Content- and Lighting-Aware Adaptive Brightness Scaling for Improved Mobile User Experience

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***Abstract*—For an improved user experience, the display subsystem is expected to provide superior resolution and optimal brightness despite its impact on battery life. Existing brightness scaling approaches set the display brightness statically or adaptively in response to predefined events such as low-battery or ambient light of the environment, which are independent of the displayed content. Approaches that consider the displayed content are either limited to video content or do not account for the user's expected battery life, thereby failing to maximise the user experience. This paper proposes Content- and ambient Lighting-aware Adaptive Brightness Scaling in mobile devices that maximises user experience while meeting battery life expectations. The approach employs a content- and ambient lighting-aware profiler that learns and classifies each sample into predefined clusters at runtime by leveraging insights on user perceptions of content and ambient luminance variations. We maximise user experience through adaptive scaling of the display's brightness using an energy prediction model that determines appropriate brightness levels while meeting expected battery life. The evaluation of the proposed approach on a commercial smartphone improves Quality of Experience (QoE) by up to $24.5\,\%$ compared to state-of-art.**

***Index Terms*—Mobile Devices, User Experience, Brightness Scaling, Display Management, Battery life Management**

I. Introduction

Display subsystems, which serve as input and output interfaces, have become the predominant user interface on mobile devices. The desire to enhance the user experience or quality of experience (QoE), defined as the users' perceivable satisfaction with services and systems, has led to the development of display subsystems with superior resolution, brightness, and faster response times that do not require a separate backlight [1]. Despite rapid advancements in most mobile system components, including the processor, memory, and display, battery technology has been slow-paced [2]. These improved components continue to place a significant power burden on the limited battery life, with the display subsystem contributing significantly to this power consumption issue. Consequently, this makes battery life an increasing concern among mobile device users, with about ninety percent of mobile users suffering from low-battery anxiety—the fear of running out of mobile battery power [3]. This indicates that, in addition to the optimal display brightness that meets the surrounding ambient light of the user [4], battery life also plays a significant role in user's QoE [5]. Therefore, there is need for an effective management strategy that maximises QoE while taking battery life into account.

Prior efforts considered dimming the display's brightness statically in order to extend battery life. Despite being effective at reducing the display's power consumption, this diminishes the user experience, as a single level of display brightness cannot guarantee user satisfaction in all situations like bright light and raining scenarios. Consequently, dynamic brightness scaling (DBS) of the display is widely adopted by both industry and the research community. However, current DBS approaches [6]–[9] consider the power trade-off with objective quality measures at an individual device level, such as structural similarity index metric (SSIM) [8], [9] and peak signal-to-noise ratio (PSNR) [10], without a direct link to QoE. In addition, screen content- and ambient lighting-awareness, which could potentially improve the user experience, have been considered only in isolation. Approaches that have either considered discrete ambient lighting conditions [4], as opposed to continuous real-world lighting conditions, or have not accounted for the user's expected battery life (i.e. hours before recharging) [11], [12], are unable to effectively maximise QoE.

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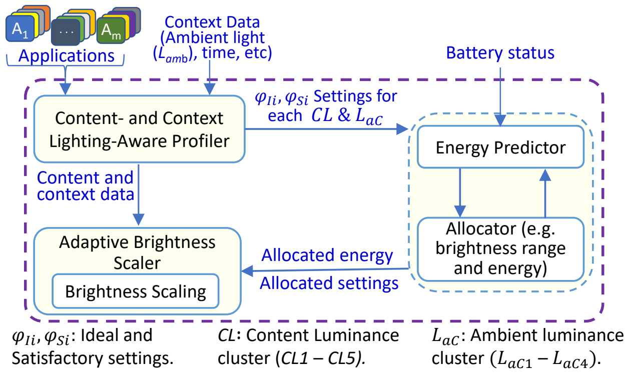

Fig. 1. System overview of proposed adaptive brightness scaling approach.

In this paper, we propose Content- and Ambient Lighting-aware Adaptive Brightness Scaling, that maximises the user's QoE across the expected battery life on mobile devices. The proposed approach leverages insights on user perception of various content and ambient luminance, and its collection at runtime enables proactive display brightness scaling. To ensure expected battery life is met, decisions are made using an energy prediction model based on the user's usage history.

II. The Content- and Ambient Lighting-aware Adaptive Brightness Scaling Approach

As shown in Fig. 1, the proposed approach has three components: content- and ambient lighting-aware profiler; energy predictor and allocator; and an adaptive brightness scaler.

The profiler is designed using an offline analysis that identifies a set of brightness levels (ideal (φ_{Ii}) and satisfactory (φ_{Si})) based on the relationship between user rating and the respective content and ambient luminance. This is accomplished by first conducting a user-based study in which users run a series of applications with varying content and environmental conditions while computing the content luminance (L_C) and collecting contextual data (such as ambient luminance L_{amb}, etc.). To cover all the cases and provide a sufficient level of control, the collected L_C and L_{amb} are then classified into five and four clusters, respectively. We then derive a QoE model using a logistic function when $L_{amb} \geq 1000$ or a quadratic function when $L_{amb} < 1000$, as shown in (1).

$$QoE_i = \begin{cases} (\alpha + \beta L_C + \gamma L_C^2) + (\delta L_C + \epsilon)\varphi + \rho\varphi^2, & L_{amb} < 1000, \\ \dfrac{1}{1 + \exp^{-(\sigma + \lambda L_C + \eta\varphi)}}, & L_{amb} \geq 1000, \end{cases} \tag{1}$$

where α, β, γ, δ, ϵ, ρ, σ, λ and η are model coefficients and QoE_i represents the brightness-dependent QoE value.

At runtime, the profiler continuously monitors the surrounding ambient light, computes the luminance of the displayed content, and matches the content and ambient luminance to their predefined clusters to determine the φ_{Ii} and φ_{Si} settings for the various content and ambient lighting conditions.

To maximise the QoE by ensuring the appropriate brightness level is set for various content and ambient luminances, while meeting the expected battery life, we determined the proportion of the user's daily time spent in each ambient cluster. Using these data and the energy consumption at each brightness level, we then develop an energy prediction model.

These φ_{Ii} and φ_{Si} settings are transmitted to the allocator, which chooses the allocated settings that minimise the difference between the predicted energy and the device's remaining energy. The allocated settings and energy are then used in conjunction with real-time brightness scaling to determine the optimal brightness for the expected battery life. This involves adjusting the brightness level within the allotted range based on the current content, ambient light, and energy requirements.

III. Experimental Results

The proposed approach was implemented on a Google Pixel 3 commercial smartphone running Android 11. The approach was compared to state-of-the-art approaches on mobile devices, such as adaptive brightness scaling *(ABS)* [13], static brightness scaling *(SBS)* whose brightness level remained unchanged regardless of changes in content and ambient conditions, and low-overhead adaptive brightness scaling *(LABS)* [9]. To compare the different approaches, a use case scenario is evaluated based on the typical proportion of a user's daily time spent on each ambient cluster ($L_{aC1} - L_{aC4}$), where L_{aC1} accounts for 5 %, L_{aC2} accounts for 80 %, L_{aC3} accounts for 10 %, and L_{aC4} accounts for 5 %. Then, we evaluate this scenario under sufficient and insufficient battery energy.

TABLE I
Battery life evaluation in each of the ambient clusters for the four approaches considered.

Approach	Energy consumption (J).				Total	% improv.
	L_{aC1}	L_{aC2}	L_{aC3}	L_{aC4}		
ABS [13]	94	1644	239	136	2112	12
SBS	90	1432	179	90	1790	-5
LABS [9]	136	1027	888	94	2145	14
Ours	90	1464	205	119	1879	0

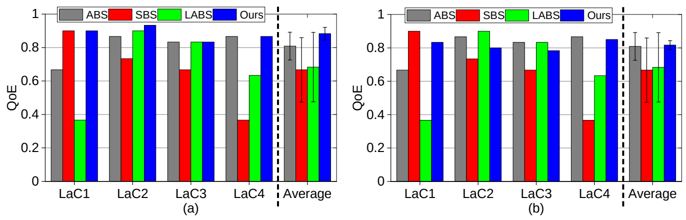

Fig. 2. Averaged QoE for the different approaches considered while under (a) *sufficient battery energy* (b) *insufficient battery energy*

Table I shows the battery life evaluation under sufficient battery energy conditions. Compared to *ABS* and *LABS*, the proposed approach improves battery life by 12 % and 14 %, respectively. Although *SBS* has a longer battery life, this comes at a considerably lower QoE.

Fig. 2 shows the evaluated average QoE under the different ambient lighting scenarios ($L_{aC1} - L_{aC4}$). As shown in Fig. 2(a), our proposed approach provides a higher average QoE across all the ambient conditions than *ABS*, *SBS* and *LABS* approaches, with average QoE improvements of 8.5 %, 24.5 % and 22.6 %, respectively. Similarly, as shown in Fig. 2(b) (under insufficient battery energy), even though the proposed approach reduces energy consumption to meet the expected battery life, it is still able to provide higher average QoE, with average QoE improvements of 1.2 %, 18.4 % and 16.3 % compared to the *ABS*, *SBS*, and *LABS* approaches, respectively.

IV. Conclusions

This paper explores a content- and ambient lighting-aware adaptive brightness scaling approach that maximises user QoE on mobile devices. The combined use of user perceptions of different content and ambient conditions, along with energy prediction and adaptive scaling at runtime, allows for battery life enhancement and QoE maximization.

Acknowledgments

All data supporting this study are openly available at https://doi.org/10.5258/SOTON/D2490.

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