A 3D Tracking Experiment on Latency and Its Compensation Methods in Virtual Environments

Jiann-Rong Wu and Ming Ouhyoung
Communication & Multimedia Lab.
Department of Computer Science and Information Engineering
National Taiwan University, Taipei, Taiwan. R.O.C. 106
ming@csie.ntu.edu.tw

ABSTRACT
In this paper, we conducted an experiment on the latency and its compensation methods in a virtual reality application using an HMD and a 3D head tracker. Our purpose is to make a comparison both in the simulation and in the real task among four tracker prediction methods: the Grey system theory based prediction proposed in 1994, the Kalman filtering which is well-known and wide-spreading since 1991, a simple linear extrapolation, and the basic method without prediction. In our 3D target tracing task that involved eight subjects, who used their head motion to trace a flying target in random motion, we have found that when the system latency is 120ms, two prediction methods, Kalman filtering (not inertial-based) and Grey system prediction, are significantly better than the one without prediction, and the former two methods are equally well in performance. Typical motion trajectories of four methods in simulation are plotted, and jittering effects are examined. In terms of jittering at 120ms prediction length, Kalman filtering was evaluated to have the largest.

KEYWORDS : Motion prediction, latency in HMD, virtual reality technology

INTRODUCTION

In virtual reality applications, one of the major issues is to provide an immersive environment which is computer generated with realistic appearance, behavior, and interaction; however, the requirement of such an ultimate display is not easily met [1]. One of the critical problems is the perceived latency [2], or lag, which is the time delay between hand movement and its corresponding motion of the virtual object on the screen. In an HMD related system, if the latency is relatively large, over 100 ms for instance, it will cause dizziness for some people with long time wearing. At the same time, the illusion of a virtual world is destroyed if the objects on the screen jitter significantly while the head is not in motion, a "swimming effect" mentioned by F. P. Brooks Jr.[3].

To compensate the latency, many proposed methods used prediction in tracking. Several HMD systems are implemented with head tracker prediction [4, 5, 6, 7, 8, 9, 15], where a "look ahead" algorithm is implemented and uses the 3D position and orientation as the input data. In this paper, we will first focus on the comparison between two prediction methods in head tracking: the well-known Kalman filtering method introduced in 1991 [5] and the Grey system based method proposed in 1994 [9]. A simple linear extrapolation method and the basic method without prediction were also included in our formal experiment.

In 1991, Liang, Shaw and Green have developed a head tracking prediction algorithm based on Kalman filtering [5]. They found that the latency felt by a user is mainly due to the delay in orientation data. Based on the above observation, a predictive Kalman filtering was designed to compensate for delay in orientation data. In 1994, Azuma and Bishop used Kalman filtering with inertial sensors mounted on the see-through HMD to improve the dynamic registration, that is, to reduce the latency [7]. The result can significantly aid the head-motion prediction in real cases; on the average, prediction with inertial sensors produces errors 2-3 times lower than using prediction but without inertial sensors, and 5-10 times lower than using no prediction at all.

In 1994, the authors proposed a prediction method using Grey system theory [9]. Grey system theory is applied to the prediction of a tracker motion for an HMD system because the behavior of the tracker output is "grey" (partially known defined as grey). In our experience, prediction with Grey system theory produces errors 5-12 times lower than that without prediction on the average. Moreover, the computation complexity of Grey system prediction method is relatively low compared to the Kalman filtering and therefore real time requirement is easily met.

Both the algorithms mentioned above give reasonable results in the tracker prediction. However, the remaining question is, if one wants to implement a virtual environment with tracker prediction, which one is best suitable and under what conditions? According to our observation, the resolution of an HMD, the system latency, and the head motion (slow motion or jerky) required in completing a task will potentially affect the results of comparison. Therefore we want to control some of the factors in a formal experiment, and try to answer the puzzles. In this paper, we first compare these two methods in a quantitative analysis through motion trajectory plot in the simulation, and then design a 3D target tracking experiment involving head motion to justify which one among four methods is more acceptable in the real case.

GREY SYSTEM THEORY BASED PREDICTION AND KALMAN FILTERING

Traditionally, to deal with a digital signal system involving noise, digital filters are usually included to analyze such a system. Prediction based systems use signals from a 3D tracker as the inputs, process them, and output the predicted data.

The following subsections briefly describe the characteristics of the Grey system method and the Kalman filtering method. The experienced reader may skip the following subsections and jump to Section 3. For detailed description of these two systems please refer to the original papers: [10, 11, 9] for the Grey system theory based prediction and [12, 5, 7] for the Kalman filtering based prediction.

Grey System Based Prediction Method

The following descriptions basically followed that of [9]. In the real world, the behaviors of most systems are uncertain [10, 11]. The effects of other systems on the system under monitoring are also unclear. In Grey System theory, the system model is established under a sequence of measured raw data which is generated by the system with unclear system characteristics. The observed tracking data is used to generate a generating sequence on a Grey Generating Space, and a Grey differential model (GM) is applied to fit the generated sequence. By using the established GM, we can predict, analyze, and program the behavior of the original system.

In most cases, the tracking data observed by measuring the system is lack of relation and is insufficient to establish Grey Model. Some manipulation on the tracking data is needed to get a more regular data sequence, and the so-obtained sequence is called the generated sequence.

The most commonly used operation of the generated sequence is called Accumulated Generating Operation (AGO). Let $x^{(0)}$ be the original tracking data sequence and $x^{(i)}$ be the generated sequence for $i > 0$. The AGO is defined as:

$$x^{(i)} = \text{AGO}\, x^{(i-1)}, i > 0 \tag{1}$$

$$x^{(i)}(k) = \sum_{m=0}^{k} x^{(i-1)}(m), i > 0 \tag{2}$$

Since the $x^{(0)}$ are all positive, after applying AGO, the generated sequence $x^{(i)}$ must be a monotonic increasing sequence and its randomness disappears respectively. Therefore, the prediction model, GM, may be established in AGO domain.

Let $x^{(0)}$ be the original tracking data sequence with n samples, and $x^{(1)} = \text{AGO}\ x^{(0)}$, then assume they satisfy the following first order Grey differential model, GM(1,1), with single variable:

$$x^{(0)}(k) + a\, z^{(1)}(k) = b, k = 1,2,\ldots \tag{3}$$

$$z^{(1)}(k) = \frac{x^{(1)}(k) + x^{(1)}(k-1)}{2}, k = 1,2,\ldots \tag{4}$$

which is obtained from the following differential equation:

$$\frac{dx^{(1)}(t)}{dt} + a \bullet x^{(1)}(t) = b \tag{5}$$

Expand Eq.(3) with the n samples in $x^{(1)}$, that is, in AGO domain, we can obtained:

$$\begin{bmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n-1) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(0)) & 1 \\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(1)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1)+x^{(1)}(n-2)) & 1 \end{bmatrix} \begin{bmatrix} a \\ \\ \\ b \end{bmatrix} \tag{6}$$

Let

$$Y = \begin{bmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n-1) \end{bmatrix} \text{ and } B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(0)) & 1 \\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(1)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1)+x^{(1)}(n-2)) & 1 \end{bmatrix}$$

Solve Eq. (6) with the minimal square approximation, we can get a and b from the following equation:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left[B^T B\right]^{-1} B^T Y \tag{7}$$

By solving a, b, and the differential equation, we can get the prediction function $\hat{x}^{(1)}(k)$ for the Grey system in AGO domain:

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(0) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a}, \text{ for } k \geq 0 \tag{8}$$

Apply prediction length, k, in terms of the update rate as k to the prediction function, we can get the predicted data in AGO domain, and then apply it to the operation of inverse AGO (IAGO) defined in Eq.(9), the output data $\hat{x}^{(0)}(k)$ from IAGO is the predicted data that we need.

$$\begin{cases} \hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \text{ for } k > 0 \\ \hat{x}^{(0)}(0) = \hat{x}^{(1)}(0) = x^{(0)}(0) \end{cases} \tag{9}$$

Here we use an example to show how prediction works by using the 3D tracker data with n=6 previous Qx points, to predict the 7th point. Note that Qx is one of the four parameters in quaternion algebra.

Assume the original sequence $x^{(0)}$ is

$$\begin{aligned} x^{(0)}(k) &= \{x^{(0)}(0), x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), x^{(0)}(5)\} \\ &= \{0.0355,\ 0.0382,\ 0.0398,\ 0.0431,\ 0.0478,\ 0.0547\} \end{aligned}$$

Apply AGO (Eq.(2)) to $x^{(0)}$, which is equivalent to accumulating the sequence

$$\begin{aligned} x^{(1)}(k) &= \{x^{(1)}(0), x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), x^{(1)}(4), x^{(1)}(5)\} \\ &= \{0.0355,\ 0.0737,\ 0.1135,\ 0.1566,\ 0.2044,\ 0.2591\} \end{aligned}$$

Note that the above sequence should be monotonically increasing and solve the differential Eq.(7) and get

$a = -0.093907$, $b = 0.031658$

And then, the prediction function for the Grey system (in AGO domain) can be formulated as:

$$\hat{x}^{(1)}(k) = (0.0355 + 0.38953)e^{0.093907k} - 0.38953$$

By Eq.(9), we predict the 7th position to be

$$\hat{x}^{(0)}(6) = 0.061469$$

Kalman Filtering Based Method

The following descriptions are from [12, 13]. The term "Kalman filtering" represents a recursive (repetitive with time) procedure which enables the estimation of signals to be determined from successive measurement in time. It's a signal processing technique and some parameters such as the system, observation, and noise model require careful study and preparation before Kalman filtering can be applied.

The way to derive the Kalman filtering is a difference equation given by

$$\hat{x}(n) = A\hat{x}(n-1) + K(n)[y(n) - HA\hat{x}(n-1)] \tag{10}$$

where $\hat{x}(n)$ is the estimate of the quantity x at time n, $y(n)$ is the observation data from a 3D tracker, A is a square matrix describing the system under test, H is the squared observation matrix, and $K(n)$ is a low-pass filter named Kalman gain. The Kalman filtering based prediction is highly dependent on the gain $K(n)$, whose value is obtained from the following set of equations:

$$\begin{cases} P_1(n) = AP(n)A^T + Q(n-1) \\ K(n) = P_1(n)H^T[(HP_1(n)H^T) + R(n)]^{-1} \\ P(n) = P_1(n) - K(n)HP_1(n) \end{cases} \tag{11}$$

This is a recursive set of equations to compute Kalman gain at time n, the quantities Q and R are the system noise and the observation noise respectively and $P(n)$ is errors in prediction and $P_1(n)$ the estimation.

For each prediction phase, the predicted data is obtained from three steps:

(a) the prediction given by $A\hat{x}(n-1)$ of Eq.(10) is the estimate at time n-1.

(b) this step is a correction step of (a) by $K(n)[y(n) - HA\hat{x}(n-1)]$ in Eq.(10), where $HA\hat{x}(n-1)$ is the prediction of the measurement and thus the difference between $y(n)$ and $HA\hat{x}(n-1)$ becomes an error which is weighted by Kalman gain, $K(n)$, which is defined in Eq.(11).

If the prediction length is involved, there is another step (c) to be considered.

(c) generate another system matrix Ψ based on the specified prediction length, applying the result of (b) with the matrix Ψ, and the output is the prediction result that we need [5].

In this paper, we use the following values for our experiment, since the update time is 40ms and the prediction length is 120ms:

$$A = \begin{bmatrix} 1 & 0.0387 \\ 0 & 0.5857 \end{bmatrix} \qquad R = \begin{bmatrix} 0.000004 & 0 \\ 0 & 0 \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 0.05 \end{bmatrix} \qquad Q = \begin{bmatrix} 0.000122 & 0.003209 \\ 0 & 0.131398 \end{bmatrix}$$

$$\Psi = \begin{bmatrix} 1 & 0.0825 \\ 0 & 0.1177 \end{bmatrix} \qquad \text{and initial } P = \mathrm{I}$$

Because of the more complicated computation of Kalman gain than Grey model, the time consumed in computation is not trivial.

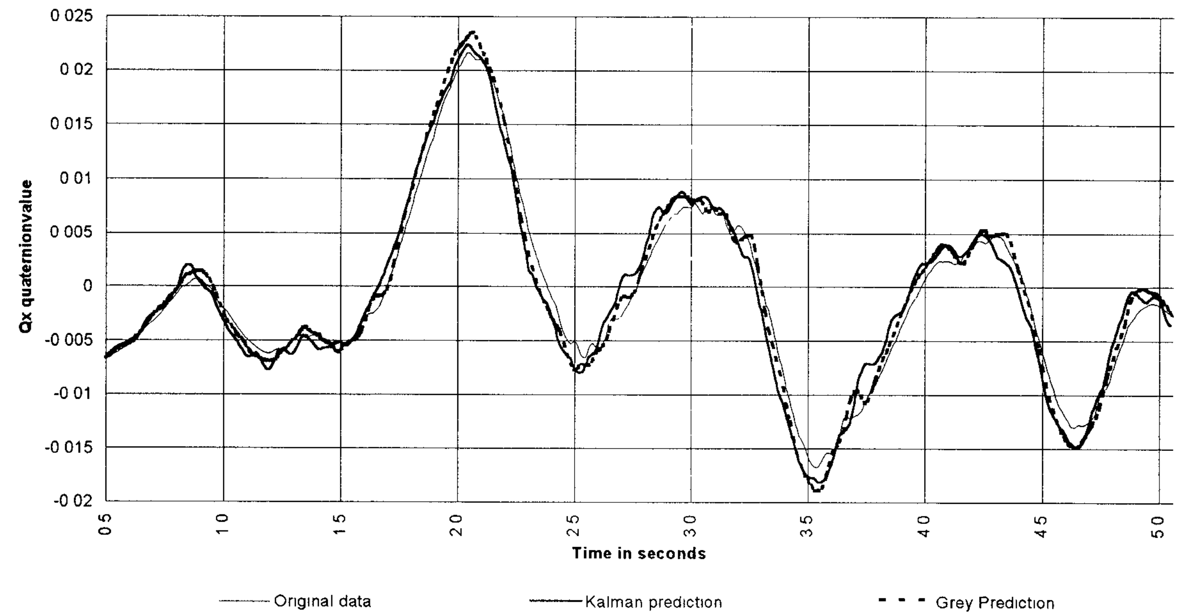

Figure 3-1 A plot of Qx curve (quaternion) with inertial-based Kalman prediction vs. Grey system.

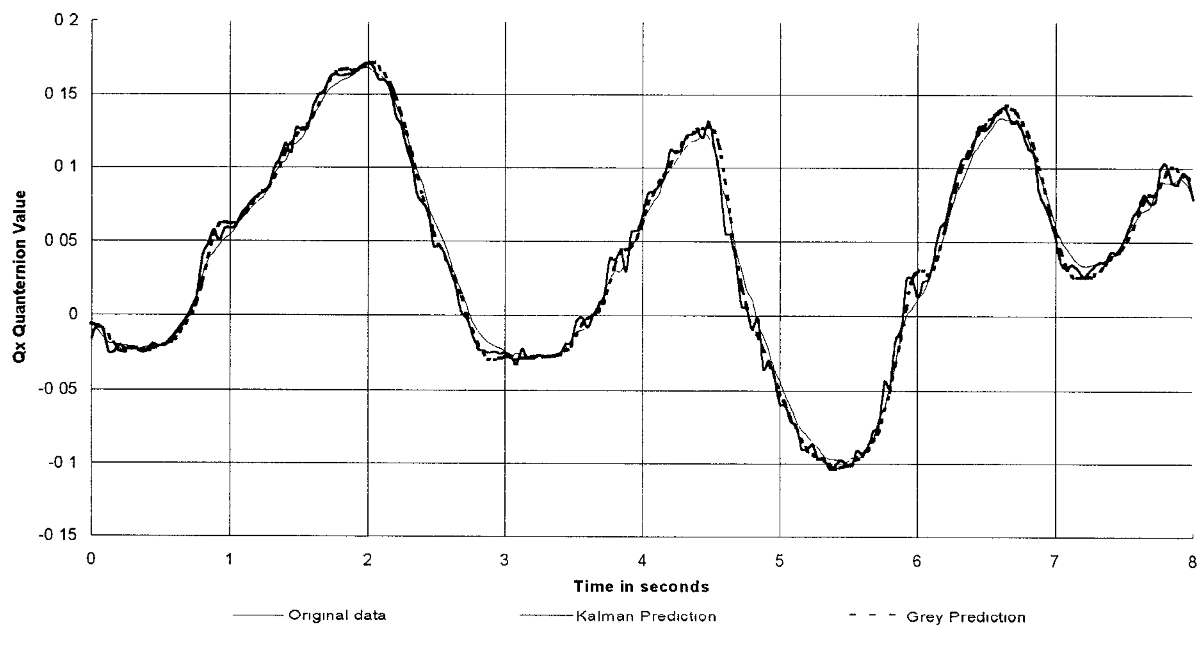

Figure 3-2 A plot of Qx curve (quaternion) with Kalman prediction without inertial sensor vs. Grey system.

QUANTITATIVE ANALYSIS

In this section, the focus is aimed at quantitative analysis between two prediction methods: the Kalman filtering and the Grey system theory in 3D orientation. Note that there is no difference between translation and orientation in the case of Grey system based prediction method, although the Kalman filtering based method do have explicit assumptions about orientation. Most cases of the behavior of these two prediction methods have similar results. So, we present two cases here as samples for our quantitative analysis.

Case 1: The original and the inertial sensor based Kalman prediction data is retrieved from the recorded data of [14], included in the CD-ROM version of SIGGRAPH'94 proceedings. It's a report from a small segment of a quaternion curve. From a high performance optoelectronic tracking system, the system update rate is about 60 times per second, and the prediction latency is set to 60ms. Applying the recorded original data as inputs to the Grey system with k=4 (prediction length = 60/16 $\cong$ 4), the three set of results are shown in Figure 3-1.

Case 2: The original data is also a small segment (about 8-second head motion) of a quaternion curve, which is recorded from our electron magnetic tracker system. We apply the data to the Kalman filtering and the Grey system to get the predicted sequence. In this case, the system update rate is 25 times per second, i.e., every 40 ms updates once, and the prediction latency is set to 120ms. A comparison of the three sets of data is shown in Figure 3-2.

Mean Square Error

The following is a table showing the mean square error in Qx curve (quaternion) with Kalman prediction (case 2 not inertial-based) vs. Grey system. From the data in Table 3-1, Kalman filtering is a little bit better than Grey system prediction in case 1, where 60 ms prediction length is used, but in case 2 where 120 ms prediction length is used, Grey system is better than Kalman filter.

	Kalman prediction	Grey system prediction
case 1	0.001641(*)	0.001774
case 2	0.007955	0.006380

(*) means inertial-based prediction was used and data was from Azuma and Bishop.

Table 3-1 A table of mean square error in Qx curve (quaternion) with Kalman prediction (case 2 not inertial-based) vs. Grey system.

Jittering Effect Measurement

In addition to the error distance in Qx curve, the jittering effect can be measured through the Fast Fourier transform (FFT), a widely used time domain to frequency domain transformation technique. The usual way is to treat the higher frequency noise as jittering caused by noisy tracker system, long prediction distance, and characteristics of prediction methods. The energy of the higher frequency noise can be calculated to measure the intensity of jittering. We assume the more the jittering effect in predicted trajectory, the larger the energy. From our observation, the U-turn like motion of the head can not exceed 5 times/sec, 5Hz, due to physical constraints, therefore we define the high frequency component as higher then 5Hz. In case 1 with 60ms lookahead, the measured three sequences have almost the same spectrum and thus the jittering effects are similar. However, in case 2 with 120ms lookahead, the jittering effect of the Kalman based prediction is so big that its energy is about 3 times larger than that of either the Grey system prediction or the raw data (Figure 3-3). That is, at the prediction length of 120ms, the jittering in the Kalman filtering appears to be the largest.

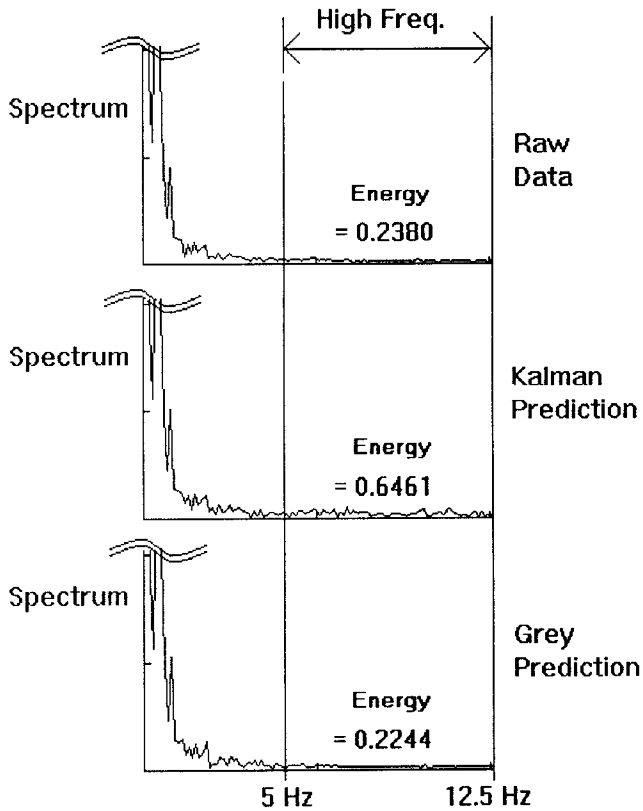

Figure 3-3 The spectrums after FFT in case 2 and the energy ranging from 5Hz to 12.5Hz.

EXPERIMENTAL DESIGN

Experimental Set-Up

With a low resolution HMD such as VPL Eyephone, there is no way to see the jittering effects, since the LCD screen is slow in response time. Because of the reason above, and the low resolution of our HMD (less than 320x240 pixels), we have determined to use CrystalEye stereo glasses instead of the VPL Eyephone as our experiment setup. The stereo glasses at least have half the resolution (half scan line for each eye in stereo mode) of the SGI Indigo[2] Extreme's screen. Therefore, participants can really see the jittering effects. We put a 3D tracker (Ascension Co Flock-of-Birds) on top of a headphone, while let a participant wear the stereo glasses to see in stereo. This setup is very different from a true immersive HMD environment, but if the head motion is limited to 15 degrees each way about the neck, the system functions the same as using an HMD.

In our experiment, using the SGI Indigo[2] Extreme for rendering (a teapot model consisting of 604 triangles in stereo) and Flock-of-Birds 3D tracker, the system latency is 120ms ~ 160ms, which is bigger than 60 ms reported in [14] using Pixel-Planes 5. "... at 130ms distance. Note that not only is the prediction less accurate, but the oscillations are much larger. The same problem occurs with or without the use of inertial sensor.", quoted from Azuma and Bishop in appendices of [14]. Since the prediction accuracy at 130ms either with or without the use of inertial sensor in Kalman filtering is not significantly different, and we are constrained in our equipment, we have chosen not to use the inertial-based Kalman filtering in the next experiment.

In our experiment, the subject is instructed to imagine to participate in a mission of dog fight simulation wearing stereo glasses, see Figure 4-1. Figure 4-2 is a diagram of the 3D target tracing task, where VPN is the view plane normal, COP the center of projection and M the vector between two eyes. The error distance in the tracing task is defined as the distance from the center of the target T to the plane passing through COP with a surface normal M.

The Kalman filtering and Grey system methods used a prediction length of 120ms with 6 historical samples while the simple extrapolation method based on Lagrange formula only predicted one sample distance away (40ms).

Figure 4-1 A photo of our experimental system.

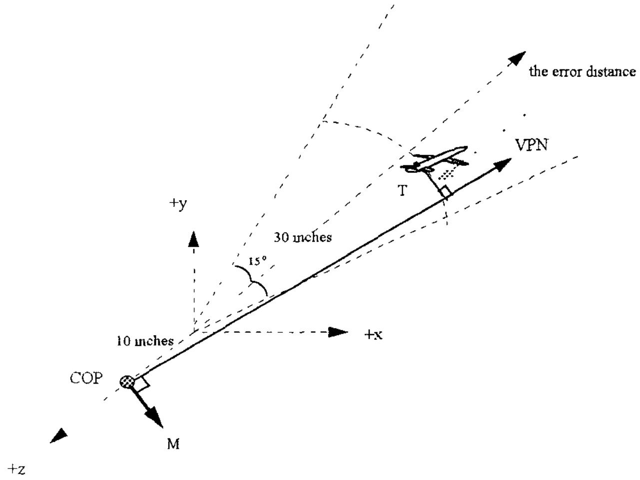

Figure 4-2 Diagram of the 3D target tracing task, where VPN is the view plane normal, COP the center of projection and M the vector between two eyes. The error distances in the tracing task is defined as the distance from the center of the target T to the plane passing through VRP with a surface normal M.

Experiment

We are interested in the performance of subjects using the following four methods in a 3D flying target tracing task with head controlled orientation:

1. Non-prediction, here called **N**.
2. Prediction with simple extrapolation based on Lagrange method, here called **E**.
3. Prediction with Grey System theory, here called **G**.
4. Prediction with Kalman filtering method but without inertial sensor proposed in [14]. This method, which was first proposed in 1991, is here called **K**.

Hypothesis

(1) Prediction methods **G** and **K** are better than without prediction **N**.

(2) The Kalman filtering **K** and Gray system **G** prediction methods are equally good in terms of this tracking experiment, since their motion trajectory in simulation data appears to be very similar in terms of error distance.

There are two weak hypotheses, which are not considered important in this paper, which state that: (i) among the three prediction methods, Kalman filtering **K** and Gray system **G** methods, being with higher order of complexity, are better than the simple extrapolation methods **E** (ii) the simple prediction method **E** is better than the one without prediction, **N**.

Procedure
For each trial, the subjects were told to trace the flying target as close as possible by minimizing the distance between center of viewport and the center of the target in 30 seconds. After a short message, pressing a specific key signals the start of each trial. A beep signals the end of trial. Each subject participated in two sessions, when slow and fast motion of the target were presented. The training took about 5 minutes for each subject, and the experiment took about 30 minutes. Each subject was trained with each method until additional training did not improve significantly, usually within 5 minutes.

The computer automatically recorded the subjects' performance in terms of error distance. Each trial was followed by a thirty second rest period.

Subjects
We used eight volunteer subjects from graduate students in the computer science department. All subjects were able to see stereo using the stereo glasses.

Design
The within-subject design is based on repeated measures, and both the multiple comparison procedures and *Student t* test is used at $\alpha = 0.05$ significant level [16].

Results
Table 4-1 shows the error distance between the center of viewport and the center of the flying target, which is set at 40 inches away in slow motion, i.e., ±0.2 degree random rotation in Y-axis every 1/25 second. Table 4-2 shows the error distance in fast motion, ±0.4 degree every 1/25 second.

The multiple comparison procedures, such as Multiple *F*, *Turky*, and *Scheffé* test, are statistical tests used to find which means differ from one another in a repeated measurement design. These procedures obtain a critical value (CV), which specifies the minimal difference between two treatment means that is statistically significant at the α level chosen. The actual difference between the means in each comparison of interest is then compared against the CV.

In the **N** vs. **G** test, **N** has a mean error of 3.827, and **G** an error of 3.142 from Table 4-1. Since differences between the former two means is 0.68, greater than the critical values of Multiple *F*, *Turky*, and *Scheffé* test at $\alpha = 0.05$ (Table 4-3), the results corroborate with our hypothesis (1), that is, **G** is better than **N** in performance. According to Table 4-3 and Table 4-4, similarly, **K** is better than **N** both in slow and fast motion (hypothesis (1)), and **G** is better than **E**, **K** is better than **E** in fast motion (weak hypothesis (i) after hypothesis (1) and (2)). However, weak hypothesis (ii) can not be corroborated by these tests, therefore we can not claim that **E** is better than **N**.

Subject	N	E	G	K
S1	3.439	2.997	2.697	2.883
S2	4.625	4.272	3.520	3.586
S3	3.564	3.457	3.411	3.057
S4	3.902	3.597	3.154	3.463
S5	4.203	3.631	3.277	3.279
S6	3.025	2.953	2.576	2.352
S7	3.901	3.414	3.203	3.239
S8	3.955	3.814	3.301	3.180
Mean	3.827	3.517	3.142	3.130

(unit : inches)

Table 4-1 Performance data (average error distance) for **N**, **E**, **G**, and **K** of a target tracing task (slow motion).

Subject	N	E	G	K
S1	4.929	4.984	4.391	4.334
S2	5.527	5.352	5.054	5.057
S3	5.432	4.989	4.299	4.219
S4	5.683	5.555	5.229	5.269
S5	5.665	5.217	4.494	4.680
S6	5.065	4.600	4.190	3.984
S7	5.983	5.712	4.987	4.808
S8	5.531	5.321	5.050	4.829
Mean	5.477	5.216	4.711	4.648

(unit : inches)

Table 4-2 Performance data for **N**, **E**, **G**, and **K** of a target tracing task (fast motion).

	N	E	G	K
N	-	0.31	0.68(a,b,c)	0.70(a,b,c)
E		-	0.37	0.39
G			-	0.01
K				-

a. $p<0.05$, Multiple *F* test; Critical Value = 0.425
b. $p<0.05$, *Turky* test; Critical Value = 0.568
c $p<0.05$, *Scheffé* test; Critical Value = 0.619

Table 4-3 A table of mean differences between any pair of two methods in slow motion, where the methods are **N**, **E**, **G**, and **K**. The (a,b,c) symbol after numbers such as 0.68 means that the difference of 0.77 between two means is greater than the critical value set by (a) Multiple *F* test, (b) *Turky* test and (c) *Scheffé* test.

	N	E	G	K
N	-	0.26	0.77(a,b,c)	0.83(a,b,c)
E		-	0.50(a)	0.57(a,b)
G			-	0.06
K				-
a. $p<0.05$, Multiple *F* test; Critical Value = 0.399				
b. $p<0.05$, *Turky* test; Critical Value = 0.533				
c. $p<0.05$, *Scheffé* test; Critical Value = 0.581				

Table 4-4 A table of mean differences between any pair of two methods in fast motion, where the methods are **N**, **E**, **G**, and **K**. The symbol denotation is like Table 4-3.

According to the multiple comparison tests above, the **G** and **K** are not significantly different, and the results can not be in corroboration of our null hypothesis. With respect to **G** and **K**, we introduced the *Student t* test to corroborate it. The *Student t* test provides an answer to the fundamental statistical question that must be answered before a conclusion is reached about the research hypothesis[12]: what is the probability that the obtained difference in **two** samples means could occur if chance (sampling error) alone were responsible?

In the **K** vs. **G** test, the *t* test values for the null hypothesis test, see Table 4-5, are 0.164 (slow motion) and 1.303 (fast motion) respectively, both not greater than 2.356 at α = 0.05 with DOF = 7, therefore, the results corroborate with our null hypothesis (2), that is, the hypothesis **K** = **G** can not be rejected and so **G** and **K** are equally good.

	target in slow motion	target in fast motion
G vs. **K**	$t = 0.164183$	$t = 1.303053$

Table 4-5 Student *t* test values for pairs of comparison of G and K corroborates with our null hypothesis.

DISCUSSION

We used complete counterbalancing among participants to reduce the multiple-treatment effects, such as practice effects and treatment-carryover effects. That is, we change the order of tests for each participant during the experiment.

Observation from Participants:

(1) Participants got tired after 30 minutes of experiment. The symptoms: stiff neck and sore eyes (feeling eyes dry) were reported from two participants.

(2) Half of the participants showed improvement rapidly during the training period in the first 5 minutes, then after twenty minutes, the average tracking distance error is actually increasing for the same task, which is a clear indication of tiredness. The reasons for causing the tiredness could be (a) intensive playing and highly focusing in target tracking task,(b) jittering objects on the screen, (c) not used to wearing shutter glasses for stereo vision.

(3) That although in the jittering effects Kalman filtering **K** was ranked the biggest, without prediction **N** being the lowest, and in the middle simple extrapolation **E** about the same as gray system **G**, there appears no significant effect in our 3D tracking task.

(4) Subjects reported that Kalman filtering **K**, although with the biggest jittering effect, appears to be the most responsive, while Gray system **G** is ranked number two in responsiveness.

CONCLUSIONS

In this paper, we have conducted an experiment on latency and its compensation methods both quantitatively and subjectively. In our 3D target tracing task involving eight subjects using their head motion to trace a flying target in random motion, we have found that two prediction methods, Kalman filtering (not inertial-based) and Grey system prediction, are significantly better than the one without prediction, and the former two methods are equally well in performance. Typical motion trajectories of four methods in simulation at 120ms of system latency are plotted, and in terms of jittering Kalman filtering appears to have the largest.

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