Abstract

Learning to mimic the smooth and deliberate camera movement of a human cameraman is an essential requirement for autonomous camera systems. This paper presents a novel formulation for online and real-time estimation of smooth camera trajectories. Many works have focused on global optimization of the trajectory to produce an offline output. Some recent works have tried to extend this to the online setting, but lack either in the quality of the camera trajectories or need large labeled datasets to train their supervised model. We propose two models, one a convex optimization based approach and another a CNN based model, both of which can exploit the temporal trends in the camera behavior. Our model is built in an unsupervised way without any ground truth trajectories and is robust to noisy outliers. We evaluate our models on two different settings namely a basketball dataset and a stage performance dataset and compare against multiple baselines and past approaches. Our models outperform other methods on quantitative and qualitative metrics and produce smooth camera trajectories that are motivated by cinematographic principles. These models can also be easily adopted to run in real-time with a low computational cost, making them fit for a variety of applications.

1. Introduction

Autonomous camera systems that track an object or action of interest need to mimic the cinematographic techniques employed by human cameramen to generate high-quality videos. The primary step towards this goal is to understand the behavior of a skilled cameraman. The cinematographic literature \cite{24} suggests that a good pan/tilt shot should comprise of three components: a static period of the camera at the beginning, a smooth camera movement, which “leads” to the movement of the subject and a static period of the camera at the end. The prior art has shown \cite{9, 8, 23} that such a behavior can be modeled as an optimization problem leading to trajectories with piece-wise constant, linear, and parabolic segments. Most of the previous works \cite{9, 8, 23} have modeled this problem as an offline optimization problem, which requires the entire video during the trajectory stabilization process. However, such offline methods cannot be adopted for real-time applications such as live broadcasts (sports, lectures, live performances, etc.). Some recent attempts have been made to tackle this problem in real-time. Chen et al. \cite{6} combined the problems of planning and smoothing of camera movement using recurrent decision trees, but their model is learned using a specific ground truth signal generated by a human operator for a basketball game dataset. Therefore the learned model is inherently tied to the behavior specific to the particular basketball setting and its ground truth. Another recent work by Wang et al. \cite{25} learns an end to end deep parametric model to directly output stabilized video frames. However, their method requires synchronized steady and unsteady frames in the form of a labeled dataset, which is challenging to collect. Since both these methods \cite{6, 25} work in the setting of supervised learning, they are not applicable for arbitrary trajectory optimization.

Real-time prediction of smooth camera trajectories is an ill-posed problem since, at any given instance, the predicted trajectory can be smoothed in multiple ways depending on the future input sequences. Thus, using direct optimization on trajectories like previous offline works in a piece-wise
manner (sliding window) for the online prediction can make the system very brittle. In this paper, we study the effect of allowing little peek into the future and applying causal constraints on pre-stabilized trajectories. We show that the proposed sliding window formulation can closely mimic an offline global optimization with a latency of just half a second. We further investigate parametric models trained with data that can learn the multimodal distribution of a smooth camera trajectory in an online setting. We hypothesize that predictive models can reduce the dependence on the latency, especially in high noise scenarios. Furthermore, the optimization can be done at much faster rates.

We propose a novel CNN based filtering approach that works in near causal fashion and can learn from patterns existing across multiple samples in the dataset. A key issue when training such models is the availability of large labeled datasets. However, our training is unsupervised and uses a set of generic objective functions to constrain the local structure of the trajectory adaptively. Thus, we do not require any ground truth labels for training, and our model is independent of the idiosyncrasies of human labels from specific settings. Moreover, our objective functions also encourage cinematographically motivated behaviors like the prediction of true statics segments without any residual motions and avoidance of sudden jerks, which is something missing from the past works. A motivating illustration is shown in Figure 1, where we compare our approach with filtering mechanisms prevalent in previous works.

1. We propose a formulation to adapt offline trajectory optimization [9, 8, 23] into an online one. The proposed framework poses stabilization as a convex optimization in sliding window fashion with minor latency and constraints on the optimized trajectory from the previous window.
2. We propose a novel CNN based filtering mechanism for learning a camera trajectory smoothing function. The predictive model offers various advantages, especially in terms of computation load and robustness to noise.
3. Our models can predict smooth trajectories in real-time (1000 FPS for the CNN model and 227 FPS for convex optimization framework on an Intel Xeon CPU). The CNN model has a low model complexity (1.2 MB in size), which enables easy deployment in live settings.
4. Both our approaches work in an unsupervised way and do not need any expensive ground truth labels as previous deep learning based models do. This makes our model-training independent of the setting in which the label was obtained, thus making it easier to extend to new settings.
5. We conduct both quantitative and qualitative evaluation of our model against baselines and previous work and show improvements in both evaluation settings.

2. Related Work

Research in autonomous camera systems dates back to more than two decades. One of the earliest systems was proposed by Pinhanez and Bobick [18], which aimed at automated camera framing in cooking shows. Their system
was based on two types of cameras, a spotting camera that watched the entire area of interest and a robotic tracking camera that followed the verbal instructions from a director to automatically frame the desired targets. The Autoauditorium [2] system extended this idea for lecture videos (a single presenter in front of a screen). The robotic camera in the Autoauditorium system crudely followed the presenter, whose position was estimated each frame using background subtraction on the spotting camera.

A series of works then followed to build upon the initial elementary efforts. We review the computational models for camera movement, proposed in these approaches. Yokoi et al. [26] present a method for automated editing of lecture videos. Their work replaces the robotic camera by a virtual camera i.e., a cropping window moving inside a high-resolution video. They use temporal frame differencing to detect the Region of Interest (RoI) around the presenter and use bilateral filtering to remove the jittery motion introduced by per-frame RoI estimations. A similar digital tracking approach was also employed in Microsoft’s icam2 system [27]. The contemporary work by [22] also tracks cropped RoI from a panoramic video; however, it employs a Kalman filter for removing the jitter. These filtering approaches successfully reduce jitter; however, they are not cinematically inspired, and they lead to unmotivated camera movements and fail to keep the camera static. Heuristics have been applied to tackle some of these challenges. For instance, [22] keeps RoI unchanged if the Kalman filter predictions of new positions are within a specified distance of the registered position, and the new estimated velocity is below a threshold. However, such heuristics are not applicable in generalized scenarios.

The virtual camerawork has been investigated for autonomous broadcast of sports. Unlike the classroom environment, where framing a single person is relatively simple, the sports videos have multiple players and fast-moving objects. Diago et al. [7] propose an offline system that uses the audience face direction to build an automatic pan control system (pan angle of the broadcasting camera). Ariki et al. [11] proposed a heuristic-based editing strategy. However, these approaches focus on the per-frame pan angle estimation and skip details on the camera motion models or smoothing algorithms. Chen et al. [5] uses Gaussian Markov Random Fields (MRF) to obtain smooth virtual camera movements. They induce smoothness by inducing inter-frame smoothness priors. Recent works [19] have shown that while inter-frame smoothness priors do induce smoothness, it fails to give aesthetically pleasing camera behavior. They augment it with an additional post-processing optimization to render professional-looking camera trajectories.

The virtual videography [10] system was one of the earliest works to model camera movement inspired by filmmaking literature [8, 24]. They define that a good tracking shot should consist only of smooth motions in a single direction that accelerate and decelerate gradually to avoid jarring the viewer while maintaining the correct apparent motion of the subject. They define a customized parametric function for the motion model and solve for parameters for each moving shot individually. Liu et al. [13] demonstrate the applicability of such a motion model in the application of automatic Pan and Scan. Jain et al. [11] build upon their work and model the camera trajectories as parametric piece-wise spline curves. However, such parametric motion models have limited applicability due to assumptions on the content (a single pan in each shot). Grundmann et al. [9] present that ‘professional cameraman like’ trajectories consist of piece-wise static, linear, and parabolic segments. They show the applicability of such a motion model for video stabilization. Their approach seems motivated by cinematic ideas, generalizes well, and has been shown to work successfully on a large scale system like Youtube. A similar formulation has been employed in applications of virtual cinematography in panoramic [8] and 360 videos [23]. However, the optimization posed in these works [9, 8, 23] is offline (and non-causal) and in our work, we extend it to online and causal settings.

Carr et al. [4] proposed a hybrid camera to aesthetic video generation in the context of basketball games. They combined robotic cameras to crudely track the game and augmented it with virtual camera simulations to get smoother camera movements. They show that the loss of image resolution can be minimized by using a hybrid system. They investigate a causal moving average filtering and a non-causal \(l_1\) trend filtering [12] to filter the crude trajectories obtained by following the centroid of player detections. They extend their work by learning per frame pan angle predictors based on the player positions in the game and further smooth it using Savitzky-Golay filter [20]. In [6], they merge the camera position prediction and smoothing into a unified framework. These works [12, 6] rely on a supervised signal generated by a synchronized human camera operator, which is difficult to obtain and also makes them domain-specific. In contrast, the proposed filter in our work is unsupervised.

Our work is also related to the work of Liu et al. [14], which proposed a framework for online video stabilization of casually captured videos. Their method performs video stabilization by optimizing vertex level motion trajectories. It runs with a single frame latency and runs optimization locally at every frame using a few previous frames. However, such exact optimization only apply to minimal cost functions like mean squared error + \(L_2\) norm smoothness (as in [14]). Such minimal functions fail to give the desired cinematic behavior. Moreover, running the optimization on every frame is computationally expensive when a
closed-form solution does not exist. We tackle this problem by controlling strides in a sliding window optimization. The proposed online convex optimization (a) uses a cinematically motivated cost function, and (b) provides more structure due to historical constraints and peek into the future frames. Moreover, beyond a standalone optimization for each window, the proposed CNN based alternative can learn priors/structures from previous data as well as temporal dependencies within a sequence.

3. The CineFilter Model

In this section, we describe our models and their unsupervised optimization procedure. Before going into the problem formulation, we list the desiderata that guide our modeling choices.

1. The smoothing filter should be online and run in real-time.
2. It should not require labeled supervisory data (e.g. ground truth trajectories from human experts).
3. Unmotivated camera movements should be avoided. For instance, when the subject in the frame is stationary, the camera behavior should be static to ensure a pleasant viewing experience.
4. Trajectory smoothing should be robust to outliers in the case of sudden changes in camera trends (should avoid abrupt jerks).
5. It should avoid the accumulation of drift, which is a common problem observed in real-time systems.

With the above noted, we first define our problem as that of predicting a smooth camera trajectory given a stream of incoming noisy trajectory positions. Let \( X_t = \{x_0, x_1, ..., x_t\} \) be the noisy input sequence that has arrived until frame \( t \) and \( Y_{t-1} = \{y_0, y_1, ..., y_{t-1}\} \) be the smoothed output sequence predicted until the previous frame \( t - 1 \). We wish to learn a nonlinear causal filter specified by a parametric model \( y_t = f(X_t, Y_{t-1}) \), which predicts the smoothed output for the current frame \( t \). At any timestep, predicting the next smooth frame is ideally a function of both the past and future trajectory directions, which is feasible to model using offline approaches. In the online scenario that we wish to operate in, learning the above mapping is an ill-posed problem as multiple solutions can exist depending on where the future trajectory goes. Therefore it makes sense to accommodate a small number of future frames into the model to constrain the direction of the trajectory.

In this work, we propose two different methods to solve the above problem. The first is an online filter that performs convex optimization on a combination of objectives. Since the final objective is convex, we can run a per-sample solver to obtain a global minimum at each timestep. However, these methods have a dependency on the solver at deployment time and are computationally intensive if run at each frame in an online fashion. These methods also do not learn a data-based model of trajectory behavior; hence, they might not be fit for cases with high variance in data statistics. The second model we propose is a learning-based solution with a 1D convolution neural network (CNN) which can learn trajectory patterns from data. Moreover, at inference, a forward pass through this model is faster and computationally cheaper than a convex solver.

The ideal camera trajectory should be composed of three types of segments, namely static segments, constant velocity segments, and segments with constant acceleration, all transitioning in a smooth manner. As opposed to previous works that use ground truth data from human operators or create large datasets for deep learning based methods, we build our model through an unsupervised multi-objective loss function that enforces such behavior without the need to collect labeled data.

3.1. Filtering Using Online Convex Optimization

We first describe the convex optimization based solution for online smoothing. The model works in a sliding window manner. The sliding window configuration is shown in Figure 2. It consists of three fragments. The first fragment is called the present window of size \( p \) from timestep \( t \) to \( t + p \). This fragment gets updated in the final predictions after optimizing the current sliding window. It is also the step-size by which we shift the window after each optimization. The second fragment is called the buffer window, which spans timestep \( t - b \) to \( t \). This is the historical trajectory information we use in the optimization. The third fragment is called the future window which holds timestep \( t \) to \( t + f \) with \( t + f > t + p > t \) and includes the present window. This provides future context for the optimization. We optimize the trajectories from timestep \( t - b \) to \( t + f \) and shift all windows by \( p \) after each optimization.

The optimization procedure for each sliding window includes: (a) a term to enforce the predicted trajectory to be close to the original trajectory in some distance metric and (b) L1-norm of the first-order, second-order and third-order
derivatives over the optimized trajectory to induce piece-
wise static, linear and parabolic behavior. L1-norm has
the property to avoid residual motions (e.g. when the path
is meant to be static, it leads to truly static outputs) and
avoids the superposition between the constant, linear, and
parabolic segments. The final objective \( J^m \) with respect to
timestep \( t \), where \( m \) indexes the \( m^{th} \) optimization pro-
dure, is given by:

\[
J^m(t) = \lambda_0 D_0^m(t) + \lambda_1 D_1^m(t) + \lambda_2 D_2^m(t) + \lambda_3 D_3^m(t)
\]

where,

\[
D_0^m(t) = \sum_{i=1}^{t+f} (x^m(i) - y^m(i))^2
\]

\[
D_1^m(t) = \sum_{i=1}^{t+f} | y^m(i+1) - y^m(i) |
\]

\[
D_2^m(t) = \sum_{i=1}^{t+f} | y^m(i+2) - 2y^m(i+1) + y^m(i) |
\]

\[
D_3^m(t) = \sum_{i=1}^{t+f} | y^m(i+3) - 3y^m(i+2) + 3y^m(i+1) - y^m(i) |
\]

The \( \lambda \)'s are hyperparameters found using cross-validation
and \( p, b \) and \( f \) are values we fix heuristically.

Note that this model has a latency of \( f \) timesteps, stores
an extra \( b \) timesteps from the past, and is run after every \( p \)
timesteps. Reducing \( f \) can reduce the latency, but will lead to
less smooth results since multiple future trajectory direc-
tions are possible. Decreasing \( p \) will lead to frequent tra-
xjectory updates but will affect the speed of the filtering op-
eration due to the larger number of optimizations required.
Finally, increasing \( b \) will provide extra historical context;
however, that will increase the time required for each in-
dividual optimization. Hence the window-related parameters
offer a way to balance the speed and accuracy trade-off.

Another problem encountered during this optimization is to main-
taining continuity over consecutive optimizations (over con-
secutive sliding windows). To mitigate this, we place a hard equality constraint on the past trajectories be-
ing currently predicted (\( y^m(t-b) \) to \( y^m(t) \)) and the past
trajectories already predicted during the previous optimization
(\( y^{m-1}(t-b) \) to \( y^{m-1}(t) \)). Finally, the objective is
changed to the following:

\[
J^m(t) = \lambda_0 D_0^m(t) + \lambda_1 D_1^m(t) + \lambda_2 D_2^m(t) + \lambda_3 D_3^m(t)
\]

\[\text{s.t. } y^m(k) = y^{m-1}(k) \forall k \in \{t-b,...,t\} \]

We use the state of the art Gurobi solver [21] for mini-
mizing the objective function (the fastest solver in the MI-
PLIB 2017 Benchmark [15]). This convex optimization for-
mulation is referred in the subsequent sections as the Gurobi
model.

### 3.2. Filtering Using 1D CNN

The Gurobi model described above allows us to obtain a
global minima for a given fragment, but there are two po-
tential issues with it. Firstly, the optimization is performed
on a per-sliding window basis and needs to run frequently
during the online operation of the filter. In addition to com-
putational burden and it has a vital dependency on the speed
of the solver. Secondly, since there is no data-based learn-
ing involved and the optimization described only works at
window-level trajectories, the model cannot build a global
model for the variation in data statistics that can be encoun-
tered by the model. Moreover, since the objective is always
an approximation to the behavior we want in the real world,
having some inductive biases directly from the data might
help in learning better models. This motivates our use of a
data-driven model to solve the smoothing problem.

We can pose the problem of estimating the current
smooth trajectory position as a sequence modeling problem.
However, popular sequence prediction models like HMMs,
RNNs, and LSTMs operate sequentially and have a high
memory footprint. Moreover, we found in our experiments
that 1D CNN based architecture better learns the local struc-
ture over the more complex recurrent counterparts and also
provides improved performance. Consequently, we use a
5-layered CNN model, which takes in the noisy trajectory
as input and predicts the smooth output trajectory. In the
absence of smooth trajectory labels, we use a similar unsu-
servised loss function (as the Gurobi optimization), which
penalizes the squared distance between the original trajec-
tory and the predictions along with the first, second, and
third-order derivative terms. We also include an additional
loss term, which penalizes the predictions linearly if they
deviate beyond a certain threshold from an original trajec-
tory. This loss is implemented using a shifted ReLU func-
tion. The final loss function for the model is as follows:

\[
L = \lambda_0 D_0 + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_3 D_3 + \lambda_4 L_{\text{safty,net}}
\]

where,

\[
L_{\text{safty,net}} = \sum_{i=1}^{n} \text{ReLU}(|y(i) - x(i)| - \delta)
\]

The parameter \( \delta \) defines the permissible limit for deviation
from the original trajectory before this term starts con-
tributing to the final loss function. The first three terms
\( D_1, D_2, D_3 \) are the same as before, but from timestep 1 to
\( n \).

The input sequence from all trajectories are divided into
overlapping subsets of \( n = 512 \) frames and the trajectory
positions from these frames is the input for the model dur-
ing training. During inference, when only the first frame
has arrived, we left-pad the input with repeated values of
the first trajectory position and use this as the input. Af-
ter the forward pass, the last indexed output is taken as the
first timestep prediction. As the new frames keep coming in during inference, we keep appending them to the right of this initial input trajectory and taking the most recent 512 frames as the input for each timestep. The prediction formulation at inference time is the same as that of the convex optimization. Since there is no optimization at test time, but only a forward pass through the model, the time is taken for the predictions is not a bottleneck to the latency, and we can run the system after every timestep. Hence, the CNN model works with $p = 1$ and thus can make updated predictions each timestep. Also note that there is no explicit constraint that enforces trajectory continuity across predictions like the one needed in the convex optimization formulation. The model has a structural inductive bias (1D convolution) that merges information from local trajectory positions, thus aiding continuity. The data itself, which is fed as a sequence, also provides an additional implicit constraint on the smoothness of the predictions.

3.3. Implementation details

We use a 5-layered 1D-CNN model with 256, 128, 64, 16 and 4 kernel sizes and 64, 32, 16, 8 and 1 filters respectively to predict the smooth sequence at each timestep. The CNN layer has a sigmoid based activation on the outputs. The videos from TLP dataset \cite{16} and Basketball dataset \cite{6} (described in Section 4.1) are used to train the model. We sub-sample from the full trajectory of the video at random frames and create a set of input trajectories each of a fixed length of 512 and use these as single instances of training data for the model. The data samples are min-max normalized before feeding them as input. We create 98k such instances through sub-sampling. The model is trained for 20 epochs for the basketball dataset and 50 epochs for the TLP dataset, each with a batch size of 16. The adadelta optimizer is used during training. We follow a learning rate schedule that decays the learning rate by a factor of 0.1 if the validation loss plateaus for more than 4 epochs. The weights associated with each loss term are obtained through cross-validation and $(\lambda_0, \lambda_1, \lambda_2, \lambda_3, \delta)$ for stage performance dataset are $(30000, 5000, 50000, 1000, 40)$ and for basketball dataset $(\lambda_0, \lambda_1, \lambda_2)$ are $(1000, 100, 2000)$. The values for $p, f, b$ used are as 8, 16, 64 respectively for the Gurobi model. For the CNN model, $p = 1$.

4. Experiments

We evaluate our approach for automated broadcast of basketball matches \cite{6} and staged performances \cite{8}. We compute results from both the proposed method, convex optimization (Gurobi) and prediction model (CNN) and compare the results with four baseline algorithms commonly used for online filtering. We also perform ablation studies to demonstrate the effect of the parameters $p, f, b$ on model performance. We now describe the datasets, baselines, and evaluation strategy in detail.

4.1. Datasets

**Basketball dataset:** We use the Basketball dataset proposed by Chen et al. \cite{6}. This dataset consists of a video recording of a high school basketball match taken from two different cameras. One wide-angle camera is installed near the ceiling and looks at the entire basketball area. The feed from the wide-angle camera is used to detect players and compute features summarizing the current state of the scene. The second broadcast camera is placed at the ground level and is manually operated by a human expert. The evaluation task is to predict the pan angle, given the current state of the match observed by the wide camera. The pan angle of the human-operated camera is considered as the ground truth (calculated by computing its homography with respect to the wide-angle camera). The dataset consists of 50 segments of 40 seconds each (overall 32 minutes of in-play data), out of which 48 segments are used for training, and 2 are used for validation and testing. Similar to \cite{6}, we train a Random Forest regressor to obtain per frame pan angle predictions. For learning the Random Forest regressor, the game features computed using the wide-angle camera are used as input and the human operator pan angle as ground truth labels. The per-frame predictions give an extremely noisy output, which are then subjected to a filtering operation. We perform comparisons on the output of CineFilter models and the baselines with the human operator trajectory as the ground truth.

**Stage Performance dataset:** We build a Stage Performance dataset that comprises of two wide-angle recordings of staged performances each of 12 and 10 minutes, respectively. The videos are selected from the Track Long and Prosper (TLP) Dataset \cite{16}. The original recordings were done using a static wide-angle camera covering the entire action in the scene. The noisy object trajectory sequences for these recordings are obtained using the MDNet tracker \cite{17}. 3 minute sequences from both recordings are kept aside for testing, and the rest is used as the training set. The filters are evaluated on the task of virtual camerawork, following an actor on the stage based on the output of the tracker. Since there is no ground truth available for these videos, we use the offline optimizer from \cite{8} as the ground truth trajectory.

4.2. Baselines

**Savitz Golar:** SG filter performs data smoothing using least squares to fit a polynomial of a chosen degree within a window of consecutive data points around every point. It takes the central value in the window as the new smoothed data point and this step is performed at each point on the time series. SG filter is non-causal and in our case we choose a window size of 51, giving a latency of 25 frames.
The degree of the polynomial is set to 3.

**Kalman Filter:** Kalman Filter is a recursive Bayesian estimation method that can be used for updating the current smooth camera state at every time step using previous predictions and the current observation. We set the parameters of the filter similar to \[6\].

**Bilateral Filter:** Bilateral filter is a non linear, adaptive, edge preserving and noise reducing smoothing filter. It uses a weighted-average approach where the weights at any given data point is computed using two Gaussians, one Gaussian on the difference of spatial distance and the other on the difference between the magnitudes of the given point with every other point in the surrounding window. It is also non-causal and we use a window size of 64, giving the latency of 32 frames.

**MeshFlow:** MeshFlow \[14\] runs with a single frame latency and runs optimization locally at every frame using a few previous frames. The optimization functions consists of two different terms. The first term is the MSE over the predicted and original values of the 1D signal. The second term is a MSE over the first order differential of the predicted signal. Window size of 20 values is considered for the experiments.

### 4.3. Evaluation Metric

For quantitative experiments on the Basketball dataset, we use the data from the human operator as ground truth and compute a metric that combines two different terms. The first term is the mean squared error between the filtered trajectory predictions and the ground truth trajectories (pan angle corresponding to the expert human operator). Assuming that the human operator selects the pan angle that best showcases the activity happening in the game, this term penalizes trajectories that deviate from the angles at which important activities are happening. The second term is the absolute difference in the slopes between the predicted and the ground truth trajectory. This measures the ability to mimic human cameraman-like behavior. It penalizes any movement of the predicted trajectory when the human operator is static and also penalizes the predicted trajectory if it moves in a different direction or at a different speed than the ground truth.

We define the two terms as Precision Loss and Smoothness Loss and combine them into a final metric called Imitation Score (how closely the predictions imitate the human ground truth). We formally define the final metric as follows

\[
l = \sum_i (y(t) - \hat{y}(t))^2 + \eta \sum_i | \frac{dy(t)}{dt} - \frac{d\hat{y}(t)}{dt} |
\]  

(9)

\(y(t)\) is the prediction, \(\hat{y}(t)\) is the ground truth from the human operator, and \(\eta\) is the relative weighting on the smoothness term in order to scale it to values comparable to the precision term. In our experiment, \(\eta = 500\). The lower the Imitation Score, the better the predictions.

Although quantitative metrics can give a good estimate about the effectiveness of the predictions, the final gold standard is the human perception of the rendered trajectory. For instance, an aesthetically pleasing viewing experience is more important even if it comes at the cost of increased precision loss. Hence, in addition to quantitative metrics, we also evaluate our model qualitatively in the form of a comprehensive user study. This is done on the video crops obtained from the task of virtual camera simulation on the Stage Performance dataset, as described in Section \[4.1\].

### 5. Results

In this section we report the results from our quantitative evaluation on the Basketball and Stage Performance datasets in Section \[5.1\]. Qualitative experiments using visual inspection and a preference study in Section \[5.2\]. Additionally, in Section \[5.3\] we show results from ablative experiments on the Basketball dataset since the human operator ground truth exists for it.

#### 5.1. Quantitative Evaluation

We first present the results for the quantitative evaluation on the two datasets. We compare against the previously mentioned baselines using the Imitation Score metric as defined in Equation \[9\]. The results from this experiment are summarized in Figure \[3\].

For the Basketball dataset which has noisier motion of the two datasets, we see that the CNN model performs the best in terms of the Imitation Score followed by the convex optimization model. Even in terms of individual loss terms, the CNN model outperforms all the baselines. For the Stage Performance dataset, which has relatively noise-free trajectories, our convex optimization formulation works the best followed by our CNN model. However a thing to note is the difference in the time efficiency of these two filters and the latency introduced due to the hyperparameters which we analyze in the ablations in Section \[5.3\].

![Figure 3. Imitation Score metric (precision + smoothness loss) for our approach and the baselines on the Basketball dataset (left) and the Stage Performance dataset (right).](image-url)
Table 1. User study results of other methods vs the CNN model.

| CNN          | Win | Loss | No Preference |
|--------------|-----|------|---------------|
| vs Kalman    | 12  | 3    | 0             |
| vs SG        | 15  | 0    | 0             |
| vs Meshflow  | 10  | 3    | 2             |
| vs Bilateral | 8   | 1    | 6             |
| vs Gurobi    | 0   | 15   | 0             |

5.2. User Study and Visual Inspection

Although the Imitation Score is a reasonable way to assess our model, it may not be able to accurately measure the adherence to cinematic principles and more importantly the final aesthetics of the rendered video. For instance, a smoother trajectory may be preferred by the user even if it is slightly drifted and increases the precision loss. Similarly, unmotivated movement can appear distracting to the user, even if they are extremely minute and may not significantly contribute to the Imitation Score. In order to validate our use of the Imitation Score, we complement our evaluation using qualitative methods. To account for the perceptual metrics i.e how the proposed filtering method performs against the aforementioned baselines in terms of aesthetics of the rendered video, we perform a study with 15 users.

We select 15 video clips from diverse set of wide angle stage recordings, which are different from the two sequences we used for training. The average duration of the clips is 27 seconds. We use each of the proposed and baseline filters for smoothly following the actor tracks. In each trial, the participants are shown two videos in a side by side manner, one rendered using CNN approach and the other using Gurobi or one of the baselines. They are instructed to choose the video that is more aesthetically appealing and better mimics human camerawork. They are also given an option to choose neither (if they do not have a clear preference) and both videos are reasonably similar in terms of aesthetics. Each user watches 9 pairs of videos, therefore each pair of videos is watched exactly once. The left and right ordering for videos is randomly switched. The results are illustrated in Table 1.

Note that our two methods are significantly preferred compared to the other baselines. Meshflow is the most competent approach among the baselines and it works well in sequence where actors are constantly moving. Kalman filter has minimal drift and is preferred in few cases, as it maintains the shot compositions well. We present some of these rendered comparison videos in the supplementary material. The convex optimization approach is consistently chosen over the CNN model (in the studied low noise scenario), which correlates with the Imitation Scores shown in Figure 1. On the other hand, since the Basketball dataset doesn’t have publicly available video sequences, we point the readers to the predicted trajectory comparison for all the baselines in Figure 1 and between Gurobi and CNN models in Figure 4. It is clear from the smoothness and the lack of residual motion in the CNN predicted trajectory that it outperforms other methods on the Basketball dataset, as also indicated by the Imitation Score in Figure 3.

5.3. Ablative Experiments

In this section, we discuss results for ablation experiments across different values for the window hyperparameters $p$ and $f$ and show performance and speed varies across the two proposed model formulations. Table 2 shows the influence of the present window size ($p$) and future window size ($f$) on the Imitation Score and speed of the Gurobi model. The tables shows how increasing the present window width can improve the speed of the filtering operation, but also needs increase in the future frames, thus increasing latency. Also, there exists a middle ground for the $p$ and $f$ values which balances the performance with the speed. We can contrast this with the CNN model which has a constant speed of around 1000 FPS with $p = 1$. For the CNN model, the values of $f = (4, 8, 16, 32)$ gets respective Imitation Scores of $(47, 44, 42, 45)$. Like the Gurobi model, the CNN model too has a peak score of 42 for $f = 16$ which we use for our experiments. The ablation experiments again show the various speed-accuracy trade-offs associated with both models across the choice of hyperparameters.

6. Conclusion

In this paper, we propose two unsupervised methods for online filtering of noisy trajectories. The first formulation poses filtering as a convex optimization over individual slid-
ing windows and is solved using iterative convex solvers. The second formulation models filtering as a prediction using a convolutional network. The unsupervised nature of the proposed methods, high operational frame rates and low memory footprint make them a generic choice across large variety of applications. We contrast the performance of the proposed methods in comparison to commonly used online filters, across two diverse applications of basketball games (fast paced, multiple players) and theatre plays (following individual actors on a stage). Thorough quantitative and qualitative experiments show that the proposed methods give superior performance over the existing filtering techniques.

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