Abstract

A power compelled contrast-improvement algorithm for emissive showcases in light of histogram evening out (HE) is proposed in this paper. We first propose a log-based histogram change plan to decrease overstretching antiques of the customary HE method. At that point, we build up a power utilization model for emissive shows and plan a target capacity that comprises of the histogram-evening out term and the power term. By minimizing the target capacity in light of the raised advancement hypothesis, the proposed algorithm accomplishes contrast upgrade and power sparing all the while. Additionally, we extend the proposed algorithm to upgrade video arrangements, and also still pictures. Simulation results show that the proposed algorithm can decrease power utilization essentially while enhancing picture contrast and perceptual quality.

Keywords: Contrast enhancement, emissive displays, histogram equalization (HE), histogram modification (HM), image enhancement, low-power image processing.

I. Introduction

THE RAPID advancement of imaging technology has made it less demanding to take and process computerized photos. Be that as it may, we regularly obtain low-quality photos since lighting conditions and imaging frameworks are not perfect. Much exertion has been made to upgrade pictures by enhancing a few variables, for example, sharpness, clamor level, shading precision, and difference. Among them, high complexity is an imperative quality component for giving better experience of picture discernment to viewers. Different difference improvement strategies have been produced. For instance, histogram evening out (HE) is broadly used to upgrade low-differentiate pictures. While an assortment of difference upgrade methods have been proposed to enhance the characteristics of general pictures, moderately little exertion has been made to adjust the improvement procedure to the qualities of showcase gadgets. Notice that, notwithstanding contrast improvement, power sparing is likewise an imperative issue in different interactive media gadgets, for example, cell telephones and TVs. An expansive part of power is devoted by showcase boards in these gadgets and this pattern is relied upon to proceed as presentation sizes are getting bigger. In this way, it is vital to build up a picture preparing algorithm, which is equipped for sparing power in presentation boards, and also improving picture contrast. Computerized picture handling assumes a crucial part in the examination and translation of remotely detected information. Particularly information acquired from Satellite Remote Sensing, which is in the advanced structure, can best be used with the assistance of computerized picture handling.

II. Video Communication

2.1.1 Digital video

Advanced video will be video data spoke to in computerized structure. Computerized representation has various key preferences over "customary" simple video and TV. All data can be spoken to in advanced structure thus the same methods and frameworks can be utilized to store, prepare and transmit an extensive variety of various sorts of information (different media or "mixed media"). The quick development in computerized preparing power implies that unpredictable handling and coding operations can be completed on advanced video information progressively and that video can be incorporated into PC applications and frameworks. This thus makes it conceivable to make intuitive applications, where the client is no more a "uninvolved" eyewitness however has the chance to connect with the video data.

Progresses in information organizing innovation have coordinated advances in registering and preparing abilities. In a short space of time, the quantity of PCs and frameworks associated by systems, for example, the Internet has become exponentially. And in addition turning out to be more boundless, systems can deal with higher volumes of information and
higher transmission rates. The current systems administration structure is approximately characterized and "heterogeneous" (comprising of a scope of interconnected systems with various advancements and capacities).

Computerized video has a characteristically high data transfer capacity, i.e. a digitized video signal requires a high information rate for transmission, which implies that so as to store and transmit this data successfully it has been important to create methods for compacting the video information (i.e. encoding it into a littler number of bits). Universal Standards for encoding video information have empowered an extensive variety of uses that make utilization of computerized video transmission and capacity. Picture coding gives a method for packing digitized photographic pictures by around 10 to 20 times though strategies for coding movement video empower video information to be compacted by somewhere around 20 and more than 50 times. By utilizing these procedures it has gotten to be functional to store, transmit and control advanced picture and video data utilizing as of now accessible stockpiling frameworks and information systems.

2.1.2 Video coding for reliable communications

In the event that coded computerized video is transmitted through an interchanges arrange then the system will give a Quality of Service (QoS) to the coded information. QoS covers various distinctive properties which influence the path in which information is transmitted through the system including mistake and misfortune likelihood, delay, delay variety and transmission transfer speed. Diverse sorts of system can bolster distinctive levels or classes of QoS. Varieties in QoS have noteworthy ramifications for the transmission of coded video information. Coded video has especially requesting QoS prerequisites: it has a generally high information rate (regularly inexact portrayed as "data transfer capacity"), it can be extremely delicate to postpone and defer variety and the visual nature of decoded video can be seriously influenced by even a moderately low mistake likelihood.

In numerous down to earth applications there is a crevice between the QoS required to bolster excellent, continuous computerized video transmission and the QoS that can be given by the system. There is a need to create methods and frameworks which endeavor to extension this hole, i.e. which empower coded video to be transmitted crosswise over down to earth systems whilst keeping up a worthy visual quality for the viewer. The point of the work portrayed in this theory is to deliver this need and to bolster dependable video correspondences. By creating strategies to enhance the dependability of advanced video interchanges over down to earth systems, it might be conceivable to enlarge the scope of utilizations and conditions in which computerized video can be utilized.

2.1.3 Addressing the problem

The initial move towards tending to this issue is to recognize QoS parameters that are liable to effectively affect coded video. To do this it is important to:

- analyze the principles and strategies which are utilized as a part of functional frameworks for coding video
- take a gander at the transmission prerequisites for video that has been coded utilizing these principles (i.e. the QoS which the application "requests" from the system, for example, transfer speed, delay, mistake probabilities, and so on.)
- look at this "interest" for QoS with the QoS that reasonable systems can bolster.

The impact of transmission debilitations or confinements (i.e. constrained accessible QoS) on coded video, and specifically on the visual nature of decoded video, is explored here. Taking into account these examinations, methods are recommended that mean to enhance the visual nature of decoded video within the sight of constrained QoS.

Advanced video correspondence can be discovered today in numerous application situations, for example, show, membership, and pay-per-view administrations over satellite, link, and physical transmission stations, wire-line and remote continuous conversational administrations, web or neighborhood video gushing (utilizing Real-Time Protocol/Internet Protocol ) and Storage positions (e.g., computerized adaptable plate), computerized camcorders, and individual video recorders). The essential correspondence issue might be acted like passing on source information with the most astounding constancy conceivable inside an accessible piece rate, or it might be acted like passing on the source information utilizing the least piece rate conceivable while keeping up indicated proliferation loyalty. In either case, a major exchange off is made between bit rate and loyalty. The capacity of a source coding framework to make this exchange off well is called its coding productivity or rate-contortion execution, and the coding framework itself is alluded
to as a codec (i.e., a framework including a coder and a decoder).

Up to this point, most video gear was composed essentially for simple video. The normal purchaser now has entry to advanced video because of keeping falling expenses. This pattern has prompted the improvement of DVD players, computerized set-top boxes, advanced TV, and the capacity to utilize the Internet for exchanging video information. At first, video contained just simple dim scale (likewise called high contrast) data. While shading shows were being created, endeavors were made to transmit shading video utilizing simple RGB (red, green, blue) information. Nonetheless, this procedure possessed 3 times more transfer speed than the present dim scale arrangement, so substitute strategies were produced that prompted utilizing YIQ or YUV information to speak to shading data.

III. Digital video processing

3.1 Fundamentals of Video Processing

Video is actually a series of still images, changing fast enough that it looks like continuous motion. A scene is sampled at a point in time to produce a frame (a representation of the complete visual scene at that point in time) or a field (consisting of odd- or even-numbered lines of spatial samples). Sampling is repeated at intervals (e.g. 1/25 or 1/30 second intervals) to produce a moving video signal. Three sets of samples (components) are typically required to represent a scene in colour. Popular formats for representing video in digital form include the ITU-R 601 standard and the set of ‘intermediate formats’.

3.1.1 Motion Estimation and Motion Compensation

Motion compensation (MC) is very useful in video filtering to remove noise and enhance signal. It is also employed in all distribution-quality video coding formats. It is useful since it allows the filter or coder to process through the video on a path of near-maximum correlation based on following the motion trajectories across the frames making up the image sequence or video. Motion is usually characterized in terms of a motion or displacement vector, \( \mathbf{d} = (d_1, d_2)^T \) that must be estimated from the data. Several methods of motion estimation are commonly used:

- Block matching
- Hierarchical block matching
- Pel-recursive methods
- Optical flow methods

Optical flow is the apparent motion vector field \( (d_1, d_2) \) we get from setting, i.e., forcing, equality in the so-called constraint equation

\[
\mathbf{x}(n_1, n_2, n) = \mathbf{x}(n_1 - d_1, n_2 - d_2, n - 1).
\]

(3.1)

All four motion estimation methods start from this basic equation, which is just an idealization. Departures from the ideal are caused by covering and uncovering of objects in the viewed scene, lighting variation both in time and across the objects in the scene, movement toward or away from the camera, as well as rotation about an axis, i.e., spatially 3-D motion. Often this basic equation is only solved approximately in the least-squares sense. Also, the displacement is not expected to be an integer, often necessitating some type of interpolation to be used.

A basic problem with motion estimation is deciding the aperture or region over which we will estimate the motion, since we effectively assume that the motion is constant over this aperture. If the aperture is too large, then we will miss detailed motion and only get an average measure of the movement of objects in our scene. If the aperture is too small, the motion estimate may be poor to very wrong. In fact, the so-called aperture problem arises as illustrated in the square region shown in Figure 3.1. If the motion of the smooth dark region is parallel to its edge, then this motion cannot be detected. Since this situation would typically only hold for small regions in natural images, this aperture effect causes our choice of aperture size to avoid being too small. We are thus led to find a good aperture size for each problem.

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**Fig 3.1 Illustration of covering and uncovering of background by an object moving in the Foreground**

An illustration of the problem of covering and uncovering is given in Figure 3.1, which shows a depiction of two successive frames \( n \) and \( n - 1 \), over which we wish to determine motion. We assume a simple object translating in the foreground over a
fixed background, not an unreasonable local approximation of video frames. We see that part of the background region in frame \( n \) is uncovered, while part of the background region from frame \( n - 1 \) is covered. Motion estimation that simply tries to match regions in the two frames will not be able to find good matches in either the covered or uncovered regions. However, within the other background regions, matches should be near perfect, and matching should be good within a textured object, at least if it moves in a tractable way and the pixel samples are dense enough. However, if we consider small regions around the object edges, we can expect problems finding good matches there.

### 3.1.2 Block matching:

We intend to estimate a displacement vector at the location \((n, \text{n)}\). In the block matching (RM) method, we match a block centred on this point to blocks in a specified search area in the previous frame, as illustrated in Figure 3.2. Often the search area size is given as \((f \text{MI}, f \text{M2})\), and if centred on the current pixel location \((n, \text{n2})\) in the previous frame, then a total of \((2M1 + 1) \times (2M2 + 1)\) matches must be done in a so-called full search, and this must be done for each pixel where the motion is desired. Often the block matching is not conducted at every pixel and an interpolation method is used to estimate the motion in between these points. Common error criteria are mean-square error (MSE), mean-absolute difference (MAD), or even number of pixels in the block actually disagreeing for discrete-amplitude or digital data. We express the MSE in block matching as

\[
\mathcal{E}(d) = \sum_k \left( x(n + k, n) - x(n + k - d, n - 1) \right)^2
\]

(3.2)

For a block centred at position \((n, \text{n2})\) as a function of the vector displacement \(d = (d1, d2)^T\). We seek the displacement vector

\[
d_\text{o} = \arg \min_d \mathcal{E}(d)
\]

(3.3)

**IV. FLAT PANEL DISPLAYS**

**4.1 Introduction:**

Display technology plays a critical role in how information is conveyed. As words generally can't do a picture justice, show innovation disentangles data sharing. Since its Commercialization in 1922 up until the late twentieth century, Cathode Ray Tube innovation (CRT) has overwhelmed the presentation business. Be that as it may, new patterns, for example, the craving for versatile hardware have expanded interest for showcases that opponent and surpass CRTs in regions, for example, picture quality, size, and power utilization. One of the most recent gadgets prone to supplant CRTs is Liquid Crystal Displays (LCD) because of their lightweight, low working force, and reduced outline. LCDs permitted gadgets, for example, advanced watches, mobile phones, portable PCs, and any little screened hardware to be conceivable. In spite of the fact that LCDs were at first made for handheld and convenient gadgets, they have ventured into zones already consumed by CRTs, for example, PC screens and TVs. Different contenders for authority in showcase innovation are Natural Light Emitting Diodes (LED), Digital Light Processing (DLP) innovation, Plasma Displays, Field Emission Displays, and Electronic Paper. Natural LEDs, being made out of light radiating polymers, can emanate their own light to offer thin and power-sparing showcases. Utilizing numerous minuscule mirrors, DLP innovation can produce huge brilliant projections on screens with up to 35 trillion hues. Plasma Displays create superb quality pictures on expansive screens. Field Emission Displays can create high determination pictures like CRTs without the cumbersome appearance. Interest for higher quality showcases will drive innovation advancement; this development will require new methodologies and creative thoughts in data presentation.

The term level board shows alludes to a class of video gadgets that have decreased volume, weight, and power necessities contrasted with a Cathode-beam tubes (CRT). A huge element of level board showed is
that they are more slender than CRTs and we can hang them on dividers or wear them on our wrists.

4.2 Types of Flat Panel Displays

We can separate flat-panel displays into two categories: Emissive displays and Non emissive displays as shown in figure 4.1. Cathode-ray tubes, plasma display panels (PDPs), organic light-emitting diode (OLED), and field emissive displays (FED) are emissive displays that do not require external light sources, whereas the thin-film transistor liquid crystal display (TFT-LCD) is a non-emissive one.

4.2.1 Plasma Display Panels (PDP):

One technology that has been very successful for large-format displays is the Plasma Display Panel (PDP). This technology has the benefits of a Cathode Ray Tube (CRT), but can be built in a much thinner structure. Plasma Displays are typically filled with a gas such as neon, and driven in a row column passive-matrix manner. They require high voltages to ignite the plasma, and careful current limiting to prevent display heating. Since the actuation mechanism ionizes gas at each pixel, PDPs create radio frequency emissions, which must be carefully controlled. PDP technology is important for large area viewing, but due to the size limitation of the plasma channels, small high-resolution displays cannot be realized, so PDPs will not be significant for portable and handheld devices in the future. Manufacturing costs will decide which technology, LCD or PDP, will be the winner for the large format display market (e. g. TV sets).

4.2.2 Vacuum Fluorescence Displays (VFD):

VFDs are an established technology still widely used as low information content displays in audio-/video devices or household appliances. The VFD technology uses the fluorescence of phosphors under electron bombardment similar as in cathode ray tubes (CRT). However, the device structure is quite different from CRTs and resembles the classical triode. Electrons evaporate from the metal cathode, a filament with around 10 µm thickness. They are accelerated by a grid voltage around 50 V. VFDs can be easily identified by the honeycomb structure of that grid which is fabricated by etching a very thin steel foil. As soon as the electrons penetrate the anode at around 100 V, light is being emitted. VFDs are robust, reliable, with a high contrast ratio and long life span. One disadvantage is their large spatial dimensions compared to the active display area.

4.2.3 Field Emission Displays (FED):

In an effort to create a thin CRT display, several companies have been developing Field Emission Displays (FEDs). FEDs resemble thin CRTs, but without the heating element in the cathode; in addition, they are organized in a one cathode per pixel passive matrix organization. Like the Plasma Displays Panels, FEDs typically require a high voltage to operate, anywhere between 200 V and 6 kV. These displays can be very thin, but thus far the production costs of manufacturing facilities have kept them out of mainstream commercial products.

4.2.4 Electroluminescence Displays (ELD):

ELDs have a very simple device structure and can entirely be built employing solid state thin film technologies. Between two electrically directing chunks (e. g. glass with organized ITO stripes in network setup) with connected protecting layers a slim electroluminescent layer is stored. Doped zinc sulfate ZnS, or strontium sulfate SrS with a somewhat wide outflow range (“white”) are utilized as EL mixes. Ordinary shading channels produce RGB hues. With the EL layer being just around 100 µm thick, completely straightforward presentations, as for OLEDs, can be accomplished. Run of the mill driving voltages are picked around 200 V AC at up to 10 kHz which requires rather costly driver ICs. With an AM driving plan (AMEL) utilizing a transistor framework on a silicon substrate, high-determination smaller scale shows have been illustrated.

V. Histogram Equalization

Numerous complexity upgrade systems have been created. HE is a standout amongst the most broadly received ways to deal with improve low-differentiate pictures, which makes the histogram of light intensities of pixels inside a picture as uniform as could be allowed. It can expand the dynamic scope of a picture by determining a change work adaptively.
An assortment of HE methods have been proposed. Here, we first audit routine HE and HM methods and after that build up a LHM plan, on which the proposed PCCE calculation is based.

An advanced picture is a parallel representation of a two-dimensional picture. The advanced representation is a variety of picture components called pixels. Each of these pixels has a numerical worth which in monochromatic pictures speaks to a dark level.

**Figure 5.1 a) Digital image b) Binary Representation**

When all is said in done, a histogram is the estimation of the likelihood dispersion of a specific kind of information. A picture histogram is a sort of histogram which offers a graphical representation of the tonal dispersion of the dark qualities in a computerized picture. By survey the picture's histogram, we can dissect the recurrence of appearance of the changed dark levels contained in the picture. In Figure 2 we can see a picture and its histogram. The histogram demonstrates to us that the picture contains just a small amount of the aggregate scope of dim levels. For this situation there are 256 dim levels and the picture just has values between around 50–100. Consequently this picture has low difference.

**Figure 5.2 a) Digital image b) Image Histogram**

A good histogram is that which covers all the possible values in the gray scale used. This type of histogram suggests that the image has good contrast and that details in the image may be observed more easily.

5.1 Improving the contrast of an image through histogram equalization

The histogram equalization spreads out intensity values along the total range of values in order to achieve higher contrast. This method is especially useful when an image is represented by close contrast values, such as images in which both the background and foreground are bright at the same time, or else both are dark at the same time. For example, the result of applying histogram equalization to the image in.

**Figure 5.3 3.**

Figure 5.2 is presented in Figure 5.3 3.

**Figure 5.4 Flow chart to implement cumulative histogram equalization**

In HE, we first obtain the histogram of pixel intensities in an input image. We represent the histogram with a column vector, whose element denotes the number of pixels with intensity. Then, the probability mass function of intensity is calculated by...
dividing the total number of pixels in the image. The cumulative distribution function (CDF) of intensity is then given by $c_k$. Let $x_k$ denote the transformation function, which maps intensity in the input image to intensity in the output image. In HE, the transformation function is obtained by multiplying the CDF by the maximum intensity of the output image.

5.3 Histogram Modification

Many image processing operations result in changes to the image’s histogram. The class of histogram modifications which we consider here includes operations where the changes to pixel levels are computed so as to change the histogram in a particular way.

5.4 Histogram Stretching

The simplest form of histogram modification is histogram stretching. For example, if the image is under-exposed its values would only occupy the lower part of the dynamic range. The conventional HE algorithm has several drawbacks. First, when a histogram bin has a very large value, the transformation function gets an extreme slope. In other words, that the transformation function has sharp transition between past and present samples and when probability mass function is large. This can cause contrast overstretching, mood alteration, or contour artifacts in the output image. Second, particularly for dark images, HE transforms very low intensities to brighter intensities, which may boost noise components as well, degrading the resulting image quality. Third, the level of contrast enhancement cannot be controlled since the conventional HE is a fully automatic algorithm without any parameter. To overcome these drawbacks, many techniques have been proposed. One of those is HM. In general, HM is the technique that employs the histogram information in an input image to obtain the transformation function. Thus, HE can be regarded as a special case of HM. A recent approach to HM modifies the input histogram before the HE procedure to reduce extreme slopes in the transformation function, instead of the direct control of the output histogram. Here we clamped large histogram values and then modified the resulting histogram further using the power law. Further reduced the histogram values for large smooth areas, which often correspond to background regions, and mixed the resulting histogram with the uniform histogram. In this recent approach to HM, the first step can be expressed by a vector-converting operation, where denotes the modified histogram.

Then, the desired transformation function can be obtained by solving

$$Dx = m'.\text{ which is the same HE procedure as in (5), except that } m'\text{ is used instead of } h', \text{ where } m'\text{ is the normalized column vector of } m.$$ 

b) Logarithmic Histogram Modification

We develop an HM scheme using a logarithm function, which is monotonically increasing and can reduce large values effectively. In [20], Drago et al. demonstrated that a logarithm function can successfully reduce the dynamic ranges of high-dynamic-range images while preserving the details. We exploit this property and apply a logarithm function to our HM scheme, which is called LHM. We use the following logarithm function to convert the input histogram value $h_k$ to a modified histogram value $m_k$. where denotes the maximum element within the input histogram and is the parameter that controls the level of HM. As gets larger, in (10) becomes a smaller number. Therefore, a large makes almost linearly proportional to since for a small.

Thus, the histogram is less strongly modified. On the other hand, as gets smaller, becomes dominant and consequently, becomes a constant regardless of, making the modified histogram uniform. In this way, a smaller results in stronger HM. Fig. 1(a) illustrates how the proposed LHM scheme modifies an input histogram according to parameter, and Fig. 1(b) plots the corresponding transformation functions, which are obtained by solving (8). In this test, the “Door” image in Fig. 1(c) is used as the input image. We see that LHM reduces the large peak of the input histogram around the pixel value of 70 and thus relaxes the steep slope in the transformation function of the conventional HE algorithm. Fig. 1(d)–(g) compare the output images of the conventional HE algorithm and the proposed LHM scheme.

Because of the steep slope, the conventional HE overstretches the contrast of the background, but it maps the input-pixel range [100, 255] to the narrow output range of variation about 10 only, wiping out the details on the door knob. On the other hand, the proposed algorithm with yields less artifacts on the door knob while enhancing the details on the background region. It is also observed from Fig. 1(a) that LHM modifies the histogram more strongly as gets smaller. In the extreme case when $u=-\inf$, the modified histogram becomes uniformly distributed. In the other extreme case when $u=\inf$, the histogram is not modified at all. Therefore, by controlling the single parameter, LHM can obtain the transformation.
function, which varies between the identity function and the conventional HE result.

**PCCE**

Here, we propose the PCCE algorithm. Fig. 2 shows an overview of the proposed algorithm. We first gather the histogram information from an input image and apply the LHM scheme to obtain the modified histogram. Without power constraint, we can solve equation in (8) to get the transformation function. However, we design an objective function, which consists of power-constraint and contrast-enhancement terms. We then express the objective function in terms of variable. Based on the convex optimization theory [21], we find the optimal that minimizes the objective function. Finally, we construct the transformation function from and use to transform the input image to the output image.

A. Power Model for Emissive Displays

We model the power consumption in an emissive display panel that is required to display an image. In [22], Dong et al. presented a pixel-level power model for an OLED module. According to their experimental results, power to display a single-color pixel can be modeled by $P$, where, and are the red, green, and blue values of the pixel. Exponent is due to the gamma correction of the color values in the sRGB format. A typical is 2.2 [23]. In other words, after transforming the color values into luminous intensities in the linear RGB format, we obtain a linear relation between the power and the luminous intensities. Also, accounts for static power consumption, which is independent of pixel values, $w_r$ and, $w_g$, $w_b$ and are weighting coefficients that express the different characteristics of red, green, and blue subpixels. In this paper, we alter pixel values to save power in a display panel. Therefore, we ignore parameter for static power consumption. Then, we model the total dissipated power (TDP) for displaying a color image by TDP. Where denotes the number of pixels in the image and denotes the RGB color vector of the $t$th pixel. The weighting coefficients and are inversely proportional to the subpixel efficiencies, which depend on the physical characteristics of a specific display panel. A blue subpixel generally consumes more power than red and green subpixels to display the same output level due to its low efficiency. For example, in a particular OLED panel in a mobile phone, the weighting ratios are about $w_r : w_g : w_b = 70 : 115 : 154$ However, we note that different display panels have different weighting coefficients. For a grayscale image, the TDP is similarly modeled by where is the gray level of the $t$th pixel. Let us recall the notations in the last section; there are pixels with gray level in the input image, and these pixels are assigned gray level in the output image by a transformation function. Therefore, the TDP in (14) can be compactly written in vector notations as TDP. Notice that the power model in (13) or (14) is applicable to not only the OLED but also other emissive displays. In [24], Rose et al. analyzed the power-consumption characteristics of several displays. First, in PDPs, the sustain power dominates the whole power consumption. The sustain power is proportional to the average picture level, which is the average of luminous intensities of all pixels in an image. The average picture level is, in turn, linearly proportional to the TDP in (14) since it is obtained by dividing the TDP by the number of pixels. Therefore, the TDP in (14) can model the power consumption in the PDP as well. Similarly, it can model the power consumption in the FED, in which the power consumption is also proportional to $wAPL$.

B. Constrained Optimization Problem

We save the power in an emissive display by incorporating the power model in (15) into the HE procedure. We have two contradictory goals, i.e., attempt to enhance the image contrast by equalizing the histogram, but we also try to decrease the power consumption by reducing the histogram values for large intensities. These goals can be stated as a constrained optimization problem, i.e., The objective function has two terms, i.e., is the histogram-equalizing term in (8) and is the power term in (15). By minimizing the sum of these two terms, we attempt to improve the image contrast and reduce the power consumption simultaneously. Here, is a user-controllable parameter, which determines the balance between the two terms. There are three constraints in our optimization problem in (16). The two equality constraints and state that the minimum and maximum intensities should be maintained without changes. In other words, if a display can express different intensity levels, the output range of the transformation function should also be to exploit the full dynamic range. The inequality constraint indicates that the transformation function should be monotonic, i.e., for every. Note that denotes that all elements in vector are greater than or equal to 0. Without this monotonic constraint, the solution to the optimization problem
may yield a transformation function, which reverses the intensity ordering of pixels and yields visually annoying artifacts in the output image.

C. Solution to the Optimization Problem

As mentioned in Section III-A, exponent in the power term is due to the gamma correction, and a typical is 2.2. For generality, let us assume that is any number greater than or equal to 1. Then, the power term is a convex function of, and the problem in (16) becomes a convex optimization problem [21]. Based on the convex optimization theory, we develop the PCCE algorithm to yield the optimal solution to the problem. According to the minimum-value constraint in (16), is fixed to 0 and is not treated as a variable. Thus, the transformation function can be rewritten as after removing from the original. Similarly, the dimensions of and are reduced to by removing the first elements, respectively, and has a reduced size by removing the first row and the first column. Then, we reformulate the optimization problem by the change of variable. Each element in the new variable is the difference between two output-pixel intensities, i.e., . Thus, is called the differential vector. Then, where By substituting variable and expressing the maximum-value constraint in terms of, (16) can be reformulated.

To solve the optimization problem, we define the Lagrangian cost function, i.e.,

\[ J(\gamma, \nu, \lambda) = \|y - \overline{y}\|^2 + a\nu (1 - (L - 1)) + \lambda y \]

where and are Lagrangian multipliers for the constraints. Then, the optimal can be obtained by solving the Karush–Kuhn–Tucker conditions [21],

\[ 1' y = L - 1 \]
\[ y \geq 0 \]
\[ \lambda \geq 0 \]
\[ \lambda y = 0 \]
\[ 2(y - \overline{y}) + \alpha D^{-1}(\nu^\gamma D^{-1}y) + \nu 1 - \lambda = 0 \]

We first expand the vector notations in (24) to obtain a system of equations and subtract the i-th equation from the ith one to eliminate. Then, we have a recursive system, i.e.,

\[ g_{i-1} = g_i + \overline{g_i} + 1 - \overline{g_i} + \frac{\alpha}{2} \left( \sum_{i=1}^{L} g_i \right) \gamma - \frac{\lambda_1 + \lambda_i}{\gamma} \quad \text{for } 1 \leq i \leq L - 2, \]

In the Appendix, we show that all values can be eliminated from the recursion in (25) using (21)–(23) and that all values can be expressed in terms of a single variable. More specifically, each is a monotonically increasing function of, given by. Then, the remaining step is to determine that satisfies the maximum-value constraint in (20). To this end, we form a function, i.e.,

\[ f(z) = 1'(y - \overline{(L - 1)}) = \sum_{i=1}^{L-1} g_i(z) - (L - 1) \]

And find a solution to . Since is monotonically increasing, there exists a unique solution to . In this paper, we employ the secant method [25] to find the unique solution iteratively. Let denote the value of at the th iteration. By applying the secant formula, i.e.,

\[ z^{(n+1)} = z^{(n+1)} - \frac{z^{(n+1)} - z^{(n-2)}}{f(z^{(n+1)}) - f(z^{(n-2)})} f(z^{(n+1)}), \quad n = 2, 3, \ldots \]

Iteratively until the convergence, we obtain solution. From we can compute all elements in since. Finally, the transformation function is the optimal solution to the original problem in (16), which enhances the contrast and saves the power consumption simultaneously subject to the minimum-value, maximum-value, and monotonic constraints. Parameter in the objective function in (18) determines the relative contributions of the histogram-equalizing term and the power term. These two terms, however, have different orders of magnitude in general. Whereas and are not affected by the resolution of an input image, histogram values in depend on the image resolution. Moreover, the power term is generally proportional to the average luminance value of the input image. It is convenient to compensate the unbalance between the two terms by dividing the power term by the image resolution and the average luminance value. More specifically, we change the variable by

\[ \beta = \alpha \times \sum_{i=0}^{N-1} Y_{input, i} \]

Where is the gray level of the ith pixel in the input image? Then, we control instead of . For example, Fig. 3 shows the results of the proposed PCCE algorithm at various values. In this test, the “Door” image in Fig. 1(c) is also used as the input image, the LHM parameter is set to 5, and is set to 2.2. In Fig. 3(a), when the power term is not considered in (18),
and we obtain the differential vector. As gets larger, the elements for low pixel values decrease, whereas values for high values increase. As shown in Fig. 3(b), these changes in lower the transformation function, reducing the power consumption. A bigger saves more power. Without the power constraint, the TDP is. At and, the proposed algorithm reduces the TDP to and, respectively. In this way, the proposed algorithm determines the transformation function that balances the requirements of power saving and contrast enhancement optimally. Furthermore, the amount of power saving can be controlled by the single parameter. Note that the output black and white levels may not be the same as the input black and white levels in some applications. The proposed PCCE algorithm can be straightforwardly modified to handle such cases. Specifically, instead of the minimum and maximum-value constraints in (16), we can use generalized constraints and to derive the transformation function, which maps the input dynamic range to the output dynamic range. For instance, Fig. 3(b) also shows the transformation function with constraints and. Parameter is set to 2.84 to consume the same TDP as the red curve in Fig. 3(b). Comparing the output images in Fig. 3(c) and (f), we see that the new constraints reduce the dynamic range and degrade the overall contrast. In the remainder of this paper, the original constraints are employed to exploit the full dynamic range.

**PCCE FOR VIDEO SEQUENCES**

We extend the proposed PCCE algorithm to enhance video sequences. The proposed algorithm provides a power-reduced output image using the power-control parameter. We can apply the proposed algorithm with fixed to each frame in a video sequence. However, a typical video sequence is composed of frames with fluctuating brightness levels. Experiments in Section V-B will show that a bright frame can be enhanced with large to save power aggressively, whereas a dark frame can be severely degraded if its overall brightness is reduced further with the same. Therefore, we develop a scheme that determines adaptively according to the brightness level of each frame. For each frame, we first set the target power consumption TDP based on the input power consumption TDP and then control parameter to achieve TDP. Specifically, we set TDPout = k. TDPin (32)

Where is the power-reduction ratio? When, the proposed algorithm saves no power during the contrast enhancement. On the other hand, when is smaller, the proposed algorithm darkens the output frame and decreases the power consumption. The power model in Section III-A indicates that a bright frame consumes more power than a dark frame. Therefore, more power saving can be achieved for a brighter frame, and the power-reduction ratio in (32) can be set to a smaller value. On the other hand, the ratio for a dark frame should be close to 1 since even a small power reduction may yield poor image quality by reducing the contrast further and erasing details. Based on these observations, we set the power-reduction ratio by

\[ r_c = \left(1 - \frac{\sum V}{L-1}\right)^{\rho} \]

Where denotes the average gray level of an input frame and is a user-controllable parameter. For a bright input frame with high, is set to a small value to achieve aggressive power saving. On the contrary, for a dark input frame with low, is set to be close to 1 to avoid the brightness reduction. To summarize, given an input frame, we determine the target power consumption TDP using (32) and (33). Then, we find parameter to achieve TDP. Since TDP is inversely proportional to, we can easily obtain the desired using the bisection method [27], which iteratively halves a candidate range of the solution into two subdivisions and selects the subdivision containing the solution. Thus, in the video enhancement, is automatically determined, and the only power-control parameter is in (33). Note that, for the same, larger Yields smaller and saves more power.

**VI. Conclusion**

We have proposed the PCCE algorithm for emissive displays, which can enhance image contrast and reduce power consumption. We have made a power-consumption model and have formulated an objective function, which consists of the histogram-equalization term and the power term. Specifically, we have stated the power-constrained image enhancement as a convex optimization problem and have derived an efficient algorithm to find the optimal transformation function. Simulation results have demonstrated that the proposed algorithm can reduce power consumption significantly while yielding satisfactory image quality. In this paper, we have employed the simple LHM scheme, which uses the same transformation function for all pixels in an image, for the purpose of the contrast enhancement. One of the future research issues is to generalize the power-constrained image enhancement framework to accommodate more sophisticated contrast-enhancement techniques, such as [10] and [11], which
process an input image adaptively based on local characteristics.

References


