Feature Extraction of Event-Related Potentials using Wavelets: An Application to Human Performance Monitoring

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Abstract

This report describes the development and evaluation of mathematical models for predicting human performance from discrete wavelet transforms (DWT) of event-related potentials (ERP) elicited by task-relevant stimuli. The DWT was compared to principal components analysis (PCA) for representation of ERPs in linear regression and neural network models developed to predict a composite measure of human signal detection performance. Linear regression models based on coefficients of the decimated DWT predicted signal detection performance with half as many free parameters as comparable models based on PCA scores. In addition, the DWT-based models were more resistant to model degradation due to over-fitting than PCA-based models.

Feed-forward neural networks were trained using the backpropagation algorithm to predict signal detection performance based on raw ERPs, PCA scores, or high-power coefficients of the DWT. Neural networks based on high-power DWT coefficients trained with fewer iterations, generalized to new data better, and were more resistant to overfitting than networks based on raw ERPs. Networks based on PCA scores did not generalize to new data as well as either the DWT network or the raw ERP network.

The results show that wavelet expansions represent the ERP efficiently and extract behaviorally important features for use in linear regression or neural network models of human performance.

The efficiency of the DWT is discussed in terms of its decorrelation and energy compaction properties. In addition, the DWT models provided evidence that a pattern of low-frequency activity (1 to 3.5 Hz) occurring at specific times and scalp locations is a reliable correlate of human signal detection performance.

Introduction

Studies have shown that linear regression models may significantly explain and predict human performance from measures of ERPs elicited by stimuli presented in the context of a task (Trejo, Kramer, & Arnold, 1995). These models have used, as predictors, measures such as the amplitude and latency of ERP components (e.g., N1, P300). Other studies have used more comprehensive measures such as factors derived from principal components analysis and discriminant functions (Humphrey, Sirevaag, Kramer, & Mecklinger, 1990). Such models work best when they have been adapted to the individual subject, taking into account the temporal and topographic uniqueness of the ERP. Even then, the models often suffer from a limited ability to generalize to new data. In addition, the cost of developing and adapting such models for individuals is high, requiring many hours of expert analysis and interpretation of ERP waveforms.

Neural-network models for ERPs may be an improvement over linear regression models (DasGupta, Hohenberger, Trejo, & Mazzara, 1990; Ryan-Jones & Lewis, 1991). However, when neural network models have been based on traditional ERP measures, such as the sampled ERP time points or the amplitude of ERP components, the improvement in correlation between ERP measures and human performance has been small, typically about ten percent (Venturini, Lytton, & Sejnowski, 1992). Transformations of ERPs prior to neural network analysis, such as the fast Fourier transform (FFT), may improve neural network models (DasGupta, Hohenberger, Trejo, & Kaylani, 1990). However, the FFT is not ideally suited for representing transient signals; it is more appropriate for continuous signals, such as sine waves.

The wavelet transform is well suited for analysis of transients with time-varying spectra (Tuteur, 1989; Daubechies, 1990, 1992) such as the ERP. Discrete wavelet transforms (DWT; Shensa, 1991) represent signals as temporally ordered coefficients in different scales of a time-frequency plane. More precisely, the DWT represents signals in a time-scale plane, where scale is related to -- but not identical with -- frequency. The concept of scale comes from the dilation of a "mother wavelet" in the time domain. Each dilation is a doubling of the wavelet length in the time domain which results in a halving of the bandwidth in the frequency domain.

Each scale of the transform corresponds to one octave of signal bandwidth beginning with the smallest scale, i.e., the scale that corresponds to the highest frequencies represented in the signal. This scale, which is referred to as *scale 0*, contains frequencies ranging from the Nyquist frequency (half the sampling rate) to one-half the Nyquist frequency. As scales increase, the bandwidth decreases by a factor of two. For example, the bandwidth of scale 1 extends from _ Nyquist to _ Nyquist, and so on. The result of this successive halving of scale bandwidth is increasing frequency resolution (narrower bands) at larger scales (lower frequencies).

Because large scales represent low frequencies, fewer coefficients are required to represent the signal at large scales than at small scales. Since the bandwidth decreases by a factor of two with each scale increase, the sampling rate or number of coefficients can also be halved with each scale increase. This process, called decimation, leads to an economic but complete representation of the signal in the time-scale plane. However, in some cases decimation may be undesirable, for example, when the temporal detail in a particular scale is of interest. In such cases, the undecimated wavelet transform may be computed.

It is convenient to refer to the bandwidths of the scales in units of Hz, and this familiar unit will be used to make the following illustration. For a one-second long EEG signal with a bandwidth of 32 Hz and 64 time points, the first and smallest scale of the DWT would represent frequencies in the range from 16 to 32 Hz with 32 coefficients. The next larger scale would represent frequencies of 8 to 16 Hz with 16 coefficients. Successively larger scales would have the bandwidths and numbers of coefficients: 4-8 Hz/8, 2-4 Hz/4, 1-2 Hz/2, 0-1 Hz/1. A single additional coefficient would represent the DC level, for a total of 64 coefficients. In practice, the scale boundaries may deviate from this perfect halving of frequency and numbers of coefficients, depending on the method of computation. In particular, the undecimated DWT computations we will use here (Shensa, 1991) lead to scale boundaries that differ slightly from this example. However, the effects of these minor differences are inconsequential.

As with the discrete Fourier transform, the DWT is invertible, allowing for exact reconstruction of the original signal. An important feature of the DWT, however, is that the coefficients at any scale are a series that measures energy within the bandwidth of that scale as a function of time. For this reason it may be of interest to study signals within the DWT representation and use the DWT coefficients of brain signals directly in modeling cognitive or behavioral data.

In this study, the effect of representing ERPs using the DWT was compared with more traditional representations such as raw ERPs, peak and latency measures, and factors derived using principal components analysis (PCA). The comparisons determined whether the DWT can efficiently extract valid features of ERPs for use in linear regression models of human signal detection performance. In addition, neural network models were tested to determine whether the relative efficiency and validity of the DWT and other ERP representations would be maintained with a non-linear method. The signal detection task was chosen because ERP-performance relationships in this task have been described and analyzed with linear regression models based on peak and latency measures of ERP components (Trejo et al., 1995).

Method

In an earlier study (Trejo et al., 1995), ERPs were acquired in a signal detection task from eight male Navy technicians experienced in the operation of display systems. Each technician was trained to a stable level of performance and tested in multiple blocks of 50-72 trials each on two separate days. Blocks were separated by 1-minute rest intervals. About 1000 trials were performed by each subject. Inter-trial intervals were of random duration with a mean of 3s and a range of 2.5-3.5s. The entire experiment was computer-controlled and performed with a 19-inch color CRT display.

Triangular symbols subtending 42 minutes of arc and of three different luminance contrasts (.17, .43, or .53) were presented parafoveally at a constant eccentricity of 2 degrees visual angle. One symbol was designated as the target, the other as the non-target. On some blocks, targets contained a central dot whereas the non-targets did not. However, the association of symbols to targets was alternated between blocks to prevent the development of automatic processing. A single symbol was presented per trial, at a randomly selected position on a 2-degree annulus. Fixation was monitored with an infrared eye tracking device. Subjects were required to classify the symbols as targets or nontargets using button presses and then to indicate their subjective confidence on a 3-point scale using a 3-button mouse. Performance was measured as a linear composite of speed, accuracy, and confidence. A single measure, $\mathbf{PF_1}$, was derived using factor analysis of the performance data for all subjects, and validated within subjects. $\mathbf{PF_1}$ varied continuously, being high for fast, accurate, and confident responses and low for slow, inaccurate, and unconfident responses. The computational formula for $\mathbf{PF_1}$ was

$$\mathbf{PF_1} = .33\ \mathbf{Accuracy} + .53\ \mathbf{Confidence} - .51\ \mathbf{Reaction\ Time}$$

using standard scores for accuracy, confidence, and reaction time based on the mean and variance of their distributions across all subjects.

ERPs were recorded from midline frontal, central, and parietal electrodes (F_z, C_z, and P_z; Jasper, 1958), referred to average mastoids, filtered digitally to a bandpass of .1 to 25 Hz, and decimated to a final sampling rate of 50 Hz. The prestimulus baseline (200 ms) was adjusted to zero to remove any DC offset. Vertical and horizontal electrooculograms (EOG) were also recorded. Across subjects, a total of 8184 ERPs were recorded. Epochs containing artifacts were rejected and EOG-contaminated epochs were corrected (Gratton, Coles, & Donchin, 1983). Furthermore, any trial in which no detection response or confidence rating was made by a subject was excluded along with the corresponding ERP.

Results

Data Sample Construction

Within each block of trials, a running-mean ERP was computed for each trial. Each running-mean ERP was the average of the ERPs over a window that included the current trial plus the 9 preceding trials for a maximum of 10 trials per average. Within this 10-trial window, a minimum of 7 artifact-free ERPs were required to compute the running-mean ERP. If fewer than 7 were available, the running mean for that trial was excluded. Thus each running mean was based on at least 7 but no more than 10 artifact-free ERPs. This 10trial window corresponds to about 30s of task time. The $\mathbf{PF_1}$ scores for each trial were also averaged using the same running-mean window applied to the ERPs, excluding $\mathbf{PF_1}$ scores for trials in which ERPs were rejected.

Prior to analysis, the running-mean ERPs were clipped to extend from time zero (stimulus onset time) to 1500 ms post-stimulus, for a total of 75 time points. Sample running-mean ERPs (prior to application of rejection criteria) for one subject from one block of 50 trials are shown in Figure 1. Over the course of the block, complex changes in the shape of the ERP are evident.

Insert Figure 1 about here.

The set of running-mean ERPs was split into a screening sample for building models and a calibration sample for cross-validation of the models. For each subject, odd-numbered blocks of trials were assigned to the screening sample, and even blocks were assigned to the calibration sample. After all trial-rejection criteria were satisfied, 2765 running-mean ERPs remained in the screening sample and 2829 remained in the calibration sample.

Linear Regression Models

A multiple-electrode (F_z, C_z, P_z) covariance-based PCA was performed on the running-mean ERPs. Each observation consisted of the 75 time points for each electrode for a total of 225 variables per observation. Usually in PCAs applied to ERP data, the data from different electrodes would be in different observations, i.e., each observation representing an epoch × electrode combination. The objective is to identify physiologically meaningful components rather than to maximally decorrelate and compress the data. However, to remain compatible with our DWT computations (see below) we chose to consider each epoch as an observation rather than each epoch × electrode combination. This is still a legitimate multivariate linear transform, where the objective is to decorrelate and compress the variables rather than to identify components. While this is unconventional, we have other evidence that the conventional approach would not have made a difference in this case. In another analysis (Trejo & Mullane, 1995), which compared DWT and PCA on the present data using a bootstrap classification approach, a traditional PCA was required more data to reach the same classification accuracy as a DWT representation of the ERPs.

The BMDP program 4M (Dixon, 1988) was used for the calculations, using no rotation and extracting all factors with an eigenvalue greater than 1. One hundred and thirty-six factors were extracted, accounting for 99.45% of the variance in the data. The decay of the eigenvalues was roughly exponential, with the first 10 factors accounting for 70.96% of the variance in the data. Factor scores were computed for each running-mean ERP and stored for model development.

The DWT (Shensa, 1991) was computed using the same ERPs as in the PCA. As for the PCA, each epoch served as an observation. However, the DWT was computed separately for each electrode within each observation. A Daubechies analyzing wavelet (Daubechies, 1990) was used to compute the DWT of the EEG data over four scales. The length of the filters used for this wavelet was 20 points. This results in very smooth signal expansions in the wavelet transform. The scale boundaries and center frequencies of the scales are listed in Table 1.

The transform was centered within the ERP epoch and decimated by a factor of 2 at successive scales, yielding a total of 70 coefficients per transform (very low frequency scales and the DC term were excluded). The number of coefficients was approximately halved with each increasing scale after decimation. For scales 0-3, the respective numbers of coefficients were 37, 19, 9, and 5. The real values of the DWT were stored for model development. No further transformations were performed.

Linear regression models for predicting performance (**PF_1**), from either the PCA factor scores or from the DWT coefficients of the running-mean ERPs, were developed using a stepwise approach (BMDP program 2R). A criterion F-ratio of 4.00 was used to control the entry of predictor variables into a model. The F-ratio to remove a variable from a model was 3.99, resulting in a forward-stepping algorithm. The performance of each model was assessed by examining the coefficient of determination, $\underline{r}^2$, as a function of the number of predictors entered ($\underline{r}^2$ is the square of the multiple correlation coefficient between the data and the model predictions and also measures the proportion of variance accounted for by the model when the sample size is adequate and distributional assumptions are met).

Using the criteria described above, 90 of the 136 PCA factors entered into models predicting **PF_1**, and 92 of the 210 DWT entered into models predicting **PF_1** (Figure 2). The $\underline{r}^2$ increased for the PCA models in a fairly smooth, negatively accelerated fashion from a minimum of .07 for a single factor model to a maximum of .58 using 90 factors as predictors. The $\underline{r}^2$ for the DWT model based on a single coefficient was .12, nearly double that of the PCA model based on a single factor. The increase in $\underline{r}^2$ for the DWT models was almost linear for models using up to four coefficients as predictors. Beyond that, further increases occurred in a piece-wise linear fashion reaching a maximum of .62 using 92 predictors. The greatest difference in $\underline{r}^2$ between the DWT and PCA models (.11) also occurred with four predictors.

Insert Figure 2 about here.

Prior experience has shown that models using more than 10 predictors have limited generality and are difficult to interpret. For this reason, cross-validation of the PCA and DWT models was performed with no more than 20 predictors. The models developed using the screening sample were applied in turn to the PCA scores and DWT coefficients of the calibration sample. As for the screening sample, performance of the models for the calibration sample was assessed using $\underline{r}^2$ (Figure 3). In addition, the significance of $\underline{r}^2$ was assessed using a F-ratio test (Edwards, 1976). This test used an adjusted number of degrees of freedom for the denominator, to allow for the serial correlation in the data introduced by computing the running means of the ERPs. In effect, the number of degrees of freedom was divided by 10, to allow for the 10-trial cycle length of the running-mean window. A conservative significance level of .001 was chosen, given the large number of models computed. The contour of $\underline{r}^2$ values at this significance level appears as a dot-dashed line in Figure 3.

Insert Figure 3 about here.

All of the PCA and DWT models tested explained significant proportions of variance in the calibration data set. For the PCA models, calibration $\underline{r}^2$ rose gradually from a nearly insignificant level to a maximum of .22 using 10 predictors. The equation for the 10-predictor PCA model was

$$\mathbf{PF}_1 = .11\ \mathbf{F}_2 - .10\ \mathbf{F}_4 + .13\ \mathbf{F}_5 - .05\ \mathbf{F}_8 - .09\ \mathbf{F}_9 + .08\ \mathbf{F}_{11} - .06\ \mathbf{F}_{15} - .08\ \mathbf{F}_{43} + .07\ \mathbf{F}_{47} - .07\ \mathbf{F}_{68} + .02,$$

where the factors are indexed according to the proportion of variance accounted for in the running-mean ERPs. The factor accounting for the greatest variance in the ERPs (Factor 1) did not enter the model. Five of the first 10 factors (Factors 2, 4, 5, 8, and 9) entered the model. Respectively, these factors accounted for proportions of variance in the ERPs of .12, .031, .0283, .0184, and .0169, or a total of .21 (21%). The entry of some of the higher factors in the 10-predictor model is surprising, given the small amount of variance in the ERPs that they account for. For example, Factors 11, 15, 43, 47, and 68 accounted for proportions of variance equal to .014, .01, .0022, .0019, and .0011, respectively, or a total of .0292 (under 3%).

Among the DWT models, the calibration $\underline{r}^2$ for a single predictor (.11) was well above that of the corresponding single-factor PCA model (.04) and rose to a maximum of .22 using five DWT coefficients as predictors. The DWT coefficients are coded by electrode (F_Z, C_Z, P_Z), scale (S0, S1, S2, S3) and time index (T0, T1, ..., TN). Actual latencies of the time points are obtained by multiplying the time index by 20 ms, the sampling period.

The best single-predictor model was based on coefficient CzS3T22, with a regression coefficient of -.03 and an intercept of .02. Beyond five predictors, the $\underline{r}^2$ for the DWT models declined slightly, and leveled off after about 10 predictors, showing no further improvement. As for the screening sample data, the greatest difference in $\underline{r}^2$ between the DWT and PCA models for the calibration sample (.10) occurred with four predictors.

The equation of the best five-predictor DWT model selected by the stepwise regression algorithm was

$$\mathbf{PF_1} = -\ 0.03 * \mathbf{F_zS_2T_6} + 0.04 * \mathbf{F_zS_2T_{22}} + 0.06 * \mathbf{C_zS_2T_6}$$
$$-\ 0.05 * \mathbf{C_zS_2T_{22}} - 0.05 * \mathbf{P_zS_2T_6} - 0.17.$$

From the five-predictor model, it is clear that a single scale, number 2, is most important for predicting task performance. This scale mainly reflects the time course of energy within the bandwidth of .078 to 1.86 Hz, which overlaps the range of the delta band of the EEG (1- 3.5 Hz) and will include some influence from low-frequency ERP components such as the P300 and slow waves. Two time intervals are indicated across electrodes: point 6 at F_z, C_z, and P_z (120 ms), and point 22 and F_z and Pz (440 ms). Frontal and parietal energy (F_z, P_z) in scale 2 at 120 ms is inversely related to $\mathbf{PF_1}$ as shown by the negative regression coefficients, whereas central activity (C_z) is positively related to $\mathbf{PF_1}$. Central and parietal energy (Cz, Pz) in scale 2 is inversely related to $\mathbf{PF_1}$ at 440 ms.

One potential problem with the wavelet analysis performed here stems from the length of Daubechies filters used (20 points). These filters had lengths over one fourth the length of the signals (75 points). While these filters produce smooth wavelet transforms, they also increase the "support" of the transforms in the time domain. This means that the transforms are extrapolated in time before and after the interval of the signal. It also means that, with respect to the filter length, the signal is short in duration and appears to be a brief impulse at larger scales. A possible complication from this is that time resolution for signal features at the larger scales may be imprecise.

It is possible to decrease the support of the wavelet transform at the expense of smoothness by using shorter filters. To test the effects of shorter filters, the current data were partially re-analyzed using Daubechies filters of 4 points in length. With these filters, the support of the transform is reasonable at all four of the scales analyzed and time resolution of signal features at the larger scales is more precise than with the 20-point filters.

The most important single predictor for the 4-point filter DWT was located at electrode Cz and scale 2, as for the best single-predictor model based on 20-point filters. However, the wavelet coefficient in the 4-point filter model, CzS2T15, was at the 15th time point or a latency of 300 ms. This lies 120 ms earlier than the scale 2 coefficient in the best single-predictor model based on the 20-point filters (CzS2T22). The regression coefficient for CzS2T15 in the 4-point filter model was .03, with an intercept of -.16. This regression coefficient is negative, whereas the regression coefficient for CzS2T22 in the 20-point filter model was positive. The difference in sign suggests that CzS2T15 in the 4-point filter model is a different feature of the

ERP than CzS2T22 in the 20-point filter model, even though it is in the same scale and at the same electrode. The cross-validation $\underline{r}^2$ for the 4-point filter based on CzS2T15 was .15, which is higher than the $\underline{r}^2$ for CzS2T22 in 20-point filter model (.11).

Neural Network Analyses

In addition to the linear regression models, feed-forward artificial neural networks were trained using the backpropagation method (Rumelhart & McClelland, 1986) to predict $\mathbf{PF_1}$ from ERP patterns. Three networks were trained: 1) raw ERPs; 2) PCA scores; and 3) DWT coefficients. For the ERP network, the inputs were the voltages in the ERP time series for electrodes F_z, C_z, and P_z. These were the same data used to derive the PCA scores and DWT coefficients used in the linear regression models described earlier. There were 75 points per electrode spanning a latency range of 0-1500 ms, for a total of 225 network inputs. For the PCA network, the PCA scores used in the linear regression models described above served as inputs. As for the linear regression models, only the first 136 factors were retained.

For the DWT network, three changes were made in the generation and selection of DWT coefficients. First, the wavelet transform was based on the 4-point Daubechies filters which appeared to be superior to the 20-point filters used in the initial linear regression models. Second, since low frequency information seemed valuable in the linear regression models, the range of the transform was extended, adding a fifth scale (Table 2). Third, selection of the coefficients was not performed by the decimation approach taken for the linear regression models. Instead, the undecimated transforms were computed (Shensa, 1991), yielding 75 points for each scale. Then the mean power of each coefficient was computed and the top 20% of the coefficients at each scale were selected as inputs to the network (Figure 4). This resulted in a set of 225 coefficients, or about the same number that would be obtained by decimation. However, this scheme selects coefficients that are high in power, and so account for large proportions of the ERP signal variance at each scale.

Insert Figure 4 about here.

Networks were trained and tested with a commercial software package (Brainmaker, California Scientific Software, Inc.). All three networks consisted of two layers. A single "hidden" layer consisting of three neurons received connections from all the inputs. These three neurons were fully connected to the output layer, which consisted of a single neuron. The teaching signal for this neuron was $\mathbf{PF}_1$. In addition to inputs from other neurons, each neuron received a constant "bias" input, which was fixed at a value of 1.0.

The output transfer function for all neurons was the logistic function with a gain of 1.0 and a normalized output range of 0.0 to 1.0. The learning rate was 1.0 and the momentum was 0.9. All inputs and the desired output ($\mathbf{PF}_1$) were independently and linearly normalized to have a range of 0.0 to 1.0. As for the linear regression models, the screening sample (half of runs) was used for training the networks and the calibration sample (the remaining runs) was used for testing. Training proceeded by adjusting the connection weights of the neurons for every input vector. The training tolerance was 0.1, i.e., if the absolute error between the network output (predicted **PF_1**) and the actual **PF_1** value for a trial exceeded 10%, then the connection weights were adjusted using the backpropagation algorithm.

Prior to training, the sequence of input vectors was randomized. Training involved repeated passes (training epochs) through the screening sample and was stopped after a maximum of 1000 training epochs. Testing was performed on the calibration sample at intervals of 10 training epochs. The validity of a trained network was measured in terms of the proportion of calibration sample trials for which **PF_1** was correctly predicted to within the criterion 10% margin of error. The curve relating the proportion of correctly predicted calibration sample trials to the number of training epochs will be referred to as the *generalization learning curve* (Figure 5).

Insert Figure 5 about here.

The probability of correctly guessing a uniform random variable with a range of 0.0 to 1.0 with a 10% margin of error is 0.2. As shown in Figure 5, two of the three networks trained to predict **PF_1** in the calibration sample better than 0.2 with as few as 10 training epochs. Beyond 50 training epochs, the generalization learning curves of the three networks begin to diverge.

The DWT network appears to "learn" to generalize about as well as it can by about 290 training epochs. For this network, the proportion correct jumps from about 0.25 to over 0.3 near 200 epochs. From that point on, a rough plateau in the curve is held, with a few dips between 800 and 1000 epochs. The maximum proportion correct of .348 occurs at epoch 930, but this is not substantially (or significantly) greater than an earlier maximum of .346 at epoch 290.

For the ERP network, a gradual rise in the proportion correct occurs between 10 and 400 epochs, reaching a maximum of .331 at training epoch 350. Beyond 400 epochs, the proportion correct for the ERP network declines gradually to near chance levels of performance.

The generalization learning curve of the PCA network exhibits the most complex shape, rising and falling repeatedly over the 1000-epoch range. Interestingly, it also shows a large step near 200 epochs, as did the DWT network, and an early maximum of 0.279 at 250 epochs, after which the curve declines and oscillates up to about 850 epochs. At that point the curve rises again, reaching a new, higher maximum of 0.288 at 940 epochs.

Although the curves in Figure 5 are complex, two generalizations seem possible. First, within the 1000-epoch scope of the training, all three networks appear to achieve near-maximal levels of generalization performance within the first 400 training epochs. Beyond 400 training epochs, further training appears to produce either declines or oscillations in generalization performance, and only small increases above the earlier maximum proportions of correctly predicted trials occur. Second, the DWT network trained most rapidly and achieved the highest and most stable level of generalization performance. The DWT network "learned" to generalize to new data faster than the ERP network by about 60 training epochs.

The raw ERP network achieved a proportion correct approaching that of the DWT network (.331 versus .348) but was not as stable. A _z_ test of the significance of the difference between these proportions based on the standard normal distribution (Fleiss, 1981, p. 23) yielded a _p_-value of .21. However, an F-test of the ratio of variances of proportions correct for the ERP and DWT networks between epochs 200 and 1000 rejected the hypothesis that the variances were equal, $F(79, 79) = 3.12$, $p < 0.000$ (the alternative hypothesis was that the true ratio of variances was greater than 1.0).

Generalization performance of the PCA network was lower than both the ERP and DWT networks. The _z_ tests of the differences between the proportions correct of DWT and PCA networks and of ERP and PCA networks yielded _p_-values of 0.0015 and 0.0162, respectively.

Decorrelation and Energy Compaction

Statistical independence of the predictor variables could be one reason why the linear regression models based on PCA scores and the DWT were more successful than the peak and latency measures used in earlier analyses. In the signal processing literature, the tendency of a transform to render independent measures from multivariate data is called decorrelation. Decorrelation efficiency compares the sum of the off-diagonal terms in the covariance matrices of the original (raw ERPs) and the transformed data (Akansu & Haddad, 1992, p. 28). A transform that perfectly decorrelates the data has a decorrelation efficiency of 1.0.

The decorrelation efficiency of the 4-scale DWT used here was 0.13. Although the factors obtained with PCA are decorrelated, the factor scores that represent the data may be correlated. For this reason, the decorrelation efficiency of the PCA, measured from the covariance matrix of the factor scores was not 1.0, but .64, which is still several times higher than the decorrelation efficiency of the DWT. However, the DWT regression models explained the same amount or more variance in the data using fewer variables than the PCA models. Thus it appears that the decorrelation efficiency of a transform alone does not determine how well it will extract important ERP features for modeling task performance.

The relatively small number of DWT coefficients needed to generalize to new data using linear regression models suggests that the DWT efficiently extracts a small but behaviorally important set of features from the ERP. The relative speed of generalization learning by the DWT neural network may also be consistent with this idea. If only a small proportion of the inputs contains information related to the output then only the weights corresponding to those inputs would require adjustment, leading to faster generalization learning.

In signal processing, the property of a transform that describes its tendency to concentrate information in a small proportion of the variables is called energy compaction (Akansu & Haddad, 1992, p. 28). Good energy compaction means having a small number of large values on the diagonal of the covariance matrix of the transform variables. It is measured as a function of the number of variables retained to fit the data, sorted in order of decreasing covariance. Energy compaction could also result in more robust models, showing less overfitting. This could occur when the variables that explain most of the variance enter first, leaving only variables of low influence to adversely affect the fits when added later.

For the data used in the linear regression models, energy compaction measures of the raw ERPs, PCA scores, and DWT coefficients for 5 variables was .06, .08, and .09. For 10 variables, energy compactions for ERP, PCA, and DWT were .11, .15, and .16, and for 20 variables, energy compactions were .20, .25, and .26, respectively. Thus over the range of models tested, the DWT was only slightly more efficient in compacting the energy (or variance) in the data than the PCA. It seems unlikely that such small differences in energy compaction (about 1%) could account for the higher efficiency of the DWT models than the PCA models.

Discussion

Linear Regression Models

Both PCA and DWT methods yielded linear regression models that significantly explained signal detection performance in a 30 s running window and generalized to novel data. Both methods also performed better than a traditional peak amplitude and latency analysis of the running-mean ERPs. For comparison, the best stepwise linear regression model developed using predictors drawn from a set of 96 multi-electrode amplitude and latency measures of the ERP on the same data set yielded an $\underline{r}^2$ of .28 for the screening sample and failed to significantly cross-validate on the calibration sample (Trejo, et al., 1995; peak amplitude- and latency-based models did cross-validate when adapted to the ERP waveforms of individual subjects).

The DWT models were clearly superior to the PCA models when based on a small number of predictors. Twice as many PCA factors were required to explain the same amount of variance in the data as DWT models based on 5 coefficients. In cross-validation, no advantage of the PCA models over DWT models was evident with any number up to 20 predictors. The PCA models showed evidence of over-fitting the data when more than 10 predictors were used, as shown by the decline in $\underline{r}^2$ for the calibration sample for models using 10 to 20 predictors. In contrast, the DWT models suffered relatively small decreases in $\underline{r}^2$ when using more than 5 coefficients.

Single-predictor models for the DWT based on 4-point filters were compared to the 20-point filters used initially to determine the sensitivity of the location estimates to filter length. The net effects of using shorter filters to compute the wavelet transform were to change the location estimate, but not the electrode or scale estimates of the best single predictor model, and increased cross-validation $\underline{r}^2$. The higher cross-validation $\underline{r}^2$ for the 4-point filter model than the 20-point filter model was unexpected. However, this result suggests that more precise temporal localization of features in the wavelet transform may provide more robust representation of the ERP or EEG features associated with task performance.

PCA is known to produce factors that resemble the shape and time course of ERP components. The information provided by the DWT is somewhat different. For example, the 5predictor DWT model indicated that a pattern of energy at specific latencies in the ERP confined to the bandwidth associated with P300, slow waves, and EEG delta band activity, was correlated with signal detection performance across a sample of eight subjects. It is well known that P300 and slow waves co-vary with the allocation of cognitive resources during task performance. However, it is not clear whether the wavelet coefficients included in the regression models are simply better measures of P300 and slow wave or if they represent new aspects of the ERP. Comparisons of ERPs reconstructed from the DWT coefficients and the average ERP waveforms will be required to express the coefficients in terms of familiar ERP peaks.

Neural Networks

As for the linear regression models, the best generalization performance of neural networks -- measured in terms of predicting $\mathbf{PF}_1$ in the calibration sample -- was achieved with the DWT representation of the ERPs. Somewhat surprisingly, neural networks trained to predict $\mathbf{PF}_1$ from raw ERPs generalized almost as well as the DWT. Both ERP and DWT-based networks generalized to new data significantly better than networks based on PCA scores.

The neural network based on the DWT required fewer training epochs than the raw-ERP network to reach a maximal level of generalization to new data. In addition, beyond the initial training period of 200 epochs, generalization performance of the DWT network was more stable than the ERP network. After about 400 training epochs, the generalization learning curve declined for the ERP network, indicating overfitting of the data in the screening sample. In contrast, the generalization learning curve for the DWT exhibited a few dips, but remained surprisingly stable over most of the training range, indicating a resistance to overfitting. This result agrees with the resistance to overfitting observed with more than the optimum number coefficients in the linear regression models based on the DWT.

General Conclusions

The results described here show that the DWT can provide an efficient representation of ERPs suitable for performance-prediction models using either linear regression or neural network methods. Furthermore, the DWT models tested here needed the fewest parameters, exhibited highest generalization and were relatively insensitive to the detrimental effects of over-fitting as compared to models based on PCA scores or raw ERPs. This result, together with the initial rise in $\underline{r}^2$ for the linear regression DWT models (Figure 3) suggest that the DWT coefficients measure unique and important sources of performance-related variance in the ERP.

The superiority of the DWT over PCA that we have seen in the models tested here cannot be explained in terms of decorrelation and energy compaction properties of these transforms. Decorrelation was actually higher for PCA than for the DWT, and energy compactions over the range of variables included in the models were about equal for the two transforms. Instead, it appears that the DWT simply provides more useful features than PCA, when utility is measured by how efficiently task performance can be predicted using ERPs.

For practical ERP-based models of human performance, ease of model development and speed of computation are also important factors. The cost of computing the DWT is trivial when compared to deriving a PCA solution, which involves inverting and diagonalizing a large covariance matrix. Even more time is required for peak and latency analyses, which depend on expert human interpretation of the waveforms.

The nature of the features extracted using the DWT merits further study. By identifying the time and scale of energy in the ERP related to task performance, specific ERP or EEG components may be indicated. For example, slow waves and delta-band activity appear in the 5-predictor linear regression DWT model of signal detection performance. In this way, The DWT may provide new insight into the physiological bases of cognitive states associated with different performance levels in display monitoring tasks.

Future work should examine the reconstructed time course and scalp distribution of the patterns indicated by DWT or other wavelet models and relate these to known physiological generators. Through inversion of the DWT, it is possible to reconstruct the time course of the energy indicated by a specific model. In addition, other wavelet transforms may provide a finer analysis of the time-frequency distribution of the ERP. For example, wavelet transforms using multiple "voices" per scale, such as the Morlet wavelets or wavelet packets, provide much finer resolution than that afforded by the DWT method used in this study. In addition, data from other kinds of tasks should be analyzed and the development of models for individual subjects should be also explored.

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Table 1. Scales of the 20-point Daubechies Discrete Wavelet Transform

Scale	Bandwidth (Hz)	Center Frequency (Hz)
0	10.50–25.00	16.20
1	4.42–10.50	6.82
2	1.86–4.42	2.87
3	0.78–1.86	1.20

Table 2. Scales of the 4-point Daubechies Discrete Wavelet Transform

Scale	Bandwidth (Hz)	Center Frequency (Hz)
0	10.88–25.00	16.49
1	4.74–10.88	7.18
2	2.06–4.74	3.12
3	0.90–2.06	1.36
4	0.39–0.90	0.59

Figure 1. Running-mean ERPs at sites F_z, C_z, and P_z for subject 2 in the first block of 50 trials. Zero on the abscissa represents the stimulus onset (appearance of the display symbol used for the signal detection task). The ordinate represents scalp voltage at each electrode site; positive is up. The running-mean ERPs for successive trials of the block are stacked vertically from bottom to top (lowest is first).

Figure 2. Coefficients of determination ($\underline{r}^2$ or variance accounted for) for PCA and DWT models developed to predict task performance ($\mathbf{PF}_1$) for eight subjects in a signal detection task. Models were based on a screening sample of running-mean ERP and $\mathbf{PF}_1$ data, drawn from odd-numbered blocks of trials. Models are assessed by the $\underline{r}^2$ as a function of the number of predictors entering into the model. Only models in which predictors met a criterion F-ratio of 4.0 to enter (3.99 to remove) are shown.

Figure 3. Coefficients of determination ($\underline{r}^2$ or variance accounted for) for the first 20 PCA and DWT models of Figure 2, cross-validated using running-mean ERP and $\mathbf{PF}_1$ data from a calibration set of data drawn from even-numbered blocks of trials. The dot-dashed line indicates the contour of $\underline{r}^2$ values significant using an F-ratio test at the p < .001 level where the numerator degree of freedom depends on the number of predictors and the denominator degrees of freedom is one-tenth of the sample size. Values above this contour are significant.

Figure 4. Mean power of the undecimated 5-scale DWT coefficients at electrodes F_z, C_z, and P_z, used for the neural network trained to predict $\mathbf{PF}_1$. The DWT coefficients for each running-mean ERP were squared, summed, averaged and plotted as a function of time relative to the stimulus. Each row of graphs represents one scale of the transform beginning with the smallest scales at the top (see Table 2) and proceeding to the largest scale at the bottom. Each column of graphs corresponds to one electrode site in the order F_z, C_z, P_z, from left to right. The 80% quantile was computed across electrodes within each scale and is shown by the horizontal line in each graph. Coefficients with mean power values greater than the 80% quantile, i.e., the top 20%, were used as inputs to the neural network.

Figure 5. Generalization learning curves of the three neural networks trained to predict $\mathbf{PF}_1$ from raw ERPs (solid line), PCA scores (dotted line), or high-power DWT coefficients (dashed line). The abscissa marks the number of training epochs (complete passes through the screening sample) and the ordinate marks the proportion of trials in the calibration sample for which $\mathbf{PF}_1$ was correctly predicted with a 10% margin of error. The solid circles mark the highest proportion correct for each network.

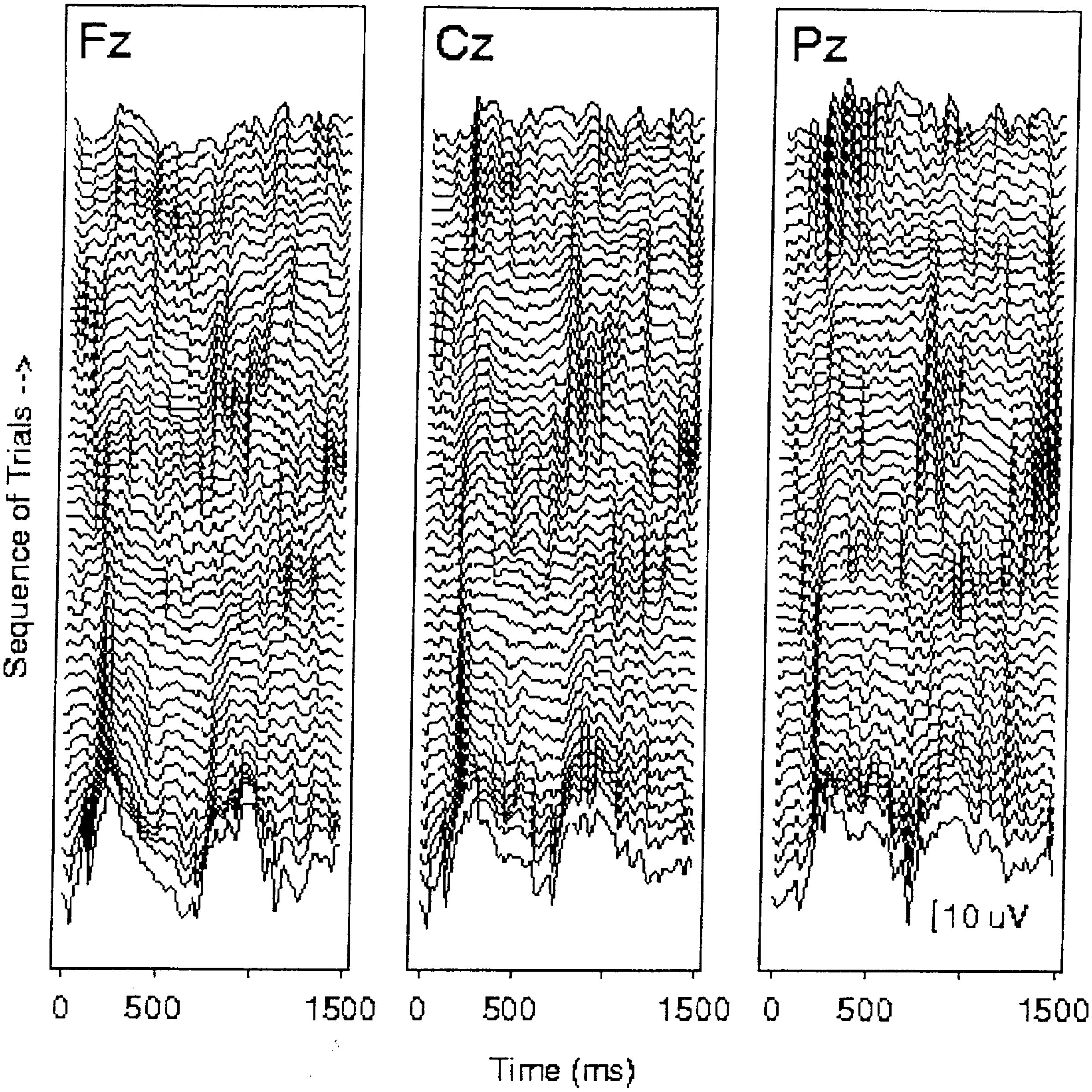

Fz
Cz
Pz
Sequence of Trials -->
[10 uV
0
500
1500
0
500
1500
0
500
1500
Time (ms)

Fig 1

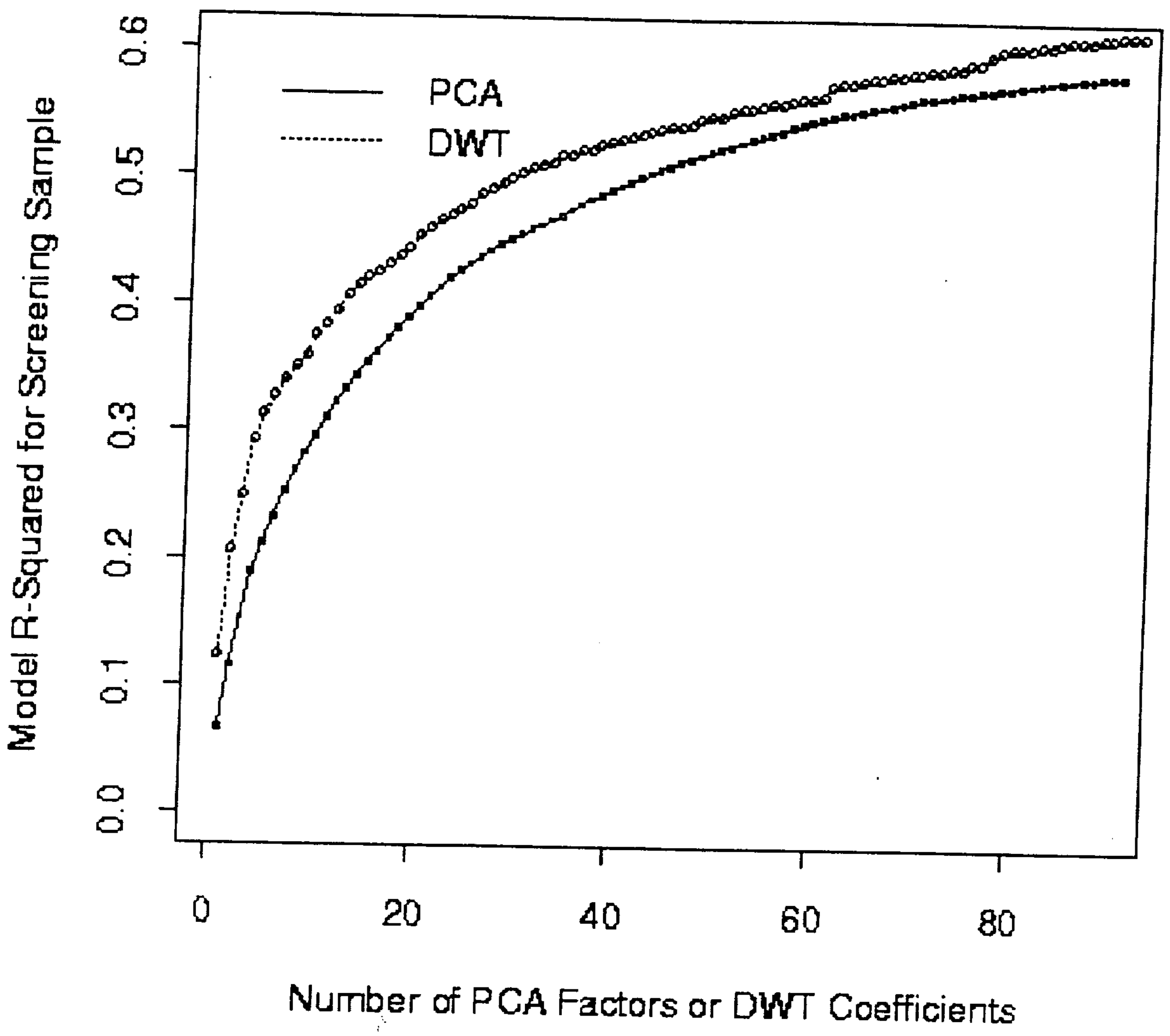
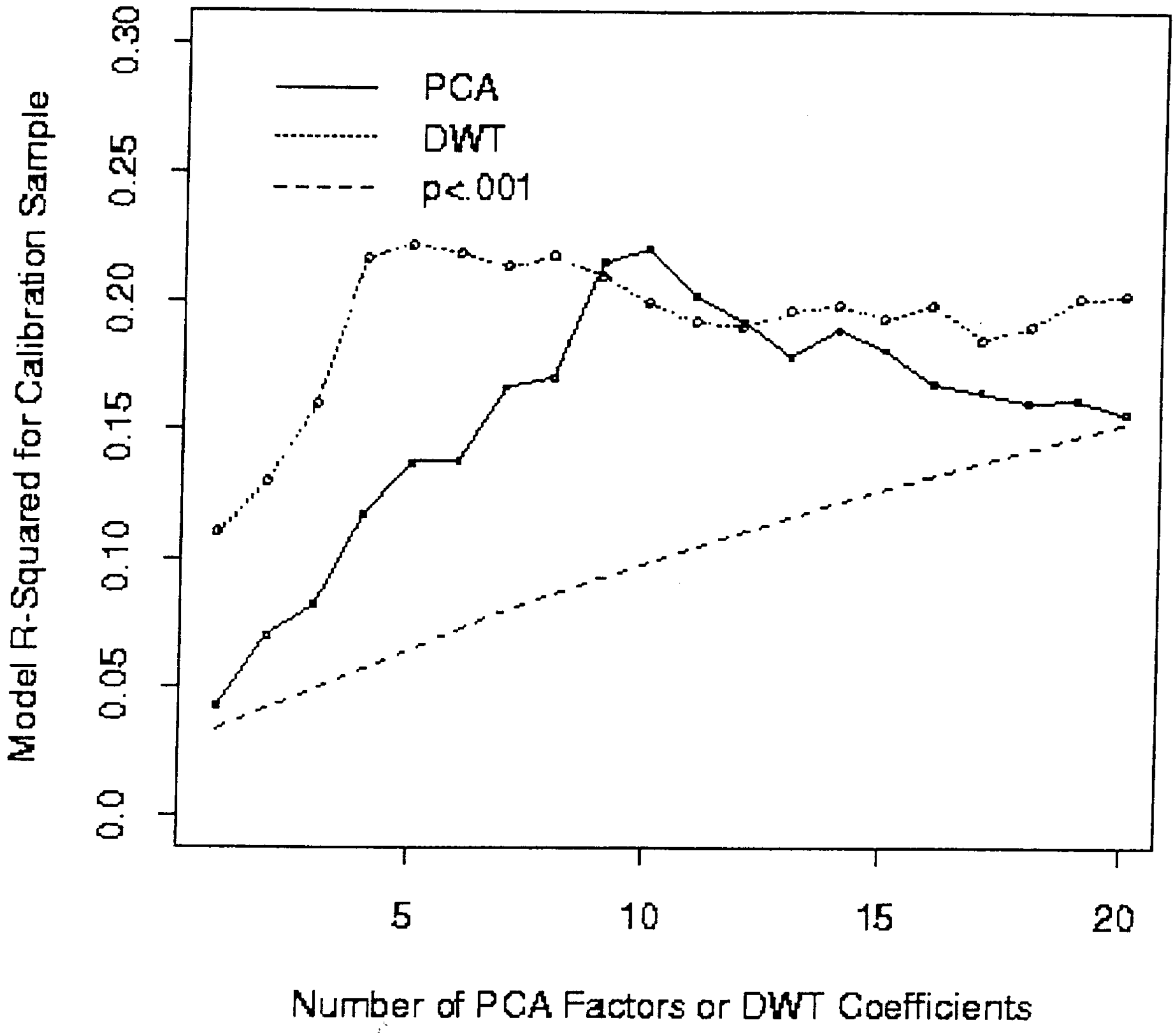
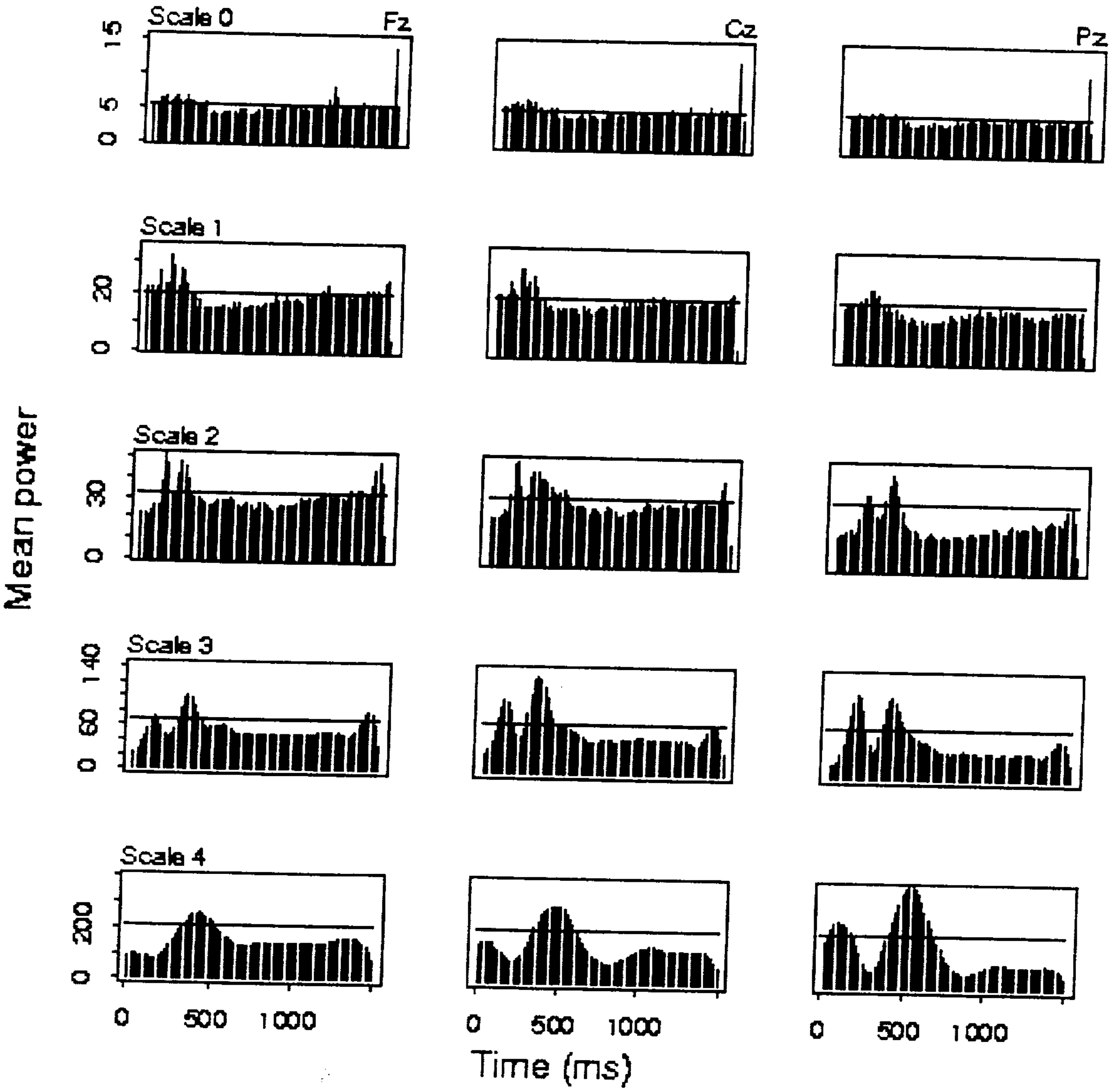

PCA
DWT
Model R-Squared for Screening Sample
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0
20
40
60
80
Number of PCA Factors or DWT Coefficients

Fig 2



Model R-Squared for Calibration Sample
0.0
0.05
0.10
0.15
0.20
0.25
0.30
PCA
DWT
p<.001
5
10
15
20
Number of PCA Factors or DWT Coefficients

Fig 3



Scale 0
Fz
Cz
Pz
0
5
15
Scale 1
0
20
Scale 2
0
30
Scale 3
0
60
140
Scale 4
0
200
Mean power
0
500
1000
0
500
1000
0
500
1000
Time (ms)

Fig 4

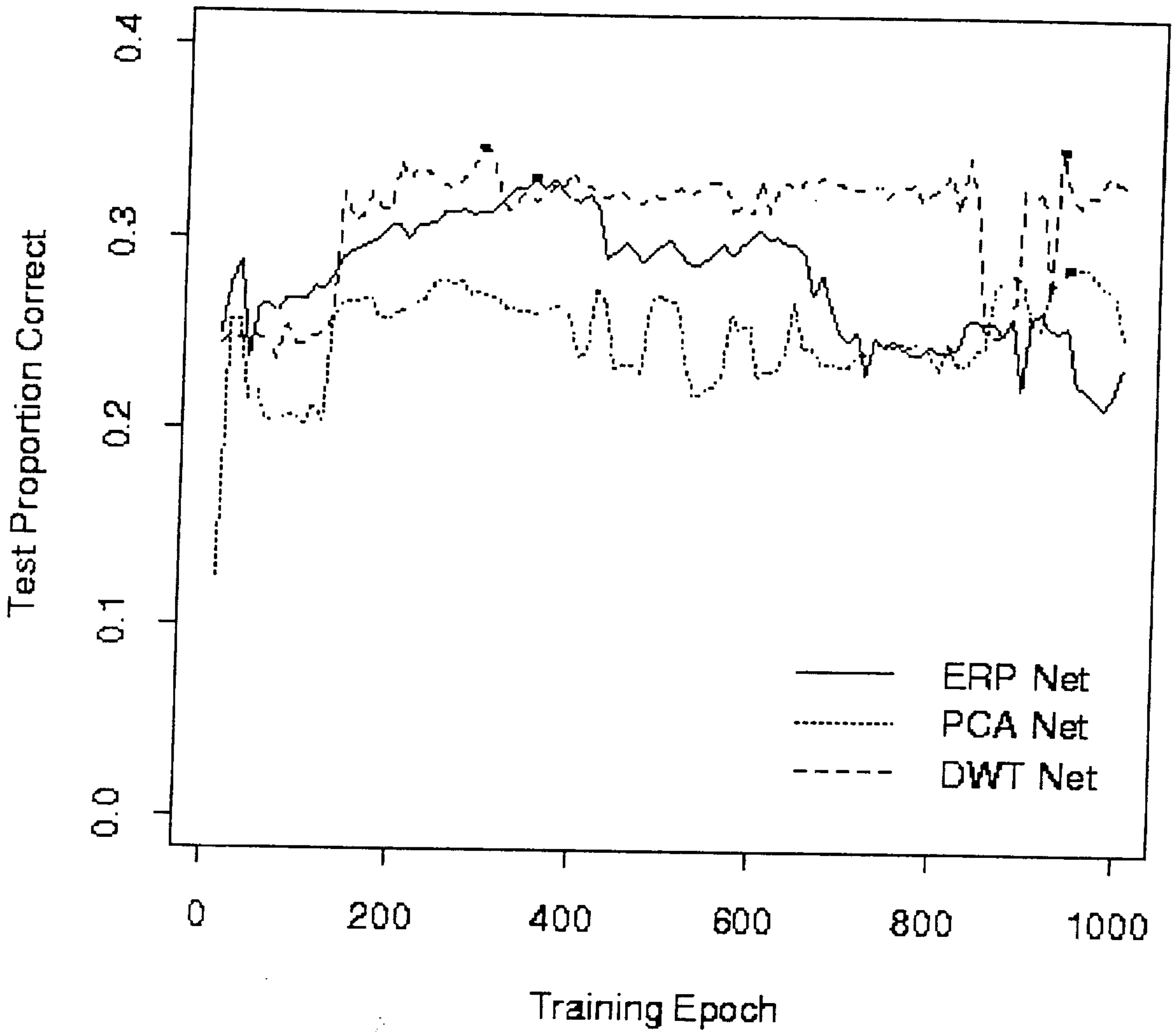

0.0
0.1
0.2
0.3
0.4
Test Proportion Correct
0
200
400
600
800
1000
Training Epoch
ERP Net
PCA Net
DWT Net

Fig 5