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Multi-Input GNL-HybELS: An Automated Tool for the Analysis of Oculomotor Dynamics during Visual-Vestibular Interactions

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Abstract— **The eyes play a major role in our everyday activities. Eye movements are controlled by the oculomotor system, which enables us to stay focused on visual targets, switch visual attention, and compensate for external perturbations. This system's response to isolated visual or vestibular stimuli has been studied for decades, but what seems to be more critical is to know how it would respond to a combination of these stimuli, because in most natural situations, multiple stimuli are present. It is now believed that sensory fusion does not affect the dynamics of oculomotor modalities, despite studies suggesting otherwise. However, these interactions have not been studied in mathematical detail due to the lack of proper analysis tools and poor stimulus conditions. Here we propose an automated tool to analyze oculomotor responses without a-priori classification of nystagmus segments, where visual and vestibular stimuli are uncorrelated. Our method simultaneously classifies and identifies the responses of a multi-input multi-mode system. We validated our method on simulations, estimating sensory delays, semicircular canal time constant, and dynamics in both slow and fast phases of the response. Using this method, we can now investigate the effect of sensory fusion on the dynamics of oculomotor subsystems. With the analysis power of our new method, clinical protocols can now be improved to test these subsystems more efficiently and objectively.**

I. Introduction

The study of the oculomotor system began with the study of its functional subsystems: the VOR (Vestibulo-Ocular Reflex), the smooth pursuit and saccadic systems, etc. [1]. All of these subsystems are essential to our normal daily functions: VOR to compensate head perturbations, smooth pursuit to follow visual targets, saccadic system to switch between visual targets [2-5]. Deficits in these systems can have devastating effects on basic daily activities [6-7]. Earlier studies of this system broke it down into its components and studied them separately [1, 8-10]. This led to models that were able to predict how these modalities would behave in different situations [11-15]. Later, identification techniques helped explain, to some extent, observed symptoms in patients [16]. Eventually, clinical protocols were developed to test the functionality of the oculomotor subsystems in humans, usually using distinct tests for each subsystem [17]. However, in almost all natural situations, these subsystems collaborate with each other. For example, when a person is driving, the VOR compensates for head perturbations, while the smooth pursuit and saccadic systems help follow the movements of the visual target, or switch visual attention. Therefore, it was only natural for researchers to start looking at the coordination of these subsystems [18-22]. But these first studies were limited in many ways. First, they did not consider the oculomotor system as a multiple-input system when analyzing visual-vestibular interaction data [20]. Second, visual and vestibular inputs were correlated, which prevents correct identification of system parameters [8]. Third, the stimuli were seriously band-limited, which prevents unbiased and robust estimation of dynamic parameters [19, 22-24]. Finally, the switching nature of the oculomotor system was ignored; oculomotor responses are nystagmic, i.e., they are either "fast" (fast phases) or "slow" (slow phases), with very distinct dynamics [24-26]. However, fast phases were most often discarded [1, 27]. To cope with switching, we recently introduced Hybrid Extended Least Squares (HybELS) for the identification of oculomotor responses [28]. We also introduced Generalized NonLinear HybELS (GNL-HybELS) for the simultaneous identification and classification of VOR responses [29]. In this work, we extend these methods to build a tool, for the first time, for the *automatic* classification and identification of oculomotor responses during sensory fusion. Currently, there is no other tool available that can perform even the classification task alone.

Until now, it was believed that sensory fusion does not affect the dynamics of oculomotor subsystems [30], despite studies suggesting otherwise [31]. This means that the dynamics of oculomotor modalities should be the same with or without sensory fusion; only the gain might change from superposition effects [20]. We hypothesize that oculomotor subsystems have different dynamics when they are in coordination than when they work in isolation, due to changes in premotor circuitry – now testable using our GNL-HybELS. This would have very important practical and clinical implications: it implies that testing subjects' reflexes in the dark does not tell us about their daily functional limits, and that subjects should be tested in more natural contexts.

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II. GNL-HybELS Algorithm

All oculomotor responses (as in the VOR) are nystagmic, i.e., they switch between slow and fast modes. These modes are called slow and quick phases in the context of the VOR, and smooth pursuit and saccade in the context of visual target tracking. To analyze this type of data, we need to separate the slow and fast phases (classification) and identify system dynamics in each phase or mode (identification). To do so, we extended GNL-HybELS [29] to multiple input cases. The extended method now identifies such a system for visual-vestibular interactions as shown in Fig. 1.

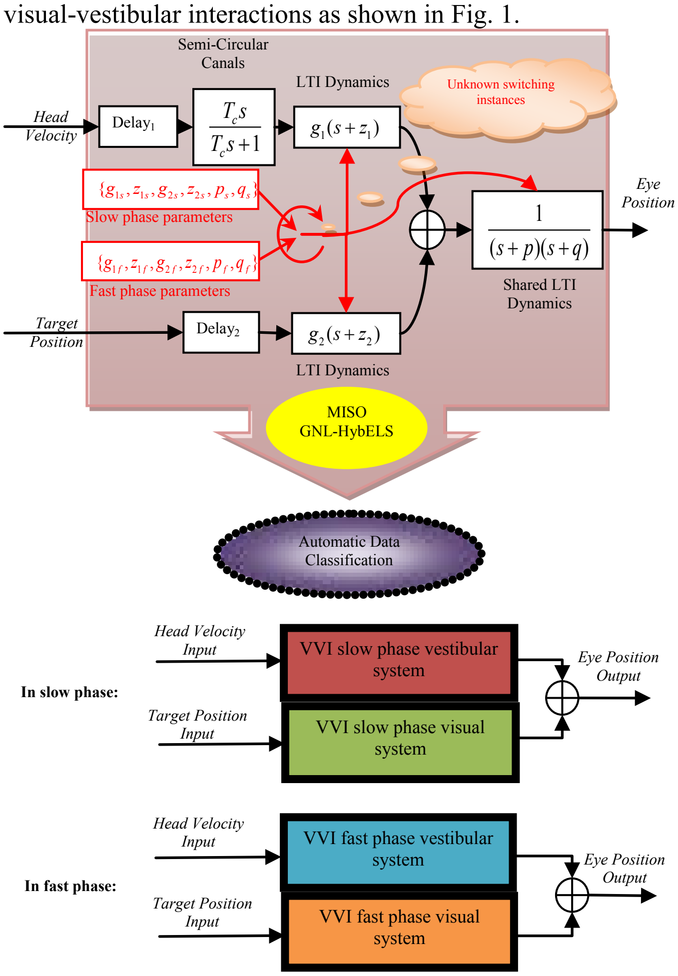

Fig. 1. The structure identified by GNL-HybELS for visual –vestibular interactions. Shared LTI dynamics include the poles that are shared between the visual and vestibular paths. LTI dynamics 1 and 2 include zeros and poles of the vestibular and visual paths.

Assuming a system structure as shown in Fig. 1, we can write the input-output equation of our multi-input hybrid (switching) system in mode m_k in the z-domain as:

$$Y(z)=H_{1k}(z)U_1(z)+H_{2k}(z)U_2(z)=\frac{\sum_{i=0}^{r}a_i z^{-i}U_1(z)+\sum_{i=0}^{p}c_i z^{-i}U_2(z)}{1+\sum_{i=1}^{q}b_i z^{-i}} \qquad (1)$$

In [32] we showed that the discrete-time input-output equation for the j^{th} data segment of length L in mode m_k, in the noise-free case becomes:

$$\sum_{i=0}^{r}a_i u_1(n-i)+\sum_{i=0}^{p}c_i u_2(n-i)-\sum_{i=1}^{q}b_i y(n-i)-y(n)=0, \quad n=j_1,\ldots,j_L. \qquad (2)$$

This translates into:

$$\begin{bmatrix}u_1(n) & \cdots & u_1(n-r) & u_2(n) & \cdots & u_2(n-p) & y(n-1) & \cdots & y(n-q) & y(n)\end{bmatrix}.\vec{\theta}_{m_k} = 0,\ n=j_1,\ldots,j_L \qquad (3)$$

where $\vec{\theta}_{m_k}$ is the parameter vector corresponding to the mode m_k. If we define our regressor vector $\vec{R}(n)$ as $\begin{bmatrix}u_1(n) & \cdots & u_1(n-r) & u_2(n) & \cdots & u_2(n-p) & y(n-1) & \cdots & y(n-q) & y(n)\end{bmatrix}$ then the above equation implies that the data points for mode m_k lie on a hyper-plane in $\mathbb{R}^{r+p+q+3}$. We can repeat the same procedure and write equations (1) to (3) for other modes of the system as well. Therefore, in the case of the oculomotor system, where we have two modes m_1 and m_2 in the data record, the data points lie on either of the hyper-planes:

$$\vec{R}(n)^T.\vec{\theta}_{m_1}=0 \quad (4) \qquad \text{or} \qquad \vec{R}(n)^T.\vec{\theta}_{m_2}=0 \quad (5)$$

We can solve for the classification (which data points belong to which hyperplane) and parameter vectors using Generalized Principal Component Analysis (GPCA) [33]. We can also search for possible input transport delays by searching for the ones that yield minimum root mean squared regression (rms) error. Once we have found the optimal delay values $\hat{d}_1$ for the first input and $\hat{d}_2$ for the second input, we replace $u_1(n)$ with $u_1\left(n-\hat{d}_1\right)$ and $u_2(n)$ with $u_2\left(n-\hat{d}_2\right)$ for the rest of the analysis, and proceed with the canal time constant detection. Since the delay of the VOR is reported to be about 5-7 ms [34], we constrain the search for the estimated delay of the vestibular path to the range of 0 to 20 ms, and constrain the delay of the visual path to 200 ms, as the reported expected value is 100-150ms [35]. After detecting the input delay, we search for the canal time constant by filtering the head input signal through a unity gain high pass filter with a variable time constant. We then compare the goodness of fit for different time constants of the high pass filter and select the time constant which results in the minimum fitting error. Once again, we replace $u(n)$ with $\left(u*h_{\widehat{TC}}\right)(n)$ (the convolution of the input with the estimated canal impulse response function) for the rest of the analysis. Since the cupula time constant is about 5-7 s [8, 36], and is reported to be 12-15 s [37] with velocity storage, we constrain the estimated time constant between 2 - 20 s.

GPCA results can have large errors in the presence of noise and in higher dimensional cases. Thus, we fine-tune our classification and identification by minimizing the (1-step) prediction errors iteratively. Note that in the presence of noise, considering an ARMAX (AutoRegressive Moving Average with eXogenous input) structure for the system, equation (2) changes to:

$$\sum_{i=0}^{r}a_i u_1(n-i)+\sum_{i=0}^{p}c_i u_2(n-i)-\sum_{i=1}^{q}b_i z(n-i)+\sum_{i=0}^{l}d_i e(n-i)-z(n)=0, \qquad (6)$$

where $z(n)$ is the observed noisy output and $e(n)$ is the additive noise. The regressors also change in turn from $\begin{bmatrix}u_1(n) & \cdots & u_1(n-r) & u_2(n) & \cdots & u_2(n-p) & y(n-1) & \cdots & y(n-q) & y(n)\end{bmatrix}$ to $\begin{bmatrix}u_1(n) & \cdots & u_1(n-r) & u_2(n) & \cdots & u_2(n-p) & z(n-1) & \cdots & z(n-q) & z(n)\end{bmatrix}$ and equations (4)-(5) change to:

$$\vec{R}(n)^T.\vec{\theta}_{m_1}=\sum_{i=0}^{l}d_i e(n-i) \quad (7) \qquad \text{or} \qquad \vec{R}(n)^T.\vec{\theta}_{m_2}=\sum_{i=0}^{l}d_i e(n-i) \quad (8)$$

Equations (7)-(8) yield the output prediction errors. Therefore, estimating the parameter vectors $\vec{\theta}_{m_1}$ and $\vec{\theta}_{m_2}$ translates into finding the parameter vectors that minimize prediction errors with the cost function:

$$f\left(\mu(n),\left\{\vec{\theta}_{m_1},\vec{\theta}_{m_2}\right\}\right)=\sum_{n=1}^{T}\left[z(n)-pred\left(z(n)\right)\right]^2$$
$$=\sum_{n=1}^{T}\left\{\left[\left(2-\mu(n)\right)(\vec{R}(n)^T.\vec{\theta}_{m_1})\right]^2+\left[\left(\mu(n)-1\right)(\vec{R}(n)^T.\vec{\theta}_{m_2})\right]^2\right\} \quad (9)$$

where $\mu(n)$ is a membership function which assigns a mode to each data point:

$$\mu(n)=\begin{cases}1 & \text{if the } n^{th} \text{ data point is classified in } m_1\\ 2 & \text{if the } n^{th} \text{ data point is classified in } m_2\end{cases} \quad (10)$$

Our goal is to find values of $\mu(n),\left\{\vec{\theta}_{m_1},\vec{\theta}_{m_2}\right\}$ that minimize *f*. The membership function $\mu(n)$ would then represent the best classification of the data, while $\left\{\vec{\theta}_{m_1},\vec{\theta}_{m_2}\right\}$ represent the identified parameters for the two modes of the system. The solution to this problem is given by

$$\left(2-\mu(n)\right)^2(\vec{R}(n)^T.\vec{\theta}_{m_1})+\left(\mu(n)-1\right)^2(\vec{R}(n)^T.\vec{\theta}_{m_2})=0, \qquad n=1,\ldots,T \quad (11)$$

and

$$\mu(n)=\left\lfloor\frac{2\vec{R}(n)^T.\vec{\theta}_{m_1}+\vec{R}(n)^T.\vec{\theta}_{m_2}}{\vec{R}(n)^T.\vec{\theta}_{m_1}+\vec{R}(n)^T.\vec{\theta}_{m_2}}\right\rceil, \qquad n=1,\ldots,T \quad (12)$$

*Identification step: T*he first solution (when $\mu(n)$ is known and we search for $\left\{\vec{\theta}_{m_1},\vec{\theta}_{m_2}\right\}$) is given by Least Squares. However, for the hybrid case, some modifications need to be made, which give rise to Hybrid Least Squares. Hybrid Least Squares is in essence the same as HybELS [32], only without the iterations.

Classification step: The second solution (now $\left\{\vec{\theta}_{m_1},\vec{\theta}_{m_2}\right\}$ is known and we search for $\mu(n)$) is achieved by assigning each data point to the mode that results in the smallest (1-step) prediction error; in other words, $\mu(n)$ is 2 when the prediction error assuming m_2, $\vec{R}(n)^T.\vec{\theta}_{m_2}$, is smaller than the prediction error assuming m_1, or $\vec{R}(n)^T.\vec{\theta}_{m_1}$. Similarly, $\mu(n)$ is 1 when the prediction error assuming $m_1, \vec{R}(n)^T.\vec{\theta}_{m_1}$, is smaller than the prediction error assuming m_2, $\vec{R}(n)^T.\vec{\theta}_{m_2}$.

In summary, to minimize our cost function, we take the initial classification and parameters given by GPCA, and optimize them iteratively using equations (11) and (12).

At every iteration, in order to avoid the biasing effects of outliers or artifacts, we take out the points with extreme residuals. However, each pass re-evaluates all prediction errors using all data producing a new associated set of outliers (they are not accumulated).

Finally, with the classification vector fixed, HybELS [32] is used to fine-tune the estimated parameters. In the end, we discard the outliers again by removing the data points with extreme residuals, and re-estimate the parameters as above, to prevent the outliers from biasing our results.

III. Results

We applied GNL-HybELS to simulated data with known classification and identification parameters, i.e., system dynamics and switching instances between fast and slow modes were known. In this case, we could validate the performance of our method in terms of both identification and classification. We chose the simulation parameters close to what we would expect to see in experimental settings. We first tested our method on noise-free simulated data, and then added Gaussian white noise with a standard deviation (STD) of 1 deg which is our expected experimental noise. The validation results indicated unbiased estimates of delays and vestibular time constant. On the other hand, classification errors changed from 0.38% to 4.4% of data points, comparing noise-free to noisy conditions, while dynamic estimates remained robust. (Bode plots, Fig. 2-3).

IV. Discussion and Future Work

In this work, we introduced GNL-HybELS as a tool for the simultaneous classification and identification of oculomotor responses. With these objective and automated analysis capabilities, clinical protocols can be significantly improved, to allow for more versatile stimuli. Since data can now be classified and identified without human intervention, the input signals need not be deterministic, and novel sensory profiles are now feasible despite apparently erratic responses to the human eye. Multiple oculomotor modalities can now be tested in a compact protocol, and there is no need for tedious isolated experiments. The results of such data analysis are expected to provide more robust information on functionality, as verified in our preliminary clinical tests [29]. GNL-HybELS can also be used to identify non-linearities in the system structure. This could unveil significant diagnostic capabilities of GNL-HybELS in the context of the oculomotor system, as it did in the context of the VOR [29].

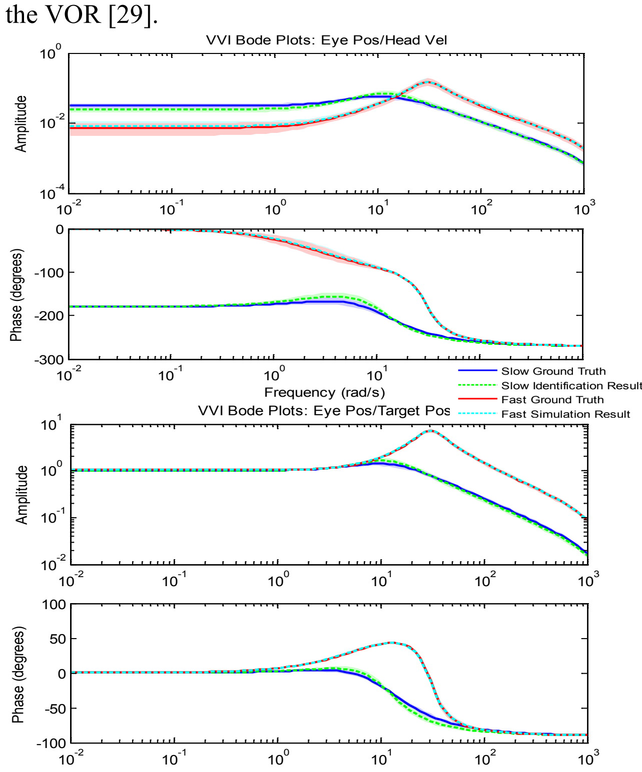

Fig. 2. GNL-HybELS results on noiseless simulated data, compared to the correct simulation parameters. Bode plots of the identified transfer functions (with 95% confidence intervals) in both slow and fast phases, as well as the correct transfer functions used in the simulation are shown.

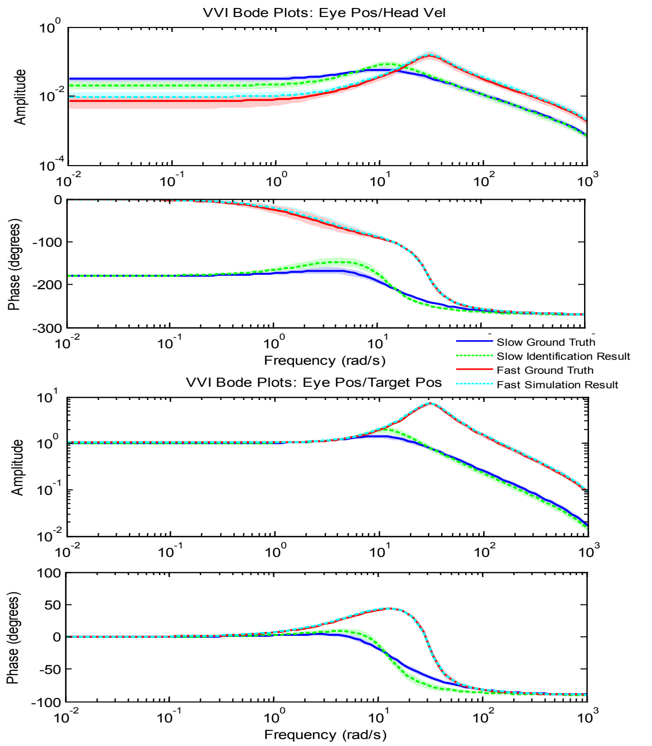

Fig. 3. GNL-HybELS results on noisy simulated data, compared to the correct simulation parameters. Bode plots of the identified transfer functions (with 95% confidence intervals) in both slow and fast phases, as well as the correct transfer functions used in the simulation are shown.

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