Learning to perceive time: A connectionist, memory-decay model of the development of interval timing in infants.

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Abstract

We present the first developmental model of interval timing. It is a memory-based connectionist model of how infants learn to perceive time. It has two novel features that are not found in other models. First, it uses the uncertainty of a memory for an event as an index of how long ago that event happened. Secondly, embodiment – specifically, infant motor activity – is crucial to the calibration of time-perception both within and across sensory modalities. We describe the model and present three simulations which show (1) how it uses sensory memory uncertainty and bodily representaions to index time, (2) that the scalar property of interval timing (Gibbon, 1977) emerges naturally from this network and (3) that motor activity can synchronize independent timing mechanisms across different sensory modalities.

Keywords: Infancy; cognitive development; interval timing; embodied learning.

Introduction

Adults from all cultures and backgrounds can accurately anticipate short-term events, can catch objects thrown to them, and can perform the enormous range of human activities that require timing. This universality may seem to imply that the sense of time does not rely on learning or embodiment, a position implicitly taken by the well-known pacemaker-accumulator models of time perception (Gibbon, 1997; Church, 1984; Gibbon, Church and Meck, 1984) and multiple-oscillator/coincidence-detection models (Miall, 1989; Church and Broadbent, 1990). But there are a number of problems with these models, most important among them, the problem of resetting the system for every event for which a time judgment might later be required. Recently, the reset problem has been avoided by suggesting that time perception depends on memory-trace decay (Staddon, 2005). Our central hypothesis is that adult timing capacities are learned in early infancy and require grounding in motor activity. For this reason, we developed a model of time-perception learning in infants.

As far as we know this is the first developmental model of interval timing. It is a memory-based connectionist model of how infants learn to perceive time and has two further novel features. First, it uses the uncertainty of a memory for an event as the measure of how long ago that event happened. This is in contrast to other memory models which use relative intensity (e.g Staddon and Higa, 1999). Secondly, it is a developmental model in which embodiment – specifically, infant motor activity – is crucial to the calibration of time-perception within and across sensory modalities. Learning and coordinated motor activity in infancy play a key role in synchronising different timing mechanism and permitting developmental predictions. In addition, the scalar property of interval timing (Gibbon, 1977) emerges naturally from the model.

This paper is organized as follows. We begin by briefly discussing the various classes of models of time perception. We then present the theoretical justification and framework for our connectionist model of timing based on memory-trace decay. We focus, in particular, on the need to calibrate this model via repetitive motor activity. Finally, we present the details of the model, including how it is calibrated by replicable signals in the motor system, and demonstrate that the well-known scalar property of interval timing (Gibbon, 1977) is a natural by-product of its operation. We also show how this model could provide developmental predictions.

Background

Time perception is central to human cognition (e.g., Grondin, 2008; Zakay and Block, 1997). Not only does it allow us to organize and make sense of physical events, it also underlies micro and macro level social interactions. At the level of the individual, time perception is linked to executive control, delayed gratification, and decision making. It, therefore, comes as no surprise that Immanuel Kant described time as an inner sense that structures and makes possible cognition. Human time perception is generally divided into three categories: precision timing (less than 500 ms), interval timing (500 ms. to 5 mins.), and

longer-term time perception, each of which appears to implicate by a different neurocomputational system (Buhusi and Meck, 2005). This paper will be concerned only with interval timing, which lies between cellularly-driven precision timing and longer-term sequence-based, schema-driven timing. This intermediate level is believed to share a common processing core with spatial and numerical magnitude estimation abilities (Walsh, 2003; Brannon, Suanda and Libertus, 2007).

There are currently three major explanatory paradigms for interval timing. The first relies on an internal pacemaker that emits regular, short pulses that are counted by an accumulator. The number of pulses stored in the accumulator gives the measure of the time that has passed (Staddon and Higa, 1999; Church, 1984; Gibbon, Church and Meck, 1984, Droit-Volet and Wearden 2001). The second class of models relies on multiple neuronal oscillators with coincidence detectors associating particular patterns of firing with given time intervals (Church and Broadbent, 1984, Matell and Meck, 2000). Process-decay models constitute the final class, where the estimation of the passage of time is derived from the decay of memory traces (Staddon and Higa, 1999; Lewis and Miall, 2006).

One of the most significant problems with both pacemaker/accumulator and oscillator/coincidence-detector models is the necessity of resetting the accumulators or oscillators for every event that could potentially be timed. Are there multiple accumulators, one for each possible event? What triggers their resetting? What, exactly, constitutes "an event?" Memory models of time-perception do not have this problem. The activation pattern for any event for which there is a memory trace will decay to a greater or lesser extent depending on how long ago the event took place. The memory-trace decay determines the perception of the amount of time that has passed.

However, models that rely on memory-trace decay need to be calibrated against the duration of events in the world. *We suggest that infant motor activity is a plausible way in which this calibration could be achieved early in development.* Numerous authors (Lakoff, 1987; Glenberg, 1997; Thelen and Smith, 1996; Piaget, 1955) have convincingly argued for the importance of motor activity in structuring early perceptual and cognitive development. We believe that infant time perception needs to be included in the range of cognitive phenomena structured by motor activity.

There is now ample evidence that infants as young as 4 months are able to keep track of short time intervals and can respond to the violation of an expectation based on a regular time interval (Colombo and Richman, 2002; Adler et al, 2008; Brannon et al, 2007; Clifton, 1974). However, this ability is not entirely mature and continues to develop well into childhood (e.g., Friedman, 2008; Droit-Volet, Tourret and Wearden, 2004; Goldberg, 1995), in concert with children's improved attentional control.

Theoretical Framework

We suggest that the development of interval time perception in infants is intimately linked to coordinated motor activity. Three main lines of argument support this hypothesis:

1. Repetitive motor activity is ubiquitous in early infancy (e.g., Piaget, 1955; Droit-Volet, Clement and Fayol, 2008), even being present in newborns (Van der Meer, Van der Weel and Lee 1995; Lewandowsky, 1993). This movement is perfectly correlated with the time that it takes to complete it. When a baby moves its hand to touch its mother's face, this is a motor activity, *but it is also a temporal activity*, because it takes a certain amount of time for the baby's hand to move from its starting position to its final position. This fact will be used to calibrate our activation-decay model of time perception.

2. Areas of the brain that are important in motor activity have recently been found to play a role in perceptual timing (Ivry, 1996; Rao, Meyer and Harrington, 2001). It is now known that the disruption of input from the motor cortex to the associative areas of the parietal cortex selectively interferes with perceptual timing (Bueti, Bahrami and Walsh, 2008).

3. Memory-trace decay is known to exist in the brain and is a well-studied and neurophysiologically plausible phenomenon (Staddon and Higa, 1999; Lewis and Miall, 2006). In contrast, after 25 years of research the neurological evidence for accumulator models remains equivocal (Staddon, 2005; Buhusi et al., 2005).

In addition, if time perception is shown to develop from embodied sensorimotor origins in infancy into more abstract adult representations then the present theory could provide a framework to explain how adult temporal concepts appear embodied despite limited neural data in adults (Kranjec and Chatterjee, 2010).

The scalar property

The scalar property for interval-timing (Gibbon, 1977) is a widely replicated finding in both adult humans and rats (see Gibbon and Allan, 1984 for a book length summary). It states that time-perception errors (E) increase as a *scalar* function of the length of the time interval (I) to be predicted. An interval twice as long (2I) produces errors that are twice the large (2E). This is surprising because the Central Limit Theorem predicts that error in cumulative processes grows more slowly – the expected error for an interval length 2I would be $\sqrt{2}E$. The mechanisms of the model that we propose in the present paper solves this problem, time-interval prediction uncertainty in our model does, indeed, increase in a scalar fashion.

The need for calibration

Memory-trace models determine the passage of time in terms of how much a memory trace has decayed. But memory-trace decay cannot be directly decoded into temporal information, unless there is (or has been) some
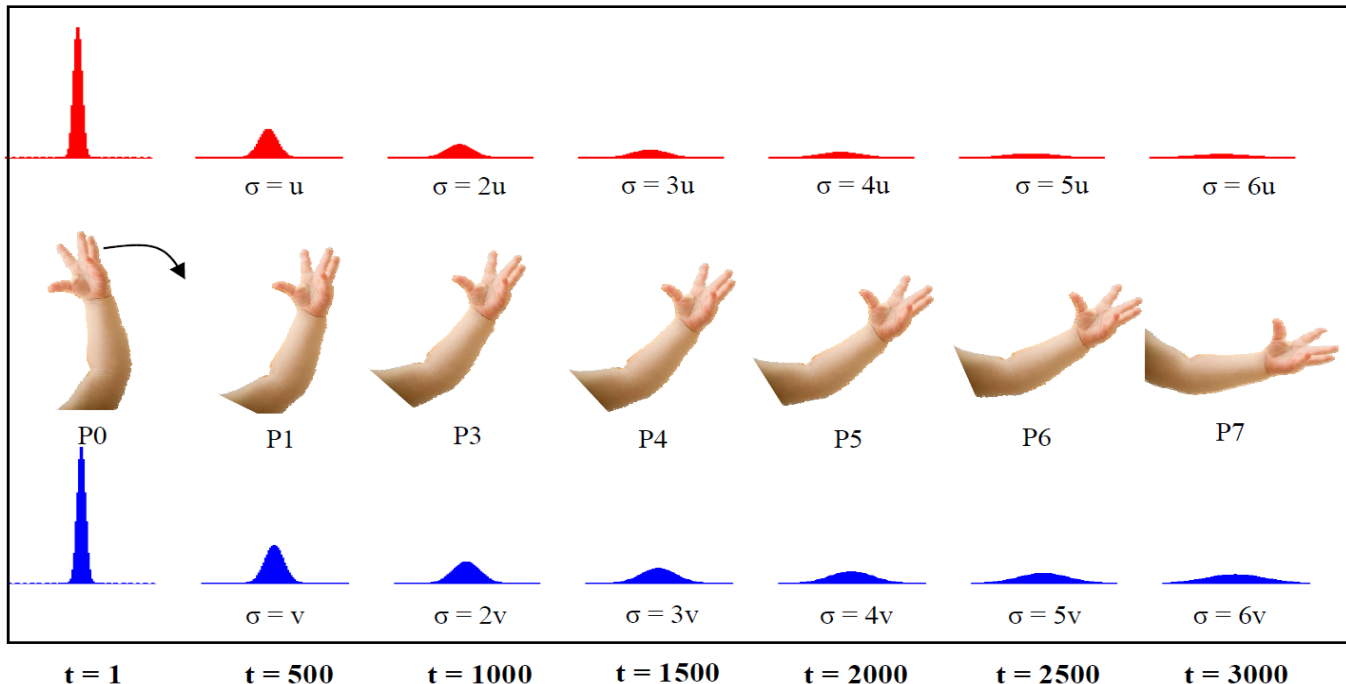
Figure 1. The two lines of graphs show hypothetical activation decay sequences ("fading gaussians") over visual columns (α=0.0045, β = 0.001, φ = 0.0105) and over auditory columns (α=0.0048, β = 0.001, φ = 0.0105) at 500 time-step intervals over 3000 time steps. Uncertainty (σ) in both modalities grows linearly and leads to the scalar property of interval timing.

means of grounding that decay in meaningful, repeatable event sequences. The central hypothesis of this paper is our suggestion that infants ground memory-trace decay through self-generated, repetitive corporeal motions (such as arm movement). A simple example illustrates this idea.

Each time a baby moves its hand from a vertical position to a horizontal position (Figure 1), it takes approximately the same amount of time and this allows different amounts of memory-trace decay to be grounded in amounts of body or arm movement.

Imagine a baby playing with some toys. The baby picks up a colored block, waves it about a bit before bringing the object to its mouth for a closer inspection. The length of time between when the baby first noticed the toy and when it arrives at its mouth will be directly proportional to the amount of arm movement the baby has carried out. In another case, imagine that a baby is lying in a cot and hears a noise to his or her left. The baby may have to manouver its whole body in order to orient its head towards the sound. Again the amount of movement is proportional to the time since the original sound.

Moreover, similar movement sequences will take broadly similar lengths of time. So body and arm movement can serves as a rough *temporal* yardstick for visual and auditory memory-trace decay. In this way, over time an association between how long ago an event took place (as measured by activation decay of a memory trace) and limb movement is gradually learned. Infant body movement serves as a metronome for the timing of memory decay.

Visual and auditory events come in all shapes, sizes and intensities. The initial activation associated with an event can therefore vary considerably in amplitude. The fading memory trace for a high-intensity event will not correspond directly to the fading memory trace for a low-intensity event. That correspondence can be established via constant-velocity body movement. The "yardstick" of repeatable, predictable body movement in space is what we propose to align the time perception for the two events.

Visual and auditory are often, but not always, correlated Many visual events are not accompanied by a simultaneous production of sound and vice-versa. It is also important to note that the calibration of visual and auditory memory-trace decay rates does not have to happen simultaneously.

Architecture of the network

For this model we used a simple connectionist architecture (Figure 2) with a "visual" and an "auditory" pathway leading to the same set of "arm position nodes." Note that arm position here is chosen as an easily graspable instance of the more general notion of proprioceptive configuration. The input layer consisted of 41 units for each sensory modality which represented a memory as time evolving guassian. These inputs connected to two independent sets of 10 hidden nodes which both connected to the same 10 output nodes which encoded arm position as a binary vector. During training a particular arm position is associated with a particular time interval in one or the other modality and the network is trained using back-propogation of error. At test

the gaussian corresponding to a particular time interval is presented in a single modality and the predicted arm position that is output serves as a proxy estimate of the amount of time since the original sensory event.

Arm position encoding

Here we use simplified topographic representations of limb position with binary encoding. Position 1 is given as [1 0 0 0…] , position two as [1 1 0 0 …] and so on. Although movement is continuous we do not code intermediate positions. Similarly, we are using a completely linear representation. This is an approximation. Further research with this model will attempt to direcly fit data from classic studies of infant timing abilities which used predictive reaching as diagnostic measure (von Hofsten, 1980) and infant electromyography (EMG) data collected as part of this research programme.

Memory decay using fading gaussians

We begin with a cluster of neuronal columns in visual cortex. The central column of the 41-column cluster is assumed to receive input from the sensory interface. The initial activation level of this column depends on the intensity of the input stimulus, which we assume to be a visual or auditory stimulus of short duration. Once the stimulus is no longer present, the peak activation value of the central column will decrease and activation will spread to neighboring columns. The activation of the ith column at time step t is designated by $A_i(t)$, Activation at time $t+1$ is determined by the following equation:

$$A_i(t+1) = \alpha(A_{i-1}(t) + A_{i+1}(t)) + (1+\beta-\phi)A_i(t)$$

where
α determines the amount of activation spreading between adjacent columns;
β determines the level of self-excitation
φ determines the amount of activation leakage.

The evolution of activation in this cluster of columns, which we refer to as "fading gaussians," is illustrated by the series of graphs at the top and bottom of Figure 1, indicating activation decay in the visual (top) and auditory (bottom) columns.

Results

We report three preliminary results from our simulations[1]. First, we show that the network does, indeed, gradually learn to associate the fading-gaussian input profiles with the various arm positions. The network gradually learns to associate the various stages of the fading visual or auditory input profiles with arm positions (Figure 3). Second, after training, we test it to determine the amount of error reduced for each time interval (Figure 4).

[1]The MATLAB code for these simulations can be downloaded from http://www.cbcd.bbk.ac.uk/people/affiliated/caspar/time
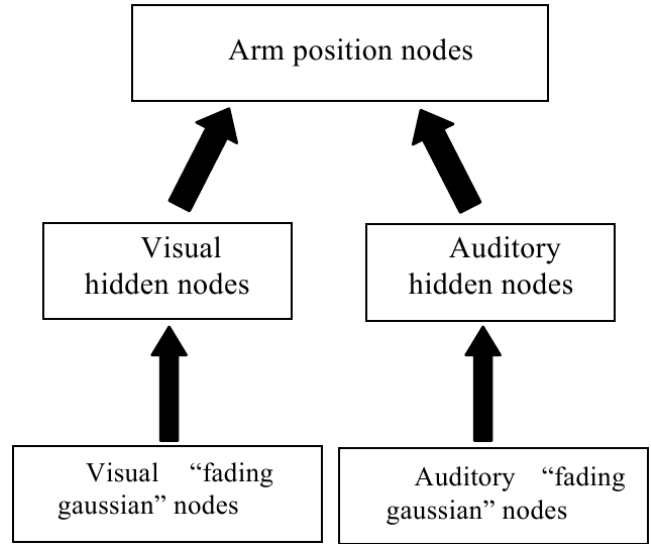

Figure 2: Schematic representation of network.

This testing is done by inputting to the network the activation gaussians corresponding to 500, 1000, 1500, etc time steps of decay (here denoted as intervals from 1 to 90 seconds). We note the average error produced from 20 seperate estimates at each time interval. Figure 4 shows that error increases approximately as a linear function of the time interval being measured, which is what Weber's Law for interval timing predicts (Gibbon, 1977). Third, in a final simulation, we show how, via arm movement, the visual and auditory fading gaussians produce correlated outputs. In other words, whether a time interval is measured in the visual modality or in the auditory modality, the output (i.e., the estimate for the length of the time interval) will be the same.

Simulation 1: Development of interval timing

This first simulation looks at the performance of a network trained in one modality (Figure 3). A naive network is initialised with small random weights and is trained with a set of randomly presented gaussian activations. Each of these is associated with a particular amount of arm movement and the network is trained to predict these values. Figure 3 shows the average output of 20 networks during training across the full range of possible time intervals. The predicted arm position given by the network is translated to the corresponding time interval to plot the figure.

As can be seen the network learns to predict the intervals quite effectively in the middle of the range. It over estimates timing on short intervals and underestimates it on long intervals. In part this is due the lack of granularity of the binary encoding. However, this general pattern of responses has been found in children's estimates of time (Droit-Volet, 2003). This model could provide an explanation for this developmental effect.
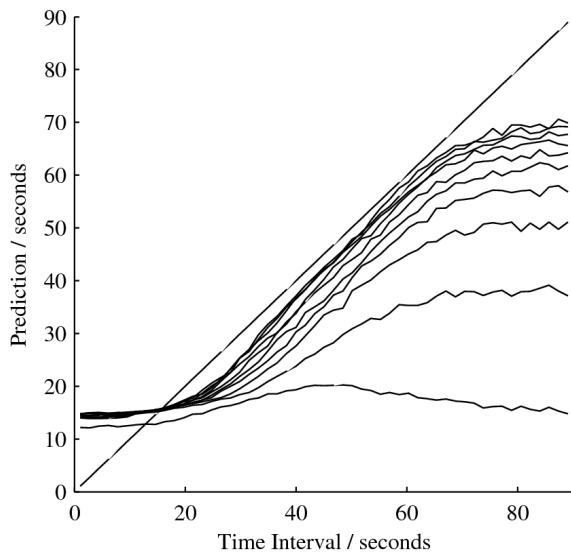
Figure 3: Learning in a single modality network. Each line represents the output of partially trained networks. As learning progresses the lines tend to converge to the 'perfect prediction' diagonal. (Each line represents an averaged over 20 equivalently trained networks.)

Simulation 2: The scalar property

The second simulation demonstrates how the scalar property of interval timing is a natural feature of this model. With a network trained to make predictons of arm location from memory decay, we a took a set of twenty responses for 50 different time points between 1 and 90 seconds. The average of these responses is plotted in Figure 4, together with error bars representing one standard deviation. The scalar property says that the size of the errors is proportional to the length of the interval. In other words error divided by interval should be a constant. We also plot this relative proportion in Figure 4. This proportion is constant which is what Weber's law predicts.

The bump appears to be due to the limited granularity of using a binary representation of arm position. It is important to note that the simplifying assumptions about bodily representaion (binary, linear) are likely to *impair* network performance. Using a non-binary representation would provide greater information. Whilst Fitts Law states that the motor system obeys a power law which suggests that motor representations also possess scalar properties. Similarly, in the current model, body position is used both to calibrate the sensory modalites and as a proxy representaion of time quantities. As an infant matures it is likely that its time representations will become more abstract, although it is beyond the scope of this paper to demonstrate this. In line with Walsh's (2003) ATOM model, we expect the brain to recruit regions of the cortex that represent quantity logarithmically. Future iterations of this model will investigate both these refinements.
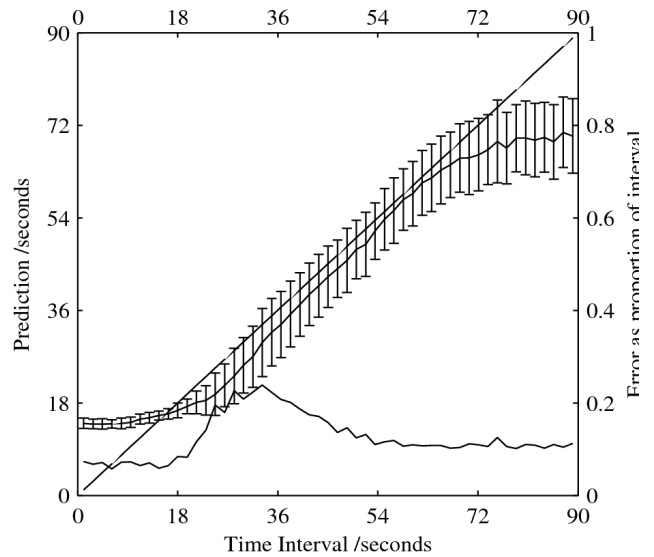

Figure 4: The scalar property in a trained network. The top line shows the average prediction at each interval and the standard deviations from 20 networks. The lower line shows this error as a relative proportion of the predicted interval.

Simulation 3: Calibration of independent modalities

The first two simulations looked at the performance of a network trained in one modality. Here we investigate how embodiment can work as a mechanism to synchronise and calibrate time interval estimates in different modalities. Droit-Volet (2003) showed that children's interval timing can differ across auditory and visual domains suggesting that there is some independence of these measures and that a development mechanism for calibration is required.
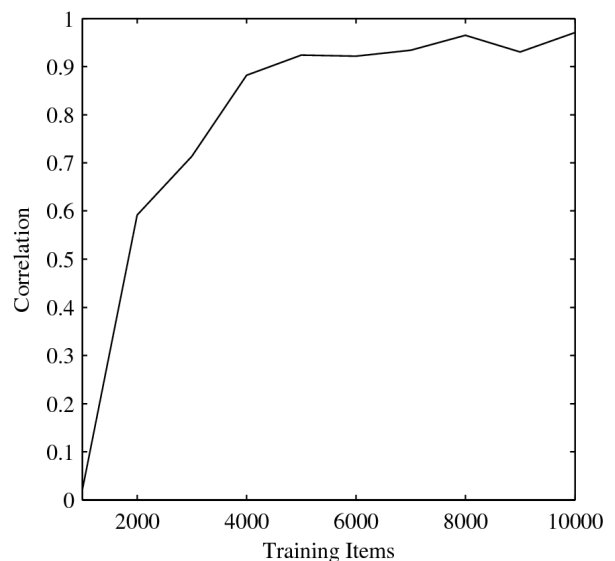

Figure 5: Correlation between network predictions in two independent modalities with training.

In our model, each modality is trained separately but is tied to the same underlying bodily representation. To show how this leads to calibration and synchronisation of clocks in different modalities, we took representative networks trained in two modalities and looked at their outputs across the full range of possible intervals (1 to 90 seconds.) Correlating these outputs for the two independent networks showed how well calibrated and synchronised the networks were. In Figure 5, we plot the evolution of this correlation as the networks both gain greater experience.

Conclusion

We have presented a new model of interval timing in infants. It is the first developmental model of time perception and has two further novel features. It is based on memory uncertainty and it utilizes embodied learning to calibrate timing across different perceptual modalities. We have demonstrated that this model captures the scalar property of interval timing and certain developmental effects. One prediction of this model is that restricting a baby's movement would impair his or her time perception. This precise prediction is part of an ongoing research project involving babies.

Acknowledgments

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