis neural networks* (see [14-15] provide overviews) as a method of a non-parametric estimation of the data's *a priori* distribution have also been applied to novelty detection [16]. A statistical semi-parametric estimation technique defining several hyperellipsoidal clusters is described by Leonard & .Kramer [17] and has been extended to novelty detection [18]. A robust statistical method for finding elliptical clusters is defined by Jolion, Meer & Bataouche, [19]. Nonlinear statistical estimation has been applied [20] where a neural network is trained to recognize a mapping of any given probability distribution to an uncorrelated Gaussian distribution. This is done with an information preservation criterion, and a simple spherical boundary detection is then applied. Other methods exist such as ART clustering techniques (see *e.g.*[15]), where new clusters are formed when novelty is observed.

Novelty detection can be geometrically visualized as illustrated in Figure 3. A number of healthy signature signals, corresponding to the hollow dots, are expressed as points in a signal space. There will be variations in the point locations of healthy status quo signals in detection of shorted windings due to effects such as brush noise, rotor speed and load. When a sufficient number of points are gathered, a surface is "shrink wrapped" around the points. In figure 3, the "shrink wrap" around the hollow points is shown as an ellipse. After this boundary is established, a new point is deemed healthy if it lies within this surface. If outside, it is novel and a shorted winding is suspect.

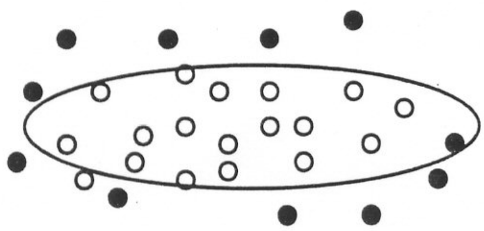

Figure 3: Illustration of novelty detection.

Novelty detection can be cast in terms of elementary hypothesis testing. The binary hypothesis test considers a given hypothesis H_0 that is to be proved, versus an alternative hypothesis H_1. In our case, H_0 is the hypothesis that the rotor is healthy. H_1 is the alternative hypothesis that the rotor has shorted winding. Inherent in all detection theory is the tradeoff between false alarm rate, α, and detection rate, β. In Figure 3, the 18 hollow dots represent healthy signature signals and the eleven solid dots represent signature signals. One healthy signal - the hollow dot lying outside of the ellipse - and one signature corresponding to a shorted winding - the solid dot lying within the ellipse - are misclassified. For this test data, a good estimate of the detection rate is $\beta = 10/11$ and the false alarm rate $\alpha = 1/18$.

Increasing β, however, invariably increases α. Conversely, decreasing α decreases β. In novelty detection, the values of α and β can be tuned by choosing how tightly we place the shrink wrap around the healthy status quo data. As the shrink wrap grows "tighter", both the false alarm and detection rates decrease. Visualize, for example, in Figure 3, the effect on β and α as the ellipse becomes smaller and smaller.

For novelty detection, the trade-off between false alarm rate, α, and shorted winding detection rate, β, can not generally be determined. Indeed, β cannot be measured. This is because, simply, access to signatures corresponding to shorted windings (*e.g.* the solid dots in Figure 3) are not available. Consider, for example, a turbine-generator. To gather data corresponding to the solid dots in Figure 3, shorts would need to be imposed in the windings and training status quo signature signals gathered while the generator was running. Doing so is clearly physically and economically prohibitive.

One method in novelty detection is to define a *constant false alarm rate* (CFAR), not to be exceeded by the training set. Unlike the detection rate, the false alarm rate of a novelty detector can be effectively estimated. Higher detection rates are obtained at the cost of choosing a higher false alarm rate.

The only way of controlling the outcome is to define a constant false alarm rate, not to be exceeded by the training set (see *e.g.* [21]). Other possible methods of finding the threshold from a given false alarm rate include the usage of parametric estimators, but assumptions about the probability distribution of the data are required.

Laboratory Emulation and Effectiveness Test of Twin Signal Sensing Novelty Detection

In order to allow inspection of both the false alarm and detection rates in a novelty detector, a test rotor was built to simulate the combined effect of applied voltage and rotation. Quick accessibility to the windings for shorting between adjacent wires was imposed on the design. The test rotor is a three foot long iron core, with four wound poles connected in series. The rotor is wound with polymer insulated stranded wires lying in 12 slots, evenly distributed around the circumference of the core, with inner and outer windings alternating in these slots. Rotation is provided by an external motor, and slip-rings connect the rotor windings to the voltage supply and the measuring circuit at one end. At the other end, the windings are accessible for connecting two and two of the wires together to produce shorts.

For an elliptical surface shrink wrap around the signature signal points (we found this to work best compared to a number of other geometries [5]), detection rates of 100% and false alarm rates of 0% were achieved when the rotor was stationary or at turning gear speed. (The rotor is in turning-gear when rotating very slowly, in our case at around 30-60 rpm.) The fast rotating rotor ran at the synchronous speed of 1800 rpm to simulate turbine-generator in full operation. Here, the detection rate was 91% and the false alarm rate was 0.4%. Separate novelty filters were required each speed but were not required for varying loads. Details of the experiment are in the paper by Guttormsson *et al.* [5].

Winding Short Localization

Winding shorts can also be *localized* using twin signal sensing. Signature signals corresponding to shorts in each of the windings are used to train a layered perceptron artificial neural network. Twin signal sensing has been applied to a turbogenerator and on an autotransformer [2-4]. Brief reviews will be given here for an autotransformer tested in a laboratory environment and a turbogenerator tested in the field.

Autotransformer

The autotransformer, shown in Figure 4, has a 22 mH inductance. During the test, the short was simulated by positioning the carbon brush of the center tap across two windings. The windings are divided into 4 sections. For each shorted turn, the signature signals are captured.

By shorting adjacent turns at several locations within the field winding, 120 training patterns were collected. A neural network with one hidden layer, thirteen input neurons, four hidden neuron and six output neurons was used. This architecture gave a lower test error than other architectures. The standard back-error propagation was used to train the neural network.

After the network was trained, it was tested for several short locations. Compared with the actual short location, the network identified the location of the short with a great degree of accuracy. The results of the neural network testing are shown in Figure 5. The diagonal line represents the actual location of the short, and the circles represent the neural network results. The results are clearly quite good.

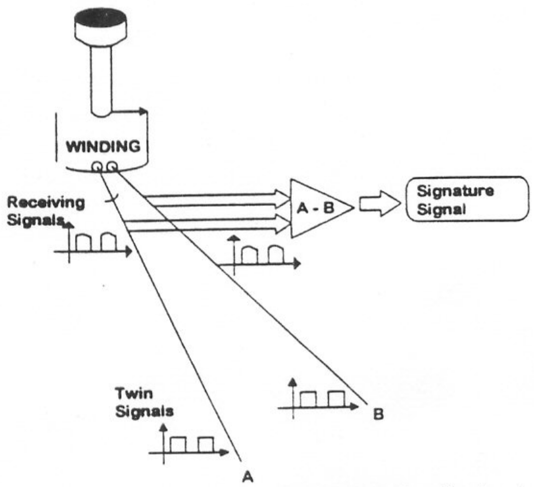

Figure 4. Test system for shorted winding localization in an autotransformer

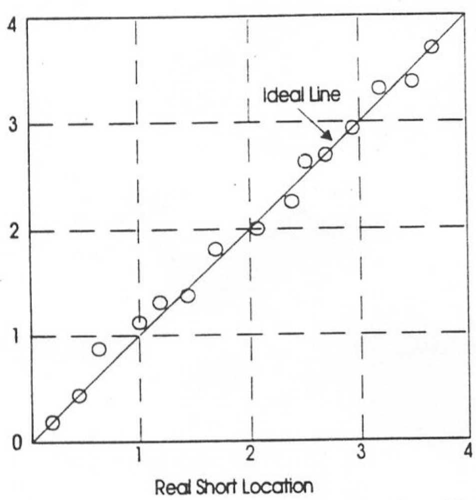

Figure 5: Neural network localization versus actual position of the shorted windings in an autotransformer as predicted by the neural network.

Turbogenerator

The twin signal sensing shorted winding *localization* method was also tested on a turbogenerator at the Southern California Edison Company [2]. The rotor is a 2-pole, 3600 rpm, 60 MVA with 7 concentric coils on each pole. Each coil has 17 turns. Thus the loss of one turn reduces the ampere-turns of that pole by about 0.85%.

To train and test the neural network, temporary shorts were introduced between adjacent windings when the rotor was off line. Corresponding signature signals were obtained at a 5 MHz sampling rate. Example signature signals for different short locations are shown in Figure 7.

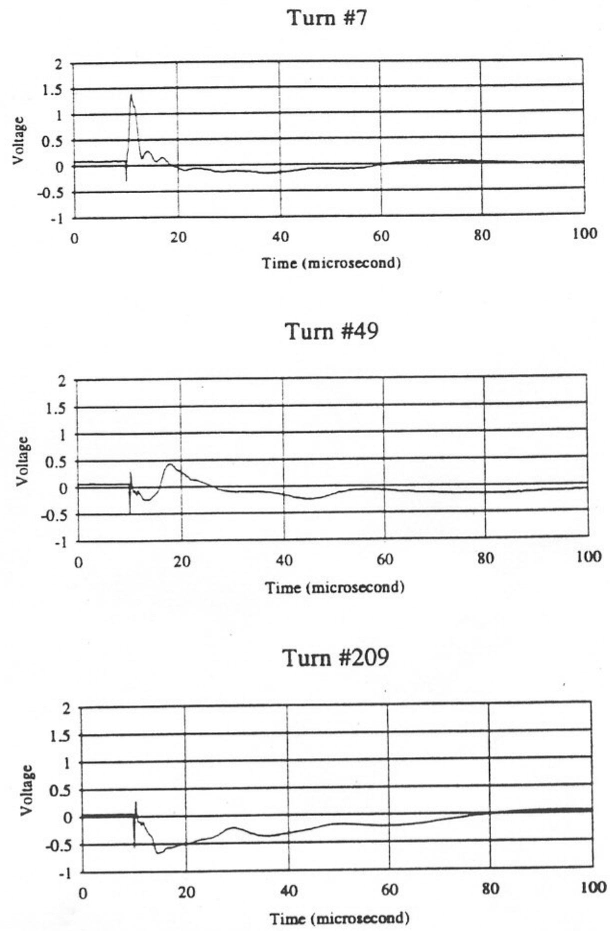

Figure 6: Signature signals from a 60 MVA Southern California Edison Company turbogenerator for shorts imposed in different windings [2].

A total of 67 training patterns were collected by shorting adjacent turns at several locations within the field winding. A neural net with one hidden layer, thirteen input neurons, four hidden neurons and six output neurons was trained. The network was trained by using the standard back-error propagation method. Remarkably, in each test case, the shorted winding was successfully localized to the proper coil. Details are in the paper by El-Sharkawi *et al.* [2].

Conclusion

Twin signal sensing is an effective method for detection and localization of shorted turns in the windings of electric machinery, surge coils and autotransformers. The methodology requires no equipment design alterations such as installation of flux meters or other sensors. It has been shown effective in both field and laboratory tests.

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Biographies

Mohamed A. El-Sharkawi is a Fellow of IEEE. He received his B.Sc. in Electrical Engineering in 1971 from Cairo High Institute of Technology, Egypt. His M.A.Sc and Ph.D. in Electrical Engineering were from the University of British Columbia in 1977 and 1980 respectively. In 1980 he joined the University of Washington as a faculty member where he is presently a Professor of Electrical Engineering and the Associate Chair. He is the Founder of the international conference on the *Application of Neural Networks to Power Systems (ANNPS)* and the Co-founder of the international conference on *Intelligent Systems Applications to Power (ISAP)*. He is a member of the administrative committee of the *IEEE Neural Networks Council* representing the *Power Engineering Society;* Video Tutorial Chair of the *IEEE Continuing Education Committee* and the *neural network council*. He is the Founding Chairman of several IEEE task forces and working groups and subcommittees. He is a member of the editorial board and associate editor of several journals including the *IEEE Transactions on Neural Networks and the Engineering Intelligent Systems*. He co-edited an IEEE tutorial book on the *applications of neural network to power systems*. He Organized and taught several international tutorials on intelligent systems applications, power quality and power systems; and organized and chaired numerous panel and special sessions in IEEE and other international conferences. He published over 120 papers and book chapters in these areas, and holds 7 licensed patents.

Robert J. Marks II is a Professor and Graduate Program Coordinator in the Department of Electrical Engineering , College of Engineering at the University of Washington, Seattle. He is Fellow of both IEEE and The Optical Society of America. Dr. Marks served as the first President of the IEEE Neural Networks Council (1990-91). In 1992, he was given the honorary title of Charter President. Dr. Marks was named an IEEE Distinguished Lecturer in 1992. Prof. Marks is the Editor-in-Chief of the IEEE TRANSACTIONS ON NEURAL NETWORKS (1992-1997) and serves as an Associate Editor of the IEEE TRANSACTIONS ON FUZZY SYSTEMS (1993-present). Dr. Marks is the author of the book Introduction to **Shannon Sampling and Interpolation Theory** (Springer Verlag, 1991) and is editor of **Advanced Topics in Shannon Sampling and Interpolation Theory** (Springer Verlag, 1993), and **Fuzzy Logic Technology and Applications**, (IEEE Technical Activities Board, Piscataway, 1994). He is a co-editor of the books **Computational Intelligence: Imitating Life**, (IEEE Press, 1994), and **Computational Intelligence: A Dynamic Systems Perspective**, (IEEE Press, 1995). Dr. Marks is serves as the faculty *advisor to the University ofWashington's chapter of Campus* Crusade for Christ. His hobbies include cartooning, song writing, Gunsmoke, posing for pompous pictures and composing short but thorough biographical sketches.