Remote Towers: Videopanorama Frame Rate Requirements Derived from Visual Discrimination of Deceleration during Simulated Aircraft Landing

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Abstract— **In order to determine the required visual frame rate (FR) for minimizing prediction errors with out-the-window video displays at remote/virtual airport towers, thirteen active air traffic controllers viewed high dynamic fidelity simulations of landing aircraft and decided whether aircraft would stop as if to be able to make a turnoff or whether a runway excursion would be expected. The viewing conditions and simulation dynamics replicated visual rates and environments of transport aircraft landing at small commercial airports. The required frame rate was estimated from the FR-extrapolation of event probabilities conditional on predictions (stop, no-stop), and from a model fit to the perceptual discriminability A (average area under all proper ROC-curves) as dependent on FR. Decision errors are biased towards preference of overshoot and appear due to illusionary increase in speed at low frames rates. Both extrapolations yield a framerate requirement FR_{min} of $35 < FR_{min} < 40$ Hz which is compared with published results [12] on shooter game scores. Definitive recommendations require further experiments with FR > 30 Hz.**

***Keywords:** remote tower; videopanorama; framerate; simulation; detection theory; Bayes inference*

I. Introduction

This paper continues the discussion of a two-alternative decision experiment with simulated aircraft landing as dependent on video-framerate characteristics under Remote Tower conditions [1][2]. We use two statistical analysis methods, Bayes inference on probability of stop vs. no-stop events (normal braking vs. runway excursion) conditional on predictions and non-parametric discriminability parameter A (= average area under all proper ROC-curves) to derive the minimum video-framerate requirement for minimizing decision errors.

Recent proposals for decreasing cost of air-traffic control at small low-traffic airports have suggested that technology may remove the need for local control towers. Controllers could visually supervise aircraft from remote locations by videolinks, allowing them to monitor many airports from a central point [3][4][14][15]. While many current towers on ASMGCS-equipped airports, even some at busy airports like London-Heathrow, can continue to operate totally without controllers ever seeing controlled aircraft under contingency conditions, it is clear from controller interviews that usually numerous out-the-window visual features are used for control purposes [5][6][7]. In fact, these visual features go beyond those required for aircraft detection, recognition, and identification [8].

Potentially important additional visual features identified by controllers in interviews involve subtle aircraft motion. These could be degraded by low dynamic quality of remote visual displays of the airport environment. In fact, the dynamic visual requirements for many aerospace and armed forces tasks have been studied, but most attention has been paid to pilot vision (e.g. [9]) and military tactical information transmission (e.g. [10]). Relatively little attention was paid to the unique aspects of controller vision which, for example, emphasize relative motion cues. Consequently, there is a need to study some of these visual motion cues to understand how their use may be affected by degraded dynamic fidelity, e.g. low visual frame rates. Such low rates could be due to typically low rates of aircraft surveillance systems, e.g. 1-4 Hz, or to image processing loads arising from the very high resolution, wide field of view video systems needed to support human vision in virtual towers.

Since preliminary investigation of the role of visual features in tower operations has shown that their principal function is to support anticipated separation by allowing controllers to predict future aircraft positions [5] we have begun to investigate the effects of frame rates on the deceleration cues used to anticipate whether a landing aircraft will be able to brake on a runway, as if to make a turn off before the runway end.

Our specific hypothesis is that the disturbance due to low frame rate affects the immediate visual memory of image motion within the video frame. Memory processes classically have an exponential decay. Accordingly, one might expect discriminability of the visual motion associated with aircraft deceleration to reflect this feature, degrading only a bit for higher frame rates but more rapidly for the longer period, lower frame rate conditions. A possible descriptive function could be of the form: 1 – exp(-k/T). This kind of model captures the likely features that the rate of degradation of motion information increases with greater sample and hold delays T but that there is also an upper asymptote of discriminability corresponding to continuous viewing which is determined by the inherent task difficulty. Significantly, fitting such a model to the drop off in detection performance provides a theoretically based method to estimate that frame rate required to match visual performance out the tower window.

Experimental Methods and results are provided in sections II, III. In section IV two alternative methods (detection theory and Bayes inference) are used for deriving estimates of discriminability A and stop / no-stop probabilities conditional on prediction, to be used in turn to provide minimum framerates for maximizing A and minimizing prediction error. We finish with a conclusion and outlook in section V.

II. METHODS

A. Subjects

Thirteen active German tower controllers were recruited as volunteer subjects for the experiment. The participants' ages ranged from 25 – 59 yrs. and were divided into 3 experimental groups of 4, 4, 5. Controllers from small, medium, and large German airports were approximately evenly distributed to the groups.

B. Apparatus

The experiment was conducted at a Remote Tower (RTO) videopanorama-console as part of the DLR Apron-and-Tower Simulator of the Braunschweig DLR facility. This simulation system was used to generate 60 landings of a lightly loaded A319 transport at the Braunschweig airport (Fig.1). The simulated aircraft would first appear on the right most monitor while in the air at 300 m altitude 32 sec before touch down (Fig.2). Then it would fly to touch down seen on the next monitor to the left. Thereafter, it would either roll through to the end of the runway or stop 250 m before the runway end.

The simulator generated 60 1-minute landing scenarios with various dynamically realistic deceleration profiles of nominally 1, 2, or 3 m/s^2 maximum (initial) braking and frame rates of either 6, 12, and 24 fps emulating the video signals potentially coming from cameras mounted near the Braunschweig tower. Only the highest deceleration (3 m/s^2) was sufficient to cause the aircraft to stop near the stopping point (Fig.1) before the end of the runway (leftmost monitor in Fig.2).The video files were then used in turn as input simulating the actual cameras so the participants could use the video console as if it were connected to actual cameras on the airfield. They present approximately a 180° view as seen from airport tower but compress it to an approximately 120°. Viewing distance between operators and monitors (21" UXGA: 1600x1200 pixels with 4/3 format: 42x33 cm, luminousity sufficient for photopic office environment) was ca. 120 cm. An upper array of tiled monitors for a second airport was present but not used during the testing.

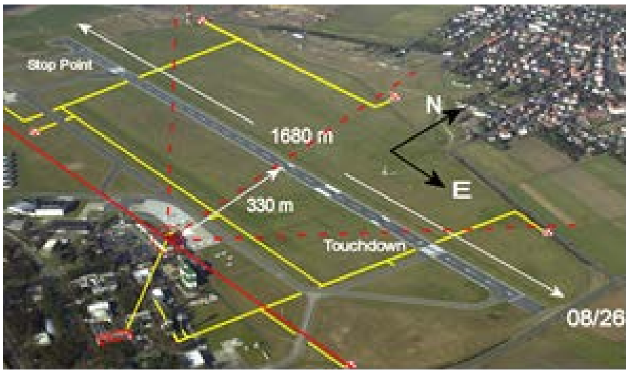

Figure 1. Aerial view of Braunschweig airport showing the circled location of the simulated cameras, fields of view of the four cameras (radial sectors), and some dimensions and reference points.

Figure 2. Participant at a simulation console judging the outcome of a landing aircraft just after touchdown. Approach on the rightmost monitor, touchdown is on the left side of second monitor from the right.

C. Experimental Design and Task

The three matched subject groups were used in an independent groups, randomized block design in which the three different landing deceleration profiles were used to produce 60 landings to the west on the Braunschweig airport's Runway 26. Each group was assigned to one of the three video frame rate conditions. The approaches were all equivalent nominal approaches for an A319 aircraft but varied in the amount of deceleration after touchdown.

The equation of motion used for the post-processing of logged simulation data assumed that the only braking force (deceleration) after touchdown is given by:

$$\ddot{x} = -b_{min} - (b_0 - b_{min})e^{-t/\tau} \qquad (1)$$

with $d^2x/dt^2(t=0) = -b_0$, and parameters obtained from exponential fits to the logged simulation data listed in Table I. Also listed are the stop times $t_{stop} = t(v = 0)$, $v(t=0) = v_0 = 70$ m/s and positions x_{Stop} as calculated from the solution to (1). The table verifies that only the highest nominal deceleration avoids runway excursion (stop for x < ca. 1500 m).

The participants' task was to report as soon as possible whether the landing aircraft would stop before the end of the runway (stop event S2 (high deceleration), no-stop event S1 (runway excursion due to low deceleration)), with response time measured by pressing the space bar.

TABLE I. DECELERATION PROFILES .

	Landing Braking Parameters		
Nominal value m/s^2	1.0	2.0	3.0
b_0 / m/s^2	1.33	1.76	2.39
b_{min} / m/s^2	0.45	1.01	1.64
τ / s	41.3	22.0	12.0
t_{stop} / s	85.1	54.4	37.4
x_{stop} / m	2544	1748	1238

In all cases they were then allowed to watch the actual outcome and use a certainty level compatible with actual operations. The three different deceleration profiles were randomized to produce a sequence of 30 landings in 3 blocks of 10. The three blocks were repeated once to provide the 60 landings in the experimental phase used for each of the independent groups. The experimental phase was preceded by a training phase during which the subjects were given familiarity practice with 20 landings similar to those used experimentally. This approach gave participants a chance to learn the task and adapt to a head mounted video-based eye tracker that they wore during the experiment. Including instructions, the experiment required 1.5-2 hr per subject. Further experimental details regarding the subjects may be found in [1].

III. RESULTS

The experimental results of this two-alternative decision experiment concerning decision errors as dependent on video framerate are summarized in the stimulus-response matrix of Table I. It shows group averages of measured probability estimates, with standard errors of mean (), of correct rejection C = P(no|S1), false alarm FA = P(yes|S1), miss M = P(no|S2), and hit H = P(yes|S2). S1 = stimulus with runway excursion, S2 = stimulus with stop on the runway, yes = stop predicted (high deceleration perceived), no = no stop predicted (low deceleration perceived). Probabilities in horizontal rows (constant stimulus) sum up to 1.

It can be seen that measured probabilities indicate a trend as dependent on framerate (FR): the hit rate p(yes|S2) increases with framerate whereas the false alarm rate p(yes|S1) decreases. We will show in the discussion section that the measured (a priori) probabilities in the response matrix allow an (Bayes) inference on risk probabilities for safety critical decisions, dependent on the video framerate as system parameter (risk for a different than predicted event).

Interestingly, during debriefings after the experiment subjects in the lower two frame rate groups reported that they felt the aircraft were moving “too fast” and that it was this extra apparent speed making discrimination hard. By “too fast” the controllers meant to refer to the apparent ground speed of a transport aircraft compared to what they would expect to see from a tower.

TABLE II. RESPONSE MATRIX.

Alternative Stimuli	Response for 3 Video Framerates: Probability Estimates				
	No-stop predicted			Stop predicted	
Low Deceleration No-stop Stimulus S1	p(no|S1) = C	6	0.86 (0.02)	p(yes|S1) = FA	0.14 (0.02)
		12	0.89 (0.03)		0.11 (0.03)
		24	0.94 (0.01)		0.06 (0.01)
High Deceleration Stop Stimulus S2	p(no|S2) = M	6	0.55 (0.06)	p(yes|S2) = H	0.45 (0.06)
		12	0.45 (0.05)		0.55 (0.05)
		24	0.22 (0.07)		0.78 (0.07)

We examined this possibility by looking at a response bias that could arise from aircraft appearing to move “too fast.” Such a bias would lead subjects to underestimate whether an aircraft actually coming to a stop would in fact stop, because it would seem to be going too fast. Aircraft in fact not stopping would not be subject to a bias since they would merely seem to be overshooting the end of the runway in any case. Thus, we would expect subjects to be more likely to incorrectly identify a stopping aircraft (S2) as non-stopping versus one that is not stopping (S1) as stopping.

Indeed, when we compared the likelihood of erroneously identifying an overshoot versus that of erroneously identifying a stop (Table II) M - FA = p(n|S2) – p(y|S1), all 13 subjects showed this bias. (sign-test, p <0.001). This general bias towards identifying an aircraft as not stopping, however, is not surprising since approximately twice as many aircraft observed in fact do not stop versus those that do and subjects quickly sense this bias during the experiment. What is interesting, however, is that the bias is a decreasing function of the frame rate.

The significance of this result, however needs support based on theoretical considerations and on alternative analysis of the detection bias. For this purpose we will present an analysis based on the Bayes theorem (inversion of probabilities) and compare this with that one obtained with ROC-analysis using discriminability (ROC-area A) and bias parameter (likelihood b). See also [2] for comparison of conventional SDT-discriminability index d’ with A. Of particular practical interest is the inferred risk of a runway excursion occurring when a stop is predicted, i.e. the conditional probability of overshoot p(S1|yes) (S1 = no stop event) due to low or abnormal braking when normal braking is perceived (stop prediction).

IV. DISCUSSION

An initial analysis of the two-alternative decision experiment and the response matrix was presented previously by means of signal detection theory (SDT) via model fit to discriminability d'(FR), leading to initial estimates of frame rate requirements for minimizing decision errors [1][2]. The present analysis will start with Bayes-inference calculation for deriving a frame rate requirement for minimizing decision errors, based on the response matrix of Ttable II. It will be compared to the minimum frame rate obtained from nonparametric discriminability A (= average area under ROC-curves). Also the response bias will be discussed in more detail.

A. *Bayes Inference*

The Bayes inference probabilities, with standard errors of mean (), about event S1 for runway excursion occuring and S2 for stop occuring conditional on response (answer "no" for excursion predicted, answer "yes" for stop predicted), from measured response probabilities (yes, or no predictions conditional on events S1, S2) are summarized in Table 3. Here the probabilities (for the same FR) of the columns add to 1.

As an example the runway overshoot probability conditional on stop predicted (Bayes inference on the probability of actual event different from prediction) is given by

$$p(S1|\ yes) = p(yes|S1)\ p(S1) / p(yes) \qquad (2)$$

Equation (1) quantifies the risk of an overshoot occurring when predicting a stop. It is proportional to the false alarm rate or probability of missing a planned overrun times the proportion of presented no-stop stimuli, divided by the overall probability of stop predictions. Fig. 3 depicts the Bayes probability estimates for an unexpected runway excursion (S1) conditional on perception of a high braking deceleration (answer "yes": stop predicted) which suggest a linear fit to the three framerate data. As expected Figure 3 shows that for decreasing frame rates (FR -> 0) the conditional probability for a runway excursion occuring when a stop is predicted rises to chance (0.48 ± 0.01).

TABLE III. BAYES INFERENCE MATRIX

Event Alternatives	Bayes Inference on Event Probabilities conditional on Prediction				
	No stop predicted (no response)			Stop predicted (yes response)	
Low Deceleration No stop event S1	p(S1|no)	6	0.78 (0.02)	p(S1|yes)	0.40 (0.03)
		12	0.81 (0.02)		0.30 (0.04)
		24	0.91 (0.02)		0.13 (0.02)
High Deceleration Stop event S2	p(S2|no)	6	0.22 (0.02) 0.19 (0.02)	p(S2|yes)	0.60 (0.03)
		12	0.09 (0.02)		0.70 (0.04)
		24			0.87 (0.02)

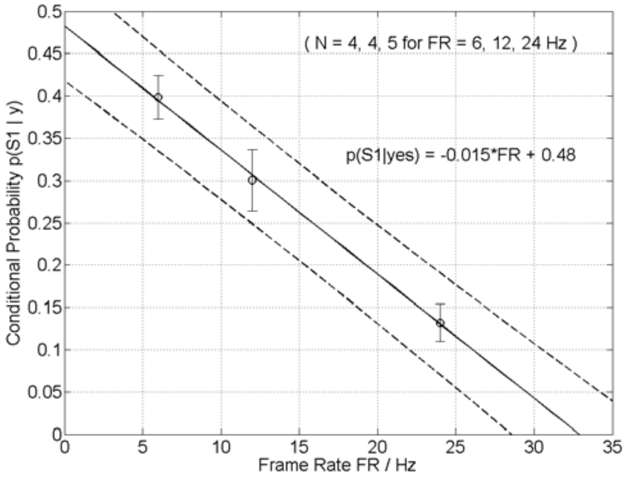

Figure 3. Bayes inference about probability of S1 "a/c will not stop before RWY-end" (braking acceleration < threshold) as calculated from measured probabilities of subjects predicting "stop on RWY " conditional on S1 (= FA). Ordinate: mean (with stderr of mean) of p(S1|stop prediction) averaged for all subjects within each of the three FR-groups. Abscissa: frame rate / Hz. Straight line = linear fit with 95% confidence intervals (dotted).

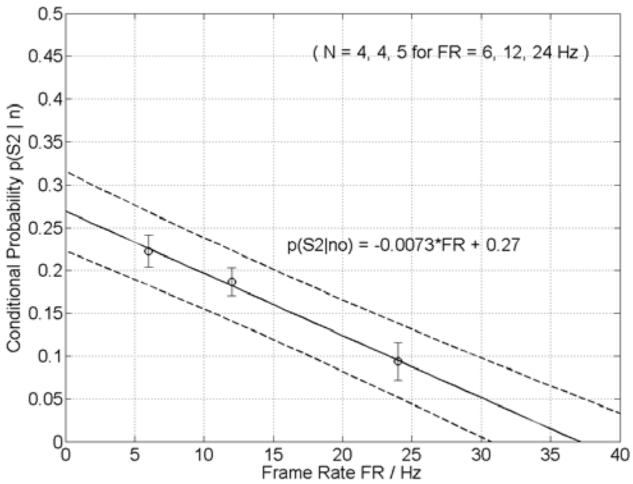

Figure 4. Bayes inference about probability S2 "a/c will stop before RWY-end" (braking acceleration > threshold) as calculated from measured probabilities of subjects predicting "overshoot" conditional on S2, via Bayes theorem. Ordinate: mean (with stderr of mean) of p(S2|no-stop response) averaged for all subjects within each FR-group. Abscissa: frame rate. Straight line = linear fit with 95% confidence intervals (dotted).

On the other hand the extrapolation of the linear fit through the three group averages indicates minimum framerate of at least 33 (± 2) Hz in order to approach vanishing probability for erraneous predictions, as required for safe operation.

The probability, that an unexpected stop occurs when predicting no-stop is obtained from p(S2|no-stop) = p(n|S2) p(S2)/p(n) (i.e. proportional to ratio of misses M to "no" response, times proportion of stop events (= 1/3)), and is shown in Fig. 4. Comparing Fig. 4 with Fig. 3 one immediately recognizes a bias, with p(S2|no) -> 0.27 for FR -> 0 Hz, indicating a significantly reduced number of stop events conditional on "no" response, as would be expected by chance. As mentioned above the S2/S1 imbalance of 1/3 stop events and 2/3 no-stop partly explains this bias: the extrapolation to FR = 0 (no movement information available), yields p(S2|n) = 0.27 and p(S1|n) = 0.73 for the complimentary case so that for low FR with large position jumping $p(S2|n)/p(S1|n) \approx 0.4$ reflects the S2/S1 imbalance of 1/2. The decrease of the p(S2|n)-bias and decision bias p(n|S2) (tendency for overshoot prediction under S2) with increasing FR goes in parallel with the decreasing overall decision error. So the Bayes analysis confirms the previously reported error bias [1][2] as quantified by M – FA = p(n|S2) – p(y|S1) which also decreases with increasing framerate. Within the 95% confidence interval of the linear fit to the data also p(S2|no) predicts zero bias and 100% correct response for frame rates > 35 Hz, which is compatible with the FR-limit of zero-error prediction obtained with the "unexpected stop"- probability.

The hypothetical visual memory effect mentioned above would suggest an exponential approach to a minimum error probability with increasing FR instead of a linear behavior. The exponential fit to our data, however yields a significantly reduced goodness (F = 140, p = 0.054) as compared to the linear case (F = 645, p = 0.025), which demonstrates the necessity of experimental data at higher framerates..

The Bayes analysis also confirms that the error bias appears exclusively connected with the preference of no-stop decisions because the false-stop prediction errors, as expected yield a chance Bayes probability p(S1|yes) = 0.5 for FR -> 0 (see Fig.3), the same being true for the complementary case p(S2|yes). The observation of no-stop decision p(n|S2)-preference under low frame rate suggests the need for counter measures, perhaps temporal filtering to smooth out the discontinuities. Such an approach would undoubtedly benefit from a computational model of speed perception. One starting point for such analysis of the speed perception error could be the spatio-temporal aliasing artifacts that introduce higher temporal frequency information into the moving images.

The measured probabilities (Table II) used for calculating the Bayes inference are based on error statistics composed of discriminability and subjective criteria, i.e. decision bias is included. The bias towards no-stop decisions, however is clearly expressed in Fig. 4 (unexpected stop). In what follows nonparametric ROC-analysis is used for separating both contributions.

B. Discriminability A and Decision Bias b

Detectability A and likelihood bias parameter b were suggested as improved "nonparametric" alternatives of the conventional discriminability d' and criterion c because it requires fewer statistical assumptions (in its final form it was presented by Zhang and Mueller in 2005 [13]). In [2] we compared A with d' to estimate user sensitivity of detection that an aircraft will stop. Discriminability A and b are independent of the distributional assumptions required for deriving the conventional d' and c parameters for detectability and bias. The Zhang & Mueller formulas yield the average area A under all possible proper ROC curves (i.e. all concave curves within the range (0,0) – (1,1)) with non-increasing slope, obtained from the measured hit (H) and false alarm rates (FA). The constant A-isopleths cut the constant b-isopleths at the group mean (<FA>, <H>) coordinates which are used for calculating the A and b-ROC-curves: $A := A_{mean}(H,FA)$ and $b := b_{mean}(H,FA)$ for the three different framerate conditions according to the Zhang & Mueller equations:

$$A = \begin{cases} \frac{3}{4} + \frac{H - FA}{4} - FA(1-H) & \text{if} \quad FA \le 0.5 \le H \\ \frac{3}{4} + \frac{H - FA}{4} - \frac{FA}{4H} & \text{if} \quad FA \le H \le 0.5 \\ \frac{3}{4} + \frac{H - FA}{4} - \frac{1-H}{4(1-FA)} & \text{if} \quad 0.5 < FA \le H \end{cases} \tag{3}$$

The associated measure of decision bias is based on the slope of the constant discriminability A-ispleths which corresponds to the likelihood ratio [13]:

$$b = \begin{cases} \frac{5-4H}{1+4FA} & \text{if} \quad FA \le 0.5 \le H \\ \frac{H^2 + H}{H^2 + FA} & \text{if} \quad FA \le H < 0.5 \\ \frac{(1-FA)^2 + (1-H)}{(1-FA)^2 + (1-FA)} & \text{if} \quad 0.5 < FA \le H \end{cases} \tag{4}$$

Figure 5 shows the measured hit rates versus false alarm rates for all subjects together with their means (black crosses, as given in Table 1) and receiver-operating characteristics (ROC's), i.e. isopleths of constant discriminability A(FR) and constant decision bias b. Individual hit rates (relative frequencies) are scattered between 0.3 and 1, whereas false alarms rates concentrate in the low probability range < 0.2, indicating conservative decisions, as would be expected for trained air traffic controllers. Circles, stars and crosses represent individual measurements (Hit, False Alarm) for FR = 6, 12, 24 Hz respectively, as obtained from the 13 subjects with repeated measurements (60 landings). Black crosses with error bars show the group mean values of the individually measured (F,H)-values and the standard errors of means for the three different framerates. Solid curves represent the ROC curves parametrized with the group mean A-values via equations (2). The three dotted curves represent the decision bias b, obtained from the parametric representation given in equation (3). b apparently decreases with sufficiently high framerate FR towards the neutral criterion value b = 1 which confirms the Bayes inference result in Figure 4 that the overestimation of speed (bias for misses) decreases with framerate: the criterion shifts to more liberal values.

The three (group-average) discriminability parameters A(FR) are depicted in Figure 6 together with an exponential fit and 95% confidence intervals (using Matlab "Nlinfit").

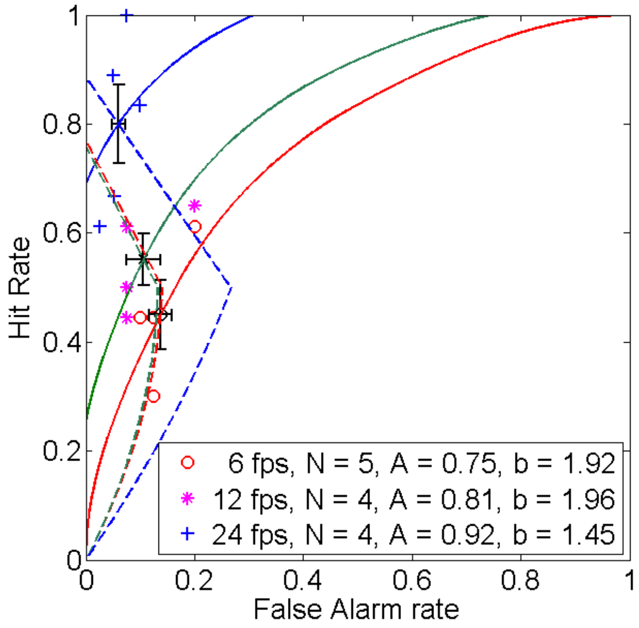

Figure 5. Measured hit vs. false alarm rates (H, FA) for all 13 subjects and the three group averages with standard errors (crosses) and with ROC-curves for the three framerates. Straight lines = constant sensitivity A-isopleths; dotted lines = constant bias (likelihood ratio) b-isopleths.

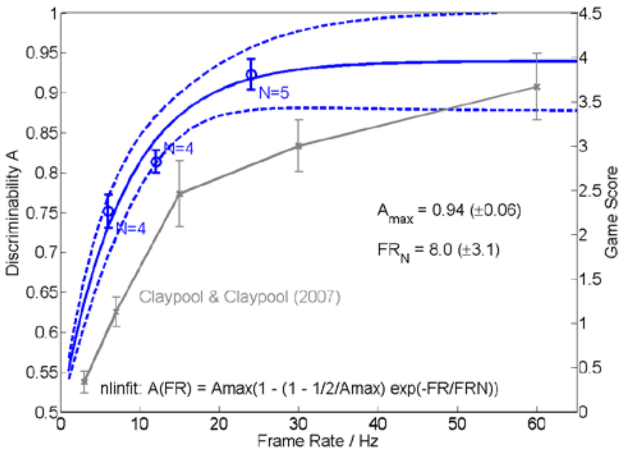

Figure 6. Group averages (13 subjects) and exponential regression model for A (darkest solid trace) of the discriminability of landings with stopping aircraft. 95% regression confidence intervals flanks the model fit. Lighter grey trace shows re-drawn comparative data from [12]

The exponential model fit to our three data points is based on the hypothesis that low framerates might disturb the visual short term memory so that with increasing visual discontinuity the speed estimate or sequential sampling of the speed information up to the decision time becomes biased. Since the A parameter unlike the classical d', does not require the usual assumptions of Signal Detection Theory (SDT), e.g., normality of both the signal and noise distributions, it may be considered to provide a better estimate of the frame rate at which participants' performance asymptotes as provided in Ellis et al. [1]. From Figure 6 this value seems to be in the range 30 - 40 fps, a value close to that estimated from Bayes analysis.

Alternatively and for the sake of parsimony our three data points, like with the Bayes analysis may be fitted with a straight line, yielding an extrapolation to ca. 31 Hz for A = 1 (maximum discriminability), which lies at the lower end of the Bayes fit confidence intervals.

Our results may be compared to the (re-drawn) published results of Claypool & Claypool [12] in Figure 6. The Claypool results were obtained with subject scores in a shooter game under different framerates. They suggest a significantly higher asymptotic framerate value for maximizing shooter scores as compared to our extrapolations.

V. CONCLUSION

It is clear from controller interviews that numerous out-the-windows visual features are used for control purposes [5][6][7], which in fact go beyond those required for aircraft detection, recognition, and identification [8]. In the present work, for analyzing frame rate effects on prediction errors we focused on the landing phase of aircraft because we expected any perceptual degradation to be most pronounced in this highly dynamic situation. Our preliminary results (FR_{min} > 30 Hz) show that a definitive recommendation of a minimum video framerate and a confirmation of our initial hypothesis of visual short-term memory effects resulting in the proposed asymptotic characteristic requires a further experiment with FR > 30 Hz. This high-FR experiment was not possible with the video replays used in the present experiments for technical reasons. Obviously the presented experimental data are not sufficient to decide in favor of the visual short term memory hypothesis versus a heuristic decision basis, e.g. sequential sampling and comparison of time dependent aircraft position with landmarks for thresholding. The latter might be modeled by some variant of a relative judgement or diffusion model of two-alternative decision making (e.g.[16]).

A formal model for predicting the hypothetical visual memory effects would also be of great help. Recent studies which might be of use for this purpose investigate neural models for image velocity estimation (e.g.[17]) and quantify the temporal dynamics of visual working memory by measuring the recall precision under periodic display presentations between 20 ms and 1 s [18][19]. Also more detailed tower controller work analysis would be useful to clarify the operational relevance of increased framerate for decision error reduction with dynamic events in the airport environment.

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