Learning to Track Predictable Target Waveforms without a Time Delay

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Humans can learn to overcome the 150 msec delay of the eye movement system and track predictable targets with no latency. The mean squared error between the target and eye position was used as a measure of the goodness of tracking. For typical subjects, this error decreased from 0.5 deg^2 to 0.1 deg^2 after 100–200 sec of viewing the target. Professional athletes had much smaller mean squared errors at the beginning of the learning period. Invest Ophthalmol Vis Sci 26:932–937, 1985

The human eye tracking system has a time delay of about 150 msec, but humans can track predictable targets with no delay. Bahill and McDonald showed that they can do this for any predictable target waveform, provided the position waveform is smooth, predictable, has a frequency between 0.1 and 1.0 Hz, and has limited accelerations.[1] They stated that it took time to learn zero-latency tracking. However, the time course of learning and forgetting was not given. In this article, we show the time course for learning, forgetting, and relearning of the cubical target waveform, which is shown in Figure 1. We also show that professional baseball players track better than graduate students.

Materials and Methods

We measured binocular eye movements with a standard photoelectric system[2]: specifically, a homemade infrared limbus tracking system, wherein photoemitters and photodetectors mounted on spectacle frames were aimed at the iris–sclera border. When the eye moved, one photodetector received more light and the other received less light; the difference of these two signals indicated eye position. When a subject fixated on a stationary point, the total of instrumentation noise and biological noise was typically less than 0.1 deg. Bandwidths were 80 and 8.9 Hz, respectively, for the eye position and eye velocity traces. Vestibulo-ocular movements were eliminated by restraining the subject's head with a headrest and bitebar. Vergence eye movements were eliminated by displaying the targets on a curved screen 57 cm in front of the subject. Details of these techniques were given by Bahill and McDonald.[1]

The subjects were 10 male and female students and three members of the Pittsburgh Pirate Baseball Club. Informed consent was obtained after the equipment and procedures were explained to the subjects.

The cubical target waveform was formed with the following third order polynomial:

$$r(t) = 10.39A[2(t/T)^3 - 3(t/T)^2 + (t/T)], \quad \text{for} \quad 0 < t < T,$$

where T represents target period and A is the amplitude. Previous studies have shown that humans track well when the target has an amplitude of 5 deg and a frequency of about 0.32 Hz, so these values were used in our experiments. The target always started with zero phase and zero offset. No warning was given before the target started. The cubical waveform was selected because no naturally occurring visual targets move with a cubical waveform; thus, our results were not influenced by previous learning. The cubical position waveform looks like a sinusoid, but the velocity is strikingly different. By analyzing the eye velocity records, we could tell if the subject had really learned the cubical waveform (as shown in Fig. 1), or if he had merely approximated it with a sinusoid.

Our standard experimental protocol began with a 6-sec square wave calibration target waveform, followed by 9 sec of the cubical target waveform, 3 sec of the square wave target waveform, another 9 sec of the cubical waveform, and finally another 6 sec of the square wave calibration target waveform. The subjects were allowed to rest for 5 min and then the sequence was repeated. This process continued for

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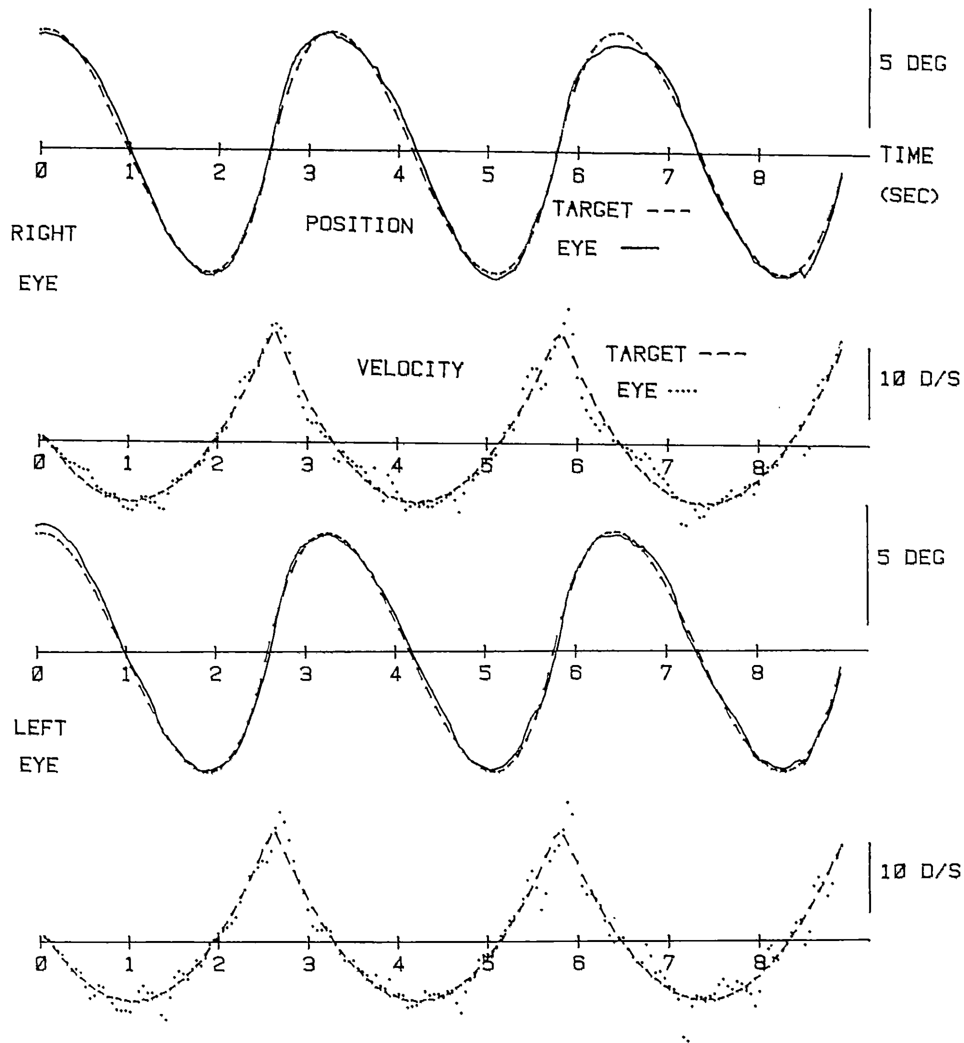

Fig. 1. Binocular eye movements for good tracking of the cubical waveform. The mean squared error (MSE) between the eye and target positions was 0.07 deg^2 for the right (dominant) eye and 0.06 deg^2 for the left eye. Upward deflections represent rightward movements.

about 2 hr. We tried many other timing schemes, but this one produced the best tracking. In particular, longer practice sessions produced larger errors, because of subject fatigue and small drifts of the instrumentation system. This scheme of 18 sec of cubical tracking every 5 min worked best for us. For other laboratories, these numbers will probably vary by a factor of two or three. Future research may narrow the range for the optimal parameters for human learning of predictable target waveforms.

Our metric for how well each subject tracked the target was the mean squared error (MSE) between the eye and target positions. For each 9-sec epoch of the cubical waveform, we first looked at the right eye records and found the 4.3-sec window that gave the lowest mse between the eye and the target positions; we were trying to quantify the optimal human performance. Next, we selected the 4.3-sec window that gave the smallest MSE between the left eye and the target.* The MSEs for the left and right eyes were then averaged together and plotted as a function of the amount of time the subject had seen the target. Exponential curves were fit to the MSE data using

* A 4.3-sec window was chosen because it was larger than the period of the target (3 sec), and it contained exactly 10 computer blocks of data. This window always contained three target turnarounds; either one or two of these were of the sharp velocity peak type, eg, between the 2- and 3-sec marks in Figure 1. This could have confounded the data analysis, if sharp velocity peak turnarounds were harder to track than the smooth velocity turnarounds. We did a retrospective analysis of the data and found that windows with two sharp velocity peak turnarounds were randomly distributed throughout the learning process. We think that whether the window had one or two sharp velocity peak turnarounds had no effect on our results. In this retrospective analysis each datum point was completely recalculated; 92% of the points were exactly the same, the others differed by an average of 0.01 deg^2. Therefore, we think the data points are accurate and free of qualitative judgement by the experimentor.

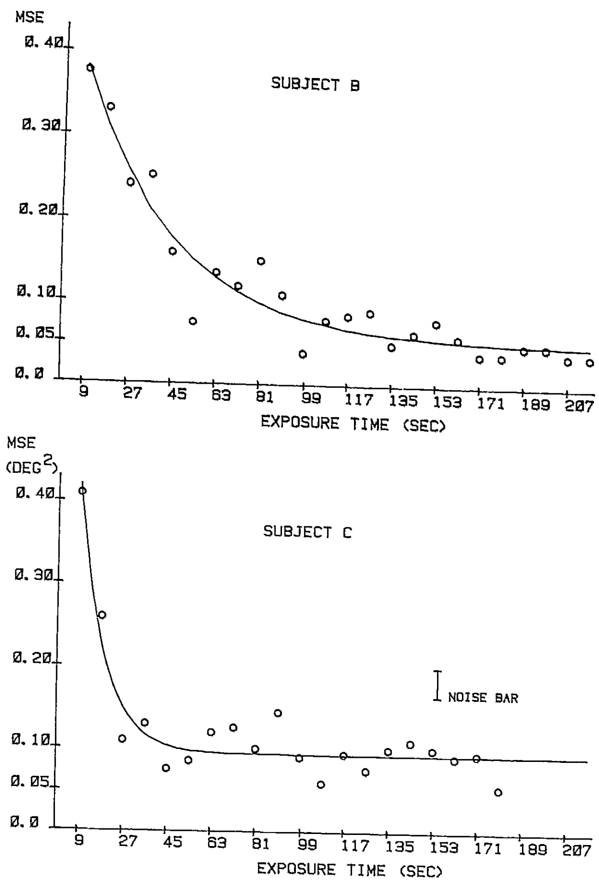

Fig. 2. Time course of learning the cubical target waveform for two subjects. Mean squared error is plotted as a function of the total time that the subject had seen the waveform. Circles are the human data points and the solid line is an exponential curve fit to the data points.

the UCLA BMDP3R statistical package.[3] The best fit was usually an exponential of the form: $MSE = Ae^{-Bt} + C$.

Results

Figure 2 shows the mean squared error (MSE) for two subjects. The circles represent the human MSE, the solid line is the best exponential fit to the data. For Figure 2B, the exponential equation is: $MSE = 0.42\ e^{-0.26t} + 0.05$. To give some feel for what these numbers mean, assume that the fovea is one-half degree in diameter. Now, if the target were always just on the edge of the fovea, then the MSE would be 0.25 deg^2. It can be seen that in the beginning, the subject is not keeping his fovea on the target; whereas, at the end, the subject is keeping the target centered on the fovea. The noise bar of Figure 2C shows the average value of the difference between the MSE of the right eye and the MSE of the left eye. It indicates the magnitude of the sum of the biological and instrumentation noise in the system. The abscissa is viewing time, not real time, because we allowed the subject a 5-min rest period between each sitting.

The solid lines of Figure 3 show the exponential curves fit to the data of four of our best students. Table 1 shows the parameters of the exponential equations for these subjects. The approximated T-ratio is the estimated value of MSE divided by asymptotic standard deviation.[3] The greater the value, the greater effect the parameter has on the fit of the equation to the data. The correlation between parameters B and C was −0.19. Therefore, there seems to be no relationship between how fast the subject learned and how low of a MSE was reached at steady state.

We were trying to quantify the ultimate capabilities of the human smooth pursuit system, so we only report the performance for our better subjects. In this article, we only show data of five of our 10 students. The other students did not demonstrate such low error tracking. This failure to record low error tracking was due to either (1) nonlinear records due to misadjustment of the eye position sensors; (2) use of a different training protocol, eg, viewing the target for 30 consecutive seconds every 3 min; or (3) intersubject variability. We note in passing that our female subjects did not track as well as our male subjects. However, these results were not statistically significant. Intersubject variability is an interesting question that we will address in a future study. For our present study, we are interested in how well the human can track.

To narrow in on this optimal performance we decided to study optimal humans performing optimally. Who is an optimal human? For eye tracking capability, we thought professional athletes would fit the bill. So, we invited some professional athletes to participate in our experiments. The MSEs for three members of the Pittsburgh Baseball Club are represented by circles, asterisks, and squares in Figure 3. In viewing the target for the first time, baseball players 1 and 2 had much smaller MSEs, 0.05 and 0.08, than our other subjects. They had never seen a cubical waveform before, yet they started out with low MSEs. Baseball players 1 and 2 play for the Pittsburgh Pirates. Player number 3 is still playing class A ball in the Pittsburgh Farm System. These data seem to indicate that the ability to track the cubical waveform is correlated with athletic performance. It is unfortunate that time constraints limited the amount of data we could collect from the professional athletes. More data will have to be collected before monetary decisions could be based on such tests.

We studied the time course of learning and relearning. Figure 4 shows the data for one student during

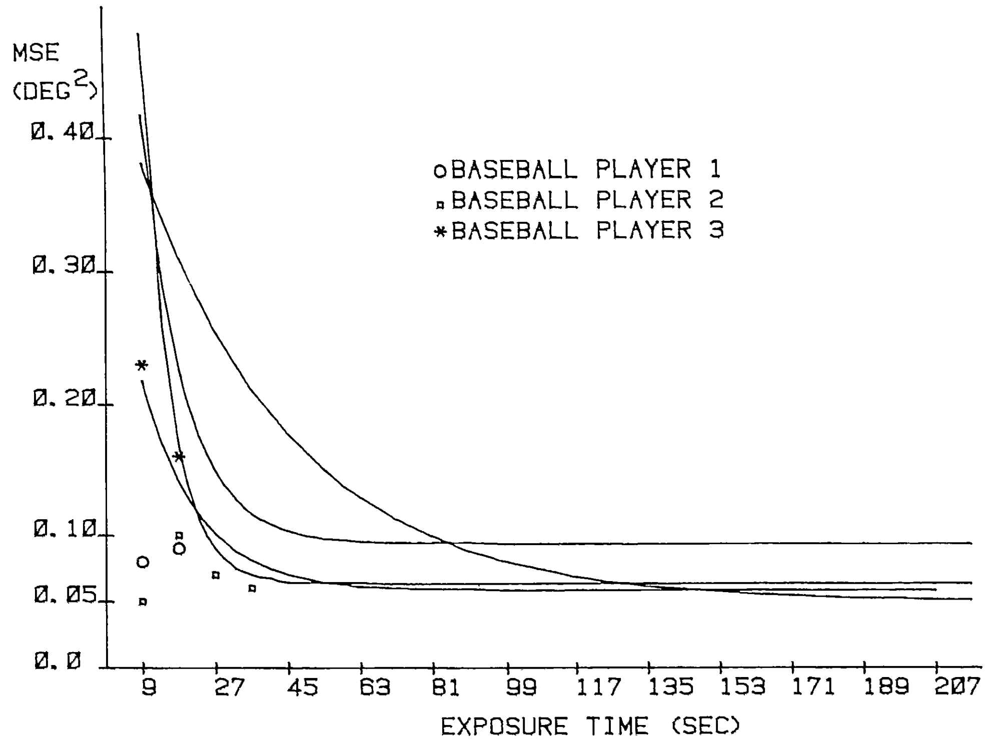

Fig. 3. Time course of learning for seven subjects. Solid lines are the exponential curves fit to the data of four students. Circles, asterisks, and squares are data points for three professional athletes.

the initial learning session, for a session 9 days later, and for a session 50 days later. For each session, the data was fit with an exponential curve. Relearning is almost instantaneous. It appears that the cubical target waveform is not quickly forgotten.

To be sure that our subjects were learning to track the cubical waveform and not just learning to track, we designed another experiment. First, the subjects learned to track a sinusoidal waveform, then they returned a week later to learn to track the cubical waveform. Data for one subject are shown in Figure 5. If he was only learning how to track, independent of the given waveform, then his second set of experimental MSEs would have been lower at the start; they were not. The subject had to learn the cubical waveform. The cubic learning started with high errors and gradually dropped to the plateau level. The sinusoid had smaller errors in the plateau region, even though it came first; therefore, sinusoids are easier to track than cubics. This is a general finding that applied to all our subjects.

Figure 1 shows excellent tracking of the cubical

Table 1. Parameters of the exponential equations fit to the data of 4 subjects

Subject	*Parameter*	*Estimated parameter value*	*Average absolute residue value*	*Average standard deviation of estimated data*	*Approximated T-ratio*
ma	A	1.636			3.7
	B	0.152	0.0198	0.0062	5.5
	C	0.063			13.2
	A	0.780			5.1
c	B	0.098	0.0187	0.0087	5.6
	C	0.094			14.2
	A	0.420			12.3
b	B	0.026	0.0174	0.0090	7.0
	C	0.050			5.2
	A	0.308			4.4
r	B	0.655	0.0143	0.0061	4.2
	C	0.059			12.5

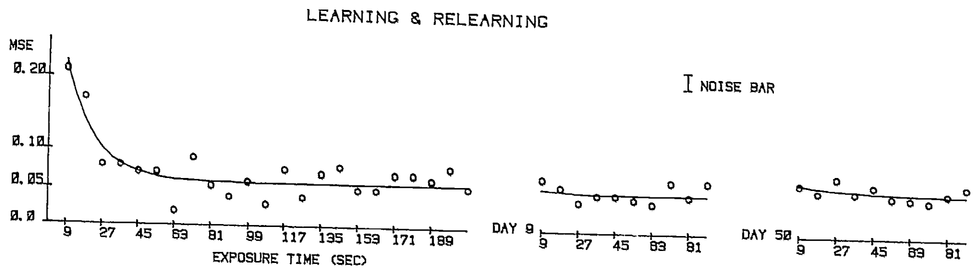

Fig. 4. Time course for learning and relearning. The subject learned the waveform, returned 9 days later to relearn, and returned 50 days after original experiment to relearn it again.

target waveform. Using only smooth pursuit eye movements, the subject was able to keep the fovea on the target for over 8 sec. Saccades were not removed or filtered out of the eye position traces; indeed, a small conjugate saccade can be seen at the 8.5-sec mark. Please note that there are differences between the movements of the right and the left eye, as can be seen in the position traces between the 6- and 7-sec marks. Comparison with the data between the 3- and 4-sec marks shows that these differences are of biological origin and are not due to instrumentation saturation. Differences of this magnitude between the right and left eye were typical of our data. To get a quantitative measure of these differences, we averaged the MSE in the steady-state region of the learning curve (eg, between 45 and 180 sec in Fig. 2C). The average MSE for the right (dominant) eye was 0.08 with a standard deviation of 0.033. The average MSE of the left eye was 0.09 with a standard deviation of 0.028. These differences are not statistically significant.

Discussion

From this study we draw the following conclusions: (1) Our subjects learned to track predictable targets best if they viewed them for about 18 sec every 5 min. This allowed adequate time to learn the waveform, yet it did not tire the subject. It also allowed the experiment to be carried out in about 2 hr of real-time. (2) The learning is specific for each new waveform, and it is a fairly permanent process. (3) The learning process can be modeled with the simple equation $MSE = Ae^{-Bt} + C$. (4) There are differences between the two eyes, but neither eye is consistently better. (5) Professional baseball players have better tracking abilities than our best students.

Our results of human learning parallel results in

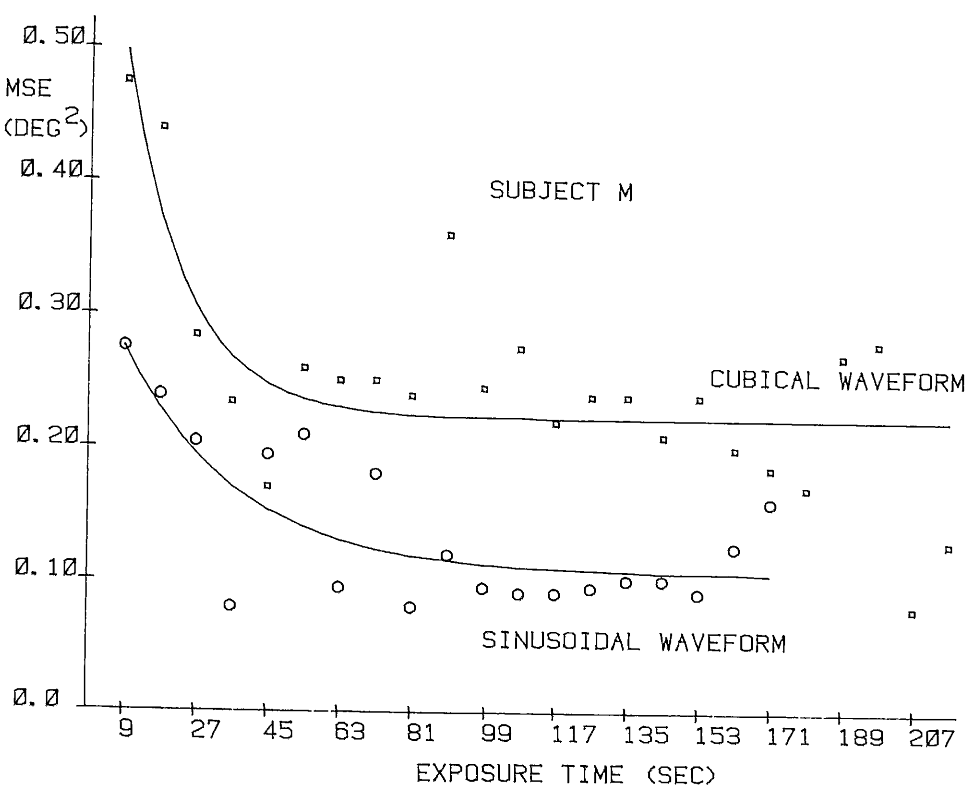

Fig. 5. Time course of learning for sinusoidal and cubical waveforms. The subject learned the sinusoidal waveform, returned 1 wk later to learn the cubical waveform. The circles are data points for learning the sinusoidal waveform and the squares are data points for learning the cubical waveform. The solid lines are the exponential curves fit to the data.

the psychological literature. Learning curves are usually exponential; and a single exponential is usually sufficient to fit the data. Periods of rest between practice sessions improve performance (although our original purpose for the rest periods was to avoid fatiguing the eye movement system). Our subjects performed best when the frequency was about 0.3 Hz. At higher frequencies, the oculomotor system cannot track. At lower frequencies, the waveform presumably becomes so long it cannot be efficiently transferred into long-term memory.

The purpose of these experiments was to study the time-course of learning of predictable target waveforms. The possible spinoffs from this study are to use the human cubic learning process in a screening of baseball players in the major league farm system, and to suggest (yet another) quantitative test of the human eye movement system for basic and clinical research.

Key words: learning, eye tracking, smooth pursuit eye movements, athletes, optimal performance, baseball players

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