DE-BAR: Device Energy-centric Backlight and Adaptive Region of Interest Mechanism for Wireless Mobile Devices

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Abstract. One of the main challenges in the smart-phone world is that they are battery constrained and the development of battery technologies have not kept pace with the required energy demand. In particular, there are still significant technological gaps on developing energy-aware solutions that would prolong the battery life of devices without affecting the quality of the distributed video/multimedia content. In this aspect, this paper proposes DE-BAR - a process based innovation that will provide a seamless battery saving mechanism, based on backlight and adaptive region of interest of the streamed multimedia content. This work intends to look at the nature of the video/multimedia content that is received in the device and adapts the energy consumption dynamically at three levels: *Screen Colour, backlight and Intensity; and adaptive Region-of-Interest* (RoI) *based variation in the multimedia content.* Notably, the work provides the mechanism for real-time adaptation. The colour intensity, number of RoI for the video sequence and the frame rate is decided by the spatial and temporal complexity of the video. The energy consumption is measured using an Arduino board while video quality is analyzed using extensive subjective tests. The results indicate that more than 50% energy could be saved in the device while retaining above average perceptual video quality.

Keywords: Brightness, backlight, energy consumption, region-of-interest, spatial and temporal complexity, video streaming

1 Introduction

The last decade has seen humongous growth in smart-phones and all kinds of graphic-intensive/multimedia applications. These applications consume significant amounts of energy when running on these devices. In fact, the biggest problem today in the mobile world is that they are battery driven and the battery technologies are not matching the required energy demand. By having devices with a large number of features and capabilities (i.e. camera, gaming, Apps, browsing, etc.) and other functionalities, the handset manufacturers' face a serious problem of a dramatic and almost unsustainable energy-consumption increase [1, 2].

The level of computations and number of services in smart-phones have both increased exponentially over the last couple of years. Presently, an enormous effort is put in the development of codecs, proposal of video compression techniques, design of efficient display screens, etc. and all will continue to become better over time. However, in the smart-phone world, battery deprecation is still one of the greatest challenges. In the literature, there are some non-adaptive energy saving techniques in i-Phones and smart-phones which permit the subscriber to switch on/switch off certain functionalities. These solutions do not provide the requisite flexibility in changing the energy consumption in real-time by a graceful degradation in services. Instead, most of them, which provide a change in their functionalities, result in abrupt and perceptible disturbance in terms of the associated video quality. Notably, there is a basic problem in the energy consumption aspect that is most often overlooked. That is, there are no well-developed sophisticated adaptive processes in a smart-phone or even a low end phone that could extend the battery life in real-time, depending on different aspects such as - nature of video content and the remaining battery energy value in the device.

It has been investigated and found from the available research work that three most energy consuming components in smart-phone are: display screen, central processing unit (CPU) and network interface card, in decreasing order of their energy consumption. Notably, there are important differences in the level of motion in the video sequences due to the multimedia content that varies significantly in terms of its content characteristics. This aspect greatly influences the encoding process and consequently the perceived video quality. Till recently, a one-solution-fits-all approach has been used for multimedia centric devices. However, to optimize the battery use, the content type should determine changes in the encoding/decoding process in order to best suit that content type. It should be noted at this stage that this is an extremely complex process. The energy consumed in screen and CPU is dependent on the content being viewed/displayed. The amount of energy savings through adaptation in screen and CPU depends on the exact nature of the multimedia content. However, an abrupt change in the quality of the video content results in a significant loss in the quality of multimedia content. Therefore, it is essential that the mentioned changes in the screen and CPU functionality are carried out dynamically and seamlessly, based on the nature of multimedia content and remaining battery life span. One of the significant technology challenges in the dynamic mechanism is in the continuous classification of multimedia content being watched, as this varies dynamically during the duration of the video sequence.

The video content could be generally classified into two categories based on spatial mobility and temporal mobility**.** Spatial mobility measures the manner in which the differences are noticed within a video frame, from one area to another. A particular example is a news-reading program where the background is often simple with no major variation between left, top and right side of the speaker. Temporal mobility measures the amount of changes happening from one video frame to another. This indicates how fast or slow most of the video content varies. A typical high temporal video sequence is selected from a high-action movie where there are many movements, explosions, scene cuts, detail-general view alternations which make any one frame very much different than another. With regard to video encoding, an encoded video comprises of I, P and B frames. Among them, I-frames are the least compressible, but do not necessitate other video frames to decode. On the other hand, the P-frames use data from previous frames to decompress and are more compressible than I-frames. On the other hand, the B-frames can use both previous and forward frames for data reference to get the highest amount of data compression.

Most of the current devices in the market have three limitations that prevent them from implementing an energy optimization scheme in devices:

1. Changing the device functionality in real-time requires more than just battery monitoring. It requires the device to decipher the changes happening in real-time, which is an extremely complex and time consuming task, hence not easily done.
2. The current energy optimal mechanisms are based on optimizing the device functionality.
3. In terms of multimedia content, the current works focus mainly on improving the multimedia codecs.

In this regard, this paper proposes DE-BAR - a process based innovation that provides a seamless backlight variation and adaptive battery saving mechanism, based on the streamed multimedia content. The novelty of this work lies in the fact that the algorithm optimizes the energy consumption in the device based on the spatio-temporal complexity of the video/multimedia content that is received/ displayed on the screen. DE-BAR not only ensures that the user gets the best video quality in the absence of any energy constraint, but also ensures that the energy consumption is optimized without significantly affecting the video quality.

The paper is organized as follows. Section II provides a detailed related work on different aspects of energy optimization in devices and associated mechanisms. Section III introduces the proposed DE-BAR algorithm and explains the different aspects in details. Further, Section IV describes testing methodology and scenarios, and presents the results of different tests. Finally, Section V concludes the paper and provides some future directions for our work.

2 Related Work and Initial Study

The area of energy optimization in mobile devices has been of great interest not only across researchers; but more importantly across device manufacturers. Hence, there have been several efforts by the industry to solve this problem. Over the years, several battery saving software solutions have been launched on energy optimization/energy savings in wireless smart-phone device. An application, “Energy-Saver” developed by Fedoroff Soft, USA [3] focuses mainly on auto switch OFF and ON during night/unused time. “Green-Phone” application developed by Mobi-Monster [4] offers few features like energy savings in the backlight display mechanism and automatic charger disconnection while charging. It supports Windows Mobile and is highly successful commercially. However, it does not provide any adaptive energy savings.

“Power Manager” is an application developed by X-Phone that adds basic dynamic power settings to the phone, like how long the screen is on during a call, if device stays on while the keyboard is open, etc. [5]. It automatically changes several settings of the device as a group. It is the most sought after APPs in Android but unfortunately, does not cater specifically to graphic-intensive battery drain in the device. Further, “Power control plus” currently available only in Android phones is a widget that lets you turn on/off more than 20 settings in the device. However, it requires manual settings and cannot/does not provide any adaptive energy savings in the device middleware. In addition, there are several patents granted, published (and some just filed with no official details available in public domain) on energy savings as can be seen below. A patent on “*Method of transmitting content with adaptation of encoding characteristics*” deals mainly with the downloading of the content file by file while switching from one encoded multimedia content to another so as to change the encoding characteristics [6]. The patent on “*Method for Reducing the Power Consumption of a Mobile Device*” deals with power reduction due to the interference occurring at the radio and is quite different from what is developed in our invention [7]. Notably, the invention [8] proposes a method and apparatus for improving energy efficiency of mobile devices through energy profiling based rate adaptation. In addition, there has been recent works on content based adaptation. For instance, the work on “*content-based adjustment*” [9] proposes a content-adaptive adjustment system and a method for a light-emitting display. It analyses the average data intensity/power consumption and the data distribution of the image data to be displayed. However, it looks at image level and does not deal with the video categorization. The work by HTC [10] proposes multiple steps on resetting the smart phone, searching for network service, operating the mobile phone system in standby mode. Further, it has a PDA system in normal mode when connected to a network, switching the mobile phone system to connection mode when establishing communication with a remote terminal, switching the mobile phone system to sleep mode when the mobile phone system has been idle for a first time period. Notably, it also offers switching the PDA system to sleep mode when the PDA system has been idle for a second time period and implementing power detection to switch the mobile phone and PDA system to off mode when the detected power is lower than a first and second threshold respectively. Another work by HTC [11] indicate power control methods for portable electronic device; wherein the portable electronic device comprises a power supply unit and a volatile memory for storing data when the power supply unit supplies power thereto. First, the portable electronic device is set to enter a deep sleep mode. Then, data accessed from the volatile memory is transferred to a non-volatile memory. Finally, except for maintaining sufficient power to restore the device, the power supply unit is turned off. Similarly, there are other works which deal with innovative system and method for managing power conditions within a digital camera device and content-aware video adaptation [12, 13].

In terms of Region-of-Interest (RoI) based adaptation, recent noteworthy techniques in optimizing energy consumption of video applications consider different aspects of RoI. Among these are RoI-based video adaptive solutions whose essential idea is to display the region of the screen where the user is more likely to focus on at higher quality than the surrounding areas. For example, while watching a tennis match, the viewer may be most interested in looking at the area around the ball (though this may not be the case for all videos). However, in reality, there are always regions in every video frame on which users focus more, as compared to other regions. It has been shown in [14] that by adapting a high-resolution window at the point-of-gaze and low-resolution window in the peripheral areas, the users had longer initial saccadic latencies in peripheral areas as compared to the scenario wherein a low resolution was uniformly displayed across the whole screen of the device. Importantly, it was found in [15] that in order to maintain a particular user-perceived video quality, if the degradation is increased in the peripheral areas, the size of the adapted high-resolution window would also have to be increased at the point of gaze. Recently, a scalable RoI (SROI) was proposed which supports fine grained granularity adaptation in RoI with low computing complexity [16]. Further, a RoI adaptive delivery scheme (ROIAS) is proposed and a detailed objective and subjective assessment and analysis has been carried out for RoI-aware adaptive streaming [17, 18]. However, the adaptation focused mainly on network-related aspects to control RoI quality adaptation. The adaptations are done in order to realize better video quality both objectively and subjectively. In principle, there are numerous techniques for discovering RoI in a video including eye-tracking (with cameras) [19]. However, to the best knowledge of the authors, a multi-level device adaptive approach for energy optimization based on spatial-temporal complexity of the video content is still not being investigated.

Before proceeding with proposing a new technique on energy optimization the authors felt it was imperative to analyze the behavior of energy consumption across different colors and different brightness levels. In order to do so, an Android-based smart-phone of Samsung was considered. A particular video frame was displayed on the screen with continuously varying colors and the resulting energy consumption in the screen was observed. Fig. 1 shows the average energy consumption across different colors for two different brightness levels – 50% and 100%. The X-axis shows the different colors and the Y-shows the value of the average energy consumed. It can be observed that during both 50% and 100% brightness level, out of RED, GREEN and BLUE colors, the BLUE and its associated colors, i.e., colors with considerably high value of BLUE color pixels consumed the maximum amount of energy. At 45% brightness level, the amount of energy consumption varied from 470mW to 516mW, up to 48mW increase in the energy consumption from the lowest value. Further, in case of 75% brightness level, this variation is from 578mW to 626mW, again an increase of up to 48mW.

The importance of the brightness level can be understood from a detailed study, carried out for different colors. It can be observed from Fig. 2a and Fig. 2b that the power consumption at minimum brightness varied between 200mW and 300mW; which increased from 650 mW to 700mW when the brightness level is set to 100%; i.e., the resulting energy consumption is increased by more than 100% by increasing the brightness level from 0% to 100%.

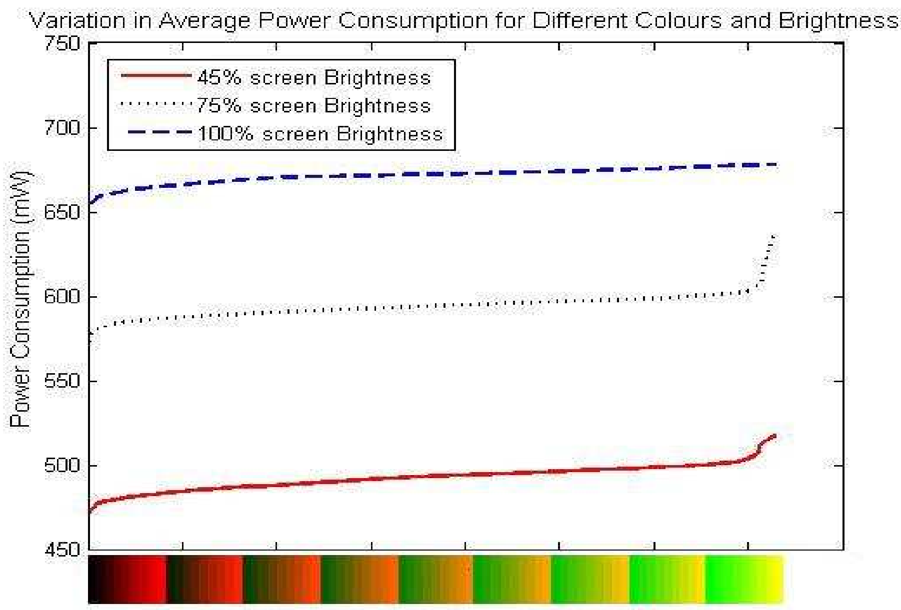


Fig. 1 Variation in the Average Power Consumption for Different Colors in a Smart-Phone

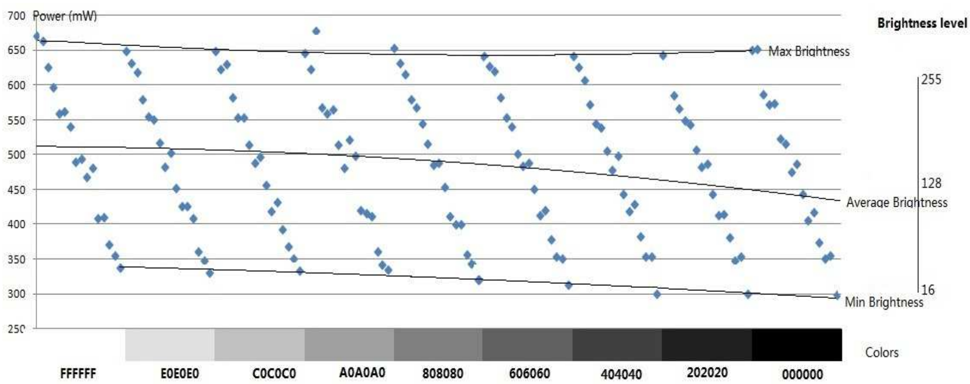


Fig. 2a Variation in the Power Consumption for Different Brightness Level of B&W Colors

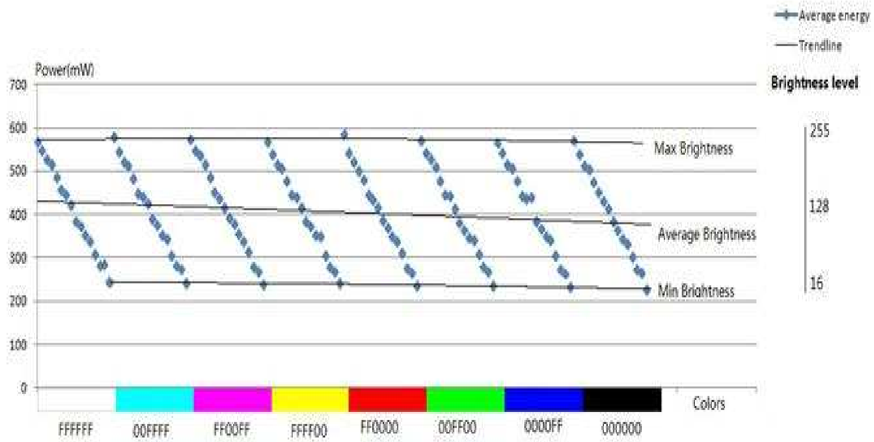


Fig. 2b Variation in the Power Consumption with Changing Colors and Brightness Level

Given the energy consumption pattern of the mobile devices as observed from Fig. 1 and Fig. 2 and the significant difference in the energy consumption across different brightness levels, a novel multi-level adaptive energy optimization technique is proposed in the next section.

3 Proposed Technique: DE-BAR

This work proposes a novel mechanism of screen and CPU functionality adaptation, based on the spatial and temporal classification of the video content. Depending on this video classification, the mechanism adjusts screen and CPU parameters in order to save power. The block diagram representation of the proposed DE-BAR algorithm is shown in Fig. 3. This involves two major steps. The first step is the classification of the video content and the second step is the content based adjustment in screen and CPU.

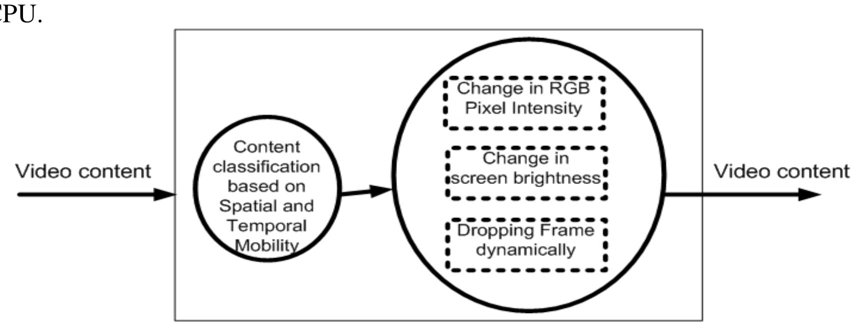


Fig. 3 Proposed Energy Optimization Algorithm for Video Content

To begin with, the video content is classified and given a score based on spatial and temporal complexity. The proposed step in the algorithm performs a real-time classification of video content into different levels of spatial mobility (*N*) and temporal mobility (*M*). This classification of video content is shown in Fig. 4. The video V is divided into a series of frame sequences with similar motion content; each sequence S composed of a number of frames F. Each sequence (*S*) of the video is assessed in terms of spatial and temporal mobility, then classified into one of the content mobility areas (in number of *N* x *M)*, as shown in Fig. 4. Accordingly, the sequence is assigned a number *s,* where *s* describes the combined effect of spatial and temporal mobility of the sequence S; and varies from 1 to *N* x *M.* A lowest score is given to a video which has both low variations in the spatial and temporal content whereas the highest score is given to the video which has the highest variation in both spatial and temporal content. This is done in order to quantify the amount of content and the rapid mobility in the content in the frames.

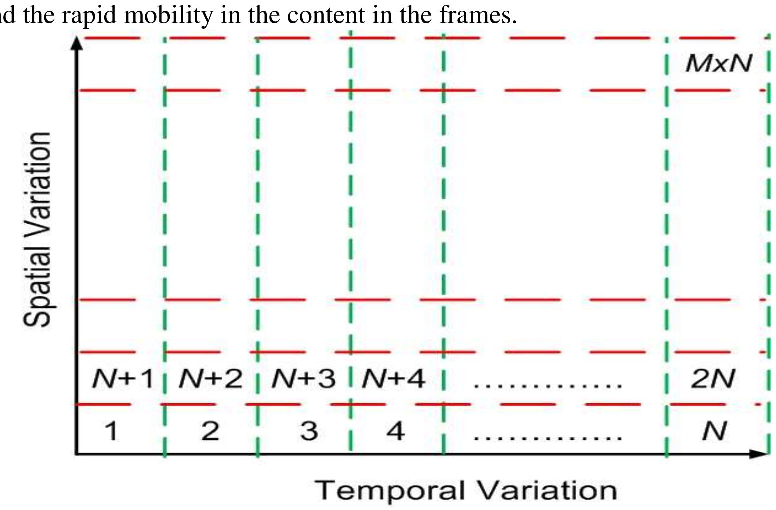


Fig. 4 Classification of Video Content based on Spatial and Temporal Mobility

Once the video content is classified, there are three aspects that are dealt simultaneously.

III.1 Dynamic Change in Screen Color and RGB Color Intensity

The screen color is changed dynamically for each sequence, by changing the pixel intensity of R, G and B colors individually. Given that R, G and B each have different energy consumption while being displayed; different pre-defined patterns (governed by strong mathematical equations) are considered in order to reduce the energy consumption while displaying these colors. To begin with, a matrix-color filter is used to change the color dynamically. The functionality of the matrix-color filter is as follows: It looks at each pixel in a source image and changes them based on how much red, blue and green is in the pixel. The RGB color intensity of the final (destination) frame depends on the color of the frame and the mechanism used to change the color. The matrix color-filter is shown in eqn. (1).

Color	Rs	Gs	Bs	A (Transparency)
Rd	a1	a2	a3	0
Gd	a4	a5	a6	0
Bd	a7	a8	a9	0
A	0	0	0	1

Table 1 Relation between Source Colors and Display Colors as per Matched-Color Filter

Rs, Gs and Bs are the color pixel values and vary from 0 to 255 each. Herein, it should be noted that the pixel intensity of each - R, G and B varies from 0 to 255. An intensity of (R, G, B) = (255, 255, 255) results in white color whereas an intensity of (0, 0, 0) results in black color. Notably, an intensity of (128,128,128) results in gray color. Our proposed invention describes how this matrix values are determined in real-time such that the resulting video frame has a different RGB color intensity; and importantly, the overall energy consumption is minimized. The RGB value of the displayed frame could be computed as follows:

$$\begin{pmatrix} Rd \\ Gd \\ Bd \end{pmatrix} = \begin{pmatrix} a1 & a2 & a3 \\ a4 & a5 & a6 \\ a7 & a8 & a9 \end{pmatrix} \begin{pmatrix} Rs \\ Gs \\ Bs \end{pmatrix} \quad ...(1)$$

In order to change the RGB color intensity, a mathematical function based solution is developed that would change the colors in the video frame. This color change depends primarily on three factors:

a. The content mobility block (*s*) that the sequence S is classified onto.
b. Pre-defined pixel intensity set for adjacent blocks (*s*-1, *s*+1, s-*N* and s+*N*).
c. Pixel intensity of the previous frame (*F*-1).

Since Red, Green and Blue color each consume different amount of energy during the display, a function is formulated for changing each source color intensity (i.e., for changing Rs, Gs and Bs). This implies that there would be one function each for each column in eqn. (1). The aim of formulating the mathematical equation is to have a gradual and deterministic pattern in the pixel number, with varying mobility content.

III.1.a Changing Color Intensity of the Displayed RED Color (Rd):

The aim of the function for Rs is two-fold:

i. To have a minimum value of pixel intensity even if there is no mobility in the video frame.
ii. Since the red color consumes the least energy, the pixel intensity could increase with an increase in either the spatial mobility or the temporal mobility content.

In case of a low mobility (both spatial and temporal), the value of s is zero or close to zero. Hence, the value of a1 (or a4/ a7) would be set to some pre-defined initial value (around 0.5). Further, as the spatial and temporal mobility of the content in the video frame increases, the pixel intensity is increased proportionally. With an increase in the spatial and temporal complexity of the content, the value of s would approach M x N. The function could therefore be written as:

$$a1 = \frac{\alpha + s}{2(M \times N)} \qquad \ldots..(2)$$

and a4 = a7 = 0

where

a. s is the content mobility block that the sequence S is claissified into
b. M and N are the number of blocks over which a spatial and temporal complexity is divided to.
c. α is the pre-defined pixel intensity value and is originally set to 0.5

In order to ensure that there is no significant difference in the average pixel intensity between the subsequent frames, the value of α could be made dependent on the previous frames. In this scenario, the value of α would be:

$$\alpha = w_{R0} \times 0.5 + w_{R1} \times \alpha_{F-1} + w_{R2} \times \alpha_{F-2} + \ldots + w_{RP} \times \alpha_{F-P} \qquad \ldots(3)$$

where the different terms imply the following:

i. F indicates the frame number,
ii. P indicates the number of previous frames over which the intensity is averaged out
iii. The subscript (R) in the weighting factors indicate the weighting factor for red color. Notably, the summation of all weighting factors (i.e., all w's) would be equal to one.

III.I.b Changing Color Intensity of the Displayed GREEN Color (Gd):

The aim of the function for Gd is two-fold:

i. To have a minimum value of pixel intensity even if there is no mobility in the video frame.
ii. There would be a change in the pixel intensity of the green color, only when there is significant change in the temporal complexity of the video content. This is done because, the energy consumption of green (and all associated colors of

green) vary over a considerable range, which is especially beneficial while distinguishing frames which has high temporal mobility.

In case of a low temporal mobility, the value of s is ***zero or close to zero***. Hence, the value of a5 would be set to 0.5. On the other hand, as the temporal complexity of the motion content increases, a large range of pixel is provided in order to have a clear picture between the different frames.

The function could therefore be written as:

$$a5 = \beta + \frac{1}{2(M+N)} \text{round}\,(s/M) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$a2 = a8 = 0$$

where

a. β is the pre-defined pixel intensity value and is originally set to 0.5

b. round() indicates the quotient of the division (s/M)

Again, like in the case of Rd, in order to ensure that there is no significant difference in the average pixel intensity between the subsequent frames, the value of β could be made dependent on the previous frames. In this scenario, the value of β would be:

$$\beta = w_{G0} \times 0.5 + w_{G1} \times \beta_{F-1} + w_{G2} \times \beta_{F-2} + \ldots + w_{GP} \times \beta_{F-P} \quad \ldots\ldots\ldots\ldots(5)$$

where, the subscript (β) in the weighting factors indicate the weighting factor for green color. Notably, the summation of all weighting factors (i.e., all w's) would be equal to one.

III.1.c Changing Color Intensity of Displayed BLUE Color (Bd):

The aim of the function for Bd is two-fold:

i. To have a minimum value of pixel intensity even if there is no mobility in the video frame.

ii. To have the pixel intensity value as a function of the current battery life in the device

iii. To change the pixel intensity of the Blue color, only when there is significant change in the spatial complexity of the video content. This is done because, the energy consumption of green (and all associated colors of green) vary over a considerable range, which is especially beneficial while distinguishing frames which has high temporal mobility.

In case of a low spatial mobility, the value of s is ***zero or close to zero***. Hence, the value of a9 would be set to 0.5. On the other hand, as the temporal complexity of the motion content increases, a large range of pixel is provided in order to have a clear picture between the different frames. The function could therefore be written as:

$$a9 = \gamma b + \frac{1}{2(M+N)} \text{rem}(s/M) \quad \ldots\ldots(6)$$

a3 = a6 = 0

where

c. γ is the pre-defined pixel intensity value and is originally set to 0.5

d. b is the remaining battery life, defined in terms of ratio (e.g. 0.7 for 70% battery life)

e. $rem(s/M)$ indicates the remainder of the division *(s/M)*

Again, like in the case of Rd, in order to ensure that there is no significant difference in the average pixel intensity between the subsequent frames, the value of γ could be made dependent on the previous frames. In this scenario, the value of γ would be:

$$\gamma = w_{B0} \text{ x } 0.5 + w_{B1} \text{ x } \gamma_{F-1} + w_{B2} \text{ x } \gamma_{F-2} + \ldots + w_{BP} \text{ x } \gamma_{F-P} \quad \ldots\ldots(7)$$

where, the subscript (γ) in the weighting factors indicate the weighting factor for blue color. Notably, the summation of all weighting factors (i.e., all *w*'s) would be equal to one. Further, unlike for Rs and Gs, the initial ratio value for b's is dependent on the battery life. This is because, the blue color takes up significant energy and hence, having the intensity value dependent on the battery life time.

III.2 Region-of-Interest based Adaptive Variation in Screen Brightness

A variation in the screen brightness changes the amount of energy consumption significantly, which in turn would affect the overall perceived video quality. In this regard, this involves having a RoI-based video adaptation in the device, wherein certain highly interesting regions of the video frame are displayed with the best video quality whereas other less-interesting regions are provided at a reduced video quality. Fig. 5 illustrates the mechanism. In this case, it is assumed that the viewer's area of most interest is in the centre of the video frame and hence, the highest quality video is shown at the centre of the device screen. Further, as the distance from the centre of the screen is increased, an ideal scenario would be to gradually decrease the video quality using a normal distribution, as shown in Fig. 5b. This is done by changing several parameters in both the device and in the video/multimedia content transmitted to the device. In order to realistically achieve a gradual degradation in the video quality, multiple-RoIs are considered for the device screen and multimedia frame, as shown in Fig. 5a. The multiple RoIs approach has as main advantage the fact that each RoI can be considered independently. This enables treating and adjusting different parameters (brightness, backlight/color, etc.) across each region independently. Notably, multiple RoI control provides support for smoother video quality adjustments that would be almost imperceptible to the user. There are two major aspects in the design of adaptive RoI mechanism. Setting the RoIs and setting the parameters to adjust across the RoIs. Both these aspects play a major role in determining the real-time energy consumption of device.

III.2.a Setting RoIs: Typically, the video played in RoI screen areas is at higher quality than that played in non-RoI zones. This result in the video played in RoI areas consuming higher energy as compared to that played in non-RoI zones. An adaptive RoI mechanism considers multiple RoIs with different quality levels. Consequently they will have different energy readings. The overall energy consumed by mobile device employing DEAR can be adjusted by varying two major parameters: the number of RoIs (N) and the area (A_x) of each RoI x of the N RoIs.

Parameters to Adjust across Different RoIs Several parameters related to both the video content and device screen affect the energy consumption of the device. They include:

i. Data rate of the video/multimedia content (R)
ii. Brightness/gamma of the screen (G)
iii. The backlight intensity of the device screen (B)
iv. The color displayed in the screen (C)
v. Frame rate of the video/multimedia content (F)

The energy consumed in the device can be altered by adjusting the values of one or more of these parameters. It should be noted that this multiple RoI mechanism has been investigated in the beginning of this research work and was called as DEAR (device-centric adaptive region-of-interest) [1]. DEAR considers multiple RoIs and the adaptation requires that each RoI be considered and controlled independently in terms of data rate, brightness, color, backlight, etc. As changing some of these parameters for areas within a frame, particularly frame rate and the color of the video content is either extremely challenging or very complex, this research work adjusted only the first three variables (R, G, B) per RoI in real-time.

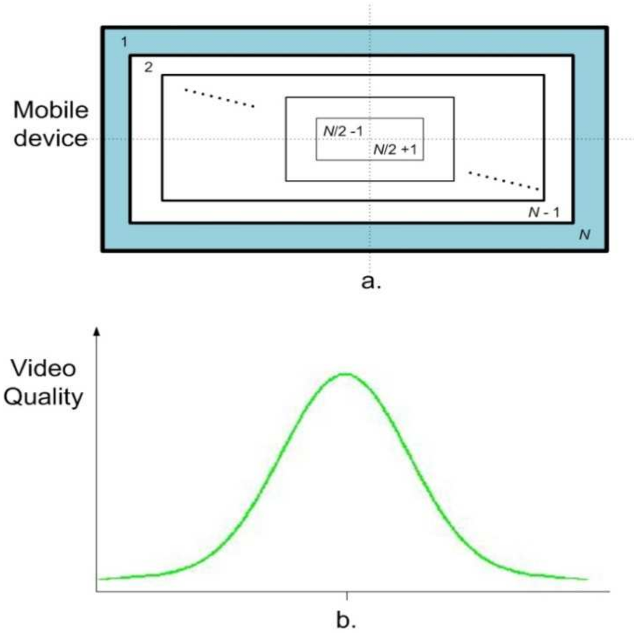


Fig. 5 Region of Interest (RoI) Adaptation in Screen
(5a) A *N*-step RoI in the Mobile Screen (5b) Variation in Video Quality from the Centre of Screen

The principle of adaptive RoI mechanism can be understood from the detailed flowchart shown in Fig. 6. The initial values of parameters are first set. Subsequently, the video quality is measured and ensured to be above the fair value (3.0 as per ITU-T P.913 standard [20], referring to user subjective quality), Further, a two-step approach is adopted. In the first step, the actual video quality is measured; while in the second step, the energy consumption in each RoI is varied. To begin with, only one RoI is considered and different parameters associated with this RoI are varied. Depending on the situation, the following is carried out:

i. If the energy consumption of the screen is very high (above a threshold) relative to the current device battery level, then the number of RoIs is changed (increased or decreased). The parameters associated with the RoIs are modified to reduce energy consumption and the energy consumption is then measured again. This process is repeated iteratively.

ii. If the energy consumption of the screen is low (below a threshold) relative to the current device battery level, the values of the different parameters are such varied to increase the quality of RoIs in the order **o**f increasing their distance to the centre of the video frame. If two RoIs have the same values for the parameters, they will be merged and the number of RoIs decreases.

III.2.b Energy Consumption Analysis: For technique with N RoIs (shown in Fig. 5a), energy consumption of each RoI x is Es_x where x € {1, N}. If As_x is the area of RoI x, the total energy consumption relative to entire screen size (divided in RoIs) is:

$$E = \sum_{x=1}^{N} Es_x\, As_x \qquad (8)$$

Further, the energy consumption for each RoI (Es_x) is a function of the above mentioned different variables. This could be written as in equation (9) or as in equation (10) when considering the parameters most feasible to be adjusted only:

$$Es_x = f(Rs_x, Gs_x, Bs_x, Gs_x, Cs_{x,}, , Fs_{x,}) \quad (9)$$

$$Es_x = f(Rs_x, Gs_x, Bs_x) \qquad (10)$$

In equations (9) and (10), Rs_x, Gs_x, Bs_x Cs_x and Fs_x represent the video bit rate, brightness, backlight intensity, display color and video frame rate associated with a particular RoI x. In case of non-RoI zones, the energy consumption is the same across the whole area and can be written as in (11) or (12) if only the selected parameters are considered.

$$Es = f(Rs, Gs, Bs, Cs, Fs) \qquad (11)$$

$$Es = f(Rs, Gs, Bs) \qquad (12)$$

In equations (11) and (12), Rs, Gs, Bs, Cs and Fs represent video bit rate, brightness, backlight intensity, display color and video frame rate associated with non-RoI. If the non-RoI adaptive approach is considered, the energy consumption across the entire non-RoI video frame could be written as: $E_{non\text{-}RoI} = N\, Es$

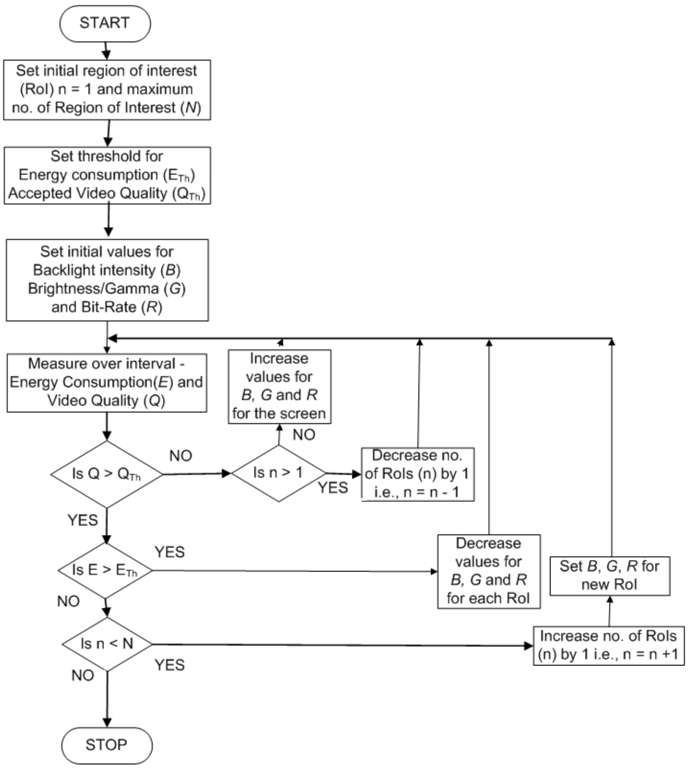


Fig. 6 Overview of Adaptive RoI Mechanism

It should be noted that a change in any variable results in a change in the energy consumption of the device screen (in fact, of the area of the screen affected). Hence, considering the energy consumption modification due to each variable change to be independent, the difference in the energy consumption in the screen due to RoI as compared to a non-RoI approach could be written as:

$$\Delta E = \Delta E_R + \Delta E_G + \Delta E_B \qquad (13)$$

In order to investigate the potential amount of energy savings due to RoI, the different parameters that affect the design are considered separately. Further, varying each parameter individually, the effect on the energy consumption is studied along with the effect on the overall video quality. In the next section, non-RoI and multiple RoIs approaches are considered with changes in only one parameter and the difference in the energy consumption is then measured.

III.3 <u>Content-based Adjustment in CPU</u>

The proposed step in the algorithm performs an adaptive frame-dropping mechanism as follows. In order to decrease the CPU usage, a dynamic frame dropping is carried out. In this context, it is the amount of changes in successive frames that determine the information quotient between the frames, i.e., it is only the temporal mobility of the frames determines the frame dependency for IPB video sequences.

Further, the CPU energy adjustment algorithm is based on frame dropping in inverse order of their importance to the overall video quality. If the temporal mobility is less, then more frames are dropped while if the temporal mobility is high, then the frequency with which the frames are dropped is low. Since the content-based adjustment in CPU is based on dynamic frame dropping, the entire set of frame (I, P and B frames) are not considered as a single entity. Also, given the high importance of 'I'-frames, they are never dropped.

Further, the rate of frame dropping depends on two factors:

a. The block (s) that the set of frame (F) is classified onto.
b. The current energy level in the device.

A 5-stage approach is considered for the dropping of frames.

Stage 0: No dropping of I, P, B frames
Stage 1: b_1% of B frames dropped, p_1%P frames dropped
Stage 2: b_2% of B frames dropped, p_2% P frames dropped
Stage 3: b_3% of B frames dropped, p_3% P frames dropped
Stage 4: b_4% of B frames dropped, p_4% P frames dropped
Stage 5: b_5% of B frames dropped, p_5% P frames dropped

where $b_5 > b_4 > b_3 > b_2 > b_1$ and $p_5 > p_4 > p_3 > p_2 > p_1$

The exact values of b_1, b_2, b_3, b_4 and b_5 and also p_1, p_2, p_3, p_4 and p_5 depends on the block(s) that the frame is assigned to; and the current energy level in the device.

4. Experimental Setup and Results

The goal of the experimental tests is to adjust the video display at the mobile device using the adaptive algorithm. However, in order to assess both the energy consumption and the video quality, the incoming video frame is categorized among 25 possible sequences (M = 5 and N = 5). Notably, for each experiment, the average video quality is observed using a subjective method. This is done in order to ensure that in the process of optimizing the energy consumption in the device, the video quality is maintained at an acceptable level.

IV.1 Experimental Set-up: The experimental set-up employed is shown in Fig. 7. The device used is Samsung Galaxy GT-I5500 mobile phone, (Android 2.3, 2.8 inch LCD touch screen with 320 x 240 pixels, battery capacity of 1200mAh). The reason for selecting a low-end smart-phone is because, it is expected that all smart-phone users will have this or a better smart-phone. Also, the researchers in this group had in the past, carried out energy-consumption analysis of several Android devices, including HTC Nexus One. Further, as opposed to other smart-phones, Samsung

GTI5500 had the advantage of a user replaceable battery. Access to battery contacts gave the researchers the ability to measure the device power consumption using hardware equipment, thus having more accurate results than using locally installed software.

The energy consumption of the device is measured using Arduino – an open source micro-controller board [11]. The Arduino board can receive multiple types of input signals and can be connected between the device and device battery. Arduino board supports USB connections and hence all measurements are logged onto a laptop via USB. The Arduino board measures the energy consumed while playing a video only. Hence, in order to calculate the energy saved due to the use of the proposed RoI-based algorithm, the energy consumption is first measured for the idle state/flight mode. Once the baseline consumption of device is known (Ebase) and the energy consumption of device during the video playing is measured (Eplay), the energy cost of video playing can be calculated as Eplay – Ebase. The set-up for carrying out the energy measurements is based on a similar set-up for measuring the energy of different components in the device, as explained in [12, 13]. There are two different video clips considered in the experimental set-up. The first video clip video1 is a 15-second trailer of the movie Toy-Story taken from a 120 second full trailer that is encoded using MPEG4 at 301 kbps. The second video clip video2 is an 18-second trailer of the movie Harry Potter which is also encoded using MPEG-4 at a rate of 180 kbps. It should be noted that Toy-Story has a lower contrast ratio, higher brightness, higher gamma level and higher data rate as compared to Harry Potter. The reason for selecting the second video is to test the difference in the energy consumption, especially if and when the energy savings is considerably higher for variation in RoI-based design. Further, the authors have followed the most recent standard released in the video quality assessment space ITU-T P.913 [20] which recommends relatively short duration of video stimuli "that range from 5 to 20 second in duration" in order to allow "viewers to take into account all of the quality variations and score properly". Given that each video had 30 frames/sec, the number of frames to be analysed were 450 frames for Toy-Story and 540 frames for Harry-Porter. This approach has been followed in accordance with the experimental set-up modelled and was used in other top level works [21, 22]. Further, before going into the results, it should be noted that previous works [23, 24] have clearly indicated that assuming a continuous video playback, it is not only the video size, but also the nature of the video content that determine the energy consumption in a device. Also, the authors' previous work on energy consumption [25] has shown that the display screen consumes the highest percentage of energy among all device components. Given that this work focuses on the display screen which varies widely across devices, the very interesting, but highly time-consuming study of energy consumption with various videos and diverse devices is left for future investigation.

To begin with, the tests measure the energy consumed in the device for different videos and for different scenarios. For each scenario, the average video quality is determined by a subjective analysis on a scale of 1-5 (mean opinion score, standardized by ITU-T) that provides a scale for perceived video quality from user's perspective [20].

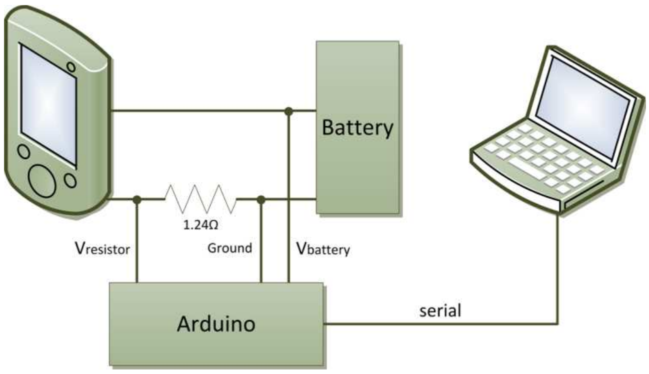


Fig. 7 Schematic Representations for Measuring Energy Consumption in Mobile Device

IV.2 Results:

Different experiments were conducted and results measured for different scenarios which are explained below.

<u>Scenario 1 - Adjusting RGB Pixel Intensity for a general RGB color frame</u>

A video frame with a pixel intensity of Rs = 255, Gs = 125 and Bs = 100 is considered. The testing conditions for this scenario are as follows:

i. A battery life of 100%, i.e., $b = 1$.

ii. The initial value set for the color factors are: $\alpha = \beta = \gamma = 0.5$.

iii. Since only one frame is considered, the RGB color intensity for this frame is not dependent on the previous frames.

iv. A brightness level of 45% was considered throughout the tests.

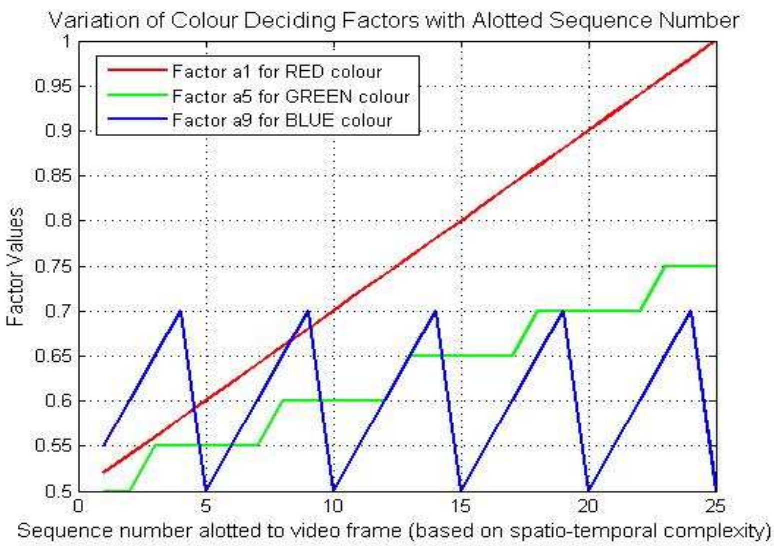


Fig. 8 Variation in the Factors (a1, a5 and a9) Deciding displayed RGB Values

The original video frame looked as follows. Further, referring to Fig. 8, the average energy consumed for displaying this frame color was 498 mW.

Fig. 9 SNAPSHOT - Original Frame (R = 255, G = 125, B = 100)

Applying the proposed algorithm, the factors (a1, a5, a9) that decide the pixel intensity of the displayed RGB colors will vary according to the video sequence to which the particular frame is allocated. Fig. 10 shows the variation in the factors with the video sequence number. It can be observed from Fig. 8, that as the sequence number is increased (i.e., with an increase in the spatial and temporal complexity), the factor for the red color increases to 1, while for the green and blue color varies; depending on whether there has been an increase in the spatial or temporal complexity. This is further corroborated in Fig. 10 which shows the new varying RGB values for different frame sequences using the proposed algorithm. The exact values of the pixel intensity for R, G and B colors over different frame sequence numbers is shown in Table II. Referring to Fig. 10, the average energy consumed when the video frame is considered to be in the first sequence (s = 1) is around 473mW; and this energy consumption increases with increasing sequence number. Notably, the average energy consumed when the particular frame was considered to be highly varying in terms of both spatial and temporal mobility and hence, given the best considered display quality. In this case, the average energy consumed was around 487mW, 11mw less than the energy consumed during non-energy save mode. Fig. 11 shows how the original video frame shown in Fig. 9 would look like, when the original frame is considered to be under different video sequence blocks.

Seq No	**Rd**	**Gd**	**Bd**	**Seq No**	**Rd**	**Gd**	**Bd**
1	133	63	55	**13**	194	81	65
2	138	63	60	**14**	199	81	70
3	143	69	65	**15**	204	81	50
4	148	69	70	**16**	209	81	55

5	153	69	50	**17**	214	81	60
6	158	69	55	**18**	219	88	65
7	163	69	60	**19**	224	88	70
8	168	75	65	**20**	230	88	50
9	173	75	70	**21**	235	88	55
10	179	75	50	**22**	240	88	60
11	184	75	55	**23**	245	94	65
12	189	75	60	**24**	250	94	70
				25	255	94	50

Table II Variation in R, G and B Values with Variation in Frame Sequence Allotment

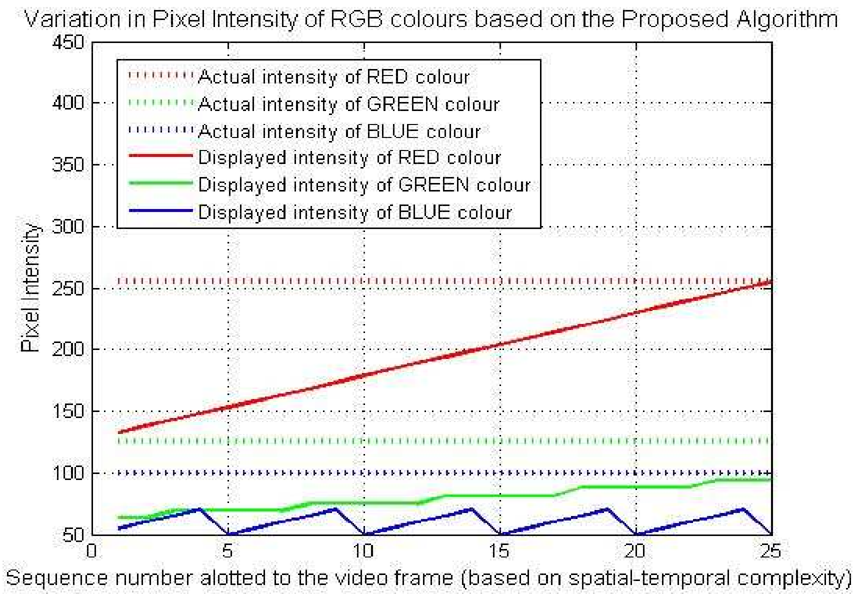


Fig. 10 Variation in Displayed RGB Colors according to Proposed Algorithm

	*Rd* = 153 *Gd* = 69 *Bd* = 50 (s = 5)
	*Rd* = 148 *Gd* = 69 *Bd* = 70 (s = 4)
	*Rd* = 143 *Gd* = 69 *Bd* = 55 (s = 3)

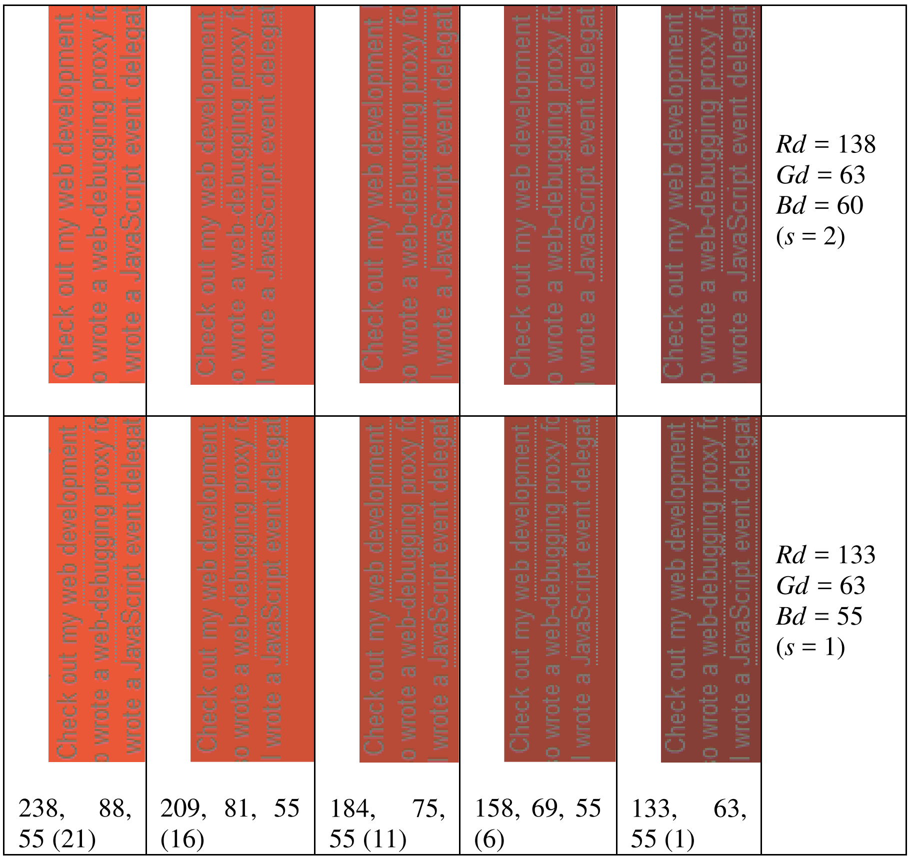


Fig. 11 SNAPSHOT - Variation in RGB Color Intensity and Resulting Displayed Frame

<u>Scenario 2 – Adjusting RGB Pixel Intensity for almost a BLUE color frame for different battery life</u>

A video frame with a pixel intensity of Rs = 50, Gs = 220 and Bs = 250 is considered. The initial value set for the color factors are: $\alpha = \beta = \gamma = 0.5$. Further, since only one frame is considered, the RGB color intensity for this frame is not dependent on the previous frames. Also, a brightness level of 45% was considered throughout the tests. The original video frame looked as shown in Fig. 12. Further, referring to Fig. 8, the average energy consumed for displaying this frame color was around 504mW.

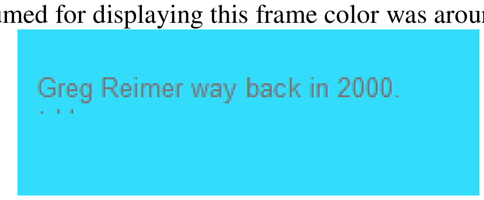


Fig. 12 SNAPSHOT - Original Frame (R = 50, G = 220, B = 250)

Two testing conditions are considered within this scenario:

i. A battery life of 100%, i.e., $b = 1$.

ii. A battery life of 50%, i.e., $b = 0.5$

i. Battery life of 100% (b = 1)

Fig. 13 shows the actual RGB pixel intensity along with the variation in the RGB pixel intensity when the video frame is allotted different sequence numbers. It can be observed that with increasing spatial-temporal complexity, the pixel value of RED color is increased consistently; and that of GREEN color is increased in steps, with increasing temporal complexity. Notably, in case of BLUE color, the pixel intensity is increased only when the spatial complexity is increased and then bought down to the original level when the spatial complexity of the frame is lowered. This is mainly done; in order to reduce the energy consumption during the display of the BLUE color.

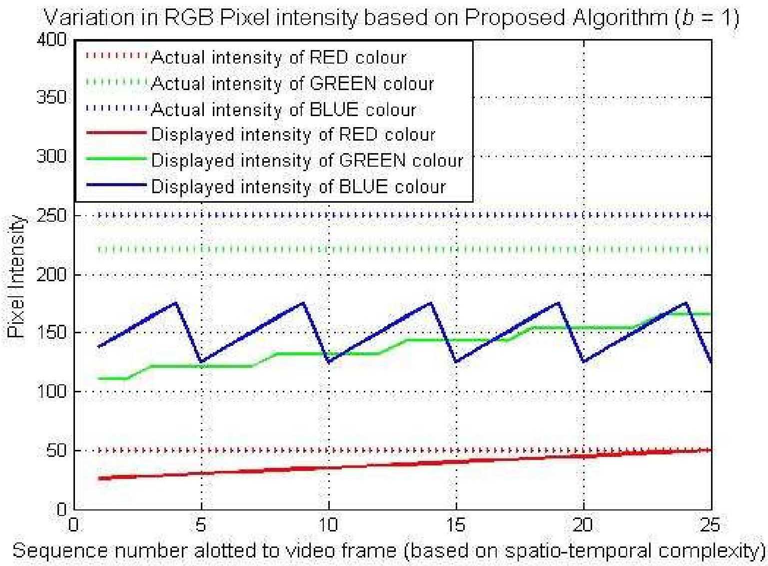


Fig. 13 Variation in Displayed RGB Colors as per Proposed Algorithm (b = 1)

s = 1	s = 13	s = 25
(R=26, G=110, B=138)	(R=38, G=143, B=163)	(R=50, G=165, B=125)
483mW	487mW	484mw

Fig. 14 SNAPSHOT - Displayed Frame with Varying Sequence Number and RGB Intensity (b = 1); along with Average Power Consumption

ii. Battery life of 50% (b = 0.5)

Fig. 15 shows the actual RGB pixel intensity along with the variation in the RGB pixel intensity when the remaining battery life in the device is 50%. Comparing the results in Fig. 13 and Fig. 15, it can be observed that the pixel intensity of BLUE color is reduced significantly, with a decrease in the remaining battery power. Further, by comparing Fig. 10 and Fig. 12, it can be observed that the change in the BLUE color alters the color of the displayed video frame marginally, while significantly reducing the overall energy consumption.

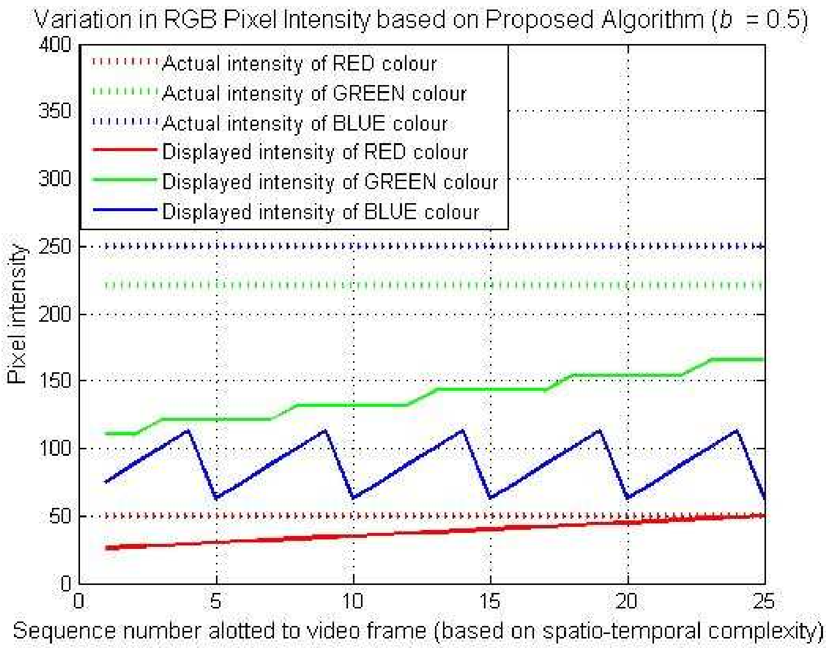
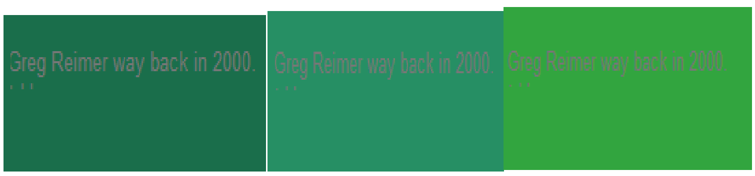


Fig. 15 SNAPSHOT - Displayed Frame with Varying Sequence Number and RGB Intensity (*b* = 0.5)



s = 1	*s* = 13	*s* = 25
(R=26, G=110, B=75)	(R=38, G=143, B=100)	(R=50, G=165, B=63)
476mW	478mW	481mW

Fig. 16 Displayed Color Frame with Varying Sequence Number and RGB Color Intensity (*b* = 0.5) and Average Power Consumption

Scenario 3 – Tests with Device Adaptation

The next scenario involves conducting device tests with different device adaptation and subsequently measuring the energy consumption and video quality.

1. Varying Data-Rates: This test is performed with 90% device brightness. A multiple concurrent RoI area is considered with different data rates across different RoIs. The RoIs are assumed to be concentric at the centre of the screen. Given the screen size of hand-held device (320x180 pixels), two different situations are considered. The first situation sees a RoI bounded by a rectangle of size 160x90 pixels, whereas in the second case, the RoIs are bounded by a square of 90x90 pixels area. Further, two different data rates are considered for the out-of-RoI area of the screen. The first data rate considered is 128 kbps while the second data rate considered is 64 kbps.

Sr. No.	No. of RoIs	Data Rate (Kbps)	Energy (mW)	Quality (1-5)
1.1	No RoI (Full screen)	180	251.88	4.93
1.2		128	243.76	4.35
1.3		64	241.03	3.02
2.1	1 RoI (Pixel Area: 160x90)	RoI: 180 Non-RoI: 128	245.97	3.93
2.2			241.97	3.70
3.1	1 RoI (Pixel Area: 90x90)	RoI: 180 Non-RoI: 128	246.13	3.65
3.2			241.36	3.50

Table III Variation in Energy Consumption and Average Video Quality for Different Data Rates

Table III shows the results of the energy consumption and the subjective video quality, across both a complete frame and a frame having both RoI and non-RoI areas. As the data rate is decreased, the overall quality also decreases (e.g. scenario 1.1 and 1.3). Importantly, this pattern remains consistent even when there are different data rates across different RoIs in the frame. Notably, if one compares a non-RoI frame with 64 kbps (scenario 1.3) with two frames containing two different RoIs patterns (128 kbps across non-RoI area, scenario 3.1), it can be observed that a reduction in data rate across non-RoI area gives the same energy consumption, while the quality of the video is slightly improved (3.5 instead of 3.02). Notably, only up to 4% savings in energy consumption could be obtained while still retaining quality above 3.0.

Sr. No.	No. of RoIs	Brightness@ RoI & non-RoI	Energy Consumed (mW)	Video Quality
1.1	No RoI	100% brightnes	266.15	4.15
1.2	No RoI	80% brightness	258.93	3.71
1.3	No RoI	60% brightness	253.93	3.32
1.4	No RoI	40% brightness	248.53	2.71
2.1	1 RoI	RoI: 100%	256.79	3.82

		Non RoI: 80%		
2.2	1 RoI	RoI: 100% Non RoI: 60%	253.03	3.42
3.1	4 RoIs	RoI:(100,75,50,25)% Non RoI: 1%	241.34	4.11
4.1	9-RoIs	RoI: (100,90,.., 20)% Non-RoI: 10%	249.76	4.04
5.1	19-RoIs	RoI:(100,95,....,10)% Non-RoI: 5%	243.43	3.96

Table IV Variation in Energy Consumption and Average Video with Different RoI

The brightness/gamma decreases from 100% for RoI at the centre of the screen to low levels at RoIs further from the centre, with a minimum value of screen brightness at the screen edge. Table IV shows the effect of this reduction on the energy consumption and resulting video quality levels when DEAR with multiple RoIs and different brightness/gamma levels is employed; in comparison with non-RoI adjustment of the brightness across whole screen area. A non-RoI video with 100% brightness across entire screen has a very high video quality (4.15) and consumes 266.15 mW. On the other hand, a non-RoI video with 40% of maximum brightness value reduces energy consumption by roughly 7% (248.53 mW) only, while it decreases the video quality drastically by more than 33%. Hence, reducing brightness across the whole screen is not a good option. Hitherto, a RoI-based reduction in brightness/gamma results in significant decrease in energy consumption, while maintaining good video quality. For example, having 19 RoIs with decreasing brightness levels (100 to 10 in steps of 5%) for different RoIs and even lower brightness (5%) for non-RoI area results in energy consumption of 243.43 mW (9% decrease in energy consumption as compared to non-RoI approach with 100% brightness), and the video quality reduces by less than 4%. This shows that device energy consumption could be reduced by employing device based adaptation with negligible effect on quality.

Scenario 3 – Tests with Varying Backlight

In order to investigate the potential benefit of varying backlight across different regions, the energy consumption of the device was measured for different backlight intensities. In order to measure the effect of different backlight levels on the energy consumption of the device and the overall video quality, a linear reduction in the device backlight is considered in the tests. The backlight is reduced from 100% to 25%. Table 3 shows the energy consumption and average subjective video quality when the brightness of the device is varied from 100% to 25%. It can be observed from Table 3 that in case of video1, decreasing the backlight to 50% reduces the energy consumption by 30% while decreasing the backlight to 25% reduces the energy consumption by 36%. The video quality reduces by only 1.6% and 9.4% respectively. This represents a significantly high energy savings as compared to varying the data-rate and the brightness levels in the device screen. In order to verify the large energy savings obtained by varying the backlight in the case of video1, video2 with darker background was used. The tests for video2 showed that decreasing the backlight to 50% and 25% reduces the energy consumption by 29.6% and 35.4% while reducing the video quality by 14.5% and 21.3% respectively. Given that video2 was already a 'dark' video, the reduction in energy consumption also resulted in important decrease in the video quality. Further, if the results of two videos are extrapolated till the video quality drops to an average of 3.0, then for these two videos, an energy saving of up to 40% could be obtained by employing DEAR focusing only on screen backlight adaptation.

Overall Energy Savings: The three test results indicate that having multiple adaptive RoI-based mechanism with variation in screen color, backlight and intensity; and adaptive region-of-interest mechanisms could result in significant energy savings. Notably, the tests indicate that a combined adaptive mechanism could result in more than 53% energy savings.

Device Backlight	**Energy Consumption(mW)**		**Video Quality(1–5)**	
	Video 1	**Video 2**	**Video 1**	**Video 2**
100%	260.89	265.75	4.76	4.66
75%	214.75	220.37	4.76	4.33
50%	182.32	187.01	4.68	3.98
25%	166.07	171.04	4.31	3.62

Table V Variation in Energy Consumption and Average Video Quality with Variation in Device Backlight

5 Conclusion

This paper proposed a multi-level real-time process for adaptively optimizing the energy consumption in a mobile device/smart-phone. This process is based on the spatial and temporal nature of the video content and has three different kinds of adaptation – changing screen colour, backlight and intensity; and adaptively varying the number of region of interest (RoI) in the device. The paper begins with a detailed investigation on the energy consumption pattern of the devices across different colours. Subsequently, the paper provides a detailed analysis of how the screen colour and intensity could be varied based on the video content. Notably, it also provides snapshots on how the visualization of the screen changes for different values of screen colour and intensity. Particularly, the paper also highlights the importance of the RoI and how multiple RoI mechanisms in a screen with gradual change in the parameters (bit rate, intensity, backlight, etc) provides considerable reduction (more than 50%) in the energy consumption, while only resulting in a gradual degradation in the video quality, but still maintaining acceptable video quality levels. Notably, the mechanism proposed in this paper provides the device manufacturers to dynamically alter the energy optimization by choosing fewer than all three mechanisms for real-time adaptation. Finally, it should be noted that this work opens up a direction wherein one could effectively use the nature of the video content to adaptively provide different functionalities to the user in his/her device.

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