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AUTISM

The Movement-Sensing Perspective

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14 Micromovements

The s-Spikes as a Way to "Zoom In" the Motor Trajectories of Natural Goal-Directed Behaviors

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CONTENTS

Computer simulations of spike trains generated by brain neurons have been a useful tool to generate questions in the field of computational neuroscience. There is, however, a paucity of such methods in the study of complex behaviors, including analyses of kinematics parameters from movement trajectories embedded in natural purposeful behaviors. This chapter explores new data types and computational techniques leading to the simulation of patterns present in actual empirical data, along with synthetic patterns generated by computational models. We discuss their utility in setting normative bounds to compare modeled data with actual data obtained from individuals with the pathology of the developing nervous systems leading to a diagnosis of autism spectrum disorder (ASD).

INTRODUCTION

In this new era of wearable sensors and mobile-health concepts, it will be very useful to have methods that exploit various layers of variability in biophysical signals. Indeed, transitioning from instrumentation output to interpretable signal readout from the nervous systems is challenging. For example, if we seek to understand the timely synchronization in repeated pointing behaviors (e.g. in Figure 14.1) to begin to relate movement and gestural language in autism, we may want to preserve the original temporal dynamics of the raw data we acquire. To do so, we may want to select smoothing techniques to convert the discretely acquired signal into a continuous waveform representing a continuous random process. Then we can examine the stochastic properties of such a waveform and assess the levels of noise and signal that the nervous systems of the person are most likely accessing from moment to moment.

What types of filtering and smoothing may be most appropriate to attain our goals of capturing signals with the potential to be physiologically informative? And what types of data could we derive from such filtering with the potential to help us automatically classify heterogeneous phenomena in autism? Figure 14.1 invites some thoughts on these questions and shows some sample data types that we can extract from noninvasive wearable sensors.

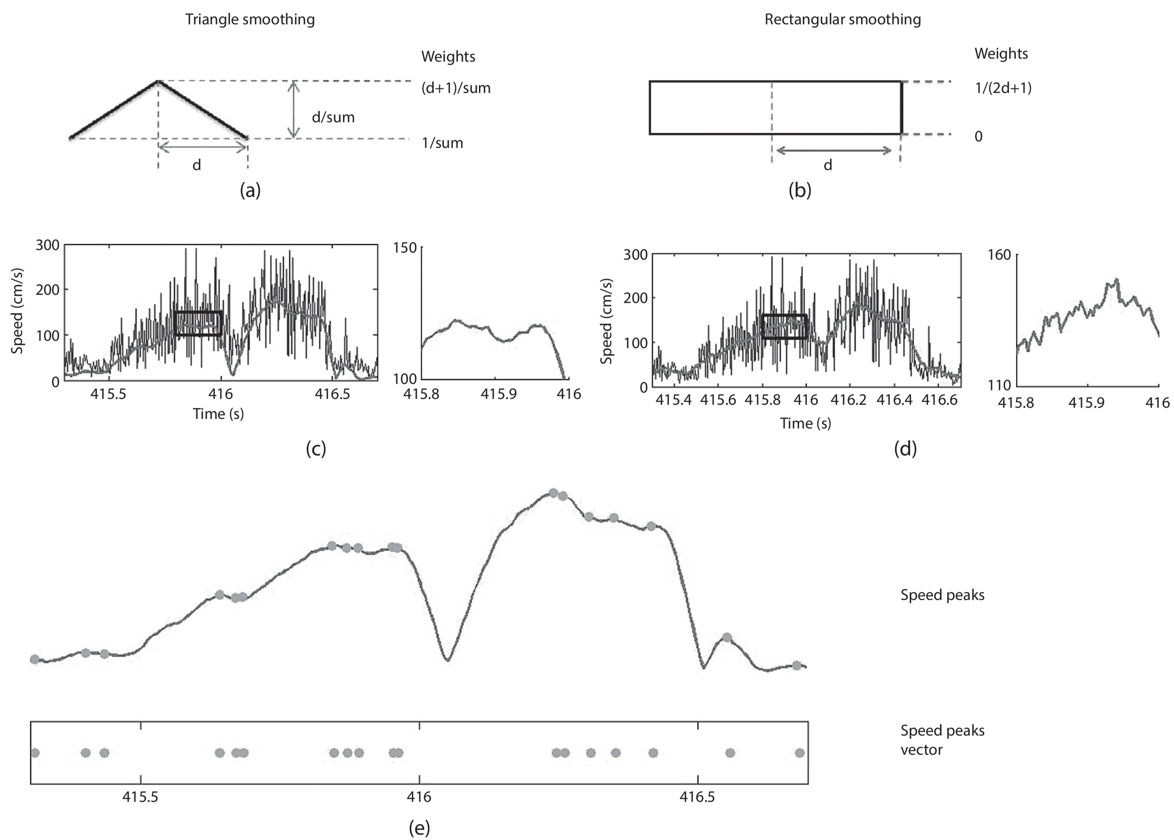

FIGURE 14.1 Filtering and smoothing process preserving the original raw data temporal dynamics while extracting new data types. Illustration of the triangular (a) and rectangular (b) smoothing algorithms. (c) The triangular smoothing algorithm preserves the internal fluctuation timings, removing the high-frequency external noise. (d) The rectangular smoothing algorithm fails to eliminate high-frequency noise, smearing the internal fluctuations. (e) New data type quantifying motor noise noninvasively at the millisecond range: identifying s-Peaks along the time profiles building up the s-Peaks' vector containing the temporal peaks' information.

An appropriate filtering algorithm should remove the unwanted nonphysiological external noise while retaining the internal motion fluctuations. Inherent motion fluctuations usually appear in the speed profile in the form of extra peaks sporadically appearing along the profile. To preserve the information possibly contained in these peaks, like their occurring rates and patterns, we selected a triangular smoothing algorithm. This algorithm was implemented by using a moving triangular window (Figure 14.1a), which replaces each point in the profile with the average of the data points in that window (the data points are weighted accordingly, as shown in Figure 14.1a). In comparison, traditional smoothing algorithms usually use rectangular filtering windows to calculate the average of the data points inside the window with the same weights (Figure 14.1b). Figure 14.1c and d plots and compares the results from applying the triangular and rectangular smoothing algorithms (having the same window size, 25 frames) on the same raw data. The zooming in of the profiles (right panels) clearly shows that the triangular smoothing algorithm works better at getting rid of the high-frequency external noise, while maintaining the curve's shape. In this chapter, the smoothing parameter was carefully selected to extract most of the information discussed below. The robustness of the parameter selection was also tested.

From Continuous Signals to "Spiking" Information

The minute fluctuations here and there along the speed profile can now be studied because their temporal dynamics were preserved. As such, Figure 14.1e shows how, after implementing the smoothing algorithm, those minute fluctuations in the speed profiles become evident. We identified the local peaks appearing along the speed profile (green dots in the plot) and named them speed peaks (s-Peaks). Temporal information about the s-Peaks (time when the s-Peaks appear) was extracted in the form of an s-Peak vector (bottom plot): when there is an s-Peak, the vector element is assigned a 1; otherwise, it is assigned a 0. In analogy to the widely used neuron action potential spike raster-gram in computational neuroscience, we then built up an s-Peak matrix with the s-Peaks' temporal information across cycles.

This new data type resembling spike trains commonly studied in the cortical neurons invites us to now think about possible peripheral activity transmitted by the peripheral nerves. Since the moment-by-moment events that these s-Peaks illustrate accumulate probabilistic information over time, it is possible to import several of the techniques already developed in the field of computational neuroscience and adapt them to understand the statistical signatures that the new data type provides.

The advantages and critical features that distinguish our approach from others in kinematics analyses within the ASD community studying motor dysfunction are that under this new platform of work, it is possible to:

1. Build analytical simulations
2. Test the predictions in the empirical arena

Further, new empirical questions can be designed to explore theoretical model-driven predictions not yet found in the empirical data. This ability to explore and empirically test artificial behaviors that can be evaluated against actual empirical data is an advantage of computational neuroscience that sets this approach apart from the traditional experimental paradigms often employed in ASD research—often constrained to the fields of psychology and psychiatry. Such fields are somehow often forced into hypothesis testing, with little to no scope for the discovery of novel or unexpected outcomes. Indeed, in our approach we use analytical techniques that later permit derivations of patterns in normative data for comparison with patterns in real experimental data obtainable from persons with pathologies of the nervous systems.

This interchange between analytical simulations and data-driven analyses is amenable to uncover self-emerging patterns and provide easier ways to interpret their possible meanings in light of the stochastic signatures they reveal. For example, we can focus on two features of the motor output data: their randomness and noise-to-signal ratio (NSR). Examining their presence and evolution over time in large cross sections of the autistic population can be rather illuminating, particularly when we do so in the context of other neurological and/or neuropsychiatric disorders. In this sense, the inherent variability in the continuously recorded data, as captured by critical points of change and temporal dynamics fluctuations, will no longer be treated as "noise." As we will see, noise can be a signal to the nervous systems.

SIMULATING PATTERNS AND EMPIRICALLY VERIFYING THEM

Random versus Periodic Behavior of Motor Output Fluctuations

Figure 14.2a presents the results of simulations that help us generate indexes distinguishing between random and periodic patterns across trials of s-Peaks. More specifically, we simulated the s-Peaks' matrix for two processes: one as a homogenous Poisson process, representing a motion process with high randomness, and the other for a partially synchronized process, representing a motion process with more control and higher periodicity.

We further introduced two tests to characterize the differences between these two processes. The first test was to measure synchronicity among cycles by calculating the cross-correlation function as a function of the binning width (Figure 14.2b). A somewhat related approach was used by Wang and Buzsaki (1996) for neuronal cortical spikes. The second test consisted of calculating the statistics of the temporal intervals between adjacent s-Peaks. This is analogous to the interspike interval (ISI) analyses done in computational neuroscience (Figure 14.2c).

When examining the actual empirical data in search of patterns of randomness and periodicity (synchronicity) in the s-Peaks, we found that in ASD the former is more common, while in typical development the latter prevails. Representative results are shown in Figure 14.3. They characterize the s-Peaks of pointing motions from children with ASD and varying degrees of spoken language capacity at the time of the experiments. Their more random s-Peak patterns contrast to the well-structured periodic ones of a neurotypical control child of similar age.

Note that the more random the patterns were, the lesser was the ability to articulate language. We posit that this type of randomness, which we also found in such motions when "zooming out" and examining the global peak speed of each forward and backward segment trajectory discussed in Chapter 7 (also see; Torres et al. 2013), may be a systemic issue in ASD. That is, these random patterns may also be found in motions executed by the orofacial structures involved in language. These structures are responsible for the control and feedback of the sensory motor apparatus responsible for the sound production, sound reception, and anticipatory synergies necessary to timely coarticulate modules of continuous speech.

The neuroanatomical structures of the face and body invite some thoughts on their functional interrelations and/or degree of independence, particularly those between the trigeminal ganglia innervating facial structures and the dorsal root ganglia underlying the structures involved in arm movements, upper-body control, and control of upright locomotion. These relations must be understood in light of the important roles of the information exchange of the peripheral nervous system (PNS) to the central nervous system (CNS) and the CNS to the PNS via efferent and afferent nerves. The above results are a first step in beginning to connect gestural and spoken language to underlying motion patterns. This connection is proposed under a unifying statistical framework that for the first time unveils potential avenues to link communication and neuromotor-sensing-based control.

In this sense, the maps in the periphery must develop properly to send proper feedback and help scaffold their corresponding projections across cortical and subcortical structures of the CNS. We posit that systems with impeded (random and noisy) peripheral feedback will have difficulties with the continuous correction and prediction of sensory motor delays. The moment-by-moment persistent randomness will most likely force the person to live in the "here and now" (Brincker and Torres 2013), relying on the current sensory information, but having difficulties anticipating the

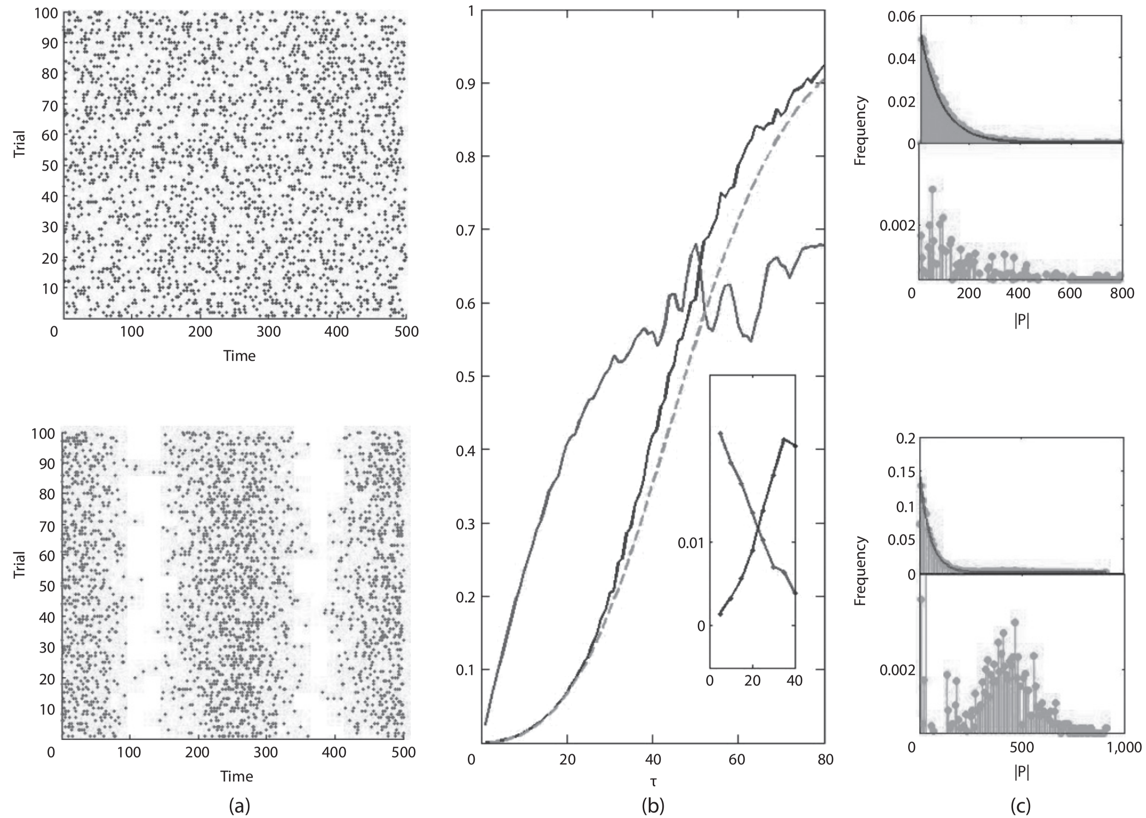

FIGURE 14.2 Simulation patterns and feature characterizations. (a) Raster-gram-like s-Peak matrices for simulated homogeneous Poisson peak train (upper) and simulated partially synchronized peak trains (bottom). (b) Population cross-correlation function, C, as a function of binning window size, τ, for (a and b). Green dashed line denotes the analytically calculated curve for random Poisson train peaks. Blue curve shows the simulated Poisson random train peaks, and the red curve the simulated partially synchronized peaks' train. Inset shows the corresponding slopes of the $C(\tau)$ curves. (c) Histogram of temporal intervals between nearest-neighbor s-Peaks in two simulated cases. Solid lines indicate the exponential fit (for values lower than 50). Bottom panels plot the histograms of the intervals outside of the exponential fit region, which distinguish these two cases.

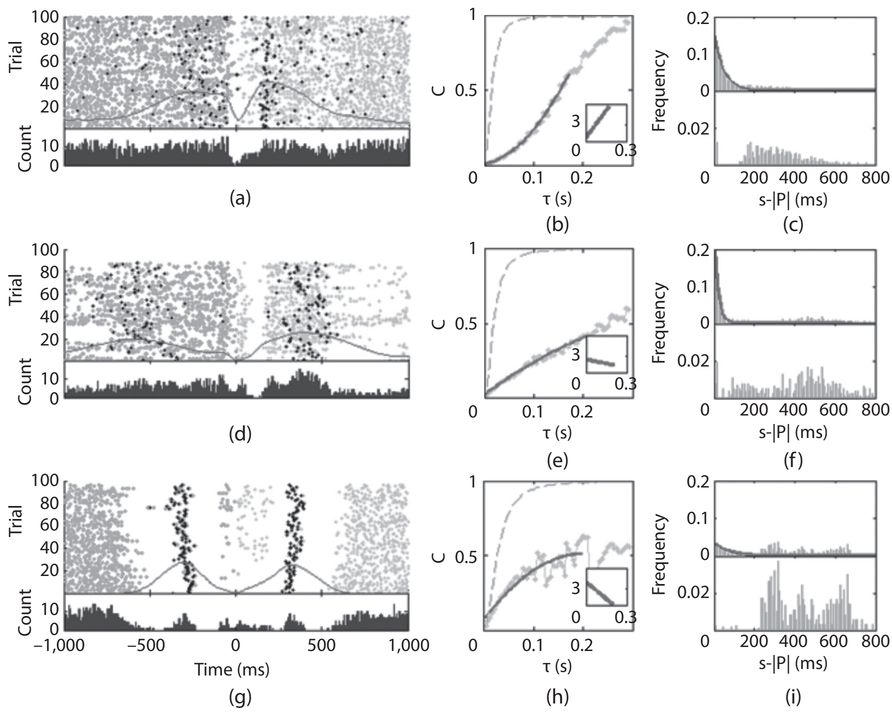

FIGURE 14.3 Sample data sets from three representative children and patterns similar to those found from the simulations in Figure 13.1. (a) Child with ASD and no spoken language. Black dots mark the global peak of the segment, while green dots are local s-Peaks forward and orange dots are s-Peaks backward. (b) Excess randomness predicted by analytical simulations and present in the actual data. (c) Inter-s-Peak times fit by the exponential and residual distributions in the tail highlighted in the bottom panel. (d) A child with ASD able to express some phrases shows a more periodic structure than the child in (a). (e, f) As before, mark differences in the periodicity and inter-s-Peak interval distributions. Specifically the s-Peaks that do not fit the exponential distribution (i.e., longer-range intervals between s-Peaks) are more noticeable than those in (a). (g) Well-structured (periodic) patterns in the neurotypical control. (h) Distinct patterns captured by a biometric developed analytically with the simulations. (i) Very distinct patterns for the inter-s-Peak interval distributions away from the exponential fit.

future sensory consequences of actions from the past sensory events that those actions themselves caused. In the face of such challenge and the disparate temporal and frequency scales of multimodal sensory transduction, how can the organism sense and perceive the world simultaneously? Clearly, if in addition to the excess randomness there is excess motor noise, the problem of neuromotor prospective control will be even harder.

CONCLUSIONS AND TAKE-HOME MESSAGE

This chapter underscores the importance of examining and modeling more than one layer of precision in data harnessed from the nervous systems. By taking seemingly smooth overt movement trajectories of the hand toward targets and obtaining variations in micromovements, we have identified a new type of spike train with the potential to facilitate detection and systematic quantification of excess noise and randomness in developing nervous systems. Such information, considered a nuisance and treated as noise under traditional averaging techniques, proves to contain signals with great utility to detect and track atypical neurodevelopment of motor control. Such involuntary micromotions possibly affect timely feedback and consequently impede the ability to properly articulate language. This work paves the way to quantify and possibly bridge elements of motor control with elements of cognition and communication at subsecond timescales.

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