Logarithmic Tools for In-camera Image Processing

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Abstract— **The LIP (Logarithmic Image Processing) tools are mathematical models dedicated to the representation and processing of gray tones images. The underlying model is derived from the observation that digital camera response function can be described as a multiplication in logarithmic domain. In this paper we extend the logarithmic models to process color images and show how they can be used to implement low-light image enhancement in digital cameras.**

***Keywords* – Logarithmic Models, Image processing, Low-light, Digital Camera**

I INTRODUCTION

Not too long after their appearance in the early 90's, digital still cameras (DSC) have become the common way of acquiring images. Nowadays, the main direction seems to be that of decreasing the size and weight of imaging devices, which has reached a pinnacle with Mobile Phone Cameras (MPC). At the same time the camera producers engage with tremendous efforts in the Megapixels race.

The trend of miniaturisation mentioned above is imposing design modifications such as reducing the size of optics and of photo-sensible area. If we discuss these issues from an end-user point of view, the problem is that of increased susceptibility of images to blur from shaking hands [1]. The small photo-sensible area diminishes the number of collisions in the photo-voltaic effects and, therefore, it reduces the correlation between the incident light and the reported image intensity. On the other hand, the small photo-sensible area decreases picture angle. Since human hand jitter is always present, the small picture angle increases the chances that the relative motion between the camera and the scene during exposure time becomes larger than a pixel size and thus leading to visible motion blur.

Since this phenomenon can significantly degrade the visual quality of images, photographers and camera manufactures are frequently searching for methods to limit its effects.

This problem has been widely studied and academic literature and industrial research abounds with attempts to deal with it. We may divide these approaches in two categories. This first approach tries to eliminate the effects of the motion blur, meaning that there will be a normal image acquisition (with a long enough exposure time that includes blur) and subsequently camera trajectory is estimated and to restore it. The restoration and the estimation processes may be simultaneous and real-time (the so-called optical image stabilization) or consecutive and digital (by means of de-convolution). However this alternative implies the use of motion sensors (which came as an extra circuit) and therefore contradict the size-diminishing goal.

The second approach works on avoiding the circumstances that generate motion blur. This is achieved by reducing the exposure time below the "motion limit". The motion limit may be based on the "q over f35 rule of thumb" [2] or dynamically deduced from computing the misalignment on consecutive frames for more precise indication of camera motion [3]. This alternate solution may be easily implemented on existing digital camera hardware, without any changes in the acquisition process. However, if such a solution is chosen, the under-exposed image must be amplified so to provide proper luminance and colour saturation level. This amplification consists of pixel-based multiplication and this operation must avoid introducing artefacts that will decrease the perceived image quality. As it will be shown in this paper, the Logarithmic Image Processing model provides a means for resolving this problem.

Considering the arguments presented above, we structure the remainder of this paper as follows: we shall begin by describing the most important features of the Logarithmic Image Processing model, we shall explain why it is suitable for the deemed purposes, and describe the actual implementations of the low-light enhancement. The paper ends with a discussion of the obtained results, conclusions and future possible work.

II LOGARITHMIC MODELS AND CRF

The homomorphic theory introduced by Oppenheim [4] may be considered the starting point of the logarithmic image processing (LIP) models. The key is a homomorphic function, which exhibits a logarithmic behaviour and is used for re-mapping the original image value range into an "artificial" domain enriched with a superior algebraic structure. Notable implementations of the LIP models are given by Jourlin and Pinoli [5] (that we will subsequently call "classical" model) and respectively by Pătraşcu [6].

The classical logarithmic model is generated via a basic isomorphic transform Ψ that maps the image value definition domain (typically denoted as the interval [0, M]), into the logarithmic space:

$$\Psi(h) = M\left(1 - \exp\frac{-h}{M}\right) \quad (1)$$

The inverse mapping is defined by:

$$\Psi^{-1}(f) = -M\left(\ln\frac{-f}{M}\right) \quad (2)$$

In the equations (1) and (2) above, h is the gray-tone function of the original image ($h \in [0; M]$), and f is the corresponding absorption function in the logarithmic space.

The LIP model upgrades a set of transmitted light images to the status of vector space structure, with an additive law and a scalar - multiplicative law, as defined in equations (3) and (4) below:

$$f \oplus g = f + g - \left(\frac{fg}{M}\right) \quad (3)$$

$$\alpha \otimes f = M - M\left(1 - \frac{f}{M}\right)^{\alpha} \quad (4)$$

It is of paramount importance to notice that the resulting algebraic structure is closed with respect to the operations of addition and multiplication defined above. This is a major advantage of the LIP models, in sharp contrast with the real number addition/ multiplication classically used for the processing of image data, that may produce results outside the normal [0; M] value range. Dealing with such overshot is usually done by hard limitation (truncation) of the resulting image values, yielding a loss of information and lack of physical, real-world support.

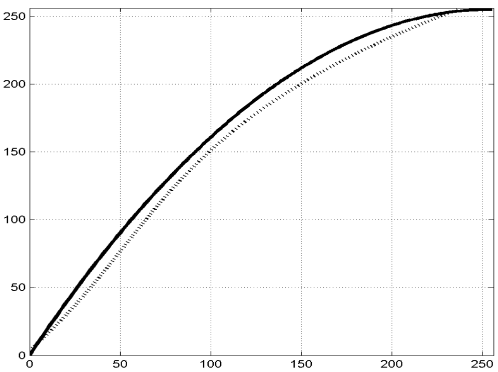

Figure 1: CRF to Log Amplification example: typical consumer camera CRF (solid line) and logarithmic multiplication with $\alpha = 1.78$ (dotted line).

The colour extension of the classical LIP is straightforward under a marginal RGB processing approach.

Even though one may find Pătraşcu's model [6] more mathematically elaborated, the classical LIP model [5] focuses on modelling the acquisition of images obtained from light transmitted through transparent environments, such as the classical photographic film [7]. The transfer function of any digital still camera, called the camera response function, exhibits a similar behaviour.

The problem of experimentally obtaining the camera response function (CRF) was intensively studied. The first attempts were based on capturing under a single exposure a uniformly illuminated graphic chart containing patches of known reflectance, such as the Gretag Macbeth colour chart [9]. Later, Mitsunaga and Nayar [10] proposed the modelling of the CRF by a low degree polynomial. The most common and relevant technique with respect to the current addressed issue is the solution proposed by Mann and Picard [11] that assumes a gamma function shaped CRF. This approach leads to the similar models for the CRF and the LIP multiplication, such as illustrated also in Figure 1.

One may argue that the use of the experimentally derived CRF provides a more accurate result for a given digital camera. Still, the use of the LIP multiplication provides more generality (which means that brings the advantage of portability) and, furthermore, allows an intuitive reasoning on the derivation and deployment of the method. Another strong point of the classical LIP model is its consistency with Weber's contrast law [8], which proved that human visual system has a logarithmic response to a linear variation of the intensity of the incident light. The same consistency

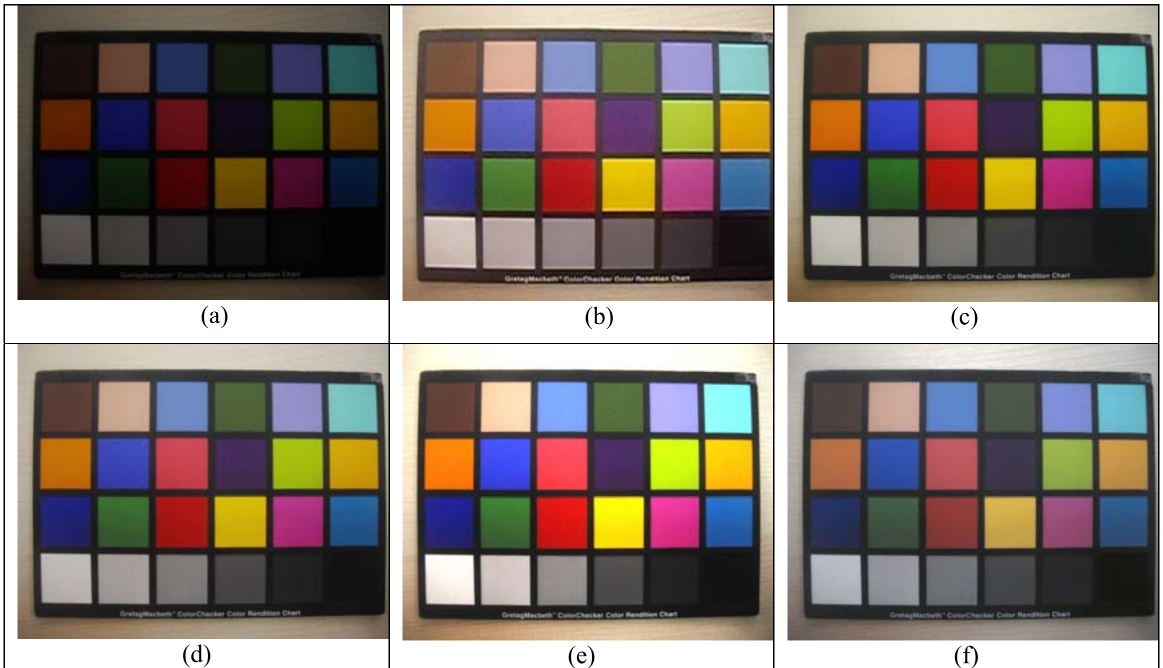

Figure 2. (a) Example of low-light main image, (b) reference, motion blurred image, (c) ideal image, (d) logarithmic enhanced image, (e) linear enhanced image, (f) auto-contrast image.

has been a guideline for photographic film manufacturers.

III LOW LIGHT ENHANCEMENT

It is a known fact that underexposing and amplifying is a solution for reducing the exposure. The camera computes the exposure time using following equation

$$E_V = -\log_2(t) + 2\log_2 N = \left(\frac{\Phi \cdot S}{K}\right) \quad (5)$$

where E_V is the exposure value, the log of t forms the time value (T_V), N is the relative diaphragm opening (by taking the log, the aperture value, A_V, is formed), Φ is the incident light, S is the sensors sensibility (or for digital cameras – the amplification) and K is a known constant. If the aperture, which has influence over the depth of field, is held constant, while the incident light is fixed, then there is a direct relation between the exposure time and the sensitivity. For older film-cameras, sensitivity was given by the amount of photo-sensible particles per square unit. If a larger density is used then a shorter time is required to capture the number of particles that change their properties under light to produce the image contrast. In the current digital cameras this solution was replaced by high ISO mode, where the S parameter determines the analogue-to-digital amplification.

A typical low-light enhancement method firstly captures an image with a short exposure time. This image is hand motion free but under-exposed. Next, the image is amplified until its luminance and colour levels match that of a reference. The reference may be intrinsic as the one provided by equation (5) with a large value for ISO parameter S or it may be an external one, such as a different image as described in [12].

The reference in the latter approach is a correctly exposed image, which may be blurred. This provides additional information than a single number derived from equation (5). For the currently proposed solution, an important demand is the relative short period between the capture moments of the two required images: the reference and the main image. This helps prevent large geometrical misalignments and, hence, avoid the time-consuming image registration required in [12].

Let us denote the main, low-light, image, which is of N x P resolution with $F(i,j)$, $i=1,\ldots N$, $j=1,..P$. The reference image (which we shall denote by $G(i,j)$) may have the same or lower resolution than the subject, image. If different resolutions are used one may a use a nearest neighbour interpolation to even the image sizes to the highest resolution

The enhancement method works in two steps; first, it performs a rough global amplification; later, it refines individual pixels by taking into consideration local information. In the following paragraphs, we shall proceed with describing the actual method.

Given the two images, G and F, the rough amplification is performed by considering a reduced set of (spatially matching) pixels from each image: $G_s \subset G$ and, respectively $F_s \subset F$, and by means of linear regression, computing a pair of coefficients ($c_1$and c_2), [13], so that:

(a)	(b)	(c)

Figure 3. Example of method failing. The underexposed subject image (a) if logarithmically amplified (c), has a poor color reproduction if compared with the motion blurred reference image (b), as one can see in the background

$$G_s \approx c_1 F_s + c_2 \quad (6)$$

The image computed using the coefficients from equation (6), $F_1 = c_1 F_s + c_2$, corresponds in most cases with the standard (simple reference) amplification methods. However, we must observe that the results are highly dependent on the choice over the set of reduced pixels, which may or may not be representative for the image. If full resolution image is used, blur artefacts may be transferred from the reference image to the main image. Furthermore, if classical real addition and multiplication are used in equation (6), the result is sensitive to range overflow. Therefore, an implementation based on equations (3) and (4) is more practical.

The second step of the enhancement, the fine amplification is performed locally, in the sense that different amplification factors are used for different pixels. To be more explicit, we shall determine the matrix *W(i,j)*, with *i=1,…N* and respectively *j=1,..P,* so that:

$$F_2(i,j) = W(i,j) F_1(i,j) \quad (7)$$

The computation of *W*'s coefficients relies on the 1-D adaptive filtering theory which has the obvious advantage of being computationally efficient. The actual implementation implies the use of a filter with a single adaptive coefficient. But first the 2-D images are converted into 1-D vectors by arranging them in lexicographic order:

$$\{W(i,j), F_1(i,j)\} \rightarrow \{W(k), F_1(k)\},\ k = (i-1)P + j$$

The equation that updates the filter is taken from sign-data LMS (Least Mean Square) algorithm and it makes use of the fact that the input data, $F_1(k)$ is always positive:

$$W(k+1) = W(k) + \mu(k) \cdot e(k) \quad (8)$$

where *μ(k)* is the step size (fixed or variable), the *e(k)* is the error signal computed as:

$$e(k) = G(k) - F_2(k) \quad (9)$$

For accurate implementation, one may use a fixed step size *μ(k) = μ = 0.005* and it may initialize the filter value with neutral multiplication element *W(1)=1*.

As previously discussed, if standard multiplication is used in equation (7), range overflow situations are often encountered in highly illuminated areas. Furthermore, in the same hypothesis of linear amplification, if one will extend the method to colour (multi-planar) images by replicating the algorithm for each colour plane, the resulting image will have over-saturated colours. In order to prevent these problems we are using logarithmic multiplication (as described by eq. (4)).

Practical implementation tends to simplify the described method. To be more precise, a single coefficient may be used in rough amplification $F_1 = c_1 F$ and a set of reduced possible values for c_1. In this case, the local amplification may be rewritten as:

$$F_2(k) = D - D\left(1 - \frac{F_1(k)}{D}\right)^{W(k)} \quad (10)$$

where *D* is the maximum image intensity (e.g. 255). Eq. (10) is rather difficult to be implemented but may be substituted with a finite set of look-up-tables, without loss in image quality.

IV RESULTS AND DISCUSSIONS

For demonstration purposes, we considered a low-light scene containing the Gretag Macbeth Colour Chart placed on a wooden support. The input images (main and reference image), as well as the results may be seen in figure 2. The reference (Fig. 2 (b)) and main image (Fig. 2 (a)) were obtained with a consumer camera held in the hands; thus they are susceptible to motion blur. The under-exposed subject image (Fig. 2, (a)) was obtained by forcing the exposure value to be $E_V=-2$. The ideal image (which is not affected by motion blur) was recorded with a tripod-mounted camera. As results, we showed our image (d), the image obtained by described amplification but performed in a linear space (e) (which is obviously over saturated in the upper part – the wooden support) and respectively the subject image processed by typical auto-contrast and auto-saturation algorithms (f). The last possibility is well known and it is used in the world of amateur photographers; its result suffers from poor colour reproduction. Concluding, it is easy to observe that the best results are obtained by using the two step logarithmic amplification.

Furthermore, we considered an extensive testing procedure which includes larger data sets, with different scenes, but under the constraint that there is no misalignment between the ideal image and the resulting one. Under these circumstances, we were able to compute a Normalized Mean Square Error. A short summary of the results may be seen in Table 1. As one can see, the results are degrading if we underexposing more; however the logarithmic amplification provides the most reliable results in all conditions.

	LOG	LIN	Auto
EV=-1	0.0053	0.0214	0.0120
EV=-2	0.0063	0.0254	0.0182

Table 1. Values of the NMSE for the logarithmic amplification, linear amplification and auto-contrast if the low-light image was under-exposed with EV=1- or EV=-2 stops.

The method has limited performances in case of severely underexposed images with more than EV=-2 (Figure. 3 shows poor colour reproduction in this case) or sizeable misalignment between acquired images. Under such conditions even if our method is the most reliable, it does not pass a visual inspection.

V CONCLUSIONS

In this paper we proposed a method that makes use of the similarity between digital still camera response function and the LIP multiplication to derive a technique for low-light images enhancement. The method has two steps (a rough and global amplification followed by a smooth and local information based enhancement). It can be easily implemented in existing digital camera and mobile phone embedded platforms and gives better results than other known solutions.

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