Vergence Variability: A Key to Understanding Oculomotor Adaptability?

Anne Marie Petrock, Dr. S. Reisman, *Senior Member, IEEE,* and Dr. T. Alvarez, *Member, IEEE*

***Abstract*—Vergence eye movements were recorded from three different populations: healthy young (ages 18-35 years), adaptive presbyopic and non-adaptive presbyopic (the presbyopic groups aged above 45 years) to determine how the variability of the eye movements made by the populations differs. The variability was determined using Shannon Entropy calculations of Wavelet transform coefficients, to yield a non-linear analysis of the vergence movement variability. The data were then fed through a k-means clustering algorithm to classify each subject, with no a priori knowledge of true subject classification. The results indicate a highly significant difference in the total entropy values between the three groups, indicating a difference in the level of information content, and thus hypothetically the oculomotor adaptability, between the three groups. Further, the frequency distribution of the entropy varied across groups.**

I. Introduction

It is known that variability in many physiological systems decreases with age. However, this phenomenon has received limited attention with respect to vergence eye movements. It will be shown that there is indeed a variability component that is associated with vergence eye movements that changes as humans age.

A key aspect of this research is the determination of a neural underpinning to the onset of presbyopia, and whether non-linear dynamic analytical tools, such as wavelet entropy, can depict changes in the components. It has been shown that people with depressed heart rate variability (HRV) have a diminished ability to respond to stress and sudden environmental changes as a result of altered interactions of the sympathetic and parasympathetic nervous branches of the autonomic nervous system [1-6]. Research on the autonomic influence over the vergence system has been limited to dark vergence, or dark accommodation. Miller et al. have suggested that accommodation is a reflection of the sympatho-vagal balance, which supports the dual-innervation theory of systems. The group also found that environmental stimuli known to elicit autonomic response affect dark vergence, as well [7]. In addition, studies by Gilmartin et al. suggest that sympathetic influence over accommodative activity is not uniformly distributed among individuals, and that only approximately one in three people display such influence [8]. Further research on myopia indicates that there is a reduction in the speed of the accommodation response, although the analysis did not include frequency analysis [9]. The studies were aimed at understanding the autonomic influence over vergence in early and late-onset myopia. It is believed that deficits in the inhibitory sympathetic innervation may cause individuals to be more susceptible to environmental factors. Further, it is hypothesized that optimal function may occur if the critical level of interaction between sympathetic and parasympathetic components of accommodation occurs [10-12]. There have not been attempts to quantify the neural activity in terms of variability, beyond variance measures, for myopic or presbyopic populations.

Three current hypotheses for the underlying reason for the onset of presbyopia are the crystallization of the lens, weakening of the cilliary muscles that surround the pupil, or a combination of the two. This research proposes that a neural component underlying a predisposition to reduced variability within eye movements may also contribute to this condition. It is also hypothesized that this reduction in variability influences the ability to adapt to different types of corrective lenses.

The purpose of this research is to combine novel statistical (cluster analysis) and non-linear time-frequency quantification measures (wavelet entropy absolute values and probability distributions) of variability with knowledge of the neural subcomponents of the visual tracking system. It is hypothesized that this approach will yield information about the influence of neural circuitry on visual components during aging, and that reduced entropy is evident in aged and non-adaptive individuals.

II. Methods

A. Subject Selection

A subset of data from an ongoing study on oculomotor learning as it pertains to the onset of presbyopia and the ability, or inability, to adapt to integrated corrective lenses was used for this research. Data from nine subjects was randomly chosen from the main study data set, which comprised 22 subjects. The subject population included three cohorts: young apparently healthy individuals

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Anne Marie Petrock is a doctoral candidate at New Jersey Institute of Technology, Newark, NJ 07102 USA (e-mail: apetrock@hotmail.com)

Dr. Tara Lynn Alvarez and Dr. Stanley Reisman are with the Department of Biomedical Engineering, New Jersey Institute of Technology, Newark, NJ, 07102 USA. (e-mail: alvarez@njit.edu, reisman@njit.edu)

between the ages of 18 and 35, presbyopic individuals who were able to adapt to the use of integrated lenses (adaptive presbyopics), and presbyopic individuals who were unable to adapt to the use of integrated lenses (non-adaptive presbyopics). Subjects were asked to wear corrective lenses and not contact lenses during the data collection and were disqualified if they had eye surgery or the possibility existed of them having metal fragments in their eyes. The data were collected at the Vision and Neural Engineering Laboratory at NJIT.

The vergence movements were recorded using the Skalar Model Series 6500 eye movement tracking system. They subjects were asked not to blink while the data were being collected. Data collection lasted three seconds. The data were digitized at 200Hz using a NI DaqCard 6024e which is well above the Nyquist frequency. The subject pressed a button to initiate an experiment. Following a random delay, the target changed illumination to initiate a convergent or divergent movement. Thus, prediction was reduced since subjects could not anticipate the time or direction of target presentation. Only convergent movements were analyzed in this study.

B. Data Analysis

The methods employed in this study are based upon a wavelet analysis. Wavelet analysis can be best described as an adaptive filter bank that yields multiple time-series that are a time-frequency representation of the original data set. The wavelet analysis is generally in the form of a time-scale analysis, where scale is approximately equivalent to the inverse of frequency, and a conversion between frequency and scale was performed on the wavelet coefficients. The general form of a wavelet algorithm is

$$C(a,p) = \int_{-\infty}^{\infty} f(t)\psi^*(a,p,t)dt, \tag{1}$$

where C is the wavelet coefficient, a is the scale parameter, p is the time shifting parameter, and Ψ is the complex conjugate of the mother wavelet, which will serve as the filtering function. Note the similarity to the Fourier transform. In this case, however, the mother wavelet is used to decompose the signal rather than a sinusoid, and the resultant signal is based upon time and frequency, not just frequency. This method is important in an analysis such as this because it provides frequency resolution over the entire course of the signal, rather than providing a time-averaged value for the frequency content of the signal. This enables the investigation of how the underlying components are changing instead of simply quantifying that they have changed.

The coefficients are then passed through an algorithm based upon Shannon entropy. This particular algorithm was first implemented by Kowalski et al. in 2003 [13], where wavelet entropy was used to detect the classical-quantum interface of two coupled oscillators in mechanics. Because the interaction of the branches of the autonomic nervous system can be viewed as two coupled oscillators, it is appropriate to employ such a method. The intermediary measures were also employed in the anlaysis. This includes the probability distribution of the entropy values at each scale a, Pa, as well as the entropy values themselves, E_a, and the total Wavelet Entropy, S_{wt}. The values were calculated based upon the following equations:

$$E_a = \sum_p |C_a(p)|^2 \tag{2}$$

$$P_a = \frac{E_a}{E_{tot}}\cdot \tag{3}$$

$$S_{wt} = -\sum P_a \ln(P_a), \tag{4}$$

where E_{tot} is the summation of E_a over all scales, a.

A cluster analysis of the data was performed to investigate whether the entropy provided clinically relevant data that could be used to determine how adaptive the subject would be. The cluster analysis program was written in Matlab and employed a cosine distance measure as the basis of the separation of the clusters, defined as $1 - \cos(\theta)$, where θ is defined as the angle between points (treated as vectors). Each centroid is the component-wise mean of the points in that cluster, after centering and normalizing those points to zero mean and unit standard deviation [14].

The only a priori data used in this study was the knowledge that there were three groups of subjects. Because a hypothesis of underlying oculomotor differences between the three groups is the loss of accommodative strength, which is measurable during the steady-state segment of the signal, only the last second of the data set was used to generate the entropy values used in this study. The analysis was performed blind to the true classification of the subjects as either young, adaptive presbyopic or non-adaptive presbyopic.

III. Results

The wavelet decomposition of the vergence movement signals was performed using the DauBechies7 mother wavelet. Figs. 1 and 2 depict the raw data and wavelet distributions for two subjects classified into separate groups. Note the difference in wavelet coefficient amplitude, an order of magnitude in this case.

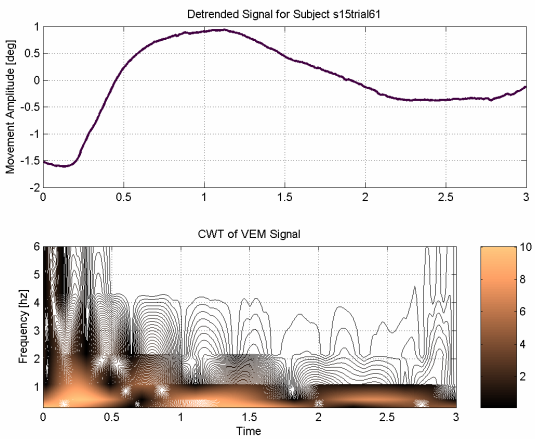

Fig. 1. Wavelet decomposition of nonadaptive presbyopic subject data. The top plot is the raw vergence movement data in time. The bottom plot is the DB7 wavelet decomposition of the top signal.

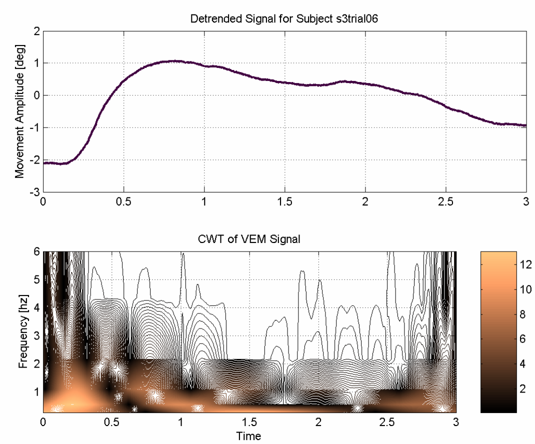

Fig. 2. Wavelet decomposition of healthy young subject data. The top plot is the raw vergence movement data. The bottom plot is the DB7 wavelet decomposition of the top signal.

The entropies derived as in (2) are orders of magnitude different between the groups. This information is useful by itself to view the distribution of the energy in the signal. Further, an analysis of variance indicated a p-value of 0.0023 between groups when looking solely at E_a. In addition, the distribution density of the energy was different for the presbyopic than for the healthy young data sets. It was found that the largest disparity between the three groups was found in the entropy values of scales 4, 5, 11, 13 and 14 and that these measurements were sufficient to separate the data into the three appropriate subject groups.

Classification of each of the nine subjects is depicted in Fig. 3, a confusion chart of the classification results. A mistake in classification was made for one adaptive presbyope, who was classified as a healthy young subject, resulting in an accuracy rate of 88.89%. Classification was based upon the values of the energy, E_a, the values of the energy distribution, P_a, and the value of the total wavelet entropy, S_{wt}, 25 values for each subject. The lowest grouping accuracy was in the adaptive presbyopic group, with tendency to group healthy and adaptive presbyopic populations together.

Significant differences between the three groups were measured in frequency ranges 0.0042-0.0085, 0.0085-0.017, 0.034-0.068, 2.16-4.33 and 4.33-8.65 Hz during the last second of the oculomotor signal. Because this is the time period during which the accommodative portion of the oculomotor control signal is located, this research supports the theory that accommodative changes may be underlying changes in visual tracking system accuracy with aging.

IV. Conclusions

Evidence is presented to support the implementation of vergence variability as a tool to measure adaptability. Further research must be done on larger population sizes; however, given the small sample size and highly significant differences, it may safely be hypothesized that a larger sample size would serve to further validate the theories presented. A study of cardiopulmonary data concurrent with vergence variability may provide a baseline for the representation capability of the vergence variability measure to indicate loss of adaptability in the autonomic control pathways.

V. Discussion

Vergence variability is a real phenomenon that can be related to adaptability of the vergence system. The wavelet entropy method detected decreasing values of entropy with age, indicating a reduced ability to adapt to changing environments manifested by decreased vergence variability. This change in vergence variability enabled the blind cluster separation of healthy subjects from presbyopic subjects who have the capacity to adapt and those who do not. Recently, two groups have separately investigated the change in binocular vision with age and early and late onset myopia. The first group found that the transient component of the vergence velocity and onset is delayed in aged populations [15]. The second group found that increases in the low-frequency components (between 0-0.6 Hz) of the signal mediated increases in the microfluctuations of the accommodative system [16].

Autonomic investigations of the cardio-pulmonary system typically investigate low frequency activity as a measure of combined sympathetic and parasympathetic activity, as well, and measure the response of the system dynamics in terms of sympatho-vagal interactions via the relationship of high (0.14-0.4 Hz) to low (0.05-0.14 Hz) frequency activity. As research has indicated that the dual-innervation theory that applies to the cardio-pulmonary system also applies to the vergence system [7-10, 17, 18], it follows that the time-frequency method of decomposition described herein would be able to detect differences in pathology using the variability that is likely a result of the autonomic influence.

		Predicted Class		
		Control	Adaptive Presbyope	Non-Adaptive Presbyope
Actual Class	Control	3	0	0
	Adaptive Presbyope	1	2	0
	Non-Adaptive Presbyope	0	0	3

Fig. 3. Confusion plot of the cluster analysis results. An adaptive presbyope was misclassified as a control.

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REFERENCES

[1] C.K. Peng, J. Mietus, Y. Liu, et al. "Quantifying Fractal Dynamics of Human Respiration: Age and Gender Effects." *Ann. of Biomedical Engineering*, vol. 30, pp. 683-692, 2002.

[2] D. Hoyer, U. Leder, H. Hoyer, B. Pompe, M. Sommer, and U. Zweiner. "Mutual information and phase dependencies: measures of reduced nonlinear cardiorespiratory interactions after myocardial infarction," *Med. Eng. & Phys.*, vol. 24, pp. 33-43, 2002.

[3] S. Havlin, L.A.N. Amaral, Y. Ashkenazy, et al. "Application of statistical physics to heartbeat diagnosis," *Physica A*, pp. 99-110, 1999.

[4] A.L Goldberger, V. Bhargava, B. West, and A.J. Mandell. "Nonlinear dynamics of the heartbeat: II. Subharmoninc bifurcations of the cardiac interbeat interval in sinus node disease," *Physica D: Nonlinear Phenomena*, vol. 17, no. 2, pp. 207-214, 1985.

[5] P. Guillen, M. Vallverdu, D. Jugo, H. Carrasco, and P. Caminal. "Non-linear dynamics in heart rate variability of normal subjects and chagasic patients," *Proc. 22nd EMBS Int. Conf.*, pp. 2414-2415, 2000.

[6] P. Guillen, M. Vallverdu, F. Claria, D. Jugo, H. Carrasco, and P. Caminal. "Complexity Analysis of Heart Rate Variability Applied to Chagasic Patients and Normal Subjects," *Computers in Cardiology*, vol. 27, pp. 469-472, 2000.

[7] R.J. Miller and Masatoshi Takahama, "Arousal-Related Changes in Dark Focus Accomodation and Dark Vergence," Invest. Opthal. Vis. Sci., vol. 29, no. 7, pp. 1168-1178, July 1988.

[8] B. Gilmartin, E. A. H. Mallen, and J. S. Wolffsohn, "Sympathetic control of accommodation: evidence for inter-subject variation," Opthal. Physiol. Opt. vol. 22, pp. 366-371, 2002.

[9] H. M. Culhane and B. Winn, "Dynamic Accomodation and Myopia," Inv. Opthal. Vis. Sci., vol. 40, no. 9, pp. 1968-1974, Aug. 1999.

[10] J.C. Chen, K. L Schmid, and B. Brown, "The autonomic control of accommodation and implications for human myopia development: a review," Opthal. Physiol. Opt., vol. 23, pp. 401-422, 2003.

[11] K. J. Cuiffreda, and M. Wallis, "Myopes show increased susceptibility to nearwork aftereffects," Invest. Opthal. Vis. Sci., vol. 39, 1998.

[12] M. Rosenfield, B. Gilmartin, "Temporal Aspects of Accomodative Adaptation," Opthal. Vis. Sci., vol. 66, pp. 229-234, 1989.

[13] A.M. Kowalski, M.T. Martin, M. Plastino, A. Proto, and O.A. Rosso. "Wavelet Statistical Complexity Analysis of the Classical Limit," Phys. Lett. A, vol. 311, no. 2-3, pp. 180-191, 2003.

[14] Mathworks (April 2, 2006). Statistics Toolbox k-means description. Available: http://www.mathworks.com/access/helpdesk/help/toolbox/stats/kmeans.html,.

[15] H. Rambold, G. Neumann, T. Sander, C. Helmchen, "Age-related changes of vergence under natural viewing conditions," Neurobiol. Aging, vol. 27, no. 1, pp. 163-172, Jan. 2006.

[16] M. Day, N. C. Strang, D. Siedel, L. S. Gray, and E. A. H. Mallen, "Refractive group difference in accommodation microfluctuations with changing accommodation stimulus," Opthal. Physiol. Opt., vol. 26, pp. 88-96, 2006.

[17] B. Winn, H. Culhane, B. Gilmartin, and N. C. Strang, "Effect of b-adrenoceptor antagonists on autonomic control of cilliar smooth muscle," Opthal. Physiol. Opt., vol. 22, pp. 359-365, 2002.

[18] R. A. Tyrell, and J. F. Thayer, "A behavioral link between the oculomotor and cardiovascular systems," Integr. Physiol. Behav. Sci., vol. 30, no. 1, pp. 46-68, Jan-Mar 1995.