Oscillation and Complexity in Early Infant Behavior

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ROBERTSON, STEVEN S. Oscillation and Complexity in Early Infant Behavior. CHILD DEVELOP-MENT, 1993, 64, 1022-1035. Cyclic fluctuation is a ubiquitous property of spontaneous motor activity in the human fetus and neonate. Oscillation occurs on the scale of minutes, and irregularity is one of its most characteristic properties. To determine whether cyclic motor activity (CM) persists beyond the neonatal period (1 month after birth), and beyond what has been called the period of the fetus ex utero (2–3 months after birth), 30 infants were studied at monthly intervals from 1 to 4 months after birth during active sleep and awake. Spectral analysis was used to quantify the rate, strength, and irregularity of CM. To examine the characteristic irregularity of awake CM more closely, a nonlinear forecasting technique, developed to study chaotic dynamics in other fields, was used to estimate the predictability of spontaneous movement in a state space reconstructed from the time series. The rate and irregularity of CM during active sleep and awake, and its strength during active sleep, did not change across the first 4 postnatal months. However, there was a pronounced drop in the strength of awake CM from 2 months onward, and a concurrent increase in the broad-band power of fluctuations faster than 2 cycles/min. The predictability of awake CM also dropped abruptly between 1 and 2 months, especially for prediction intervals less than 20 sec. The changes at 2 months reflect the introduction of a source of variation with a shorter time constant than fetal-neonatal CM, and which is specific to awake periods. The source of these effects may be moment-to-moment interactions between CM and attention.

In the human fetus and neonate, it is now well established that spontaneous motor activity oscillates on a scale of minutes (Robertson, 1990). Similar temporal patterns have been described in the embryo or fetus of other vertebrate species (Corner, 1977; Hamburger, Balaban, Oppenheim, & Wenger, 1965; Oppenheim, 1975). This cyclic motor activity (CM) is an order of magnitude slower than other biological oscillations that have rather clear adaptive significance, such as the respiratory and cardiac cycles. CM is also an order of magnitude faster than the cyclic alternation of sleep states (Anders & Keener, 1985; Prechtl, 1974) or periods of rest and activity (Aserinsky & Kleitman, 1955). Thus CM appears to fill a gap in the broad spectrum of behavioral and physiological oscillations in the human, and further illustrates the ubiquity of oscillations in living systems (Aschoff, 1981). Understanding CM will require knowledge of its possible

functional significance, its underlying mechanism, and its ontogeny (Tinbergen, 1963), at least. The study reported here charts the early postnatal development of human CM, and examines its characteristic irregularity in real time using techniques developed in other fields to predict the future behavior of chaotic dynamical systems.

The functional significance of CM has not been studied extensively, and the existence of CM is not necessarily evidence of its utility (Gould & Lewontin, 1979). However, based on the known importance of movement and neural activity in prenatal neuromuscular maturation (Drachman & Sokoloff, 1966; Harris, 1981), and the utility of oscillation in other biological systems (Rapp, 1987), it has been speculated that cyclic organization in spontaneous motor activity may balance the benefits of activity and quiescence (Robertson, 1989). It is also possi-

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ble, especially after birth, that CM may regulate interactions between the infant and its physical and social environment, with beneficial, neutral, or adverse consequences (Robertson, 1989). For example, recent evidence indicates that, in the first 3 months after birth, the rates of change in visual attention and spontaneous activity are tightly coupled on a scale of seconds (Robertson & Bacher, 1992), and that irregular, rapid fluctuations are suppressed during social interaction (Lalley, 1992).

The mechanism underlying CM has been investigated using two complementary approaches that have been successfully combined in the study of other biological oscillations (Aschoff, 1981). One approach has been to identify the neural substrate of CM in an animal model (Oppenheim, 1975; Provine & Rogers, 1977; Smotherman, Robinson, & Robertson, 1988). Spinal cord transection in the fetal rat indicates that there are at least two sources of CM in that species, with rostral sources oscillating slower than caudal sources, but with the faster caudal sources dominant in the intact animal (Robertson & Smotherman, 1990a). Another approach has been to investigate the dynamic properties of the mechanism without specific regard to their neural substrate. For example, an experiment with neonates (Robertson, in press) using a classic resetting paradigm (Winfree, 1980) to probe the mechanism responsible for CM suggested that a simple, one-source model in which the amplitude of oscillation is unimportant may be adequate to explain human CM, although a multisource model based on the fetal rat data cannot be ruled out. In addition, recent work indicates that both human and rat CM may be the output of a system governed by chaotic dynamics with relatively few degrees of freedom (Robertson, Cohen, & Mayer-Kress, in press; Robertson & Smotherman, 1990b). Thus both the persistence and the irregularity of the oscillations in spontaneous motor activity (the core characteristics of CM) may be equally fundamental properties of the same mechanism.

Previous longitudinal studies have revealed that CM is present in the human fetus by midgestation (Robertson, 1985), and ultrasound observations raise the possibility that it may be present in the first trimester (deVries, Visser, & Prechtl, 1982). The characteristic properties of CM change very little during prenatal development in normal fetuses (Robertson, 1985), and birth does not induce any detectable changes either (Rob-

ertson, 1982, 1987; Robertson, Dierker, Sorokin, & Rosen, 1982). The developmental stability of perinatal CM has been replicated in fetuses and newborns of diabetic mothers (Robertson, 1988; Robertson & Dierker, 1986). Although maternal diabetes affects fetal CM early in the third trimester, especially its rate (Robertson, Klugewicz, & Lalley, 1992), all the measured properties are normal by the end of gestation and remain so after birth, suggesting that the development of CM is relatively well buffered from the effects of an abnormal metabolic environment in utero.

Given the ubiquity and stability of CM in the fetus and neonate, a major unanswered question concerns the postnatal development of human CM: is it strictly a fetal-newborn phenomenon, or does it persist after the widespread changes in other aspects of neural and behavioral organization that occur 2-3 months after birth (e.g., Banks & Salapatek, 1983; Chugani & Phelps, 1986; Emde, Gaensbauer, & Harmon, 1976; Hopkins & Prechtl, 1984; Wolff, 1984) and that are thought to mark the end of the period of the fetus ex utero (Prechtl, 1984)? In addition to being a central developmental question, the postnatal fate of human CM has implications for understanding its functional significance. If CM persists, there is the possibility that it might play new or continued roles in early development with either beneficial or adverse consequences. Therefore, the postnatal development of CM was investigated in the present study by analyzing the spontaneous motor activity of 30 infants during active sleep and awake states at monthly intervals between 1 and 4 months after birth.

In addition to describing the results of the longitudinal study, a second purpose of this report is to examine the irregularity of CM in more detail. The time series in Figure 1 illustrates that the cyclic fluctuations in spontaneous motor activity are not rhythmic; the period of oscillation is irregular (Robertson, 1989). Most of the CM work to date has focused on the cyclic organization in spontaneous motor activity, but has neglected its irregularity. However, irregularity is arguably the most characteristic property of CM. It would also appear to be a significant barrier to *predicting* the fluctuations in spontaneous motor activity.

The irregularity of CM has been quantified indirectly by measuring the width of the dominant peak in the movement spectrum (see Method). In spite of its proven use-

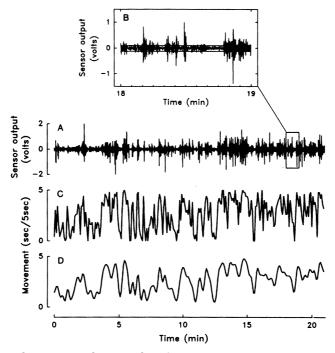


Fig. 1.—Data reduction procedures used to obtain a movement time series. A, Amplified output of the movement sensors during an awake period in a 3-month-old infant. B, Close-up of 1 min from panel A showing thresholds set at 98 and -122 mV to exclude sensor activity associated with breathing movements (e.g., at 18:45). The horizontal axis is marked in 5-sec intervals. C, Time series obtained from panel A by measuring the duration of sensor activity above the upper threshold or below the lower threshold (panel B) during successive 5-sec intervals. D, Time series from panel C after low-pass filtering, as described in the text.

fulness, this measure has (by design) no strong theoretical basis, and its indirectness may render it insensitive to changes in the dynamics responsible for CM. As noted above, recent work suggests that CM may be the output of a low-dimensional system with chaotic dynamics. Thus, at least some of the observed irregularity in the fluctuations of spontaneous motor activity may be deterministic or rule-governed, rather than the result of random factors. In constrast to noise, CM may have some short-term predictability (Guckenheimer, 1982). Therefore, in order to investigate the complexity of CM as the output of a relatively low-dimensional dynamical system, a new technique is introduced which has been developed to study the predictability of such systems.

If we knew (and could measure) the important state variables in the dynamics of CM, a straightforward approach to studying its irregularity would be to study the predictability of future states defined by those variables. However, we do not know the important state variables for CM, so it is not possible to study directly the trajectories followed by the system in its state space (in

which the coordinate axes are the state variables). This is a common problem faced by experimentalists studying dynamical systems. What we have is a single-variable readout of the system: the movement time series. Intuitively, this time series should contain some information about the dynamical system generating it, although perhaps not in a form that can be easily interpreted. The possibilty of working backward from the time series to study the underlying dynamics was proposed recently by Packard, Crutchfield, Farmer, and Shaw (1980). Theorems proved by Takens (1981) provide the mathematical justification for this approach. in which trajectories are reconstructed from a time series by an embedding process. Takens showed that important properties of the dynamics can be recovered from an analysis of the reconstructed trajectories (Robertson et al., in press).

Using this approach, a d-dimensional space is formed whose coordinate axes are successive values of the time series, separated by a constant delay, Δ . Thus, if x_i is the time series, the vectors $\mathbf{y}_i = [x_{i-(d-1)\Delta}, x_{i-(d-2)\Delta}, \ldots, x_i]$ are formed, which define

points in the reconstructed state space. The sequence of states, y_i , y_{i+1} , ..., then defines a trajectory in the reconstructed state space.

Working in the reconstructed state space, there are numerous ways to go about predicting the future states of the system given its current state. Farmer and Sidorowich (1987, 1988) and others (e.g., Casdagli, 1989; Sugihara & May, 1990) describe both global and local methods. In general, global techniques try to find the functional relation between y_t and y_{t+T} using all the data. Farmer and Sidorowich point out some of the problems with many of the global techniques, including a strong dependence on the specific representation or function used to describe the relation between past and future states. They recommend local approximation techniques, in which the state of the system at t + T is predicted using only those previous states of the system located within a small neighborhood of the current state. In terms of the time series itself, this means that future values of x_t are predicted using earlier values of the time series with a history that is similar to the history of the current point. For example, if a threedimensional state space was formed by taking successive values of the time series (i.e., a delay of 1), states that are nearby in the reconstructed state space correspond to similar three-point sequences in the time series. Local techniques for making predictions therefore focus on the past behavior of the system which resembles the behavior of the system leading up to its current state, from which predictions are to be made.

The relation between the nearby states and their future states T time units later is then analyzed (linear regression is often used) to obtain a prediction for the future of the current state, y_t , at time t + T. It is common to use the scalar values in the time series corresponding to the nearby points in the state space for this purpose. For example, x_t would be the point in the time series corresponding to the point $y_t = [x_{t-(d-1)\Delta},$ $x_{t-(d-2)\Delta}, \ldots, x_t$] in the state space. An overall measure of predictability can then be obtained by repeating this procedure at each point along the trajectory of the system in its reconstructed state space, and then calculating the proportion of variance in the set of future values that is accounted for by the predictions.

The purpose of this report is twofold. The first is to describe the postnatal development of CM from 1 to 4 months. The pri-

mary motivation for conducting the longitudinal study was to determine whether cyclic organization, which is such a robust characteristic of spontaneous activity during prenatal and perinatal life, is a fetal pattern that disappears soon after birth, or persists and thereby has the potential for playing a more extensive role in early infant development. The second purpose of this report is to introduce a new approach to studying prediction, a central problem in science, using techniques based on the theory of dynamical systems. In the context of CM, the main motivation for doing this was to begin to analyze what is perhaps the most characteristic property of CM, its irregularity.

Method

Subjects.—Thirty infants (17 male) were studied at monthly intervals from 1 to 4 months after birth. All were healthy neonates, with birthweights between 2.61 and $4.25 \text{ kg} (3.46 \pm 0.34, \text{mean} \pm \text{SD}) \text{ and gesta-}$ tional ages between 38 and 42 postmenstrual weeks (40 \pm 1). Gestational ages were based on the date of the mother's last menstrual period before the pregnancy, except for three cases in which ultrasound measurements of the fetus were used because of uncertain dates of the last menstrual period or irregular menstrual cycles before the pregnancy. All infants' birthweights were appropriate for their gestational ages (Usher & McLean, 1969). Postnatal ages at the time of study were 30 ± 4 days (24–37, except one at 43) at 1 month, 59 ± 5 days (53-72) at 2 months, 86 ± 4 days (80–93) at 3 months, and 114 ± 4 days (106-123) at 4 months. None of the infants suffered any serious illness during the 4 months of study, although a few sessions were rescheduled due to minor illnesses (e.g., colds, ear infections). An additional five infants did not complete the study; three families had to be out of town for some of the sessions, one mother withdrew her infant because she felt he was colicky, and one family withdrew their infant for reasons not known to us. Information about the race and economic background of the subjects and their families was not collected.

Procedures.—In consultation with the infants' parents, study sessions were scheduled to maximize the chance of obtaining usable data from sleep and awake states, rather than to control the time of day at which they were studied. Although this means that systematic diurnal variation (if any exists) in the properties of CM appears as error variance

in the data, sources of variability associated with the quality of sleep and wake states were at least partially controlled, and the need for rescheduling to obtain usable data was minimized. Although some infants were studied in the evening (5 of the 120 sessions started after 18:00), most infants were studied during the daytime (76 sessions started before 12:00, 39 between 12:00 and 18:00), with similar distributions at each age.

Parents were asked to bring their infant to the lab just before an expected feeding and to feed the infant in the lab before data collection began. If an infant arrived awake and happy, feeding was delayed while an attempt was made to obtain usable awake data. Study sessions lasted from 1.0 to 4.8 hours (152 \pm 53 min), with similar distributions at each age. Data acquisition was continuous except when the infant was picked up to be soothed or fed.

The laboratory was acoustically insulated and the ambient sound level was maintained at 50 ± 2 dbA by an audio frequency white noise generator. Colorful, high-contrast posters were mounted on a neutral background approximately 100 cm from the infant to provide an interesting but static visual environment during awake periods and thereby maximize the amount of non-fussy awake time obtained. Light levels were approximately 300 lux at the infant's face when awake; lights were dimmed when the infant was asleep. Infants were lightly clothed to minimize restriction of limb movement. With two exceptions, infants were studied in an infant seat while awake and asleep so that state and postural differences would not be confounded. The seat was tilted back slightly so that the infant's head did not fall forward during sleep; a rolled diaper provided lateral head support. Parents reported that their infants routinely spent both awake and sleep time in an infant seat. The remaining two infants were studied prone (while asleep) at the mother's request.

Data acquisition.—Movement was detected by two piezoelectric sensors mounted in the back and bottom of the infant seat. The sensors were connected in parallel and AC coupled to a general purpose bioelectric amplifier and filter (Coulbourn S75-01). Sensor output was band-pass filtered between 1 and 40 Hz to remove slow baseline fluctuations and electrical noise. Respiration was detected by a strain gauge placed around the infant's abdomen over any clothing and secured with tape (to the clothing) in back. The gauge was a 10-cm length of thin (1 mm

diameter), mercury-filled, elastic tubing (with permanently attached lead wires) that served as one arm in a bridge circuit (Parks Electronic Plethysmograph 271). Respiration was used to distinguish active and quiet sleep and to determine thresholds for detecting body movement, as described below. Eye opening was observed directly through a small opening in the sound-proof divider separating the infant from the observer and apparatus, and recorded with a hand-operated switch. Vocalization was detected by a microphone that activated a voice switch (Coulbourn S28-24).

The movement, eye opening, and vocalization signals, plus a timing pulse (at 1 min intervals) and a manually controlled event switch, were digitized on-line at 50 Hz (Data Translation DT2801A) and stored for later analysis. All signals, including respiration, were simultaneously recorded on chart paper at 2 mm/sec (Astromed MT8500) for backup and to facilitate later data reduction.

Data reduction.—Data reduction was done off-line. First, the chart recording was used to code each non-fussy minute as quiet sleep, active sleep, or awake using criteria developed in previous studies (e.g., Robertson, 1987). Quiet sleep: eves closed for a total of more than 90% of the minute, regular respiration (see below), and no movement except for a maximum of two startles. Active sleep: eyes closed for a total of more than 90% of the minute, and either irregular respiration or movement (other than one or two startles). Breathing was considered to be irregular if, in the absence of body movement, breath-to-breath intervals changed by a factor of 2 or more (within 20 sec) twice or more during the minute, or there was a pause in breathing that exceeded 3 sec. Awake: eyes open for a total of more than 90% of the minute, and fussing for less than 10% of the minute. Using these criteria, agreement between independent coders is high (94% for awake vs. sleep, and 95% for active vs. quiet sleep).

Periods of stable state exceeding 5 min were then identified. After 2 min in a particular state, 1 or 2 min in a different state were ignored if they were followed by 2 or 3 min, respectively, of the original state. For the purpose of later analysis, a period of stable state ended if the infant was picked up, repositioned, or disturbed in any way. Periods of less than 10 min were not used unless there were none longer for the infant in that state at that age.

For each period of stable state, move-

ment time series were constructed by measuring the duration of suprathreshold movement sensor activity in successive 5-sec intervals (Fig. 1). Thresholds (positive and negative) were determined individually for each period of stable state and were set to exclude chest wall or other body movements associated with respiration.

Rate, strength, and irregularity of CM.—The cyclic organization of spontaneous movement in each time series was analyzed using methods described in detail in previous reports (e.g., Robertson, 1987) and summarized here. First, the time series was Fourier analyzed, and the resulting cumulative variance distribution was compared to the theoretical distribution of white noise with a Kolmogorov-Smirnov test to determine whether the fluctuations in movement were random (Jenkins & Watts, 1968). If they were nonrandom, the detrended time series was spectral analyzed using a Tukey lag window with a bandwidth of .32 cycle/ min to identify and describe any cyclic organization (Jenkins & Watts, 1968). A spectral peak was considered to reflect the presence of cyclic organization in the time series if it exceeded the 99% confidence limits for the spectral estimates of white noise.

Three measurements were made on the dominant peak in each movement spectrum to quantify the properties of the corresponding cyclic organization in the time series: (1) The frequency at which the peak occurred was used as a measure of the dominant rate or frequency of oscillation in motor activity. (2) The height of the peak was used as a measure of the relative strength of the dominant cycle in motor activity. (3) The width of the peak at its half-maximum point was used as a measure of the dispersion of movement variance around the peak in the frequency domain and hence irregularity in the dominant cycle of activity.

In addition to properties of the dominant motility cycle, the relative strength of broad-band, high-frequency fluctuations in motor activity was also determined. Specifically, the percentage of movement variance in each time series due to fluctuations faster than 2 cycles/min was calculated from the area under the corresponding spectral density curve (Jenkins & Watts, 1968) between 2 and 6 cycles/min (the Nyquist frequency). The average amount of motor activity in each time series (the mean of the sequence of 5-sec data points), which does not reflect its cyclic organization, was also calculated.

Predictability of CM.—The predictabil-

ity of the fluctuations in spontaneous motor activity was examined using the local approximation technique suggested by Farmer and Sidorowich (1987, 1988) and discussed above. The computational routines were written by Schaffer and Tidd (1991). Because the measure of predictability employed tends to increase with longer data sets (explained below), all time series were truncated at 10 min, and those shorter than 10 min were not used. A longer minimum length would have substantially reduced the number of time series available for analysis. In addition, time series in which the dominant rate of oscillation (based on the movement spectrum) was slower than 0.20 cycle/ min were not used, since long cycle times provide few opportunities for close recurrences of similar states in the reconstructed state space, and hence little data on which to base forecasts. It should be noted that much larger data sets are needed for a full analysis of predictability using these techniques. Thus the analysis of predictability based on the small data sets available in the present study was limited to comparisons between different ages and prediction intervals. The usable time series were detrended and then low-pass filtered (frequency response of 10% at 3.3 cycles/min) in order to focus on the predictability of the dominant, slower fluctuations characteristic of CM.

Each time series, x_i , $i = 1 \dots 120$, was then rescaled to [0, 1] and embedded in a three-dimensional space by constructing vectors whose components were the three successive values of the time series ending with x_i . The vectors, $y_i = [x_{i-2}, x_{i-1}, x_i]$, therefore defined points in a reconstructed state space where the coordinate axes are movement measured in three successive 5sec intervals, and the sequence y_i , y_{i+1} , . . . defined a trajectory in the reconstructed state space. The effects of longer delays were not investigated in this study, although others claim the results are not sensitive to the delay unless it is large (Sugihara & May, 1990). A three-dimensional embedding space was used because previous analyses (Robertson et al., in press; Robertson & Smotherman, 1990b) have suggested that CM dynamics are at least that complex. An embedding dimension greater than 3 was not used because it requires more data and because preliminary analysis of longer versions of some of the present time series revealed no important differences in the results.

For a given point in a time series, x_i , future values were predicted using all ear-

lier points in the reconstructed state space, y_i , j < i, within a distance of .15 (recall that the data were rescaled to [0, 1]). This distance was selected to be as small as possible in order to maximize the accuracy of predictions, but large enough to include some neighboring points. Prediction began with the twenty-fifth point so that there would be an initial library to search for nearby states. The prediction was based on the linear regression of x_{i+T} on x_i , where x_i are the points in the time series corresponding to the nearby states, y_j , in the reconstructed state space, and x_{i+T} are the values T sec later in the time series. The prediction intervals, T, were 5, 10, 15, 20, and 25 sec. Longer intervals resulted in consistently low predictability. The measure of predictability employed was the proportion of variance in the time series accounted for by the predictions, r^2 , using those points for which predictions were generated.

Time series from active sleep were not analyzed. Preliminary analyses indicated that the measure of predictability depended strongly on the length of the periods of motor quiescence that are common in active sleep. During periods of no movement, the trajectory lingers in a small volume in the reconstructed state space and thereby increases the overall measure of predictability. Although this is a valid result, it is not particularly interesting. In any case, the main motivation for examining predictability in the present study was the drop in the strength of CM and concurrent increase in highfrequency power during awake states at 2 months, described below.

Results

Existence of CM.—Analysis of the individual movement time series revealed strong evidence for CM in both active sleep

and awake states at 1, 2, 3, and 4 months after birth (Table 1). In 274 of the 297 usable time series, the cumulative variance distribution derived from the Fourier analyses departed from that of white noise (p < .05), indicating that the fluctuations in spontaneous movement were not random. Subsequent spectral analysis of those 274 time series provided evidence of cyclic organization in motor activity in all but 22, indicated by a peak exceeding the 99% confidence limits for the spectral estimates of a white noise process. No more than five of the infants with usable data for a particular state and age had no evidence of CM in the time series available. In none of the 30 infants was CM absent at all ages in either active sleep or awake states. The results from multiple time series from an individual infant at a particular age and state were averaged before conducting the group analyses reported in subsequent sections.

In spite of the near ubiquity of CM, it appears that CM was more likely to be absent after the neonatal period in this sample (see Table 1). At 1 month, 97% of the usable time series had statistical evidence of CM. From 2–4 months, CM was present in 78%–83% of the usable time series. The drop at 2 months is not simply an artifact of the number of usable time series available, since the numbers of usable time series have opposite trends across months in active sleep and awake states.

Rate, strength, irregularity.—The postnatal development of CM was examined with separate state (active sleep, awake) × age (months 1, 2, 3, 4) analyses of variance for the frequency, height, and width of the dominant peaks in the movement spectra (Fig. 2). Pairwise comparisons using all available data were done to explore effects revealed by the overall analyses of variance.

TABLE 1

MOVEMENT TIME SERIES WITH EVIDENCE OF CM

State	AGE (Months)			
	1	2	3	4
Awake	23/24	26/33	28/35	28/35
	(23/23)	(24/28)	(26/30)	(23/27)
Active sleep	50/51	41/48	31/37	26/34
	(30/30)	(28/28)	(25/28)	(21/26)

Note.—The number of time series with statistical evidence of CM and the total number of usable time series. In parentheses are the number of infants contributing time series with evidence of CM and the total number of infants with usable time series.

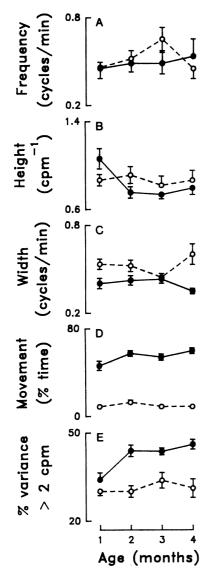


Fig. 2.—The (A) frequency, (B) height, and (C) width of the dominant peak in the movement spectra; (D) the average amount of movement in the corresponding time series; and (E) the percent of the total movement variance accounted for by fluctuations faster than 2 cycles/min, in active sleep (open circles) and awake (filled circles) states at 1-4 months after birth (mean \pm SEM). The numbers of infants contributing data are shown in the Table. Overall state × age analyses of variance reported in the text were based on 12 infants with CM in both states at all four ages. Pairwise comparisons between ages were based on the following numbers of infants during awake and active sleep, respectively: 19, 28 for 1-2 months; 19, 25 for 1-3 months; 20, 21 for 1-4 months; 20, 23 for 2-3 months; 19, 20 for 2-4 and 3-4 months. Comparisons between states were based on 23 infants at 1, 2, and 3 months, and 17 infants at 4 months.

Type I errors were controlled at .05 for each family of comparisons with a layered Bonferroni technique for adjusting α for each comparison (Miller, 1966; Ryan, 1960).

Rate of oscillation (Fig. 2A) was stable across the first 4 postnatal months, with no evidence of consistent state differences, as indicated by the absence of any main or interaction effects in the state \times age analysis of variance for the frequency of the spectral peak (all p's > .45). The apparent increase in the rate of oscillation during active sleep at 3 months was due primarily to two outliers with frequencies above 1.4 cycles/min.

The strength of CM (Fig. 2B) dropped precipitously at 2 months during awake states and remained stable thereafter, as indicated by a main effect of age, F(3, 33) =3.78, p = .02, and a state \times age interaction, F(3, 33) = 3.82, p = .019, in the analysis of variance for the height of the spectral peak. There was no main effect of state, F(1, 11)= 0.00, p = .99. Pairwise comparisons between ages revealed that CM strength at 1 month exceeded CM strength at 2 months [t(18) = 4.77, p < .001], 3 months [t(18) =3.13, p = .006], and 4 months [t(19) = 2.66,p = .016]. There were no age differences during active sleep, and the two states did not differ at any age. The strength of CM at 1 month during awake states is not likely to be a spuriously high value, since it corresponds to levels found in newborns in previous studies (Robertson, 1987, 1988).

The irregularity of CM (Fig. 2C) was stable across the first 4 months, but greater in active sleep than during awake states, as indicated by a main effect of state in the analysis of variance for the width of the spectral peak, F(1, 11) = 25.34, p < .001. There was no main effect of age, F(3, 33) = .45, p = .722, and only a marginal state \times age interaction, F(3, 33) = 2.26, p = .10. Pairwise comparisons indicated that the state difference was due largely to the greater irregularity of CM at 1 month [t(22) = 2.27, p]= .034] and 4 months [t(16) = 2.98, p =.009]. The absence of any differences at 2 and 3 months apparently contributed to the marginal state \times age interaction.

As might be expected, infants spent more time moving while awake than during active sleep, and these levels were stable across the first 4 months (Fig. 2D), as indicated by a main effect of state in the analysis of variance for the average amount of movement, F(1, 11) = 475.90, p < .001. There was no main effect of age, F(3, 33) = 1.00,

p = .405, and no state \times age interaction, F(3,33) = .862, p = .471. Pairwise comparisons confirmed large and consistent differences in the amount of movement during active sleep and awake states at each age (all p's < .001). The absence of any consistent state differences in CM's rate and strength of oscillation in spite of these large state differences in the amount of movement is consistent with findings in newborns (Robertson, 1987, 1988).

High-frequency power.—The drop in the relative strength of the dominant oscillation in awake CM from 2 months onward, without any evidence of increased irregularity or the appearance of other stable oscillations, suggested that more complex fluctuations outside the range of normal CM might have emerged. This possibility was examined by calculating the percent of the total movement variance accounted for by fluctuations faster than 2 cycles/min (Fig. 2E).

There was a consistent increase in the relative strength of these rapid fluctuations at 2 months that persisted through 4 months, as indicated by a main effect of state in the analysis of variance for percent variance above 2 cycles/min, F(1, 11) = 19.90, p =.001, and a main effect of age, F(3, 33) =3.45, p = .028. There was no interaction between state and age detected in the analysis of variance, F(3, 33) = 1.85, p = .157. Pairwise comparisons revealed increased highfrequency power during awake states (compared to 1 month) at 2 months [t(18) = 3.97,p = .001], 3 months [t(18) = 3.17, p = .005], and 4 months [t(19) = 3.82, p = .001]. These increased levels of high-frequency power during awake states exceeded the levels during active sleep at 2 months [t(22) = 5.61, p]< .001], 3 months [t(22) = 3.25, p = .004], and 4 months [t(16) = 3.78, p = .002].

Predictability.—Because of the added constraints imposed by requiring at least 10 min of usable data to do the nonlinear forecasting calculations, there were not enough infants with sufficient data during awake states at all ages to justify an overall analysis of variance. Pairwise comparisons between ages were therefore conducted with separate age × prediction interval (5, 10, 15, 20, 25 sec) analyses of variance.

The predictability of CM in the reconstructed state space of three dimensions dropped abruptly between 1 and 2 months during awake states (Fig. 3), as indicated by a main effect of age in the analysis of variance for r^2 , F(1, 6) = 30.44, p = .001. The

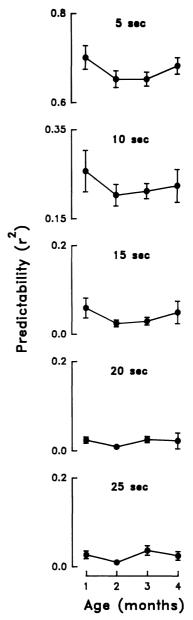


FIG. 3.—The proportion of variance (mean \pm SEM) in awake time series 1–4 months after birth accounted for by predictions made using the nonlinear forecasting technique described in the text. The prediction intervals are 5, 10, . . . , 25 sec. Each panel is plotted with the same scale on the vertical axis to facilitate comparisons. The numbers of infants contributing data at 1–4 months are 11, 19, 14, and 8. Pairwise comparisons between ages were based on the following numbers of infants with data at both ages: 7 for 1–2 months; 6 for 1–3 months; 5 for 1–4 months; 8 for 2–3 months; 6 for 2–4 months; 5 for 3–4 months.

drop occurred mainly at short prediction intervals; predictability was low for the longer intervals at both ages. This pattern is reflected in the interaction between age and prediction interval, F(4, 24) = 4.73, p =.006. The strong main effect of prediction interval, F(4, 24) = 152.28, p < .001, reflects the rapid decrease in predictability at longer prediction intervals at both ages. Specific comparisons revealed a drop in predictability between 1 and 2 months at prediction intervals of 5 sec [t(6) = 3.79, p = .009], 10sec [t(6) = 3.75, p = .01], and 15 sec [t(6) = 3.75, p = .01]. There was a marginal decrease in predictability between 1 and 2 months at a prediction interval of 20 sec [t(6)]= 2.87, p = .029], but no reliable decrease at 25 sec [t(6) = .70, p = .509]. Predictability increased enough in months 3 and 4 so that none of the statistical analyses revealed any differences between month 1 and months 3 and 4. Months 2, 3, and 4 did not differ.

Discussion

The main results from this longitudinal study demonstrate that the intrinsic oscillations in spontaneous motor activity of the fetus and newborn infant do not disappear in the first few months after birth. Fetal CM persists beyond the neonatal period (1 month after birth) and beyond what has been called the period of the fetus ex utero (approximately 2–3 months after birth). It seems appropriate to call the persistent cyclic organization in spontaneous activity fetal CM because the rate of oscillation, which is the defining property of any cyclic process, does not change from fetal to neonatal to postneonatal life.

What happens in the first few months after birth is that the relative strength of oscillation during awake periods declines abruptly at 2 months, and remains low. At the same time, the complexity of the temporal organization of awake motor activity increases, as reflected by the jump in broadband power at frequencies well above the normal range of CM. The increased power at higher frequencies is not due to the emergence of distinct, dominant oscillations similar to those characteristic of CM at lower frequencies. Rather, the increased power is distributed across the range of frequencies above 2 cycles/min in each infant.

The decrease in the strength of awake CM is a striking developmental change in view of the stability of this property during active sleep in the late fetal, neonatal, and postneonatal periods (Robertson, 1985, 1987, 1988; Robertson & Dierker, 1986). Neither the basic neurobehavioral changes that occur in the last 2 months of gestation (e.g., Nijhuis, Prechtl, Martin, & Bots, 1982) nor the dramatic physiologic changes that accompany birth (Rivers, 1984) seem to influence the relative strength of CM. In the present study, CM strength in active sleep was unchanged across the first 4 months after birth. This pattern of results across studies suggests that a basic form of CM persists and is expressed relatively directly in active sleep, but that other systems with more complex dynamics may begin to compete for control of spontaneous activity during awake periods by 2 months after birth.

The absence of any change in the irregularity of CM across the first 4 months after birth is similar to the results of previous longitudinal studies of fetal and perinatal CM development (Robertson, 1985, 1987, 1988; Robertson & Dierker, 1986). The greater irregularity of CM in active sleep compared to awake states, found in the present study, has also been a consistent finding in previous studies where state differences have been examined (Robertson, 1987, 1988), and is probably the result of variation in the balance of descending excitatory and inhibitory input to spinal motor circuits that is characteristic of active sleep (Vertes, 1984). The present results provide further empirical support for the conclusion that *irregular*ity is a developmentally stable and statespecific property of human CM. It may also be a stable characteristic of CM in real time: a recent experiment showed that a pulsatile perturbation of spontaneous activity that results in CM slowing leaves its irregularity unchanged (Robertson, in press).

In spite of the constant irregularity of CM based on spectral analysis of the movement time series, analysis of the trajectories in a reconstructed state space using a nonlinear forecasting technique revealed a small but reliable drop in predictability from 1 to 2 months after birth. The drop in the predictability of spontaneous motor activity was mostly for short prediction intervals (less than 20 sec). Although based on a small number of infants, these results suggest that there are changes in CM dynamics at 2 months that do not influence the average recurrence time of similar states as measured by the frequency of the dominant peak in the movement spectrum, or its variability as measured by the width of the peak. Both are

properties of CM defined over multiple cycles of activity. However, the changes in CM dynamics at 2 months do appear to alter the extent to which future states of the system can be accurately predicted in the short term, that is, during a fraction of a cycle.

What might be happening at 2 months after birth? During the neonatal period, predictability in the fluctuations of spontaneous activity may be based on the intrinsic dynamics of CM in relative isolation from other systems. The increased high-frequency power at 2 months clearly reflects the introduction of a source (or sources) of variation with a much shorter time constant than fetal CM. Furthermore, the source is specific to awake states. Its emergence may induce subtle changes in CM dynamics that result in a small but real decrease in the predictability of low-frequency oscillations over short intervals of 5 to 15 sec.

The source of these short-term effects in awake infants may be the moment-tomoment interaction between CM and attentional systems. Although speculative, it seems reasonable to think that a mechanism controlling the temporal flow of behavior might interact on this time scale with mechanisms that support exploration of the environment and extraction of information from it (Allport, 1989). There is some evidence that the quality of motor control in general (Hopkins & Prechtl, 1984), and the organization of looking behavior in particular (Banks & Salapatek, 1983; Bronson, 1991; Canfield & Haith, 1991), exhibit important changes during this period of development that reflect a shift in the coupling between thought and action. In the case of CM, recent data from 2-3-month-old infants provide some preliminary evidence for coupling between movement and attention on the scale of seconds to minutes (Robertson & Bacher, 1992). When allowed to look ad libitum, infants exhibited a tight inverse relation between the rates of change in motor activity and visual attention. Although they could move and look at the same time, changes in one entailed opposite adjustments in the other. The quantitative details of the lead-lag relation between motor activity and visual attention remain to be worked out, but the relation appears to be variable at this age. The ways in which the coupling changes over the first 4 months have not been investigated.

What might be the consequences of an interaction between CM and visual atten-

tion? In the early stages of interaction between the two, coupling might result in a fairly rigid action system in which movement drives much of visual exploration. Rigid coupling of this sort could nevertheless facilitate periodic disengagement and redirection of attention in an infant who might otherwise become captured by salient features in the local visual environment (Bronson, 1991; Johnson, 1990). It might also form a basis for more efficient informationforaging strategies. Some have argued that chaotic dynamics have particular benefits for biological systems ranging from cardiac function (Goldberger, West, & Bhargava, 1985) to olfaction (Skarda & Freeman, 1987) to creativity (Crutchfield, Farmer, Packard, & Shaw, 1986). Most of these speculations are based on the premise that some unpredictability may be good, forming a basis for rapid adaptability and the generation of novel patterns of activity (Conrad, 1986). CM dynamics, to the extent that it interacts with the control of visual attention, might therefore be a useful source of complex variation that could increase the fraction of the visual environment that is scanned. Analogous benefits have been described for random components in other types of search behavior (Hoffmann, 1983). Decreased predictability could, of course, be of no particular value, or even interfere with systematic search behavior and disrupt interactions with dynamic environments where predictability may be important, as in social interactions.

Regardless of how subsequent empirical research judges these speculations, it is important to note that some of the key results of the present study came from the application of techniques in nonlinear forecasting that have been developed to study dynamical systems in other fields. The potential power of these techniques rests in part on their strong theoretical basis. First, the time series is not viewed as a mere string of measurements, but as a stream of information about the dynamical properties of the system generating it. Using the time series to reconstruct a state space, and then examining the system's behavior in the state space, can potentially reveal some of that information. Second, making predictions about the future by focusing on *nearby* points in the state space respects the dynamics generating the behavior, even if the dynamic rules themselves are unknown. That is, predictions of the output of the system (as measured by the

time series) are made by analyzing the output at other times which have a similar history.

In spite of these strong conceptual advantages, the techniques of nonlinear forecasting such as the one employed here have serious practical limitations. Perhaps the most important limitation is their requirement for large amounts of data (Farmer & Sidorowich, 1988). Their advantages over other methods may also be limited to low dimensional systems governed by chaotic dynamics. However, with proper respect for their limitations, their utility in the study of CM raises the possibility that these techniques and the theory they are built on could lead to new insights in other aspects of behavior and development as well.

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