Supplementary material for Perceptual Model for Adaptive Local Shading and Refresh Rate

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1 CAMOJAB ABLATION STUDY

To gain an understanding of the contribution of each component of our model, we perform an ablation study. We isolate three main components of our model: variable-rate shading (VRS) blur and downsampling (B_m, S, R), eye-motion blur (B_h, B_e), and temporal distortion model (d_t). We disable different combinations of the three components at a time and refit the model to the data. The goodness of fit (RMSE) is reported in Table 1. The results indicate that in isolation, each model provides a poor fit to the data. Eye-motion blur and temporal distortion model are integral in explaining the motion quality in Denes et al. [1] data but fail to capture the effect of shading resolution on motion quality, i.e., Block-PC, Block-Mobile, and Block-VR. VRS blur and downsampling, and eye-motion blur are crucial and sufficient in explaining the results of our experiment. This is because the test and the reference conditions only varied in resolution, making the temporal distortion negligible compared to spatial distortion ($d_t^{ref} - d_t^{test} \ll d_s^{ref} - d_s^{test}$) for this data. Similarly, the temporal distortion model is sufficient to predict Denes et al. [1] Exp. 3 results because this experiment ensured equal spatial distortion between reference and stimulus conditions in their experiment. As seen from the "Total" column of Table 1 that reports the aggregated RMSE values for all datasets together, we get the best fit when all three components are enabled.

Table 1. Ablation Study. ✓implies if the component was enabled. Numbers denote the RMSE values for each configuration.

$\{B_m, S, R\}$	$\{B_h, B_e\}$	d_t	Block-PC	Block-Mobile	Block-VR	MARRR Exp. 1	MARRR Exp. 3	**Total**
		✓	2.31	1.75	1.19	0.53	**0.02**	1.42
	✓		2.31	1.75	1.19	0.55	0.21	1.43
✓			1.25	1.22	0.63	3.11	0.21	2.11
✓	✓		**0.73**	**0.56**	**0.53**	0.6	0.21	0.6
✓		✓	1.19	0.98	0.55	0.5	0.05	0.79
	✓	✓	2.31	1.75	1.2	**0.37**	0.05	1.41
✓	✓	✓	0.74	0.57	**0.53**	0.38	0.03	**0.53**

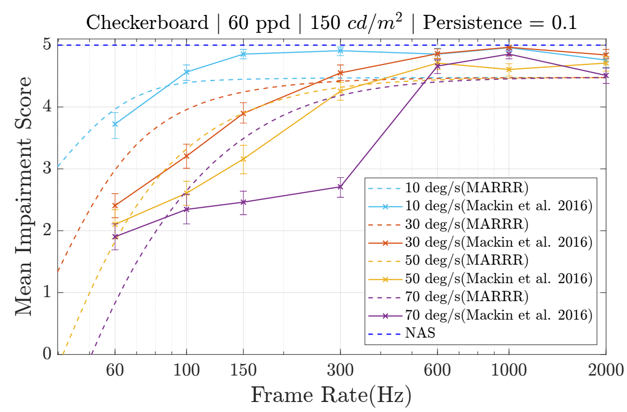

Fig. 1. NAS and MARRRR predictions on Mackin et al. [2] data

2 MOTION QUALITY MODELS COMPARISON

Here we provide additional plots for NAS and MARRR performance on our Experiment 1 data (Figure 2) and Mackin et al. dataset[2] (Figure 1). MARRR being a perceptually motivated but content-independent model, fails to predict the change in quality due to texture in Experiment 1, but performs well on Mackin et al.'s dataset. While NAS predicts different quality for different textures in Exp. 1 and correctly captures the reduction in artifacts visibility with velocity, it doesn't predict the correct trend between the textures. It also cannot capture change in quality due to refresh rate in Mackin et al.'s dataset.

3 OPTIMAL DYNAMIC PROGRAMMING SOLUTION FOR KNAPSACK FORMULATION

In Section 6 of the paper, we formulated the problem of maximizing the quality of a frame for a given shading budget b_{frame} as:

$$\underset{\boldsymbol{B}_{jk}}{\arg\max} \sum_{j=1}^{N} \boldsymbol{Q}_{jk} \quad \text{subject to} \quad \sum_{j=1}^{N} \boldsymbol{B}_{jk} < b_{\text{frame}}. \tag{1}$$

Here, we provide an optimal dynamic programming solution for the above problem.

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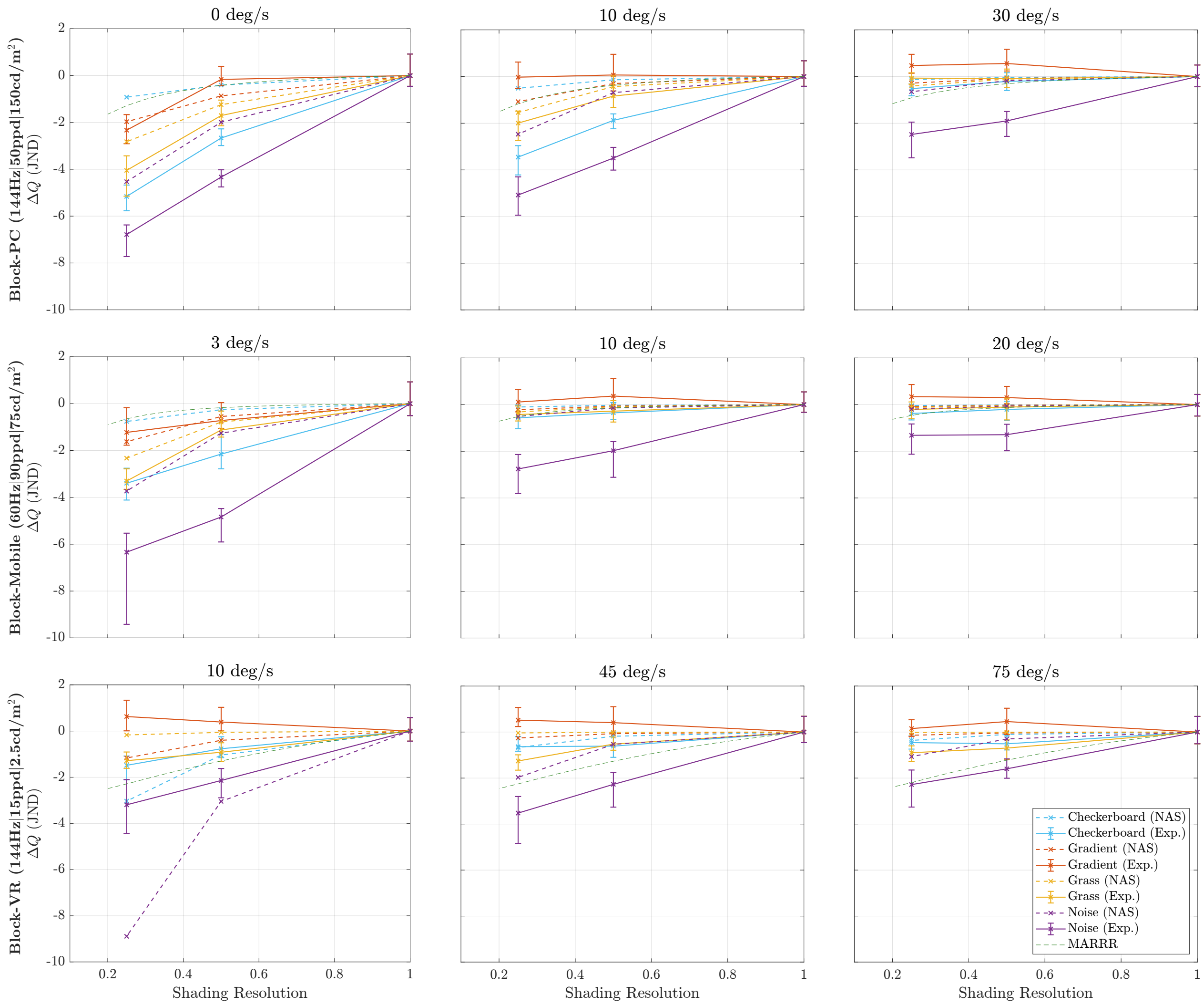

Fig. 2. NAS and MARRR predictions on our Experiment 1 results. Both models were linearly fitted to the data for fair comparison. MARRR is content independent and hence fails to capture change in quality dues to texture. NAS doesn't capture the correct trend between textures. Also, it can old predict quality for half and quarter shading resolution.

For each $j \in 0..N$ and each c between 0 and B we define a *sub-problem*, as follows: $\mathbb{Q}(j, c)$ is the maximum quality possible when only tiles 1 to j are considered and the maximum bandwidth is at most c. Our goal is to compute $\mathbb{Q}(N, b_{\text{frame}})$. Note that, unlike the traditional 0-1 knapsack problem, we cannot skip any tile but only vary its bandwidth and quality by selecting its shading rate.

We start with trivial cases and work our way up. The trivial cases are "no tiles" and "total bandwidth 0". In the first case, maximum quality is 0. The second case is impossible because of our constraint of not skipping any tile. We denote the quality in such cases as $-Inf$.

$$\mathbb{Q}(0, c) = 0 \;\forall\, c \qquad \text{and} \qquad \mathbb{Q}(j, 0) = -Inf \;\forall\, j \tag{2}$$

Consider next the case $j > 0$ and $c > 0$. To find $\mathbb{Q}(j, c)$, we iterate over all possible shading rates. For the k^{th} shading rate of tile j, the maximum achievable quality is $\mathbb{Q}(j-1, c - \boldsymbol{B}_{jk}) + \boldsymbol{Q}_{jk}$, because we obtain a quality of $\boldsymbol{Q}_{jk}$ for the given tile, and must use an optimal solution for the first $j-1$ tiles under the constraint that the total bandwidth is at most $c - \boldsymbol{B}_{jk}$. Of course, this is only feasible if $c \geq \boldsymbol{B}_{jk}$. We summarize this discussion in the following recurrence for $\mathbb{Q}(j, c)$.

$$\mathbb{Q}(j, c) = \begin{cases} 0, & \text{if } j = 0 \\ -Inf, & \text{if } c = 0 \\ max\{(\boldsymbol{Q}_{jk} + \mathbb{Q}(j-1, c - \boldsymbol{B}_{jk}) \\ \qquad\qquad \forall\, k = 1, ..., |\boldsymbol{\mathcal{R}}|\}, & \text{if } j \geq 1 \text{ and } \boldsymbol{B}_{jk} \leq c \\ -Inf & \text{if } j \geq 1 \text{ and } \boldsymbol{B}_{jk} > c \end{cases} \tag{3}$$