Leveraging Data Complexity: Pupillary Behavior of Older Adults with Visual Impairment During HCI

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The current ubiquity of information technology has increased variability amongst users, creating a corresponding need to properly capture and understand these individual differences. This study introduces a novel application of multifractal statistical methods to distinguish users via patterns of variability within high-frequency pupillary response behavior (PRB) data collected during computer-based interaction. PRB was measured from older adults, including two groups diagnosed with Age-related Macular Degeneration (AMD) maintaining a range of visual acuities (n=14), and one visually healthy control group (i.e., disease-free, 20/20 – 20/32 acuity) (n=14). Three measures of the multifractal spectrum, the distribution of regularity indices extracted from time series data, distinguished the user groups, including: 1) Spectral Mode; 2) Broadness (e.g., spectral width); and 3) Left Slope. The results demonstrate a clear relationship between the values of these measures and the level of visual capabilities. These analytical techniques leverage the inherent complexity and richness of this high-frequency physiological response data, which can be used to meaningfully differentiate individuals whose sensory and cognitive capabilities may be affected by aging and visual impairment. Multifractality analysis provides an objective, quantifiable means of uncovering and examining the underlying signatures in physiological behavior, which may account for individual differences in interaction needs and behaviors.

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1. INTRODUCTION

Human-computer interaction (HCI) research efforts have recently focused on the examination of the relative interaction needs and behaviors of individuals with varying abilities. Of particular interest are the effects of cognitive, motor, and sensory impairments on computer task performance [see Jacko and Vitense 2001]. In the last decade, the relative needs and abilities of older adult users [Emery et al. 2003; Hutchison et al. 1997; Morrell and Echt 1997] and users with visual impairments [Jacko et al. 2001; Jacko et al. 2003b; Vitense et al. 2003], both numbering in the millions in the United States, have received considerable attention. Researchers have found that the concomitant effects of age on visual abilities have hampered computer-based task performance, often resulting in increasing task time and error rates [Birren and Fisher 1995; Craik and Salthouse 2000; Mead et al. 2000]. Particularly, HCI researchers have examined the needs and abilities of "low vision" users, who possess impaired vision below "normal" or healthy levels of visual functioning [Biglan et al. 1988; Jacko et al. 2005; Jacko and Vitense 2001]. These individuals with visual impairments number 10 million, with several million of these users reporting computer access and/or use [American Foundation for the Blind 2005].

As both aging and visual impairment are of interest to HCI researchers, it is a natural fit to study individuals with Age-related Macular Degeneration (AMD). AMD affects millions of Americans and is the leading cause of new blindness and visual impairment for individuals 55 years and older [American Macular Degeneration Foundation 2002; Schepens Eye Research Institute 2003]. AMD affects the central area of the retina (a.k.a., the macula), which contains the majority of photoreceptor cells responsible for central, fine detail, and color vision [Gass 1996]. The cellular damage associated with AMD creates degradation in central and high-resolution vision, impairing the ability to perform focus-intensive activities – including computer-based tasks [Schepens Eye Research Institute 2003]. Initial HCI-based research has illustrated that users with AMD and severe vision loss consistently perform worse than visually healthy users on computer-based tasks such as iconic target selection [Jacko et al. 2002; Jacko et al. 2000] and drag-and-drop [Jacko et al. 2005; Jacko et al. 2003b]. This research has demonstrated that clinically-assessed measures of visual functioning can be used as factors for the prediction of task performance of individuals who are visually healthy and people with visual impairments [Jacko et al. 2000; Jacko and Sears 1998].

However, researchers have also found that performance differences can exist between users on an intrinsic level not revealed through clinical measures or questionnaires. A recent study by Jacko and colleagues [2005] revealed clear, consistent performance differences between users with and without AMD, despite an absence of intergroup significant differences with respect to all demographic (e.g., age, gender, computer experience) and clinically-assessed measures of visual function (e.g., visual acuity, contrast sensitivity, color perception). However, aside from the differences in ocular diagnosis of AMD, participants did differ in their subjective perceptions of how their visual health affected their performance of daily living activities. These results support the presence of underlying, subclinical differences in functional visual abilities, unexplained by overt differences in common demographic and clinical user characteristics. These underlying individual differences drive the differences in task performance between individuals possessing normal, unaffected vision (e.g., 20/20 visual acuity) with and without ocular pathology.

Despite the clinical resources and considerable expense required to perform clinical, visual testing, there were still differences in the functional abilities of users to perform the HCI tasks. When underlying functional differences (e.g., in terms of being able to perform computer-based tasks) cannot be forecast by differences in demographic variables and/or common clinical tests, researchers must turn to new measures of user characterization. Pupillary response behavior (PRB) refers to changes in pupil diameter – in terms of pupil dilation or constriction – in response to simple or complex stimuli. PRB has long been used as a measure of cognitive workload, a critical component of HCI. Examination of PRB collected from individuals during performance of HCI tasks may yield new insight into these underlying user differences.

In this study, we propose two advanced statistical concepts, wavelets and multifractality, for the purposes of extracting meaningful characteristics from the PRB data of older adults with and without visual impairment. Analysis of multifractality involves the characterization of irregularity within a data signal across scales with respect to the magnitude and persistence of signal fluctuations. It is a novel, yet promising analytical technique for uncovering such subtleties in seemingly noisy, high-frequency physiological data. These analytical techniques are of particular interest for this application, as it is well established that the PRB of individuals who are aging and/or have visual impairments has a tendency to exhibit muted and anomalous patterns in behavior [Berezovsky et al. 2001; Bergamin and Kardon 2002; Bremner et al. 1999;

Loewenfeld 1999; Van Gerven et al. 2004]. Analysis of multifractality within the PRB of individuals, especially those who are aging or have ocular disease, may provide new avenues for using PRB to differentiate users of varying abilities or as a measure of information processing or cognitive workload.

The PRB data examined in this study represented the physiological pupil responses exhibited by these individuals during performance of a common computer-based direct manipulation task – the drag-and-drop. The results of this study suggest that there may be underlying, unique patterns hidden within complex, high-frequency PRB. These patterns can be thought of as the 'signatures' that reveal the effects of underlying cognitive, sensory, or motor problems that manifest themselves as functional impairments to HCI task performance. Analysis of multifractality in high-frequency, time series physiological data is a useful tool for detecting these signatures and differentiating individuals based on these unique patterns in their physiological behavior. This has important implications for HCI researchers who are trying to understand the intrinsic individual differences, which are driving the functional differences in terms of using computers in an efficient and effective manner. This is especially true when those individual differences cannot be revealed through common profiling efforts. By leveraging these novel user characterization methods, system and interface developers can target instances in which facets of the tasks, users or the interaction of the two, lead to difficulties in task performance or unacceptably high levels of cognitive workload.

2. RELATED RESEARCH

2.1 Use of PRB Data

It is becoming increasingly clear that using common user and task performance measures or user demographics is not sufficient for the full exploration and understanding of the interaction that occurs between human users and information technology [Dillon and Watson 1996]. Measurement of cognitive workload is one method used by Human Factors and HCI researchers to further explore individual differences in performance of psychomotor tasks or use of information technologies. It is becoming a necessary part of user, system and interaction evaluation to continually track the unobservable cognitive demands that a system imposes on a person [Luximon and Goonetilleke 2001]. For example, Moray [1988] found that optimizing cognitive workload could reduce human error, improve system safety, increase productivity, and increase operator satisfaction.

One popular objective measure of cognitive workload is pupil diameter or, more accurately, the changes in the constriction and dilation of the iris. The relationship between cognitive processing and PRB was suggested well over 100 years ago, as scientists observed pupillary dilation in response to environmental stimuli and mental processing tasks (e.g., multiplication) [Beatty and Lucero-Wagoner 2000]. Research has long supported that changes in pupil diameter correspond with the information acquisition and processing requirements that occur during a task [Backs and Walrath 1992; Beatty and Lucero-Wagoner 1978; Kahneman and Beatty 1966]. More recently, PRB has been used to predict the cognitive demand users experience in the context of HCI [Iqbal and Bailey 2005; Iqbal et al. 2004]. For example, a recent study by Iqbal and colleagues [2005] used percentage change in pupil size to examine how mental workload changes during different types of computer-based tasks and sub-tasks, as well as task boundaries. This knowledge can help to inform the design of systems that manage users' attention, such as managing when to interrupt or prompt users during task performance.

While PRB data have been used successfully as a measure of cognitive workload, several problems arise when trying to use these data with user populations who are aging and/or have visual impairments. There are well-documented effects of aging, ocular disease, and trauma on PRB. Extensive research has found that aging naturally leads to ocular changes including shrinking pupil size and slower, smaller pupil response to visual stimuli [Loewenfeld 1999]. A considerable body of research has also documented the detrimental effects of ocular disease and trauma on PRB [Barbur 2003; Bremner et al. 1999]. Individuals with central visual field loss, such as those with AMD, show distinct differences in pupillary activity compared to individuals with healthy visual capabilities. Individuals with central vision deficits exhibit a significantly higher amount of pupil escape, meaning that these individuals have less control over the sustained movement of the iris. Additionally, pupillary light reflexes have been shown to differ significantly between individuals with central visual field loss, combination central and peripheral visual field loss, and unimpaired visual fields [Bergamin and Kardon 2002].

This has very practical implications for researchers. Van Gerven and colleagues [2004] discovered these problems in a recent study comparing the cognitive PRB of younger and older users during a memory search task in which the size of the memory set (e.g., number of digits to be remembered) was varied. This study found that pupil dilation in the older users remained fairly constant even in the presence of increasing load on the memory, although younger participants illustrated the expected positive linear trend of increasing pupil dilation with increasing memory load. With respect to ocular disease, Berezovsky and colleagues [2001] were unable to detect differences in the steady state pupillary activity following dark adaptation between individuals with retinitis pigmentosa and those without ocular disease, which is in contrast to well-supported clinical theories of the effects of this ocular disease on pupillary reactivity.

The inability to observe or extract meaningful or significant changes in the PRB of older and/or visually impaired adults, even under conditions of changing cognitive workload, is extremely problematic for examining cognitive workload in the rapidly increasing number of aging individuals. Given the increasing number of individuals with visual impairments, including age-related visual impairments, this inability to utilize pupillometric data becomes even more serious. The complex effects of aging and visual impairment on PRB create a need for analytical tools that are powerful enough to detect muted and irregular patterns and allow for examination of cognitive workload during interaction with information technologies.

2.2 Analysis of PRB & Wavelets

To date, traditional statistical methods have not been successfully used for examining the PRB of older adults or individuals with visual impairments. Researchers have traditionally utilized fairly simple statistical methods for analyzing PRB. These techniques often include comparing the relative mean or variance (or percentage) of pupil size deviation (i.e., dilation or constriction) in response to a stimulus (e.g., the task-evoked pupillary response or TEPR), for different individuals or different conditions [e.g., Beatty 1982; Beatty and Lucero-Wagoner 2000; Van Gerven et al. 2004]. Some studies have also utilized more sophisticated techniques, such as power, frequency and spectral analyses using mathematical tools such as Fast Fourier Transform (FTT) [Ludtke et al. 1998; McLaren et al. 1992; Neumann 2002].

However, many of these techniques do not properly equip researchers with the analytical means to account for anomalous, erratic or muted PRB inherent to older adults and those with visual impairment. To overcome these challenges, analytical tools must account for and characterize the underlying patterns within time-dependent PRB data. In an initial effort at making the analysis of high-frequency PRB data more manageable and meaningful, Marshall [2000] proposed the use of specific data filtering algorithms for data preprocessing, combined with wavelet analysis, to isolate the effects of mental activity from within the data signal. Marshall’s efforts were primarily directed at helping to separate a user's pupil dilation reflex in response to light from a dilation reflex in response to a task requiring cognitive processing. Use of Wavelet-based statistical techniques can provide information on the local scale signature features of pupil behavior, which would otherwise remain unrealized by other statistical techniques.

Wavelets are a statistical approach well suited to analyze complex time series data, creating a domain in which the scaling properties of signal energy become visible [Graps 1995; Vidakovic 1999]. Wavelets help to de-noise rich and large time series data, at finer and finer levels of resolution in order to reveal the 'hidden' important events in the data. Such events include localized features, discontinuities and smoothness, which are often lost with techniques that use smoothing filters and non-localized algorithms [Vidakovic 1999]. The real advantage lies in the ability to explore these local, atomic features within the data signal without affecting or suppressing the rest of the data signal, as happens with many transforms (e.g., Fourier transforms) [Graps 1995]. Such local analysis can be done in many scales simultaneously. The wavelet atomic functions are localized with respect to frequency and space (time), making them well suited for the analysis of time-dependent, transient data signals that include significant locality and non-stationarity – such as PRB. As such, wavelet-based statistical tools appear to be a solution for identifying and extracting the finest systematic changes or localized features in PRB that might otherwise be overlooked or mistaken for noise.

While the efforts of Marshall and colleagues [Marshall 2000; Marshall et al. 2002] are leagues beyond the previous efforts of data averaging, comparing changes in pupil diameter between adjacent observations or based on a baseline observation (e.g., the TEPR), or signal smoothing techniques, these studies still merely examine the PRB data of relatively young, visually healthy individuals. Applying wavelet analysis techniques to reduce dimensionality or denoise PRB data may not be specific enough to distinguish meaningful patterns from the PRB of older adults, especially those with visual impairment. As these techniques still require the use of some signal averaging and smoothing to derive comparable measures (e.g., average dilation during 1000 msec after stimulus), they may not be sensitive enough to distinguish seemingly flat or irregular pupil reactivity, as commonly occurs in older adults with visual impairment. Thus, analysis of multifractality is suggested to provide new measures that characterize the overall complexity or irregularity present in these data signals.

2.3 Multifractal Analysis

The appropriateness of using analyses of multifractality for examining PRB data is supported by previous use in other domains (e.g., biomedical) in which high-frequency and/or complex data exist. For example, long-range correlations and wavelet-based multifractality have been successfully used for tissue classification in digitized mammograms to support clinical diagnosis [Kestener et al. 2001]. Additionally, these analytical tools have also been used in the identification and prediction of heart failure [Havlin et al. 1999; Ivanov et al. 1999]. This success of applying these statistical tools to noisy, seemingly erratic physiological data signals supports the potential utility of these analytical tools for similarly complex PRB. However, it should be noted that multifractal analysis has never been used in an HCI-based application, for PRB or otherwise.

Fractals refer to signals exhibiting strong similarity across different scales. That is, if a part is taken from the signal, and properly rescaled, then it looks similar (in a statistical sense) to the whole of the signal. Fractal signals are typically classified as either monofractal or multifractal according to the richness of their irregularity [Riedi 1999]. In the case of fractality, irregularity refers to the extent to which there is considerable fluctuation or deviation in the signal around a single point. This degree of regularity is captured by a Hölder regularity index (α). The richness of this regularity, or the range of this regularity, refers to the variability within the regularity indices (α's). If there is more variability amongst the values of the α's, then the signal deviates from the monofractal – a fact that can be very informative.

Such irregularities can be summarized via distributions called multifractal spectra [Riedi 1999]. A multifractal spectrum represents the distribution of the Hölder regularity indices (α's) calculated for all local neighborhoods (i.e., a set of data points within a specified segment of length x) in the observed dataset. These α's represent estimates of local smoothness (or regularity) for each point along a data sequence, characterized in terms of the relative deviation of the surrounding data points from the value of the target point.

Multifractal analysis is focused on the distribution of the regularity indices, rather than simply on the estimation of the global, single index itself [Vidakovic 1999]. That is, multifractal analysis focuses on exploring and understanding the nature of the irregularities of the data signal and not on the single, most frequent irregularity or global trend. In this way, the components of the signal are characterized in terms of their inconsistency or inhomogeneity with respect to the relevant signal characteristics (amplitude, persistence of change, autocorrelation). Multifractality provides an additional window through which to look at the data, not possible with more common statistical analysis approaches.

Interestingly, multifractal spectra can be found even for monofractal processes. The spectra generated from monofractal processes are ramp-like with a dominant (modal) irregularity corresponding to the theoretical monofractal index, the Hurst Exponent [Riedi 1999]. Monofractal processes or signals can be characterized by a few canonical descriptors, including: 1) the maximum point, representing the Spectral Mode (SM) or most frequent value of the Hölder regularity indices; 2) a vertical line, representing the Left Slope (LS) of the distribution of Hölder regularity indices; and 3) the unity Right Slope (RS) of the distribution. The spectral width, subsequently referred to as 'Broadness' (B), represents the relative variability of the Hölder regularity indices. Broadness is actually a higher-level descriptor, which is modulated by the three canonical descriptors – Spectral Mode (SM), Left Slope (LS), and Right Slope (RS). Multifractal signals, on the other hand, possess a smooth distribution of various scaling exponents (e.g., irregularities or inhomogeneities). These geometric descriptors of the multifractal spectrum are illustrated in Figure 1.

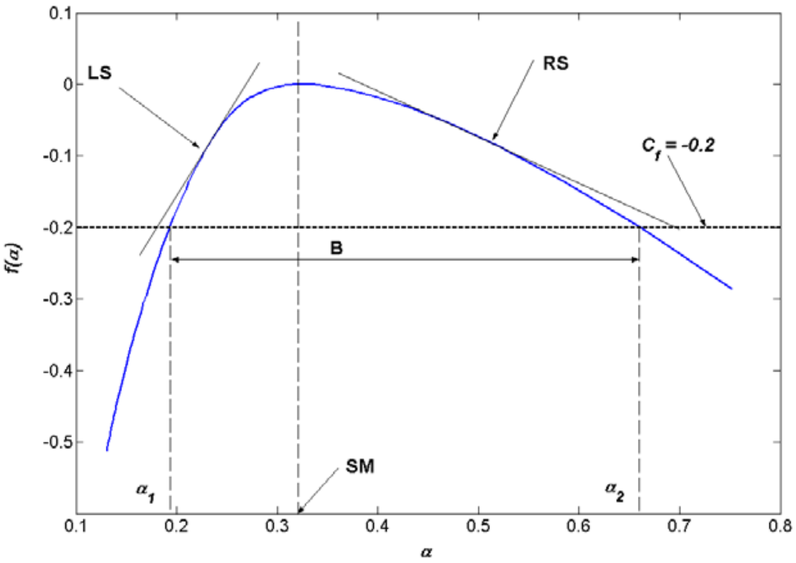

Figure 1. Illustration of geometric attributes of multifractal spectrum. Note: The x-axis (α) represents the value of the Hölder regularity index (α), while the y-axis represents values that are proportionate to the relative frequency of these indices ($f(\alpha)$), scaled in such a way that the maximum value is at 0. In this case, the maximum of this spectrum (e.g., the SM) is at $\alpha = 0.33$.

Multifractal processes (or signals) represent instances in which there is a deviation from the monofractality, which can be assessed through changes in these canonical measures. Understanding the SM and LS measures is straightforward. SM represents the apex of the spectrum or the most common (i.e., the mode) Hölder regularity index (α) found within the data signal. LS represents the slope of the distribution produced by the collection of Hölder regularity indices (α's) with smaller values than the mode (SM). However, Broadness (B) is more intricate compound descriptor of the multifractal spectrum. More detail on the empirical calculation of this measure is provided in the electronic appendix that accompanies this article. B is believed to be a more meaningful measure than RS because it is a compound measure representing the overall nature of the multifractal spectra, taking into account the overall variability amongst the Hölder regularity indices (α*'s*). Additionally, B partially accounts for RS in its calculation, as the resultant value of B is based on the relative values of RS and LS.

SM, B, and LS are measures of the relative richness of the regularity indices within the data signal, with increasing richness corresponding to increasing variability amongst the α's and increasing deviation from monofractality. In terms of the actual nature of the data signal, this refers to the variability in the magnitude and persistence of changes in the data signal. Within this concept, SM is a measure of the overall relative smoothness of the signal, LS is a measure of the deviation from monofractality, and B is a measure of the overall variability in the signal change patterns. It is the differences between the users, with respect to the variability amongst the α's, that is the key discriminatory characteristic. These differences correspond to actual differences in physiological activity captured in users' PRB. These three descriptors of the multifractal spectrum will be the focus of this study, used to differentiate users with varying ocular profiles based on PRB during a computer-based task.

2.4 Summary

These geometric characteristics of the multifractal spectrum are abstract representations of actual physiological behavior. With regard to actual pupil movement, as the dynamic PRB signal becomes more multifractal, the pupillary behavior becomes more complex and irregular at finer scales of resolution. The minute changes on finer time and location scales become more dynamic and inhomogeneous with increasing multifractality. For example, in terms of pupil diameter, the magnitude of change, rate of change, and persistence of change may all become more complex as multifractality increases. In this way, the analysis of multifractality will be able to discriminate the underlying complexity within the PRB of users with varying visual health profiles. The measures introduced in this paper hold potential for leveraging the richness within PRB data of older adults performing a computer-based task. The proposed method extracts differences in the PRB based on its complex patterns of irregularity. The internal fractal structure of the PRB is likely the key for true discriminatory potential.

3. METHODOLOGY

3.1 Objectives

The primary objective of this study is to explore the utility of this novel application of multifractal statistical tools for the purpose of distinguishing individuals of varying visual capabilities and ocular health, based on their dynamic PRB, within the context of HCI (e.g., during the performance of computer-based tasks by human users). This study seeks to establish three measures of multifractality within PRB as effective descriptors of users with varying abilities. Specifically, we examine the use of three geometric characteristics of the multifractal spectrum to differentiate aging users of varying ocular health: 1) the Spectral Mode (SM) or maximum of the spectrum; 2) the Broadness (B) or width of the spectrum; and 3) the Left Slope (LS) of the spectrum.

3.2 Participants

Participants in this study included 28 older adults, solicited from the patient pool of the Bascom Palmer Eye Institute of the University of Miami School of Medicine (9 men and 19 women; mean age = 76.29, SD = 5.20). Compensation for participation included $50 and free comprehensive ophthalmologic examinations by licensed ophthalmologists and technicians. Participants were selected on the basis of having either no ocular disease or only Age-related Macular Degeneration (AMD), as assessed by patient history and clinical testing. Participants were assigned to groups based on the diagnosis of AMD and their best eye near distance (40 cm) visual acuity. Individuals in the two experimental groups (Groups 1 and 2) had varying visual acuity and were diagnosed with AMD. Group 1 can be described as a set of individuals with AMD and low to moderate loss of functional vision. Group 2 can be described as a set of individuals with AMD and more severe loss of functional vision. A control group was also recruited, in which individuals possessed healthy, unaffected (or "corrected-to-normal") vision and no evidence of any ocular disease or trauma. Table I provides a summary characterization of the user groups.

Table I. User Group Characterization Summary

Group	N	Visual Acuity	AMD	Number of Data Sets
Control	14	[20/20 – 20/32]	No	105
Group 1	8	[20/32 – 20/70]	Yes	80
Group 2	6	[20/80 – 20/200]	Yes	102

Note. N represents the number of individuals in the group; Visual Acuity represents the range of Snellen acuity scores for the individuals in the given group, AMD represents if the individuals in a given group were diagnosed with age-related macular degeneration (or not) and Number of Data Sets represents the number of 2,048 length data sets that were extracted from the collective data sets of the individuals within a given group.

Several visual capabilities were assessed, including: visual acuity, contrast sensitivity and color perception. Visual acuity, an individual's ability to resolve fine detail, was assessed with a protocol that generates Snellen scores [Ferris et al. 1982; University of Maryland 1980], which were (for analytical purposes) converted and quantified by means of the logMAR transform [Bailey and Lovie 1976; Scott et al. 2002]. Contrast sensitivity (normal score 48), an individual's ability to detect characters at increasingly lower levels of contrast, was assessed using a Pelli-Robson chart [Pelli et al. 1988] and were converted to a weighted average score of 75% of the better eye score plus 25% of the worse eye score [e.g., Scott et al. 2002]. This weighted visual acuity score is a simple corrective factor used to account for binocular summation, which inherently occurs during use of both eyes. Color perception, an individual's ability to detect differences between hues, was assessed with the Farnsworth Dichotomous Test for Color Blindness [Dain 2004; Farnsworth 1947].

In addition to these objective, clinical measures of ocular functioning, participants also performed the National Eye Institute Visual Functioning Questionnaire (NEI VFQ-25) [Mangione et al. 2001]. This questionnaire includes several subscores based on questions concerning the level of self-perceived difficulty, based on their visual capabilities, individuals experience with daily activities. Previous research has supported the reliability and validity of this tool for detecting fine differences with problems associated with visual health for both individuals who are visually healthy and individuals who have visual impairments, including those with AMD [Clemons et al. 2003; Mangione et al. 2001; Mangione et al. 1998].

ANOVA and chi-square tests were performed, using SPSS® 12.0 for Microsoft® Windows®, to test intergroup differences in continuous and discrete subject variables, respectively. As expected, significant intergroup differences were found on all objective (clinical) and subjective visual functioning measures, including visual acuity ($F_{2,25}$ = 127.73, p < 0.01), contrast sensitivity ($F_{2,25}$ = 24.39, p < 0.01) and color vision (χ^2_{27} = 11.91, p < 0.01), as well as the majority of the NEI VFQ-25 subscales including general vision ($F_{2,25}$ = 40.59, p < 0.01), near activities ($F_{2,25}$ = 45.45, p < 0.01) and distance activities ($F_{2,25}$ = 30.38, p < 0.01). All of these significant differences between the groups were expected, with individuals in the Control group possessing the best (clinical and subjective) visual capabilities, while the visual capabilities of individuals in Group 1 were significantly worse than the Control group and individuals in Group 2 were significantly worse than both the Control group and Group 1.

Aside from these clinical measures of vision, the user groups were equivalent (p > 0.05) with respect to many other demographic variables, which may have impacted PRB during computer-based task performance, including: gender, ethnicity, and computer experience (current and past), as assessed by background questionnaires; and physical and mental health, as assessed by the Short Form-12 Health Survey [Ware et al. 1995] and a questionnaire of medical comorbidities. However, it should be noted that, as AMD is an age-related ocular disease, it is expected that there were inherent differences between the user groups with respect to age and age-related declines, such as motor abilities [Craik and Salthouse 2000]. While there were intergroup differences with respect to both age and manual dexterity, as measured by the Purdue Pegboard test [Tiffin and Asher 1948], this is an unfortunate consequence of studying this particular population. The users in Group 2, possessing more severe AMD, were fully expected to be older, and (by extension) possess less manual dexterity, than the individuals in Group 1 and the Control group. To the extent possible, this study tried to ensure intergroup equivalency with respect to both age and manual dexterity.

3.3 Experimental Task

For this study, participants performed a drag-and-drop task, as presented in previous work by Jacko and colleagues [2005; 2003a; 2003b]. The ubiquity of this interaction paradigm in the graphical user interface (GUI) environment can be illustrated by the focus of research on the mouse-based drag-and-drop task for more than a decade [e.g., Inkpen 2001; Mackenzie et al. 1991; Sellen et al. 1990, 1992]. The experimental task performed in this study was a simplified version of previous drag-and-drop task paradigms used in HCI research [Brewster 1998; Vitense et al. 2003], yet represents a complex interaction for individuals with impaired vision. For these reasons, this fundamental GUI interaction task was chosen, as it likely represents both a common, yet (perhaps surprisingly) difficult task for older adults – especially those with AMD.

The drag-and-drop task was comprised of the selection and movement of a computer file icon into a target folder via computer mouse movement. The participant's objective was to select the file icon with the mouse, position the file icon over the target folder icon and release the file into the folder. A single Microsoft Word® file icon location was held in a fixed location at the bottom, center of the display, while a single Microsoft® Windows folder icon was randomly located amongst one of 15 set locations. These 15 folder locations were arranged in sets of 5 equidistant (to the file icon) positions, arranged along three arcs. This arrangement of screen positions was used to account for the potential effects of visual field limitations, likely to be experienced by those individuals with advanced ocular disease. Only one file icon and one folder icon were present on the screen during a given trial. For each trial, the target folder position was randomly repositioned to one of the 15 locations. A sample screenshot of the program used is presented in Figure 2.

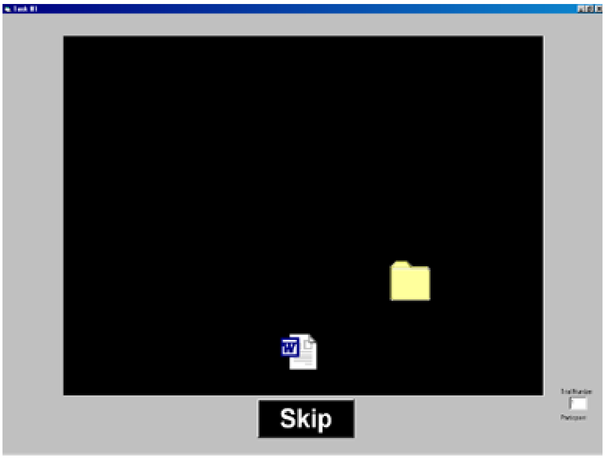

Figure 2. Sample screenshot of the Multimodal AHV 2.0 program used for the experimental task. For each trial, participants were instructed to drag the file icon to the folder icon as quickly and accurately as possible. For each trial, the location of the folder was randomly assigned to one of fifteen screen locations.

Users were provided with different combinations of sensory feedback, via visual, auditory and haptic modalities during task performance. This feedback was provided to users to indicate that the file icon was correctly positioned over the target folder icon; releasing the file would result in a successful ‘drop’. Once the file icon was released, the feedback ended and a new trial began. The visual feedback consisted of a purple colored highlight of the file and folder icons. The auditory feedback consisted of a metaphorical auditory icon, imitating the sound of a suction cup. The haptic feedback consisted of a gentle, mechanical vibration of the mouse, generated by a Logitech WingMan® mouse. Participants performed a series of 105 trials of the drag-and-drop task.

3.4 Apparatus

Participants worked on an IBM®-compatible machine and viewed a 20-inch viewable flat screen monitor, with 1152 X 864 pixel resolution and 32-bit color depth, while seated approximately 20 inches from the screen. The Multimodal AHV 2.0 software program (as seen in Figure 2) was developed for this study. This program was based on key features of the interface used in a baseline study of multimodal feedback with a general user population [Vitense et al. 2003]. This program utilized Microsoft® Word and Windows icon bitmaps for the mouse cursor, file icon, and target folder screen elements. The file icon and target folder sizes were 36.8mm (diagonal distance), based on the previous findings by Jacko and colleagues [2000].

All participants worked under controlled lighting conditions to account for the effects of ambient light conditions on pupillary dilation or constriction. Pupil size was measured with the Applied Science Laboratories (ASL)® Model 501® head-mounted optics system, which uses a bright pupil optical detection technique. PRB was recorded at a rate of 60 Hz during task performance, over the period of 105 trials. Pupil size was assessed as the total number of pixels present in the recorded pupil image, calculated as the sum of the pixels in the portion of the scanned horizontal lines comprising the bright pupil image. The pupil was determined by real-time edge detection. Pupil diameter (in millimeters) is determined by multiplying the overall pixel value of the pupil image by a scaling factor based on the physical distance from the camera to the participant’s eye.

3.5 Design and Procedure

This study employed a repeated-measures, within-subjects design, with each participant performing the several trials and receiving all experimental conditions (e.g., forms of feedback). All participants performed the same experimental task under the same conditions, thus the level of task difficulty was identical for all participants. All participants received the same feedback, although the order in which feedback conditions were received was randomly assigned across participants. Each participant received all 15 folder locations the same number of times, although this order was randomly assigned across conditions and participants. Visual functioning group (i.e., Control, Group 1 and Group 2) was the independent, between-subjects variable.

Participants were first provided with a comprehensive ophthalmic exam to ensure the clinical diagnosis of AMD and knowledge of their current visual capabilities. Where appropriate, participants were provided with temporary frames, which were outfitted with the appropriate corrective lenses to ensure that the experimental task was performed using the participants' best-corrected vision. Participants were then familiarized with the experimental task and equipment and given practice on a similar drag-and-drop task. Finally, participants performed the series of 105 drag-and-drop trials.

3.6 Data Analysis

The multifractal characterization of participants' PRB in this study consisted of a five-step procedure summarized in Figure 3. This process begins with the cleaning, preparation and preprocessing of the data sets and ends with the estimation of geometric characteristics of the multifractal spectra generated from each data set. These six steps include: 1) Data cleaning and denoising; 2) Data segmentation; 3) Application of the Discrete Wavelet Transform (DWT); 4) Wavelet-based estimation of the multifractal spectrum; and 5) Estimation of the geometric characteristics of the multifractal spectra. The details of each step are discussed in more detail in the accompanying electronic appendix, which can be found in The ACM Digital Library (http://www.acm.org/dl).

The data analysis process consisted of first cleaning the data by applying a simple heuristic for removing the blink and equipment artifacts [Marshall 2000] (Step 1) and then segmenting the data stream for each participant into equal length pieces of 2,048 observations or 34 seconds of PRB when recorded at 60 Hz (see Table I) (Step 2). The overall average trial time (e.g., the time required to perform one drag-and-drop instance) was approximately 3.5 seconds. Thus, each data segment of 2,048 pupil data points actually represents nearly 10 experimental trials.

Following this process of data preparation, a discrete wavelet transform (DWT) was applied [Vidakovic 1999] (Step 3), which serves as the basic tool for examining multifractality [Gonçalvès et al. 1998]. Hölder regularity indices (α's) are estimated by considering the data in the wavelet domain, using wavelet coefficients (Step 4). Finally, the multifractal spectra were generated from the wavelets coefficients and Hölder regularity indices (α's), in a manner described in the scientific literature [Gonçalvès et al. 1998]. A multifractal spectrum was generated for each one of the 287 data sets. From these multifractal spectra, estimates of the three summary measures, the Spectral Mode (SM), Broadness (B), and Left Slope (LS), were determined (Step 5). Finally, a standard one-way ANOVA with appropriate post-hoc test was performed for each multifractal spectrum summary measure in order to compare the user groups.

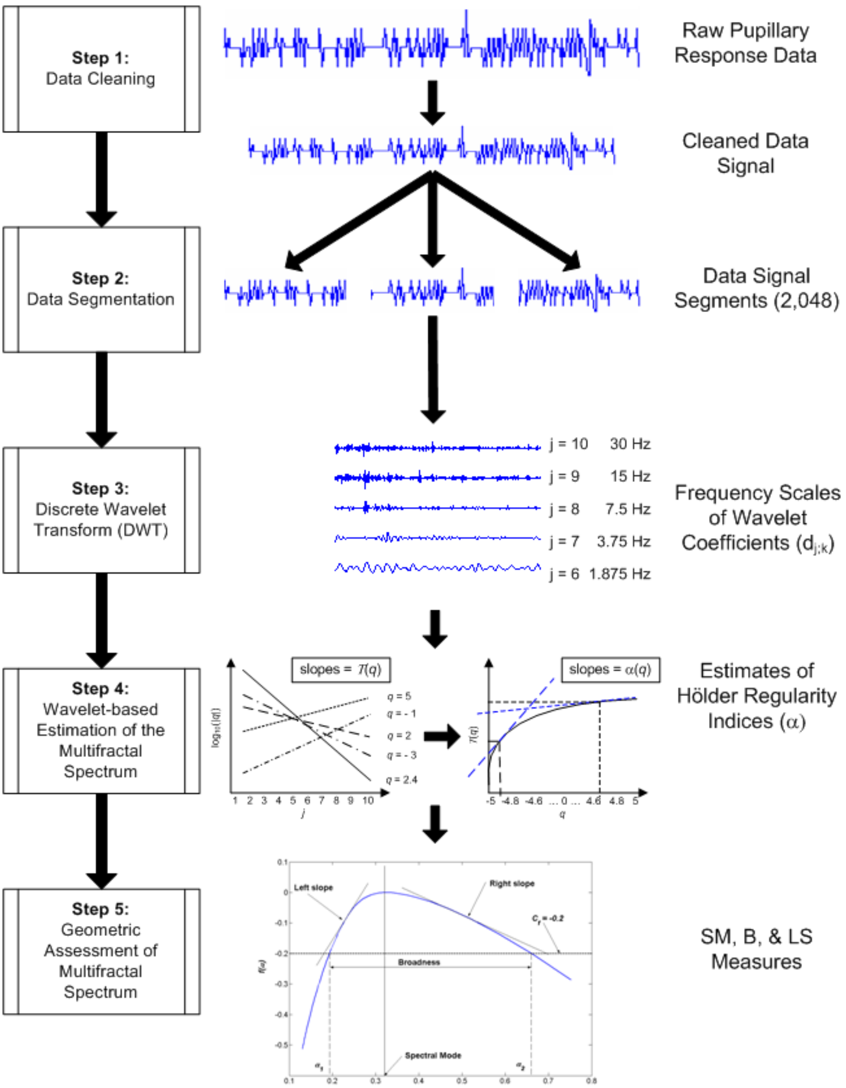

Figure 3. Diagrammatic representation of the data analysis procedure used in this study.

4. RESULTS

This study focused on three features of the multifractal spectrum: SM, B, and LS. For the purposes of illustrating the utility of the multifractal analytical technique, as well as two representative multifractal spectra generated during the data analysis, a simple comparison will be provided. Figure 4 illustrates a PRB data segment (2,048 pupil diameter readings) for a visually healthy individual (left) and an individual with AMD (right). Note that this figure is merely for illustrative purposes and is intended to demonstrate the benefits of these novel statistical techniques. It is not intended to serve as a representation of the overall trends found in the full set of data presented in this study.

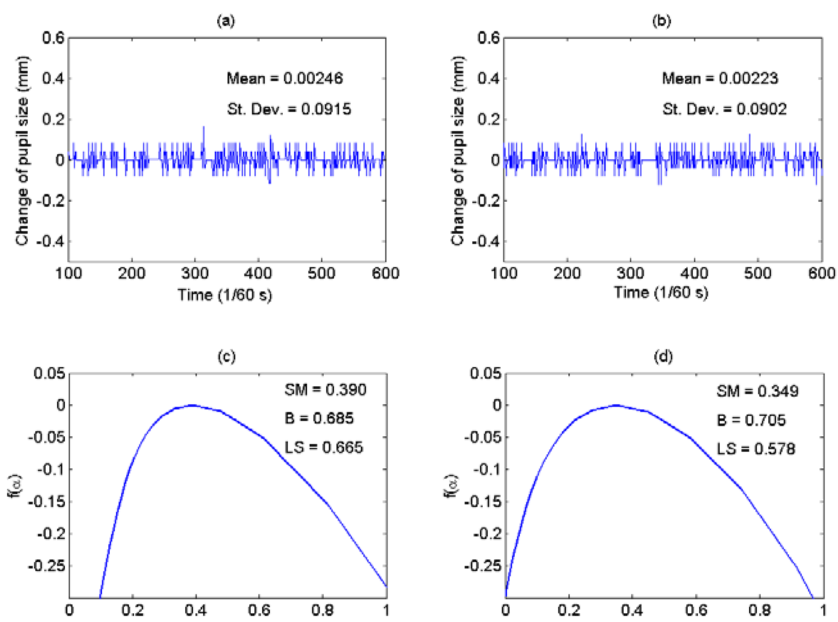

Figure 4. Illustration of the utility of multifractal analyses over traditional statistics. Figures 4a and 4b represent the time series plots of the pupil diameter deviations of an individual without and with AMD, respectively. Figures 4c and 4d represent the corresponding multifractal spectra generated from these datasets.

As can be seen in the top half of Figure 4, the pupil diameter change data of individuals without (4a) and with (4b) AMD have nearly equal mean and standard deviation. Using traditional statistical techniques, such as comparing TEPR values, these two individuals would be seen as exhibiting equivalent PRB. However, analysis of multifractality within the PRB of these individuals reveals clearer differences. The individual with AMD (4d) exhibits a PRB signal that can be characterized as more multifractal than the PRB of the individual without AMD (4c). This increased multifractality is evident in the smaller SM and LS values. In terms of the pupil signal, this indicates that the individual with AMD exhibits PRB that is relatively more multifractal, with larger and anti-persistent (i.e., irregular) changes in pupil diameter (smaller SM and LS) with richer variability in these patterns of irregularity (larger B). These distinctions could not be identified either visually or statistically from the raw pupil signal, using traditional methods of examination and analysis (see 4a and 4b). Finally, it should be noted that while the value of B slightly increases from the PRB of the individual without AMD to the individual with AMD in Figure 4, an opposite trend was found in the overall set of data as will be presented in the results.

Table II provides descriptive statistics of the three geometric features of the multifractal spectra for the user groups. As can be seen, there are clear monotonic trends for SM, B, and LS across the participant groups. The Control group exhibited the largest values for all three measures, followed by Group 1 and then Group 2. These monotonic trends are present in both the mean and median values, suggesting that these trends are not simply due to a few extreme values. Figure 5 illustrates these clear monotonic trends, indicating that the multifractal spectrum features (e.g., SM, B, and LS, Figures 5a, 5b, and 5c, respectively) decrease with increases in the severity of visual impairment (both in terms of degrading visual acuity and increasing severity of ocular disease).

Table II. Descriptive Statistics Group Summary

Group	Statistic	SM	B	LS
Control	Mean	0.4268	0.7980	0.5002
	Median	0.4201	0.7688	0.4777
	St. Dev.	0.1375	0.2227	0.1524
Group 1	Mean	0.3908	0.7429	0.4088
	Median	0.3670	0.7227	0.3869
	St. Dev.	0.1399	0.2548	0.0959
Group 2	Mean	0.3551	0.6820	0.3750
	Median	0.3579	0.6601	0.3672
	St. Dev.	0.1406	0.1839	0.0806

Note. SM = Spectral Mode. B = Broadness. LS = Left slope.

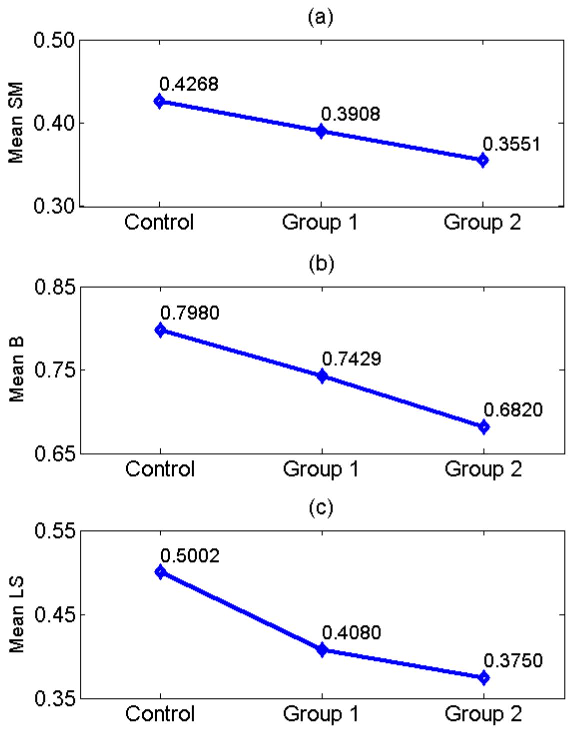

Figure 5. Monotonic relationship between (a) SM, (b) B, and (c) LS and ocular functioning. The multifractal spectrum measures decrease in value as the degree of visual impairment increases from the Control group to Group 1 to Group 2.

To provide support for significant differences between the user groups, one-way analyses of variance (ANOVA) with post hoc tests were performed using SPSS® 12.0 for Microsoft® Windows®. The ANOVA revealed that the user groups significantly differed with respect to the SM ($F = 6.849$, $p < 0.01$), B ($F = 7.281$, $p < 0.01$) and LS ($F = 32.258$, $p < 0.01$) multifractal features of their PRB. As the sample sizes were unequal (see Table I), and the test for homogeneity of variance revealed that there were significant differences amongst the group (sample) variances for SM (Levene = 0.600, $p = 0.550$), B (Levene = 2.174, $p = 0.116$) and LS (Levene = 7.828, $p = 0.01$), the Games-Howell test was used as the post-hoc comparison method. Table III provides the results of these post hoc tests, including the intergroup mean differences and their level of significance, for the three multifractal measures. The results reveal that the PRB of the three groups can all be distinguished by significant differences ($p < 0.05$) on one or more of these multifractal measures.

Table III. ANOVA Post Hoc (Games-Howell) Comparison of Group PRB on Measures of the Multifractal Spectrum.

Comparison	SM ($p = 0.001$)	B ($p = 0.001$)	LS ($p < 0.001$)
Control v Group 1	0.0361	0.0551	0.0914**
Control v Group 2	0.0717**	0.1160**	0.1252**
Group 1 v Group 2	0.0356	0.0608	0.0338*

Note. The values reflect the intergroup mean difference (e.g., Control v Group 1 = Control mean – Group 1 mean) for each paired comparison and each multifractal measure. * Difference between the groups for the given measure is $p < 0.05$. ** Difference between the groups for the given measure is $p < 0.01$.

5. DISCUSSION

The presence of significant differences between the user groups supports our objective of being able to successfully distinguish users with this analytical approach. While all three multifractal measures were able to distinguish between the Control group and Group 2, only one of the multifractal measures – LS – was able to significantly distinguish the PRB between the Control group and Group 1 and between Group 1 and Group 2.

The separation of the Control group from the AMD groups illustrates the sensitivity of these multifractal measures to differences in both clinically assessed and functionally assessed (e.g., task performance [not reported]) ocular health. The distinctions between the Control group and the two user groups with AMD (especially Group 2) is not an unexpected result, as research has found that individuals with central visual field loss (e.g., AMD), have considerably less controlled, sustained, smooth changes in pupil diameter [Bergamin and Kardon 2002]. These underlying behavioral differences in the control of the iris are likely to be revealed through changes in the complexity and irregularity of the PRB. Overall, the results suggest that the Control group's PRB contained smoother and more controlled movements. On the other hand, the AMD groups, especially Group 2, exhibited PRB with a higher degree of multifractality (i.e., with larger and more anti-persistent changes in pupil diameter).

The illustration in Figure 4 is important for two reasons: 1) it illustrates the additional diagnostic ability of multifractal analyses over traditional statistical methods; and 2) it illustrates the general trends for visually healthy (i.e., Control) users and those with AMD. It is important to note that both individuals exhibit PRB that is multifractal. However, the difference between the individuals' PRB lies in the degree to which the physiological behavior deviates from the standard monofractal. The individual with AMD (4b and 4d) exhibits PRB that can be characterized by a relatively rough, irregular signal containing larger and more anti-persistent changes in pupil diameter. It may be that, in the case of PRB, the effects of ocular disease may result in a pupillary control mechanism that has been disrupted and no longer allows for the normal, sustained control of dilation and constriction in during performance of HCI-based psychomotor tasks.

The monotonic trends illustrated in Table II and Figure 5 represent a clear relationship between ocular health and multifractality in PRB, with certain aspects of multifractality increasing with declining ocular health. It is important to note that these differences in PRB are not necessarily large in magnitude (in terms of millimeters), as one would see with normal patterns of pupil dilation and constriction in response to a stimulus. However, the magnitude of the change is not the focus of the analyses. All user groups will naturally exhibit PRB that is multifractal to some extent. Thus, the relative degree of multifractality (or irregularity), quantified through the three measures, is being used to distinguish these users, who are older and/or have ocular disease, and naturally tend to have 'muted' PRB [Beatty and Lucero-Wagoner 2000; Loewenfeld 1999].

As this is the first study of its kind, there are no established baselines for these multifractal measures. The actual numerical values of the multifractal measures have little practical meaning, as opposed to more traditional HCI measures, such as the time taken to perform a task or the number of errors a user commits. Table IV provides a more pragmatic interpretation of the numerical values revealing the meaning of the relative values in terms of the actual PRB of participants.

Table IV. Interpretative Summary of Multifractal Measures of Group PRB

Group	Meaning
Control	SM: Changes in diameter are smaller and more regular (persistent). B: Richer α variability with more "regular" indices (> SM). LS: Signal is less multifractal and smoother.
Group 1	SM: Changes in diameter are moderately sized and fairly anti-persistent. B: Moderately rich α variability with "regular" and "irregular" indices. LS: Signal is moderately multifractal and relatively rough.
Group 2	SM: Changes in diameter are larger and anti-persistent. B: Less rich α variability with more "irregular" indices. LS: Signal is more multifractal and rougher.

Note. SM = Spectral Mode. B = Broadness. LS = Left slope.

The Control group exhibited PRB that was relatively smooth and less multifractal, with smaller and less anti-persistent changes in pupil diameter, although these changes were more irregular, overall. Group 2, on the other hand, exhibited PRB that was much more multifractal in nature, with larger and more anti-persistent changes in pupil diameter resulting in a rougher data signal, although these changes were fairly regular, overall. Group 1 exhibited PRB that was in between the Control group and Group 2, with moderate multifractality and signal complexity (in terms of regularity, magnitude, and persistence of pupil diameter changes).

Overall, the LS measure was the most sensitive measure for detecting intergroup differences in multifractality within the PRB data. These results suggest that in terms of LS, which represents the degree of multifractality and signal roughness, Group 2's exhibited PRB was the most multifractal (resulting in the roughest signal), followed by Group 1 and finally the Control group. In this sense, signal "roughness" corresponds to a relative lack of smoothness, as marked by significant deviations or changes in the signal in terms of fairly large, anti-persistent, and dynamic changes in pupil diameter. Thus, it seems that both the presence of an ocular disease (AMD) and/or differences in visual acuity may cause PRB to become more multifractal in nature. This may suggest that differences in the fractality of PRB data are modulated by the presence of ocular disease, involving physiological trauma to the eye-brain interface (the retina), as well as differences in clinical visual metrics, such as visual acuity.

The SM and B measures were less sensitive, only distinguishing the Control group from Group 2 ($p < 0.01$ and $p < 0.01$, respectively). With respect to both the SM and the B measures, the Control group's PRB yielded wider multifractal spectra (B) with larger spectral maxima (SM) compared with Group 2. The inability of the SM and B measures to provide differentiation between the Control group and Group 1 or between Group 1 and Group 2 may indicate that these measures are not particularly sensitive to smaller differences in ocular health or visual function parameters. However, the lack of significant differences is not completely disheartening, as the results of Table II and Figure 5 illustrate that the groups did display clear trends in the values. It may be that more data needs to be collected to further examine these measures.

With respect to the SM, the results suggest that the Control group's PRB signal was relatively smooth (e.g., smaller and more persistent changes). The lower SM values for Group 2 suggest that these individuals exhibited PRB that could be characterized by relatively more variability in pupil diameter changes across the scales of resolution. In terms of physiological behavior, the pupils of Group 2 individuals exhibited larger and more anti-persistent changes in diameter, compared with the Control group. This may suggest that the ocular disease affecting Group 2 individuals' ocular condition may also be affecting the pupillary control mechanism, resulting in more uncontrolled, unsustained pupil movements, which is supported by the previous clinical findings that individuals with central field losses (e.g., AMD) tend to have unsustained, transient pupil movement [Barbur 2003; Bergamin and Kardon 2002; Loewenfeld 1999].

Because the other geometric features of the multifractal spectrum modulate the spectral width, the physical interpretation of B is not immediately obvious. Increasing values of B correspond to increasing richness in the variability of the Hölder regularity indices (α) (e.g., the irregularity). That is, the data signal contains a wider variety of α's. The larger B values of the Control group are an indication that their PRB exhibited a larger variety of changing irregularities, while the PRB of Group 2 contained significantly less irregularity. This may be a result of the normal, unaffected movement of the pupil of those individuals in the Control group, indicative of the complex pupil control mechanisms.

However, in light of the trends with the LS results, an interesting interpretation of B arises. SM serves as the threshold between "regular" α's (to the right) and "irregular" α's (to the left). As both LS and B are decreasing moving from the Control group to Group 1 to Group 2, this may mean that Group 2's PRB is characterized by more "irregular" α's (e.g., smaller in value than SM) relative to the Control group. Geometrically, since the distance between SM and the cutoff for B is fixed (at C_f = -0.2), if LS and B are decreasing concurrently, then it is likely that the RS is actually increasing, which makes the majority of α's found in Group 2's PRB "irregular". In this sense, the "irregular" α's are those that correspond to larger or more anti-persistent changes in pupil diameter. Thus, Group 2's PRB signals may contain more irregularity, in terms of large and anti-persistent changes in pupil diameter (e.g., a rougher signal), while also containing (overall) less variability amongst the α's (e.g., less signal richness). This may be an effect of ocular disease on the internal neural mechanisms that regulate the pupil's movement in response to external stimuli and cognitive processing.

This ability to differentiate individuals, known or likely to demonstrate differences in functional abilities (e.g., the ability to use a computer), on the basis of covert physiological processes is important to HCI researchers as they try to more fully understand the underlying individual differences that lead to differences in functional abilities. Future controlled studies will be needed to further extract the various relative effects of age and age-related declines in abilities that may influence PRB during visio-motor tasks. In this study, given the emphasis on older adults with AMD, it is recognized that users with more severe visual impairment are likely to be older and, by extension, possess related declines in other abilities as well. Thus, the differences in the multifractality of the PRB of the user groups may also account for some effects of both age and manual dexterity (i.e., motor coordination), which are inseparably linked to the ocular disease, AMD. Nonetheless, this study presents an initial step towards utilizing these measures of physiological response behavior to understand the underlying differences between users of varying abilities.

6. CONTRIBUTIONS & IMPLICATIONS

The overarching goal of this study was to explore the potential utility of multifractality as a novel statistical method for differentiating users by means of the unique signatures within their high-frequency PRB signals. A specific aim of this study was to use measures of multifractality in PRB to better understand the underlying functional differences between users with varying visual capabilities. These findings have several implications in the future development and refinement of new analytical techniques to improve the ability of researchers to make use of the rich, yet noisy, eyetracking data in HCI research. These methods can be applied to all contexts of interest, including other physiological measures, user groups, or interactive HCI tasks.

One meaningful implication of this research applies specifically to HCI researchers examining users with sensory, cognitive, or motor impairments. While there are certainly financial costs associated with the purchase of eyetracking equipment, as well as computational costs associated with the analytical procedure, these costs are much less than continued clinical testing in the long term. The costs of clinical exams, medical record review, and medical staff time and resources can be tremendous for empirical studies. The ability to leverage eyetracking equipment (or other physiological monitors), likely already being used by many HCI and Human Factors research, through the application of new analytical techniques is an added plus. Additionally, these techniques also help to leverage the richness of physiological response data, potentially reducing the need for additional data collection and subject recruitment, which are commonly limitations when working with specific user groups, such as individuals with particular sensory, cognitive, or motor impairments. While we are not suggesting that these techniques completely supplant clinical testing, multifractal analyses may prove useful when clinical resources are unavailable or unattainable.

While this paper demonstrates an innovative approach to the characterization of visual impairment based on PRB data, the underlying methodological contribution should also be considered. As physiological data becomes more relevant and important for work in HCI, and researchers continue to look for objective measures of internal user states, these types of novel analytical methods will become more important as well. Wavelet, multiscale and multifractal analytical techniques better exploit the natural complexity and richness of high-frequency physiological response data. In the case of this study, multifractal analysis leveraged the inherent variability of PRB from individuals who are aging and/or have visual impairments.

This research has implications for the measurement and examination of cognitive workload via PRB data as well as furthering the understanding of the unique needs and behaviors of aging users when interacting with information technologies. Other potential applications for this research include improved diagnosticity of underlying conditions that arise in irregular or erratic PRB, such as ocular disease, drug use, neurological or psychological disorders and fatigue [Beatty and Lucero-Wagoner 2000; Berezovsky et al. 2001; Bergamin and Kardon 2002; Loewenfeld 1999; Wilhelm et al. 1998], as well as instances in which the design of a system, interface, or workflow is unduly increasing cognitive workload to inappropriate or undesired levels.

7. CONCLUSIONS & FUTURE WORK

We are optimistic that with additional exploration of the underlying construct of the measures, the usefulness of PRB data in the field of HCI and elsewhere can be realized. Furthermore, we suggest future studies be conducted that examine other types of dynamic data (e.g., eye movements, neural signals, interaction behaviors), other types of users (e.g., other ocular diseases) and other types of tasks (e.g., text editing, navigation, object discrimination). Despite the computational complexity for large datasets [Turiel and Perez-Vicente 2003], wavelet and multifractal analyses should be further explored as tools for handling the complex data that arise from the physiological, cognitive, and behavioral phenomena of human users.

Recent work by Iqbal and colleagues [2005; 2005; 2004] can serve as an excellent starting point for designing and selecting interactive tasks for further data collection. Additionally, recent equipment acquisitions will aid in the synchronization of the eyetracking data with the task performance data, which will link the interpretation of increased instances of variability amongst the regularity indices (α's) in PRB data with actual HCI events that occur during task completion. Both of these advances will allow for a more systematic examination of how these measures of multifractality in PRB can be used as indications of changes in mental workload.

It may also be of interest to begin building a collection of baseline measures and representative multifractal spectra for various user profiles, such as different ocular pathologies or age ranges, and for various types of HCI tasks, in terms of cognitive workload or information processing requirements. A database of "standard" multifractal summary measures, based on user or task characteristics, can help to direct researchers and interface or system designers to instances in which users are having trouble or are experiencing unacceptably high levels of cognitive workload. Having established baselines would go a long way to help diagnose instances in which task performance or user satisfaction measures are clearly suffering, although evidence of a cause via subjective workload questionnaires and demographic user profiles is lacking.

It may also be useful to apply these multifractality measures as predictive classification metrics. Objectively and reliably classifying individuals based on underlying nuances of their covert psycho-physiological behavior has several prospective applications in the field of HCI beyond the domain discussed in this paper. A system that could apply these analysis techniques real-time could inform adaptive systems for not only individuals with visual impairment, but also for individuals with temporary, or situationally-induced impairments (SII) [Sears et al. 2003] in contexts not traditionally optimal for the collection of PRB data. In this way, an adaptive system could take more or less responsibility dependent on cognitive workload levels gleaned from a user's PRB. While automated or predictive classification was not the particular focus of this study, we are currently working to build predictive models of user classification, based on these multifractal spectrum summary measures, as well as other multiscale measures [Shi et al. 2005a; Shi et al. 2005b].

Finally, we suggest that Human Factors, HCI, psychology and other researchers, who examine complex and/or high-frequency physiological and behavioral data from human subjects, collaborate more with mathematicians and statisticians, as their largely theoretical work can have very meaningful applications in our fields of research. As in the case of this study, the novel analytical methods proved useful in beginning to solve the issues of dealing with the problematic PRB of older adults, including those with visual impairments. A tighter coupling between researchers in HCI and their colleagues in statistics and mathematics is needed to help advance the analytical techniques used to examine complex human behavior during HCI tasks.

ELECTRONIC APPENDIX

Additional details on the theoretical background and a primer on the mathematics underlying the wavelet-based analysis of multifractality used in this study can be found in the electronic appendix to this article, which can be found at The ACM Digital Library (http://www.acm.org/dl).

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REFERENCES

AMERICAN FOUNDATION FOR THE BLIND. 2005. *Statistics and Sources for Professionals: Prevalence*. Retrieved May 16, 2005, from http://www.afb.org/section.asp?SectionID=15&DocumentID=1367

AMERICAN MACULAR DEGENERATION FOUNDATION. 2002. *What is macular degeneration?* Retrieved November 2, 2003, from http://www.macular.org/disease.html

BACKS, R. W. and WALRATH, L. C. 1992. Eye movement and pupillary response indices of mental workload during visual search of symbolic displays. *Applied Ergonomics, 23*, 243-254.

BAILEY, I. L. and LOVIE, J. E. 1976. New design principles for visual acuity letter charts. *American Journal of Optometry & Physiological Optics, 53*, 11, 740-745.

BARBUR, J. L. 2003. Learning from the pupil: Studies of the basic mechanisms and clinical applications. In *The Visual Neurosciences*, L. M. CHALUPA and J. S. WERNER (Eds.). MIT Press, Cambridge, MA, 641-656.

BEATTY, J. 1982. Task-evoked pupillary responses, processing load, and the structure of processing resources. *Psychological Bulletin, 91*, 377-381.

BEATTY, J. and LUCERO-WAGONER, B. 1978. Pupillometric signs of brain activation vary with level of cognitive processing. *Science, 199*, 1216-1218.

BEATTY, J. and LUCERO-WAGONER, B. 2000. The pupillary system. In *Handbook of Psychophysiology* (2nd ed.), J. T. CACIOPPO, L. G. TASSINARY and G. G. BERNSTON (Eds.). Cambridge University Press, Cambridge, UK, 142-162.

BEREZOVSKY, A., SALOMAO, S. R., and BIRCH, D. G. 2001. Pupil size following dark adaptation in patients with retinitis pigmentosa. *Brazilian Journal of Medicine & Biological Research, 34*, 8, 1037-1040.

BERGAMIN, O. and KARDON, R. H. 2002. Greater pupillary escape differentiates central from peripheral visual field loss. *Ophthalmology, 109*, 4, 771-780.

BIGLAN, A. W., VAN HASSELT, V. B., and SIMON, J. 1988. Visual impairment. In *Handbook of Developmental and Physical Disabilities*, V. B. VAN HASSELT (Ed.). Pergamon Press, New York, NY, 471-502.

BIRREN, J. E. and FISHER, L. M. 1995. Aging and speed of behavior: Possible consequences for psychological functioning. *Annual Review of Psychology, 46*, 329-353.

BREMNER, F. D., SHALLO-HOFFMAN, J., RIORDAN-EVA, P., and SMITH, S. 1999. Comparing pupil function with visual function in patients with Leber's Hereditary Optic Neuropathy. *Investigative Ophthalmology & Visual Science, 40*, 2528-2534.

BREWSTER, S. A. 1998. Sonically-enhanced drag and drop. In *Proceedings of the International Conference on Auditory Display*, Glasgow, UK, 1-7.

CLEMONS, T. E., CHEW, E. Y., BRESSLER, S. B., and MCBEE, W. 2003. National Eye Institute Visual Function Questionnaire in the Age-Related Eye Disease Study (AREDS): AREDS Report. *Archives of Ophthalmology, 121*, 2, 211-217.

CRAIK, F. I. M. and SALTHOUSE, T. A. 2000. *The handbook of aging and cognition* (2nd ed.). Lawrence Erlbaum Associates, Inc., Mahwah, NJ.

DAIN, S. J. 2004. Clinical colour vision tests. *Clinical and Experimental Optometry, 87*, 4-5, 276-293.

DILLON, A. and WATSON, C. 1996. User analysis in HCI: The historical lesson from individual differences research. *International Journal of Human-Computer Studies, 45*, 6, 619-637.

EMERY, V. K., EDWARDS, P. J., JACKO, J. A., MOLONEY, K. P., BARNARD, L., KONGNAKORN, T., et al. 2003. Toward achieving Universal Usability for older adults through multimodal feedback. In *Proceedings of the Accepted for publication in the Proceedings of the 2003 ACM Conference on Universal Usability (CUU 03),*, Vancouver, BC, Canada., November 10-11, 2003, 46-53.

FARNSWORTH, D. 1947. *The Farnsworth Dichotomous Test for Color Blindness: Manual*. The Psychological Corporation, New York, NY.

FERRIS, F. L., III, KASSOFF, A., and BRESNICK, G. H. 1982. New visual acuity charts for clinical research. *American Journal of Ophthalmology, 94*, 91-96.

GASS, J. D. 1996. *Atlas of Macular Diseases* (4th ed.). Elsevier Science, Amsterdam, NL.

GONÇALVÈS, P., RIEDI, R., and BARANIUK, R. 1998. A simple statistical analysis of wavelet-based multifractal spectrum estimation. In *Proceedings of the 32nd Asilomar Conference on Signals, Systems and Computers*.

GRAPS, A. 1995. An Introduction to Wavelets. *IEEE Computational Science and Engineering, 2*, 2, 50-61.

HAVLIN, S., AMARAL, L. A. N., ASHKENAZY, Y., GOLDBERGER, A. L., IVANOV, P. C., PENG, C.-K., et al. 1999. Application of statistical physics to heartbeat diagnosis. *Physica A: Statistical Mechanics and its Applications, 274*, 1-2, 99-110.

HUTCHISON, D., EASTMAN, C., and TIRRITO, T. 1997. Designing user interfaces for older adults. *Educational Gerontology, 23*, 497-513.

INKPEN, K. M. 2001. Drag-and-drop versus point-and-click mouse interaction styles for children. *ACM Transactions on Computer-Human Interactions, 8*, 1, 1-33.

IQBAL, S. T., ADAMCZYK, P. D., ZHENG, X. S., and BAILEY, B. P. 2005. Towards an Index of Opportunity: Understanding Changes in Mental Workload during Task Execution. In *Proceedings of the ACM/SIGCHI Conference on Human Factors in Computing Systems (CHI'05)*, Portland, Oregon, April 2-7, ACM Press, 311-320.

IQBAL, S. T. and BAILEY, B. P. 2005. Investigating the effectiveness of mental workload as a predictor of opportune moments for interruption. In *Proceedings of the ACM/SIGCHI Conference on Human Factors in Computing Systems (CHI'05)*, Portland, Oregon, ACM Press, 1489-1492.

IQBAL, S. T., ZHENG, X. S., and BAILEY, B. P. 2004. Task-evoked pupillary response to mental workload in Human-Computer Interaction. In *Proceedings of the ACM/SIGCHI Conference on Human Factors in Computing Systems (CHI'04)*, Vienna, Austria, ACM Press, 1477-1480.

IVANOV, P. C., AMARAL, L. A. N., GOLDBERGER, A. L., HAVLIN, S., ROSENBLUM, M. G., STRUZIK, Z. R., et al. 1999. Multifractality in human heartbeat dynamics. *Nature, 399*, 461-465.

JACKO, J. A., BARRETO, A. B., SCOTT, I. U., CHU, J. Y. M., VITENSE, H. S., CONWAY, F. T., et al. 2002. Macular Degeneration and visual icon use: Deriving guidelines for improved access. *Universal Access in the Information Society (UAIS), 1*, 2, 197-206.

JACKO, J. A., MOLONEY, K. P., KONGNAKORN, T., BARNARD, L., EDWARDS, P. J., LEONARD, V. K., et al. 2005. Multimodal feedback as a solution to ocular disease-based user performance decrements in the absence of functional visual loss. *International Journal of Human-Computer Interaction, 18*, 2, 183-218.

JACKO, J. A., ROSA, R. H., JR., SCOTT, I. U., PAPPAS, C. J., and DIXON, M. A. 2000. Visual impairment: The use of visual profiles in evaluations of icon use in computer-based tasks. *International Journal of Human-Computer Interaction, 12*, 1, 151-164.

JACKO, J. A., SCOTT, I. U., BARRETO, A. B., BAUTSCH, H. S., CHU, J. Y. M., and FAIN, W. B. 2001. Iconic visual search strategies: A comparison of computer users with AMD versus computer users with normal vision. In *Proceedings of the 9th International Conference on Human-Computer Interaction (HCII '01)*, New Orleans, LA, August 5-10, 2001, Lawrence Erlbaum Associates, Inc., 423-427.

JACKO, J. A., SCOTT, I. U., SAINFORT, F., BARNARD, L., EDWARDS, P. J., EMERY, V. K., et al. 2003a. Older adults and visual impairment: What do exposure times and accuracy tell us about performance gains associated with multimodal feedback? *CHI Letters, 5*, 1, 33-40.

JACKO, J. A., SCOTT, I. U., SAINFORT, F., MOLONEY, K. P., KONGNAKORN, T., ZORICH, B. S., et al. 2003b. Effects of multimodal feedback on the performance of older adults with normal and impaired vision. *Lecture Notes in Computer Science (LNCS), 2615*, 3-22.

JACKO, J. A. and SEARS, A. 1998. Designing interfaces for an overlooked user group: Considering the visual profiles of partially sighted users. In *Proceedings of the ASSETS '98: The Third International ACM Conference on Assistive Technologies*, ACM.

JACKO, J. A. and VITENSE, H. S. 2001. A review and reappraisal of information technologies within a conceptual framework for individuals with disabilities. *Universal Access in the Information Society (UAIS), 1*, 1, 56-76.

KAHNEMAN, D. and BEATTY, J. 1966. Pupil diameter and load on memory. *Science, 154*, 1583-1585.

KESTENER, P., LINA, J. M., SAINT-JEAN, P., and ARNEODO, A. 2001. Wavelet-based multifractal formalism to assist in diagnosis in digitized mammograms. *Image Analysis & Stereology, 20*, 169-174.

LOEWENFELD, I. E. 1999. *The Pupil: Anatomy, Physiology, and Clinical Applications* (2nd ed. Vol. 1). Butterworth-Heinemann, Oxford, UK.

LUDTKE, H., WILHELM, B., ADLER, M., SCHAEFFEL, F., and WILHELM, H. 1998. Mathematical procedures in data recording and processing of pupillary fatigue waves. *Vision Research, 38*, 19, 2889-2896.

LUXIMON, A. and GOONETILLEKE, R. S. 2001. Simplified subjective workload assessment technique. *Ergonomics, 44*, 3, 229-243.

MACKENZIE, I. S., SELLEN, A., and BUXTON, W. A. S. 1991. A comparison of input devices in elemental pointing and dragging tasks. In *Proceedings of the ACM Conference on Human Factors in Computing Systems: Reaching through Technology (CHI '91)*, New Orleans, LA, 161-166.

MANGIONE, C. M., LEE, P. P., GUTIERREZ, P. R., SPRITZER, K., BERRY, S., and HAYS, R. D. 2001. Development of the 25-Item National Eye Institute Visual Function Questionnaire. *Archives of Ophthalmology, 119*, 7, 1050-1058.

MANGIONE, C. M., LEE, P. P., PITTS, J., GUTIERREZ, P. R., BERRY, S., and HAYS, R. D. 1998. Psychometric properties of the National Eye Institute Visual Function Questionnaire (NEI-VFQ). NEI-VFQ Field Test Investigators. *Archives of Ophthalmology, 116*, 11, 1496-1504.

MARSHALL, S. P. 2000. Method and apparatus for eye tracking and monitoring pupil dilation to evaluate cognitive activity. US Patent No. 6,090,051, *U. S. Patent and Trademark Office*. Washington, DC: USA.

MARSHALL, S. P., PLEYDELL-PEARCE, C. W., and DICKSON, B. T. 2002. Integrating psychophysiological measures of cognitive workload and eye movements to detect strategy shifts. In *Proceedings of the 36th Hawaii International Conference on System Sciences (HICSS '03).*

MCLAREN, J. W., ERIE, J. C., and BRUBAKER, R. F. 1992. Computerized analysis of pupillograms in studies of alertness. *Investigative Ophthalmology & Visual Science, 33*, 3, 671-676.

MEAD, S. E., SIT, R. A., ROGERS, W. A., JAMIESON, B. A., and ROUSSEAU, G. K. 2000. Influences of general computer experience and age on library database search performance. *Behaviour & Information Technology, 19*, 2, 107-123.

MORAY, N. 1988. Mental workload since 1979. *International Reviews of Ergonomics, 2*, 123-150.

MORRELL, R. W. and ECHT, K. V. 1997. Designing written instructions for older adults: Learning to use computers. In *Handbook of Human Factors and the Older Adult*, A. D. FISK and W. A. ROGERS (Eds.). Academic Press, San Diego, CA, 335-362.

NEUMANN, D. L. 2002. Effect of varying levels of mental workload on startle eyeblink modulation. *Ergonomics, 45*, 8, 583-602.

PELLI, D. G., ROBSON, J. G., and WILKINS, A. J. 1988. The design of a new letter chart for measuring contrast sensitivity. *Clinical Visual Science, 2*, 187-199.

RIEDI, R. H. 1999. Multifractal processes. In *Theory and Applications of Long Range Dependence*, P. DOUKHAN, G. OPPENHEIM and M. S. TAQQU (Eds.). Birkhäuser, Boston, MA, 625-715.

SCHEPENS EYE RESEARCH INSTITUTE. 2003. *Eye disease information and resources: AMD fact sheet*. Retrieved January 27, 2004, from http://www.theschepens.org/amd_fact_sheet.htm

SCOTT, I. U., FEUER, W. J., and JACKO, J. A. 2002. Impact of visual function on computer task accuracy and reaction time in a cohort of patients with age-related macular degeneration. *American Journal of Ophthalmology, 133*, 3, 350-357.

SEARS, A., LIN, M., JACKO, J. A., and XIAO, Y. 2003. When Computers Fade...Pervasive Computing and Situationally-Induced Impairments and Disabilities. In *Human-Computer Interaction: Theory and Practice* (Vol. II), C. STEPHANIDIS and J. A. JACKO (Eds.). Lawrence Erlbaum Associates, Inc., Mahwah, NJ, 1298-1302.

SELLEN, A. J., KURTENBACH, G. P., and BUXTON, W. A. S. 1990. The role of visual and kinesthetic feedback in the perception of mode errors. In *Proceedings of the International Conference on Human-Computer Interaction*, 667-673.

SELLEN, A. J., KURTENBACH, G. P., and BUXTON, W. A. S. 1992. The prevention of mode errors through sensory feedback. *Human Computer Interaction, 7*, 141-164.

SHI, B., MOLONEY, K. P., LEONARD, V. K., JACKO, J. A., SAINFORT, F., and VIDAKOVIC, B. (2005a). *Multifractal discrimination model of high-frequency pupil-diameter measurements*. Atlanta, GA: Department of Industrial & Systems Engineering, Georgia Institute of Technology.

SHI, B., MOLONEY, K. P., PAN, Y., LEONARD, V. K., VIDAKOVIC, B., JACKO, J. A., et al. 2005b. Wavelet Classification of High Frequency Pupillary Responses. *Journal of Statistical Computation and Simulation*, in press.

TIFFIN, J. and ASHER, E. J. 1948. The Purdue Pegboard: Norms and studies of reliability and validity. *Journal of Applied Psychology, 32*, 234-247.

TURIEL, A. and PEREZ-VICENTE, C. J. 2003. Universality classes of multifractal systems: Manuscript submitted to *Europhysics Letters*.
UNIVERSITY OF MARYLAND, S. O. M., DEPARTMENT OF EPIDEMIOLOGY AND PREVENTATIVE MEDICINE. 1980. *Early treatment diabetic retinopathy study, Manual of Operations* (Vol. 12). ETDRS Coordinating Center, Baltimore, MD.
VAN GERVEN, P. W. M., PAAS, F., VAN MERRIËNBOER, J. J. G., and SCHMIDT, H. G. 2004. Memory load and the cognitive pupillary response in aging. *Psychophysiology, 41*, 167-174.
VIDAKOVIC, B. 1999. *Statistical Modeling by Wavelets*. John Wiley & Sons, New York, NY.
VITENSE, H. S., JACKO, J. A., and EMERY, V. K. 2003. Multimodal feedback: An assessment of performance and mental workload. *Ergonomics, 46*, 1-3, 58-87.
WARE, J. E., KOSINSKI, M., and KELLER, S. D. 1995. *How to Score the SF-12 Physical and Mental Health Summary Scales* (2 ed.). The Health Institute, New England Medical Center, Boston, MA.
WILHELM, B., WILHELM, H., LUDTKE, H., STREICHER, P., and ADLER, M. 1998. Pupillographic assessment of sleepiness in sleep-deprived healthy subjects. *Sleep, 21*, 3, 258-265.