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Maximising mobile user experience through self-adaptive content- and ambient-aware display brightness scaling

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ABSTRACT

Display subsystems have become the predominant user interface on mobile devices, serving as both input and output interfaces. For a better quality of user experience (QoE), the display subsystem is expected to provide appropriate resolution and brightness despite its impact on battery life. Existing display brightness approaches either consider content- and ambient-light in isolation or do not account for the user's expected battery life, thereby failing to maximise the QoE. This paper proposes *aCADS*, a self-**A**daptive **C**ontent- and **A**mbient-aware **D**isplay brightness **S**caling in mobile devices that maximises QoE 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 luminances variations. We maximise QoE through adaptive scaling of the display's brightness using an energy model that determines appropriate brightness levels while meeting expected battery life. The evaluation on a commercial smartphone shows that *aCADS* improves QoE by up to 32.5 % compared to state-of-the-art.

1. Introduction and related work

Display subsystems, which serve as input and output interfaces, are the prevalent user interface on mobile devices today. In an effort to enhance the user experience, or quality of experience (QoE), which is defined as the users' perceived satisfaction with services and systems, display subsystems with higher resolution, brightness, and faster response times have been developed [1]. In spite of the rapid technological advancement of the majority of mobile system components, such as the display, processor, and memory, battery technology has been comparatively slow-paced [2]. These advanced 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 [3,4]. This indicates that, in addition to the optimal display brightness that meets the surrounding ambient light of the user [5], battery life also plays a significant role in user experience [6]. Therefore, there is need for an effective management strategy that maximises user experience while taking battery life into account.

Liquid crystal display (LCD) and organic light-emitting diode (OLED) are the prevalent display technologies in mobile devices, and their power consumption vary [7]. While backlight, which illuminates the screen in LCD consumes most of the energy depending on the brightness level, power consumption in OLEDs is dependent on the pixel intensities as OLEDs do not need external lighting [8]. Therefore, considerable research has been conducted to reduce the backlight and pixel energy consumption of LCDs [5,9–14] and OLEDs [7,8], respectively. Built-in brightness policies in the majority of mobile systems, such as manual brightness settings, allowed for the static dimming of the display's brightness in order to extend battery life. Despite being effective at reducing the display's power consumption, this degrades the user experience, as a single level of display brightness cannot guarantee user satisfaction in all circumstances, such as bright light and rainy conditions. Consequently, dynamic or adaptive brightness scaling (DBS) of the display is widely adopted. However, current DBS approaches [9–11,15–17] consider the power trade-off with objective quality measures, such as structural similarity index metric (SSIM) [8,12] and peak signal-to-noise ratio (PSNR) [13] at an individual device level, without a direct link to QoE. In addition, content- and ambient light-awareness, which could potentially improve the user experience (QoE),

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have been considered only in isolation. Approaches that take this into account either consider discrete ambient lighting conditions [5], as opposed to continuous lighting conditions in the real world, or do not account for the user's expected battery life (i.e., the number of hours a user uses the device before recharging) [14,18], and thus are unable to effectively maximise the user experience. Maximising the user experience on mobile devices is challenging because it necessitates determining when and how much power-to-display quality trade-off should be applied. While ignoring display-quality-to-power trade-offs entirely can shorten battery life over the discharge cycle, blindly enforcing a trade-off without content- and context-awareness (for example, the ambient light, battery status, etc.) can degrade the user experience when maximum or low brightness is desired by the user. Ideally, the display-quality-to-power trade-off should only occur when the user's expected battery life cannot be met over the duration of the battery discharge, and should continuously adapt to the changing content and context conditions. In addition, the display brightness scaling should occur within a user-acceptable range so that the screen content is not rendered unusable or unreadable.

To address the aforementioned challenges, this paper proposes *aCADS*[1], a self-**a**daptive **C**ontent- and **A**mbient-aware **D**isplay brightness **S**caling that maximises the user's QoE across the expected battery life on mobile devices. The proposed approach leverages insights on user perceptions of various content and ambient luminance, and its collection at runtime enables proactive display brightness scaling. To ensure the user's expected battery life is met, informed decisions are made using an energy prediction model based on the user's usage history.

This paper makes the following novel contributions:

1. A series of user studies that identify the relationship between user perception and display brightness, content, and ambient light.
2. An online self-adaptive display brightness scaling approach, *aCADS*, that leverages insights from the user perception studies to maximise the QoE.
3. An energy prediction model based on a user's historic usage, which helps achieve a user's expected battery life.
4. A practical implementation and evaluation of *aCADS* on a commercial smartphone, demonstrating up to 32.5 % improvement in QoE compared to state-of-art.

The rest of the paper is organised as follows: Section 2 describes the proposed self-adaptive content- and ambient-aware display brightness scaling approach. The QoE user perception study is discussed in Section 3. Section 4 presents the experimental results and show the benefits of the proposed approach in comparison to state-of-the-art approaches. Section 5 concludes the paper.

2. Self-adaptive content- and ambient-aware display brightness scaling approach

As shown in Fig. 1, the proposed self-**a**daptive **C**ontent- and **A**mbient-aware **D**isplay brightness **S**caling (*aCADS*) approach has three components: Content- and context lighting-aware profiler, energy predictor and allocator, and an adaptive display brightness scaler. The profiler continuously monitors the surrounding ambient light, computes the relative luminance of the displayed content, and matches the content and ambient luminance to the ideal and satisfactory brightness levels known as φ_{Ii} and φ_{Si}, respectively. The values of φ_{Ii} and φ_{Si}, which represent the brightness levels at different QoE levels are computed

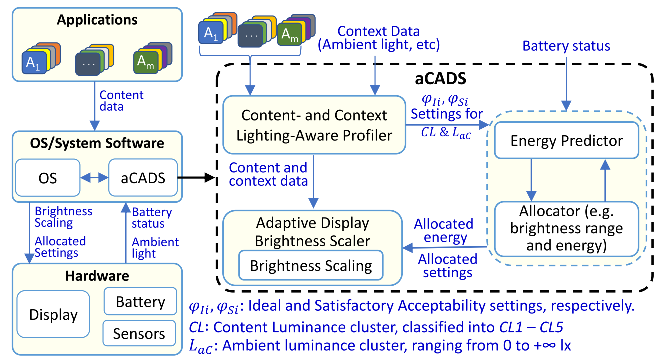

Fig. 1. System overview of the proposed Self-Adaptive Content- and Ambient-aware Display Brightness Scaling.

Algorithm 1: Content- and ambient lighting-aware profiling

Input : App with different content-and ambient luminance
Output: φ_{Ii}, φ_{Ai}

Run an app with different content and under different ambient luminance;
$R_{ij}G_{ij}B_{ij}$ ← *compute the respective average RGB values*;
$L_C \leftarrow \omega_r R_{ij} + \omega_g G_{ij} + \omega_b B_{ij}$;
L_{Cc} ← cluster L_C based on the range of the values;
L_{amb} ← collect the ambient luminance;
L_{aC} ← cluster L_{amb} based on the range of values;
if L_{aC} == *4* **then**
  QoE model: ← apply logistics function;
  return values;
else
  QoE model: ← apply quadratic function;
  return values;
end

based on content and ambient clusters referred to as CL and L_{aC}, respectively. Then, based on the estimated energy from the prediction model, the content, and the ambient luminance, the online adaptive scheme determines the appropriate brightness level that meets the expected life. Details of the components are as follows.

2.1. Content- and ambient lighting-aware profiler

The profiler is designed using an offline analysis that identifies a set of brightness levels, e.g., ideal (φ_{Ii}) and satisfactory (φ_{Si}), based on the relationship between user rating and the respective content and ambient luminance (Section 3). At runtime, the profiler works in conjunction with the allocator and online adaptive brightness scaler to choose the appropriate brightness settings for the display.

Algorithm 1 shows the steps involved in determining the set of φ_{Ii} and φ_{Si} settings for different content- and ambient lighting conditions. As shown in the algorithm, we begin by running a series of applications (A_1 to A_m) with varying content and ambient conditions while computing the content luminance (L_C) and collecting the ambient light. Then we calculate the average RGB values of each loaded content, which is expressed as Eq. (1),

$$RGB = \sum_{i=1,j=1}^{i=W,j=H} R_{i,j} G_{i,j} B_{i,j} \quad (1)$$

where W and H are the content resolutions. Using the BT.601 [20] standard—the digital TV encoding parameters for standard 4:3 and 16:9 wide screen aspect ratios, as recommended by the International Telecommunication Union (ITU), we determined the relative content

[1] This article is an extended version of the conference paper, "Content- and Lighting-Aware Adaptive Brightness Scaling for Improved Mobile User Experience", which appeared at the 2023 Design, Automation and Test in Europe Conference and Exhibition (DATE 2023) [19].

Table 1
The Quadratic and Logistics Coefficients for Ideal (I) and Satisfactory (S) Acceptabilities of the model.

Ambient cluster	Quadratic function coefficients		
	α	β	γ
L_{aC1} - I	−0.37	2.365e−03	−1.326e−05
L_{aC1} - S	−0.1907	2.603e−03	−1.094e−05
L_{aC2} - I	−0.2801	7.549e−04	−9.629e−06
L_{aC2} - S	−0.5986	2.542e−03	−1.205e−05
L_{aC3} - I	−0.2016	1.198e−03	−5.583e−06
L_{aC3} - S	−0.5387	−1.071e−04	−2.911e−06
Ambient cluster	Quadratic function coefficients		
	δ	ϵ	ρ
L_{aC1} - I	6.687e−06	2.765e−02	−2.393e−04
L_{aC1} - S	4.861e−06	3.874e−02	−3.726e−04
L_{aC2} - I	3.876e−05	1.532e−02	−1.076e−04
L_{aC2} - S	1.424e−05	4.327e−02	−3.478e−04
L_{aC3} - I	1.840e−05	9.069e−03	−2.856e−05
L_{aC3} - S	6.929e−06	4.140e−02	−2.988e−04
Ambient cluster	Logistic function coefficients		
	σ	λ	η
L_{aC4} - I	−10.2094	0.0120	0.1008
L_{aC4} - S	−7.9775	0.0191	0.0918

luminance (L_C) based on the respective average RGB values, as shown in Eq. (2):

$$L_C = \omega_r R + \omega_g G + \omega_b B \tag{2}$$

where ω_r, ω_g and ω_b represent the respective RGB component weights. These calculated L_C values range from 0 to 255, with higher and lower values showing brighter and darker contents, respectively. This is performed once per every loaded content. To cover all the cases and provide a sufficient level of control, L_C is then classified into five distinct clusters, $CL1 - CL5$: $CL1$ $[0, 51)$, $CL2$ $[51, 101)$, $CL3$ $[101, 151)$, $CL4$ $[151, 201)$, and $CL5$ $[201, 255]$. This was accomplished by exploring a range of values aimed at identifying the most appropriate classification range. For example, when considering more than five clusters, it became apparent that while this offered increased control, it also incurred additional overhead in terms of memory and computational resources. In contrast, the selection of fewer than five clusters raised concerns regarding the potential for missing optimisation opportunities. Similarly, the ambient light (L_{amb}) is also collected through the smartphone's built-in ambient light sensor, which is measured in lux (lx). This data is then divided into four clusters (L_{aC}), as illustrated in lines 5–6 of Algorithm 1 and discussed in Section 3.1. According to the collected L_{amb} values, which vary from 0 lx to several thousand depending on the time and environment of the user, the four L_{aC} clusters are: L_{aC1} [0, 100) for dim or dark light, L_{aC2} [100, 400) for normal light, L_{aC3} [400, 1000) for bright light, and L_{aC4} [1000, $+\infty$) for extremely bright light. The ambient clusters are selected to reflect the real user environment with more realistic and continuous ambient conditions, as opposed to existing approaches that either ignore the impact of ambient luminance or consider discrete ambient values such as 0 lx, 100 lx, etc.

Finally, depending on the ambient cluster (L_{aC}), we derive the QoE model using a logistic function when $L_{amb} \geq 1000$ and a quadratic function when $L_{amb} < 1000$, as expressed in Eq. (3) (Details in Section 3.2.),

$$QoE_i = \begin{cases} (\alpha + \beta L_C + \gamma L_C^2) + (\delta L_C + \epsilon)\varphi + \rho\varphi^2, & L_{amb} < 1000 \\ \dfrac{1}{1 + \exp^{-(\sigma + \lambda L_C + \eta\varphi)}}, & L_{amb} \geq 1000 \end{cases} \tag{3}$$

where α, β, γ, δ, ϵ, ρ, σ, λ and η are model parameters whose coefficients are given in Table 1. Similar to [5], these quadratic model coefficients and logistics model coefficients are determined using linear least squares estimation and maximum likelihood estimation, respectively. QoE_i represents the corresponding QoE value (ideal or satisfactory) based on the brightness level. Solving Eq. (3) for φ, we determine the appropriate brightness settings (φ_{Ii} and φ_{Si}) based on the specific content (L_C), ambient luminance (L_{amb}), and QoE level, see lines 7–12 of Algorithm 1. These values, along with the content and ambient clusters, are then used as inputs for the self-adaptive display scaling (Section 2.3).

2.2. Energy prediction model and allocator

To maximise the QoE by ensuring the appropriate brightness level that is set differently for different content and ambient luminance while meeting the expected battery life, it is necessary to have insight into the energy consumption based on the user's past behaviour. To achieve this, we determined the proportion of the user's daily time P_a spent in each ambient cluster L_{aC}. Using these data and the energy consumption at each brightness level, we then construct an energy prediction model similar to that in [21]. The model is given as Eq. (4),

$$E_P(\varphi, P_a) = T_{req} \sum_{i=1}^{i=m} (\omega_i \varphi_i P_{ai}) + \kappa \tag{4}$$

where φ represents the brightness scaling magnitude of the ith L_{aC}, P_{ai} is the ith element of the L_{aC}, T_{req} represents the expected time required (otherwise known as the expected battery life and is specified by the user in this context), m denotes the number of L_{aC}, ω_i and κ are the weights of the model that are determined offline using regression.

The job of the allocator is to select the appropriate range of brightness from the available levels for each content and ambient cluster in order to achieve the expected battery life. This is accomplished by selecting a brightness range between the ideal and satisfactory levels such that the difference between the predicted energy for the user's required time and the energy remaining in the battery, is minimum.

2.3. Online self-adaptive display brightness scaler

The goal of adaptive brightness scaler is to find the appropriate brightness level for varying content under various context conditions (L_{amb}, battery status, etc.) in order to achieve the user's expected battery life. This depends on the available brightness settings (values between φ_{Ii} and φ_{Si}) for each ambient cluster and the predicted energy values.

To accomplish this efficiently, we developed a subjective QoE model based on the relationship between the content, ambient luminance, and brightness level. The subjective QoE relationship was then used to determine the ideal and satisfactory settings for each content and ambient cluster conditions. These ideal and satisfactory settings are transmitted to the allocator, which selects the range (allocated settings) that minimises the difference between the predicted energy and the device's remaining energy as shown in lines 1 to 3 of Algorithm 2. The allocated settings and energy are then used in conjunction with real-time brightness scaling to determine the appropriate brightness that meets the expected battery life (line 4 of Algorithm 2). This involves adjusting (increasing or decreasing) the brightness level within the allocated range based on whether the current content is darker or brighter than the previous content and the energy requirement if the user is within the same ambient cluster. Similarly, when an app or a different app with different content is loaded or when the user's environment changes, the online scaler monitors and matches these new content and/or ambient settings to appropriate content and ambient clusters, and then determines the appropriate brightness, as shown in lines 5–9 of Algorithm 2. The brightness scaling is performed in a manner consistent with the state-of-the-art [22], by adopting the same scaling frequency of 0.5 Hz. This avoids negatively impacting the QoE when performed too aggressively or frequently, as it is implemented on a real-world commercial mobile device.

Algorithm 2: Adaptive Display Brightness Scaling

Input : $\varphi_{Si}, \varphi_{Ii}, B_L, B_C, CL, L_{aC}, T_{req}$

Determine the battery energy E_T;
Predict E_P using Equation (4);
Set appropriate φ such that $min|E_T - E_P|$;
Increment or decrement φ based on E_P and L_C;
while *app with different content is running* **do**
  $L_{Cc} \leftarrow$ collect and compute Content luminance;
  Find L_{ambC} and CL that matches the L_C and L_{amb};
  $\varphi_{Si} \leftarrow L_{ambi}\ L_{Ci}$;
  $\varphi_{Ii} \leftarrow L_{ambi}\ L_{Ci}$;
end

3. QoE user perception study

The purpose of the user study is to assess the effect of varying brightness levels on the mobile user experience under different content and context conditions. This involves logging contextual data (e.g., ambient light) and periodically adjusting the display brightness, as well as allowing the user to rate their experience. The collected data are utilised to determine the QoE relationship with the brightness level, content- and ambient light. For the sake of clarity, it is important to note that the data was collected under real-life scenarios, which changes drastically in terms of ambient light, content, user perception, and battery life. This section describes the experimental setup and the way QoE relationship is derived.

3.1. User study setup

Test Devices: The experiment was carried out on ten distinct mobile devices, from manufacturers including Google, Samsung, Huawei and Techno. Their display sizes range from 5.5 to 6.8 inches.

Participants: A total of thirty participants over the age of 18 were recruited via email for the study. This included friends, research students, and university staff. Twenty-two participants used the smartphones provided, while the other eight used their own smartphones to take part remotely. The number of participants satisfies the subjective ITU-R standard [23] for evaluating the quality of displayed content. In addition, we took measures to ensure that none of the participants had direct involvement in the development of the system under study. This precaution was taken to prevent any potential bias resulting from specific and detailed knowledge of the system. Ethical approval for the study was obtained from the University's ethics committee with reference number 72179.

Test App:[2] We modified an open-source Android library (Android Five Stars) to collect user ratings and associated contextual data from the mobile device. When the app is launched, it determines the average RBG values of the displayed content while periodically adjusting the screen brightness with a scaling magnitude of ten in random order (e.g., 50 %, 90 %, 20 %, etc.). After a few seconds of interacting at a set screen brightness level, for example, 20 %, a rating window appears (details under quality assessment), asking the user to rate their experience with the set screen brightness. The brightness is then adjusted, and the rating window reappears so that the user can rate the same content at different brightness magnitude. This is repeated until the various brightness levels have been exhausted, i.e., from 100 % to 10 %. The process is repeated with at least three different items under the same ambient light before changing to different locations with varied lighting conditions, equivalent to the day-to-day lighting that the user encountered during smartphone usage.

[2] The test app is openly available at https://github.com/sisuwa/UoS_Study.

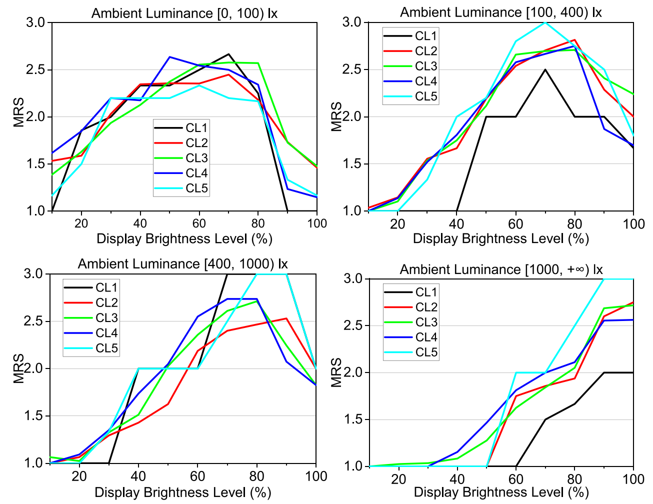

Fig. 2. The Mean Rating Scores (MRSs) of content displayed with the different relative content luminance clusters under varying ambient luminances. $CL1 - CL5$ are the five clusters with varying relative luminances.

Quality Assessment: To avoid ambiguity in the rating by the user, we used a 3-point scale to evaluate quality, with 3, 2, and 1 representing ideal, acceptable, and unacceptable ratings, respectively. The ideal rating shows that the set screen brightness level is perfect or exceeds the user's expectations given the content and ambient lighting. The acceptable rating is the brightness level with little to no variation in screen brightness that, despite its shortcomings, provides a pleasant or manageable viewing experience in daily life. The unacceptable (too dark or too bright) rating indicates that you are unable to view or understand the content at the specified brightness level in presence of the surrounding light. This could be because the brightness level is set too low, resulting in an unusable dark screen (unacceptable — too dark), or it could be because the brightness level is set too high, resulting in an irritable bright screen (unacceptable — too bright).

3.2. QoE relationship

The thirty participants in the subjective study provided a total of over 4000 test data. The relationship between the mean rating score (MRS) and display brightness level under varying L_C values and ambient luminance is depicted in Fig. 2. The figure depicts two types of variation: ambient luminance below 1000 and above 1000. For ambient luminance levels <1000, an initial increase in MRS values is observed with increasing brightness, followed by a decrease. This is because users are happy with the brightness level under these ambient conditions up to a certain point, but once this limit is exceeded, the brightness level becomes irritating to the user because it is too bright. This corresponds to the variation of a quadratic function; therefore, a quadratic function is used to fit the curve. For ambient luminance levels greater than 1000, however, the MRS values increase as the brightness level rises. This is consistent with a sigmoid function, where logistic regression is utilised to fit the curve.

In fitting the respective curves, acceptability was used as the QoE metric, similar to the one defined in [24], but we considered two categories, ideal and satisfactory, whereas [24] only considered one category. This enables the use of ideal QoE settings in scenarios with sufficient battery energy, thereby maximising the QoE. For ideal acceptability (A_I), only ideal user ratings were considered, whereas for satisfactory acceptability (A_S), acceptable and ideal user ratings were

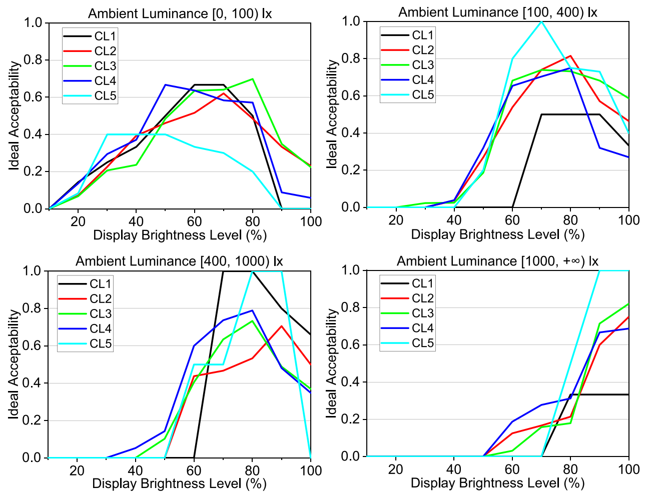

Fig. 3. The Ideal Acceptability (A_I) of content displayed with the different relative content luminance clusters under varying ambient luminances.

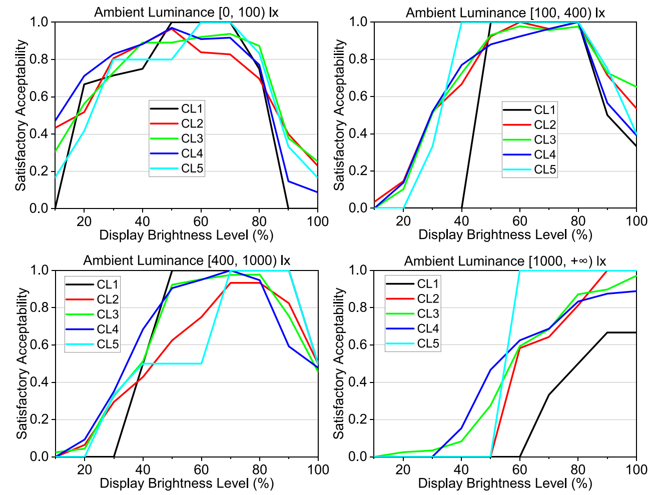

Fig. 4. The Satisfactory Acceptability (A_S) of content displayed with the different relative content luminance clusters under varying ambient luminances.

used (i.e., $ratings \geq 2$). Consequently, the respective acceptabilities are defined as:

$$A_I(L_C, \varphi, L_{amb}) = \frac{N_I}{N_T}$$
$$A_S(L_C, \varphi, L_{amb}) = \frac{N_S}{N_T} \tag{5}$$

where N_I, N_S and N_T represent the number of ideal ratings, the number of satisfactory ratings, and the total number of ratings for each level of brightness. $A_I(L_C, \varphi, L_{amb})$ and $A_S(L_C, \varphi, L_{amb})$ denote the ideal and satisfactory acceptability for content with luminance L_C, ambient luminance L_{amb} and brightness scaling magnitude φ. Therefore, writing Eq. (5) in terms of QoE yields Eq. (6):

$$QoE_I(L_C, \varphi, L_{amb}) = A_I(L_C, \varphi, L_{amb})$$
$$QoE_S(L_C, \varphi, L_{amb}) = A_S(L_C, \varphi, L_{amb}) \tag{6}$$

where $QoE_i(L_C, \varphi, L_{amb})$ is equivalent to the subjective user study's QoE of the content displayed. Using the acceptability values obtained from Eq. (5), we can derive the fitting functions for the various ambient clusters ($L_{aC1} - L_{aC4}$). The MRS values in Fig. 2 are then converted to their respective acceptability values, as depicted in Figs. 3 and 4. This is then used to fit the relationship to the ideal and satisfactory acceptabilities.

Table 1 displays the fitting results for the quadratic and logistic model coefficients, respectively. The respective φ_{Ii} and φ_{Si} values are computed by solving Eq. (3) based on the content and ambient clusters, and QoE level desired.

4. Experimental results

This section describes the experimental setup, which includes the platform and evaluated approaches. In addition, an evaluation of the proposed approach and its advantages over previous approaches, as well as the associated overhead, are discussed.

4.1. Experiments and implementation of *aCADS*

To implement *aCADS* and other state-of-the-art algorithms, we use the Google Pixel 3, a commercial smartphone designed by Google running Android 11 (Red Velvet Cake) operating system with kernel version 4.9.248. Since the majority of smartphone usage will involve a combination of text and images, video, and user interaction with the content displayed on the screen, the test app was designed to reflect these activities in a real-life scenario by incorporating a document editor, video player, and image viewer while determining the average RGB value of the displayed content. This was chosen so that the average RGB values could be calculated, as this is not possible with a third-party app on a real-life commercial device. The behaviour of the test app is comparable to that of the vast majority of contemporary mobile applications. Using the standard Android application API, contextual data such as ambient light and battery contexts are obtained from the device's sensors. The average RGB value of the loaded content is utilised to determine the content's luminance. All presented results already account for all the overhead incurred. However, the energy overhead of the approach is less than 2 % of the battery energy.

4.1.1. Relevant existing approaches for comparison:

The proposed approach is compared with state-of-the-art brightness scaling techniques on mobile devices to demonstrate QoE maximisation while meeting expected battery life.

Adaptive or Automatic Brightness Scaling (ABS) [22]: Focuses on determining the optimal screen brightness for mobile devices based on ambient lighting. It is an option available in the display settings of the most recent flagship mobile devices that learns from the user's typical ambient lighting conditions and habits. It eliminates the need to manually adjust the display's brightness settings and extends battery life. We compare against *ABS* as it is the most widely used ambient light-aware brightness scaling approach.

Static or Manual Brightness Scaling (SBS): Aims for either optimal brightness or maximum battery life by allowing the user to manually set the brightness level. Due to the non-automatic nature of this setting, the initial brightness level will remain constant unless changed manually again, hence the term static or manual brightness scaling. *SBS* is considered because it is widely accessible and the most popular approach on the majority, if not all, smartphones. For comparison, a fixed brightness level of 46 % was chosen, which is a typical range for indoor lighting conditions that is neither very high to consume more energy nor very low to degrade QoE.

Low-Overhead Adaptive Brightness Scaling (LABS) [8]: Optimises the trade off between energy consumption and content modification. This entails determining the optimal content-dependent brightness scaling factor for each displayed content. To ensure a fair comparison, we evaluate our approach using a modified version of LABS. In contrast to LABS, we used the optimal brightness scaling factor to determine the displayed content's brightness level. This reduces the additional computational burden incurred during pixel transformation, allowing the technique to be implemented in real-time.

Table 2
The Quadratic and Logistics Model Evaluation for Satisfactory (S) and Ideal (I) Acceptabilities.

Ambient cluster	Quadratic model accuracy		
	R^2	$RMSE$	MAE
L_{aC1} - S	0.90	0.10	0.08
L_{aC1} - I	0.79	0.11	0.09
L_{aC2} - S	0.86	0.13	0.10
L_{aC2} - I	0.63	0.19	0.16
L_{aC3} - S	0.83	0.15	0.14
L_{aC3} - I	0.74	0.15	0.12
Ambient cluster	**Logistics model accuracy**		
	$Accuracy\ score$		ROC
L_{aC4} - S	1.0		1.0
L_{aC4} - I	1.0		1.0

Table 3
Energy consumption evaluation across each of the ambient clusters for the four approaches considered. Additionally, the capability of each approach to meet the expected battery life is evaluated.

Approach	Energy consumption (J)				Total	Met expected battery life?
	L_{aC1}	L_{aC2}	L_{aC3}	L_{aC4}		
ABS [22]	94	1644	239	136	2112	No — depleted 36 min early
SBS	90	1432	179	90	1790	Yes
LABS [8]	136	1644	222	94	2095	No — depleted 30 min early
aCADS	90	1464	205	119	1879	Yes

4.1.2. Evaluation methodology:

For extensive evaluation, we also consider three typical range of usage scenarios, which the participants fall into based on the typical proportion of a user's daily time spent on each ambient cluster (L_{aC1} - L_{aC4}) for a device's entire usage before recharging. The usage scenarios are determined based on the data collected from test participants, as outlined in Section 2.2, and involve clustering the proportions into these representative categories. For *Scenario 1*, L_{aC1}, L_{aC2}, L_{aC3} and L_{aC4} contribute 5 %, 80 %, 10 % and 5 %, respectively. In *Scenario 2*, L_{aC1}, L_{aC2}, L_{aC3} and L_{aC4} account for 10 %, 65 %, 15 % and 10 %, respectively, whereas in *Scenario 3*, L_{aC1}, L_{aC2}, L_{aC3} and L_{aC4} represent 15 %, 75 %, 5 %, and 5 %, respectively. Using these scenarios, we validate the energy prediction model (Eq. (4)) that was trained using data of varying content and brightness levels. The actual energy consumed was compared to the predicted energy, and the average error percentage across 20 runs was 5.6 %. Similarly, we compare the battery life and QoE for these scenarios with and without sufficient battery energy. For clarity, we define *"insufficient battery energy"* as a situation in which the actual battery energy cannot support the smartphone's normal operation for the user-specified number of hours before recharging. For instance, in a situation where the user needed to use the smartphone for 7 h but the battery energy could only last only for 6 h.

4.2. Model validation

To demonstrate the effectiveness of our QoE model, we conducted a thorough analysis of its accuracy and performance metrics. For the quadratic function, we calculated relevant key metrics, such as the R-squared value (R^2), root mean squared error (RMSE), and mean absolute error (MAE) of the model. We also determined the confidence interval for the coefficients and presented the results in Table 2. Similarly, the accuracy score, area under receiver operating characteristics curve (AUC-ROC or ROC score) and confidence interval for the logistics regression were computed and also reported in Table 2.

Table 4
Summary of the average QoE (%) and expected battery life index (EBLI) (%) for the considered scenarios and approaches under insufficient battery energy.

Approach	Scenario 1		Scenario 2		Scenario 3	
	QoE (%)	EBLI (%)	QoE (%)	EBLI (%)	QoE (%)	EBLI (%)
ABS [22]	85.33	86.09	84.17	84.35	83.50	87.42
SBS	71.67	100.00	70.33	100.00	73.67	100.00
LABS [8]	85.33	86.96	81.00	85.22	80.33	84.33
aCADS	80.25	100.00	80.58	100.00	80.67	100.00

The results from Table 2 show an R^2 value of 0.90, an RMSE of 0.10, and an MAE of 0.08 for the Satisfactory category of L_{aC1} ambient cluster, with a 95 % confidence interval for the coefficients. The high R^2 value of 0.90 indicates that the model explains a large portion (≈90 %) of the variance in the data, while the low RMSE and MAE values of 0.10 and 0.08, respectively, indicate that the model's predictions are consistently close to the actual values. This indicates a strong fit and that our model can accurately predict QoE for the L_{aC1} cluster. Similar results were also observed for both the Ideal and Satisfactory categories of the L_{aC2} and L_{aC3} clusters, further demonstrating the model's efficacy in predicting QoE. For the logistics function metric shown in Table 2, the model accuracy score is 1.0 % with a ROC score of 1.0 % within 95 % confidence interval, indicating that the logistic regression model performs exceptionally well. It accurately predicts the class labels of the instances in the dataset and has a perfect discriminative ability, ensuring no false positives or false negatives.

Overall, these analyses provide strong evidence for the effectiveness of our QoE model and *aCADS* approach. The model's high accuracy and good performance metrics, along with the confidence intervals for the coefficients, support its use in predicting QoE for varying ambient and content conditions.

4.3. Comparison of battery life

Table 3 shows the energy consumption evaluation under sufficient battery energy. As shown in Table 3, the insight from the user perception to different content and ambient conditions enable the *aCADS* approach to select an appropriate brightness that maximises the users' QoE (Section 4.4) while meeting the expected battery life. Compared to ABS [22] and LABS [8], *aCADS* energy saving (battery life) is improved by 12.4 % (6 %) and 11.5 % (5 %), respectively. Similarly, the energy saving is improved by 12.4 % and 11.1 % for scenario 2, and by 11.4 % and 15.5 % for scenario 3, as compared to ABS and LABS, respectively. This is because the ABS approach varies brightness based on ambient luminance, while the LABS approach is based on content luminance. This demonstrates the significance of display management that considers both ambient and content luminance. Although SBS, whose brightness level remained unchanged regardless of changes in content and ambient conditions, has more energy saving than the other approaches considered, this comes at a cost for the QoE (Section 4.4).

Similarly, the energy consumption for ABS, SBS, and LABS approaches remained unchanged for the respective scenarios under insufficient battery energy, as they are unaware of the energy-budget constraints. This is because for all three approaches—ABS, SBS, and LABS—the same brightness settings will be selected for identical ambient and content conditions, irrespective of the battery energy. In contrast, the energy model and allocator enabled *aCADS* to determine the appropriate brightness levels to meet the required time. Consequently, improving the battery life by 17.3 % (1.6 h) and 16.4 % (1.5 h) for scenario 1, 18.8 % (1.8 h) and 17.4 % (1.7 h) for scenario 2, and 15.6 % (1.4 h) and 19.8 % (1.8 h) for scenario 3, compared to the ABS and LABS approaches, respectively (Fig. 6(b)).

Table 5
Comparison of the expected battery life index (%) and the ability to meet the expected battery life for the scenarios and approaches evaluated on the Google Pixel 6 smartphone.

Approach	Scenario 1		Scenario 2		Scenario 3	
	Expected battery life index (%)	Met expected battery life?	Expected battery life index (%)	Met expected battery life?	Expected battery life index (%)	Met expected battery life?
ABS [22]	81.44	No — depleted 1. 58 h early	81.04	No — depleted 1.61 h early	81.89	No — depleted 1.54 h early
SBS	100.00	Yes	100.00	Yes	100.00	Yes
LABS [8]	81.59	No — depleted 1.56 h early	81.26	No — depleted 1.59 h early	80.87	No — depleted 1.63 h early
aCADS	100.00	Yes	100.00	Yes	100.00	Yes

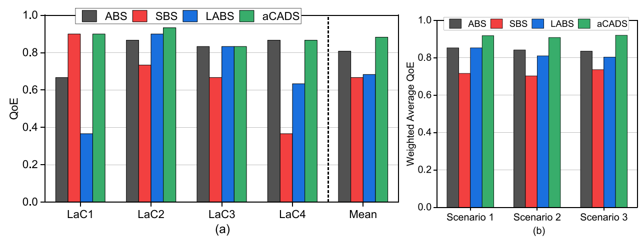

Fig. 5. The average and weighted average QoE evaluation for the various approaches considered for a real-life scenario with *sufficient battery energy* (a) under each ambient-light cluster and the average across the clusters (b) weighted average QoE based on the percentage of user's daily time spent in each cluster for the three scenarios.

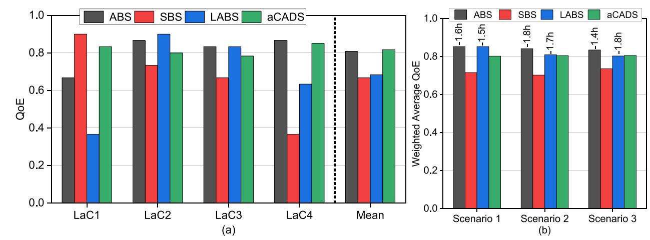

Fig. 6. The average and weighted average QoE evaluation for the various approaches considered for a real-life scenario with *insufficient battery energy* (a) under each ambient-light cluster and the mean across the clusters (b) weighted average QoE based on the percentage of user's daily time spent in each cluster for the three scenarios, as well as annotated negative battery life indicating the number of hours these approaches failed to meet the expected battery life.

4.4. Comparison of average QoE

Fig. 5 shows the evaluated average and weighted average QoE under the different ambient lighting scenarios (L_{aC1} - L_{aC4}), as well as across the average percentage of a user's daily time spent with sufficient battery energy. In Fig. 5(a), the QoE is computed using the acceptability metric in Eq. (5) for each of the ambient conditions (L_{aC1} - L_{aC4}) that comprise a complete smartphone usage cycle prior to recharging, and the average is then normalised to the ideal rating score. Fig. 5(b) depicts the weighted average QoE for the entire usage cycle, which is the weighted average of all the respective QoE values in each of the ambient conditions (shown in Fig. 5(a), as an entire usage cycle consists of these conditions), for the proportion of time users spent in the ambient clusters based on the three typical usage scenarios. In Fig. 5, where sufficient battery energy is available for the required time, the *aCADS* approach provides a higher average QoE across all ambient conditions than ABS, SBS, and LABS, with total average QoE improvements of 9.3 %, 32.5 % and 29.3 %, respectively. While SBS has the lowest energy consumption, as shown in Table 3, it also has the lowest average QoE of 67 % compared to 88 % for *aCADS*. Fig. 5(b) also shows the weighted average QoE improvement for the three typical usage scenarios, with *aCADS* providing total average improvement of 7.6 %, 28.1 % and 7.6 % for scenario 1, 7.9 %, 29.1 % and 12.1 % for scenario 2 and 10.2 %, 24.9 % and 14.5 % for scenario 3, compared to *ABS*, *SBS* and *LABS*, respectively.

Similarly, Fig. 6 shows the average and weighted QoE for the ambient clusters and considered scenarios involving insufficient battery energy. While *aCADS* approach reduces the energy consumption to meet the expected battery life, it is still able to provide comparable higher average QoE, with total average QoE improvements of 1.7 %, 22.5 % and 19.5 % over the ABS, SBS and LABS approaches, respectively (Fig. 6(a)). This lower improvement in QoE is observed in this scenario as a result of *aCADS*' efforts to further reduce energy consumption while still providing acceptable QoE to meet the expected battery life.

Fig. 6(b) also shows similar comparative weighted average QoE across the three typical range of usage scenario considered. In addition, the *aCADS* approach is able to improve battery life by up to 18.8 % and 19.8 % compared to *ABS* and *LABS* approaches, respectively, while maintaining ≈80 % weighted average QoE across the three scenarios.

For better insights, Table 4 provides a summary of the average QoE and expected battery life index for the considered scenarios and approaches when battery energy is insufficient. The expected battery life index (EBLI), expressed as a percentage (%), represents the ratio of the amount of time the device can operate on a single charge or with a specific battery capacity under typical usage conditions and settings to the user's expected battery life. The results demonstrate that the proposed approach can maximise user QoE while meeting battery life requirements. This is in contrast to state-of-the-art approaches, such as ABS and LABS, which often fail to meet expected battery life, or the SBS approach, which consistently provides a low average QoE.

4.5. Scalability to other hardware platforms

We analysed the scalability of the *aCADS* approach on the Google Pixel 6, a flagship smartphone released in 2021, which has a larger screen and increased battery capacity than the Pixel 3 [25]. The results are presented in Table 5, showcasing the expected battery life index and the ability to meet the expected battery life for the various scenarios and approaches on the Google Pixel 6. Our findings indicate that the *aCADS* approach can achieve substantial improvements in battery life, reaching up to 22.79 % (1.58 h) and 22.56 % (1.56 h) improvement over the ABS and LABS approaches for scenario 1, respectively. Similarly, battery life improvements of 23.39 % (1.61 h) and 23.06 % (1.59 h) were observed for scenario 2, and 22.11 % (1.54 h) and 23.66 % (1.63 h) for scenario 3 when compared to the ABS and LABS approaches, respectively. While SBS does achieve a 100 % battery life index and successfully meets the expected battery life for all three scenarios, similar to the *aCADS* approach, it notably lags behind both *aCADS* and the other two approaches in terms of average QoE. Specifically, it exhibits the lowest average QoE, with only ≈71 %, as shown in Table 4. It is noteworthy that despite the larger screen size and increased battery capacity of the Google Pixel 6, the improvements in expected battery life index and battery life are comparable to those achieved on the Google Pixel 3.

Similarly, the average QoE enhancements for the Pixel 6 are consistent with the results depicted in Figs. 5 and 6. This demonstrates the scalability of the *aCADS* approach across a variety of devices, provided that the device supports adaptive display brightness scaling. However, it is essential to recognise that the extent of battery life improvement will depend on several factors, including the device's battery capacity, technology, display size, and display technology.

5. Conclusions

This paper presents *aCADS*, a self-adaptive content- and ambient-aware display brightness scaling approach for mobile devices that maximises user QoE for a given battery life. The proposed method considers user perception, ambient, and content luminance when determining screen brightness for a given battery life. The leveraged insight of user perception to different content and ambient conditions, coupled with energy prediction and adaptive brightness scaling at runtime, enables battery life enhancement and QoE maximisation. The evaluation of the proposed method on a commercial smartphone demonstrated that up to 32.5 % QoE improvement can be achieved while meeting the expected battery life. This demonstrates that user experience can be maximised with a display management approach that takes ambient and content luminance, as well as battery life goals, into account.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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