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SUBPIXEL BASED IMAGE SCALING USING CONTINUOUS DOMAIN ANALYSIS

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Abstract:

The apparent resolution of displayed images can be improved by sub-pixel based image scaling. The individual sub-pixels are controlled rather than whole pixels; while maintaining the sharpness of the image it is very difficult to reduce the color error because the improved luminance resolution brings chrominance distortion. The various sub-pixel arrangements and arbitrary scaling factor developments are challenging schemes. In this system, continuous domain analysis model is used and it considers the low-pass nature of the Human Visual System (HVS). For discrete image and grid-like sub-pixel arrangement, the signals are recognized by the HVS system and modeled as 2D continuous image. The main aim is to minimize the difference between the perceived image and the continuous target image, which we call Continuous Domain Analysis for Sub-pixel based Scaling (CASS). The ideal low-pass filtering in CASS causes the ringing artifacts, which should be eliminated. CASS with Laplacian-of-Gaussian filtering (CASSL) is proposed to reduce the ringing artifacts. Both CASS and CASSL achieve state-of-art method. CASSL is efficient method to increase the apparent resolution.[1]

Index Terms: Human Visual System, Subpixel, Image Scaling & Messing

1. Introduction:

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of single processing in which inputs is an image and output maybe image or characteristics associated with that image. Nowadays, image processing is among rapidly growing technologies. Image processing basically includes the following three types,

- ✓ Importing the image via image acquisition tools.
- ✓ Analyzing and manipulating the image.
- ✓ Output in which result can be altered image or report that is based on image analysis.

Tonal range and color were controlled in the lighting and also image processing but mostly through the control of lighting. Areas too light can be darkened, areas too dark can be lightened, and color can be altered. Processes that used to take enormous amounts of time can now be achieved using the computer.As well as all of the above one needs to understand that a professional will mostly shoot in digital 'RAW' format and the image readily visible. This RAW format gives the highest quality possible in capture. It also represents Red, Green, and Blue respectively.The final stage of processing is the sharpening of the image. Sharpness is required on most images and the amount of sharpening can vary from the image to image, depending on the number of pixels subject has.The RAW image has to undergo several phases of editing and processing to overcome flaws and obtain original information. All types of data have to undergo three general phases of digital technique:

- ✓ Pre-processing
- ✓ Enhancement and extraction
- ✓ Information extraction

Systems used to manipulate multi-dimensional signals maybe simple digital circuits to more advanced parallel computers. This digital technology manipulates images with three goals in consideration,

- ✓ Image processing
- ✓ Image analysis
- ✓ Image understanding

2. Guided Filter:

Outdoor scenes, especially those distant photographs in bad weather, are usually degraded due to the presence of particles or droplets in the atmosphere. With lowered contrast, the degraded dull images lose their visual vividness and color fidelity. Consequently, image dehazing is a significant issue in many image-relevant applications. However, single image dehazing is non-trivial because it is highly under constrained – the local transmissions, which depend on the scene depth for homogeneous atmosphere, have to be estimated. To solve this, techniques that rely on their own assumptions or priors have been come up. Among those successful priors, the dark channel prior can serve as a simple but effective guidance to estimate the local transmissions for hazy images. Unfortunately, refining the transmission map with close-form matting is computationally expensive.

The guided filter, proposed recently infilters the input by considering the content of a guidance image. Since the guided filter has close theoretical connection with the closed-form matting framework and it also has O(N) time algorithm, that it is possible to apply guided filter to refine the transmission map obtained by dark channel prior, and the running time of the dehazing process can be reduced significantly.Guided filter is a type of edge-preserving smoothing operator, which filters the input image under the guidance of another image. Since the recovered haze-free images usually look quite dim, enhance their brightness for better display. It gives the detailed information of the input.However, guided image filtering is actually an approximation of soft matting. Refining the transmission map with guided filter may not always work. Firstly, the dehazed result contains noticeable halos, this happens because the depth change at the object edge is too abrupt; the guided filter needs a larger filtering radius *r* to suppress the halos. On the other hand, in the refined transmission map, the details of the pedestrian are captured by the local linear model and the transmission is under estimated, results in over-saturation in the recovered image. This problem can be resolved by reducing the filtering radius *r*; however, a smaller *r* makes the halo effect even more severe. As a result, when the input hazy image contains discontinuities that are too abrupt, it is difficult to find an appropriate filtering radius that compromises between the halo effect and over-saturation. Therefore the low complexity of this dehazing algorithm comes with the price of some failures.To address the mentioned problem, future improvements may focus on adjusting the parameters *r* dark and *r* locally within the image, at the cost of inevitable higher computation.

3. Pixel Based Down-Sampling with Anti-Aliasing Filter:

Image down sampling using subpixel techniques to achieve superior sharpness for small liquid crystal displays (LCDs). Such a problem exists when a high-resolution image or video is to be displayed on low-resolution display terminals. Limited by the low-resolution display, we have to shrink the image. Signal-processing theory tells us that optimal decimation requires low-pass filtering with a suitable cutoff frequency, followed by down sampling. In doing so, we need to remove many useful image details causing blurring. Subpixel-based down sampling, taking advantage of the fact that each pixel on a color LCD is actually composed of individual red, green, and blue subpixel stripes, can provide apparent higher resolution**.**Single pixel on a color liquid-crystal display (LCD) consists of several primary colors, which are typically three colored stripes ordered (depending on the display) either as blue, green, and red (BGR), or as red, green, and blue (RGB). The colored stripes are called subpixels. The colors of the three subpixels are fused together to appear as a single color to the human visual system (HVS) due to the blurring by the optics.A simple way called Direct Pixel-based down sampling (DPD) is to perform down sampling by selecting one out of every pixel. It can incur severe aliasing artifacts in regions with high spatial frequency. An improved method is called Pixel-based Down-sampling with an Anti-aliasing Filter (PDAF), in which the anti-aliasing filter is applied before DPD. It suppresses aliasing artifacts at the expense of blurring the image, as only low-frequency information can be retained in the process. Note that neither the DPD nor the PDAF incur color artifacts. Since the number of individual reconstruction points in an LCD can be increased three times by considering the subpixels, the application of subpixel rendering in down sampling schemes may lead to an improvement in apparent resolution.Higher apparent resolution is always attractive to consumers, because, for a given physical size of display, higher resolutions can make images more realistic by rendering details. However, the low-pass filter relieves color fringing at the expense of image blurring and can only be adopted as an enhancement technique for achromaticimages.

4. Optimization-Based Method:

The goal of a filter for subpixel rendering is to suppress color aliasing to be unnoticeable while keeping a high spatial resolution of the luminance signal. Platt's approach to derive an optimal filter for RGB stripe matrix displays. This assumes that a display pixel has k = 3 subpixels, i.e., a red, green, and blue subpixel. It also assumes that the RGB image signal is sampled at subpixels, denoted as a_k. At each subpixel position, an RGB color value g_k is sampled from the image signal. The design of an optimal filter is inspired by a perceptual error metric, that seeks to minimize the error that is introduced when displaying an RGB color value g_k of the image signal with only the single color intensity a_k of the k-thsubpixel in an arbitrary scan line of the display. Computing this error in a way that exploits the characteristics of the HVS for optimal display requires a conversion to an opponent color space.To control the intensity of each subpixel, one obtains three discrete filter kernels for every subpixel color, which combine all three RGB values into a single intensity a_k of the k-thsubpixel. To control the intensity of each subpixel, one obtains three discrete filter kernels for every subpixel color, which combine all three RGB values into a single intensity a_k of the k-thsubpixel.

A. 1D Subpixel Pattern: We now extend the basic analysis to arbitrary 1D subpixel patterns. Exemplify this with the Pen Tile RGBG subpixel layout, which is commonly found on mobile devices such as smart phones. Exploiting the different sensitivity characteristics of the HVS, these displays offer less resolution for the red and blue color channels. To that end, each pixel of the Pen Tile RGBG display is built of a green plus either a red or blue subpixel, for irregular sampling patterns we use zero padding by introducing virtual subpixels that are laid out in a regular pattern and then align the centers of each physical subpixel of the irregular layout to the virtual subpixels.

B. 2D Subpixel Pattern: In Messing extend the mathematical framework to two-dimensional subpixel patterns. However, we use the original formulation by Platt insteadof constrained optimization, since most subpixel geometries exhibit rectangular structure, which is quite amenable to astraight-forward extension of the 1D approach. In situations where subpixel shape is not negligible, we can introduce virtual subpixels.

C. 2D RGBW Pattern: The analysis to the 2D Pen-Tile RGBW pattern, where 2×2 subpixels containing red, green, blue and white primaries form a single pixel. To be able to consider such a pattern for optimal filtering we need to treat white as a primary color and thus employ a matrix that can convert from RGBW into the $Y_0C_1C_2$ opponent color space.As most images and textures are given in RGB color space, we need to convert them first to RGBW. We do this by computing the minimum of all three RGB color channels, then subtracting that value from each component, treating it as pure white.In rendering algorithms, texture filtering is an integral component. A single subpixel may cover a large texture region which must be filtered in order to avoid distracting artifacts due to under sampling of the texture. We propose subpixel texture filtering in order to increase the perceived display resolution, yielding textures that appear sharper.

5. Continuous-Domain Analysis for Subpixel-Based Scaling (CASS):

The representation of the grid-like sub-pixel arrangement and the image models in the continuous domain, we formulate the sub-pixel-based image scaling as a minimum mean squared error (MMSE) problem. Specifically, by treating $S_{(R)}(x, y)$ as the optimization variable, we minimize the difference between the perceived image $S_P^{(R)}(x, y)$ and the target image $L_T^{(R)}(x, y)$. Note that SP and LT are of different scales. For comparison, the small image $S_P^{(R)}(x, y)$is enlarged $1/\alpha$ times both horizontally and vertically, leading to

$$S_P^{(R)}(\alpha x, \alpha y) = \Delta_S^{(R)}(\alpha x, \alpha y) * d^{(R)}(\alpha x, \alpha y) * h(\alpha x, \alpha y) \quad (1)$$

A. Representation of the Perceived Image Based on HVS: The pixel values of the small image S(R) can be represented as impulses on a 2D plane in the continuous domain, where the 2D series of δ-impulses is

$$\Delta_S^{(R)}(x, y) = \sum_{k=0}^{m-1} \sum_{t=0}^{n-1} S^{(R)}(k,l) \cdot \delta(x - k, y - l) \quad (2)$$

Red pixels on the display as a binary function $d^{(R)}(x, y)$, which is the aperture function,

$$d^{(R)}(x, y) = \begin{cases} 1, & (x, y) \in A(R) \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

2D series of δ-impulses is defined to represent the data from the image $L^{(R)}$ as impulses.

$$\Delta_L^{(R)}(x, y) = \sum_{k=0}^{m-1} \sum_{t=0}^{n-1} L^{(R)}(k,l) \cdot \delta(x - k, y - l) \quad (4)$$

The high-frequency component of the interpolated image needs to be further removed so as to avoid aliasing in the down-sampled image *S*(R). This is achieved by applying another ideal LPF *I (x, y)* which has horizontal and vertical cut-off frequencies no more than $\alpha\pi$. Since $\alpha \le 1$, we have,

$$L_T^{(R)}(x, y) = \Delta_L^{(R)}(x, y) * I_\pi(x, y) * I(x, y) \quad (5)$$

$$= \Delta_L^{(R)}(x, y) * I(x, y) \quad (6)$$

The small image is enlarged 1/α times both horizontally and vertically, leading to

$$S_P^{(R)}(\alpha x, \alpha y) = \Delta_S^{(R)}(\alpha x, \alpha y) * d^{(R)}(\alpha x, \alpha y) * h(\alpha x, \alpha y) \quad (7)$$

Perceptual error is defined as, $E^{(R)}(x, y) = S_P^{(R)}(\alpha x, \alpha y) - L_T^{(R)}(x, y)$ (8)

Consequently $G_I(x, y)$ is seperable into two 1D filters:

$$G_I^{(v)}(x, y) = \sqrt{C} \cdot F^{-1}[\tilde{I}^{(v)}(u) / \tilde{h}^{(v)}(u)] \ \ldots(9)$$

$$G_I^{(h)}(x, y) = \sqrt{C} \cdot F^{-1}[\tilde{I}^{(v)}(u) / \tilde{h}^{(v)}(u)] \ \ldots(10)$$

Two nonnegative constants $X^{(R)}_{k,l}$ and $Y^{(R)}_{k,l}$ related to the image region

$$L_C^{(R)}(x, y) \text{ with } (x, y) \in \tilde{A}_{k,l}^{(R)} \quad (11)$$

$$E^{(R)}_{k,l} \le X^{(R)}_{k,l} p^{-r} + Y^{(R)}_{k,l} q^{-r} = \le X^{(R)}_{k,l} p^{-2} + Y^{(R)}_{k,l} q^{-2} \quad (12)$$

The average error of the whole image Sis also bounded, and we denote the mean absolute error (MAE) of the image S induced by the approximation as e_S.

$$e_s = O(p^{-2} + q^{-2}) \quad (13)$$

6. CASS with Laplacian-of-Gaussian Filtering (CASSL):

Its sharp cut-off in the frequency domain translates to oscillations in the spatial domain, leading to observable ringing artifacts. To resolve this defect, GI (x, y)is replaced by a Laplacian-of-Gaussian(LoG) filter, leading to the scheme CASS with LoG filtering(CASSL). In this scheme, instead of GI (x, y), a LoG filter with a high-boost characteristic is applied to $\Delta_L^{(R)}(x, y)$. Similar to GI (x, y), the derived LoG filter is a combination of an LPF and HBF, but has smooth transition in the frequency domain and does not bring ringing artifacts. Because the concerned 2D LoG filter is also separable into two 1D filters like GI (x, y), we subsequently show the derivation of the vertical filter. The horizontal filter can be obtained in the same manner.

$$LoG(x) = ((x^2/\sigma^4) - (1/\sigma^2)) \exp(-x^2/2\sigma^2) \quad (14)$$

This subsection presents the general form of the LoG filter to be used. Consider a 1D Gaussian kernel exp with variance σ2. Its second order derivative (Laplacian) gives the 1D LoG filter

$$LoG(x) = ((x^2/\sigma^4) - (1/\sigma^2)) \exp(-x^2/2\sigma^2) \quad (15)$$

$$L\tilde{o}G(x) = \sqrt{2\pi}\, \sigma\, u^2 \cdot \exp(-\sigma^2 u^2/2) \quad (16)$$

Inspired by the following filter,

$$\tilde{G}_L^{(V)}(u) = C.(\beta u^2 + 1).\exp(-\sigma_L^2 u^2 / 2) \qquad (17)$$

The DC gain of $\tilde{G}_L^{(V)}(u)$ is always the constant C. the

$$\tilde{G}_L^{(V)}(x) = C/\sqrt{2\pi}.(1/\sigma_L + \beta/\sigma_L^5).\exp(-x^2/2\beta^2) \qquad (18)$$

To bound the error in the implementation of G(v)L (k), proceed to determine the number of taps (total length of the filter) that are needed. Specifically, we solve for *x* in the following inequality:

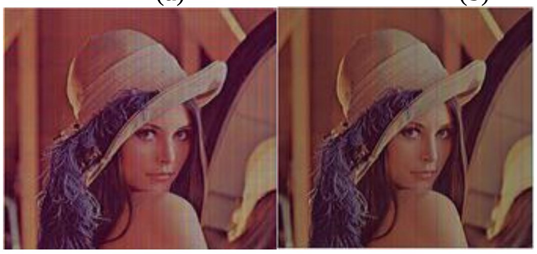
$$f_1(r) = (\sqrt{2\pi}\,\sigma_L^3 r / 2C\beta).\exp(\sigma_L^2 + \beta/\beta) \qquad (19)$$

$$f_2(r, k) = \sigma_L\sqrt{(-2W_K(f_1(r)) + \sigma_L^2/\beta + 1)} \qquad (20)$$

7. Simulation and Result:

When CASS and CASSL are applied for image up sampling, the only change is to let their filters $G_I(x, y)$ for CASS and $G_L(x, y)$ for CASSL have horizontal and vertical cut-off frequencies of π. Since subpixel-based image scaling does not bring much impact to up-sampling, we focus on the experimentation of image down-sampling.

(a) (b)



(c) (d)

(e)

Figure 1: Down-sampled images. (a) Input (RAW). (b) PDAF. (c) Messing. (d) CASS. (e) CASSL

The sizes of the test images range from 512×512 to 1080×1920 (full-HD) for a wide coverage. For the proposed CASS, as its filter $G_I(k, l)$ oscillates around zero and has an infinitely long response, we truncate it to a $(K \times K)$ tap filter with $K = 61$, while for CASSL, we let $r = 10-8$ to obtain the corresponding number of taps. We set the constant $C = 1$in both methods. We use the RGB stripe arrangement with 2:1 down sampling, and set $p = q = 6$ for a good trade-off between approximation error and complexity. For CASS, we set $c_I \in \{0.8, 1.0, 1.2\}$ and let σ_I vary within [0.1, 0.6]. As for CASSL, we set $c_L \in \{0.8, 1.0, 1.2\}$ then let σ_L change within [0.7, 1.6].The results are then slightly low-pass filtered to simulate the effect of the HVS. For display purposes, the brightness of the image is also mildly adjusted. The proposed CASS and CASSL give the sharpest and most vivid down-sampled images with little color distortion, and CASSL remedies the ringing artifacts of CASS. The results of PDAF look quite blurred, while Messing's method provides results with more detail. CASS has better objective performance but it brings ringing artifacts to the results. Hence CASSL is proposed as an alternative.

8. Conclusion:

Thus the developed system overcomes the problem of sub-pixel based image scaling on a continuous domain analysis model. CASS scheme is used to minimize the difference between perceived image and the target image. CASS scheme brings the ringing artifacts. Thus the scheme CASSL is generally proposed to eliminate the ringing artifacts and this method is comparable with the state-of-art method.Thus, the findings of this research have opened up new method to improve the apparent resolution and the image scaling of the displayed images. With the same rationale, it is possible to generalize our proposal for arbitrary subpixel arrangements, which is left for future investigation.

9. References:

1. L. Fang, O. C. Au, K. Tang, and A. K. Katsaggelos, "Antialiasing filter design for subpixel down sampling via frequency-domain analysis," IEEE Trans. Image Process., vol. 21, no. 3, pp. 1391–1405, Mar. 2012.
2. S.-J. Kang, "Color difference-based subpixel rendering for matrix displays," J. Display Technol., vol. 9, no. 8, pp. 632–637, 2013.
3. D. S. Messing, L. Kerofsky, and S. Daly, "Subpixel rendering on nonstriped colour matrix displays," in Proc. IEEE Int. Conf. Image Process., vol. 3. Sep. 2003, pp. II-949–II-952.
4. S.-J. Kang, "HSI-based color error-aware subpixel rendering technique," J. Display Technol., vol. 10, no. 4, pp. 251–254, 2014.
5. R. G. Keys, "Cubic convolution interpolation for digital image processing," IEEE Trans. Acoust., Speech, Signal Process., vol. 29, no. 6, pp. 1153–1160, Dec. 1981.
6. M. A. Klompenhouwer and G. D. Haan, "Subpixel image scaling for color-matrix displays," J. Soc. Inf. Display, vol. 11, no. 1, pp. 99–108, Mar. 2003.