Components of Disparity Vergence Eye Movements: Application of Independent Component Analysis

John L. Semmlow*, *Fellow, IEEE* and Weihong Yuan

***Abstract*—The "dual mode" theory for the control of disparity vergence eye movements states that two control components, a preprogrammed "transient" component and a feedback-controlled "sustained" component, mediate the motor response. Although prior experimental work has isolated and studied the transient component, little is known of the sustained component's contribution to the dynamic vergence response. The timing between the two components and their relative magnitudes are of interest as they relate to the strategies used by the brain to coordinate and control the two components. Modeling studies provide an estimate of component magnitudes, but cannot uniquely identify component timing nor can the provide detailed information on component dynamics. Here, an eigenvector analysis is applied to a multivariate data set consisting of multiple responses to a step stimulus to confirm the presence of two major components in the vergence response. Next, a new application of independent component analysis is used to estimate the activation patterns of the two components. Results from five subjects show that the sustained component is activated concurrently with the transient component, dominates the later portion of the response, and maintains final position.**

***Index Terms*—Disparity vergence response, eye movements, independent component analysis, principal component analysis, vergence components.**

I. Introduction

VERGENCE movements, the inward or outward turning of the eyes, develop in response to several visual and psychological clues associated with depth and the major drive is provided by target vergence angle and the associated disparity [1], [2]. Disparity vergence was traditionally thought to be the result of a single control process [3], [4], one which uses feedback to produce the very small error in fixation which follows a vergence response (of the order of minutes of arc [5]). However, considerable experimental evidence amassed in our laboratory [6]–[10] and elsewhere [11] indicates that responses to simple step changes in target vergence are mediated by at least two control processes: a preprogrammed component giving rise to a fast "transient" motor response, and a "sustained" feedback component which more slowly brings the eyes to the final, highly accurate vergence position. The motivation for this multicomponent strategy is the need to generate rapid, precise eye movements using computational elements (i.e., neurons) that have substantial processing delays. The basic strategy used by vergence neural processes to coordinate the transient and sustained components is unknown.

To study these control components, it would be helpful to find some way to isolate them, as has been done with other vergence components.[1] Studies that employ careful model simulation of vergence responses can be used to estimate hidden features such as the underlying components, but this approach requires a fair number of assumptions including the relative timing of the two components [13]. (These studies could only provide a range of possible delay times between the onset of the transient and sustained component [13].)

Here, we introduce a new approach to evaluating the contribution of vergence control components to a combined response. While the technique will be applied to vergence motor responses, it is applicable to any time response that may be controlled by multiple components provided multiple observations can be obtained. The technique is based on independent component analysis (ICA) [14]–[17] applied to ensemble response data. In its usual applications, ICA requires several different signals representing various linear combinations of the sources. These signals are acquired from measurements taken at different physical locations. In this application of ICA, each of a number of vergence responses produced by the same stimulus is treated as a separate signal. The underlying components are the transient and sustained components that are combined in a normal response. ICA requires that the components be independent and small errors are introduced by the loss of independence between the neural sources due to stimulus-induced synchronization. A corrective algorithm has been developed and is described in Sections II and III. Simulations of a two-component model of disparity vergence [10], [13] will be used to evaluate the corrective algorithm and the ability of ICA to identify the underlying components.

Various methods exist to estimate the number of independent components. Here, we use the traditional "Scree" plot which graphs eigenvalue against component number. Typically, such plots show a steep initial fall in eigenvalue after which the curve flattens. The data dimension is chosen as the number just before the curve flattens [18].

II. Methods

A. Instrumentation

The ICA technique used here requires a number of repetitive responses (observations) for the behavior being analyzed.

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[1]Blur-driven vergence was first isolated by Johannas Müller in 1842 [12].

Simulations indicated that 25 individual responses were sufficient to determine accurate estimates of the two components (under certain constraints detailed below). Here, we will use from 30–45 individual responses to vergence step stimuli. A typical example of an ensemble of disparity vergence responses is shown in Fig. 1. Similar data were acquired on five subjects all of which had normal uncorrected binocular vision and could perform the experiments without difficulty.

The stimulus apparatus and data acquisition has been described in detail elsewhere [6]–[10], [13]. The stimulus target consisted of two short (2°) vertical lines viewed as a stereoscopic which were manipulated to produce a 4° step change in vergence position. While the amplitude was predictable, stimulus onset was randomized to discourage prediction. Only convergence (inward moving) responses were used in this analysis. At least 80 responses were usually acquired to insure the required number of artifact-free responses. Common artifacts that necessitated rejection of a response included large or badly timed saccades and occasional blinks. Binocular eye position was recorded by means of a Skalor infrared eye movement monitor (Model 6500). Calibration on done on each response, and responses were sampled at 200 Hz., well above the Nyquist frequency for vergence eye movements.

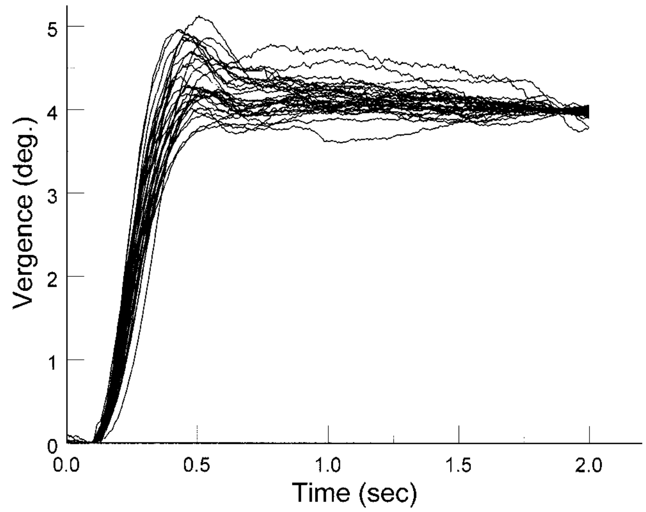

Fig. 1. An ensemble of 40 disparity vergence responses to a step change in stimulus. Substantial movement-to-movement variability is seen. Subject: C01.

B. Independent Component Analysis

ICA is an analytical method that can isolate individual components from a linear mixture provided the components are nongaussian and sufficiently independent [14]–[17]. The basic principles behind ICA are well described in number of references [14]–[17] and a readable, comprehensive treatment can be found in reference [14]. The ICA model is a generative model: it attempts to explain how the sources (in this case the components) are mixed to generate the observed signals based on a linear mixing model [14]–[17]

$$\mathbf{x} = \boldsymbol{A}\mathbf{s} + \mathbf{noise}$$

where $\mathbf{x}$ includes m response vectors (m is the number of signals in most applications, but the number of individual responses in our application), and $\boldsymbol{s}$ includes n source vectors (n is the number of sources, or components in our application). The noise vector represents the disturbances in the form of additive noise independent of the source vector $\mathbf{s}$. The goal of ICA is to identify the linear mixing matrix $\boldsymbol{A}$. Inverting the mixing matrix produces an "unmixing" matrix, $\boldsymbol{U} = \boldsymbol{A}^{-1}$, that can be used to estimate the unobservable source vector $\mathbf{s}$ ($\mathbf{s} = \boldsymbol{U}\mathbf{x}$). Determining the mixing matrix is accomplished by linear transformations of the data set (i.e., rotations and scalings) with the goal of optimizing some objective function related to statistical independence, such as a measure of nongaussianity. There are a number of different approaches for estimating $\boldsymbol{A}$, differing primarily in the objective function that is optimized and the optimization method [14].

The critical assumptions in ICA are that the variables are statistically independent, have nongaussian distributions, and are linearly mixed. Application of ICA requires verification of the existence of the sources and that they mix linearly. Vergence responses are certainly nongaussian, and while no biological process is likely to be truly linear, extensive eye movement data indicate that separate neural signals, such as those from version and vergence neural centers do combine more-or-less linearly. While the sources are thought to be produced by different neural centers, the initial portions of these components may not be completely independent due to stimulus-induced synchronization; that is, activation by a common stimulus could induce a temporary correlation between their responses. As these responses continue, this "stimulus effect" diminishes so that the components become independent during the latter portion of the response. To avoid this stimulus induced synchronization, the evaluation of the mixing matrix, $\boldsymbol{A}$, was performed only on the latter portion of the responses. The unmixing matrix, $\boldsymbol{U}$, obtained from the partial responses was then applied to the entire response (including the initial portion) to estimate the underlying motor components, $\mathbf{s}$. In some cases, this produced an error in the initial portion of the response which could be corrected by an additional rotation as described in Section III-B.

Several popular ICA algorithms are available from the Web as MATLAB script files. In this study, we investigated two such algorithms: the "FastICA" algorithm developed by the ICA Group at the Helsinki University[2] and the "Jade" algorithm for real-valued signals developed by J.-F. Cardoso [3] Although the two algorithms performed nearly the same on both simulated and experimental data, the "FastICA" algorithm was selected as it was found to converge somewhat more reliably than the Jade algorithm. Both algorithms were implemented under Windows-based Matlab, and performed the analysis in only a few seconds on a 500-MHz PC.

To apply ICA to ensemble vergence response data, each response is treated as an observed signal. The responses consisted of 2 s of dynamic vergence following a 4° step stimulus. (Vergence is taken as the difference in the position of the two eyes and is computed from the individual eye movement recordings.)

[2]http://www.cis.hut.fi/projects/ica/fastica/fp.html.

[3]http://sig.enst.fr~cardoso/stuff.html.

An ensemble of 40 individual responses is shown in Fig. 1. Simulations showed that the algorithms produced more accurate results if the data sets were symmetrical, so each response was modified by adding the inverted response to the end of the actual response to make the ensemble data symmetric. While this operation does not add any new information to the data set, it does change its statistical properties. Specifically, a modified, symmetrical data set showed a greater difference in the ratios between the first three eigenvalues as compared with the original data set. After analysis, the inverted responses were discarded.

Results presented below show that the vergence responses contain only two major components, so the ICA algorithm was set to isolate two sources. When the number of sources is less than the number of observations, as is the case here, the FastICA algorithm uses a preapplication of principal component analysis (PCA) to reduce the dimensionality of the data set [14]. Due to inherent ambiguities, ICA cannot determine the scale of the components. The initial preresponse period can be used to establish a zero reference for the components. To determine the amplitude, we note that the sum of the two components should equal the average vergence response. Hence, the amplitude of the individual components was adjusted until their sum equaled the average response. Since there were only two components with quite different time characteristics, the amplitude scaling was uniquely determined by matching the average response. Amplitude scaling was implemented using the MATLAB basic optimization routine.[4]

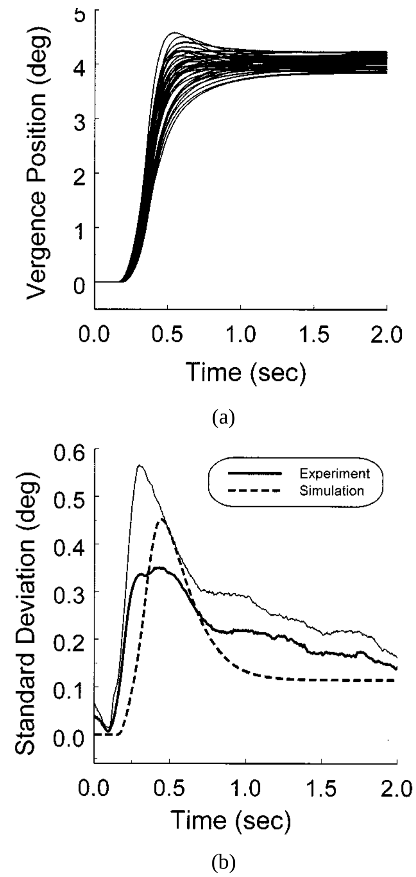

Fig. 2. (a) An ensemble of 40 simulated disparity vergence responses to a step change in stimulus produced by the model in Fig. 2. (b) Ensemble standard deviations derived from experimental and simulated response ensembles. Solid lines: Ensemble standard deviation from the responses of subjects C01 and L01. Dashed line: Ensemble standard deviation of simulated data.

C. ICA Evaluation, Compensation and Model Simulations

Model simulations were used to verify that this application of ICA was able to identify the underlying control components. Simulations were also used to develop and evaluate the algorithm to correct for errors related to stimulus-induced loss of independence as described below. The model used for simulations was the well-established Dual-Component model developed in our laboratory. Details of the model's structure, parameters and behavior are well described elsewhere [10], [13], [19]. The advantage of this model-based evaluation is that the underlying control components are directly available as model outputs. Ensemble averages were determined for each component after the component was filtered by the oculomotor plant. Usually 40 model responses were simulated.

Component variability was simulated by randomly varying seven model parameters associated with the two component processes. Specifically, variability in the transient component was simulated by randomly varying onset time, the pulse width, and the amplitude of the transient pulse. Variation in the sustained component was produced by randomly varying the onset time, the dynamics (a slew rate parameter), and the amplitude. In addition, the major time constant of the motor plant was varied within known physiological ranges [20]. The range over which these various parameters should be randomly varied was empirically determined to provide an approximate match to the variability seen in experimental data. Fig. 2(a) shows a typical ensemble of simulated disparity vergence responses. Fig. 2(b) (dashed line) shows the ensemble standard deviation computed from the simulated responses of Fig. 2(a) along with the ensemble standard deviation computed from experimental response ensembles of two subjects (solid lines). Although the general structure of the ensemble standard deviation of real data is more complicated than that produced by the model, Fig. 2(b) shows that the variability of the simulated data is roughly similar to that of the real data and the magnitude of this variability (as represented by the standard deviations) falls between that of the two subjects. The simulations will be used only to evaluate the ICA analysis procedures, so an approximate match between simulated and experimental data is sufficient. Since the delay between the onset of the transient and sustained component was not known, simulations were done with nominal delays between 0.0 and 200 ms.

D. Principal Component Evaluation of the Number of Independent Components

Several criteria exist for selecting the number of significant components in a multivariate data set. The technique used here examines the data set eigenvalues searching for a knee or breakpoint in a plot of eigenvalue against number of components (the so-called "Scree" plot [18]). The eigenvalues were determined using the MATLAB "princmp" routine which is based on singular value decomposition. Fig. 3 (upper left) shows the Scree plot obtained from the simulated responses of Fig. 2(a).

[4]The routine "fins," recently renamed "fminsearch" uses the Nelder–Mead simplex, or direct search, method.

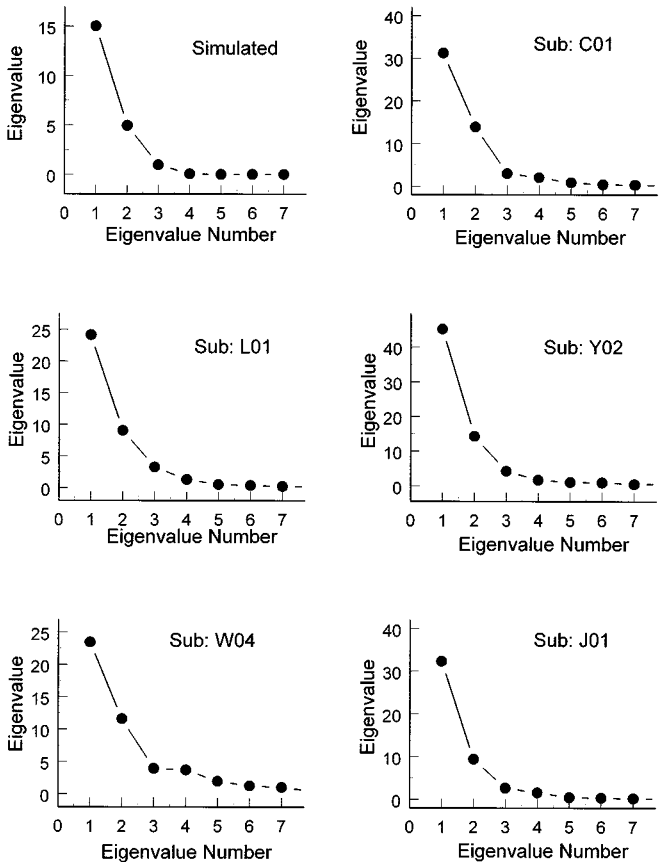

Fig. 3. Scree plots, plots of the eigenvalues found for the data set against eigenvalue number, for the five subjects (labeled) and simulated data (upper left). The simulated data is known to contain only two components and the curve flattens for eigenvalue numbers three and higher. The plots from the subject data are qualitatively similar indicating the subject data also contains two components.

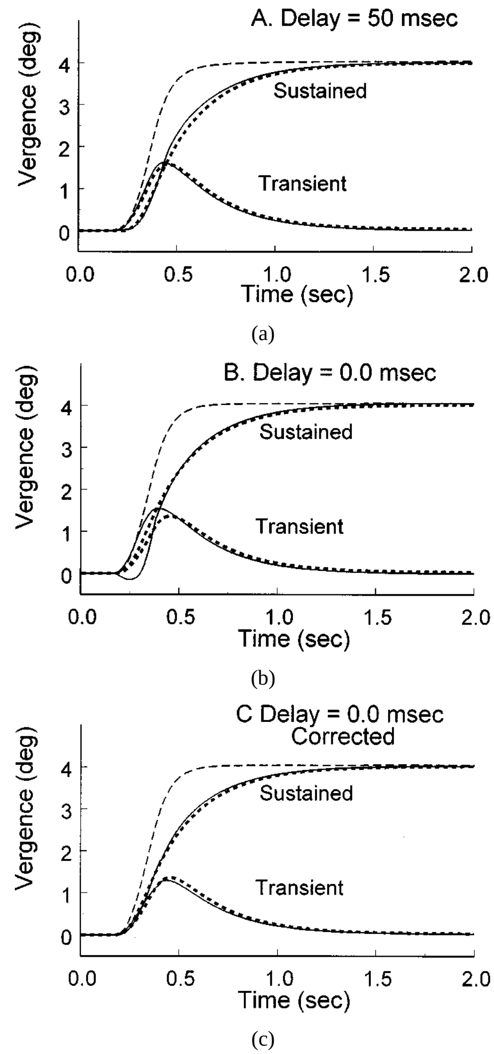

Fig. 4. Components found by ICA in simulated data (solid lines). The dashed lines are ensemble averages of the two simulated motor components. The overall response average is also shown (thin dotted line). (a) The sustained component follows the activation of the transient component by 50 ms in this simulation. A close match is found between the component averages and the components identified by ICA. (b) When the sustained and transient components were activated simultaneously (or less than approximately 30 ms apart), a small error is seen in the initial portion of the component estimations. (c) Application of an additional post rotation and scaling to the initial portion of the response essentially eliminates this error. Note that this corrective algorithm was not required in the analysis of actual vergence data shown in Fig. 5 even if the two components had the same onset time. Delay = (a) 50 and (b) 0.0 ms; (c) 0.0 ms corrected.

The curve descends steeply then flattens for eigenvalue numbers greater than three. This would indicate that the data set contains only two uncorrelated sources, as is known to be the case with this simulated data.

III. Results

A. Number of Components

Fig. 3 plots the Scree plots for the five subjects studied as well as that of the simulated data. Note that all subjects show Scree plots that are qualitatively similar to the Scree plot of the simulated data: the curves tend to flatten above the second eigenvalue. This indicates that the subject data also consisted of two primarily components.

B. Simulation Results

Unlike experimental conditions where only the combined response can be measured, simulations can provide the underlying components directly. Fig. 4(a) shows the average transient and sustained component (components labeled) along with the overall average response (dashed lines) which is simply the sum of the two components. Note that the contribution of the two components to the combined response is not the same as the neural signals themselves, but rather reflects these neural signals after they are filtered by the oculomotor plant. In Fig. 4(a) the average delay between the transient and sustained component was 50 ms and the components identified by the ICA analysis closely match the actual average component generated by the model. When the two components were activated simultaneously (or for separations less that approximately 30 ms), small errors were noted in the estimates of the initial segments, Fig. 4(b), although the later segments are estimated correctly. The source of this small error is attributed to the loss of independence between the components due to their simultaneous activation by the stimulus, and an additional rotation and scaling was used to correct this initial error. Specifically, the initial segment of the components was orthogonally rotated

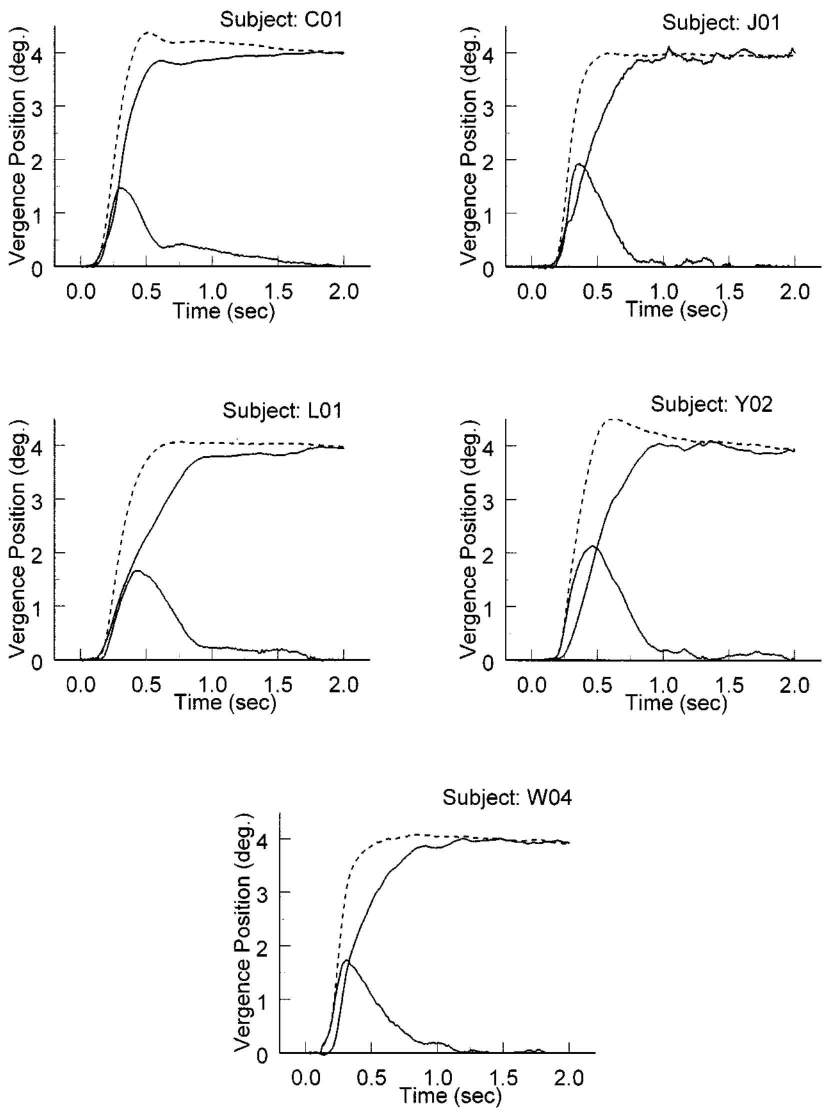

Fig. 5. Components of disparity vergence found by ICA in five subjects along with the response average (dashed line). No compensation was required for these data.

until both components were nonnegative. Following rotation, the components were re-scaled to the match the later component segments which were unaltered by the compensation process. Fig. 4(c) shows that this correction algorithm resulted in a very close match between simulated and estimated component responses. We note that this correction algorithm was never required for real data; that is, the sustained component evaluated from actual subject data never showed the negative values seen in Fig. 4(b). This indicates that there is greater independence between two components in the real situation than in simulated data. We speculate that this independence is likely the result of a greater number of fluctuating variables in the real physiological system than represented in the model.

C. Experimental Results

Fig. 5 shows the component contributions found from the ensemble disparity vergence response data of our five subjects. Also shown are the average responses computed from the ensemble data (dashed line). The dynamics of the average response (dashed line) varies considerably across the five subjects, yet the underlying components are qualitatively similar: a transient component is found in the initial portion of the response that decays to near zero after 600–800 ms; and a sustained component becomes active at approximately the same time and dominates the latter portion of the response. In most subjects, the sustained component shows a fairly rapid rise in the first 500–800 ms followed by a gradual rise to the final value during the subsequent 1.5 s.

IV. Discussion and Conclusion

ICA can be applied to ensemble data to extract the underlying components from a combined response, but some caution must be observed. In our application, a correction to the initial segment of the components was required to compensate for stimulus induced loss of independence in simulated data, although this correction was not needed for subject data. It is also important to use data that are relatively free of artifact as only a few responses with large artifacts can adversely affect the analysis.

A major limitation of the method is that it can only be applied to an ensemble of responses, and it provides estimates only of component averages. This precludes its application to those problems were only a single, or a small number of responses can be obtained. A problem related to the averaging nature of the technique can occur if the variability in the onset delay (i.e., the response latency) is large in comparison to the response dynamics. A wide variation in a component's onset time will tend to reduce the dynamics of the ensemble average,[5] resulting in an inaccurate estimate, particularly of the faster component (in our case, the transient component). Simulations in which the variability in the latency was large in comparison to the response dynamics (25% of the approximate time constant) showed that the transient component was underestimated by 20% with a corresponding overestimation of the sustained component. Hence, for responses that have large latency variations compared with their dynamics, such as saccadic eye movements, the variability will have to be reduced either by shifting the data into better alignment or carefully editing the data to eliminate responses with widely varying onset latencies.

The primary finding of our ICA-based analysis is the identification of a sustained and transient component and exposition of their related dynamics. The component dynamics were qualitatively similar in all five subjects: the components were activated at approximately the same time (although one subject, W04, showed a slight delay in sustained component onset); and the sustained component dominated the latter portion of the response as the transient component decayed to zero. A previous model-based analysis also showed that two components, similar to those found by ICA, could accurately represent the vergence response. ICA provides confirmation of this previous finding, but it provides stronger evidence because it requires far fewer assumptions about the processes that generate the data. As with all complex analyses, both model-based and ICA, decomposition techniques are predicated on certain assumptions. Both techniques assume the existence of two primary components[6] and both assume these components are linearly mixed. In addition, both approaches require component independence, and the problems and related compensatory techniques associated with ICA have been discussed. In addition to these basic assumptions, the model-based approach requires a number of additional assumptions regarding component timing and the dynamic characteristics of the neural processes that generate the two components. Although the model-based analysis requires a far larger set of assumptions, it does have the advantage that it can be applied to a single response as opposed to the response ensembles required by ICA.

The ICA algorithm used here assumes the noise contribution is small, yet some noise is present as can be seen in Fig. 1. This noise is likely to be due to measurement artifact or small embedded saccades (so-called microsaccades) and appears as high-frequency noise. This noise should not be confused with response variability which manifests as modifications in the overall response trajectory. The algorithms used here appear to be robust to the noise levels in our eye movement recordings, although it is also possible that this noise may affect some small details of the isolated components.

As an analysis procedure, ICA is relatively new and the techniques are changing almost daily. It is likely that the advances will extend the method to be more generally applicable, require fewer number of observations, and be more tolerance of noise. However, in its current state of development, ICA can be profitably applied to a large number of biological behaviors. Future applications in our laboratory will study the changes in components associated with fatigue, adaptation, and the use of prediction.

[5]The variable onset time results in a "smearing" of the responses in the averaging process.

[6]Our eigenvalue analysis, based on a yet another approach, PCA, does provide independent support for this assumption.

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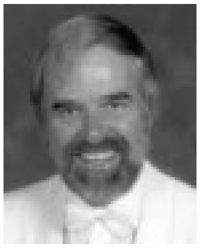

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