

Improving the Quality of Photos and Videos for Mobile Visual Media Processing

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Abstract- For generations, people have taken pictures and videos to preserve memories for personal reflection as well as for sharing experiences with others. As a result of the convenience, ease of use, and quality improvements in smart phone cameras, many people now opt to use a smart phone instead of a digital camera for multimedia capture. Advances in photo optics and digital imaging are making it possible for smart phones to embed high-quality digital cameras with the added bonus of connectivity, value, and convenience. In addition, many smart phone devices now have both front-facing and rear-facing cameras, which further highlights the pivotal part that the smart phone camera plays in smart phone design and usage.

Keywords: Mobile Media, ACE Algorithm, Visual quality, HSV, YcrCb, Encoder-integrated denoising, Deblurring, Stabilization.

INTRODUCTION

Many smartphones can do a good job of delivering high-quality photos under normal lighting. However, the quality can noticeably deteriorate under other lighting conditions. Because of this, picture quality under low-light conditions has become one of the major evaluation criteria of smartphone cameras. Under low-light conditions, a smartphone camera picture degrades mainly because of three factors: reduced color dynamic range, distorted color distribution, and excessive sensor noise. Contrast and color enhancement and denoising can help reduce picture degradation resulting from these effects. Many features, such as auto focus, auto exposure, and different scene modes, have been developed to help

people take beautiful pictures. However, backlight images are still common because of camera quality, lack of skill in using available photography techniques, and differing photo environments. In cases where there is a strong light in the background environment, the key foreground objects, such as faces, are often under exposed, appearing too dark. Because many image editing tools and advanced cameras require user intervention to fix the problem, an automatic method of backlight compensation would be preferable. When taking image and video with a smartphone camera, many users also have a tough time holding the camera steady. Camera movement causes blurred images and shakiness within video. To correct these issues and improve the image and video quality, deblurring and video stabilization processes can be performed and optimized for the mobile platform. A set of key mobile media processing techniques can be introduced to mitigate such quality problems. The art of mobile media processing technologies lies within the capability of enhancing digital imaging sensing via post processing to deliver picture-perfect photos to nonprofessional consumers. Fig illustrates several crucial mobile visual media processing components, which we will discuss here, to achieve that goal.

PROBLEM STATEMENT

However, existing methods generally do not perform well on real mobile photos for several reasons:

- 1) Requiring additional hardware support other than the smart phone itself is impractical.
- 2) Consumer photos are usually large, greater than 8 MP. Previous methods mostly work on less than

1 MP images, which already take minutes or hours on PCs.

3) Real mobile photos have PSFs with simple, yet dense shapes because of the fast shutter speed (in milliseconds), which are difficult to be estimated accurately.

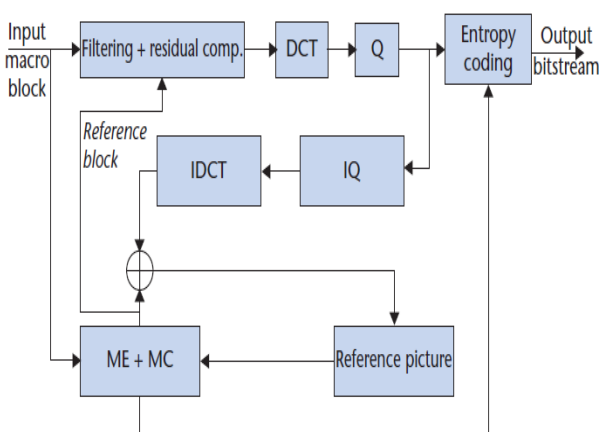
4) Normal users do not have an interest in parameter tuning, so it should be avoided.

5) Users have a low tolerance for artifacts, especially over human faces. A practical system should gracefully fail without generating excessive artifacts.

PROBLEM DEFINITION

We propose an efficient sensor-assisted image deblurring framework on mobile devices. Modern smartphones are usually equipped with many sensors. Information about the camera motion obtained from such sensors can be used to compute the PSF. By operating within a sliding observation window (usually 8 frames long), the proposed algorithm realizes one-pass video stabilization. Together with the light-weight algorithm components such as DS-ME, a simple geometric motion model with the simplified calculation, it proves to be a good candidate for real-time online video stabilization.

PROPOSED SYSTEM ARCHITECTURE



Denosing is important for improving the quality of photos and videos captured by mobile phones. Compared With digital single-lens reflex (DSLR) and point-and-shoot cameras, mobile phone cameras

usually have smaller lens and sensors, resulting in less light captured by the sensor, and therefore a smaller signal-to noise ratio and more noise. One significant denosing issue on mobile phones is the low computation and memory capacity of mobile devices compared with PCs or laptops. On the other hand, today's smartphone cameras typically output HD videos and photos with more than 5 megapixel (MP) resolution.

Although many high-performance denosing algorithms already exist, only a limited number of denosing algorithms can be feasibly implemented on smartphone platforms for real applications. For example, the bilateral denosing algorithm with a 2D implementation, which is a well-known denosing algorithm, is too slow for smartphone camera applications. For fast denosing on mobile platforms, we developed accelerated denosing algorithms for both photo and video processing. The new denosing algorithm uses a spatial recursive bilateral filter. However, the recursive filter is a causal filter, so it is not symmetric in the spatial domain. To realize symmetric filtering, we designed a two-pass algorithm, where the forward pass scans the image from the left to right, and the backward pass scans from the opposite. The result is the average of the output of the two passes.

IMPLEMENTATION

a) Algorithm:

ACE algorithm:

It has been developed that consists of eight steps:

1. An optional tiling mode is performed during which an image is partitioned into overlapping tiles and each tile is processed in parallel from steps 2 through 7.
2. The image is down sampled into a lower resolution and the scaling factor is determined based on a threshold dependent on the desired processing speed and image size.
3. The image is transformed into the HSV color space.
4. For the V channel in the HSV color space, the ACE values are calculated using local adaptation for each pixel.

5. The ACE values are extended to the full range of [0, 1], and gamma correction is applied.
6. The enhanced image is transformed back to its original color space.
7. The enhanced image is up sampled to its original resolution by utilizing the joint bilateral up sampling algorithm.
8. If the tiling mode is enabled in step 1, all enhanced tiles are fused together.

b) Picture Quality:-

However, the quality can noticeably deteriorate under other lighting conditions. Because of this, picture quality under low-light conditions has become one of the major evaluation criteria of smartphone cameras. Under low-light conditions, a smartphone camera picture degrades mainly because of three factors: reduced color dynamic range, distorted color distribution, and excessive sensor noise. Contrast and color enhancement and denoising can help reduce picture degradation resulting from these effects.

c) Color and Contrast Enhancement:-

As we mentioned earlier, a smartphone camera picture degrades under low-light conditions as a result of reduced color dynamic range, distorted color distribution, and excessive sensor noise. The human visual system is often modeled to develop color and contrast enhancement algorithms in order to compensate for the visual degradation caused by the imaging sensor. Using the HSV color space, the brightness and contrast of low-light pictures are greatly enhanced, while the color balancing is well maintained along with only processing one channel versus three channels for RGB. The tiling mode partitions the image into overlapping tiles and processes each tile in parallel.

d) Backlight:-

We propose a method of content-aware adaptive backlight image compensation that analyzes two aspects of the image. One is determining the backlight level based on a gray-world method. Another is detecting the image as a portrait image or scenic

image based on face detection. After determining the backlight level, the exposure compensation function is utilized to make a fully automatic, parameter-free adjustment. Based on the statistical analysis of large sets of backlight images, one observation is that for scenic pictures, or scenic backgrounds in portrait pictures, adjusting the V channel in HSV color space can result in more vivid colors. For face regions in portrait pictures, the HSV color space has more distortions. However, adjusting the luminance in the YCrCb color space is more natural. In this method, image compensation is jointly performed with adaptive weights on the HSV and YCrCb color spaces. The weights depend on whether the image's main scene is portrait or scenic.

e) Video denoising:-

For video denoising, previous algorithms often use a motion-compensated spatio-temporal algorithm for denoising. However, motion estimation itself is a computationally expensive process and is difficult to implement in real time for HD videos. Because videos are usually compressed and saved after capture, we developed an encoder-integrated spatio-temporal denoising algorithm⁴ in which motion estimation is realized by reusing the motion estimation results from the encoder, so there is minor computation overhead for motion estimation. Figure 5 illustrates the encoder-integrated video denoising algorithm, which is based on H.264 compression. The algorithm can be easily adapted to other block-based compression schemes, such as MPEG.

RELATED WORK

Video captured by a mobile device (such as a smartphone or tablet) often exhibits certain degree of jitter due to hand shakiness. Video stabilization aims to reduce or remove the undesirable artifact to improve video quality. There are different approaches to stabilizing a shaky mobile video, but here we will focus on digital video stabilization. Digital video stabilization relies on CPU power and video processing algorithms to realign video frames so that they appear to be visually stable. Compared with the

optical stabilization often found on high-end mobile devices, this is a low cost and flexible digital solution. However, it is still a challenge for a mobile digital stabilizer to produce stable videos comparable to the ones produced by an optical mechanism, especially on the fly. Video stabilization has been an active research topic for more than a decade. Despite its remarkable advances in performance, 9,10 the majority of the existing algorithms are designed for offline editing, which means that they often require scanning a video multiple times and are computationally demanding.

The relative motion between two consecutive frames. To maintain low complexity, diamond-search (DS) based motion estimation (ME) is applied. DS produces a motion field between each pair of consecutive frames, based on which a motion model is estimated using a RANSAC (random sample consensus) estimator. A simple four-parameter geometric model is adopted to describe the motion, which can stabilize common camera jitters resulting from zooming, rotation, and translations.

A common strategy for realtime video stabilization is to treat intentional camera motion and unwanted camera shakiness as the low- and high-frequency components in a camera trajectory, respectively, and apply low-pass filtering to obtain a smoothed trajectory. However, it is difficult to set an appropriate cut-off frequency and have a perfect low-pass filter, so residual jitters often remain in a stabilized video.

As the current frame proceeds to the next, the window moves accordingly in a sliding window fashion with a new set of calculated geometric means. These values are continuously fed into a Kalman filter to estimate the associated intentional camera motion that occurs when a frame is captured. Compared with short-term, random vibrations, intentional camera motions are more consistent and last longer and thus should have a more substantial motion accumulation over the observation period. Therefore, we compare the Kalman filter estimate against a set of preset thresholds and declare an intentional camera motion when any of its

motion parameters is significant enough. A detected intentional motion is then compensated by “subtracting” its effect from the corresponding motion model.

The main task of the view synthesis module is to take the accumulated motion models output from the motion filtering module and apply them to warp the corresponding frames. By operating within a sliding observation window (usually 8 frames long), the proposed algorithm realizes one-pass video stabilization. Together with the light-weight algorithm components such as DS-ME, a simple geometric motion model with the simplified calculation, it proves to be a good candidate for real-time online video stabilization for mobile platforms. Our experimental results show that our algorithm produces more stable video than digital stabilizer-based smartphones such as the Samsung Galaxy S4 and Apple iPhone 5. It also has more dampened vibration than the optical stabilizer based Nokia Lumia 1020 with occasionally less continuous motion in case of excessive shakiness.

CONCLUSION

Mobile media processing technologies enhances digital image sensing. Technologies within mobile media processing, including color and contrast enhancement, backlight image compensation, deblurring, denoising, and video stabilization, improves smartphone camera quality with the goal of enhancing the user’s imaging experience. Our improved ACE algorithm resulted in better overall visual quality, produced a vivid color balancing with a better reduction in the noise level. HSV and YCrCb color space adjustments resulted in optimal quality of images. Enhancements were done to the mobile visual media effectively and efficiently. Significantly improved peak to signal noise ratio, gives effective deblurring and denoising results in less than a minute and one pass video stabilization is achieved.

FURTHER SCOPE

In the future, new applications will continue to emerge for mobile devices along with new mobile devices being created. As mobile devices continue to make

hardware speed and quality improvements and new capabilities materialize, mobile media processing will also need to continue to evolve in order to effectively utilize different sources of information and improve the overall user experience.

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