parceled out into overlapping waveform pieces that mimic the mother wavelet in the time domain. However, if the goal of neural waveform analysis is to identify specific neural events or components, it is advantageous to choose wavelets that match the shapes of the signals of interest.

The wavelet that most closely resembles the waveshape of a neural signal is the best scale-independent analyzing function for that signal in a matched filtering sense. Wavelets that are poor shape matches to a waveform or component will tend to produce more distributed energy patterns, complicating the detection, classification, and estimation of the signal of interest.

An important potential application of neural wavelets is in statistical estimation models designed to efficiently separate and measure specific ERP components that may partially overlap in time or frequency. Recently, a statistical wavelet model of this sort has been presented by Raz and Turetsky [4]. In principle, the particular wavelet used in such models determines the robustness of component separation and the extent of acheivable data compression. Wavelets that match the general spectral properties of ERPs and the particular spectral properties of individual components will typically be the most efficient ones to use in such component identification models.

1.2 Matching Algorithm

Previously, wavelets used in studies of neural signals have been based on standard mathematical functions or recursive algorithms like Daubechies' algorithm, with no attempt to directly match wavelets to specific neural signals. Chapa and Raghuveer [10] recently derived an algorithm that designs Meyer wavelets to match specified band-limited signals as closely as possible in a least squares sense. The algorithm can design Meyer wavelets that closely match nearly any real neural signal of interest to the neuroscience and neuroclinical communities.

The Chapa and Raghuveer algorithm uses samples of $S(\omega)$, the Fourier transform of signal $s(t)$, to determine a function $G(\omega)$, the Fourier transform of wavelet $g(t)$, such that $|G(\omega)|^2$ is close to $|S(\omega)|^2$ in a least squares sense while satisfying all requirements for the energy spectrum density of Meyer wavelets. The group delay of $G(\omega)$ is also matched to that of $S(\omega)$ in a least squares sense. A scaling function and impulse responses for filter implementation are also obtained.

Raghuveer and Chapa [11] give the closed form of the magnitude matching algorithm as:

$$A(\omega) = C/2 + [B(\omega) - B(2\pi - \omega) - B(2\omega) + B(4\pi - 2\omega)]/2, \quad (2)$$

where $C = \frac{1}{\pi}\int_{2\pi/3}^{8\pi/3} B(\omega)d\omega$, $A(\omega) = |G(\omega)|^2$, and $B(\omega) = |S(\omega)|^2$, for $2\pi/3 \le \omega \le 4\pi/3$. For $4\pi/3 \le \omega \le 8\pi/3$, use $A(\omega) = A(2\pi - \omega/2)$.

Phase matching minimizes the error function in (3), subject to constraints on the group delay for band-limited wavelets. See Chapa and Raghuveer [10] for details.

$$\gamma_\Omega = \sum_{n=-N/2}^{N/2-1} \left[\Omega(n)(\Gamma_s(n) - \Gamma_g(n))\right]^2 \quad (3)$$

where $\Omega(n)$ is a normalized weighting function that limits the phase match to the passband $2\pi/3 \le |\omega| \le 8\pi/3$, and $\Gamma_S(n)$ and $\Gamma_g(n)$ are the signal and wavelet group delays, respectively.

2 SAMPLE MATCHED NEURAL WAVELETS

We focus on clinically relevant auditory and visual evoked potentials (EP), namely the auditory brainstem evoked response (ABER) used widely to evaluate hearing loss and brainstem integrity, and the visual odd-ball EP containing a P300 component used to evaluate cognitive processing.

2.1 Matched ABER Wavelet

The ABER reflects neural activity in the auditory pathway from cochlea to primary auditory cortex, developing within 10 milliseconds after auditory stimulation. Figure 1 shows ABERs from routine clinical evaluations of four adult normal-hearing patients. Each ABER is an average based on 2000 click stimuli. The six typical positive peaks are visible in each ABER, including the prominent IV-V complex used routinely in clinical evaluations.

We isolated the IV-V component complex in the rectangle, zero padded on both sides and fit an orthogonal Meyer wavelet to it. This wavelet is superimposed on the original ABER in Figure 1a. The ABER IV-V wavelet tracks the contours of the major positive crest and the characteristic deep negative trough following it quite well.

Figures 1b-1d show scaled versions of the same wavelet superimposed on the other three ABERs. The close fits indicate good shape generalization from patient to patient. These examples also show that the IV-V complex undergoes substantial time scaling from patient to patient. Up to 13% variation in time scaling is apparent. Due to its natural scaling property, the continuous WT of these ABERs, using the ABER 1 wavelet, would contain a peak in the time-scale plane at the right scale and time lag for each ABER IV-V complex.

Properly matched Meyer ABER wavelets will generally provide the most reliable and distinct identification of their target component, regardless of how the component's scale varies over patients, conditions, or trials. Such a wavelet might be used, for example, in simple pattern recognition algorithms to reliably locate similarly shaped instances of the IV-V component in noisy recordings from the same subject, independent of inter-recording variability in the scale of the component.

Increased precision due to shape matching will also improve the high noise performance of more sophisticated wavelet and wavelet-packet based component identification algorithms [4], suggesting a clear clinical application of matched neural wavelets for detecting and identifying low stimulus intensity ABER components in automated