Investigation of Different Aspects of Image Quality

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by

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CERTIFICATE

It is certified that the work contained in this thesis, titled "Investigation of Different Aspects of Image Quality " by Murtuza Bohra, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date	Adviser: Prof. Vineet Gandhi

To my Friends and Family

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Abstract

Image quality is a fundamental problem in computer vision. For variety of applications, for instance scanning documents, QR codes, bar codes or algorithms like object detection, recognition, tracking, scene understanding etc. images with good contrast, high illumination and sharpness are desired. Similarly in computer graphics for information visualisation, animations, presentations etc. aesthetically pleasing design and good colorization of the images are desired. Therefore the definition of image quality depend on the context and application of the image. In this thesis we attempt to address various challenges pertaining to image quality, (1) for natural imaging, we explore a novel approach for predicting the capture quality of the images taken in the wild. (2) For Graphics designs, we explore the aesthetic quality of images by suggesting multiple aesthetically pleasing colorization of graphics designs.

Due to increasing advancements and portability of smartphone cameras, it has become a default choice for capturing images in the wild. However, there are quality issues with camera captured images due to reasons like lack of stability during capture process. This hinders the automatic workflows which takes camera captured images as input e.g. Optical Character Recognition (OCR) for documents image, face detection/recognition from human image etc. Part of this thesis is focused on Image Quality Assessment (IQA), the aim is to quantify the degradation like out-of-focus blur and motion artefacts in a given image. One of the major challenge in IQA for images captured in the wild is that, we do not have ground truth to measure the capture quality. Therefore various previous attempts of IQA require human in loop for creating the ground truths for capture quality of images. Large user studies are conducted and mean human opinion scores are then used as measure for quality. In this work we use a signal processing based technique to generate the IQA ground truth, and propose a comprehensive IQA dataset which is a good representative of the real degradation during the process of capture. Further, we propose deep learning based approach to predict image quality for captures in the wild. Such IQA algorithm can be helpful in the cause by either giving online quality suggestion during capture or rating the quality post capture.

Another dimension to the image quality is aesthetic quality. Increasing usage of internet, social media and advancement in the mobile camera, photography has become a very popular hobby and interest to a large section. Even for a well captured image, people use varieties of filters and effects post capture to enhance the appearance of the image e.g. adjusting color temperature, contrast or even blurring part of

the image (bokeh effect) etc. Therefore the capture quality is not enough to define the aesthetic quality of the image.

However, one of the major factors defining the aesthetic quality of image is colorization. Particularly in computer graphics domain, where artificially generated images already have well defined structures, shape and components. Therefore sharpness or capture quality are not relevant, but on the other hand, color quality plays a very important role in visualization and appearance of the image. In natural images, largely colors are associated with semantics e.g. sky is always blue or grass are green etc. whereas in animations and computer graphics where objects are loosely associated with semantics, this lead to more choices of colors. Hence the problem of colorization becomes more challenging in graphics domain, where overall appearance of the images are more than its naturalness. Therefore, this work also covers aesthetic quality of graphics images, here instead of measuring the color quality, we propose algorithm to produce better coloring suggestions for the given graphics images.

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Chapter 5

Conclusions

In this thesis, we discussed two algorithms, (1) Exploring the utility of SFR as ground truth for image quality assessment to train a No-Reference IQA model. (2) An automatic colorization of graphics designs by exploiting the color aesthetics from artists created images.

Our experiments on IQA have shown that previously used synthetic data for IQA do not cover the distortions caused during real captures. And the models trained on synthetic data fails to predict image quality for real captures. The GSFR dataset proposed in this work, contains the real images with varying levels of degradation during the process of capture. The ground truth for image quality is measured as SFR on the slanted edges placed around the images. The dataset contains various types of textures e.g. clothes, wood, magazines, documents, ID cards etc. We train a neural network using this data and achieve high correlation with the ground truth SFR values. Also the network used in proposed method is a shallow network with much less parameters as compared to state-of-the-art methods. We also test our network on unseen IQA datasets for further testing and achieve state-of-the-art results for sharpness related distortion types. Another benefit of our approach is that, it can capture the local variation in image quality. In future, the proposed algorithm for quantifying sharpness based on MTF50 can be extended to camera auto-focusing in real time.

We also proposed a novel approach for the automatic colorization of gray-scale graphic templates. In contrast to previous approaches, our method tackles both the problems of palette selection and color assignment in a unified framework. The colorization is posed as the propagation of colors from a retrieved artist-colored reference image to input template. The propagation problem is formulated as a color graph and matching between reference and template image. Using two separate judgment studies, we show that the coloring suggestions generated using our model are preferred over state of the art approaches for patterns colorization.

The adaptability of our approach is demonstrated using results on a variety of applications, including graphics arts, infographics and cartoon images. The polynomial-time complexity of our model makes it suitable for coloring the templates, even with a large number of distinct color groups. Figure 4.11 demonstrates some of the qualitative examples with cartoon templates having only a few colors (second row) to infographics with a large number of distinct colors (rows 3 and 4). Our model attempts to preserve the original look and feel of the artist by preserving neighborhood and compositions of colors from the reference image. Future work would further explore the adoption of the proposed approach in applications like websites and interior designs and also explore extensions of the framework for colors suggestion for a partially colored template or color suggestions to replace only particular color group.

Related Publications

1. Murtuza Bohra, Sajal Maheshwari and Vineet Gandhi. **TextureToMTF: Predicting Spatial Frequency Response In The Wild**. In *Signal Image Video Processing, Journal*, 2020.

2. Murtuza Bohra and Vineet Gandhi. **ColorArt: Suggesting Colorizations For Graphic Arts Using Optimal Color-Graph Matching**. In *Graphics Interface*, 2020.

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