# Motion Regularization for Matting Motion Blurred Objects

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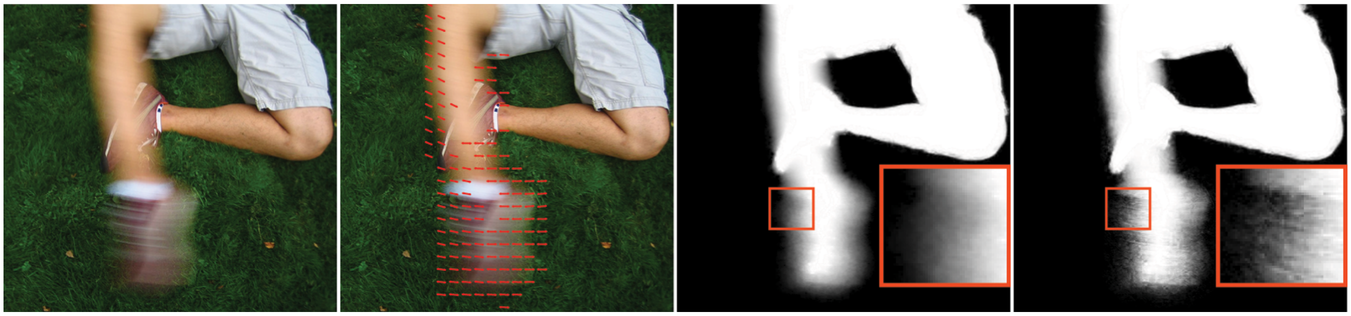

Input image Estimated motion Matte with motion regularization Matte without motion regularization

Figure 1: Example showing our estimated motion and its ability to improve the alpha matte of motion blurred objects.

## 1 Introduction

We address the problem of matting motion blurred objects from a single image. Existing single-image matting methods are designed to extract static objects that have fractional pixel occupancy. This arises because the real scene object has a finer resolution than the discrete image pixel and therefore only occupies a portion of the pixel. For a motion blurred object, however, fractional pixel occupancy is attributed almost entirely to the object's motion over the exposure time. While conventional matting techniques can be used to matte motion blurred object, they are not formulated in a manner that considers the object's local motion. Not surprisingly, these existing techniques often produce less than satisfactory results when used to matte motion blurred objects, especially when not on solid colored background.

In this work, we show how to obtain better alpha mattes by imposing a simple regularization in the matting formulation to account for the object's motion. In addition, we introduce a method for estimating the local object motion based on local gradient statistics from the original image. For completeness sake, we also discuss how user markup can be used to denote the local direction in lieu of motion estimation. As far as we are aware, this work serves as the first attempt to explicitly modify the matting procedure to deal with motion blurred objects.

## 2 Our Approach

Our approach works by first determining the local motion of the foreground object. Instead of assigning a single motion vector per pixel, we assign a weight, $w_d$, for each of discrete angular directions $d$, where $d \in \{0, \frac{\pi}{8}, \frac{2\pi}{8}, \ldots, \frac{6\pi}{8}, \frac{7\pi}{8}\}$. These motion direction weights can be estimated directly from the input image by examining local gradient properties in the blurred regions. In particular, we can compute the local gradient distributions within a sliding window along the eight different radial directions. For each of these eight directions we analyze the shape of the gradient distributions by fitting a Laplacian to each directions distribution. The idea is that there are fewer image gradients in the direction of the motion due to blurring, thus distributions with more gradients about 0 represent the underlying local motion. The weight $w_d$ is computed as the area under the estimated Lalpacian for each direction $d$. Similar analysis of the gradient distribution has been exploited for blur detection [Levin 2006] and blur classification [Liu et al. 2008], but not yet for estimating local blur direction.

We also allow the user to markup local motion by drawing scribbles on top of the image in the direction of the motion. Based on the user provided directions, we obtain a set of sparse local motion directions along the scribbles. These sparse direction labels can be propagated to other unmarked via a diffusion process. To compute the discrete direction weights, the user supplied motion is projected to the two closest of the eight discrete directions. For regions with no motion, the user can simply draw a "dot" meaning that the regularization weights at that local region is zero in all directions.

Based on the local motion, we add the following regularization term to constrain each alpha value per-pixel, defined as:

$$R_m(\alpha) = \sum_{d=1}^{8} w_d (\nabla_d \alpha)^T (\nabla_d \alpha), \qquad (1)$$

where $\nabla_d \alpha$ is the $\alpha$-gradient in direction $d$, $w_d$ is the weight of regularization for direction $d$. This constraint suppresses the matte gradient according to the local motion direction. If an image region does not contain motion blur, $w_d$ will be similar in all directions and thus have little effect on the alpha matte's solution.

We have compared the results obtained by adding our regularization into two matting approaches: closed-form matting [Levin et al. 2006] and robust-matting [Wang and Cohen 2007]. We found that results are noticeably improved when using our regularization scheme. Moreover, we found that our automatic motion estimation is effective on the vast majority of input images. Future work is to incorporate this same constraint into other conventional matting procedures and to extend this to matting of video objects.

## References


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