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Camera Image Quality Tradeoff Processing of Image Sensor Re-mosaic using Deep Neural Network

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Abstract

Recently, with the release of 108 mega pixel resolution image sensor, the photo quality of smartphone camera, including detail, and texture, is getting much higher. This became possible only because by utilizing the remosaic technology which re-organize color filter arrays into the Bayer patterns compatible to existing Image Signal Processor (ISP) of commodity AP. However, the optimized parameter configurations of the remosaic block require lots of efforts and long tuning period in order to secure the desired image quality level and sensor characteristics. This paper proposes a deep neural network based camera auto-tuning system for the remosaic ISP block. Firstly, considering the learning phase, big image quality database is created in the random way using reference image and tuning register. Second, the virtual ISP model has been trained in order that predicts image quality by changing sensor tuning registers. Finally, the optimization layer generates the sensor remosaic parameters in order to achieve the user's target image quality expectation. By experiment, the proposed system has been verified to secure the image quality at the level of professionally hand-tuned photography. Especially, the remosaic artifact of false color, color desaturation and line broken artifacts are improved significantly by more than 23%, 4%, and 12%, respectively.

Introduction

Recently, the mobile camera has been developed by more than 108M pixel resolution CIS (CMOS Image Sensor) products. These CIS's are implemented as "Nona-cell" or "Tetra-cell" which is a technology to capture bright scene in low-light condition and high resolution image in normal light condition. Depending on the scenario of high resolution usage, the remosaic pixel relocation algorithm is implemented by hardware inside CIS (called, ISP, Image Signal Processing).

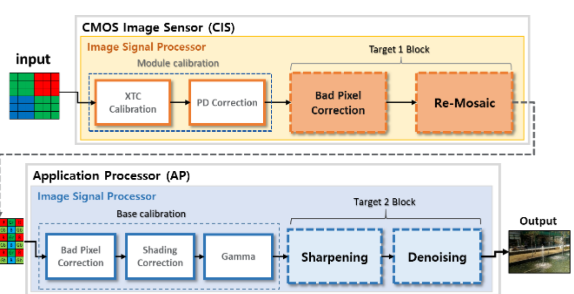


Figure 1. ISP pipeline of CIS and AP

During the rearrangement of pixel groups into the Bayer pattern, the interpolation is considering the direction, color and noise figures of neighboring pixels. While these remosaic technologies has high resolution advantages, many side effects such as false color and desaturation are inevitable. In order to overcome such difficulties, tuning the remosaic and BPC (Bad Pixel Correction) block of CIS is crucial challenge at the commercial camera development in Figure. 1.

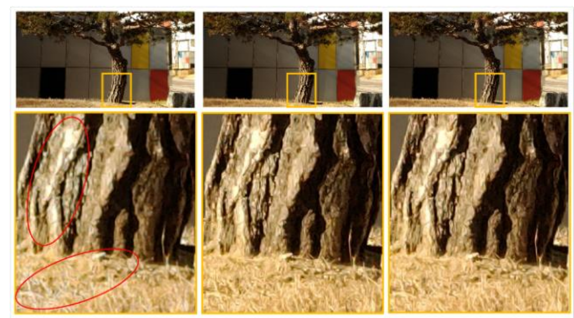


Figure 2. Evaluation of image quality. (left: initial image, center: proposed, right: hand-tuned). Color desaturation and detail were improved from the initial sampling set using the proposed approach.

We have applied the deep neural network (DNN) technology in the image quality tuning system. Firstly, we generate big data that can evaluate general image quality [2-5] and the remosaic artifacts. Secondly, the deep network system learns the pre-trained ISP model in order to enable generate quick tuning parameters. Finally, it generates optimal parameters with the user preferred image quality by optimization of shallow network.

Related Works

Recently, the level of image quality camera of flagship smart phones is very demanding task, which usually takes more than three months. Moreover, the 108M resolution CIS along with state-of-the art Image Signal Processors (ISP) have made the tuning process the bottleneck period of set development and also requires lots of human resources. Especially, the remosaic algorithm has trade-off characteristics between de-noise and sharpening quality, for example. The process of tuning the optimal parameter requires a lot of experience and takes lots of limitation. As therefore, recently there evolve huge interest in auto-tuning systems based on machine learning. Nishimura J. et. al. proposed a non-linear optimization and automatic generation method of reference image [6]. Ethan Tseng, E. et al. find the auto-tuned ISP parameters by leveraging differentiable mapping between the ISP parameter and image metrics [7]. Both approaches need to set up a target quality by reference images. Then, the similarity is evaluated with reference images by only changing the ISP parameters. Previously, we proposed an Image Quality Metric (IQM) measurement that

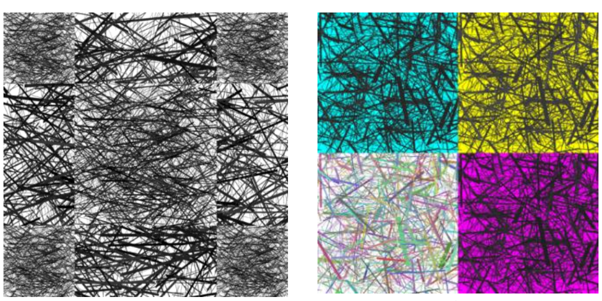
(a) (b) (c) (d)

Figure 3. Example of remosaic artifacts: (a) false color, (b) color desaturation, (c) line broken, (d) corner dots

can be utilized in the ISP parameter optimization process. As a key differentiation, we set the reference performance with the desired IQM score rather than image itself. In order to improve noise and detail, we proposed black box modeling based approach [1] for automatically obtaining the ISP tuning parameters and AP. This paper proposes a system for the optimization automation of image quality of a smart phone camera by considering various sensor artifacts. In new approach, we proposed six image quality metrics and five quality artifacts in addition to the previous work. Once camera system consisting of CIS and AP are modeled using a Neural Network, very fast parameter evolution can be tried without handing real image during the optimization with various register type support. By doing so, many different image styles can be explored by giving target image quality score. This is our very unique contribution to the camera image quality tuning automation.

Proposed System

As shown in Figure. 5, the proposed system consists of three parts, 1) data generation, 2) Machine Learning (ML) training and 3) auto-tuning. The system generates large scale image database, image quality prediction model, and optimized sensor remosaic configuration. Initially the raw image of TE42 chart has been captured and resultant final image after "nona" remosaic processing and ISP have been quantitated. One important key to the system is to connect the interface that it can control the sensor configuration and the Neural Network.



(a) (b)

Figure 4 Special measurement charts for: (a) false color, (b) color desaturation

Quantification of Image Quality

Image quality metrics is key ingredient for our proposed system. Exact modeling guarantee the automatic tuning result can be utilized in the actual projects without much human engagement. Also this will control the general image quality and minimize the artifacts of nona remosaic processing.

Table 1. Image quality metrics for remosaic artifact

False Color	$M_{FC} = \left\| \sqrt{{I_a}^2 + {I_b}^2} - \sqrt{{\hat{I}_a}^2 + {\hat{I}_b}^2} \right\|, in\ Figure\ 4\ (a)$
Desaturation	$M_{CD} = \sqrt{{I_a}^2 + {I_b}^2}, in\ Figure\ 4\ (b)$
Line Broken	$M_{LB} = \|I(x_l, y_l) - \hat{I}(x_l, y_l)\|,$ $where\ (x_l, y_l) : detected\ line\ position$
Line Noise	$M_{LN} = std(L_{diff}),$ $where\ L_{diff} = \begin{cases} abs(L(i,j) - L(i,j+1)) & if\ horizontal\ edge \\ abs(L(i,j) - L(i+1,j)) & if\ vertical\ edge \end{cases}$
Corner	$M_{CN} = distance([x_I, y_I], [x_{\hat{I}}, y_{\hat{I}}]),$ $where\ (x, y) : detected\ corner\ position$

As seen in Figure. 3, the remosaic processing produces the noticeable artifacts in real natural images. For evaluating these artifacts quantitatively, we introduce five image quality metrics in Table 1, false color, desaturation, line broken, line noise and corner artifact. False color is an artifact that occurs along the edges of the high-frequency region while referring to the wrong color information against the texture in adjacent pixels. In addition, desaturation occurs as a side effect of the function for eliminating the false color. Two charts of Figure. 4a and Figure. 4b are attached to the TE42 [10] to acquire the raw image and then we quantify the false color and desaturation in the CIELab color space [11].

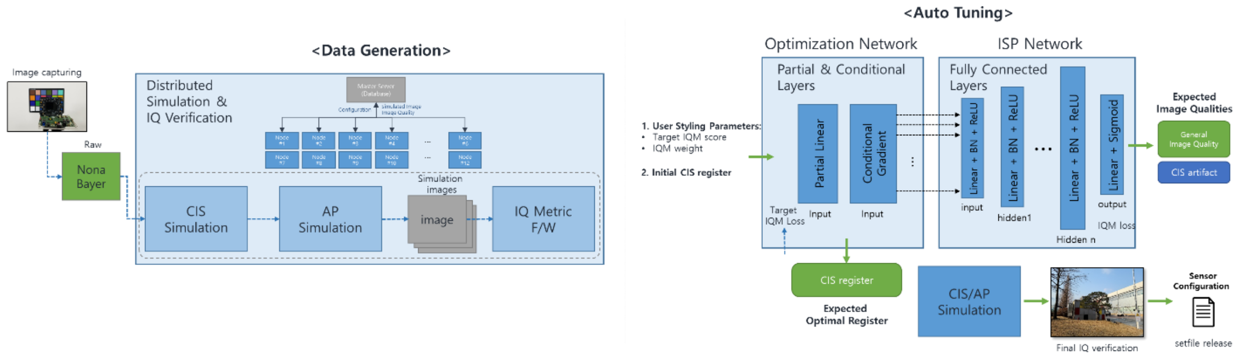


Figure 5. Overall architecture for Camera Auto-tuning System

Line artifacts, such as line broken and line noise, are mainly caused by misjudgment of directionality around the texture. Line broken shows a broken phenomenon in the middle of a continuous line, and the artifact level is measured by the difference between the pixel value of the actual measured line and the ground truth of the estimated line. Line noise refers to the unwanted artifact around the straight line, and is quantified by calculating the standard deviation of the first derivative from the horizontal and vertical edges with the surrounding lines [12]. Corner artifact represents a cracking phenomenon that occurs around the corner, and is measured by the difference between the measured corner/edge position and the estimated ground truth of the corner/edge position.

1st Phase: Raw Image Capturing

In the first step of the of proposed system, the target sensor is selected, for example 0.8um pixel pitch 108M resolution sensor, and a raw image is captured under daylight conditions as shown in Figure. 6. The number of image captures depends on the needs of the light conditions.

Figure 6. The proposed system uses a customized TE42 chart. This chart measures the various types of image quality with single capture.

2nd Phase: Camera Simulation System

The distributed system quickly generates training data similar to the human tuning methodology and know-how shown in Figure. 7. In this system, image sensor simulation, AP (Application Processors) simulation and IQ Metric Framework processes are executed in sequential way. According to the randomly generated sensor control parameters, various image has been created along with sensor and AP simulation from raw image. For each image, more than 10,000 images, fourteen metrics used for the image quality measurement as Table 1.

This is very time-consuming computation intensive work. As therefore, 32 node based Multi-Processing based camera simulation system has been scheduled for each simulation. Each node is responsible for creating and measuring the score of results image, and report to master database. By doing so almost 90% of computation time has been reduced compared to single processing environment.

Figure 7. The proposed system uses a customized TE42 chart. This chart measures the various types of image quality with single capture.

3rd Phase: ISP Optimization System

When training pre-trained ISP model, the accuracy of the model is highly related to the trained image quality of the final image. Otherwise, there are potential risks to generate outlier with quality degradation at the optimization step. For the robust model, we use multi-output DNN that consists of fully connected layers with Rectifier Linear Unit (ReLU) activation function as shown in Figure. 5. During the learning process, the objective function of multi-output regression has been used for modeling the relation between ISP parameter x and IQM score y. Additionally, Adam (adaptive moment estimation) [8] optimizer method is used for stochastic optimization with a learning rate of 0.001. The output is the predicted IQM score normalized to [0,1]. In the calculation of cost function, we use the mean square error. During the parameter optimization step, the distance between the current setting and the desired image quality is calculated as user weighted Mean Squared Error [1]. As a similar form to the model training process, we use back-propagation method [9]

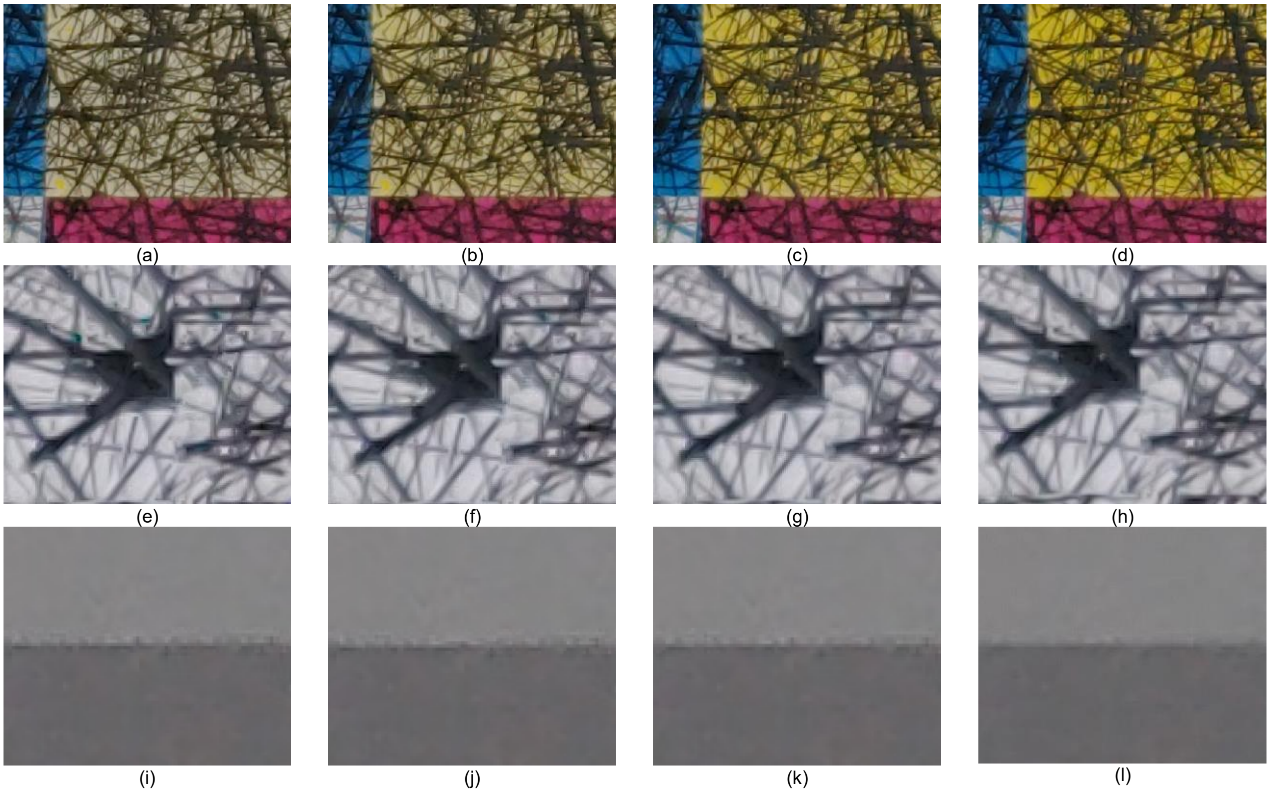


Figure 8. (b,f,j) after 50 epoch, (c,g,k) after 100 epochs, (d,h,l) after 150 epochs. (a-d) tuned by color desaturation metric only, (e-h) tuned by false color metric only, (i-l) tuned by line broken metric only. Each image quality (color desaturation, false color, line broken) can be improved using the proposed system independently.

and Partial Connected Network (PCN) in order to inference the optimal ISP. To improve image quality, we use the gradient descent method with Adam. (1) shows the updated weight calculated by considering tuning parameter conditions.

$$
\begin{aligned}
w_{t+1}^{j} &= \begin{cases} w_t^j - \Delta w_t^j, & \text{if } c_{min}^j < z < c_{max}^j \\ do\ not\ update, & otherwise \end{cases} \\
v_t &= \beta_1 \times v_{t-1} - (1-\beta_1) \times g_t \\
s_t &= \beta_2 \times s_{t-1} - (1-\beta_2) \times g_t^2 \\
\Delta w_t &= -n \frac{v_t}{\sqrt{s_t + \epsilon}} \times g_t
\end{aligned}
\tag{1}
$$

where, c is the constraint of the ISP parameters region, j is an order of input dimension, n is a learning rate in optimization, z is the result of $w_t^j - \Delta w_t^j$, g_t is sum of gradients at time step t and a subscript of w_t means the updated status.

Experimental Results

In the experiments, we used a System LSI 0.8um unit pixel 108M resolution CIS and the state-of-the-art AP. We have evaluated of 108M Nona image quality of the proposed approach compared to the hand-tuning results of commercialized smartphone camera, *i.e.,* Galaxy S20 Ultra.

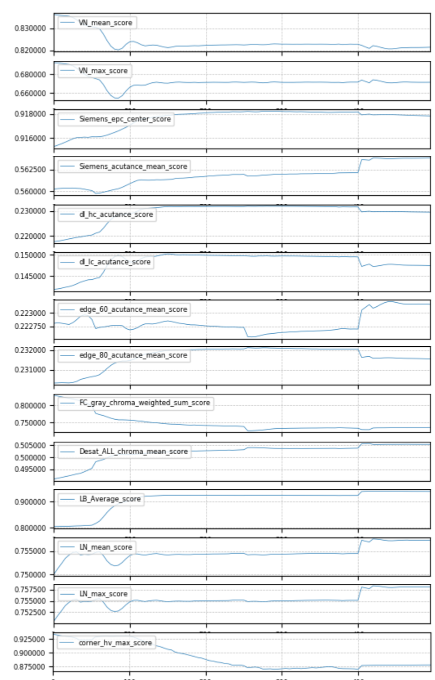


Figure 9. Real-time transitions of 14 IQM score, where the IQM scores are improved by incorporating user's weight and target.

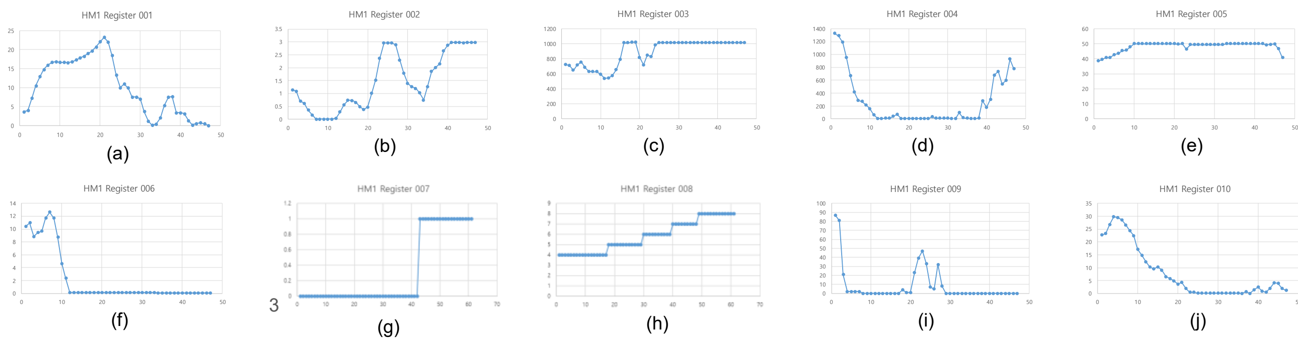


Figure 10. Example of parameters fluctuation during optimization. Proposed system controls various type of remosaic registers. (a-e,f,i,j): float type register, (h): integer type register, (g): binary integer type register. During one epoch of optimization, proposed system can control concurrent 196 parameters with considering of the multi-IQM scores.

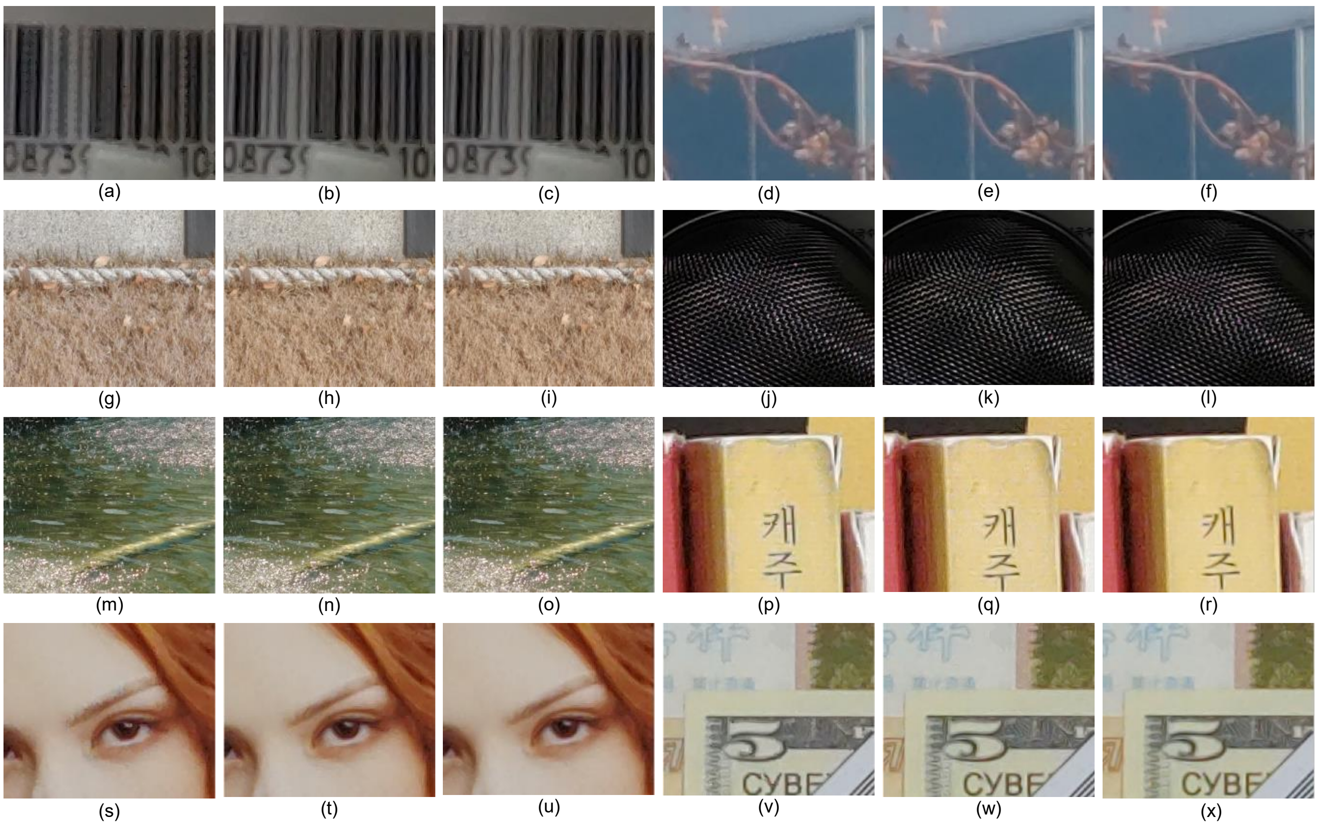


Figure 11. Final image quality comparison: (a,d,g,j,m,p,s,v) initial set, (b,e,h,k,n,q,t,w) tuned by proposed system, (c,f,i,l,o,r,u,x) hand-tuned.

Independent Image Quality Enhancement

The proposed system supports fourteen IQ control scores. Firstly, we just set the weight of target IQ to 1 for individual tuning and set to 0 for the another IQ. Figure. 7 shows the results of individual tuning on color desaturation, false color and line broken artifacts using the proposed system. Epoch 1, 50, 100, and 150 show the score progress which is secured at each optimization step.

Dealing with Image Quality Trade-off

In this experiment, the proposed system controls fourteen multiple image quality simultaneously in order to generate optimized tuning parameter sets. Figure. 8 shows the real time image quality changes, which have a trade-off between noise and resolution / texture, resolution / texture and false color and false color and desaturation. Binary integer type control parameter (for example Figure7e) can cause drastic IQ changes as shown in Figure. In order to model customer specific styling, the target score has been set higher than a reference quality. In consequence, the initial image quality was improved by the proposed method as shown in Table2. In results, key image quality metric, Siemens EPC center, Siemens acutance mean and color desaturation scores, are significantly improved. As shown in Figure2, the desaturation artifact, which is very critical at interim stage, also has been improved at the final stage by the proposed methodology. Figure9 shows the change of parameters fluctuation during each EPOCH of the optimization iteration.

The optimization network directly controls the tuning parameters to be close to the user's target image quality. It supports various types such as float and integer. Figure. 10 (a, d, g, j, m, p, s, v) shows the result of applying worst case setting to the initial value. (b, e, h, k, n, q, t, w) is the improvement result using the proposed system. And (b, e, h, k, n, q, t, w) is a result by an expert hand tuning.

Table 1. Image quality results of initial setting, proposed method system and hand-tuned reference image.

Type	Image Quality	Initial	Proposed	Ref.
General Image Quality	VN mean score	84.4748	83.1651	83.5580
	VN max score	69.6374	68.5450	68.8021
	Siemens EPC center score	88.4282	91.1439	90.1007
	Siemens acutance mean score	51.5550	53.9122	52.8451
	DL HC acutance score	20.7206	21.6974	21.6011
	DL LC acutance score	13.9048	14.0878	14.5194
	Edge 60 acutance mean score	19.0289	21.7421	21.6787
	Edge 80 acutance mean score	20.5813	23.1128	22.9348
Nona Artifact	False color score	52.0822	75.8287	70.1535
	Color desaturation score	44.1925	48.8316	49.4532
	Line broken score	81.1316	94.0244	93.3046
	Line noise mean score	76.8015	77.6043	77.9750
	Line noise max score	75.0314	75.7596	76.3510
	Corner score	95.7567	86.9327	88.0056

Conclusion

In this paper, we proposed the End-to-end Camera Automated Image Quality Optimization System (IQ Machine) using deep neural network which can be applied for image quality tuning with high resolution remosaic architecture in the state-of-the-art smart phone camera. By experiments, we presented that it can provide the desired style of image quality with minimized artifact. By applying multi-processing environment, the reference image creation time has been innovatively reduced. The proposed method would be advantageous in obtaining the initial image quality for new pixels or new sensors without long tuning period by experts. Another major advantage is that the fast-changing state-of-the-art ISP pipeline and customized quality preferences can be reflected in the proposed frameworks in a real-time basis.

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