LookOut! Interactive Camera Gimbal Controller for Filming Long Takes

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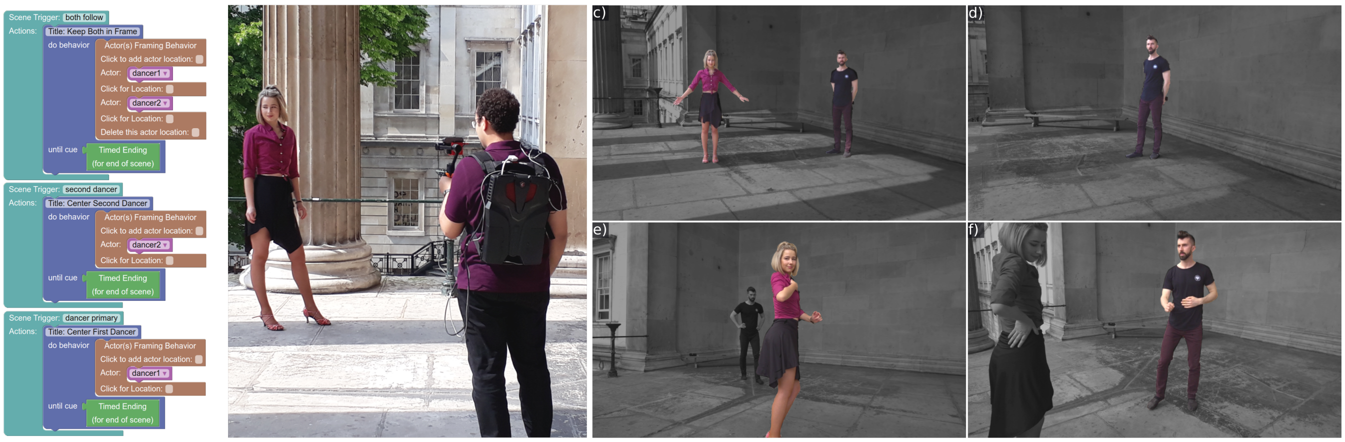

a) Script Creation b) Guided Setup c-f) Interactive Filming

Fig. 1. a) Script Creation: The LookOut GUI enables a user to pre-script where the camera should point. It allows the user to define multiple alternate scripts, as seen here, and to switch between them on-the-fly. A script consists of one or more behaviors chained together. A behavior can be as simple as a pan, or as complex as positioning multiple subjects in different parts of the frame. Each camera behavior is triggered by a cue, such as the appearance of a specific actor, someone issuing a voice command, or the actor reaching a specific zone within the frame. b) Guided Setup: For field-use, LookOut resembles a very simplified dialog system, guiding the user through system checks and scene-specific initialization. The user-worn LookOut rig consists of a light backpack computer, a hand-held motorized gimbal, dual cameras (normal and wide-view), earphones, a lapel microphone, and a joystick for initial setup. When first turned on, LookOut prompts the user, through text-to-speech, to set audio levels, choose a script, and assign actor identities as needed. c-f) Interactive Filming: Four frames from a LookOut-captured video, but with false-coloring to visualize which actor(s) the scripted behaviors were attending to at the time. At the user's instruction, LookOut frames (c) both dancers, then (d) orients the gimbal to center on the male, then the female (e), and back to the male (f). The user receives audio feedback when switching between camera behaviors. Without a field monitor, the user can watch where they're going, while trusting our controller to handle their dynamic requests.

The job of a camera operator is more challenging, and potentially dangerous, when filming long moving camera shots. Broadly, the operator must keep the actors in-frame while safely navigating around obstacles, and while fulfilling an artistic vision. We propose a unified hardware and software system that distributes some of the camera operator's burden, freeing them up to focus on safety and aesthetics during a take. Our real-time system provides a solo operator with end-to-end control, so they can balance on-set responsiveness to action vs. planned storyboards and framing, while looking where they're going. By default, we film without a field monitor.

Our LookOut system is built around a lightweight commodity camera gimbal mechanism, with heavy modifications to the controller, which would normally just provide active stabilization. Our control algorithm reacts to speech commands, video, and a pre-made script. Specifically, our automatic monitoring of the live video feed saves the operator from distractions. In pre-production, an artist uses our GUI to design a sequence of high-level camera "behaviors." Those can be specific, based on a storyboard, or looser objectives, such as "frame both actors." Then during filming, a machine-readable script, exported from the GUI, ties together with the sensor readings to drive the gimbal. To validate our algorithm, we compared tracking strategies, interfaces, and hardware protocols, and collected impressions from a) film-makers who used all aspects of our system, and b) film-makers who watched footage filmed using LookOut.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; Robotics.

Additional Key Words and Phrases: cinematography, videography, video editing, camera gimbal

1 INTRODUCTION

Filming for journalism and movies is a creative and often collaborative process, where the budget dictates if the roles of director, director of photography (DP), and camera operators are fulfilled by a team, or rest on just one person's shoulders. Ultimately, the person holding the camera has the responsibility of delivering both the content and style that was agreed in advance, while safely adapting to dynamic changes on set.

After budget, time is the next biggest constraint. We consider two types of filming scenarios: one type where a journalist or documentary-maker must catch a one-off unrepeatable event, and the other type where actors and crew follow a storyboard with blocking, repeating the performance until the director is happy. Our system, called "LookOut," is designed help with both types of filming, if the aim is to capture a long take with a moving camera.

Long takes stand out as novel and complex to choreograph in big-budget films[1], though they are common for journalism, documentaries, and run & gun videos - so the majority of working video/cinematographers. Moving the camera helps keep long takes interesting for the viewer [3, 25, 35]. However, moving cameras and moving people stretch the attention of camera operators, who are trying to simultaneously walk about and adequately frame their stars. Usain Bolt was famously run over by a cameraman who suffered from task overload while steering a Segway at the World Athletics Championships in 2015.

Speaking informally with independent film-makers, we found there was some interest in drone cinematography systems like [15, 38, 52], but a strong desire for three things: 1) to have interactive control while filming, 2) for a system that tracks indoors and outdoors without special costumes, and 3) ideally, to work with lightweight hand-held hardware, because drones are prohibited in many populated areas, and most countries require a pilot's license. This seeded our research process, which, with feedback and validation from filmmakers, has led to our proposed LookOut system (see Fig 1).

The overall LookOut system serves as an interactive digital assistant for filming long takes with a camera gimbal. LookOut consists of software and 3D printed hardware that augments an existing lightweight motorized camera gimbal ($130), with a video feed and rudimentary two-way speech-interface connected to a backpack computer. Without innovations, some of the individual components existed in principle, but would not integrate into a usable or responsive video-making algorithm. Therefore, our two main technical contributions are:

- A visual tracking system that detects and tracks actors in realtime. It re-frames them dynamically, based on requested "behaviors."
- A combined controller that dynamically balances script-induced constraints like smoothness and intentional framing, while still being responsive to tracker outputs that have inherent noise and drop-outs.

The camera operator often wears many other hats, but from their perspective, during the critical moments of filming, the LookOut system responds to voice commands and follows alternative or sequential pre-specified behaviors. It rotates and stabilizes the camera within its joint limits, to follow the actors and to compensate for the operator's trajectory through the scene. For our experiments, operators didn't see a monitor while filming, so were free to look around and keep one hand spare as they walked, climbed, or cycled through different environments.

[1]See the films *1917* [36] and *Birdman [21]*, both filmed to look like one take, versus Michael Bay's average shot length of 3 seconds [39].

2 RELATED WORK

The graphics community has a long history of exploring camera placement [6] and control systems, striving to be automatic and cinematic. For "offline" scenery special effects, motion control camera systems have been used since the work of computer graphics pioneer John Whitney in the 1950's [53]. While programmable camera trajectories can help with stop motion animation, and with layered compositing of scenery and special effects, they require hiring of specialized crew, are usually constrained to a short track, and the systems ignore actors and other dynamic events. We therefore focus this review on the context of our system, so following and framing of actors in video. This includes stabilizing gimbals, visual active tracking, and the efforts in drone cinematography.

2.1 Stabilizing Gimbals and Steadicam

Camera gimbals play a crucial role in isolating rotational movement of a camera. They are essential for smooth video capture, especially when the whole assembly is held by a walking camera operator. The Steadicam [4] was invented by Garrett Brown in 1975 and allows for a camera operator to physically move the camera and simultaneously capture smooth footage. It has been famously used in many Hollywood film productions, including *Rocky* (1976) [1], *Goodfellas* (1990) [43], and *Indiana Jones and the Temple of Doom* (1984) [46]. Steadicams provide an extra layer of isolation from the camera operator compared to gimbals, in that they also dampen camera translation. Some are motorized to provide active stabilization and manual motorized control over the direction of the camera. Although the camera operator no longer has to worry about keeping the camera steady, the operator must still point the camera while moving, either electronically through a joystick or manually by rotating the camera assembly. BaseCam Elecronics [12] develop different hardware and software components for the construction of stabilizing gimbals. Their firmware offers control and flexibility over every stabilization parameter. We build on top of their BaseCam Handy gimbal, which offers 3-axis control over camera orientation. Communication to the gimbal is achieved through a serial API that allows for online control and settings changes on the fly.

2.2 Active Tracking Systems

Many early active tracking systems focus on surveillance applications. Daniilidis et al. [8]'s pan-tilt camera control system orients a camera to focus on motion in a static scene. Dinh et al. [9] and Funahasahi et al. [14] propose multi-camera or multi-focal length camera systems for identifying pedestrians through facial recognition. These systems are among the many that actively controlled pan, tilt, and zoom.

Closest to our own hardware is the DJI Osmo Mobile [10]. It is a commercial real-time handheld active tracker. It uses a motorized gimbal and inertial measurement units (IMUs) to control a smartphone camera's orientation. The gimbal enables the user to create stabilized camera footage and select a single object to actively track. A smartphone is used as the camera and processing unit. The tracking algorithm is not made public. Unlike our system, users have no control over framing and complex scripting, and no ability to track multiple targets.

2.3 Tracking

Most trackers in the literature are designed with different requirements in mind. Generally, the ability of a tracker can be measured based on some high level performance criteria. Among them are speed, accuracy including robustness to ID switching or drift, number of trackable objects (usually one vs. many), robustness to appearance changes, and the ability to be run online.

We focus almost entirely on trackers that can approach real-time speeds. The MOT challenge [37] provides performance metrics on trackers for multiple people in crowded scenes. The average shot length in MOT is ~31 seconds with most targets exhibiting shorter life spans. While MOT includes metrics that measure ID swaps, the metrics still reward trackers for continued tracking of a person with a new ID after an ID swap. A target swap during filming would very likely ruin a take and cause delays. Our application requires robust tracking of a handful of targets for long durations (>20 minutes). Robustness to ID switches and target re-acquiring after occlusion, especially in busy and cluttered environments, are crucial to our use case.

The VOT challenges [28–30] cater to single target tracking of any class. The VOT Short-Term Challenge allows tracks to be reset, with a penalty and a timeout of five frames, to make use of the entire dataset. Trackers in the main VOT challenge are not required to deal with longer term occlusion and confidence reporting. In our use case, actors often appear and disappear as filming progresses. While the VOT Long-Term Challenge evaluates trackers with metrics that put a greater emphasis on longer term tracking (the average video is 2m04s long and contains 10 occlusions lasting 52 frames [30]), it does not run trackers in a multiple object regime.

A family of single object trackers are built on top of Siamese network architectures [2, 47, 49, 57]. Most notably, SiamMask [49] achieves state-of-the-art performance on the VOT2018 challenge for object tracking while operating at around 50Hz for bounding box prediction. DaSiamRPN [57] includes a "distractor aware" module and a training sampling strategy in an effort to prevent distractors from causing track loss errors. DaSiamRPN performs well at 110Hz and achieves first place on the VOT2018 real-time challenge, and second place on the long-term tracking challenge. We experiment with both trackers and show how they are both prone to imposters of the same object type in long takes and cluttered environments.

Among the lightweight high scoring MOT multi-person trackers, DeepSORT [50] and MOTDT [34] stand out. Both incorporate a tracking-by-detection paradigm and use a combination of IOU and appearance costs via ReID networks for assignment. Assuming detections are precomputed in advance, they could theoretically operate at 120Hz and 60Hz respectively. In Sec. 7 we compare against these trackers and show that while they are capable of tracking in dense scenes with short lived tracks, as in MOT, they are not robust to ID switches when tracking people in frame for longer videos, making them inadequate for our use case.

While these trackers offer good performance across a wide range of metrics and for different classes of objects, no one tracker satisfies all the requirements of our use case, especially for people tracking.

2.4 Informed Automatic Drone Cinematography

Though drones are contentious with safety restrictions in many countries, we share many objectives with drone-based cinematography. The Skydio R2 [45] is an autonomous drone made for hands-free aerial filming and houses an NVIDIA TX2, six 200° cameras for navigation, and a 12.3MP camera (20mm). It can fly autonomously, avoid obstacles, and keep a target in the center of the frame. The R2 can also perform different localization moves relative to the target to achieve motion shots such as follow, lead, and orbit.

DJI provides a line of drones with Active Track capability [11]. These drones can follow a target while also achieving certain motion objectives. Like DJI's gimbal models, the drone-based tracking algorithms are not public, the user has limited control over framing, and multiple actors can not be tracked in series or in parallel.

Galvane et al. [15] formulate a system for drone path planning and actor based framing, and utilize the Prose Storyboard Language (PSL) [42] for a high level description of subject framing. In Nägeli et al. [38], multiple drones can be scripted to fly through specific paths in a scene and be guided by actor location. Huanget al. [19] control the location of a drone around a subject in a clutter free environment, using actor pose as input. Similarly, Joubert et al. [23] control two subject framing in drone filming. While these methods either use limited UIs and/or non-visual means of actor tracking (GPS and infrared markers), they showed promise for the concept of scripted and actor-driven camera control.

Xie et al. [52] construct a feasible drone path given user-defined way-points for videography of landmarks. Huang et al. [20] learn a motion control model for drone cinematography by training on videos filmed with expert pilots.

While we share the excitement around drone-based filming, drones are not always the correct or perhaps even legal tool for the task. Most actor driven shots take place in close quarters, with the camera closely following actors in the middle of the action. Drones are often only operated outdoors in accordance with size and safety restrictions. Further, while dubbed audio may be used in scenes, the noise they produce will ruin on-set audio.

3 LOOKOUT SYSTEM OVERVIEW

At a very high level, the proposed LookOut system lets a user specify what they want to track, and then aims the camera gimbal at that target during filming. Achieving that aim required many iterations of hardware and software, user interfaces, and especially (1) innovations in long-term visual tracking and (2) a novel control system. Here, we outline the components of the system, and how they help the operator to design and safely film the long takes they want.

A solo camera operator, without specialized programming skills, uses our GUI for offline pre-production, and our rig for live filming. We consider post-production only as part of Future Work. Interestingly, Leake et al. [32], Wang et al. [48], and Zhang et al. [55] built interfaces that use learning to assist precisely with film-editing of existing clips. Instead, through our GUI, the user defines their intentions up-front - somewhat like telling an assistant what to expect. Those intentions are saved into scripts, that are later parsed by the LookOut control system during filming. On set, the camera operator wears a backpack-computer (see Fig 2) as the control-center and

Fig. 2. **A novice camera operator filming using the LookOut system:** (a) is an existing active camera gimbal, designed to stabilize mobile-phone filming. The mini-joystick is inactive by default, The orange 3D-printed handle channels the cables and protects the USB connectors from being bumped. (b) is the backpack computer, connected to the gimbal by one USB cable and connected to (d) with another. Not shown, the backpack also has headphones and a lapel mic, for two-way speech communication with the operator. (c) is the primary camera, recording high quality footage to local memory. (d) is the guide-camera, which has a wider field of view than (c), and whose video is fed to the backpack computer for real-time analysis.

sensor-hub. The user also holds the camera gimbal in one hand, and has dialog with the LookOut controller, by wearing a microphone and headphone.

We give a brief overview of these components here, before providing their specifics in Sections 4 through 6.

GUI: Before filming takes place, the camera operator uses LookOut's GUI to "tell" the camera gimbal how to behave and what to expect. The behaviors are chained together into a relative timeline. Instead of absolute times, user-specified cues will conclude and then trigger each subsequent behavior in turn. Through the script file saved by the GUI, non-programmer users instruct the LookOut control system with what to look for in the audio and video sensor inputs, and how to react. Please see the supplemental materials where we show the Blockly-based LookOut GUI for designing long takes. There, we explain how non-programmer users build script files by assembling chains of behaviors. A resulting script file encapsulates how one or more actors (and even non-actors) should be framed while filming. The script file switches between behaviors when triggered by user-controlled cues, that LookOut checks for continuously: Speech cues, Elapsed Time, Actor Appearance/Disappearance, Actor in Landing Zone, and Relative Actor Size. We are proud of the GUI for being easy to learn and for matching many of the wishes voiced by consulted film-makers.

System Startup and Setup: When the LookOut hardware is first switched on, the user selects which scripts to load into the system. LookOut then parses these scripts and asks the user, through guided audio feedback, to enroll actors for tracking. The user adds an actor by pointing the camera roughly in the actor's general direction and pressing a button on a small joystick. LookOut guides the user for each additional actor. The system then prompts the user to utter each script-relevant speech trigger. This ensures all speech triggers are registered by LookOut using the user's current hardware audio configuration. LookOut informs the user that setup is complete and remains in *Manual Mode* until the user requests *Automatic Mode*. Every mode switch and behavior trigger is met with audio feedback.

Controller: The controller reconciles the input script(s) with incoming sensor data, to dynamically drive the gimbal motors. When a script sets out the camera behaviors, the controller listens for the relevant audio-cues, and analyzes the video feed to monitor spatial relationships between enrolled actors. It then dynamically drives the gimbal to achieve the desired framing and smoothness. Finally, it gives audio feedback to the user, so they know that the LookOut system is correctly following the script and the current actions.

Visual Tracking: Dynamic framing of one or more actors requires our system to follow along, monitoring where people are on-screen, even when they are briefly occluded or on the edge of the field of view (FoV). For these aims, we needed a visual tracker that can detect people and distinguish between them for long periods of time, despite imposter-objects, e.g. people or things that could resemble the main actor(s). Our tracker balances the need for accuracy against the need to feed low-latency tracks to the controller.

4 INFRASTRUCTURE

In this section, we describe the hardware and software on which LookOut is built. Please see Figs 2, and 3 for close-ups.

Backpack: Our system requires low latency feedback control in the wild. We use a VR backpack computer with a Quadcore Intel i7 7820HK CPU@2.90GHz and a mobile Nvidia GTX 1070 GPU.. The backpack can operate for 1.5-2 hours, allowing for very long shots and multiple takes, and is light at 3.6kgs.

Stabilizing Gimbal: We use the Basecam Handy gimbal to carry the camera assembly. The gimbal is programmable through a serial API and allows high speed low latency control and telemetry data transfer up to 80Hz. The gimbal has an Inertial Measurement Unit (IMU) on the camera frame assembly, and an encoder for each axis for tight closed loop feedback control. We have exclusive control over velocities on yaw (ψ), pitch (θ), and roll (ϕ) on the camera frame assembly, regardless of the orientation of the handle. We disable any internal low pass filters on velocity to ensure controllability. We tune the gimbal's internal PID loop for the tightest possible axis velocity control, while ensuring loop stability, given our camera array.

Camera: We use two cameras in our system. One serves as a guide camera for visual tracking over a 90° field of view. It operates at 60Hz and at a resolution of 1280×720. We also use a *star camera* for capturing high quality footage. This configuration was preferred by filmmakers in our initial scoping. It allows for cinematic freedom over camera parameters, without hurting the performance of the visual tracking. We design and 3D print a carrier assembly for the cameras, shown in Fig 3. It maximises the balance on all gimbal axes, while minimizing the distance between the optical centers of both cameras within the gimbal's confined space.

Remote Screen: We use a remote HDMI transmitter and screen when turning the system on. Once the system is setup, the screen is put away.

Audio: The user wears a lapel mic and earphones to speak commands to the system during filming, and to receive feedback throughout actor-enrollment and filming. We use an online wake word

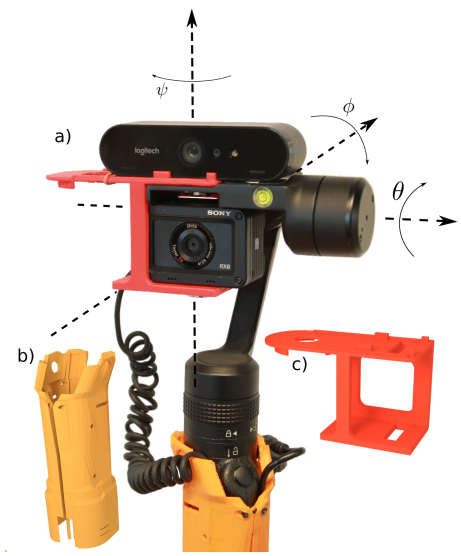

Fig. 3. a) Camera frame axes with pitch (θ), roll, (ϕ), and yaw (ψ). The LookOut controller drives the orientation of the camera assembly. On top is the guide camera, while the bottom camera is the "star" camera. b) Gimbal handle enclosure to allow for wire pass through and a comfortable grip. c) Camera assembly engineered for balance, and alignment of camera optical axes.

detection framework, Porcupine [40], for recognizing speech commands.

5 TRACKER

To achieve LookOut's aim of framing actors, the system needs to know their locations in screen space. The tracking component must work reliably for filming impromptu run-and-gun situations. Attaching real tags to actors such as in [15, 38] is often impractical. To this end, the tracker must be completely visual in nature. The requirements of the tracker are that it must:

(1) be capable of locating multiple targets of interest simultaneously, with a focus on actors,
(2) reacquire actors when they appear back in frame, while being robust to ID switches, and
(3) maintain a high online refresh rate (>30Hz) and low latency to ensure fast actor movements are captured and acted on by the control feedback loop discussed in Sec 6.

We cover the current state-of-the-art in Sec 2.3. Broadly, the trackers that are fast enough (>20Hz) fall into two categories, single object trackers aimed at the VOT [5] and OTB [51] challenges, and multi-target trackers from the MOT [37] challenge. We compare against the best trackers from these challenges in Sec 7.1. Notably, while single object trackers like DaSiamRPN [57] and SiamMask [49] perform well when keeping track of an object in frame, they are prone to tracking imposters when an object is occluded and reappears in frame, not satisfying (2). To satisfy (1), a different instance of each tracker would need to run separately for each actor; this compromises (3) since the runtime now scales linearly with the number of actors.

For trackers competing in the MOT [37], almost all trackers use tracking-by-detection, where detection bounding boxes for each scene are provided in advance and taken for granted. Multiple detectors in the literature are aimed at real-time performance at acceptable accuracy. A good choice of detector allows for real-time performance. Combining this with a budgeted algorithm for assigning detections to tracks at each timestep, trackers of this kind would suffer a relatively small penalty for each additional target. However, the MOT dataset has scenes whose mean length is only ~31 seconds, where targets only occasionally change view throughout their short life, and rarely reappear after long term occlusion. If a target is reacquired with a different ID, the tracker is only given a small penalty for ID switching/reassignment and is still given points for continuing to track with the wrong ID, breaking requirement (2).

To this end, we take inspiration from the high scoring trackers with relatively high throughput from the MOT challenge, DeepSORT [50] and MOTDT [34]. We add three contributions:

- a reworked cost structure for data association and detection/track assignment, with a concentration on tracking a handful of targets robustly,
- a recovery phase and mechanism, and
- a set of lightweight long term appearance-encoding history-management strategies, to aid in track recovery after long occlusion.

Appearance encodings are what the tracker relies on for differentiating actors and other people during filming. They are made by storing encodings of matched detections during tracking. A reliable per-actor feature gallery is important for tracking and recovery. All three components, explained below and in pseudocode in the Supplementary Material, focus on maintaining correct IDs for each actor, especially after occlusion.

Cost Formulation and Data Association: At the heart of a tracking-by-detection tracker is an assignment problem. It involves minimizing an overall assignment cost for matching a set of targets $T = t_1, ..., t_i$, including appearance and bounding box information, to a set of detections in the current frame $D = d_1, ..., d_j$. Taking inspiration from DeepSORT [50], we combine c_{ij}^{IOU}, the IOU bounding box cost [22, 37], with c_{ij}^{feature}, the cosine distance on appearance features, born from the Siamese network in [56]. We do not use a Kalman filter state based cost, as detections from our choice of lightweight detector, tiny-YOLOv3, are very noisy spatially over time.

IOU costs are useful when a target is in isolation, but useless when overlaps occur or when coming out of a long occlusion. Complimenting IOU, appearance costs are crucial for locating a target after long absences or during partial occlusion scenarios. However, a target's appearance changes over time as they move in and out of different lighting and exhibit out of plane rotation. A collection of appearance encodings, an encodings gallery, must be accumulated early in the track's life before we can rely on the appearance cost. To this end, we formulate a dynamic cost structure specific to each target, that emphasizes robustness by relying on IOU when no more than one detection competes for the same target, and the appearance cost when a target is crowded. The cost for associating each target and detection, $c(t_i, d_j)$, when that particular target, t_i, is under normal tracking (not being recovered nor while lost) is given by

$$c(t_i, d_j) = \begin{cases} c_{ij}^{IOU} & \text{if } c_{ik}^{IOU} > \tau^{\text{overlap}} \text{ where } k \neq j \\ c_{ij}^{\text{feature}} + c_{ij}^{IOU} & otherwise. \end{cases} \tag{1}$$

τ^{overlap} is set to a high strict value to prevent ID switches when a target is occluded by other people, i.e. the individual cost of assigning the target to all other detections based on IOU alone should be very high to rely on IOU. To further reduce target switches, a track/detection pair are deemed incompatible if either the IOU cost or the appearance cost exceed defined low maximums.

Each appearance cost c_{ij}^{feature} is assigned the smallest cosine distance between d_j and all versions of t_i in that target's encoding gallery. As discussed later in this section, great care is taken to discourage imposter appearance encodings from entering a target's history. In the case that a rogue or noisy encoding is included, a further step is taken to reduce ID switches. An average of the N lowest appearance costs from the target's history is computed and if found to exceed a predefined maximum, no match is allowed with this combination of detection and target.

Finally, all costs are passed along to a linear assignment step [31] where globally optimal target and detection assignments are found.

Recovery: Actors of interest will go into planned or unplanned short and long term occlusion throughout filming. During occlusion, the tracker must not confuse imposters with actors, and should then recover these actors when out of occlusion. We use appearance costs, c_{ij}^{feature}, exclusively for this step. However, the appearance encodings available to us on detections and targets are temporally noisy. An imposter detection might present a noisy appearance encoding in one frame that matches to a lost target. To prevent these types of false matches, we define a recovery phase that is begun when a detection is matched to a lost target. For a target to come out of recovery, it must be matched to a detection for R sequential timesteps. This mechanism sacrifices a few frames of tracking for recovery in the short term, but greatly improves the tracker's resistance to ID switching and long term tracking. We test our tracker without a recovery step in Table 1.

Feature History Management: In dense scenes and in a target's recovery phase, the tracker relies solely on each target's appearance encoding gallery, $\mathcal{R}_i = \{r_1, ..., r_L\}$ for data association. Ideally, an infinitely sized history would allow for the most accurate representation of the target's appearance. However, encoding comparisons for calculating appearance costs would get expensive with longer target life cycles - 10 minutes at 30Hz yields 18,000 appearance encodings. In dense scenes, encodings that are produced on occluded bounding boxes might later allow an imposter to match to this target incorrectly. We explored methods for maintaining the most informative but small gallery of a target's appearance.

To address the faulty encodings issue, encodings are added exclusively in normal tracking when only one detection competes for the current target. This prevents encodings produced by imposters overlapping our target from producing ID switches later in tracking. In Table 1, a tracker without this check is referred to as Faulty Encodings.

	$TP \uparrow$	$MT \downarrow$	$FP \downarrow$	$\overline{D} \downarrow$	T (ms)$\downarrow$
Our Tracker	**0.822**	0.152	**0.026**	**22.6**	19.3
No Recovery	0.745	**0.088**	0.166	35.8	**18.7**
Faulty Encodings	<u>0.785</u>	<u>0.140</u>	0.075	<u>26.1</u>	19.0
Greedy Encodings	0.698	0.234	<u>0.068</u>	41.2	19.0
Simple History	0.688	0.182	0.131	50.7	<u>19.0</u>

Table 1. Ablation study on the two test sequences and the metrics we establish in Section 7.1. Simple history is a flavor of our tracker but with no feature history management, only the last seen L encodings are stored in memory. *No recovery* is our tracker but without a recovery stage. If a detection matches a target once, it is accepted as the target, leading to stray incorrect tracks on distractors, a high FP score, and a lower TP score in the long term. *Greedy Encodings* stores a new incoming encoding into the feature gallery even if similar ones exist, filling up the gallery faster, thus leading to a restrictive appearance memory. *Faulty Encodings* accepts detection encodings that are overlapped with other detections in the scene. This pollutes the gallery with noisy encodings and detracts from the tracker's ability to avoid distractors. Since the gallery sampling strategy is random, all trackers are run 40 times to ensure fairness.

Almost all MOT trackers use a fixed size gallery, typically $L = 50$, and drop encodings older than 50 frames, allowing for an appearance memory of ~3 seconds. This strategy works well for short sequences (~30 seconds) as in the MOT challenge, where targets do not have a long life cycle and whose appearances do not vary greatly. However, this is less successful for longer sequences where a target may reappear either with different lighting or pose than when they went into occlusion. We address the rapid increase in the gallery's size by selectively adding encodings to the appearance gallery on every time step. An encoding is added only if it is sufficiently distant, via the cosine distance, from all other encodings in the gallery. This slows down the growth of the gallery by an order of magnitude and prioritizes space and time on informative encodings.

Although these steps help reduce the expansion of the gallery's size and maintain its integrity, they only delay the pruning problem when the gallery is full. We explored informed techniques that cluster encodings to select the most informative ones. However, most clustering techniques are iterative and time consuming, especially in this high dimensional space. A simple k-means run consumes 7ms for each target. Alternatively, a simple and effective solution is to randomly sample L_k from the gallery when it is full. Randomly sampling on each iteration is still expensive, so we only sample once the gallery is 10% larger than L_k. This has the effect of maintaining new appearances of a target while keeping a fading memory of older appearances for longer, since with every sampling step, encodings of an older age stamp are less likely to be propagated forward. Table 1 shows the performance of a tracker with a naive last-L_k encodings history.

Speed: All trackers in the MOT challenge report refresh rates with bounding boxes for detections computed in advance. In our real-time and purely online application, we must include time taken for computing detections. A survey of the detection field shows that single shot object detection, either YOLOv3 [41] or SSD [33], are best suited for this application for their attractive trade-off between speed and performance. With a CPU and GPU constrained system, tiny-YOLOv3 [41] produces detections at a rate of 40Hz, and so meets our requirements for low latency and reasonable accuracy. This detector is trained for numerous object categories, but our default LookOut experiments keep only people, cars, and bicycles. As shown in the Supplementary Videos, we also experimented with DaSiamRPN [57], which allows enrollment of novel objects, such as a shop window and a garden gnome. GPU tasks, such as computing detections and appearance encodings are all kept in a separate computation thread. We keep all other tracker tasks in a separate thread running concurrently. The completely online implementation of our tracker runs at 34Hz with an average latency of 30ms in a constrained system, satisfying (3).

We downsample all camera update frames to 740×416 for input to tiny-YOLOv3. Our choice of detector does however produce temporally noisy and intermittently missing detections - especially for small objects. We tune the Kalman Filters that we use for tracking updates to reduce spatial noise passed to any control loops down the pipeline.

Subject Enrollment: Our tracker allows a subject to be enrolled by using a chosen detection as a start point. The tracker allows tracking to take place immediately and it learns the appearance of the subject as the scene progresses. An optional extra step just before filming can help improve the tracker's robustness. This is done by having the target turn around and ideally even enter differently lit areas of a scene during setup.

6 CONTROL SYSTEM FOR FRAMING ACTORS

We drive the camera gimbal to re-frame actors dynamically over time. Actuators adjust mostly the yaw and pitch of the camera assembly to achieve the user's desired framing of one or more actors. The controller reconciles live sensor data with the user's instructions. The interface for user instructions is discussed in the supplementary materials, and actor location tracking was in Section 5.

The controller must cope with both a set of moving targets and camera and needs to handle a variety of filming scenarios and behaviors - from single actor to multi actor, from action scenes to calmer slower paced scenes, and the transitions between them. We therefore design the controller to pursue these design objectives:

1. **Achieve desired user framing:** on every loop, the system should minimize the difference in required actor framing vs. actual actor framing. Logical compromises should occur when framing multiple actors at once.
2. **Only move the camera if motivated:** the user can provide an ellipse for each actor in each behavior, indicating an area around the actor. There, their movements do not result in camera panning. The controller should also ignore noise from raw tracker estimates so the camera does not oscillate and produce unpleasant motion. This is discussed in Section 6.1.
3. **Enable smooth transitions:** As behaviors change, different actors come in and out of scene. The transitions between different actors must be smooth. This is done in Sec 6.2.

The visual servoing community has made tremendous progress in constructing methods for moving cameras and robotic arms to desired positions in space and/or orienting them based on some external visual signal [27]. The bulk of visual servoing end use-cases are in robot end effector control in manufacturing. Usually these methods involve the solution of a Jacobian matrix [7, 13] that encodes tasks and joint movement constraints. While some work explores modulating the variance of the mean position of all visual points of interest in image space [16, 54], none has provided a transparent formulation for controlling per target variance nor does one provide a framework for gradual change between different tasks and constraints. We borrow themes from the visual servoing literature while constructing a task specific control scheme.

Appealing camera positioning and orientation is essential for effective video game design, as such the video gaming has generated methods and implementation tricks for implementing dynamic cameras that follow in-game action on-the-fly [17]. While these methods assume that targets are known with certainty and that control over camera properties is instantaneous, we take hints from the community when designing our own control scheme and incorporate strategies to both mitigate and cope with real world noise.

We built a closed loop feedback system with proportional-integral-derivative (PID) [26] controllers at its heart. At an abstracted level, an error signal $e(t)$ measures the disagreement between the current state at time t vs. the user requirements encapsulated in the script. If we ignore image space distortions and make the approximation that the transformation between image space pixels and 3D Euler angles is constant throughout the entire frame, assume a simplified and noise-free world, and assume the objective of tracking a single actor, then $e(t)$ is just the screen-space difference between the tracker and where the actor should be on-screen. The horizontal and vertical correction signals, $\dot{\psi}$ and $\dot{\theta}$ respectively, are computed by two PID controllers based on the x and y components of the error signal, so

$$\dot{\psi} = \mathrm{PID}(e_x(t)) \text{ and } \dot{\theta} = \mathrm{PID}(e_y(t)). \tag{2}$$

We tune our PID controllers using a relaxed version of the Ziegler-Nichols procedure [58] to achieve the tightest response possible, while minimizing overshoot, given delay and processing constraints. In practice, a naive $e(t)$ could only handle a single actor. Worse, it would cause the camera to incessantly jerk abruptly as the actor walks, as the tracker jitters, and each time the transitions between behaviors are triggered.

The $e(t)$ signal driving the PID controller is computed based on these objectives. Specifically, $e(t)$ comes from a weighted Procrustes module, that we simplified: it aligns the current 2D actor location(s) with the location(s) required by the user, subject to the available degrees of freedom. We found that in-plane rotation for framing wasn't helpful, and our star camera lacks external control over focal length. Therefore, in all our experiments, we used a Procrustes model that simply finds the translation vector $\mathbf{T^c}$ as the weighted difference of the average actual locations and the average required location; $\mathbf{T^c}$ acts as our error vector $e(t)$. This addresses design objective (1). On each each time step, a new $\mathbf{T^c}$ is found and sent as a corrective signal to the PID controllers on each axis.

6.1 User Defined Motivated Camera Movement

Looking from the controller's perspective, we have addressed design objective (1). For (2), we run Procrustes as described, and align the "Required" actor locations $\mathbf{P^R} = \{\mathbf{p^R_1}, ..., \mathbf{p^R_n}\}$ not to the set of raw

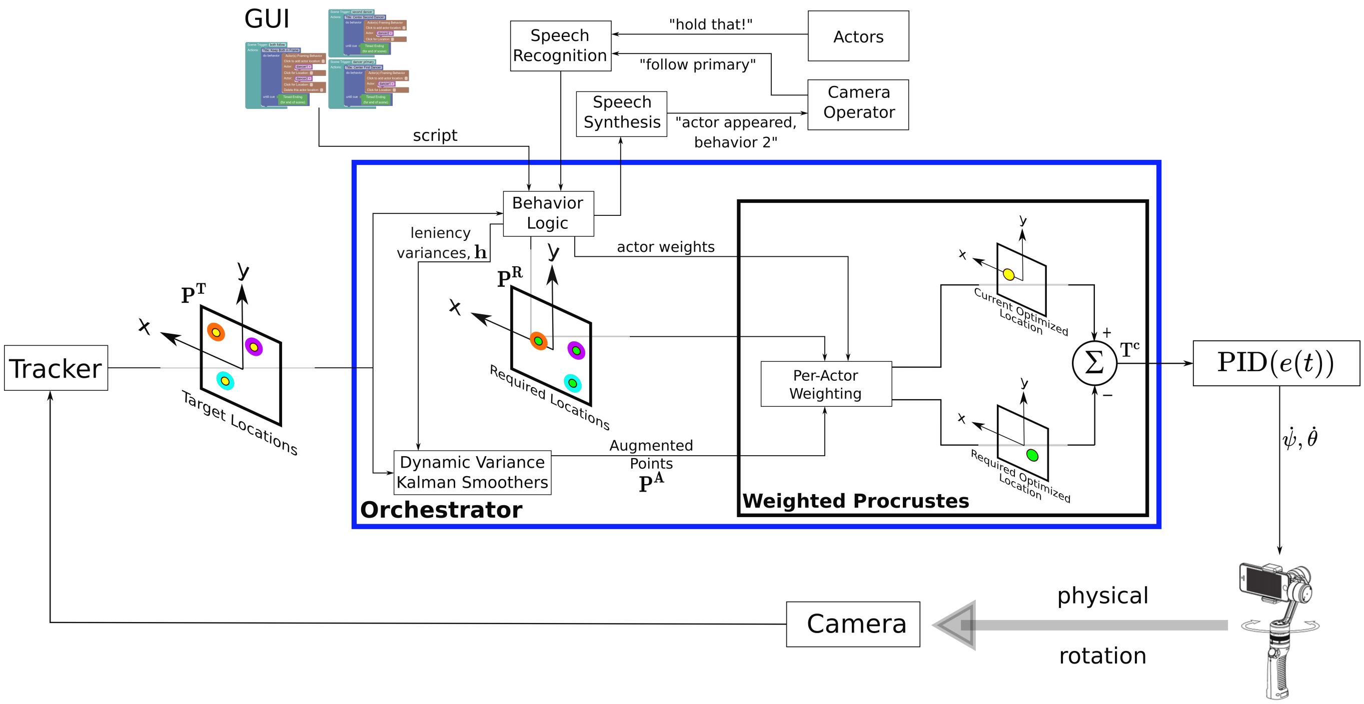

Fig. 4. High level control loop view of how LookOut fulfills subject framing. On top, user inputs come in the form of the GUI during pre-production and through the use of speech commands on-set. At the bottom, the tracker converts camera footage into raw tracks, $\mathbf{P_T}$. All of these inputs enter the orchestrator, whose job is to drive the gimbal through the PID controller. By modulating process variances, $\mathbf{h}$, the controller balances between responsiveness and smoothness for one or more actors. $\mathbf{h}$ is among the outputs from behavior logic, which had access to augmented track points from the last timestep (not pictured) and current target points, $\mathbf{P_T}$. $\mathbf{h}$ helps compute the augmented points, $\mathbf{P_A}$, which go into the procrustes module. The other main input to the procrustes module is the required locations for each actor, $\mathbf{P_R}$. Finally, the weighted difference between required locations and augmented locations drives the gimbal update. Not seen here is a velocity fading module that fades between different velocities at the transition from one type of behavior to another.

tracker points $\mathbf{P^T} = \{\mathbf{p_1^R}, ..., \mathbf{p_n^R}\}$, but against the *tracked-smoothed-augmented* points ("Augmented") $\mathbf{P^A}$. The obvious means of making augmented versions $\mathbf{P^A}$ is via Kalman filtering, so

$$\mathbf{p_i^A} = \text{KalmanFilter}(\mathbf{p_i^T}, \mathbf{h_i}), \tag{3}$$

where $\mathbf{h_i}$ is a process variance. A high $\mathbf{h_i}$ means an augmented point follows its tracked point quickly, allowing for an immediate change in the error term for that actor and an immediate correction signal from Procrustes resulting in a very responsive camera to the action. A small $\mathbf{h_i}$ allows for the opposite: each $\mathbf{p_i^A}$ lazily follows its track point $\mathbf{p_i^T}$ resulting in a less immediate corrective signal and less eager camera panning.

However, fixing $\mathbf{h_i}$ does not allow for areas of no action around where an actor is at rest and if we set $\mathbf{h_i}$ too small, the camera will never move to follow the actor. Instead we modulate $\mathbf{h_i}$ based on $\mathbf{d_i^{LE}}$, the current discrepancy between the tracked point $\mathbf{p^T}$ an its augmented point $\mathbf{p^A}$ from the previous time step. We make $\mathbf{h_i}$ proportional to $\mathbf{d_i^{LE}}$, so that with a small $\mathbf{h_i}$ the Kalman filter will ignore new updates given by $\mathbf{p_i^T}$ and instead choose to maintain the older location of $\mathbf{p_i^A}$. As a point $\mathbf{p_i^T}$ moves too far from its $\mathbf{p_i^A}$, the distance, $\mathbf{d_i^{LE}}$ ramps up and the Kalman filter is more sensitive to new incoming updates via $\mathbf{p_i^T}$.

The relationship between $\mathbf{d_i^{LE}}$ and $\mathbf{h_i}$ is user definable and based on a family of exponential functions. We define a set of artistic quantities:

- Zero Error Lift, v: This forces a non-zero value when $\mathbf{d_i^{LE}}$ is at zero. The result of a high v is an immediate responsive pan from the camera when the actor moves small distances from rest.
- Agnostic Gap, a: This defines how much distance the subject has to travel before the camera pans,
- and Curve Profile, q: This defines the ramp up at the edge of the allowed area of leniency and determines how sharply the camera will pan when an actor begins to leave that leniency area.

We also set a hard limit on $\mathbf{h}$ via η. This cap limits the impact from temporal instabilities in the tracker, and was experimentally set to 0.01 for vertical motion and 0.05 on horizontal motion in all experiments. We include a qualitative experiment for comparing between these using these smoothing functions and raw tracker values in the supplemental video. For each actor, each component of $\mathbf{h} = (h_x, h_y)$ is computed as

$$h_x = \eta_x \operatorname{clamp}(0, 1, e^{q_x(d_x^{LE} - a_x)} + v_x) \text{ and}$$
$$h_y = \eta_y \operatorname{clamp}(0, 1, e^{q_y(d_y^{LE} - a_y)} + v_y).$$

These equations are not obvious, but the three input parameters have interpretable connections to the radii (r_x, r_y) of each ellipse drawn by the user in the GUI. The functions relating radii $\mathbf{r}$ to each of these parameters are given in the Supplementary Material. In brief, for large axes ranges in $\mathbf{r}$, v is reduced such that almost no movement occurs at zero error, a is made to satisfy the distance defined by $\mathbf{r}$, and q is set so that the transition is smooth. Conversely, for a small $\mathbf{r}$, v is kept high for immediate reaction, a is set so that the point at which the curve increases happens earlier, and q is set so that the curve is sharp. See Fig 5 for different curves corresponding to different user input radii. We include an example of multiple actor leniency in the supplemental video.

Note that multi-actor leniency cannot be achieved by simply weighting the error associated with the ith actor to zero when the actor is in some allowed radius. Most situations result in an optimal optimization where required actor locations are not fulfilled perfectly due to physical limitations. A zero weight for an actor would result in a new optimization and, counterintuitively, produce camera motion when none was required. Figure 6 for an illustratuin of this.

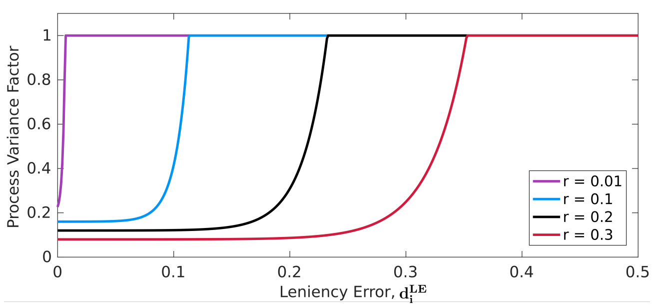

Fig. 5. Curve profiles for different user prescribed leniency radii. These radii represent areas around the actor where no camera motion should happen if the actor moves in that area. The y-axis is applied to η to produce each Kalman filter's process variance, $\mathbf{h}$. The x-axis is the difference, $\mathbf{d}_i^{LE}$, between the augmented version of the actor's location from the previous timestep, $\mathbf{p}_i^A$, and the raw tracker location, $\mathbf{p}_i^T$, and is normalized relative to screen space size. A smaller ellipse radius limits the area where the actor can move without a camera pan, as the process variance ramps up immediately. A larger ellipse allows for more actor movement before the camera starts panning.

6.2 Actor Transitions and Path Behavior

To allow for smooth transitions between subjects, satisfying (3), each actor is assigned a weight, w_i, that modifies the actor's error term in the Procrustes optimization. When an actor appears in frame and is part of the current behavior, their weight is increased progressively and decreased when they either disappear from frame, either due to occlusion or tracking failure, or are no longer included in the behavior.

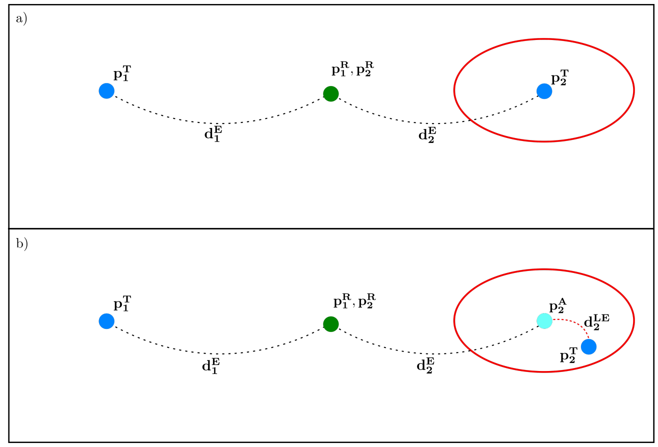

Fig. 6. Both a) and b) show an example where the user specifies that both actors should be framed in the center given by required locations $\mathbf{p}_1^R$ and $\mathbf{p}_2^R$. However, the actors' relative locations at $\mathbf{p}_1^T$ and $\mathbf{p}_2^T$ make it impossible for that requirement to be fulfilled. As such, the best framing possible at steady state is where both are equidistant from the center. Also note that the user has asked for a leniency ellipse on actor 2 given by the red ellipse. Consider a), if we were to modulate the error term $\mathbf{d}_2^E$ by some measure of where $\mathbf{p}_2^T$ is within the ellipse, then a new correction would be output that allows for better framing on actor 1, resulting in a camera pan and a disregard for leniency. Instead in b) we formulate a new augmented point $\mathbf{p}_2^A$ that is output from a Kalman filter on $\mathbf{p}_2^T$ whose process variance is modulated by the distance $\mathbf{d}_2^{LE}$ w.r.t to the ellipse. The actor can move around the augmented point and as long as they are in the ellipse, $\mathbf{p}_2^A$ will not move since the process variance $\mathbf{h}_2$ remains low. The error term $\mathbf{d}_2^E$ remains relatively unchanged, and so the camera does not move to compensate.

For each actor, we also apply Kalman filters on user selected required points as they transition between different behaviors so that no discontinuities occur. Separately, a behavior can be intentionally shaky to give the viewer a hand-held impression. To achieve shakiness or intentional banking behavior (like an airplane changing course), the controller reads the gimbal IMU accelerations on the camera's horizontal axis, applies smoothing, and actuates the roll axis. See the supplemental video for an example of a path behavior.

7 RESULTS AND EVALUATION

The LookOut system has been used to film over 12 hours of footage. To measure its strengths and find its weaknesses, we split up validation into five components:

(1) Tracker performance,
(2) Controller Evaluation,
(3) Hands-on evaluation by film-makers,
(4) Discussion of LookOut footage with senior film-makers, and
(5) Qualitative showcase of LookOut in different scenarios.

Videos can be found at http://visual.cs.ucl.ac.uk/pubs/lookOut/. For (1) and (2) we also compare performance against the DJI Osmo Mobile 3 in the supplemental videos.

7.1 Tracker

We test our tracker's performance on the VOT Long-Term Challenge [30], and on two long manually annotated videos that better represent our film-production use case. Market (one actor scene at 3m20s with annotations every frame) and TwoPeople (two actor scene at 10m30s with annotations every five frames.) are challenging scenes with representative clutter, many occlusions by distractors, variable appearance before and after occlusion, and lighting changes (See Fig 7). Crucially, the subjects' appearance changes to something not seen before when emerging after an occlusion. While our tracker and others can sometimes be shown the subject from all angles to build a representative history, this test also checks for pickup-and-go filming performance, so no such five second grace training period is given. We ultimately advocate our tracker for the tracking of people in our use case. However, we include all videos from the VOT challenge in the comparison.

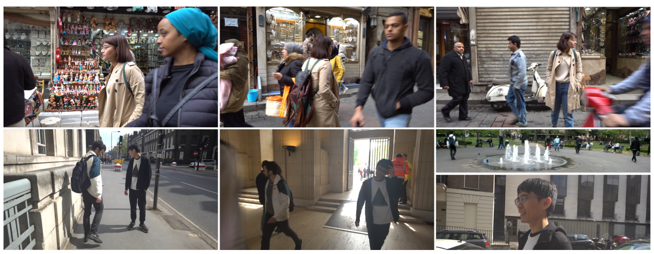

Fig. 7. Sample frames from annotated videos used for benchmarks. Top: Market, a 3m20s scene of the actor in the beige coat walking through a crowded market. There are many occlusions in this scene, including where the target appears in frame with a different appearance than when they went into occlusion. Bottom: TwoPeople, a 10m30s scene of two actors on a walk through a campus and a park. Both actors wear similar looking clothes, occlude one another, disappear from frame entirely, are seen at different scales, and walk at various distances away from the camera.

We obtain a ground truth bounding box by manually annotating input videos at 740×416. Market is annotated every frame, and twoPeople has annotations for both actors every five frames. Similar to the VOT-LT challenge, we do not include estimated annotations for when the actor is completely occluded. Based on VOT [5] and MOT [37], we emply metrics suited for actor tracking. A tracker is awarded a true positive (TP) point for a frame if it either correctly predicts the bounding box of the actor or correctly predicts that the actor is occluded. We use a bounding box IOU threshold to determine if the correct bounding box is output. If a tracker outputs an incorrect bounding box, regardless of whether or not the actor is occluded, it is given a false positive point (FP) for that frame. If a tracker does not output a bounding box when the actor is unoccluded, it is given a missed track (MT) point. We distinguish between FP and MT in this way to highlight errors that would point the camera away from the targets of interest, as is expressed with FP. We also compute the pixel distance between the center of the ground truth box and the center of the track, D, and obtain a mean over all updates, $\overline{D}$. The center of frame is used instead of the tracker's output when the tracker is lost, and in case the tracker outputs some bounding box but the target is actually occluded. All trackers are instantiated only once, using the first ground truth bounding box. Detection based trackers are all run on tiny-YOLOv3 output, and given the detection best fitting the groundtruth as a start point. All trackers are run in a single thread, including ours. We report raw unnormalised results for Market and TwoPeople (average of both actors) and normalized results on VOT-LT2019 [30] sequences in Table 2. Since our tracker has a random component, we average 40 runs on the same LookOut backpack computer.

We also ran a qualitative experiment with the leading VOT 2018 real-time tracker, DaSiamRPN [57]. We filmed an actor walking in a pedestrian area using both our tracker and DaSiamRPN [57] in separate takes. The rest of LookOut is kept constant, including actor weighting and actor specific leniency that both help to mitigate tracker noise and errors (but don't affect tracking). We run two takes each and show all takes in the supplementary video. These takes show the importance of our robustness to imposters in filming.

7.2 Controller Evaluation

In order to evaluate the controller components responsible for translating script commands to target camera frame radial velocities, we film multiple qualitative videos and also run an ablated version of the system.

We film two takes of the same running scene at the same location and with the same predetermined path making sure to keep the relative motion between the camera and actor consistent. One take was filmed using our full system, including a minor leniency that's close to the minimum allowed. The second take was filmed with an ablated version of the control system, or 'Standard Control.' The ablated version of the system passes raw tracker values as is to the PID controller without actor control weight adjustment (Sec. 6.2) and the leniency mechanism (Sec. 6.1). Fig. 8 shows camera frame radial velocities for both modes throughout this scene. Overall, the full controller satisfies scripted actor framing and largely ignores both actor track noise and camera translational motion that manifests itself as screen space motion. Following these internal and external noise sources would lead to an uncontrollably erratic camera. Please see *Control Ablation* in the supplemental for both the illustrated visualization and the star footage of this targeted comparison.

We also film scenes showing switching between multiple actors to test leniency and control weights. We also film scenes to show the effect of variable leniency on a single actor and for multiple actors. In the supplemental, please see video illustrations of actor control weights, leniency ellipsis, and actor process variances displayed when available in filming metrics.

7.3 Hands-on and End-to-end Evaluation

We designed and ran a small field study, composed of two parts. Part 1 consisted of participants building a script using the LookOut GUI, while part 2 involved the same participants filming the scene they have programmed.

Participants: In total we had 5 participants: four participants completed both parts, while one participant only completed part 1. We recruited the five volunteers (two female) by posting an advert on an amateur film-makers' group and through our own social networks. Three of them work within the film and entertainment

	Market, 3m20s, one actor					TwoPeople, 10m30s, two actors					VOT-LT2019 [30], ~2m24s, one target				
	$TP\uparrow$	$MT\downarrow$	$FP\downarrow$	$\overline{D}\downarrow$	T (ms)↓	$TP\uparrow$	$MT\downarrow$	$FP\downarrow$	$\overline{D}\downarrow$	T (ms)↓	$TP\uparrow$	$MT\downarrow$	$FP\downarrow$	$\overline{D}\downarrow$	T (ms)↓
Our Tracker	**4765**	769	**71**	**17.5**	18.5	**2655**	562	**132**	**34.8**	20.0	0.200	0.764	**0.036**	65.0	11.7
MOTDT [34]	4468	777	362	25.5	31.6	1770	1258	320	42.1	32.3	0.229	0.690	0.081	61.3	23.0
SiamMask [49]	4213	78	1316	56.1	14.9	1783	72	1493	91.7	30.1	**0.554**	0.153	0.292	85.5	12.8
DaSiamRPN [57]	2259	1732	1616	68.0	**7.9**	1709	528	1110	87.7	**14.2**	0.494	0.275	0.230	80.9	5.9
DeepSORT [50]	3961	554	1092	57.5	21.1	765	439	2143	147.0	22.6	0.186	0.752	0.061	68.8	13.2
KCF [18]	623	3552	1432	94.2	87.3	377	2819	151	123.3	73.7	0.173	0.736	0.090	**47.2**	4.4
TLD [24]	18	**56**	5533	239.4	32.2	670	**1**	2676	146.1	57.5	0.152	**0.010**	0.837	159.2	37.2

Table 2. We evaluate our tracker and other leading state-of-art real-time trackers on the VOT long-term tracking dataset. Other algorithms outperform ours on VOT. However, the VOT videos are qualitatively different in appearance from our use cases. So we introduce two further test sequences with 12,300 manually labeled annotations. These videos are more representative because of their cinematic style, both long and short term occlusions, and the presence of distractors, including people in cluttered environments. A high TP (true positive) is obviously advantageous. A low FP discourages the camera from moving onto a distractor. Some missed tracks, MTs, are tolerable, but especially after a long occlusion, missing the target could lead to catastrophic target loss. While a low MT score is important, a trivial tracker that always outputs a bounding box, whether or not the target is occluded, would allow the tracker to be distracted. In the short term, this will lead to FPs, and in the long term, it will pollute that actor's appearance representation. FPs are especially detrimental for LookOut, because the camera is controlled by tracker output. An inaccurate position will move the camera away, further decreasing the chances of recovery and ruining a take. All run times include detector latency when appropriate.

Operation	T (ms)↓
Frame Grab	8.2
Frame Resize	3.1
Gimbal Control	0.7
Gimbal Metrics Retrieval	8.9
Miscellaneous	1.6
Total	22.5
YOLOv3 and NMS	13.1
Cosine Encoding Network	3.8
Total	16.9
Tracker, Detection/Track assignment	3.3

Table 3. Breakdown of task times in LookOut. There are three main threads. One main thread handles communication and control of the gimbal along with scripting logic. Gimbal Metrics Retrieval and Frame Grab are softly run in parallel. Tracker tasks are split into two threads, one handles GPU computation and the other handles the final detection/track assignment. All threads run in a pipelined manner.

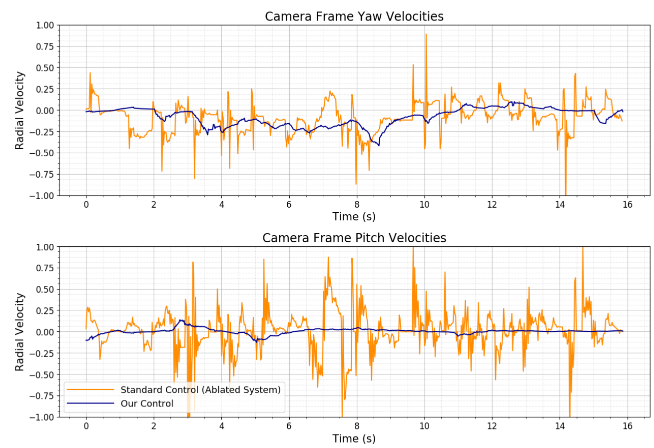

Fig. 8. Yaw (top) and pitch (bottom) camera frame radial velocities for both our full system and ablated control throughout the control ablation running scene. The standard controller (ablated system) does not ignore tracker noise and translates changes in perceived actor location from the tracker directly to an error in the PID controller. This leads to massive over corrections and an uncontrollably erratic camera. Instead, our full controller can handle tracker noise and camera translation by using modifiable leniency (Sec. 6.1) on raw tracker locations and applying control weight adjustment (Sec. 6.2). Note that these are not gimbal motor velocities, rather these are target radial velocities for the camera frame to achieve. Raw gimbal axis velocities and torque are a function of required camera frame velocities and external forces acting on the gimbal assembly.

industry (one lighting technician, one backstage support, and one director), while two are university students.

All participants had prior experience with filming, from beginner to amateur. Filming experience ranged from filming static scenes to action shots using Steadicams, from short clips for the Web to short movies. None of the participants were familiar with computer vision, nor had they been exposed to the system before the study. One of the participants reported being familiar with Blockly from toys such as the Sphero™, which she previously encountered in her part-time work.

Experimental Design: The study was designed to expose participants to the full operation of the system, from the creation of the configuration scripts using the GUI, to the actual filming of the action. To harmonize the task complexity across participants, we asked them to film a predefined sequence, communicated to them through a storyboard (printed in color on a single A3 page). Note that this form of study does not check creativity in run & gun scenarios, but rather productivity [44] when a DP is working solo.

Designing a suitable storyboard required careful consideration, to balance conflicting requirements. On one hand, we wanted a setting that really challenges visual tracking algorithms, and the storyboard to be particularly complex for a single operator to film in one shot.

These requirements were to assess the system's ability to deal with challenging filming situations, and the ability of the GUI to expose a spectrum of behaviors.

On the other hand, the storyboard design was constrained by concerns around the health and safety of participants (and to satisfy our research ethics review requirements). These concerns made us rule out any sequences involving stairs, streets with vehicles, or any other scenes that could be deemed unsafe. We also limited the number of actors required to two, and the overall study duration for each participant to one hour.

After a number of iterations, involving consultation with a separate filmmaker, we agreed on the storyboard in Figure 9. Like many long takes, it incorporates a variety of shots, some of which would be quite hard to implement with standard filming techniques. One such difficult shot implements a sudden camera transition between the two actors, followed by the participant having to run to keep up with the actor named "Blue."

Another hard shot is the swooping pan where the camera starts low and ends up high as the participant moves around the tree until they are behind actor "Red." This would normally be hard to execute as it involves the camera operator moving from a crouched to a standing position while ensuring the actor is kept within frame. With LookOut, the camera angle is adjusted automatically to frame the actor, letting the camera operator focus on their own movement.

As confirmation that the story and park setting were challenging themselves, two of our participants commented that, if they had the option, they would split the scene into separate shots ("I would segment the scene into different shots" and "normally I would split the scene into several parts").

Procedure: Participants were given verbal instructions providing a brief overview of the user interface and the scene they were required to film. The setting was a local park, in late afternoon through dusk. Participants were handed a copy of the storyboard and left on a bench to create the required configuration scripts on a laptop running the GUI. Figure 10 shows an example of a script created by a participant.

Once participants declared that they were satisfied with the scripts, they were provided with a quick overview of how the rest of LookOut works, and invited to start filming. As they tested their scripts, they were allowed to go back to the GUI and change aspects they thought did not work very well. For example, one participant went back and changed the speed of transitions, having realized that the "very fast" setting might miss locating the actor entirely.

Within 50 minutes of the start of the study, or as soon as participants filmed a scene they were satisfied with, the filming ended, and participants were asked to take part in a short interview (10 minutes) about their experience.

Configuration Scripts and GUI: All five participants who attempted part 1 of the study were able to successfully use the GUI to create configuration scripts to match the storyboard. This process lasted between 20 to 25 minutes, and was carried out independently by participants, although they were allowed to ask the experimenters questions. Participants were generally pleased with the UI's functionality. One participant commented that, "programming the framing was like coding so it was simple enough" while another participant stated that he was happy with the UI's behavior possibilities: "already a lot with actor recognition and speech recognition." However, some participants did mention the need for a "zoom function or focal length change." In addition, one participant wanted a feature to track objects: "e.g. if you wanted to track a statue while walking around it." Although LookOut supports object tracking, the UI did not offer this possibility at the time, only letting them select actors.

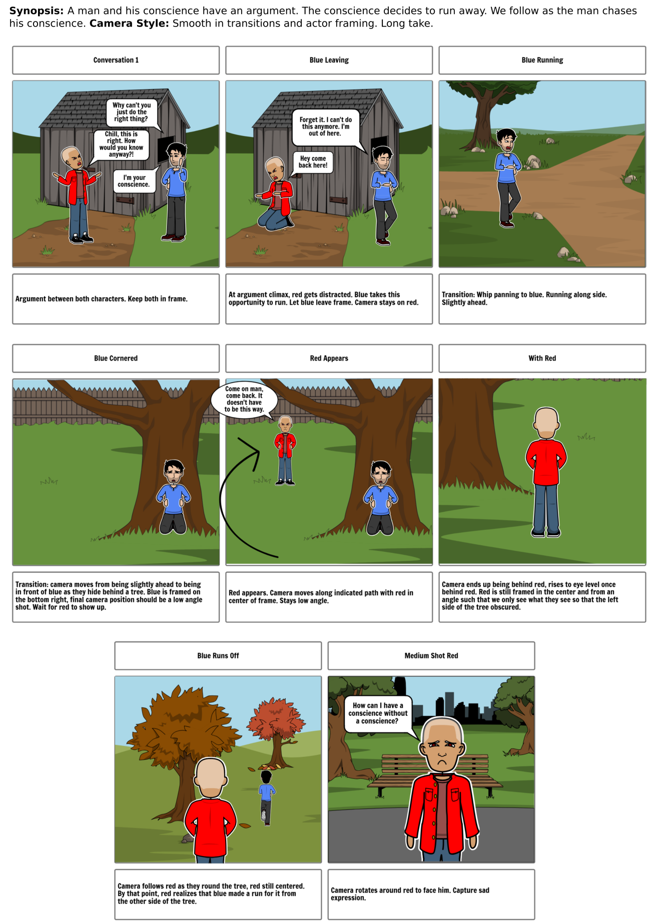

Fig. 9. Storyboard given to participants to film using LookOut during the user study.

In some cases, after one or more attempts at filming the scene, participants realized that they were not happy with some of the details in their configuration scripts. In these cases, participants edited the configuration scripts using the GUI. In one case a participant realized that the duration for a timed cue was too short, so they adjusted the value. In another case they were not happy with the angle of the yaw in a pan, so they increased it. The adjustments took less than 5 minutes as the performed changes were minor parameter settings. No issues were reported or observed with the interface.

These findings confirm that the task of scripting the behavior of the LookOut controller can be completed with minimal training by novice users. The editing of the parameters after a script was tested

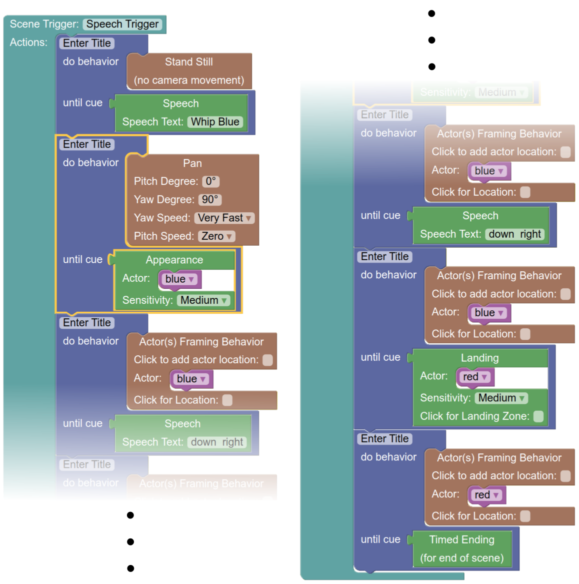

Fig. 10. An example of a configuration script programmed by one of the participants. They opted to use whip pans and actor based cues to automate most of the camera's behavior change.

indicates that participants were able to relate the two, and could refine the script behavior to match their needs.

Filming and Resulting Footage: In the remaining 15-25 minutes, two of four participants had enough time to record a long take that they were happy with for this scene. In the other two cases, there were issues with the tracking of actors that led to the scene not being adequately filmed within the prescribed time frame. This was caused by the lighting being uncharacteristically bad: on most film sets, there would be procedures in place to reduce the effect of strong sunlight filtering through the trees, to keep the actors consistently lit.

One participant pointed out that even though the camera was not giving feedback about the filming through a GUI, she could see the physical movement of the camera and thus knew whether the camera was doing what she wanted it to do: "from the physical movement of camera it looked smooth."

Participants also spoke about the convenience of having an automatic movement of the camera as it meant they could focus on other aspects of the filming, such as keeping up with the actors. One participant described the task of keeping the camera focused on an actor as "you can just track someone without caring about it."

Participant Comments: The aim of the storyboard was to have several different types of shots, some of them that would be harder to execute with traditional filming equipment. One of these shots involved having the camera quickly panning between the two actors: "the whip pan was easier with the AI, it found and tracked the subject automatically. Otherwise I would have to rehearse that 3-4 times to get it correctly." By using LookOut, the participant was able to correctly capture the shot from the first take.

Participants were particularly pleased with using voice as a trigger for the next action in the scene: "voice activating the cues worked very well." One participant stated that they "could see directors using that to program in actor's lines." This feature simplified the filming process for participants, with all participants who attempted part 2 using speech triggers within their scripts.

7.4 Critique by Senior Film-Makers

We sought out three senior film-makers, separate from the film-makers who influenced the design of LookOut, and separate from those who did the Hands-On Evaluation (Section 7.3). Each of them has been working as a professional Director of Photography, for 9, 13, and 25 years respectively. Each of them has a mix of experience, in both scripted scenes with crew and actors, and run & gun filming for documentaries or journalism. We interviewed them separately, each time showing the same three unedited video examples, shot using the LookOut system (see Fig 11). We asked the same pre-defined set of questions to prompt them to think aloud while watching the videos.

Fig. 11. Videos shown to senior film-makers. a) Rocky escarpment - camera operator climbing on foot and with one hand free. a) Bike ride. Camera operator also riding a bike. c) Pyramids - camera operator walking backwards on stairs.

The questions are listed in the Supplementary Material, but can be broadly grouped as concerning i) the equipment and people needed to film these long takes normally (without LookOut), and ii) critiques of both the footage and current LookOut capabilities.

First, to shoot such takes without LookOut, two of the film-makers have used drones, and would consider using them here, if a licensed pilot were available, and the noise wasn't prohibitive. Two of them said they would use cranes for video-A, if the budget allows. One complained, however, that multiple cranes have bad placement of viewfinders, resulting in them shooting blindly for long periods. For videos B and C, one said he would use a Steadicam, and the other two had specific two- or one-handed gimbals (like that modified for LookOut), that they would try again, despite having small and awkward viewfinders.

They each would need a second person at minimum, and usually more, to help with typical stabilization-only filming. Independently, they all said that if only one extra helper were available, then that person would be the spotter for the operator. A spotter physically guides the operator around obstacles.

Second, their views of the footage and the LookOut system were very positive, with some caveats. The two more senior ones expressed the sentiment that LookOut would have no place in a big-budget project, because the Director and DP can give orders verbally, that get carried out eventually. Also, those two would need to use LookOut multiple times before they'd trust its reliability, and ideally, prefer if colleagues make some films with it first. Extracts from the comments are in the supplemental material, including "That would be so helpful! Especially in those run and gun situations, documentary, travel, journalism. If you're filming something that won't happen again, you can focus on the other things" and "I could be more creative once I got used to it."

7.5 Qualitative LookOut Results

LookOut has been used by the authors, by test-subjects, and by novices who usually (but not exclusively) filmed using existing behavior scripts. A representative cross-section is shown in the supplemental videos web-page. Some noteworthy examples include sports where the operator is participating, such as skateboarding, or using one hand while e.g. playing frizbee, scrambling, or cycling. For the Gnome and Plumbing-shop sequences, we filmed, as an exception, using the DaSiamRPN [57] tracker within LookOut, to cope with unusual object categories, though this required multiple takes. In contrast, the vast majority of takes using our tracker worked out on the first try.

8 LIMITATIONS AND DISCUSSION

The LookOut premise, software, and hardware, each have limitations. While it would be informative to do the end-to-end evaluation under run & gun conditions, which represent the vast majority of users, those situations are rarely repeatable, and considered dangerous from an ethical experimentation perspective. That led us to use simple scripted scenarios for that evaluation. The senior film-makers are likely right that big-budget productions will be reticent to use LookOut. The field-study tested with participants from our low-budget demographic of film-makers with a fixed storyboard, but an ideal comprehensive user study would focus on adventure-athletes and journalists in somewhat dangerous conditions, to check real run & gun scenarios.

The LookOut GUI worked better and more intuitively than expected. The detector and tracker combination too, perform admirably across really diverse scenarios, though they are designed initially for tracking actors across occlusions in hand-held films, and are unremarkable on the standard Computer Vision benchmarks MOT [37] and VOT [30]. The single weakest component across the LookOut system is the detector. We've seen it confuse the tracker when the actor hides or gets too small, there is too much motion blur, or actors wear the same uniform. For now, better detectors are available, but not with the low-latency required by the controller. LookOut is built in Python, which is not optimized for real-time and multiple threads. We chose this for easier comparison with other trackers and rapid prototyping, so efficiency gains are possible. Like other appearance encodings, ours is susceptible to harsh and variable lighting (see Fig 12), which makes the system most vulnerable at dusk or dawn, and possibly when switching between indoors and outdoors.

Fig. 12. Harsh light and lens flares can upset the detector, and lead to gaps in tracking. If such a lighting change is fast enough and then long lasting, the tracker may not adequately associate new encodings with known actors, leading to a loss of tracking.

There are potentially two improvements for the hardware. First, some users requested that LookOut also manage focus-pulling and zooming, so this would require a star-camera where focal length is software-controllable in real-time. We have not found a suitable model yet. Further, we use a guide camera with a limited field of view. 360° cameras are rarely used for cinematic filming due to limited resolution, but could function as guide cameras. Then, new behaviors could better "anticipate" actors that aren't in-frame for the star camera yet. We will release the LookOut blueprints and code.

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