AI-Driven Timing Optimization for Enhanced Visual Performance in HOP 3.0

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Abstract

Hybrid Oxide Polysilicon (HOP) 3.0 technology revolutionizes display performance by enabling ultra-fast response times and exceptional visual fidelity. However, realizing the full potential of HOP 3.0 displays hinges on precise optimization of numerous timing parameters. Traditionally, this tuning process has been a time-consuming and labor-intensive manual endeavor, requiring expert knowledge and iterative adjustments. This paper introduces a machine learning driven solution to automate the timing optimization process for HOP 3.0 displays, thereby significantly accelerating development cycles and ensuring consistent high-quality visual output. Our approach leverages models trained on a comprehensive dataset encompassing diverse timing parameter configurations and their corresponding Flicker (FLK) and Voltage Refresh Rate (VRR) characteristics. This model learns the complex relationships between timing parameters, display patterns, and luminance levels, enabling it to predict optimal timings with high accuracy. We rigorously evaluate our AI-based optimization method across a wide range of display scenarios, showcasing its ability to consistently achieve superior Flicker and delta JND performance compared to manual tuning techniques. Furthermore, we analyze the computational efficiency of our approach, demonstrating substantial reductions in tuning time while maintaining exceptional visual quality. Our findings pave the way for streamlined HOP 3.0 display manufacturing, empowering engineers to rapidly iterate on designs and deliver cutting-edge visual experiences with unprecedented efficiency.

Author Keywords

Mobile Displays, Variable Refresh Rate(VRR), HOP 3.0, Global Bias Timing, Seamless between variable frequencies, AI-Based Optimization, Timing optimization, Prediction Model based-AI, Regression

1. Introduction

The pursuit of enhanced visual experiences in mobile devices has led to the widespread adoption of variable frequency driving (VFD). This technique enables dynamic adjustments to refresh rates, optimizing response speed and power consumption. However, VFD introduces a critical challenge: luminance variations across different frequencies, potentially leading to noticeable visual artifacts. To address this issue, various technologies have emerged, with HOP proving particularly effective in minimizing luminance discrepancies. HOP 3.0, featuring an 8T2C structure, has become the dominant architecture in contemporary mobile displays due to its superior performance compared to earlier versions like HOP 1.0. However, achieving optimal Variable Refresh Rate (VRR) characteristics in HOP 3.0 hinges on precise pre-tuning of the gate black (GB) timing, which controls the common bias voltage and individual bias levels for all display subpixels. Inaccurate GB timing can manifest as flicker (FLK) at low frequencies, resulting in perceptible visual differences due to on-bias variations across frequencies (Fig. 1). As customer expectations for display quality continue to rise, manufacturers face increasing pressure to deliver seamless VRR experiences. The current manual tuning process is time-consuming and susceptible to human error. This paper presents an innovative solution: an AI-based timing optimization algorithm tailored specifically for HOP 3.0 displays. Our proposed approach aims to automate and expedite the GB timing optimization process, enabling manufacturers to achieve superior VRR performance while significantly reducing development time and costs. By leveraging machine learning techniques, our algorithm identifies the individual influence of each parameter on VRR characteristics and derives optimal timing combinations under diverse display conditions. This advancement paves the way for a new era of enhanced visual quality and user experience in mobile devices utilizing HOP 3.0 technology.

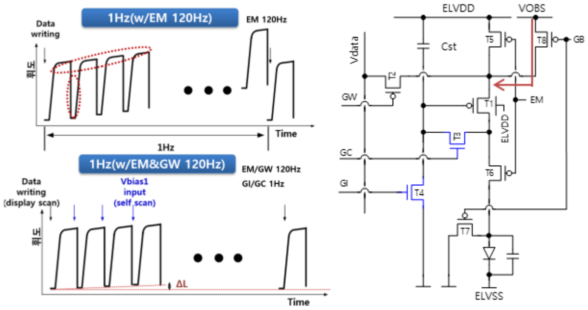

Fig. 1 Maintaining stable display luminance is crucial, especially at low refresh rates where hysteresis in the T1 driving transistor can cause noticeable flicker. Applying a bias voltage (VOBS) during the self-scan phase effectively mitigates this issue by fine-tuning the T1 bias. This control mechanism, influenced by the GB signal, ensures consistent luminance and reduces flickering artifacts, particularly at frequencies between 1 and 10 Hz.

2. AI-based search algorithms for optimal timing parameters

As previously mentioned, HOP 3.0 requires pre-tuning of its GB timing to achieve optimal VRR characteristics. This process is time-consuming due to the multitude of controllable GB parameters (six in total) across both address scan and self scan phases, (Fig. 2) each with a significant impact on FLK and VRR performance across various display brightness levels (DBVs) and grayscale values. Complicating matters further, FLK and VRR must be optimized concurrently, as they often have conflicting optimal timing ranges. Even if engineers manage to identify suitable parameters through laborious trial-and-error, these settings may

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become invalid when driving conditions change, necessitating a complete re-evaluation. To overcome these challenges, we propose an AI-based approach that leverages machine learning to predict FLK and VRR performance based on diverse driving conditions and timing combinations. This predictive model enables efficient exploration of the parameter space, identifying optimal timings without requiring exhaustive re-evaluation when conditions change. Furthermore, by employing explainable AI (XAI) techniques, we aim to analyze the interdependencies between parameters, providing engineers with insights for customized fine-tuning.

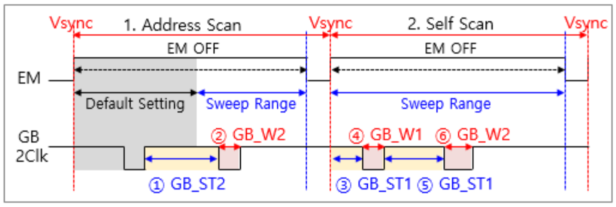

Fig. 2 Timing tuning parameters and ranges based GB 2 clocks, ①~⑥

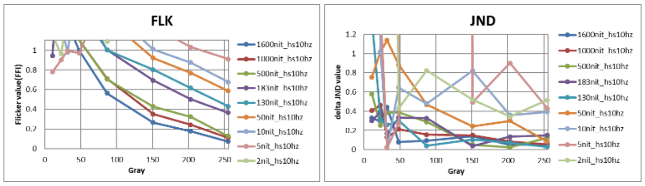

Fig. 3 FLK/VRR characteristics graph for each pattern before timing tuning. The GB timing should be adjusted so that the FLK and VRR values are minimized in all DBVs and grays (Color lines in graph means DBVs and x-axis means grays.)

2-1. Data Analysis

Several factors influence VRR characteristics, but their precise relationships have traditionally been understood through empirical observation rather than quantitative analysis. To gain a deeper understanding of these interactions, we utilize SHAP (SHapley Additive exPlanations) values, enabling efficient analysis of feature importance and complex dependencies. We collected a dataset comprising FLK and VRR measurements across varying luminance patterns. The FLK index quantifies blinking at the minimum frequency (10Hz), while the VRR index represents the Just Noticeable Difference (JND) between luminance at the minimum (10Hz) and maximum (120Hz) Frequency (Equation 1). We selected key GB timing parameters (width and delay, denoted as W and ST respectively), GB cycle settings for address and self scan phases, and the emission driver (EM) OFF signal control as primary features. Additionally, VEH (VOBS, a voltage applied equally to address and self scan) and VEH Offset (a voltage used to compensate bias differences between address and self scan) were included due to their significant influence on VRR characteristics. Initial voltage (VINT), which indirectly affects T1 bias, and initial timing (GI) clock count were also considered as features. Based on these feature combinations, we collected FLK and VRR data across high, medium, and low luminance patterns. Three measurements were taken at each condition to ensure accuracy. For normalization purposes, conditions with FLK or VRR values exceeding 10 (the minimum stimulus difference perceptible by most observers) were excluded. SHAP analysis revealed complex trade-off relationships between factors influencing FLK and VRR. Figure 4 illustrates this for a specific pattern (approximately 28 nit). Increasing GB delay in the address scan (GB_ST2 in Fig. 4) reduces FLK but increases VRR, while the opposite trend is observed in the self scan phase (GB_BIAS_ST1 in Fig.4). Furthermore, VEH Offset exhibits conflicting effects on FLK and VRR depending on its polarity. This trade-off extends to patterns with different luminance levels, even when only considering FLK indices (Figure 5). The optimal GB width for minimizing FLK varies depending on luminance level, highlighting the complexity of achieving a universally optimal timing configuration.

Equation 1. VRR(△jnd) Index Calculation

$$\Delta jnd = abs(jnd(max\ freq.) - jnd(\min freq.))$$

$$jnd(L) = A + B \cdot Log_{10}(L) + C \cdot (Log_{10}(L))^2 + D \cdot (Log_{10}(L))^3 + E \cdot \left(Log_{10}(L)\right)^4 + F \cdot (Log_{10}(L))^5 + G \cdot \left(Log_{10}(L)\right)^6 + \mathrm{H} \cdot \left(Log_{10}(L)\right)^7 + I \cdot (Log_{10}(L))^8$$

$A = 71.498068, B = 94.593053, C = 41.912053, D = 9.8247004, E = 0.28175407, F = -1.1878455$
$G = -0.18014349, H = 0.14710899, I = -0.017046845$

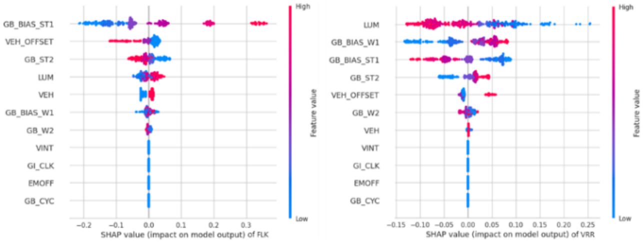

Fig. 4 SHAP values comparing FLK and VRR within the same pattern. The suffix "_ST" denotes delay, while "_W" indicates width, with numerical suffixes representing clock positions. Parameters designated with "_BIAS" pertain to the self-scan phase.

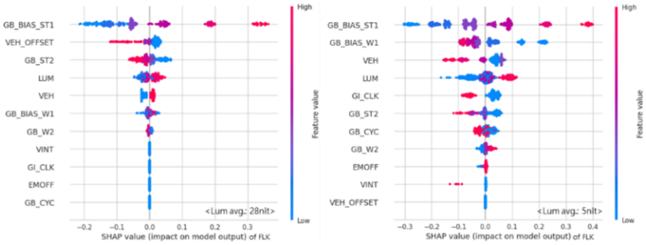

Fig. 5 SHAP Value of FLK between different luminance

2-2. Prediction Mechanism of Optimal Timing Model

We developed a prediction model using CatBoost, a gradient boosting algorithm known for its robustness and effectiveness in handling complex datasets. This model predicts FLK and VRR based on input GB parameters and driving conditions.

(1) FLK/VRR Prediction Model: We compared the Mean Squared Error (MSE) of three boosted regression models—XGBoost, CatBoost, and LightGBM—to select the optimal architecture for our prediction task. These models were selected based on their superior performance in FLK-based simulations, achieving the highest R-squared values as determined by

PyCaret's automated machine learning toolkit. The CatBoost model demonstrated the lowest MSE, indicating superior predictive performance. (Figure 6) FLK-based simulations were prioritized due to the inherent accuracy advantages of FLK measurements compared to VRR. This preference stems from the susceptibility of VRR measurements to oscillations, which can introduce inaccuracies.

(2) Black-Box Function, f(x): Bayesian optimization was employed to explore the parameter space and identify optimal timing configurations. This technique maximizes an objective function, denoted as f(x), which incorporates our FLK/VRR prediction model. Given a specific luminance level and driving conditions, f(x) searches for GB signal combinations and VEH voltage ranges that minimize the sum of average predicted FLK and VRR values. The target of f(x) is set to the sum of the average of FLK and the average of VRR predicted for each input condition.

(3) Search for the optimal solution: To ensure minimization of FLK and VRR, we modify the objective function by adding a negative sign to the target (Sum) value, effectively guiding the search towards optimal solutions that improve VRR characteristics (Equation 2). Once f(x) identifies candidate solutions within predefined GB timing ranges, these combinations represent potential optimal timings or voltages for the panel.

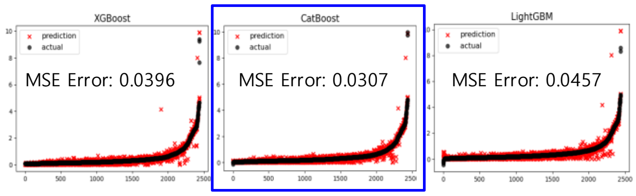

Fig. 6 the result of comparing MSE using Optuna

Equation. 2 The target of Objective Function

$$f(x) = -\max\left(Avg(Pred\_FLK_1,\ \ldots,\ Pred\_FLK_n) + Avg(Pred\_VRR_1,\ \ldots,\ Pred\_VRR_n)\right)$$

2-3. Evaluating Model & Performance

We measured FLK and VRR values by applying the timing to the actual panel to confirm the consistency of the timing explored by the AI model. As a result of comparing the manual-tuned timing with the AI model-predicted timing for the panel that conducted data learning, we were able to confirm that the GB width and delay parameter of self scan were almost identical. (Fig. 7) In addition, when we evaluated FLK/VRR applying the two timings respectively, there was no significant difference between the two results. (Fig. 8) Although the GB timing of the address scan is slightly different, the evaluation results are similar because the GB of the self scan has a higher effect on the VRR characteristic. Figure 9 shows the results of applying AI model for the other mobile product currently under development. When Timing selected as the timing optimization algorithm is applied, we can confirm that FLK/VRR values are improved in all patterns compared to before application. Even if the searched timing is the optimal parameter, it is necessary to analyze VRR influencing factors under various luminance conditions through XAI, because customers sometimes require additional tuning to suit their needs.

Using XAI interpretation as a guide, we can set detailed tuning directions according to the characteristics preferred by customers between FLK and VRR. For instance, explainable AI (XAI) analysis reveals that luminance (LUM) exerts the strongest influence on both FLK/VRR performance. (Fig. 10) Notably, GB timing parameters within the self-scan phase demonstrate a greater impact than those in the address scan. Additionally, VEH OFFSET exhibits a more pronounced effect compared to VEH voltage. This knowledge empowers us to tailor timings based on customer preferences. For instance, if VRR is prioritized over FLK, expanding GB delay during self-scan, increasing GB width in the address scan, and lowering VEH offset voltage can effectively achieve the desired outcome.

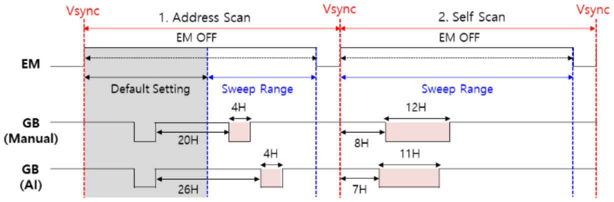

Fig. 7 The result of comparing manually tuned timing with AI-predicted timings.

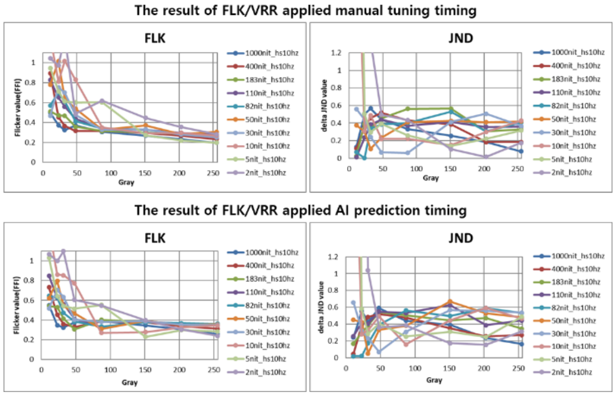

Fig. 8 This figure presents the FLK/VRR evaluation results for each pattern when using both manually tuned timings and AI-predicted timings. The colored lines represent different DBV levels, and the x-axis indicates grayscale values.

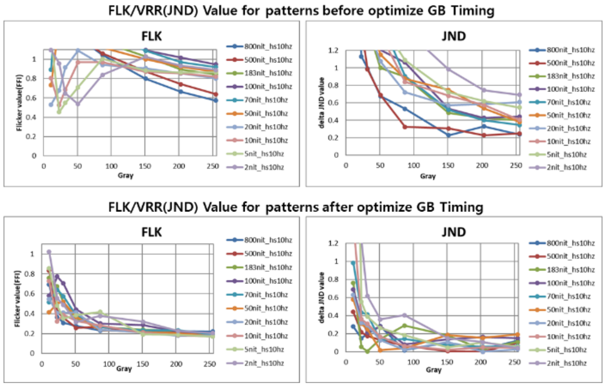

Fig. 9 This figure compares FLK/VRR Values for different patterns between reference timings and timings optimized using AI model

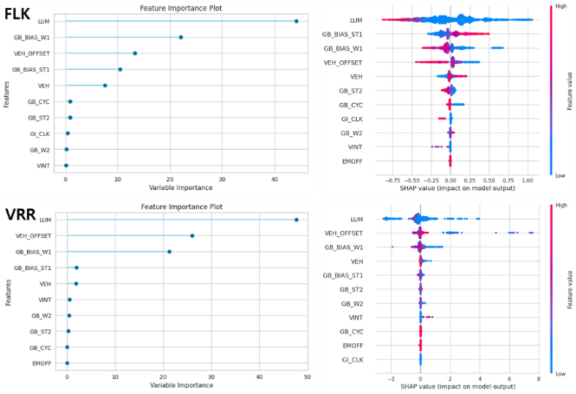

Fig. 10 Explainable AI (XAI) analysis

3. Conclusion

The research presented in this paper demonstrates that an AI-based timing optimization algorithm can effectively explore all possible timing combinations, reducing the risk of missing optimal settings. This approach provides clear and efficient tuning directions compared to traditional trial-and-error methods. The study shows significant improvements in VRR/FLK characteristics by optimizing timing parameters, particularly in HOP 3.0 displays. The AI model's predictions were consistent with manual tuning results, showing no significant difference in FLK/VRR values. This consistency underscores the reliability and accuracy of the AI-based approach. By leveraging advanced machine learning techniques, the algorithm is able to identify optimal settings more quickly and accurately than human experts can through trial-and-error methods. The use of SHAP (Shapley Additive Explanations) values provided valuable insights into which factors have the most significant impact on VRR characteristics. This interpretability is crucial for understanding how the AI model makes decisions and can guide future tuning efforts more effectively. The results indicate that the AI-based method not only improves performance but also provides a deeper understanding of the underlying mechanisms affecting display quality. The findings suggest that this approach offers a faster and more reliable way to improve display performance, making it a valuable tool for future optimization tasks. By reducing the time required for manual adjustments and providing clear tuning directions, the AI model can significantly enhance the efficiency and effectiveness of timing optimization in display technology. Overall, the study highlights the potential of AI-based methods in optimizing display characteristics and improving overall performance. The results provide a strong foundation for further research and practical applications in the field of display technology.

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