Interactive High-Quality Green-Screen Keying via Color Unmixing

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Due to the widespread use of compositing in contemporary feature films, green-screen keying has become an essential part of post-production workflows. To comply with the ever-increasing quality requirements of the industry, specialized compositing artists spend countless hours using multiple commercial software tools, while eventually having to resort to manual painting because of the many shortcomings of these tools. Due to the sheer amount of manual labor involved in the process, new green-screen keying approaches that produce better keying results with less user interaction are welcome additions to the compositing artist’s arsenal. We found that — contrary to the common belief in the research community — production-quality green-screen keying is still an unresolved problem with its unique challenges. In this paper, we propose a novel green-screen keying method utilizing a new energy minimization-based color unmixing algorithm. We present comprehensive comparisons with commercial software packages and relevant methods in literature, which show that the quality of our results is superior to any other currently available green-screen keying solution. Importantly, using the proposed method, these high-quality results can be generated using only one-tenth of the manual editing time that a professional compositing artist requires to process the same content having all previous state-of-the-art tools at his disposal.

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1. INTRODUCTION

As computer-generated imagery became convincingly realistic, compositing synthetic backgrounds and objects into live-action shots became a common practice in feature film production. The widespread use of composite shots over pure live-action is often motivated by the higher degree of artistic control over the final shot, as well as the potential to reduce production costs. Usually, the first step in a digital compositing workflow is the performance capture of the actors and various other live-action elements against a controlled — typically green — background. Then, in post-production, one needs to obtain RGBA foreground layers corresponding to the live-action elements that ideally carry no trace of the green-screen background. This process is often referred to as keying. Finally, one or more foreground layers are combined with the desired computer generated scene elements to obtain the composite shot.

Keying is a crucial intermediate step in any compositing workflow, as later in the workflow seamless blending between the synthetic and live-action elements is highly dependent on obtaining high-quality keying results. The keying process usually starts with the compositing artist obtaining preliminary foreground layers by using multiple software tools in concert, some of the most popular ones being The Foundry’s Keylight, Nuke’s Image Based Keyer (IBK) and Red Giant’s Primatte. Often, this first step already involves significant manual labor in the form of parameter tweaking or drawing roto-masks. Ideally, the preliminary foreground layers would already be sufficiently high quality so that one can move on to consecutive steps in the compositing pipeline. Unfortunately, this is rarely the case in practice and the imperfections in the foreground layer still have to be corrected by manual painting before moving forward. In professional circles, the combined manual work required for both obtaining preliminary keying results and later their refinement by manual painting is recognized as a significant bottleneck in post-production.

While the shortcomings of the currently available keying tools are well-known in the industry, the focus of relevant academic research is almost exclusively on the related natural matting problem. An important distinction between natural matting and keying is in their end goals. While the end result of the keying process is one or more RGBA foreground layers with both correct colors and precise alpha maps, natural matting methods very often solely focus on the extraction of alpha maps. In fact, the widely used natural matting benchmark [Rhemann et al. 2009] evaluates perfor-
pipeline can be seen in Figure 1. For a different query frame (b), the global color model is refined into local color models (c) (Section 4.2) which are utilized for extracting multiple color layers via color unmixing (d) (Section 3). A subset of layers is then combined to get the final keying result (e). The layers can be used for compositing as well as color editing (f).

Fig. 1. Major steps of our method. First, parameters of a global color model are obtained from a key frame via a simple scribble interface (a) (Section 4.1). For a different query frame (b), the global color model is refined into local color models (c) (Section 4.2) which are utilized for extracting multiple color layers via color unmixing (d) (Section 3). A subset of layers is then combined to get the final keying result (e). The layers can be used for compositing as well as color editing (f).

Fig. 2. High-quality alpha maps do not necessarily result in high-quality foreground layers for keying. While both alpha maps capture the intricate details of the actor’s hair, the foreground layer computed by comprehensive sampling [Shahrian et al. 2013] (left) has noticeable color artifacts, while the foreground layer generated by our method has the correct colors.

2. RELATED WORK

Green/Blue screen keying has received little attention in the research community. In order to solve the under-constrained keying problem, Smith and Blinn [1996] and Grundhöfer et al. [2010] proposed methods that capture the same foreground with two different backgrounds, providing additional equations to the linear system. A radiometric compensation method was proposed by Grundhöfer and Bimber [2008] in order to solve the problem also against arbitrary backgrounds. However, these methods require specialized setups which limit their practical use. Our method, in comparison, requires a regular video stream shot against only a single background. Thus, its practical use is similar to commercial keying software such as Keylight, IBK or Primatte.

Commercial keying tools often use chroma-based or luma-based algorithms. In feature film post-production, these tools are operated by specialized compositing artists for obtaining a preliminary keying result. Preliminary results often require further manual processing, because, despite the parameter tweaking and the usage of roto-masks, they often fall short of the quality level demanded in professional productions. Figure 10 shows various examples where a trained artist simply cannot achieve production-level quality due to the various limitations of currently available tools. Since such keying results are unacceptable in professional production, the preliminary keying results undergo an extremely tedious manual painting process, where each pixel in the video is cleaned off of keying errors by hand.

Natural alpha matting methods are generally classified as sampling- or propagation-based. Local propagation-based methods [Sun et al. 2004; Levin et al. 2008a; Levin et al. 2008b; Singaraju et al. 2009] typically rely on the assumption that there is a smooth transition between foreground and background layers and solve the matting problem by identifying these transitions. The matting Laplacian introduced by Levin et al. [2008a] has been employed or improved by numerous methods [Singaraju et al. 2009; Gastal and Oliveira 2010] and applied to multiple layers [Singaraju and Vidal 2011]. Non-local propagation-based methods [Lee and Wu 2011; He et al. 2013; Shi et al. 2013; Chen et al. 2013] make use of the non-local principle introduced by Lee and Wu [2011].

Sampling-based methods can be divided into parametric and non-parametric ones. Non-parametric sampling-based methods [He et al. 2011; Shahrian and Rajan 2012; Shahrian et al. 2013; Johnson et al. 2014] propose strategies to effectively select many samples from foreground and background, and conduct matting by finding foreground-background sample pairs that can represent an observed mixed pixel by their weighted sum. Parametric sampling-based methods [Ruzon and Tomasi 2000; Chuang et al. 2001; Wang...
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3. COLOR UNMIXING

The central component of our method is an energy minimization framework, where the color \( c \) of a pixel is hypothesized to be a mixture of a number of underlying colors \( u_i \). The problem solved by our framework is the estimation of the underlying colors and their mixing ratios \( (\alpha_i) \), such that the linear combination of the underlying colors weighted by corresponding mixing ratios gives the original pixel color \( c \). To that end, we build and utilize a parametric representation of all the colors present in the scene which we refer simply as the color model. The color model comprises \( N \) distributions in RGB space. Both the number and the parameters of these distributions are obtained through user interaction. We assume that the color model for an input scene is already known to us throughout this section, and rather focus on the formulation and efficient solution of the color unmixing problem. A detailed discussion on building the color model of an input scene will follow in Section 4.

We start formulating our color unmixing framework by defining three basic constraints that each pixel should satisfy: (i) an alpha constraint which states that the alpha values \( \alpha_i \) should sum up to unity, (ii) a color constraint which states that we should obtain the original color \( c \) of the pixel when we mix the underlying colors \( u_i \) using the corresponding alpha values, and (iii) a box constraint that limits the space of possible alpha and color values. Formally, we express these constraints as follows:

\[
\sum_i \alpha_i = 1, \quad \sum_i \alpha_i u_i = c, \quad \text{and} \quad \alpha_i, u_i \in [0, 1].
\]

The cost associated with the occurrence of an underlying color \( u_i \) in a mixture \( c \) is defined by how well it fits to the corresponding distribution \( N(\mu_i, \Sigma_i) \), where \( \mu \) and \( \Sigma \) denote the mean vector and the covariance matrix, and \( N \) is the normal distribution. We use the squared Mahalanobis distance as our measure of goodness of fit:

\[
D_i(u) = (u - \mu_i)^T \Sigma_i^{-1} (u - \mu_i),
\]

and define our energy function \( F \) of selecting a particular mixture of \( N \) underlying colors accordingly as follows:

\[
F = \sum_i \alpha_i D_i (u_i).
\]

This energy function favors layer colors that have the best likelihoods according to their corresponding color distributions, especially for the layers with higher alpha values. Minimization of this energy subjected to the color constraint makes sure that the resultant layers successfully represent the color mixture that formed the observed pixel color.

While the energy function \( F \) may seem straightforward, we found that its minimization is non-trivial. Since the energy function \( F \) and the color constraint defined in Equation 1 are nonlinear, we are faced with a nonlinearly constrained nonlinear optimization problem. Specifically, the color constraint in Equation 1 constrains a single alpha value for three underlying color channels at once. This makes our energy function \( F \) prone to get stuck in local minima within the vicinity of the initial point if the constraints are enforced from the start. What we need instead is an algorithm that strictly enforces the constraints only after allowing to find some reasonable alpha and color values first. To that end, we utilize the method referred as the original method of multipliers [Bertsekas 1982]. We express the deviation from the constraints in Equation 1 as:

\[
\mathcal{G}_\alpha = \left( \sum_i \alpha_i - 1 \right)^2 \quad \text{and} \quad \mathcal{G}_u = \left( \sum_i (\alpha_i u_i - c) \right)^2,
\]

where \( (\cdot)^2 \) denotes the elementwise squaring operation. This leads to the constraint vector \( \mathcal{G} = \left[ \mathcal{G}_\alpha^T, \mathcal{G}_u^T \right]^T \). The vector containing the
variables $x$ that are the arguments of the optimization is:

$$
\mathbf{x} = [\alpha_1 \ldots \alpha_N \, \mathbf{u}_1^T \ldots \mathbf{u}_N^T]^T.
$$

Note that $\mathbf{x}$ contains the variables for unmixing a single pixel. The optimization is performed independently for every pixel, where for each pixel we solve for both the alpha values and the underlying colors simultaneously. Further details of our optimization procedure are discussed in Section 3.1.

Once $\mathbf{x}$ is computed for all pixels of an input video frame, for each pixel we obtain $N$ underlying colors and corresponding alpha values. If we visualize the $i^{th}$ underlying color for all pixels of the video frame with their alpha values, we obtain the RGBA layer corresponding to the distribution $\mathcal{N}(\mu_i, \Sigma_i)$. Green-screen keying can be seen as a special case where we remove the RGBA layer corresponding to the green-screen background.

In contrast to our color unmixing method, related works on parametric natural matting use Bayesian formulations with either local [Ruzon and Tomasi 2000; Chuang et al. 2001] or global models [Tai et al. 2007]. Local methods solve for alpha values first and then estimate colors. On the other hand, Tai et al. [2007] iteratively estimates the alpha values and colors for all pixels of an input image, which makes it feasible for only low-resolution images. In contrast, our formulation is easily parallelizable as each pixel is treated independently, and thus, our method easily scales to HD resolutions and beyond.

Sampling-based natural matting methods such as comprehensive sampling [Shahrian et al. 2013] take alternate approaches to compute foreground layer colors where they try all the possible background-foreground color pairs to get the best match from a limited set of color samples. Certain priors commonly utilized by these methods, such as matte sparsity [Wang and Cohen 2007; Gastal and Oliveira 2010], are often violated in green-screen keying due to color spill.

On the other hand, commercial chroma-based keying tools simply suppress the background green-screen color everywhere in the frame, which often distorts the colors of the foreground objects especially if they are similar to the color of the green-screen background. Around intricate object boundaries or motion blur, they extend the foreground region without actually unmixing the colors, and as a result they leave an unnatural halo around difficult regions.

To summarize, the natural matting methods in the literature, as well as commercial keying tools, fail to achieve production-level quality in green-screen keying and as a result they leave an unnatural halo around difficult regions. We call the subset of distributions that participate to the green-screen background.

In the next section, we continue with a discussion of the two-step user interaction process and other details of the color model, which we treated as a black box so far.

### 3.1 Minimization of the color unmixing energy

The color unmixing energy introduced in Equation 3 is optimized using Algorithm 1. The function minimized in line 1 is composed of the original energy function and the deviations from the constraints. Minimization at this step is done using the nonlinear conjugate gradient method that takes $\mathbf{x}_k$ as the initial value. The step size of the nonlinear conjugate gradient at each iteration is determined by a line search in the direction determined via the Polak–Ribiére formula. The box constraints are enforced at each iteration of the nonlinear conjugate gradient method by clipping the elements to be in the range $[0, 1]$ and setting the gradients of the elements at the boundaries 0 and 1 to zero if they are positive or negative, respectively. As the parameters $\rho_k$ and $\lambda_k$ increase at each iteration of Algorithm 1 (lines 2 and 3), the energy $F(x)$ is minimized while allowing smaller and smaller deviations from the alpha and color constraints in line 1. $\lambda_k$ punishes deviation from individual constraints, while $\rho_k$ increases the constraint enforcement globally. The input to Algorithm 1, initial values for $\alpha_i$ and $\mathbf{u}_i$, are taken as:

$$
\alpha_i = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \quad \mathbf{u}_i = \begin{cases} \mathbf{e} & \text{if } i = j \\ \mu_i & \text{otherwise} \end{cases},
$$

where $j = \arg \min_i \mathcal{D}_i(c)$, i.e. only the alpha value corresponding to the most likely distribution in the color model is initialized to be 1. Note that the optimization procedure we described is independent for each pixel in an image.

#### Algorithm 1 The Original Method of Multipliers

**Input:** $\mathbf{x}_0$

**Define:** $k = 0, \rho_0 = 0.1, \lambda_0 = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}$, $\beta = 10$, $\gamma = 0.25$, $\epsilon > 0$

1. $\mathbf{x}_{k+1} = \arg \min_x (F(x) + \lambda_k^T \mathbf{G}(x) + \frac{1}{2} \rho_k \| \mathbf{G}(x) \|^2)$
2. $\lambda_{k+1} = \lambda_k + \rho_k \mathbf{G}(\mathbf{x}_{k+1})$
3. $\rho_{k+1} = \begin{cases} \beta \rho_k & \text{if } \| \mathbf{G}(\mathbf{x}_{k+1}) \| > \gamma \| \mathbf{G}(\mathbf{x}_k) \| \\ \rho_k & \text{otherwise} \end{cases}$
4. if $\| \mathbf{x}_{k+1} - \mathbf{x}_k \| > \epsilon$ then
5. $k \leftarrow k + 1$
6. go to Step 1
7. else
8. return $\mathbf{x}_{k+1}$

### 4. BUILDING THE COLOR MODEL

The energy function $F$ we defined in Equation 3 requires a parametric representation of the colors that formed the color mixture, which we refer as the color model. A set of distributions is obtained in the first step of the user interaction of our method. The resulting global color model (Section 4.1) is assumed to be able to represent the whole image. The global color model is locally overcomplete since very often each pixel color $\mathbf{e}$ is a mixture of only a subset of the scene colors. We call the subset of distributions that participate in the color mixture in a certain region of an image as the active color distributions. In Section 4.2, we refine the global color model such that each pixel is associated only with its active color distributions. This refinement process is performed automatically by utilizing a Markov Random Field optimization, but we also allow the user to edit the resulting local color models in an optional second user interaction step.
In comparison, commercial green-screen matting software packages offer a multitude of interaction modes ranging from background/foreground color selection to rotoscoping interfaces. They also typically offer user control over various parameters that control the amount of chroma suppression, matte blurring or matte bleed. Although this high level of control allows compositing artists to fine-tune keying results, it also makes the process highly time-consuming. On the other hand, natural matting methods typically require trimaps (dense approximate segmentation of the image into foreground, background and unknown regions), which are in practice extremely tedious to generate especially for video sequences, and have been criticized for influencing the result only indirectly [Levin et al. 2008a]. Some natural matting methods instead rely on the user drawing a sparse set of scribbles, which often results in a more convenient user interaction.

The goal of the user interaction in our method is to extract the information we need to build the color model as intuitively and efficiently as possible. Consecutively, instead of relying on complex user interactions like commercial keying tools or requiring prohibitively time-consuming inputs like a trimap, we utilize a two-step interaction that involves drawing a small number of scribbles (typically 7-8) and an optional pointing-and-clicking step.

### 4.1 Global Color Model

The user interaction typically starts with the user loading the first frame of an input video using the interface of our method. The goal of the first user interaction step is building the global color model, which is achieved by the user drawing a scribble over each of the dominant scene colors. The number of the scribbles, $N$, and hence the number of dominant scene colors, is determined by the user depending on the scene. For example, in Figure 8-b (Our result, input) each different color on the person’s wig is selected separately as a dominant color, whereas in Figure 8-a (Our result, input), the actor’s natural hair color is marked as a single dominant color. Each scribble identifying a dominant color is used to extract the parameters of a distinct normal distribution. The mean and covariance of each distribution are computed simply from the pixels underneath the corresponding scribbles (note that we do not use any scribble propagation). Importantly, the results of our color unmixing method are not sensitive to the exact placement, size or shape of the scribbles (Figure 3). This property is very useful in practice, as high-quality results can be obtained quickly from roughly drawn scribbles. Additionally, once the global color model is created for a single frame, it can typically be used for the remaining frames of the shot assuming the dominant colors do not change significantly. In fact, the global color models of all video results presented in this work were generated from a single frame (typically the first frame). The motivation behind this first user interaction step is utilizing the inherently good cognitive skills of the users for clustering colors. These cognitive skills are especially helpful in dealing with specific situations such as the presence of strong color spill. Figure 10-d (Original) shows an example where the color of the actor’s robe is affected by the indirect illumination from the green-screen, except for only very few small regions. In this case, recognizing the color spill and selecting unaffected regions as a dominant color are trivial for a human user while the same tasks are extremely difficult for an automatic color clustering algorithm. In fact, although we experimented with methods for automatically building the global color model (see Section 5.3), we found that in most practical cases user interaction would be necessary, and, therefore, favored our current interactive approach. The ability to select the dominant colors also gives the user artistic control over the color composition of the resulting RGBA layers, which is especially useful for compositing artists.

### 4.2 Local Color Model

One shortcoming of the global color model is the assumption that the color of each pixel of the input video is a mixture of $N$ underlying colors from the $N$ distributions that make up the color model. However, in practice, this assumption is almost always incorrect. For example, in the original image in Figure 4, skin tones are only present in a small region near the actor’s face and neck. If we solely rely on the global color model, we would have to use the distribution corresponding to the skin tones for unmixing pixels in completely unrelated image regions, such as the far edges of the green-screen background. This may cause the color unmixing to hallucinate non-existent colors with small alpha values in such regions. Thus, we perform a Markov Random Field (MRF)-based optimization procedure over superpixels to estimate the active subset of color distributions for different regions in an image.

In the local color model computation step, local color distributions are formed for every frame, and we propagate the local color model of each frame to the following frame through simple superpixel matching. For every superpixel in a new frame, we find a corresponding superpixel in the previous frame in a small spatial neighborhood with the closest mean color. The active distributions of a superpixel in the new frame are defined as the active distributions of its match in the previous frame. An example local color models, a typical user edit, and propagation to consecutive frames are illustrated in Figure 4.

The local color model computation step can loosely be related to the sample selection process employed by sampling-based natural matting methods such as shared sampling [Gastal and Oliveira 2010], where the goal is also to find the best-fitting distributions for every pixel. However, their brute-force approach is fundamentally different from our MRF optimization process.

Several natural matting methods such as comprehensive sampling [Shahrian et al. 2013] utilize localized color models. While we select a subset of the global color model as the local color model, comprehensive sampling estimates a set of normal distributions from the closeby foreground and background regions for a mixed-color pixel. Although this approach provides some robustness against complex backgrounds, it has several shortcomings in the green-screen keying case. Under heavy color spill, estimating distributions locally is typically insufficient since the pure-color re-
regions may occur in a very limited part of the image and can not be integrated into the local models. It also inherently increases the number of necessary distributions to represent the image, making the direct user-edits inconvenient if not impossible. The resulting localized layers then require additional temporal coherency steps to be applied to image sequences, since spatially they are expected to change from frame to frame. Hence, we found our definition of local color models as a subset of a global model to be practically well-fitting to our target application of green-screen keying.

4.2.1 Local Color Model Estimation. We represent the active distributions of a pixel as a binary vector \( A \) of length \( N \), and define the cost of activating a subset of distributions for a pixel as the sum of two terms. The first term is the minimum energy defined in Equation 3 when the subset of distributions is fed to the energy minimization algorithm detailed in Section 3, denoted by \( \mathcal{F}_A \). The intuition here is that if the optimization is conducted with distributions that fail to effectively represent an observed color, the minimized energy will still be high. The second term \( G_A = \| A \| \), \( \| \cdot \| \) representing the Euclidean norm, is added to this cost in order to favor fewer active colors for each pixel. Following these definitions, the unary potentials are defined as:

\[
\mathcal{U}_A = \mathcal{F}_A + \delta G_A,
\]

where \( \delta \) is a user specified weight parameter typically in the range \([5, 10]\). The binary potentials between neighboring pixels are defined as:

\[
\mathcal{B}_{p,q} = \| A_p - A_q \| e^{-\|p-q\|/\sigma},
\]

The energy function we want to minimize in order to determine active color distributions is:

\[
\mathcal{E} = \arg\min_{\mathcal{A}} \sum_p \mathcal{U}_A + \sigma \sum_{(p,q)\in\Omega} \mathcal{B}_{p,q},
\]

where \( \sigma \) is the smoothness parameter, typically selected in the range \([0.01, 0.05]\) and \( \Omega \) is the set of 8-connected pixels.

The problem we defined in this section is analogous to multi-label segmentation if we treat each possible subset of active color distributions as a label. The minimization of the energy defined in Equation 9 is NP-hard [Boykov et al. 2001]. We approximate the global solution of this energy minimization using \( \alpha - \beta \) swap algorithm presented in [Boykov et al. 2001], using the publicly available implementation by the authors [Kolmogorov and Zabih 2004; Boykov and Kolmogorov 2004].

Although we presented our energy formulation in this section at the pixel level, computing \( \mathcal{F}_A \) for every subset and every pixel can be time-consuming especially if \( N \) is high. In order to make the local color model estimation more efficient, we instead construct the random field using SLIC superpixels [Achanta et al. 2012] (typically 10k superpixels for a 1080p frame). This allows a user controllable trade-off between quality and computational efficiency.

5. RESULTS

Our method is suitable for parallel computation as discussed in Section 3. For a 1080p frame, our current C++/CUDA implementation typically requires 10 seconds for local color estimation (assuming 8 dominant colors), another second to propagate the local color model to the following frame, and approximately 3 seconds for color unmixing. Thus, at this resolution, the total computation time for a still image is 13 seconds, which drops to 4 seconds per frame for image sequences.

In this section, we evaluate our method and present results for various applications. In the absence of a comprehensive ground truth dataset of green-screen content, in our experiments, we utilize computer generated ground truth, as well as keying results generated by a paid independent professional compositing artist. In contrast, all user interaction with our method was performed by people with no prior experience in digital keying or compositing.

5.1 Statistical Validation

In this experiment, we test how distinct two colors have to be for our unmixing algorithm to work successfully. To that end, we generated a total of 480 images, each obtained overlaying 2 or 3 images created by randomly sampling from one of 720 different normal distributions with varying mean vectors and covariance matrices. The images were overlayed via a known alpha matte, which served also as the ground truth. Examples of these test images are shown in Figure 5. For the distinctiveness measure, we use Bhattacharyya distance\(^1\) that models the amount of overlap between two normal distributions. Figure 5 shows that our method can successfully unmix colors up to a point when they become hard to distinguish by a human observer.

\(^1\) Bhattacharyya distance between \( N(\mu_i, \Sigma_i) \) and \( N(\mu_j, \Sigma_j) \) is defined as:

\[
\frac{1}{2} (\mu_i - \mu_j)^T \Sigma^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left( \frac{\det(\Sigma)}{\sqrt{\det(\Sigma_i) \det(\Sigma_j)}} \right);
\]

\[
\Sigma = \frac{\Sigma_i + \Sigma_j}{2}.
\]
Evaluation on Synthetic Video

Due to the absence of ground-truth data for green-screen keying, we prepared a test set of computer-generated video sequences (Figure 6) rendered with a live-action green-screen in the background. We used this ground-truth data to compare the performance of our method with three leading commercial keying tools (IBK, Keylight, and Primatte). In a first experiment, we compared the out-of-the-box performance by providing only minimal user input to all methods, i.e. by selecting a reasonable background color for the commercial tools and selecting 5-9 dominant colors for our method.

In a second experiment, we asked a paid compositing artist to generate the best possible result separately with each commercial tool. The artist reported spending 105-120 minutes with each tool. For comparison, we also processed the same sequences with our method to achieve the best possible keying result, for which we spent 10 minutes mostly refining the local color maps.

Table I shows that our keying results are objectively better than the three commercial tools for all test sequences, both with minimal and optimal level of user input. In some cases, such as the performance of Primatte in the Swing sequence, we observed that further processing by the artist is essential to get a more reasonable result, which means that for a novice user, it is harder to get a good initial estimate. Note also that the user interaction of our method is an order of magnitude more efficient when one seeks to obtain the best possible result.

Color Model Estimation using EM

As an alternative to scribble-based interaction to infer the global color model, we tried to estimate the distributions using expectation maximization.

The main problem with expectation maximization is that it is unable to separate the areas with color spill (indirect illumination from the green-screen material) from the clean areas. As Figure 7 shows, the distribution corresponding to the white robe of the actor appears greenish regardless of the number of distributions estimated by EM. This is expected since the pure white color appears in very limited regions while the greenish white is dominant due to the strong color spill. Using our scribble interface, the user can select regions without color spill and our color unmixing algorithm is able to separate the spill from the robe.

### 5.4 Green-Screen Keying

5.4.1 Comparison with Natural Alpha Matting Methods. We compare our method to four natural matting methods with publicly available implementations. All four methods, namely KNN matting (KNN)[Chen et al. 2013], shared matting (SM)[Gastal and Oliveira 2010], weighted color and texture sampling (WCTS) [Shahriari and Rajan 2012] and comprehensive sampling (CS)[Shahriari et al. 2013] compute not only alpha values but also the corresponding foreground colors. For this comparison, we first prepared a very detailed and narrow trimap and dilated the unknown regions by 6 and 12 pixels to obtain two additional trimaps (following the procedure from the alpha matting benchmark [Rhemann et al. 2009]). For scenes with substantial color spill, we prepared two sets of trimaps, where one considers the regions with spill as unknown, and the other as foreground. The final trimaps and corresponding results can be seen in Figure 8 and in the supplementary material.

The intricate object boundaries in Figure 8-a demonstrate a fail case for sample selection strategies of WCTS and CS as they partly use samples from the actor’s face rather than his hair, causing the hair to appear to have a red hue. SM gives the cleanest result in this case among the natural matting methods. Figure 8-b, shows that the presence of the color green on the actor’s wig degrades the performance of KNN, WCTS, and CS while the local color model
The assumption of SM helps to extract a cleaner foreground. However, SM fails to extract the fine details as our method does, possibly due to the sparsity assumption of SM.

The scenes shown in Figure 8 are selected to highlight several challenges of green-screen keying. The results show that our method performs favorably against the state-of-the-art natural matting methods.

5.4.2 Comparison with Commercial Keying Software. As mentioned in Section 2, several methods have been proposed to solve the keying problem by capturing the same foreground against different background colors. Figure 9 shows that our algorithm gives comparable results to such a method [Grundhöfer et al. 2010] using only a single background.

The keying tools that are widely used in production do not rely on any special setups. In this section, we compare our method with some of the leading commercial keying tools, namely Keylight, Primatte and IBK. To that end, we used green-screen shots from the open source movie Tears of Steel\(^2\) as well as some content that we shot with a Sony \(\alpha 7s\) camera.

In order to present a fair comparison, we asked a paid professional compositing artist to generate a separate result with each tool for each test scene. Based on the artist’s feedback that in most real-world scenarios all three tools would be used sequentially to take advantage of their individual strengths, we decided to ask the artist also to generate another set of result where he is allowed to use all of the three tools. We did not impose any constraints on the artist other than asking him to avoid manually painting pixels.

For the four sequences in our test set, the artist reported a total of 9 hours to get the results using multiple tools and reported an estimated 12 hours for fixing any remaining issues. Our results, on the other hand, were generated by ourselves using our tool in less than an hour. Almost the entire time was spent on refining the local color models using point and click interface of our method\(^3\).

The results presented in Figure 10 show that our results compare favorably to the artist’s results, even when the artist uses all the tools at his disposal and spends approximately an order of magnitude more time on manual editing. Additionally, the complex workflow and heavy local editing employed by the artist may result in temporal coherence artifacts. In contrast, our results for the same sequences do not suffer from such artifacts, as illustrated in Figure 13.

Because of the high amount of spill on the actor in scenes shown in Figures 10-b and 10-d, actors appear transparent in the extracted foreground layer. Discriminating between transparency occurring from color spill or motion blur in a principled way is not a trivial

\(^{2}\) (CC) Blender Foundation — mango.blender.org

\(^{3}\) Refer to the supplemental video for a demonstration of user interaction.
Interactive High-Quality Green-Screen Keying via Color Unmixing

Fig. 10. Commercial keying tools, even when operated by a specialized compositing artist, may not be able to extract the fine details near intricate object boundaries (a), fail to extract highly blurred objects (b), distort the foreground color if it is mixed the background color (c), or create unnatural artifacts around blurred regions (d), while our algorithm is robust against such scenarios.

Fig. 11. The main real-world application of our method is digital compositing. The figure shows a number of toy examples that we generated using the foreground layers obtained with our prototype implementation. Background images courtesy of Flickr users milanboers (a) and jeremylevinedesign (c).

problem. In order to account for this, we apply a simple post processing composed of boosting $\alpha$ values of the foreground layers with high spill to 1 except for the edges of the layers. For instance, the layer corresponding to the white robe in Figure 10-d appears transparent after color unmixing. The robe layer is post-processed such that it has unity alpha values in regions that are not on the edges of the robe. The edges are left untouched to account for the smooth transition and the motion blur around the edges. While this post-processing is not completely fool-proof, i.e. its performance will degrade if there is strong color spill on layers with high transparency, we found it to be helpful for compositing and left the classification of non-unity alpha values to color-spill or transparency.
5.5 Further Applications

5.5.1 Non-Green-Screen Keying. We also tested our method using scenes with non-green-screen backgrounds. Figure 14 shows an example in which our per-pixel color unmixing approach proves to be robust against complex foreground structures. Another example, one that includes reflections from a semi-transparent medium, is shown in Figure 15. While the backgrounds in these examples are admittedly simple, the results presented in this section suggest that our method could be useful for an extended set of applications beyond green-screen keying. However, it is worth noting that our method is limited to simple backgrounds and is not suitable for general purpose natural matting.

5.5.2 Color Manipulation. Representing the image with multiple layers rather than just foreground and background opens up new application areas such as color editing. By giving the artist freedom to edit layers of each dominant color in the scene, interesting results can be achieved easily while not being limited by scenes with motion blur, as demonstrated in Figures 1 and 15.

The layers extracted by our unmixing algorithm can also be used for photo recoloring similar to soft segmentation [Tai et al. 2005; 2007] or palette-based recoloring algorithms such as [Chang et al. 2015], as seen in Figure 12.

6. LIMITATIONS AND DISCUSSION

While in our experiments we have not noticed any significant temporal consistency issues, our test scenes had admittedly near constant illumination. In practice, keying may need to be performed in outdoor scenes (such as driving), where the illumination can change...
drastically from one frame to another. Due to the absence of any mechanism to enforce temporal coherence, we expect the performance of our method to decrease in such settings, as demonstrated in Figure 16.

The global color model as a small set of distributions may not be able to effectively represent non-green-screen backgrounds. We tested our method on several images from the alpha matting benchmark [Rhemann et al. 2009]. Figure 17 shows typical natural matting results where our method works well when our main assumptions are satisfied, but fails when they are violated.

Our scribble interface for extracting the color model requires the unmixed colors to be present in at least one of the frames. For highly transparent media such as thin smoke, the pure color cannot be determined via the proposed interaction and hence it is not possible for our keying system to extract the layer with only smoke. Devising an algorithm that can infer the colors that only appear mixed with others in a scene is an interesting direction for further research.

The proposed color unmixing algorithm may slightly overestimate the alpha values of some layers in some cases. Since the energy minimization favors underlying colors that are closer to the mean vector of the distributions, the foreground layer might get a small portion of the color mixture since matte sparsity is not enforced in the color unmixing energy minimization by design. This mainly occurs when the underlying color of one of the layers is not well-represented by the corresponding distribution. These artificially occurring alpha values being very small, we observed that this behavior does not result in any disturbing artifacts in the keying results.

7. CONCLUSION

In this paper, we proposed an interactive technique for green-screen keying, which is a highly relevant problem in the post-production industry due to the popularity of digital compositing. We presented a novel energy minimization-based color unmixing algorithm which relies on global / local parametric color models and can achieve high-quality keying results even in challenging cases. We show that our algorithm outperforms the state-of-the-art in natural matting in the case of green-screen keying. Our technique also substantially decreases the interaction time required for achieving production-ready keying quality when compared to commercial keying tools.

Future research directions include the investigation of temporal coherency for scenes with dramatic illumination changes, evaluating whether the discriminative power of our algorithm can be improved by using a perceptually uniform color space instead of RGB, and exploring further applications of our color based segmentation such as local contrast editing.

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