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Examining individual differences in infants' habituation patterns using objective quantitative techniques

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Abstract

The assessment of individual differences in infant habituation patterns is important for answering basic questions about continuity in cognitive development. Nevertheless, there are flaws with existing methods for determining relevant parameters of the cognitive processes associated with habituation. In this paper, a more rigorous, model-based alternative approach is illustrated. The approach demonstrates how the habituation data of individual infants may be fit by specific functions, how habituation may be distinguished from random responding, and how the parameter estimates of individual infants' habituation functions might be analyzed for meaningful subgroups or clusters. The model-based approach provides novel insights about individual subgroups when applied to a real habituation data set and thereby demonstrates the feasibility and utility of the techniques advocated.

Keywords: Habituation; Individual; Habituation patterns

1. Introduction

Since the first seminal studies by Fantz (1964), the phenomenon of looking time habituation has provided the foundation for a substantial literature on infant perception and cognition. Most research using habituation methods has not focused on habituation per se, but on other perceptual or cognitive questions that recovery from habituation can shed light upon. Nevertheless, there has been and continues to be substantial interest in individual differences in habituation (Bornstein, 1998; Bornstein & Benasich, 1986; Colombo & Mitchell, 1990; McCall, 1979) and in fixation patterns that might underlie developmental differences in visual attention (Frick,

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Colombo, & Saxon, 1999). The general finding from this body of research has been that a number of measures of attention, including fixation duration and the rate of decline in fixation duration during habituation, show low to modest short-term stability and longer-term predictability with respect to a number of measures of cognitive development (Bornstein, 1998; Colombo & Mitchell, 1990). The general thesis of this paper is that in order to make further progress toward understanding these relationships, one must have a more rigorous and quantitative description of habituation that operates at the level of the individual infant.

The justification for this view is straightforward. As it stands now, the low to moderate correlations between various indices of attention could be due to one or more of several causes: a high level of within-infant variability unrelated to the question at hand, high levels of between-infant variability, variations in experimental procedures, or even inappropriate measures. Of course, the problem of determining which aspects of variability within infants and between them are meaningful and which are not is a general one that many investigators interested in many aspects of early development continue to struggle with. The approach we advocate involves a systematic partitioning of the likely sources of variability into different classes by fitting specific quantitative models to the observed behavioral data of individual infants. In principle, this approach allows one to distinguish between sources of variability, and thereby improve the sensitivity of existing measures. Moreover, by fitting functions to the data of individual infants, the approach we advocate yields parameter estimates of potentially meaningful dimensions of behavior. These parameter estimates are likely to provide more precise characterizations of an individual infant's behavior than are other measures, and the pattern of parameter estimates across a sample should provide more complete information about the range and types of behavior under study. While the focus here is on characterizing individual patterns of habituation, the methods advocated could be applied more generally to other problems concerning variability and stability in early development.

Most theoretical accounts of habituation derive from comparator theory (Sokolov, 1963). In the case of infant visual habituation, comparator theory implies that the magnitude of attention or duration of fixation is an index of the degree of discrepancy between an internal representation of a stimulus or set of stimuli and the currently presented display. As the representation increasingly resembles the presented display, the infant's attention level wanes, according to some function that we might call the habituation function. The rate of change in this unknown habituation function reflects, among other factors, the speed or efficiency of information storage. Consequently, the variables of interest to the investigator include the relative magnitudes of the internal representations as reflected by differences in the habituation function and the rate of change in that function. Comparator theory has been criticized for failing to explain certain features of observed habituation patterns, such as transient increases in attention that may occur early on in both physiological variables (Groves & Thompson, 1970) and infants' visual attention (Bashinski, Werner, & Rudy, 1985; Hunter & Ames, 1988; Kaplan & Werner, 1986) due to the presumed influence of two separate processes. Nevertheless, most investigators assume that decrements in infant visual attention do reflect processes of the sort envisioned by comparator theory, and that there is some unknown underlying function that governs infants' responses.

Clearly, a central question is measuring the relevant parameters of these functions for individual infants. The core problem is that observed responses in an habituation experiment are some joint function of the infant's unknown habituation function and random error. We might reify this basic idea with the simple statement:

$$\text{Habituation Data} = \text{Habituation Function} + \text{Error}.$$

We need not assume additive error, of course, but without some formal framework there is no possibility of separating the infant's true habituation function from the considerable noise likely to be present. Thus, whether a peak or trough in the observed habituation data represents a feature of the unknown habituation function or is simply a noisy gyration cannot be answered without imposing some kind of structure on the system. The structure we favor is to assume that all infants share an underlying habituation function that is similar in mathematical form, but which varies in specific shape by taking on different parameter values, such as the minimum and maximum duration of looking, and critically, the rate of change in attention across exposures (Thomas & Gilmore, 2002). In this perspective, the problem of determining whether there are relevant individual differences in habituation becomes one of estimating an habituation function for each infant and examining the parameters of the fitted function, not the observed values which are distorted by error. Although some investigators have suggested related ideas (Ashmead & Davis, 1996), this approach represents a substantial departure from current practice. Moreover, as we will now show, alternative approaches to studying individual differences in habituation (Bornstein & Benasich, 1986; McCall, 1979) have flaws that the model-based approach we propose does not.

One problem with early efforts to capture differences in infants' rates of habituation stemmed from the choice of inappropriate measures. Simulation studies showed that measures of habituation rate based on the number of fixed duration trials to a preset habituation criterion were biased (Dannemiller, 1984). The procedures were subsequently abandoned. Other approaches focused on whether there were subgroups in overall patterns of infant habituation data. One such approach derives from McCall (1979). Here, a matrix with habituation data from a set of infants is first run through a procedure similar to principal components analysis (Tucker, 1966). The output is a subjects by factors matrix. In the second stage, the matrix is passed to an iterative cluster rotation method for clustering the infants (Overall & Klett, 1972). Bornstein and Benasich (1986) used a visual inspection procedure to sort observed infant habituation functions into three patterns which they called (a) Exponential Decrease, (b) Increase–Decrease, and (c) Fluctuating. Consider Fig. 1A which displays the first three trials of nine simulated habituation functions. One might view infants 1, 4, and 7 as belonging to the Exponential Decrease category, infants 2, 3, and 6 as Increase–Decrease, and 8 and 9 as Fluctuating. These classifications are illustrative only. Bornstein and Benasich (1986) invoked additional criteria not applied here. The important point is that the *observed* data strongly suggest the existence of different habituation patterns, and accordingly, different underlying habituation functions among the infants.

We conducted McCall's analysis on the nine habituation function data sets illustrated in Fig. 1A. The analysis yielded 3 clusters. Infants 1, 2, 4, 5, and 7 formed one cluster; 3 and 6 another; and 8 and 9 a third. Except for infants 2 and 4, the classification is similar to the Bornstein and Benasich categories. McCall (1979) averaged the infants' responses within each cluster. Fig. 1B shows these averages for the functions within each cluster. The results seem especially satisfying because both factor analysis (McCall, 1979) and visual inspection

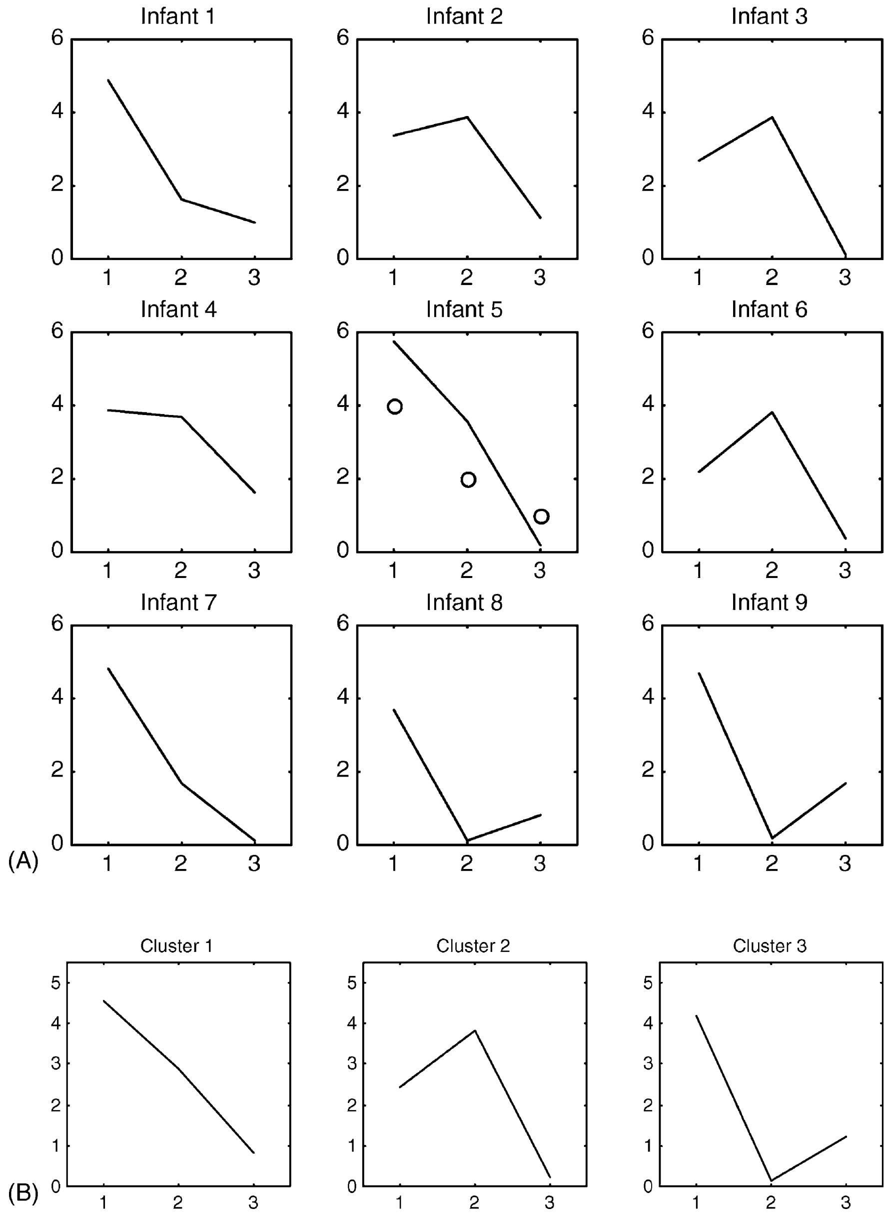

Fig. 1. (A) Three habituation trials for nine simulated infants. (B) Mean habituation values for each of the three clusters identified by the McCall (1979) clustering procedure applied to data generated by the same habituation function.

(Bornstein & Benasich, 1986) reach essentially the same conclusion—there are three distinct habituation patterns represented.

The problem is that these clusters are an artifact. The nine data sets were in fact generated from the *same* underlying habituation function combined with additive random error. The function used to generate these data was simply

$$X(t) = \begin{cases} 4 + U(t), & t = 1, \\ 2 + U(t), & t = 2, \\ 1 + U(t), & t = 3. \end{cases}$$

where U represents a uniform random variable on the interval $[-2, 2]$. The model's expected values of 4, 2, and 1 are illustrated by the open circles in the plot for infant 5 (Fig. 1A). The specific numbers were selected for illustrative purposes only. But, they clearly illustrate that both of the existing procedures for determining whether there are clusters or patterns of performance in observed habituation data may easily and erroneously capitalize on random error variation. Further, this particular example is no fluke. Extensive simulation studies using McCall's (1979) procedure have explored the estimated *expected* number of clusters obtained given various scenarios. The method leads to particularly egregious errors if infants share a common function, as in the example above. Sometimes the procedure does better if there is more than one habituation function represented in the data, but how would one gauge, a priori, whether this is so? In fact, it can be shown analytically that as the variance of random error $U(t)$ grows large, the expected shape of an observed habituation pattern can depart substantially from the underlying habituation function which generated it. Not only are "wrong" observed habituation functions more probable with large error, these functions will appear more extreme and so be potentially misleading, as well (Thomas, 2001). Thus, it is clear that the size of error variance is critical to addressing issues of habituation types, but this error cannot be specified without comparing it to some specific model.

Accordingly, a precise and quantifiable characterization of habituation at the level of the individual infant seems essential. We will now describe an approach to characterizing individual differences in habituation which illustrates the key features of such an approach by fitting proposed habituation functions to actual habituation data, devising objective, quantifiable measures for comparing the fit of different habituation functions, and then analyzing the fitted *parameter estimates* of the habituation function for distinctive patterns using a more rigorous clustering scheme than has been adopted previously.

2. Method

2.1. Participants

Thirty-five 4-month-old (117–129 days; 16 female) healthy full-term infants provided data. All were born between 38 and 42 weeks gestational age as determined from due dates estimated by the mothers' physicians. The infants were recruited by telephone from information contained in birth announcements published in the newspaper.

2.2. Apparatus and procedure

Infants sat in an infant seat 90 cm from a large computer-controlled video monitor located in a darkened room. The stimulus display presented a series of computer-generated movies of

67 randomly distributed moving white dots on a black background. The movie simulated the experience of an observer translating linearly along a ground plane at 30 m/s. At the specified viewing distance, each dot was 0.5° with viewing region 40° (H) by 30° (V). During habituation, infants viewed repeated presentations of a display that simulated motion in one of two directions: forward (0°) or backward (180°). An observer, blind to the conditions, monitored the infant's direction of gaze by means of a video camera mounted above the display. The observer pressed keys to indicate when the infant was and was not looking at the display. Accumulated looking times to the display were recorded by the computer during each trial. Individual trials were terminated after 60 s of accumulated looking or when the infant looked away from the display for 1 s. The 60-s cut-off was adopted to ensure that infants provided the five trials necessary for the habituation algorithm. The 1-s look away was used to account for the observer's response times to changes in the infant's direction of gaze.

The same display was presented on subsequent trials until the look time in a trial dropped below the habituation criterion or until a maximum of 15 trials had been presented. The habituation criterion was determined on-line using Ashmead and Davis' (1996) proposal. Following the fifth habituation trial, a second order polynomial was fit to the data. When the fitted look time following a given trial dropped below 50% of the fitted (predicted) look time for the first habituation trial, habituation was achieved. Four test trials followed, in which both novel and familiar directions of motion were displayed in alternating order that was counterbalanced across infants. For example, if an infant had viewed 0° during habituation, the post-habituation trials were 0 and 180°. Recording of look duration during the test phase was identical to the habituation phase.

Reliability was assessed by having a second observer code 20% of the trials from videotape. The correlation between looking times determined on-line and those assessed off-line was .98.

2.3. Analysis strategy

The general analytical strategy had two essential features. First, we fit two models to the habituation data of individual infants. The first or null model was simply a line with zero slope centered on the overall mean response across the habituation phase. The second or habituation model was an exponential function with three parameters that corresponded to the floor or minimum level of response, the slope or rate of change in responding, and the depth or distance from the floor to the maximum response level. Then, we selected between the null and habituation models for each infant by computing an objective model selection criterion called BIC. The strategy was to pit the null model against the proposed habituation model for every infant, using data to decide which model best described each individual's performance. For those infants for whom we could reject the null or constant model based on this measure, we then examined whether there were clusters or patterns in the parameter estimates of their fitted functions. Specifically, we conducted tests which allowed us to determine whether the distribution of a single parameter estimate was best fit by a single normal distribution or by a mixture of distributions. The results of this procedure allowed us to determine whether there were clusters or groups of infants based on the fitted parameter estimates of their habituation functions. These parameter estimates presumably better characterize the relevant psychological processes than do the raw looking time data.

2.3.1. Null function

Most investigators are concerned with determining which infants have truly habituated, and which show no systematic decline but achieve the habituation criterion by chance. However, to do so rigorously requires that a null or no habituation model be specified. A natural one regards the infant as showing no change in response across trials, merely random responding around some constant value. For our purposes, the value chosen was the mean response, μ, across the set of habituation trials for each infant. Since we view observed habituation responses $Y_i(t)$ for infant i on trial t as reflecting the combination of the unknown habituation function plus error, the resulting model is:

$$Y_i(t) = \mu_i + E_i(t),$$

where μ_i refers to the mean level for infant i, and $E_i(t)$ is a mean zero independent random error value that has the same distribution for any fixed i.

2.3.2. Habituation function

We chose the following function to describe the expected pattern of habituation:

$$h_i^*(t) = \beta_i^2 \exp(-\delta_i^2(t-1)^2) + \alpha_i^2.$$

Here, the parameters α_i, β_i, and δ_i are all constrained to be greater than or equal to zero, and so for ease of estimation they are indicated in a quadratic or squared form. This equation indicates that level of attention h_i^* for each infant i varies with trial t according to a decreasing exponential function. h_i^* is only one possible function that might be used although this function meets several criteria that plausible habituation functions should satisfy such as having a maximum, minimum, and smooth or monotonic transition across trials (Thomas & Gilmore, 2002). The indexing by i indicates that the parameters of this function are specific to each individual. The parameters are also relatively transparent to interpretation. β_i^2 represents the magnitude of change from the maximum to the minimum. Specifically, $\beta_i^2 = h^*(1) - h^*(\infty)$. δ_i^2 represents the rate of change or "slope" and reflects how quickly the infant's habituation response declines over trials. The larger the value of δ_i^2 the more rapidly the infant habituates. In fact, when δ_i^2 is large a step-like function results. This avoids the need to propose two distinct functions to account for rapid vs. slow habituators (Cohen & Menten, 1981). Finally, α_i^2 represents the minimum or asymptotic level of attention.

2.3.3. An objective criterion for distinguishing between the models

Having defined the null and habituation models, the next step is to determine objectively whether a given infant is actually habituating or is merely fluctuating randomly around some mean value. In other words, which model best fits each infant's data? The method we propose for distinguishing between the null and habituation models is Bayesian Information Criterion (BIC) (Schwarz, 1978). The basic rationale for BIC is straightforward. Better models fit the data by capturing more of the variance. Also, simple models are preferred over more complex ones, and complexity is measured by the number of parameters. The more parameters in a model the easier it is to fit the model to data, but adding parameters should have a cost. So, the "best" model is one which captures the most variance with the fewest parameters. Practically, this is achieved by deriving an expression for a cost or penalty term that instantiates both of these ideas in a quantitative way. We call this term BIC.

In the present setting BIC is defined as:

$$\mathrm{BIC}_i(M_j) = T_i \log(\hat{\sigma}^2_{E_{ij}}) + p_j \log(T_i).$$

Here M_j simply denotes the model as indexed by j, where M_0 denotes the null model and M_1 the habituation model, h_i^*; p_j denotes the number of estimated model parameters, one for the null model representing the mean value, and three for h_i^*, representing the floor, ceiling, and rate of change. $\hat{\sigma}^2_{E_{ij}}$ denotes the estimated error variance—variance *not* accounted for under the designated model. T_i denotes the number of trials for infant i. The penalty term for additional parameters is $p_j \log(T_i)$, and it is three times larger for the habituation function than for the null model because there are three free parameters in the habituation function vs. one in the null model.

Implementation is straight forward. Both models are fit to the data. BIC for each is computed. The model with the smallest BIC value is considered the best model for infant i. Essentially BIC is a conservative strategy—the penalty is high for deciding to declare the non-null model h_i^* a better fit than the null. It means that the reduction in variance accounted for by the habituation model relative to the null must be substantial.

2.3.4. Estimation details

Estimation of the parameters for the null model is straightforward. It involves simply computing the ordinary sample variance and sample mean of the observed responses. In contrast, estimation of the parameters of h_i^* requires non-linear methods. The approach used here is non-linear least squares, using Newton's method. Specifically, the estimation model is equation 13.25 of Seber and Wild (1979). Using this approach the solutions obtained converge reliably and quickly so that the procedure can be implemented in real time with today's fast PCs. The solution provides estimates of the parameters, error variance and standard errors. The estimation algorithm is given elsewhere (Thomas & Gilmore, 2002).

2.3.5. Mixture of normals analysis

As indicated in Section 1, current procedures for detecting individual patterns of habituation are fraught with difficulty and highly susceptible to artifacts. Given the importance of determining individual differences in habituation patterns, a more objective method is clearly warranted. The technique we illustrate here is called a mixture of normals analysis. It assumes that among the population of non-null infant habituation functions there are K different slope values, and that each $\hat{\delta}_i$ represents a normally distributed excursion about one of these K slope values. Given membership in one of the K distributions, the fitted slope values $\hat{\delta}_i$ are assumed to be independently and identically distributed. Actually, we prefer to think of this model, which is a finite normal mixture model, as being an approximation to reality, in which each identified group represents infants or their $\hat{\delta}_i$ which are more similar to one another than are infants from different groups.

The finite mixture model in this context has the following structure:

$$f(\hat{\delta}) = \sum_{k=1}^{K} \pi_k f_k(\hat{\delta}).$$

The composite distribution of the slope parameter, $f(\hat{\delta})$, consists of K component normal distributions each with its own mean and variance. K represents the number of subgroups in the mixture, or equivalently the number of different types of habituation patterns. The π_k are the population proportions that fall into each group, and the π_k sum to 1. The results of fitting a mixture of normals to a data set are the mean values of the different clusters, the number of such clusters, and the proportion of infants who fall into each cluster. Here again we use a form of BIC to determine the number of clusters K, given the data. The method also allows each individual infant's parameter estimate to be assigned to its correspondingly most probable distributional component, not forced by deterministic assignment as in some alternative procedures. In the present case, BIC is defined as follows:

$$\text{BIC}(K) = -2\log L(K) + (3K - 1)\log(n).$$

L denotes the likelihood function for K components and n is sample size, here $n = 20$. As before, the strategy is to select the value of BIC for which BIC is smallest as K ranges from 1 to the presumed maximum number of clusters, say 3. Obtaining estimates of the parameters of the mixture model requires iterative routines. For estimation details, see Everitt and Hand (1981).

3. Results

The null and habituation models were fit to the data for each infant, and BIC under each model was determined. Among the 35 infants, 20 had BIC values smaller under the habituation model relative to the null and thus were declared to have habituated rather than having randomly varied in attention levels. Note that all 35 infants met the Ashmead and Davis (1996) habituation criterion within the actual context of the data collection, so the model fitting procedure illustrates that a substantial fraction of infants in the sample may not have actually habituated. Among the 15 infants for which BIC under the null model was smallest, the mean constant value was 19.58 (4.44–34.3 s; SD = 9.96).

The fit of h_i^* to the remaining 20 infants was good; r values averaged .95 (SD = 0.04) and ranged from .88 to .99. We then examined whether the distribution of the slope estimates $\hat{\delta}_i$ might consist of subgroups or clusters of infants. We focused on this parameter for two reasons. One, mixtures analysis on the other two parameter estimates suggested that a single component best fit the data. Two, most theoretical accounts presume that the rate of habituation reflects important underlying psychological processes such as the rate or efficiency of information accumulation.

Fig. 2 provides a histogram of the fitted $\hat{\delta}_i$ estimates. It provides visual evidence that there may be two different types of infants based on the fitted slopes of their habituation functions. The data reject a formal test of the hypothesis of a single common underlying distribution, $p = .014$ (Anderson–Darling). This suggests that a mixture model may be appropriate. Subsequently, we found that the value of the BIC term was maximal, and therefore the fit best, when there were two distinct normal distributions fit to the data. Further, the mean slope parameter estimate for what we might call the "slow" group (1.06) was almost four times smaller than for the

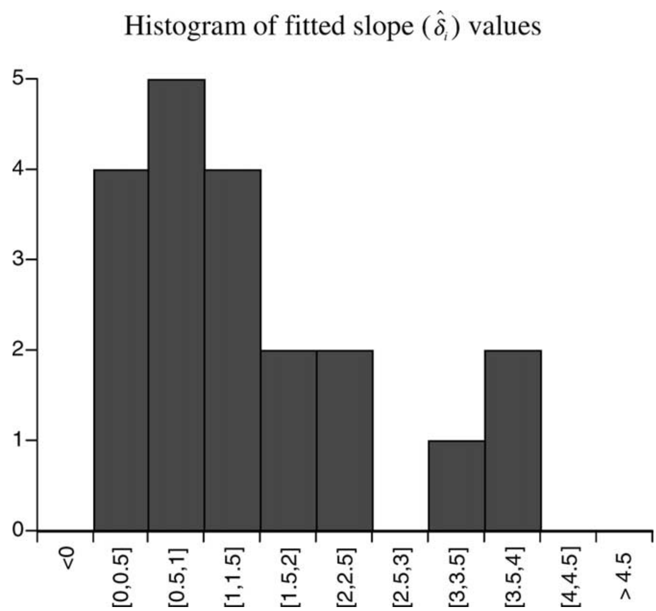

Fig. 2. Histogram of fitted slope ($\hat{\delta}_i$) values for the $N = 20$ infants for whom h^* fit better than the null model.

"fast" group (3.86), and 0.85 or 17 out of 20 infants could be classified in the "slow" habituator group. Fig. 3 shows representative habituation curves for one infant in each of these groups in comparison with the mean level across the trials that represents the null model. There are two things to note in these plots. One is that by fitting separate parameters for the minimum (α_i^2), slope (δ_i^2), and depth (β_i^2), h_i^* can accommodate a wide range of infant habituation patterns. Also, under h_i^*, the "fast" (Fig. 3B) group resembles performance under a sudden drop or what Cohen and Menten (1981) termed an all-or-none model. Thus, in combination with the

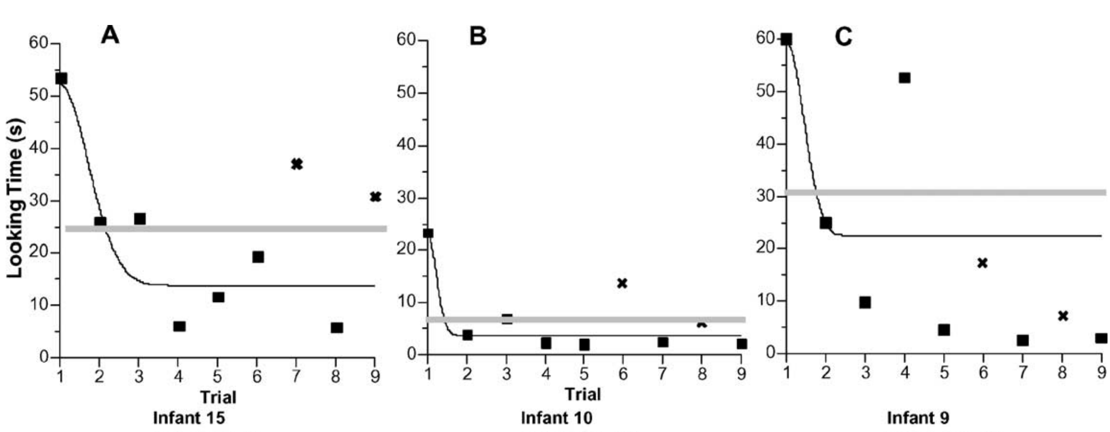

Fig. 3. Illustrative data from three actual infants. The solid line shows the fitted function h^* e.g., $h^*(3.7, 6.2, 1)$ in (A) denotes the estimates of alpha, beta, and delta. The hatched line shows the mean or null model. (A) "Slow" habituator. (B) "Fast" habituator. (C) Non-habituator.

null vs. habituation comparison, there appears to be evidence in these data for at least three different types of infants: one group that fluctuates randomly around some mean level but does not clearly habituate (Fig. 3C), and two groups that habituate at substantially different rates (Fig. 3A and B).

4. Discussion

The determination of the form and psychologically relevant parameters of the habituation functions of individual infants is clearly an important problem in infant cognitive research, but we have argued that existing procedures for doing so (e.g., Bornstein & Benasich, 1986; McCall, 1979) are plagued with numerous problems. The approach demonstrated here consists of three specific and innovative steps that address these issues. The first is to fit specific functions to the habituation data of individual infants, thereby providing data about the likely form of the underlying function that characterizes infant attention levels in the absence of noise. The second is to determine whether habituation has or has not actually occurred by comparing how well a null or constant model fits each infant's data in comparison to a proposed habituation function in which attention is presumed to decline over trials. The third is to then compare infants on the basis of clusters or groups in the parameter estimates of the fitted functions.

We showed how such an approach might proceed by analyzing data from an actual habituation experiment (Gilmore & Rettke, in press). The results demonstrated the utility and feasibility of the approach, despite the increase in computational complexity. The comparison between the null and habituation models using the BIC measure clearly indicated that despite having satisfied a modified 50% decrement criterion advocated by Ashmead and Davis (1996), a substantial fraction (43%) of the infants in the study may only have exhibited randomly fluctuating attention levels. At the same time, the data from the remaining infants was fit quite well by the proposed habituation function, h_i^*, and the procedure provided for each infant estimates of three parameters—slope, minimum, and magnitude of change—that would not otherwise have been available. When we examined these parameter estimates for clusters or subgroups using the mixtures of normals procedure, we found using BIC, that the rate or speed parameter δ_i supported two distinct normal distributions and not more. As a result, we now have evidence that of the 35 infants in the original study, 15 did not habituate, 17 habituated slowly, and 3 habituated rapidly.

There are several strengths of this approach. It is objective, based both on the infants' own data and on well-specified decision making criteria. It is specifically focused on the responses of individual infants, and provides ways of quantifying the performance of individual infants based on the idea that observed responses represent a combination of some underlying habituation function plus noise. In principle, by examining the parameter estimates of a fitted habituation function rather than the observed data, one should have a more accurate picture of the infant's actual performance. In addition, by specifying and fitting an habituation function with transparent parameters, the current procedure should make it easier to assess patterns of stability or change in individual infants' performance over time by comparing the fitted parameter estimates, not observed data, over time. Indeed, we speculate that some of the early difficulties in demonstrating strong, clear relationships between habituation performance in infancy and later cognitive measures (e.g., Bornstein, 1998; Colombo & Mitchell, 1990) may stem in part from the use of observed, not fitted, values of various dimensions of infants' habituation functions.

For example, if the parameter estimates for each infant do, in fact, reflect more accurately the infant's state, then the quantitative relationship between the parameter estimates should also be strong, over the short-term at least. This is because estimating individual habituation function parameters reduces the within-infant variability that would otherwise have led to lowered correlations between testing sessions. A similar logic applies to comparisons across testing intervals, where the question is whether a given infant's habituation function remains the same or develops due to change in one or more of the underlying parameters. The prediction that parameter estimates of infant habituation will be more stable and show better long-term predictability than other measures based on observed data remains untested, but we are beginning to address this and related issues in our laboratory. Even if the parameter estimates of infants' habituation functions turn out to be no more stable than previous measures of the process, there are still two reasons to try to estimate them.

One is that our approach has already indicated that there are latent groups of infant habituators, as defined by differences in their estimated habituation function parameters. Not only does the identification of latent groups of habituators permit investigators to examine the relationship between habituation and other measures of individual variability, but examining developmental patterns among latent groups is almost certain to increase the overall predictability of habituation measures in general. Second, it is almost certainly the case that the *variance* of the parameter estimates will be smaller than the variance of conventional indices. And, if the *variance* of the parameter estimates is small, that means that small differences in parameter estimates probably reflect true and meaningful differences in state or development. In sum, the approach illustrated here can help developmentalists make progress toward understanding development in habituation and other domains by untangling the multiple sources of variation that influence infant behavior, thereby bringing into sharper focus what is stable across development and what is not.

At the same time, the approach has several apparent weaknesses. One is computational complexity. In fact, the actual routines for most of the procedures we illustrate seem more complex on their face than they actually are to implement. From an initial estimation perspective the current proposal is more complex than other proposals that suggested similar functional forms for habituation, but once implemented, its complexity is largely hidden from the user in much the way complex statistical package procedures are largely hidden from the user. Moreover, while iterative, the routines run quite quickly on today's fast personal computers.

Another weakness pertains to certain assumptions of the mixtures of normals analysis. This analysis assumes that infants within the same component k share a common variance which means that the variance of the slope estimates $\hat{\delta}_i$ is the same for all i in the same component or cluster. These quantities vary among infants within each component group. In the present case, however, because the two normal components $f_1(\hat{\delta})$ and $f_2(\hat{\delta})$ are sharply separated, as the two disjoint masses in Fig. 2 illustrate, this concern is not likely to be important.

Also, we would not make the claim that h_i^* or any single parameterized function is necessarily the correct one for all infants. That is an empirical question we hope to explore in future work. However, similar functions have been proposed by others and used to fit group habituation data (e.g., Cohen & Menten, 1981; Dannemiller, 1984). The focus here, of course, has been to estimate the parameters for individual infants. The approach of Ashmead and Davis (1996) is similar in spirit. They fit a second order polynomial to simulated habituation data, and showed how an habituation procedure based on the fitted parameters of such a function might be used to determine habituation thresholds. Unfortunately, these authors did not focus on capturing individual infants' habituation behavior, and even if they had, polynomial functions do not yield parameters that are as easily interpretable as h_i^*. In short, the approach illustrated here can provide more information about a data sample than was previously available and is certainly a workable beginning.

A skeptic might argue that we have not demonstrated the new techniques will ultimately provide better predictive power than previous ones. We concur that the current results are largely illustrative, and we have begun an extensive effort to test out these ideas more systematically. At the same time, we argue that the flaws in existing techniques for studying individual patterns of habituation make it essential that we explore alternative approaches in order to address what are clearly fundamental questions in early cognitive development such as the stability of rates of learning over time. Model-based approaches that attempt to examine and quantify the attentive behavior of individual infants seem to us a first and promising step.

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