Region-based Temporally Consistent Video Post-processing

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The consumption of videos is increasing dramatically in video streaming and surveillance systems. This results in mass demands for video enhancement of exposure, color, contrast, etc. In computer vision, there exist many image enhancement algorithms such as exposure correction \cite{1}, color grading \cite{2}, etc. Their enhancement effects are very impressive, and they are used in many video applications and systems such as video editing softwares like Adobe Premiere (Pr), mobile phone apps like Instagram, etc.

However, there are usually significant flickering artifacts when performing video enhancement, or image enhancement methods frame by frame for videos, due to lack of built-in temporal consistency. To remove these artifacts is non-trivial because they have a profound effect on the visual quality. In addition, in practical systems, we usually only have access to the input videos and the original enhancement videos (with flickering artifacts), and do not know or cannot have access to the enhancement algorithms. For example, 1) the enhancement algorithms of industrial softwares are not known to the public, like Pr and Instagram. 2) For embedded/hard-ware enhancement algorithms, the device may not provide interfaces to revise the algorithms for temporal consistency. 3) In practical development of a software or an application for video editing, several enhancement algorithms may be required which are all different. So designing a temporally consistent method for each separate algorithm will be time-consuming. In such cases, it is desirable to do temporally consistent enhancement as post-processing, by simply analyzing the input videos and original enhancement videos.

In this paper, we study the problem of temporally consistent video post-processing when the original input and enhancement videos are available. The goal is to keep both temporal consistency and fidelity of the output videos. 1) Temporal consistency means that for the same objects in different frames, the enhancement should be consistent. 2) Fidelity means that the final results should have similar effects as the original enhancement videos. In the other words, the output frames should be similar with the original enhancement results at non-flickering frames, and the objects in flickering frames should be adjusted referred to the corresponding objects in non-flickering frames. The challenges of the problem include: 1) the original enhancement methods are unknown and cannot be revised at all, 2) motions of videos are complicated, 3) the method should be able to remove flickering artifacts caused by different enhancement methods.

We discover experimentally the spatially consistent enhancement (SCE) prior which is valid for many leading image enhancement methods, including Pr auto color, auto level, auto contrast, exposure correction \cite{3}, and color grading \cite{1} \cite{2}. The prior is based on the observation that in a local region, image enhancement methods tend to keep the enhancement values consistent for pixels with the same rgb values. Based on this prior, we propose a region-based temporally spatially consistent adjustment method. The pipeline is shown in Fig. 1. The inputs include the original input frames and the original enhancement frames. 1) Based on the prior, each frame is segmented into several regions. 2) Corresponding regions between different frames are estimated. 3) a Markov Random Field (MRF) optimization model is used to adjust the enhancement of regions of all frames.

The SCE prior can be described that within a local region \(i\), there will exist an enhancement curve \(\alpha_i\) to reconstruct the region \(i\). \(\alpha_i\)'s independent variable is only the intensity of the pixels and the reconstruction results should be very similar with the original enhancement results \(E\), i.e.,\n\[ E_i \approx \alpha_i(I(x)), x \in i. \]
We define
\[ R_i(x) = \alpha_i(I(x)), x \in i, \]
where \(R_i\) is the reconstruction result of region \(i\) using \(\alpha_i\). Borrowing the concept of reconstruction quality from video coding, we use Peak Signal-to-Noise Ratio (PSNR) to measure the similarity between \(R_i\) and \(E_i\), i.e.,
\[ RQ_i = PSNR(R_i, E_i) \]