High Resolution Framework For Motion Layer Decomposition

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***Abstract*--**we consider the problem of decomposing a video sequence into a superposition of (a given number of) moving layers. For this problem, we propose an energy minimization approach based on the coding cost. Our contributions affect both the model (what is minimized) and the algorithmic side (how it is minimized). The novelty of the coding-cost model is the inclusion of a refined model of the image formation process, known as super resolution. This accounts for camera blur and area averaging arising in a physically plausible image formation process. It allows us to extract sharp high-resolution layers from the video sequence. The algorithmic framework is based on an alternating minimization scheme and includes the following innovations. 1) A video labeling, we optimize the layer domains. This allows regularizing the shapes of the layers and a very elegant handling of occlusions. 2) We present an efficient parallel algorithm for extracting super-resolved layers based on TV filtering.

Keywords: *Image decomposition, image motion analysis, optimization, video signal processing*

I. INTRODUCTION

The decomposition of videos into a superposition of moving layers is of central importance to scene interpretation, video coding, and movie compression. In this paper we present an energy minimization framework that allows us to partition a given video into a set of super-resolved moving layers. Fig. 1 shows an example result of this algorithm. Given an input image sequence, the algorithm reconstructs moving layers corresponding to the foreground tree and the background in a higher resolution than the individual input frames. That is, we show that, by more accurately modeling the image formation process, and we obtain sharp fine-detailed layer images, whereas previous methods produced blurry ones. Moreover, we propose a graph-cut-based algorithm to estimate layer domains, where we show how to derive appropriate expansion moves in order to efficiently perform the layer partitioning.

A. Related Work

Motion layer decomposition builds on a rich literature in motion analysis. We briefly sketch the main lines of research to organize the abundance of existing approaches.

1) Motion Estimation: Given a sequence of consecutive frames, *motion estimation* aims at computing for each frame of the sequence a velocity vector associated with each point relating it to a corresponding point in the subsequent frame. Optionally, one can identify points that are occluded in the subsequent frame, but this is rarely done. The two major approaches to motion estimation are the local and global ones. Local approaches determine a single parameter vector to describe the motion in a fixed usually rectangular sub region of the image. By using overlapping regions, each pixel is assigned its own velocity. In contrast, global approaches determine a single velocity field for each frame, taking into account the entire image information at once [16]. These methods regularize the gradient of the velocity field in a variation framework. State-of-the-art methods use robust M-estimators which is a trend that arose earlier for local approaches with regularizes adapted to rigid body motion and strong contrast edges, these global approaches were shown to provide some of the most accurate optic-flow fields [38] on established benchmarks. The algorithms are by now rather mature, providing high-quality motion fields for 640 480 images at more than 60 frames per second.

2) Motion Segmentation: By *motion segmentation*, we mean the estimation of motion and the determination of the *boundaries* of differently moving objects. Respective algorithms have been developed in a spatially discrete MRF formulation or in a spatially continuous level-set formulation. Motion segmentation is generally considered a *chicken-and-egg problem*; it is easy to determine an accurate segmentation for a given motion field or *vice versa* to determine accurate motion models for a given segmentation. To solve for both at once has however proven to be a very difficult problem. State-of-the-art methods solve this by minimizing a single energy functional via alternating optimization schemes. Precursors include methods based on pixel-flipping thresholding soft decisions. Since both motion estimation and segmentation are based on intensity comparisons of consecutive frames only, they typically suffer from two limitations. First, they do not exploit *long-range* temporal consistency, i.e., the fact that the *same* intensity layer is deformed over the entire sequence is not taken into account. Second, they do not account for the fact that pixels may be occluded in certain frames and reappear at later stages.

3) Layered Motion Segmentation: Approaches for *layered motion segmentation* augment the framework of motion segmentation by occlusion reasoning. Dupont introduce a sophisticated occlusion model into traditional motion segmentation and minimize it using graph cuts and expansions moves. Xiao and Shah compare each frame in the sequence to a reference frame. They introduce an occlusion order constraint that approximately holds for short sequences and, after a sophisticated initialization stage, minimize using graph cuts on three-state pixel graphs.Although these methods improve over traditional motion segmentation, they