Novel insights into activity patterns in children, found using functional data analyses

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Abstract

Continuous monitoring of activity using accelerometers and other wearable devices is revolutionizing the measurement of physical activity by providing objective, unbiased observation in unprecedented minute-by-minute detail. Accelerometers have already been widely deployed in studies of healthy aging, recovery of function after heart surgery, and other outcomes. Commonly, analysis of accelerometer data reduces thousands of data points to a single summary variable, such as the total activity count, which conceals timing and patterns in diurnal activity that might shed light on many pressing scientific questions. However, regression models from functional data analysis (FDA), an area with an established statistical literature, can leverage the temporal structure inherent in accelerometer data. In this article we describe the application of such models to analyze data collected during warmer months in New York City (May to September) from 151 children participating in a Head Start program. The FDA models reveal several new, meaningful associations that are missed when data are aggregated, including shifted activity patterns for children of foreign-born mothers and time-specific effects of asthma on activity.

Keywords: Accelerometer data, regression, spline smoothing, statistical methods

1 Intro

Accelerometers have become an appealing alternative to self-report techniques for studying physical activity in observational studies and clinical trials, largely because of their relative objectivity. Accelerometers can be worn comfortably and unobtrusively for days at a time. During observation periods, the devices measure activity through electrical signals that are a proxy measure for acceleration (Spierer et al. 2011, Trost, McIver, and Pate (2005), Ward et al. (2005)). "Activity counts" are then devised by summarizing the voltage signals across a short period known as an epoch to quantify the amount and intensity of activity; one-minute epochs are common. Thus, accelerometers produce around-the-clock observations of physical activity and may yield unique insights into the timing and structure of activity during the day.

Despite the richness of accelerometer data, available analyses focus on the total or average activity count aggregated over hours or days as a single observed measure of physical activity (Freedson, Pober, and Janz 2005, Kim, Beets, and Welk (2012), Troiano et al. (2008), Trost, McIver, and Pate (2005)). This strategy implies that all activity counts are equivalent, regardless of their timing within a day or distribution across days. Understanding patterns of behavior is essential for the development of effective physical activity interventions; children with differing patterns of physical activity may require different interventions to increase their overall level of physical activity (Jago et al. 2010, Lee et al. (2012), Trilk et al. (2012)). The influence of the built environment and neighborhood disadvantage on physical activity may vary by time of day and day of the week (weekend vs weekday). Features of the built environment may influence the frequency and duration of bouts of moderate or vigorous activity and sedentary time (Kimbro, Brooks-Gunn, and McLanahan 2011). Neighborhood disadvantage may impede physical activity at night but not during the day. Even if these risk factors do not have a detectable effect on total activity count, their effects on patterns of physical activity may have important implications for health and quality of life. Recognition of activity patterns may open the door to effective interventions to promote physical activity and limit childhood obesity (Kraus et al. 2015).

In parallel to the rising popularity of accelerometers, the statistical subfield of functional data analysis (FDA) has been under intense methodological and theoretical development. In this context, "functional" refers to the data structure rather than to, say, patient or cognitive function. The key concept in FDA is to treat a completely observed trajectory, in this case parameterized by time, as a single unit of observation instead of considering each minute of each day as a separate, disconnected data point (Ramsay and Silverman 2005). This framework depends on the notion of temporal structure and ordering, and thus allows the examination of time-specific effects and associations. Although FDA is clearly relevant to many open research questions, it has rarely been described outside the statistical literature.

Our purpose is to articulate the use of regression models with functional responses and scalar predictors for accelerometer studies. The term"functional response" refers to the complete temporal trajectory recorded by the accelerometer analyzed as as the dependent variable or outcome of interest; the term "scalar predictor" refers to any traditional covariate, such as age or gender, used as a predictor of the activity response trajectory. Such models are the subject of a growing statistical literature (Guo 2002, Morris and Carroll (2006), Reiss, Huang, and Mennes (2010), Goldsmith, Zipunnikov, and Schrack (2015)). This article presents an application of function-on-scalar regression to accelerometer data, emphasizing the interpretation of the models and estimated coefficients, to demonstrate the usefulness of FDA for uncovering previously unknown associations. An interactive graphic showing the results of our analysis is available online, and to encourage readers to try using such models we have made all code used in this application publicly available.

2 Dataset and original analysis

Our data have been discussed and analyzed previously, and we provide only an overview here; for more complete details see (Rundle et al. 2009, Lovasi et al. (2011)).

Study participants were recruited from 50 Head Start centers in northern Manhattan, the Bronx, and Brooklyn, in neighborhoods with high rates of pediatric asthma. After obtaining informed consent from the enrolling parent and using a study protocol approved by the Institutional Review Board of the Columbia University Medical Center, we used a survey instrument to collect data on the child’s age, race, gender, asthma symptoms and other medical conditions, birth order and family-related factors, and features of the home environment. Field staff measured the child’s height, weight, and skin-fold thicknesses The staff then attached the accelerometer to the child’s non-dominant wrist with a hospital band. To allow the child to become comfortable with the device before it began recording, staff and programmed it to delay starting data collection until 11:50 pm the first day; it then recorded the child’s physical activity for six days, 24 hours per day, using 1-minute epochs

Rundle et al. (Rundle et al. 2009), analyzed these accelerometer data using standard techniques, with the goal of identifying variables associated with physical activity in children. Multiple linear regression models were used to examine effects of child demographics (sex, age), mother's demographics (age, birthplace, occupation), behavioral variables (>2hr per day of TV, > 1hr per day of video games), and season (warmer months May to September or colder months October to April) on the mean per-minute accelerometer count during awake minutes. A primary focus of the study was on the association of asthma symptoms with physical activity.

With minor modifications, we reanalyzed the data on activity during the warm months only, because Rundle had found more variables associated with activity in the warmer months than in the colder months. That finding and the findings of other investigators that children gain weight more during summer break than during the school year, indicated a need for improved understanding of activity patterns during warmer months (Downey and Boughton 2007, Christodoulos, Flouris, and Tokmakidis (2006), Von Hippel et al. (2007), Wang et al. (2015)). The results of our re-analysis were quantitatively and qualitatively similar to those of the original analysis. Briefly, we found that aggregated activity counts as a single outcome were associated with gender, whether the mother works or attends school, the number of rooms in the home, and whether the child watches hours of TV per day. Maternal birthplace (United States or elsewhere) was not significantly associated with average counts, nor were asthma symptoms “before or after control for the sociodemographic and behavioral correlates."

3 Functional data analysis

We now introduce the conceptual framework for functional data analysis (FDA); see (Sørensen, Goldsmith, and Sangalli 2013) for a recent review article and (Ramsay and Silverman 2005) for a book-length treatment of the area.

As noted in the introduction, FDA regards the complete, structured timeseries for a subject as a single functional data point, often denoted as $y_i(t)$. Thus, the data observed for each child i are indexed by the time of day t, and the temporal structure of the timeseries is incorporated into all subsequent analyses. Thus accelerometer data lend themselves easily to FDA.

The figure below plots accelerometer data used in our analysis. We focus on children observed in the warm months and restrict our analysis to the daytime hours (6:00am to midnight). We average across days, so that $y_i(t)$ is the average of activity counts at time t for child i across all observation days, to avoid a multilevel structure. Finally, we aggregate data into 10-minute epochs to reduce the computational burden of our analysis. The resulting trajectories are plotted for all children in the top left panel below, with the population average trajectory emphasized as a bold curve. The remaining panels show the same data but separate children into groups based on observed covariates, showing group-specific means again as bold curves.

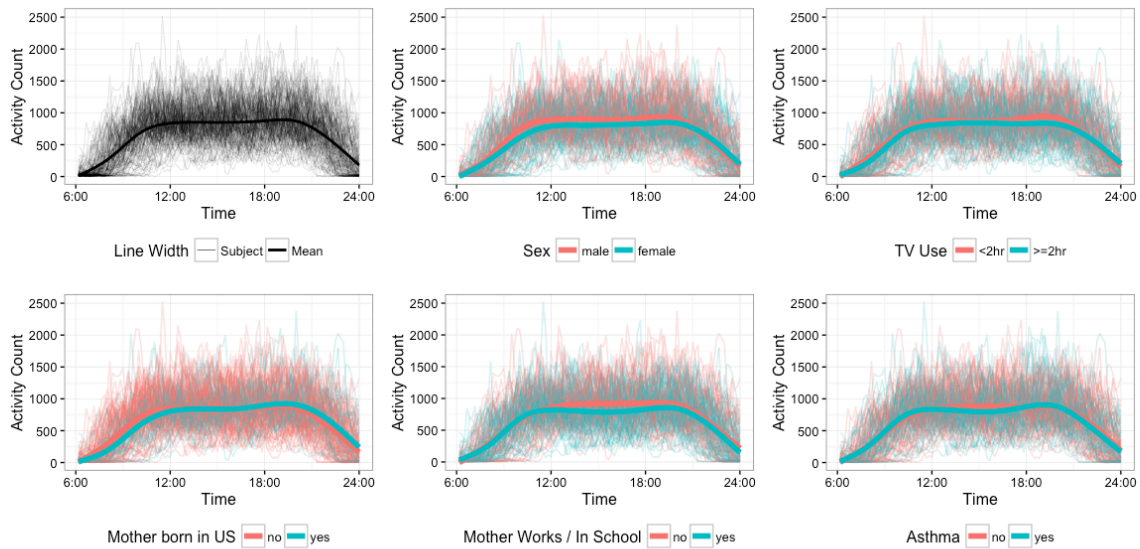

Figure 1: Observed accelerometer data for all subjects (faded curves) and group averages (bold curves). In the top left panel, data are shown in the same color for all subjects; in remaining panels, data are colored according to covariates.

Comparisons of group-specific mean curves suggest that covariate effects are often time-specific. For example, girls have on average lower activity than boys during daylight hours but equal (or even higher) activity in the evening. Children who watch ≥ 2 hours of TV have lower activity than children who watch < 2 hours of TV, but this difference is largely confined to the evening hours. To better understand these associations, to adjust for possible confounding, and to establish statistical significance, we make use of regression modeling.

Function-on-scalar regression (FoSR) relate functional responses $y_i(t)$ to scalar covariates x_i (e.g. age, sex, asthma diagnosis). As a starting point, the function-on-scalar model that is analogous to simple linear regression is

$$y_i(t) = \beta_0(t) + \beta_1(t)x_i + \epsilon_i(t).$$

The coefficients $\beta_0(t)$ and $\beta_1(t)$ are interpreted analogously to coefficients in a simple linear regression -- the intercept is the expected response in the reference group, and the slope is the expected change in response for each one unit change in the predictor -- with the exception that they, like the outcome, are defined for all time points during the day. Similarly, the error term $\epsilon_i(t)$ indicates the departure of the observed data from its conditional expectation at each time t. Errors are assumed to be correlated over time t, so that above-average activity in the morning may indicate above-average activity in the afternoon, but are independent across subjects i. Details on the estimation of the FoSR model appear in the Appendix; here we focus on the interpretation and results of these analyses.

The following property of the FoSR model is useful in the context of accelerometer analyses. Integrating a curve over t takes the average of that curve: $\int y_i(t)\,dt = \overline{y}_i$ is the average activity observed for subject i. Analogously, $\int \beta_0(t)\,dt = \overline{\beta}_0$ is the average activity in the reference group, and $\int \beta_1(t)\,dt = \overline{\beta}_1$ is the expected change in the average activity for each one unit change in the predictor. These values can be compared to the coefficients estimated in a multiple linear regression for average activity to provide a heuristic check for the validity of results and to indicate that the FoSR model retains the information in models for aggregate activity.

4 Application of Function-on-Scalar Regression to the Head Start Study

We use the FoSR model, directly extended from the above formulation to include multiple scalar covariates, to study the association between activity trajectories and child demographics (sex, age), mother's demographics (age, birthplace, occupation), behavioral variables (>2hr per day of TV, > 1hr per day of video games), and asthma symptoms. For context, we also repeat the Rundle's multiple linear regression analysis, using average activity counts between 6:00am and midnight (rather than in awake minutes) as the scalar response. The table below shows coefficient estimates and p-values for the multiple linear regression in the first two columns; they are comparable to those found in the original publication. The remaining columns show the integrated coefficient functions and the p-values resulting from a test of the null hypothesis $H_0: \beta(t) = 0$ for all t.

A comparison of covariate effects in Table 1 indicates agreement between the multiple linear regression and the function-on-scalar regression model in terms of the sign and magnitude of coefficients, and in most cases the statistical significance of the estimates. For example, both models suggest that girls are less active than boys, and that children who watch < 2 hours of TV are significantly more active than children who watch ≥ 2 hours.

	Beta, MLR	P-value, MLR	Beta, FoSR	P-value, FoSR
Intercept	777.145		759.743	
Sex (ref: Male)	-80.657	0	-81.921	0.001
Number of Rooms in the House	19.686	0.05	17.648	0.216
Mother Works / is in School	-62.618	0.002	-56.340	0.008
Mother Born in the US	-1.966	0.938	18.951	0.014
>2hr TV per day	-45.673	0.024	-42.209	0.056
>1hr Video Games per day	-25.719	0.244	-31.926	0.091
Child age (in months)	1.309	0.319	0.849	0.151
Child has Asthma	-24.365	0.25	-27.908	0.226

Table 1: Estimated coefficients ("Beta") and p-values from two analysis strategies. Multiple linear regression (MLR) results are shown in the first columns; function-on-scalar regression (FoSR) results are shown in the second columns. For the FoSR model, estimated effects are the integrated coefficient functions and p-values are global tests of significance for the coefficient function.

4.1 Function-on-scalar regression refines understanding of previously known effects

The results in Table 1 mask the temporal structure of the function-on-scalar regression by focusing on $\int \beta(t)\,dt$. Examining the coefficient functions $\beta(t)$ illustrates that the effect of covariates can differ over the course of the day. In the top row of Figure 2, we show the intercept function $\beta_0(t)$ and the coefficient functions for sex and TV use in the left, middle, and right panels, respectively (these plots can be compared to the plots in the top row of Figure 1, which show the observed data for all subjects and the data separated by sex and TV use). Similarly, the bottom row of Figure 2 shows the coefficient functions for mother's birthpalce, mother's occupation, and asthma in the left, middle and right panels, and can be compared to the plots in the bottom row of Figure 1. For each coefficient function, we include pointwise 95% confidence intervals to indicate the strength of association at each time.

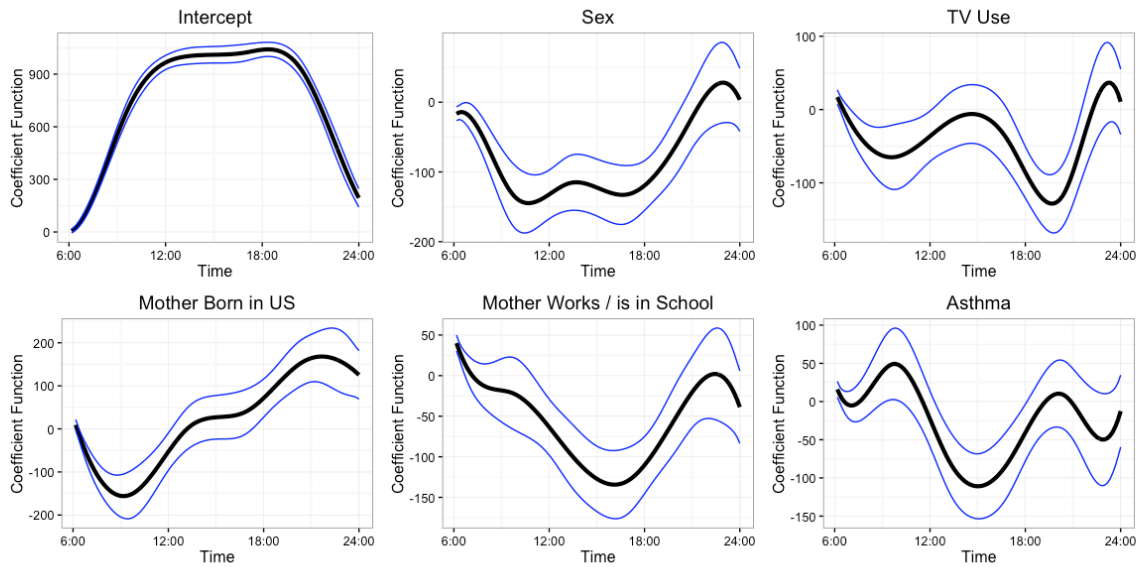

Figure 2: Estimated coefficient functions in the function-on-scalar regression model (black curves), with pointwise 95% confidence intervals (blue curves). Panels correspond to the variables used to color the data in Figure 1.

The intercept is the expected activity count trajectory for a child in the reference group; not surprisingly, the expected activity level is low in the early morning, high and roughly constant from mid-morning to early evening, and declining in the late evening and night. The coefficient function for sex indicates that the difference between boys and girls is substantial and consistent during daytime hours, when girls are less active than boys, but not in the evening. TV watching has localized effects: children who watch ≥ 2 hours of TV have are less active than others in the morning and in the evening but not in the afternoon. The inclusion of temporal structure in the function-on-scalar regression approach thus provides more detailed insights into behavioral differences than can be detected when the outcome is an overall average of activity, even for variables with known effects on activity. Lastly, the coefficient for mother's occupation, a binary variable indicating that the mother works outside the home or is in school, suggests that the mother’s absence has a significant negative effect on activity in the afternoon and early evening, but no effect in the morning or later in the evening.

4.2 Function-on-scalar regression identifies new effects

Although the sign and magnitude of aggregate effects in similar for the multiple linear regression and function-on-scalar regression models, the significance of the effect of the mother having been born in the United States is quite different. The multiple linear regression suggests that children of foreign-born mothers and children of mothers born in the United States do not differ in activity (p-value 0.938),), but the function-on-scalar regression models indicate that mother’s birthplace has is indeed associated with children’s physical activity (p-value 0.014). The coefficient function for this effect, in the left panel below, explains the discrepancy: the children of mothers born in the United States are less active in the morning and more active in the evening than children of mothers born elsewhere. Because these differences are offsetting in aggregate, the multiple linear regression misses the true effect.

A primary hypothesis of this study was that children with asthma have different activity levels than children without asthma. As Table 1 indicates, the aggregate model found no effect of asthma on total activity, a conclusion that was reported in (Rundle et al. 2009). A test of the hypothesis $H_0: \beta_{asthma}(t) = 0$ for all t in the function-on-scalar regression model also fails to reject the null, but examining the effect over the daytime hours indicates periods of decreased activity among asthmatic children. At many time points during the day asthma is not associated with activity, and these times limit the power to reject the preceding null hypothesis; the same situation often arises in multiple linear regressions when conducting a global F-test of many coefficients. However, the confidence interval for the coefficient function does not include 0 from 12:00 to 18:00; children with asthma are less active than other children in this time window.

5 Discussion

Our re-analysis of accelerometer data using function-on-scalar regression has improved our understanding of physical activity in children in several important ways. The analyses provide nuanced information about the specific time course of differences in physical activity that were previously identified more grossly using simple linear regression analyses of total activity count data. For instance, a deficit in activity has been previously observed with more time spent watching TV and the mother either working or attending school; in our analysis the time course of this deficit is evident. More importantly, the FoS analyses identify additional, previously hidden, associations between physical activity and socio-demographic characteristics – the lower morning activity of children of mothers born outside the United States – and between physical activity and health – the dip in activity during the afternoon among children with asthma.

The FoS analyses show that while children of mothers born in the U.S. and children of mothers born outside the United States have similar total weekly counts of activity, the two groups of children achieve their activity levels on different schedules. The analyses suggest that interventions to increase total physical activity among children of mothers born outside the United States might focus on activity patterns before the noon hour. The analyses do not tell us why children of mothers born outside the United States are less active in the morning than other children, but the results at least raise a question we would not otherwise know enough to ask. We can then undertake qualitative research studies to understand the causes and use that understanding to formulate interventions to increase activity in the morning hours.

The relative drop in activity in the afternoon among children with asthma as compared to children without asthma is of particular interest: prior analyses of total physical activity in this data set showed no difference in activity by asthma status (Rundle et al. 2009). Ground level ozone levels peak in the summer months, in the early afternoon, and ozone exposure is associated with increased emergency department (ED) visits and hospitalizations for asthma a few days after high ozone exposures (Kheirbek et al. 2013, Sheffield et al. (2015)). The dips in activity observed among children with asthma during the early afternoon may reflect mild respiratory function impairment or irritation of the respiratory tract associated with ozone exposure among asthmatics (Gent et al. 2003, Gold et al. (1999), Ierodiakonou et al. (2015), Khatri et al. (2009)). FoS analyses of accelerometer data may be useful for identifying more subtle effects of environmental pollutants on behavior among at-risk children.

The novel insights presented in this paper were made through the application of recently developed statistical models to physical activity trajectories. This analysis strategy is an alternative (or complement) to standard analyses of accelerometer data that aggregate minutes into a single summary and, in doing so, obscure potentially important information about the timing and structure of activity. Several barriers to the broader adoption of such methods exist, and one goal of this article is to reduce those barriers by building awareness of functional data approaches and clearly interpreting the results of such analyses. The interpretation of our model and results is very much aided by the use of interactive graphics, which are available online. To facilitate the implementation of similar analyses, all code used for this paper and for the interactive graphic is publicly available in the R statistical computing language.

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Conflicts of Interest

The authors have no conflicts to disclose. The results of the present study do not constitute endorsement by ACSM.

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