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Low complexity image interpolation method based on path selection

Bo Yan *, Yue Chen

School of Computer Science, Fudan University, Shanghai, China

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ABSTRACT

Image interpolation, the problem of producing a sequence of intermediate frames between two input images, is of significant interest. The application of image interpolation is numerous, including animation of still images, view interpolation and temporal interpolation. In this paper, we achieve an improved path-based interpolation method based on the original path-based framework, by introducing two innovative improvements. On one hand, we use optical flow to decide the direction of path, to constraint the path length and to maintain the global path coherency, which improves the efficiency significantly. On the other hand, we introduce the pixel interlacing model to obtain more accurate optical flows so that the accuracy of path selection will be improved a lot. Our improved path-based method performs as well as the original method in various interpolation applications in image quality and surpass the original method by a large scale in efficiency.

1. Introduction

Image interpolation addresses the problem of generating a sequence of plausible intermediate frames between two input images which can be used for a wide range of applications, such as animation of still images, view interpolation and temporal interpolation.

There have been a variety of interpolation methods before our improved path-based method, such as optical flow, warping and morphing, video processing, poison reconstruction and the original path-based framework.

For optical flow, pixels are projected from the input images using the forward and backward flows [1] and then these results are blended together to decide the final optical flow for interpolation [2]. However, this linear blending can lead to ghosting and blurring [3].

There exist a variety of techniques to warp the input images to create intermediate frames. However, most of these methods focus on view interpolation. What is more, morphing [4] usually requires user-specified correspondences [5,6].

As for the method of video processing [7], the inputs are the images or videos and the output is also an edited or composited image or video respectively. The concept of having transition points, which is also involved in the original path-based method, gets implemented here [8].

In the algorithm of poisson reconstruction [9], gradients are copied from the original images and pixel values are reconstructed using the gradients [10]. However, the problem is that the gradient fields in the input images/videos remain static [11–13].

The original path-based method [14] is based on the intuitive idea that a given pixel in the interpolated frames traces out a path in the source images. It simply moves and copies pixel values from the input images along the computed path. A key innovation is to allow arbitrary transition points, which preserves the frequency content of the originals without ghosting or blurring, and maintains temporal coherence. Most importantly, the framework makes occlusion handling [15,16] particularly simple.

In this paper, we propose two innovative improvements based on the original path-based interpolation method.

As the first improvement, optical flow [17–19] is heavily involved in the improved method. We obtain the relatively accurate optical flow with the classic iterative Lucas Kanade algorithm [20,21] and then use it to decide the direction of path, to downsize the path set and to maintain the global path coherency in a much more efficient way.

Sub-pixel strategy is introduced as the other important improvement. We construct sub-images of the original inputs and do the optical flow computation at sub-image level which is more accurate [21]. And then we propagate it to the corresponding pixel in the original image with one (out of the three neighboring pixels) pixel adjustment.

As a result of these two improvements, we are able to achieve quite good interpolation results in the following various applications, with a much less cost of time and space.

Animating two still images is not an easy problem. With the improved path-based interpolation framework, we are able to capture the local deformations to produce a plausible interpolation of the input images, which looks natural.

For low frame rate videos, up-sampling is usually used to produce a visually more pleasing sequence where the scene varies

* Corresponding author.
E-mail address: byan@fudan.edu.cn (B. Yan).

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slowly and smoothly. Our new method can produce a full sequence by interpolating between only two successive video frames.

View interpolation [22] deals with interpolation of input images captured with different camera locations. Not only do we preserve the spatial frequencies of the input images, but we can also handle comparatively larger disparity with good occlusion handling with our improved new method.

Though the original path-based method can also produce interpolation results of almost the same quality in these applications, our improved method surpass the original one in efficiency by a large scale.

Our paper is organized as follows. In Section 2, we provide a brief summary of the original path-based method, based on which we will construct our improved new method. Then two innovative improvements will be introduced in Section 3, including use of Optical Flow and implementation of Sub-pixel strategy. In Section 4, we compare the algorithm complexity of our improved method with the original path-based framework in detail and show that our new method consumes much less space and time. Experimental results are presented in Section 5, with our new method applied in both view interpolation of a rotating mobile and animation of the little girl. Finally, we make the overall conclusion.

2. Conventional methods

The path-based method [14] is based on the simple and intuitive notion that a given pixel in the interpolated frames will trace out a path in the input images. In order to implement the path-based method, firstly path is computed hierarchically. A finite set of all possible discrete paths, denoted by L, is to be constructed.

Fig. 1(a) shows two images A and B. Image B is a shifted version of image A. The path (Fig. 1(b)) starts at p in A, moves through the pixels in A to p_A, makes a transition to p_B in B and then moves through pixels in B to reach p. At the transition point, the intensity values in the two images match, and hence there exists a visually plausible interpolation. The interpolated values at p can then be found by moving the pixels along this path and copying their values at p. The transition point can be arbitrary and asymmetric, whose major contribution is to greatly simplify occlusion handling [14].

2.1. Optimization for paths: computing transition point

Once the paths are defined, the best path for each pixel will be selected by minimizing the energy function, which is combined with the correspondence term and coherency term [14].

Correspondence: For a path ω at p, define its cost as $C(p,\omega)$, which is decided by the weighted sum of color matching and gradient matching terms [2] of the transition points.

$$\|\nabla A(p_A) - \nabla B(p_B)\|^2 + 0.5\|A(p_A) - B(p_B)\|^2 \quad (1)$$

where ∇represents the gradients in the image domain [14].

Coherency: It is expected that neighboring pixels have similar motions and hence similar paths. $V(\omega,\omega_N)$ represents the pair-wise smoothness cost between the respective paths ω and ω_N at the two neighboring pixels p and p_N (refers to the 4-neighborhood of p). Every path has a length $d = |m_A + m_B|$ and direction $\underset{A}{\hat{v}} = \underset{B}{\hat{v}}$ associated with it. $V(\omega,\omega_N)$ is defined as

$$V(\omega,\omega_N) = \min(|d \underset{A}{\hat{v}} - d_N \underset{A_N}{\hat{v}}|, \delta) \quad (2)$$

where δ is a discontinuity preserving threshold [14].

Global energy function: A global energy function E is defined for interpolation, which needs to be minimized. E is the sum of the path cost C (Eq. (1)) and the coherency cost V (Eq. (2)) for all the pixels in the image. Thus

$$E = \sum_p C(p,\omega) + \lambda \sum_p \sum_{p_N} V(\omega,\omega_N) \quad (3)$$

where λ is the regularization parameter and controls the contribution of the coherency cost relative to the path cost. Any suitable global optimization technique from the minimization literature can be used to minimize the energy function in Eq. (3), for example, a fast iterative expansion algorithm based on graph-cuts [23,16].

2.2. Occlusion handling

A plausible path is found even in the occluded regions [24,15]. The path-based method can detect the occlusions as a simple post-processing step, and correct the paths accordingly.

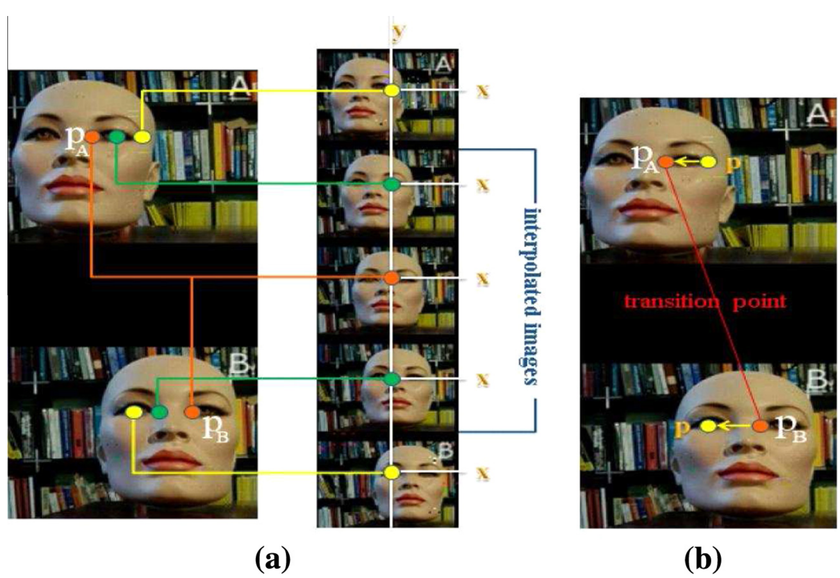

Fig. 1. Path-based framework. (a) Path-based interpolation. (b) Corresponding path.