

The Amorphous Fixation Measure Revisited: with Applications to Autism

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Abstract

The analysis of eye-tracking data hinges on the ability of automated algorithms to separate rapid saccadic eye movements from stable eye fixations. However, though it has long been known that changing the parameters of fixation-identification algorithms can lead to very different qualitative impressions, less is known about how algorithmic parameters interact with quantitative eye-tracking measures. In this study we show that by manipulating aspects of fixation identification, we can completely reverse the patterns of observed results for mean fixation duration, a measure traditionally associated with cognitive load. However, by linearly mapping mean fixation duration over its parameter space, we obtain a new formulation which addresses many of the deficits of the standard analysis. We use our methods to analyze the gaze patterns of toddlers with autism spectrum disorder and control populations and discuss the observed differences in terms of the physical and cognitive ramifications of our methodology.

Keywords: eye-tracking; cognitive load; fixation; saccades; autism.

Introduction

Knowing where a subject is looking provides a wealth of information regarding his motivations, expectations, and innate preferences. For this reason, eye-tracking has become a standard tool for cognitive and psychological investigation. However, though the direct examination of the scanpath obtained by eye-tracking systems tells us where individuals are looking, it does not tell us why they choose to look at different locations, and, of course, it does not tell us what these differences mean. In order to answer the more difficult question, that of how scan patterns should be interpreted, more sophisticated methods for distilling information from raw visual trajectories are required.

The core method by which gaze trajectories are first dissected is through fixation identification algorithms (Duchowski, 2003; Salvucci and Goldberg, 2000). These algorithms take as an input the raw stream of visual positions provided by an eye-tracker and group the data points of that stream into a series of saccades (rapid, ballistic movements of the eye) and fixations (periods where the point of regard by the eye is spatially relatively stable). This dichotomous parsing is employed for two reasons. First, there is psychological and neurophysiological evidence that visual field processing is suppressed via saccadic masking during rapid movements of the eye (Burr,

Morrone, and Ross, 1994; Erdmann and Dodge, 1898) and so it makes sense to discard saccades from experiments that focus on conscious perception. Second, the ability to deal in quanta of fixations simplifies analysis and interpretation, as each fixation can be seen as being associated uniquely with a particular spatiotemporal location which in turn can be associated with particular perceptual qualities of the visual scene. Fixations can then be aggregated at many different levels, resulting in a wealth of psychophysical measures such as the total amount of time spent in fixations, the average duration of fixations, the number of fixations, latency of the first fixation after stimulus presentation, etc. (Inhoff and Radach, 1998; Jacob and Karn, 2003).

However, though the concept of a fixation is crucial for standard scan pattern analysis, the actual identification of these fixations can be quite challenging. Karsh and Breitenbach in “Looking at Looking: The Amorphous Fixation Measure” (1983) showed that, by varying the parameters of a fixation identification algorithm, different qualitative patterns of scanning emerged. This was a point also confirmed by Widdel (1984), for a different fixation identification algorithm, while examining the expected number of fixations over a grid of points. From these studies it was generally concluded that the interpretation of scan patterns could be quite ambiguous if the exact algorithm and parameters of analysis were left unreported.

Unfortunately, though many of the most popular fixation identification algorithms were developed more than thirty years ago (e.g. see Anliker, 1971), and despite the caveats of many eye-tracking researchers, the difficulties in eye-tracking analysis resulting from fixation identification instabilities have persisted. Not only is there still no consensus as to which fixation identification algorithm should be used, there is no agreement even within a particular algorithm as to what choice of parameters should be employed. Part of the difficulty, of course, stems from the multifaceted and diverse applications in which eye-tracking now finds a role. A study of reading, for instance, does not have the same spatial and temporal constraints as a study investigating face processing. Similarly, the demands of a visual search task are quite different from those in the free-viewing of artwork. However, many problems arise simply due to an indifference towards consistency in eye-tracking. There has been, for example, no great push for different manufacturers of commercial eye-tracking systems to use the same exact algorithms for fixation identification

or to allow for the ability to cut scanpaths with an assortment of different algorithms. The lack of motivation for finding agreement is possibly attributable to the fact that the use of different parameters or algorithms can quite often generate qualitatively similar results (Figure 1). This leads to the assumption that different algorithms for fixation identification are interchangeable and that their raw parameters are somewhat comparable. This assumption is false (Shic, Chawarska, and Scassellati, 2008). As we will later discuss, though the basic behavior of different algorithms may be similar, the specific correspondence of the parameters upon results, especially when considering quantitative measures, can be very different.

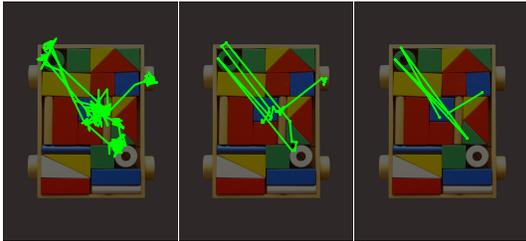


Figure 1: Effects of fixation identification algorithm parameter changes on processed gaze trajectories. The raw scanpath (left) is converted by a distance-dispersion algorithm with a low (mid) and high (right) spatial constraint parameters.

This paper examines the instabilities that arise from using different algorithms and different parameters in drawing conclusions from eye-tracking data. Whereas it has been known that variations in parameters lead to variations in qualitative impressions and quantitative measures, we demonstrate that the extent of these variations is even greater than what has been previously established, going so far as to completely reverse observed trends. We examine parameter effects on stimulus comparisons (faces versus blocks), diagnostic categories (children with autism spectrum disorder (ASD), children with developmental delay without autism symptoms (DD), and typically developing children (TD)), and for several different algorithms, extending our previous work along similar lines.

For all of our analyses, we focus on the quantitative measure of mean fixation duration. The mean fixation duration has been taken as a measure of cognitive load (Crosby, Iding, and Chin, 2001; Jacob and Karn, 2003; but also see Irwin, 2004), with fixation duration positively correlated with increasing task demands. We show that the structure of this measure, despite its variation, is remarkably simple. This simplicity allows us to build a correspondingly parsimonious model of the effect of parameter changes on mean fixation durations, giving us a formulation which may allow us to discuss fixation duration behavior differences between groups, conditions, and algorithms in a language free from the traditional biases. We illustrate how the facets of this model may be interpreted by examining differences between children with ASD and control groups as these children view static images of faces and blocks.

Fixation Identification Algorithms

There are several different categories of fixation identification algorithms, and here we consider two of the most common: velocity-threshold algorithms and dispersion (dwell-time) based algorithms (Duchowski, 2003; Salvucci and Goldberg, 2000). Velocity-based algorithms target saccades by finding points in the stream of gaze behavior with velocity v exceeding some threshold velocity v_t . The contiguous regions that do not correspond to saccades are marked as potential fixations. By contrast, dispersion-based algorithms mark a group of contiguous points $\{p_i..p_j\}$ as being part of some fixation F if those points satisfy a spatial constraint $S(F) \leq s$, where s is some spatial threshold. Regions not marked as fixations are considered saccades.

In addition to spatial constraints for both classes of algorithms, there are temporal constraints which affect velocity and dispersion algorithms differently. The temporal constraint is a minimum duration requirement for fixations, t_{min} . Every candidate fixation with a duration t is admissible as a true fixation only if $t \geq t_{min}$. For velocity algorithms this is a pure rejection criterion for the entirety of a fixation. For dispersion algorithms, this leads to a sliding window effect: if a group consisting of points $\{p_i..p_j\}$ are part of a candidate fixation F' but the duration of time covered by F' does not exceed t_{min} , the next set of candidate points becomes $\{p_{i+1}..p_{j+n}\}$ where n is increased until the spatial constraint over the candidate points fails.

In this study, we consider one velocity algorithm and two dispersion algorithms: 1) a velocity-threshold algorithm (Anliker, 1976); 2) a distance-dispersion algorithm where $S(F)$ is the maximal distance between any pair of points in F ; and 3) the I-DT algorithm by Salvucci and Goldberg (2000), where $S(F)$ is the maximal horizontal distance between any pair of points in F plus the maximal vertical distance between any pair of points (the pairs need not be the same for horizontal and vertical calculations).

Subjects and Methods

Participants in this study were 16 typically developing children (TD) (age 25.9 ± 4.7 months), 12 children diagnosed with autism spectrum disorder (ASD) (age 23.9 ± 4.6 months), and 5 children diagnosed with developmental disabilities but without autistic syndrome (DD) (age 25.4 ± 5.8 months). Children were presented with 6 color images of faces (Lundqvist, Flykt, and Öhman, 1998) and 6 color images of blocks (Figure 2) on a 20" (51cm) widescreen (16:9 aspect ratio) LCD monitor centered at a distance 75cm from the centerline of the children's eyes. Each image was 12.8° wide and 17.6° tall. Gaze patterns were recorded using a SensoMotoric Instruments IView X RED table-mounted dark-pupil 60Hz eye-tracker.

Stimulus images were preceded by a central fixation to refocus the child's attention and were then displayed as long as was required for the child to attend to the image for a total of 10 full seconds. Actual trials could last longer than

10 seconds; however, to maintain comparability, only the first 10 seconds of each trial were used in our analysis, and trials which did not contain at least 5 seconds of valid eye-tracking data, or which did not meet other automated quality criteria, were discarded. Furthermore, only data falling within the stimulus image area were considered in analysis. This task was embedded within a visual paired comparisons recognition task (Fantz, 1964), i.e. was followed by exposure to both the same face and a novel face on either side of the screen. We do not consider the recognition phase in this study. In total, TD children contributed 26 trials on faces and 44 trials on blocks; ASD children 34 faces and 40 blocks; DD children 13 faces and 15 blocks. Loss of data was typically caused by poor affect (e.g. crying) or poor attention and was within the range expected for this subject population.

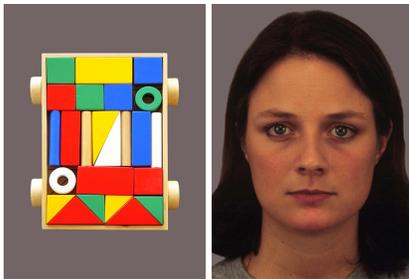


Figure 2: Experimental stimuli – Blocks and Faces

In order to characterize the behavior of mean fixation duration over the various algorithms, diagnostic groups, and stimulus classes, custom code was developed in MATLAB for handling the eye-tracking data processing pipeline from raw input stream to final outcome measure. Mean fixation duration was calculated for each algorithm and trial over a uniform grid of temporal ($N=16$) and spatial ($N=21$) parameter selections.

The Amorphous Measure

We first examine the effect of changing spatial and temporal constraints on mean fixation duration behavior for TD children as they view faces for each of the three algorithms in this investigation (Figure 3). Note that the dispersion algorithms share a somewhat similar scale as they are both in units of spatial degrees, whereas the velocity algorithm has units of degrees per second. For display purposes only, velocity was scaled down by a factor of 10 spatially. Results for ASD and DD populations were similar.

If the two dispersion algorithms were comparable in terms of parameters, they would directly overlap one another. However, the two surfaces are offset and have different slopes, implying that they are not comparable. In other words, a spatial constraint of 1° for the distance algorithm is not equivalent to a spatial constraint of 1° for the I-DT algorithm. Likewise, the velocity algorithm has no natural basis for comparison with other algorithms. We also note that the mean fixation duration behavior of the algorithms, within the chosen range, appears linear, with mean fixation

duration increasing as the spatial and temporal thresholds increase. The spatial and temporal ranges are quite large, implying that the observed trend is stable even to the limits of foveal vision, though we should note that, as observed in previous work (Shic et al., 2008), if we keep extending the range (e.g. for $s > 7^\circ$ in the distance algorithm) a saturation effect appears as the fixation algorithms begin to pull all points in the scanpath into a small number of fixations.

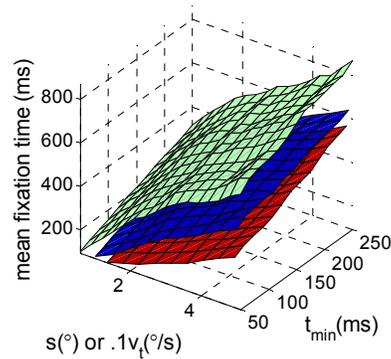


Figure 3: Mean fixation duration of TD children viewing faces for different algorithms as a function of spatial and temporal parameters. The velocity algorithm has been scaled down spatially by a factor of 10 for comparability.

In order to examine the stability of stimulus class effects, we chart the difference between mean fixation durations for viewing faces and for viewing blocks (Figure 4) as a function of spatial and temporal parameters. We find that as parameters change the pattern of results can reverse. This effect was primarily driven by spatial parameters changes, though we should note that we had no knowledge of this before we plotted the parameter space.

In the interest of brevity, we only consider the distance-dispersion algorithm onwards from this point as other algorithms give similar results.

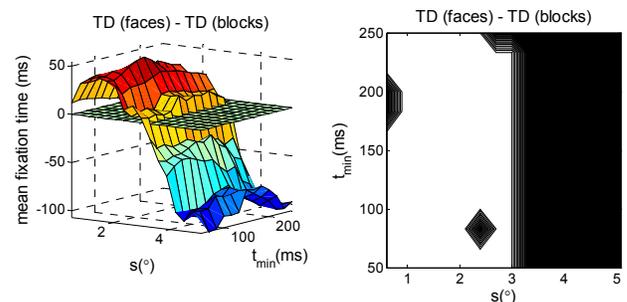


Figure 4: Differences in mean fixation duration between different stimulus classes (Faces-Blocks) for TD children under the distance-dispersion algorithm. The difference surface is shown on the left. Areas where differences are positive are shown in white on the right, negative in black.

In order to examine the stability of outcome measures for making comparisons between diagnostic groups, we also examine the difference in mean fixation duration as a

function of parameter changes. As there was little effect due to temporal parameter changes, we plot only a representative example at a common t_{\min} (Figure 5).

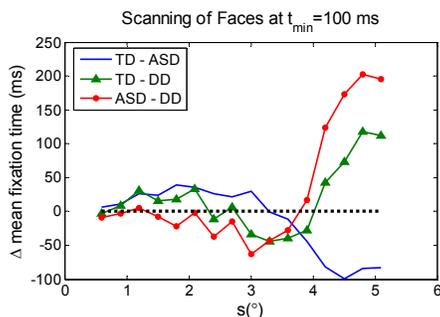


Figure 5: Differences in mean fixation duration between diagnostic groups for faces under the distance-dispersion algorithm at $t_{\min}=100\text{ms}$. The crossing of the zero-line by comparison lines represent effect reversals.

We can see that by manipulating the parameters associated with fixation identification algorithms, our reported results can reverse. With one set of parameter choices one group is associated with longer mean fixation durations. With another set of parameters, a different group becomes the group with longer fixations. Notice, however, that the regimes of behavior are fairly large and contiguous, extending to the border of the parameter space. This implies that rather than some random effect, the reversals are tied with some specific spatiotemporal transition.

The reversals of mean fixation duration are quite prominent in the results we have shown. In a traditional analysis, a particular choice of spatial and temporal parameters would be chosen *a priori* and the observed effect would be taken as representative of some global psychological effect. For example, one might look at the low spatial regime of Figure 5 while focusing on the fixation duration differences between TD and ASD children. From just this small slice of the analysis, one might conclude that typical individuals experience a greater cognitive load when observing faces than do children with ASD; from Figure 4 one might conclude that, for TD children, blocks do not engage as many neural mechanisms as do faces. However, such analyses miss the larger pattern of behavior which includes the reversals occurring at higher spatial parameter settings. Furthermore, as shown by the essentially flat behavior of algorithms in Figure 3, a natural, universal parameter scale for mean fixation duration does not exist. This, combined with the differences observed for stimulus classes, argues against the existence of a unique set of parameters that can be appropriately selected in advance.

The Amorphous Measure Revisited

Faced by a confusion of algorithms and parameters and struck by effect reversals in every comparison, we might be tempted to throw our hands up in surrender and either decide that measures on fixations have no inherent value or decide to escape into a corner of the parameter space with

neurophysiological constraints, such as the diameter size of the foveola, as our shelter. However, though both of these decisions would not be completely without merit, we believe that there is in fact a better solution, one which will allow us not only to model and interpret the reversals that we have observed, but will also give us a hope for unifying the disparate results of prior work which to date defy comparison for lack of a common language.

The hint for our method lies in the strikingly simple, linear behavior observed in Figure 3. If the behavior of mean fixation duration can be well modeled by a regression, we would be able to summarize the variations we observe through 3 coefficients: a temporal slope, $slope_t$, a spatial slope, $slope_s$, and an offset, t_0 . Furthermore, this would also provide us scaling factors which would allow us to convert one algorithm's results into another algorithm's domain.

In order to examine this, we first ensured that all algorithms were within a comparable regime by pegging them to the distance algorithm. This was accomplished by first choosing, for each stimulus type, a candidate set of temporal ($50 \text{ ms} \leq t_{\min} \leq 250 \text{ ms}$) and spatial ($0.6^\circ \leq s \leq 5.1^\circ$) parameters for the distance algorithm and observing the minimum and maximum mean fixation duration for TD children over this range. This candidate set served as a reference algorithm. Every other algorithm's range was then restricted so as to fall within the mean fixation duration limits of the reference algorithm.

We then collapsed (by averaging) the trials associated with each algorithm-diagnosis-stimulus combination. The resultant mean fixation duration, t_{fix} , was then fit by a linear regression (1) (Table 1):

$$t_{\text{fix}}(t_{\min}, s) = slope_t \cdot t_{\min} + slope_s \cdot s + t_0 \quad (1)$$

Table 1: Linear Regression of Mean Fixation Duration

diag.	Distance-Dispersion Algorithm							
	$slope_t$		$slope_s$		t_0		R^2	
	Face	Block	Face	Block	Face	Block	Face	Block
NC	0.67	0.74	142	175	83	-2	.981	.997
DD	0.80	0.78	128	183	86	-15	.922	.987
ASD	0.63	0.57	172	171	21	4	.996	.996
diag.	I-DT Algorithm							
	$slope_t$		$slope_s$		t_0		R^2	
	Face	Block	Face	Block	Face	Block	Face	Block
NC	0.63	0.64	97	118	64	-26	.989	.997
DD	0.85	0.68	105	116	-6	-13	.934	.985
ASD	0.55	0.49	118	119	-7	-32	.995	.996
diag.	Velocity-Threshold Algorithm							
	$slope_t$		$slope_s$		t_0		R^2	
	Face	Block	Face	Block	Face	Block	Face	Block
NC	0.95	1.11	11.2	11.4	-138	-205	.984	.983
DD	0.97	1.09	9.6	12.6	-104	-229	.993	.981
ASD	1.04	0.94	13.7	13.5	-244	-271	.914	.949

As we can see, the linear regressions fit the data quite well, with the worst case still accounting for over 90% of sample variance. The good match suggests that converting between algorithms should be fairly straightforward and effective. In Figure 6, we use the coefficients from Table 1 to convert all algorithms to a common axis.

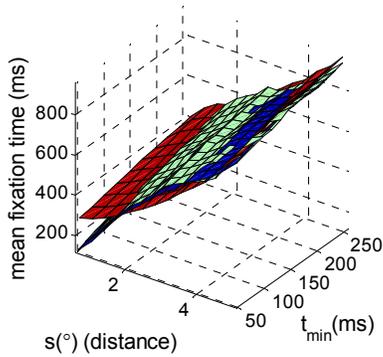


Figure 6: Mean fixation duration of TD children viewing faces for different algorithms as a function of spatial and temporal parameters all scaled to distance algorithm as given by coefficients in Table 1. Compare to Figure 3.

We also can simulate idealized versions of mean fixation duration behavior. For instance, the comparison of Figure 4, which examines how TD children differentially treat faces as opposed to the less ecological block designs, can be modeled ideally (Figure 7). These results suggest that the variation and reversals observed when manipulating fixation identification algorithms is partly due to the natural structure and dependencies of the measure and not some spurious error nor an artifact to be hidden.

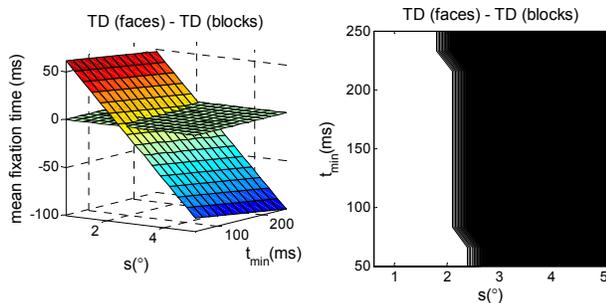


Figure 7: Idealized model of Figure 4, showing a correspondence between theoretical and experimental reversal patterns.

Interpretations and Applications

Though it appears that, owing to its limitations, the strategy of choosing a single set of fixation-identification parameters for analyzing mean fixation duration is lost, the regression model coefficients may offer a practical replacement. In this section we focus on interpreting coefficients from the distance-dispersion algorithm. We focus on this particular algorithm as it is perhaps the most transparent of dispersion algorithms (Shic et al., 2008); velocity algorithms deserve a separate treatment which will be a future exploration.

With the caveat that our investigation into interpreting these coefficients is very preliminary, we have developed a model which may elucidate the function of some of the coefficients. We employ an idealized model of saccade

generation. In this model, the distribution of saccades is power law distributed (Brockmann and Geisel, 1999):

$$p(a) = ka^{-\alpha} \quad (2)$$

where $p(a)$ is the probability of a saccade of amplitude a , α is a constant (1.2 to 1.35), and k is a normalizing constant for the discrete range-limited case only. The duration of each saccade is given by the square-root main saccade rule (Lebedev et al, 1996):

$$t(a) = .17\sqrt{a} \quad (3)$$

By increasing α we increase the spatial slope, $slope_s$ ($\alpha=1.2$, $slope_s=132$; $\alpha=1.4$, $slope_s=179$). This suggests that higher spatial slopes correspond to denser scanning patterns.

The temporal coefficient, $slope_t$, characterizes how the mean fixation duration increases as the minimum time requirement t_{min} increases. A larger temporal slope, counter-intuitively, implies a greater loss of data: by removing fixations with shorter durations, the average fixation duration tends to increase. This process explains the discrepancy in temporal slopes for the velocity algorithm as compared to dispersion algorithms. The temporal constraint for velocity algorithms is a pure rejection criterion; by comparison, dispersion algorithms have a chance to partially recover a fixation as the candidate fixation window slides. In terms of scanpath effects, a larger temporal coefficient implies more non-recoverable short-time fixations, i.e. short time fixations which are separated by large distances.

The duration offset, t_o , is a parameter for which we are currently seeking simulation results. This offset may be viewed as a constant added to every fixation regardless of spatial or temporal parameters, reflecting an overhead which might be associated with increased cognitive processing, greater affective charge, or difficulties in disengaging. In terms of differences between the subjects in our study, we note that for blocks all groups should very little contribution due to t_o . However, both the NC and DD groups show an increased load to faces, whereas the ASD subjects showed only a minor increase.

The crucial point regarding these parameters is that together the three coefficients capture the behavior of mean fixation duration quite well. If we examine the behavior of TD and DD individuals in Table 1, we find that there is a modulation of coefficients as the stimulus changes from faces to blocks. This suggests that there is some distributional reaction to the difference in stimuli for these two subject populations. By comparison, the ASD group is largely invariant to the change. This effect is consistent with known face processing abnormalities and social difficulties in autism (Boucher and Lewis, 1992). It is possible that individuals with autism, especially at this young age, view the face in a more pattern-like fashion than their TD or DD peers, unfortunately setting the stage for a cascade of future deficits.

Discussion

This current study has several limitations. First, the populations under study are extremely young children. It is

possible that the highly linear effect that we see for mean fixation duration is reflective of the simplicity of early perceptual processing systems. For this reason, this study should be replicated in adults. However, if it turned out that adults did in fact, generate nonlinearities that were not found in children, this would be extremely interesting in its own right, as it would imply that some cognitive mechanism coming online was intercepting the more primitive process in children. Furthermore, such a finding would actually strengthen our case for charting the parameter space, because such an effect would likely be poorly characterized by single *a priori* choices in parameter settings.

The task that we use is free-viewing embedded within a recognition task. It might be possible that the free-viewing aspects of the experiment are responsible for the simple structure we observe for mean fixation duration and that the imposition of any greater experimental structure would break this effect. Again, however, it is important to note that revealing this would not be possible except by charting parameters as we have suggested.

Finally, though the subject sample we have chosen is certainly unique, it is small. Notably, there are only five subjects in the DD population. It is our hope that future studies with larger populations and extended experimental conditions will bear out the main results of this study.

Conclusions

We have shown that choosing a single set of parameters for calculating mean fixation duration is a problematic task, as effect reversals occur both between diagnostic groups and between stimulus classes. We have also shown that no natural comparability exists between different algorithms. However, by computing mean fixation duration over a range of parameters, we are able to model mean fixation duration in a straightforward manner. This gives us the capability to better understand the underpinnings from which differences in mean fixation duration arise, and gives us a method for unifying the multitude of disparate fixation identification methods. Finally, the coefficients of our model have given us insight into autism, showing us that even at the very young ages of the subjects in our study, differences in processing the world are already apparent.

Acknowledgments

This project was supported by NIH Research Grant U54 MH66494 funded by the National Institute of Mental Health (NIMH); the National Institute on Deafness and Other Communication Disorders (NIDCD); the National Institute of Environmental Health Sciences (NIEHS); the National Institute of Child Health and Human Development (NICHD); and the National Institute of Neurological Disorders and Stroke (NINDS). This study was supported by a NSF CAREER award #0238334, NSF award #0534610 (Quantitative Measures of Social Response in Autism) and generous funding through research and training grants by Autism Speaks and NAAR.

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