Estimation of human signal detection performance from event-related potentials using feed-forward neural network model

Miloš Koska*, Roman Rosipal, Artur König
Institute of Measurement Science
Slovak Academy of Sciences
Dúbravská cesta 9, 842 19 Bratislava
Slovakia
umerkosk, umerrosp, umerkoni@savba.sk

Leonard J. Trejo
Department of Psychology
University of Illinois at Urbana–Champaign
603 East Daniel Street, Champaign, IL 61820
USA
ltrejo@psych.uiuc.edu

Abstract

This paper extends the previously reported results on using two layer feed-forward neural network models for estimating human performance from event-related potentials (ERP) elicited by task-relevant stimuli [12]. Individual models were constructed using principal-component analysis regression (PCAR) and radial basis function (RBF) networks.

1 Introduction

In many safety-critical applications (e.g., air traffic control, power plant operation, military applications) the control is based on the ability of human operators to detect and evaluate task-relevant signals in presented visual data. Performance quality of operators varies over time, often falling bellow acceptable limits

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and may result in errors with serious consequences. The likelihood of such errors could be reduced if an objective method for assessment of human display-monitoring performance were available.

A fundamental part in development of such method is to construct the model reflecting the dependence between selected physiological metrics of mental workload (e.g., ERPs) and performance characteristics of human operator (reaction time, accuracy and confidence). The main difficulty in such an effort is that due to the character of measured data we are confronted with the curse of dimensionality.

In this contribution we describe our attempt to overcome this problem using projective data reduction technique (PCAR) and exploiting RBF network.

2 Methods

2.1 Data sample construction

ERPs reflect mental processes and are known to be related to human performance, including signal detection, confidence ratings, target identification and recognition, memory, tracking and mental computation (see the references in [11]).

We have used ERPs acquired in an earlier study [11], during signal detection task from five 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 3 s and a range of 2.5–3.5 s. The entire experiment was computer-controlled and performed with a 19–inch color CRT display (Figure 1).

Triangular symbols subtending 42 minutes of arc and of three different luminance contrasts (0.17, 0.43, or 0.53) 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 non-targets 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, PF1, was derived using factor analysis of the performance data for all subjects, and validated within subjects. The computational formula for PF1 was

$$\text{PF1} = 0.33*\text{Accuracy} + 0.53*\text{Confidence} - 0.51*\text{Reaction Time}$$

using standard scores for accuracy, confidence, and reaction time based on the mean and variance of their distributions across all subjects. PF1 varied continuously, being high for fast, accurate, and confident responses and low for slow, inaccurate, and unconfident responses.

ERPs were recorded from midline frontal, central, and parietal electrodes (Fz, Cz, and Pz; [7]), referred to average mastoids, filtered digitally to a band-pass 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. Epochs containing artifacts were rejected and EOG-contaminated epochs were corrected [5]. Furthermore, any trial in which no detection response or confidence rating was made by a subject was excluded along with the corresponding ERP.

Within each block of trials, a running-mean ERP was computed for each trial (Figure 2). 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 10–trial window corresponds to about 30 s of task time. The PF1 scores for each trial were also averaged using the same running-mean window applied to the ERPs, excluding PF1 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.

2.2 Choice of regressors

The first step in model development is the choice of regressors. In our case the running-mean ERPs form the input variable $\mathbf{x}_i$ and running-mean performance factors PF1 form the output variable $f(\mathbf{x}_i)$, where $i = 1, 2, \ldots, N$ and N is the number of ERPs for particular subject. The input variable $\mathbf{x}_i$ is represented by vector of dimension 225 (75 time points for each of 3 electrodes). The output variable $f(\mathbf{x}_i)$ is represented by a scalar.

Since, N gets values only between 400 and 900 (see Table 1, column ERPs) we are confronted with the curse of dimensionality for the approximation of multidimensional function $f(\mathbf{x}_i)$. It was pointed out by Friedman and Stuetzle [3] that although a general solution to problem of approximating d-dimensional function is difficult, for many applications, good results can be obtained by observing that in the sparse estimation data $\{\mathbf{x}_i, f(\mathbf{x}_i)\}$, $\{\mathbf{x}_i\}$ are "concentrated" in one or a small number of regions with dimensions much less than d. In such cases the d-dimensional function, $f(\mathbf{x})$, can be approximated by

$$\hat{f}(\mathbf{x}) = \sum_{k=1}^{K} w_k f_k(\mathbf{P}_k \mathbf{x}) \tag{1}$$

where $f_k(.)$ is a function defined for the kth region, w_k is its "weight" and $\mathbf{P}_k$ is the corresponding projection operator and a $d_1 \times d$ matrix, where $d_1 \ll d$.

In order to compare various projection operators the following steps have been taken:

- For each electrode covariance-based PCA was computed and the 10 most significant factors were chosen. Typically, they accounted for 73 – 82 % of variance in the data. Factor scores were computed for each running-mean ERP and stored for model development.

- AR modeling has been often used for feature extraction from EEG data ([6], [4],[13]). ERPs from each electrode were parameterized by AR model of order 10. The order of model was determined by Akaike's final prediction error criterion

$$FPE(k) = \log(\hat{\sigma}_k^2) + \frac{2k}{p}$$

  where k is model order, $\hat{\sigma}_k^2$ is the variance of residuals and p is the number of observations.

- For subject D also the multiple-electrode covariance-based PCA was computed and the 30 most significant factors, which accounted for 93 % of data variance, were chosen. Factor scores were computed for each running-mean ERP and stored for model development.

All of the above transformations reduced the dimension of input vector $\mathbf{x}_i$ from 225 to 30.

2.3 RBF networks

Results of J. Zhang et al. [14] indicate that in the case of "concentrated" data good results may be achieved with RBF networks [1].

RBF network with n inputs and a scalar output is given by

$$f_r(\mathbf{x}) = \sum_{i=1}^{m} \lambda_i \phi(||\mathbf{x} - \mathbf{c}_i||)$$

where $\mathbf{x} \in R^n$ is the input vector, $\phi(.)$ is a given basis function from R^+ to R, $||.||$ denotes the Euclidean norm, λ_i, $0 \leq i \leq m$, are the weights of basis functions, $\mathbf{c}_i \in R^n$, $1 \leq i \leq m$, are the RBF centers, and m is the number of basis functions. The advantage of RBF networks is that when the centers $\mathbf{c}_i$, their number m and shape of basis functions $\phi(.)$ are all fixed they can be viewed as a special case of linear regression model. Then it is possible to apply the orthogonal least squares algorithm for subset selection. The algorithm has the property that each selected center maximizes the increment of the explained variance of the approximated function and does not suffer numerical ill-conditioning problems [2].

There are two ways of applying (1) to RBF network. The first scheme is related to the classical principal-component analysis regression (PCAR) [10] and has the following form:

- $K = 1$ and $c_k = 1$;
- $\mathbf{P}_1$ to be a matrix whose row vectors are the significant eigenvectors of the covariance matrix of $\mathbf{x}$,
- $f_1(.)$ be the RBF network

The second and more elaborate scheme is related to projection regression pursuit regression (PPR) [3], in which c_k, $f_k(.)$ and $\mathbf{P}_k$ are optimized to minimize the training error. In this papers we have dealt only with PCAR approach.

2.4 Linear regression models

Performance of RBF networks was compared with ordinary linear regression models which have been constructed from PCA factors and AR coefficients using forward–selection stepwise approach (SAS PROC STEPWISE). F-ratio test significance level α for including and removing regressors was set to 0.15.

2.5 Model validation

Both models, RBF networks and linear regression models, were validated using 10-fold cross-validation, i.e. running-mean ERPs gathered for each subject were divided into 10 equally sized parts, and each part was used as a validation set for a models build on remaining data.

3 Results

Simulations were implemented in MATLAB using the package of routines provided by M. J. L. Orr [8]. In RBF networks thin-plate-spline function

$$\phi(\nu) = \nu^2 \log(\nu)$$

was used as nonlinearity and direct links between input and output layer were included in order to easily capture the linear properties in regressions [9]. The quality of approximation was measured in terms of normalized mean square error

$$NMSE = \frac{\sum_{k=1}^{N} (f(\mathbf{x}_i) - \hat{f}(\mathbf{x}_i))^2}{\sum_{k=1}^{N} (f(\mathbf{x}_i) - \bar{f}(\mathbf{x}_i))^2}$$

where

$$\bar{f}(\mathbf{x}_i) = \frac{1}{N} \sum_{k=1}^{N} f(\mathbf{x}_i)$$

and N is the number of ERPs for particular subject.

Results are summarized in Tables 1 to 3. One can see that RBF networks performed substantially better than linear models. The best results were achieved with RBF networks using PCA representation (Table 1). The case of subject D (Table 3) indicates that multi-electrode PCA representation provides only a slight improvement over the separate electrode PCA, but this topic requires further study.

4 Discussion

In this paper we have compared approximation capabilities of linear models and RBF networks at an example of display-monitoring performance data. The obtained results show that RBF networks represent an improvement over linear regression models. However, this results were achieved at expense of computational costs. For future study, it would be of an interest to examine the application of PPR wavelet networks proposed in [14].

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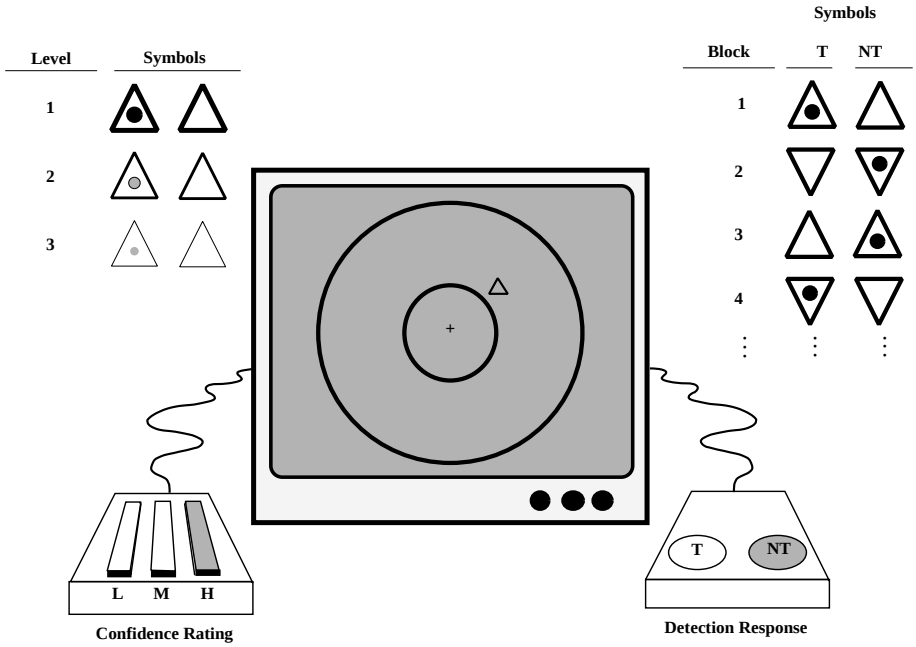

Figure 1: Display, input device configuration and symbols for task-relevant stimuli for the signal detection task.

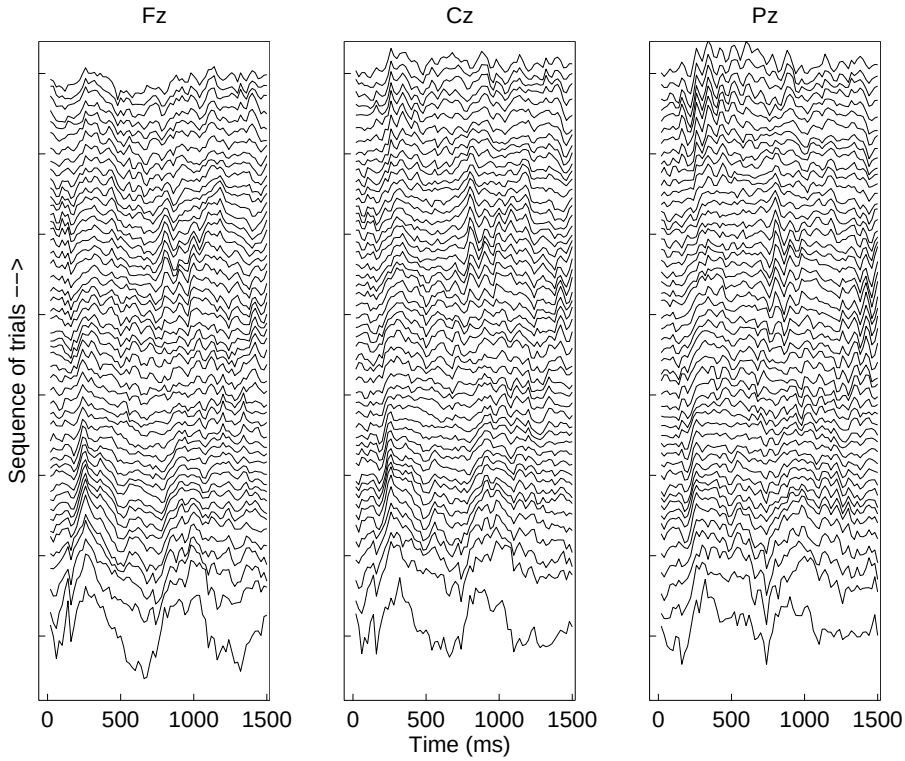

Figure 2: Running-mean ERPs at sites Fz, Cz and Pz for subject B in the first 50 running-mean ERPs.

Subj.	ERPs	**Linear models**				**RBF networks**			
		Model order		Test set NMSE		Hidden units		Test set NMSE	
		mean	(std)	mean	(std)	mean	(std)	mean	(std)
A	891	15	(3)	0.699	(0.029)	378	(56)	0.163	(0.030)
B	592	17	(3)	0.543	(0.046)	171	(42)	0.119	(0.028)
C	417	16	(1)	0.604	(0.113)	175	(26)	0.231	(0.050)
D	734	17	(2)	0.248	(0.027)	249	(109)	0.080	(0.020)
E	776	19	(2)	0.553	(0.037)	249	(60)	0.175	(0.025)

Table 1: Comparison of approximation errors (NMSE) achieved at test set with linear models and RBF networks using PCA representation. The values represent an average of 10 simulations with standard deviation in parentheses.

Subj.	ERPs	**Linear models**				**RBF networks**			
		Model order		Test set NMSE		Hidden units		Test set NMSE	
		mean	(std)	mean	(std)	mean	(std)	mean	(std)
A	891	12	(4)	0.836	(0.040)	436	(79)	0.378	(0.106)
B	592	18	(4)	0.694	(0.100)	260	(52)	0.384	(0.067)
C	417	6	(2)	0.799	(0.057)	197	(30)	0.454	(0.161)
D	734	14	(3)	0.657	(0.077)	373	(53)	0.372	(0.063)
E	776	6	(4)	0.861	(0.032)	286	(37)	0.346	(0.052)

Table 2: Comparison of approximation errors (NMSE) achieved at test set with linear models and RBF networks using AR representation. The values represent an average of 10 simulations with standard deviation in parentheses.

PCA	**Linear models**				**RBF networks**			
	Model order		Test set NMSE		Hidden units		Test set NMSE	
	mean	(std)	mean	(std)	mean	(std)	mean	(std)
S	17	(2)	0.248	(0.027)	249	(109)	0.080	(0.020)
M	25	(0)	0.308	(0.023)	234	(56)	0.069	(0.014)

Table 3: Comparison of approximation errors (NMSE) achieved at test set with linear models and RBF networks using separate (S) electrode and multi-electrode (M) PCA representation for subject D. The values represent an average of 10 simulations with standard deviation in parentheses.