Nano Drone-based Indoor Crime Scene Analysis*

Martin Cooney,[1] Sivadinesh Ponrajan,[1] and Fernando Alonso-Fernandez[1]

Abstract— **Technologies such as robotics, Artificial Intelligence (AI), and Computer Vision (CV) can be applied to crime scene analysis (CSA) to help protect lives, facilitate justice, and deter crime, but an overview of the tasks that can be automated has been lacking. Here we follow a *speculate prototyping* approach: First, the *STAIR* tool is used to rapidly review the literature and identify tasks that seem to have not received much attention, like accessing crime sites through a window, mapping/gathering evidence, and analyzing blood smears. Secondly, we present a prototype of a small drone that implements these three tasks with 75%, 85%, and 80% performance, to perform a minimal analysis of an indoor crime scene. Lessons learned are reported, toward guiding next work in the area.**

I. INTRODUCTION

The current paper reports on gaps and lessons learned designing a prototype of a small drone for indoor crime scene analysis.

Automation of crime scene analysis (CSA) is an important problem: For example, violence alone was estimated to cost 14.76 USD trillion globally in 2017 [1]. When crimes occur behind closed doors, investigation can be required to reveal the truth of what transpired. Currently, however, investigators can suffer physical danger from criminals or traps at the scene, illnesses from contagious or toxic materials, and psychological harm [2]. Victims as well often do not receive justice, given numerous challenges such as human error, bias, contamination, understaffing and underfunding; degradation of evidence over time; and old-fashioned methods that can be inefficient and inaccurate such as measuring bloodstains by hand, paper and pencil drawings, carrying and changing light box filters, or working in the dark with flashlights and potentially missing evidence [2].[1] As in Fig. 1, we imagine that small drones like in Table I, that can navigate in tight indoor spaces, could help to reduce risks to investigators and facilitate justice for victims by accessing crime scenes quickly, reducing risks of contamination, and using sensory and visualizing modalities not available to humans to better capture and share information. Thereby, the idea is not that humans should be replaced, but that a drone can help humans by providing rapid initial processing.

Here, the term "drone" is defined loosely to comprise unmanned aerial vehicles (UAV), unmanned aircraft systems (UAS), unmanned aircraft vehicle systems (UAVS), remotely

Fig. 1. Basic concept: a drone could help to quickly and safely analyze crime scenes, (a) accessing the scene to gain situation awareness, (b) gathering evidence, (c) and conducting initial analysis for an investigation.

TABLE I
SOME NANO DRONES THAT COULD BE USED FOR INDOOR CRIME SCENE ANALYSIS (CSA).

Harvard RoboBee [3]	0.08 g
AeroVironment Nano Hummingbird	19 g
Blade Nano QX	22 g
Crazyflie	27 g
Zano	55 g
Teledyne FLIR Black Hornet 3/4	32 g/70 g
Trashcan drone [4]	72 g
DJI Ryze Tello	80 g

piloted aerial vehicles (RPAV), and remotely piloted aircraft systems (RPAS), including quadcopters, quadrocopters, quadrotors, and micro aerial vehicles (MAVs). Furthermore, we follow the convention that "nano drones" are defined as less than 250 g.[2]

A challenge is that it's unclear which tasks nano drones could do, since CSA is highly complex. To gain insight, we follow a *speculative prototyping* approach [5], guided by the *STAIR* tool from forensic science, which states that an analyst must understand the *Situation*, carry out *Tasks*, *Analyze* evidence, and *Investigate*, to obtain *Results* [6]. [3] Thus, our contribution here is two-fold:

- **Theoretical**. We *speculate* on how drones could be useful for crime scene analysis, including a list of some potential desired capabilities.
- **Practical**. We *prototype* drones that can semi-autonomously carry out some actions within a mock-up crime scene.

The remainder of the paper is structured as follows: In Section II, we position the current paper in regard to previous work, identifying gaps. In Section III, we explore three gaps via prototyping, with evaluation results discussed in

[1]universalclass.com/articles/law/setting-crime-scene-perimeters.htm

[2]euro-sd.com/2024/04/articles/37409/nano-uav-and-micro-uav-developments

[3]https://online.campbellsville.edu/infographics/7-steps-of-a-crime-scene-investigation/

Section IV. Our aim is to provide insights that could inspire discussion and interest, toward bringing justice in a faster, more accurate way.

II. RELATED WORK

To survey the area, top results were analyzed from ACM, IEEE Xplore, and Google Scholar with the search phrase "(drone OR UAV OR robot) AND (crime)". Bibliographies of relevant papers were scoured, and some known papers also added. To try to avoid missing important information, we also followed up with some extra queries to Scite.AI and ChatGPT. Results outside of the scope of the paper were removed, regarding crimes by drones, security of drones, and forensic analysis of drones to catch human criminals. This led to 32 papers being reviewed (newest: 2024, oldest: 1991), which are summarized below according to the STAIR framework.

A. Situation Awareness

The Situation step in STAIR involves accessing a crime scene to infer if the threat has passed and what has happened (where and when, and to whom).

Previous work has begun to describe how robots can be piloted to go quickly to crime scenes (e.g. from rooftops in Sweden, like a mini-helicopter),[4] detect doors and windows,[5] and enter buildings by opening doors,[6], breaking walls or being thrown inside by a human.[7] Drones can even acrobatically pass through narrow gaps [7]. Some drones capable of threat detection have also been designed to detect dangerous traps, pathogens, and criminals, such as Improvised Explosive Devices (IEDs) with radar, disease-carrying animal carcasses via thermal camera [8], and escaping or hiding people [9].[8] In regard to detecting offenses, cameras have also been used to recognize fighting [10]. More generally, robots have used observation to automatically infer rules underlying human behavior and interact, in games like chasing, follow-the-leader, and tag [11].

Thus, much remains to be done in this area. Our brainstorming suggested that gaps could include:

- **Access in challenging cases**. Drones could traverse partially open windows or doors, or pick locks.
- **Threat detection**. Indoor hiding criminals and victims who are paused or moving to avoid detection (e.g. in a closet, under furniture, or behind a wall in a neighboring room) could be detected via radar or thermal cameras.
- **Offense detection**. Foundation models and Large language models (LLMs) could be shown multimodal data (e.g., surveillance footage of crimes) and queried; i.e., to determine roles (even for groups coming and going), infer past/future actions, estimate levels of force,

pinpoint focal points of a crime (location and cause, like where a person was stabbed or a fire or explosion started), detect anomalies (such as broken lamp), and generate crime scene sketches, etc.

B. Tasks

The Tasks step in STAIR involves dealing with active threats to ensure safety; freezing and controlling a perimeter; detecting, gathering, and preserving evidence; as well as cleaning.

Robots have been designed to deal with threats like IEDs (improvised explosive devices) [12], disinfect complex surfaces with ultraviolet irradiation [13], and safely extract samples from corpses [14]. To avoid psychological harm to humans or privacy infringements, video can be altered via blurring, masking, or mosaics [15]. Our previous work also lists various robots carrying weapons such as explosives, stun guns, pepper spray, water, firearms, or nets, some of which have been used to detect, negotiate with, or neutralize threats, including via computer vision [16]. A makeshift perimeter to protect evidence could also be created by dropping bricks at appropriate locations, a strategy which has been used previously by drones to construct a building [17].

As shown in Table II, previous exploratory work in securing evidence can be roughly split into work manually piloting a drone or using a lidar to take 3D scans of a mock-up crime scene to assess potential benefits or demerits of technology for CSA; variables of interest have mainly been bloodstains, guns, knives, and bodies. Furthermore, some datasets have been created that could be used to train a visual system to detect evidence for crime scene analysis, as exemplified in Table III. Various photogrammetry tools also exist that could be used to create 3D models, such as 3DF Zephyr,[9] Scaniverse,[10] Luma AI,[11] OpenDroneMap,[12] and DroneDeploy.[13]

Thus, much remains to be done in this area. Gaps include:

- **Handling threats**. A drone could estimate backdrops and infer where and when force could be used; as well, drones could clear rooms and enter in a fast, effective, unpredictable, and safe way, like a SWAT team.
- **Geofencing**. In relation to detecting where a crime took place, a drone could create a perimeter, establish a "path of contamination" or common approach path, and manage the scene–preventing unauthorized entry and improper actions.
- **Handling evidence**. When mapping, useful information, like the distances between evidence (e.g., blood and body and weapon/objects) should also be calculated. Another important step after detecting evidence is gathering it (e.g., blood with a swab). For blood, presumptive testing could be conducted with luminol or tetramethylbenzidine (Hemastix) mounted to a

---

[4]youtube.com/watch?v=wV8rNjvqM9A
[5]github.com/sayedmohamedscu/YOLOv8-Door-detection-for-visually-impaired-people
[6]youtube.com/watch?v=wV8rNjvqM9A
[7]wired.com/2016/07/11-police-robots-patrolling-around-world
[8]straitstimes.com/singapore/courts-crime/keeping-watch-from-the-skies-police-unveil-two-new-drones-for-crowd-management-search-and-rescue

[9]https://www.3dflow.net/3df-zephyr-photogrammetry-software/
[10]https://scaniverse.com/
[11]https://lumalabs.ai/dream-machine
[12]https://www.opendronemap.org/
[13]https://www.dronedeploy.com/

TABLE II

CRIME SCENE EVIDENCE.

Urbanova et al. [18]	drone/CV (3D scanning outdoors via a piloted drone and photogrammetry (Agisoft PhotoScan))	dummy, bones, and artificial blood, in grass
Georgiou et al. [19]	drone/CV (piloting a DJI Spark drone outdoors for accurate, fast, reliable detection)	colored square foam pads
Cooney et al. drone/CV [20]	drone/CV (piloting a Ryze Tello drone indoors to detect via YOLO/heat traces)	hidden cameras
Bucknell and Bassindale [21]	drone (piloted a Parrot AR.Drone 2.0 at various heights to check the effects of downwash on sensitive evidence)	textile fibres on various substrates
Rymansaib et al. [22]	drone/sonar	mannequin "body" (future target possibly also weapons, narcotics, or IEDs)
Araujo et al. [23]	simulation of a drone detecting evidence based on AirSim/Unreal Engine/YOLO	body, bloodstain, gun, and knife (augmented MS-COCO data set)
Butt et al. [24].	CV (YOLO)	bullet holes
Nandhini and Thinakaran [25]	CV (classification 7-layer CNN) in infrared images	firearms, knives, money, blood, animals, cars, and cellphones (some unclarity regarding datasets)
Buck et al. [26]	3D scanning	bullet trajectories, and damage to bodies and objects
Esposito et al. [27]	3D scanning	locations and distances between corpses, bloodstains, and weapons, bullet trajectories, paths where the victim might have moved before dying, balcony height
Galanakis et al. [28]	3D scanning	"dead body" and various objects such as a phone, screws, tape, and a box (dataset released)
Liscio et al. [29]	3D scanning (using an apparatus)	"cast-off" bloodstains–from blood flying off a weapon such as a bat, hammer, knife or pipe–estimating a "Path Volume Envelope" for the path the weapon took

TABLE III

SOME DATASETS.

Weapons	Weapon detection datasets[14]	9261, 10039, 23,672, 3000, 2078, 3255 images
Weapons	Internet Movie Firearms Database[15]	31,147 articles
Shoe prints	Crime Scene Footwear Impressions Database [30]	170 samples
Shoe prints	MUES-SR10KS2S dataset [31]	10,096 samples
Shoe prints	FID-300 dataset [32]	1,475 samples (not public)
Various	Roboflow Universe[16]	350 million+ images, 500,000+ datasets

drone. Other targets that could be important to detect include footprints/shoeprints, clothing (e.g., gloves, shoes), other weapons (bullets, bullet casings, clubs), restraints (e.g., cable ties, handcuffs), extra DNA evidence (skin, hairs, body fluids other than blood–e.g., like saliva on cigarettes, drinks, food, or cutlery), and objects which might have broken due to an altercation (e.g., glass/pottery fragments, paints, particulates, and fragment patterns ("fractography")). Furthermore any object close to evidence such as a corpse or blood might also be interesting. Basic inference could be conducted on corpses (identity, pose, age, gender, and estimated time of death (e.g., based on body temperature detected with thermal camera)). As well, a thermal camera could be used to estimate when a person last touched evidence like weapons or drugs if the drone arrives fast enough.

- **Visualizing**. RViz in Robot Operating System (ROS), Unreal Engine (UE), or Unity, could be used to visualize, "replay" crimes, update models when new evidence is discovered, and prepare initial reports. The data could be accessed also via Extended Reality (XR) or 3D printed, and different evidence could be marked with different colors.
- **Cleaning**. A robot such as Roomba could be used in simple cases.[17] More complex cases might require removing all carpet, scrubbing floors, and more intensive cleaning. Such a robot could be designed for easy washing and sterilization.

C. Analysis and Investigation

In the Analysis step, theories can be drawn from the raw data about motives, opportunities, and means. Theories from multiple sources (e.g., witness testimonies and physical evidence) are then compared in the Investigation step to narrow down what likely happened.

Various work is starting to be done with blood pattern analysis (BPA). For example, a review from Weber and Lednev describes how time since deposition (TSD) can be estimated using CV via magenta values, brightness, or blood pool/crack ratio/colorimetric analysis, despite challenges due to effects of substrate, environment (temperature, humidity), and contamination [33]. Bergman et al. also describe using CV (CNN-based classification) to discriminate between passive drip vs. active spatter bloodstains [34]. As well, various mathematical models exist; for example, in a crime scene with a broken teapot, a model could be used to infer how the teapot broke [35].

Regarding investigation, one robot was designed to publish a report summarizing anomalies it detected along with interviews from nearby people [36]. More generally, logic programming languages like Prolog, and inference approaches such as Maximum Likelihood Estimation (MLE)

---

[17]www.irobot.com/en_US/roomba.html

or its Bayesian counterpart Maximum a posteriori inference (MAP) can also be used to narrow down possibilities.

However, it seems little work has focused so far on the analysis and investigating steps for CSA robots, possibly since they build on the simpler preceding steps that have mostly not yet been implemented in robots. A few examples of specific gaps are as follows:

- **Transfer stains**. In some cases, blood patterns could carry information about how people moved and so-called "second locations". Moreover, composite scenes comprising various kinds of patterns could be analyzed.
- **Affordances**. The possibility for nearby objects to be used as makeshift weapons could be assessed when hunting for a missing weapon in a violent crime.
- **Motive Inference**. For example, a missing or open safe could indicate a robbery; conversely, a murder victim with a wallet could indicate an alternative motive. Also, a distinctive modus operandi could suggest the work of a serial criminal.

Thus, while much inspiration can be taken from the literature, we did not encounter an overview of how drones could be used for crime scene analysis; however, it appeared that many opportunities exist for development, some of which we explore in the next section.

III. METHOD

Prototyping can reveal challenges and opportunities that might not be apparent if only theory is considered. From the identified gaps, we first chose three initial capabilities that seemed feasible and useful to explore: accessing a crime scene through a partially opened window, mapping evidence, and analyzing motion from a bloody path.

Then, we constructed proof-of-concepts. For hardware, a DJI Ryze Tello drone was augmented to be able to see both below and in front, by popping out its side camera to point downwards, and adding a 3D printed stand on top of its chassis to carry an ESP32-Cam, powered by a lithium polymer battery. The Ryze Tello drone is inexpensive, easily programmed, and has a large payload (> 60 g); ESP32-Cam is also inexpensive and easily programmed to wirelessly stream SVGA@30fps from its 2 Megapixel OV2640 camera to a python client. We also set up some software on an external laptop, including OpenCV[18] and YOLO 11.[19] Fig. 2 and Fig. 3 visually depict some of the challenges and successes we encountered using this setup, which are detailed below.

A. Capability 1: Situation. Access via a partially open window

Rapid access is a crucial reason for using drones, and humans cannot be expected to be on scene to let them in, so drones could seek to gain entry in various ways, including via windows. In some cases, however, a window might be partially open, such that acrobatic entry could be difficult,
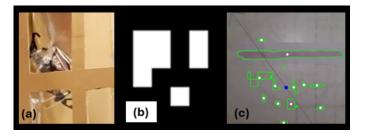
Fig. 2. Examples of initial challenges: (a) getting caught, (b) markers not being detected, and (c) false detections in poor illumination
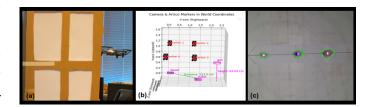

Fig. 3. Examples of successful trials: (a) pushing open a window, (b) mapping distances, and (c) inferring direction

and lock-picking unnecessary, but how to handle such cases was unclear. Although hardware is continually advancing, clearly it could be difficult currently for a nano drone to force open a tough window. For example, Yeong et al. estimate that opening a door requires 35 N [37]–whereas, based on Newton's second law of motion (F=ma), a drone like a Ryze Tello with approximate mass 100 g and acceleration 5m/s2 would have only 0.5 N of thrust force. While there are larger drones like DJI Matrice and first person view (FPV) racing drones with high acceleration, safety was also a concern.

Thus, our goal was to explore how to safely get started with testing ideas. We chose to prepare an initial mock-up window using a cardboard box with plastic wrap in place of glass. Of the four basic kinds of window–rotating horizontally (casement) or vertically (awning), and translating horizontally (sliding) or vertically (double hung)–a common "casement" form was selected. Various opening mechanisms for the drone were also considered, from wedges to actuated tongs. Eventually, a simplified approach was selected by adding a plastic spike to the underside of the drone with putty.

Initial trials with manually piloting the drone to open the window with the spike indicated substantial challenges with low force, downwash (inaccurate control), and propellers getting caught, with a performance of roughly only 20%. Therefore, we redesigned the test window to be lighter (91 g), without deep walls, and with paper in place of plastic wrap, and conducted 20 trials. The result was 75% successful performance. A main factor in the five failed attempts was the imperfect control due to the inexpensive drone used: for example, the drone sometimes came into contact with the window near the hinges where torque would be insufficient or was knocked outside of the area of the window.

B. Capability 2: Task. Mapping evidence

After gaining access, a drone should map the crime scene, calculating distances between samples and gathering evidence, which was unclear how to realize. Our approach consisted in setting the drone to fly twice, once to create a 3D map, and the second time to find evidence. To simplify our initial exploration, a small 2m x 2m mock-up murder crime scene was created using some photos of guns, bullet casings, and blood, and four ArUco markers to mark walls. The gun was placed on a table, and the other photos on the ground.

First, a 3D map was initialized. The Ryze Tello drone took off and rotated to detect markers via its side camera (ESP32-Cam), whose video feed was streamed through WiFi to an external laptop. The first marker detected was set to be located at the origin relative to the x and z axes and at a height along the y axis inferred based on the drone's height given by its bottom infrared range sensor. As the drone rotated, newly detected markers were sequentially localized with respect to the first marker. Once mapping was complete, the drone landed.

Second, the drone took off again, looking for evidence within the 3D map, by moving between markers. The drone's video feed from its downward facing camera was again relayed to the external laptop, which used YOLO 11 with a GPU to detect three classes of object (blood, guns, and bullet casings). Visual servoing was conducted to center the drone over the detected evidence. Then, information about evidence was added to the 3D map, based on the drone's estimated location and altitude. Furthermore, the drone was set to land on the center of the detected evidence to mimic gathering a sample (e.g., harvesting blood via a swab on its underside). Finally, when the drone's search ended and its map was completed, the distances between all detected objects was calculated and output.

Initial trials indicated problems with ArUco markers being too small to be detected when the drone was far or too big when the drone was close. Some trials were conducted with multiple markers. Eventually, a 4x4 ChArUco Board was adopted, which combines a chess board pattern and multiple ArUco markers to enhance accuracy and handle partial occlusions.

To evaluate the system, 20 trials were conducted. Accuracy of detecting objects was 85.0%. Reasons for some inaccuracy included illumination and lack of contrast between the bloodstain and the floor, as well as limited amounts of training images. The average discrepancy between actual distances and estimated distances was also found to be 2.395 cm (SD 0.496 cm). This error might have been due to challenges with the stability of the drone when capturing images, illumination, and the limited resolution of the drone's cameras (ESP32-Cam), as a lower resolution was used to avoid lag. Additionally, we noted that YOLO worked at 24 fps, and trials took approximately three minutes.

C. Capability 3: Analysis. Blood smear inference

Once evidence has been documented, it should be analyzed. For example, BPA on transfer stains such as smears and swipes could indicate where a criminal went or if a body was moved, given that it could be hidden to delay or confuse investigators.

For initial exploration, a simplified dataset was created using red carmine dye (cochineal- E120) on white paper. Body parts, continuity, and direction were varied. Continuity involved if the body part was constantly in contact with the paper ("legato", like a corpse being dragged) or set down at regular intervals (e.g., "staccato", like a shoe). Specifically, we walked over paper with dyed shoes and crawled on our hands to mimic a criminal or victim fleeing; and, dragged a hand, and touched down or dragged an amorphous blob using a soaked tissue, to mimic a corpse being moved. In total, twenty samples were created: five samples of each were obtained, which were viewed four times each by a rotating drone to point up, down, left, and right.

A python program was written to calculate the perceived direction of motion using a simplified approach involving color picking and image moments, given that the centroid should be closer to the start position where there is more blood than the end position where little blood remains. First, red color was detected via hue (two ranges), then contours. Then a line was fitted to the centroids of contours. Finally, the position of the centroid of centroids along the line was used to estimate the direction the bloody object was moved with dot product and an adjustment for the quadrant. A codebook vector/class label was selected as the closest to the resulting angle, and the error between prediction and ground truth calculated.

Initial trials showed various challenges, such as many small false contours using standard hue values for red, lines not being fit for long "legato" smears with a single contour, as well as some errors estimating direction with multiple contours, given that area was not taken into account. Therefore, the range for orange-red hue was removed, contour area was checked, code was written to handle base cases (e.g., if only one contour, which can happen if blood picking is good and an object is being dragged, moments are used to find a line based on the contour's shape), and the midpoint of the detected blood pixels was used in place of the center of centroids to estimate direction.

As a result, accuracy was 80%, with an average error of 50.3 degrees. Hand staccato, shoe staccato, hand legato were completely detected. However, the amorphous "tissue" stains seemed to be predicted at the level of random chance (50%). We noted that we could also not tell from observation ourselves which side was the start or end point. As well, the reason the average error was large was because of the four error cases, mostly again the "tissue" samples: three were 180 degrees wrong (in other words, the "line of motion" is estimated correctly in 19 of 20 cases, so that the error would be much less if the start and end are not required). Thus, the results indicated that some cases can be easier to infer than

others.

IV. DISCUSSION

We presented an overview of indoor crime scene analysis (CSA) by a nano drone. First, we identified theoretical gaps, based on a "big picture" (rapid scoping) review. Second, practical challenges were explored by iteratively designing three prototype capabilities with performances of 75%, 85%, and 80%. While nano drones do not seem capable yet of, e.g., opening windows, skillfully gathering evidence, and analyzing complex blood patterns in the real world, we believe that our results suggest the feasibility of initial ideation and testing within a laboratory setting. A video summarizes this work. [20]

A. Limitations and Future Work

Our approach is exploratory, involving rapid, low-fidelity prototyping; i.e., using red paint in place of blood and photos of guns instead of real firearms. Furthermore, wireless transmission of potentially sensitive data from drones to remote laptops for processing could present an security threat, allowing criminals to intercept and possibly alter communications between drone and humans. As well, the scope of this paper did not allow us to explore all of the identified gaps.

Future work should move farther from the laboratory into the real world. Stronger drones will autonomously fly in more accurate settings, onboard sensors like lidars will be used rather than markers for mapping, and real blood stain patterns will be analyzed. Processing should be preferably done by computers on the drone. Additionally, we have started to explore a broader range of capabilities we identified as potential gaps, conducting some development on each of our ideas. These additional scenarios are visualized in Fig. 4, and in the accompanying video.

In conclusion, while much work remains to be done to make this vision of nano drones helping to solve crimes a reality, we believe that the day is not too far off in which such technologies will be help preserve justice and impact society in a positive way.
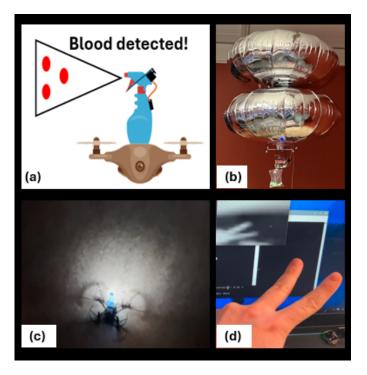

Fig. 4. (a) Revealing hidden blood stains, (b) documenting evidence without disturbance via a blimp, (c) using a flashlight to operate in the dark, and (d) detecting hidden people with thermal or radar.

REFERENCES

[1] M. Iqbal, H. Bardwell, and D. Hammond, "Estimating the global economic cost of violence: Methodology improvement and estimate updates," *Defence and Peace Economics*, vol. 32, no. 4, pp. 403–426, 2021.

[2] S. Police, personal communication (project workshop 2024-10-30), 2024.

[3] E. F. Helbling, S. B. Fuller, and R. J. Wood, "Altitude estimation and control of an insect-scale robot with an onboard proximity sensor," *Robotics Research: Volume 1*, pp. 57–69, 2018.

[4] S. Li, "Visual navigation and optimal control for autonomous drone racing," Ph.D. dissertation, Delft University of Technology, 2020.

[5] M. Tironi, "Speculative prototyping, frictions and counter-participation: A civic intervention with homeless individuals," *Design Studies*, vol. 59, pp. 117–138, 2018.

[6] R. Gehl and D. Plecas, "Strategic investigative response," *Introduction to Criminal Investigation: Processes, Practices and Thinking*, 2017.

[7] D. Falanga, E. Mueggler, M. Faessler, and D. Scaramuzza, "Aggressive quadrotor flight through narrow gaps with onboard sensing and computing using active vision," in *2017 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2017, pp. 5774–5781.

[8] J. Rietz, S. T. van Beeck Calkoen, N. Ferry, J. Schlüter, H. Wehner, K.-H. Schindlatz, T. Lackner, C. Von Hoermann, F. J. Conraths, J. Müller *et al.*, "Drone-based thermal imaging in the detection of wildlife carcasses and disease management," *Transboundary and Emerging Diseases*, vol. 2023, no. 1, p. 5517000, 2023.

[9] Y.-J. Zheng, Y.-C. Du, H.-F. Ling, W.-G. Sheng, and S.-Y. Chen, "Evolutionary collaborative human-uav search for escaped criminals," *IEEE Transactions on Evolutionary Computation*, vol. 24, no. 2, pp. 217–231, 2019.

[10] M. Perez, A. C. Kot, and A. Rocha, "Detection of real-world fights in surveillance videos," in *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 2662–2666.

[11] C. Crick and B. Scassellati, "Controlling a robot with intention derived from motion," *Topics in Cognitive Science*, vol. 2, no. 1, pp. 114–126, 2010.

[12] J. Gwozdz, N. Morin, and R. P. Mowris, "Enabling semi-autonomous manipulation on irobot's packbot," *Worcester Polytechnic Institute*, 2014.

[13] A. G. Sanchez, N. Bernhart, and W. D. Smart, "Improving uv disinfection of objects by a robot using human feedback," in *2024 33rd IEEE International Conference on Robot and Human Interactive Communication (ROMAN)*. IEEE, 2024, pp. 1697–1704.

[14] M. Neidhardt, S. Gerlach, R. Mieling, M.-H. Laves, T. Weiß, M. Gromniak, A. Fitzek, D. Möbius, I. Kniep, A. Ron *et al.*, "Robotic tissue sampling for safe post-mortem biopsy in infectious corpses," *IEEE transactions on medical robotics and bionics*, vol. 4, no. 1, pp. 94–105, 2022.

[15] Z. Jiang, B. Tong, X. Du, A. Alhammadi, and J. Zhou, "Beyond visual appearances: Privacy-sensitive objects identification via hybrid graph reasoning," *arXiv preprint arXiv:2406.12736*, 2024.

[16] M. Cooney, M. Shiomi, E. K. Duarte, and A. Vinel, "A broad view on robot self-defense: Rapid scoping review and cultural comparison," *Robotics*, vol. 12, no. 2, p. 43, 2023.

[17] F. Augugliaro, S. Lupashin, M. Hamer, C. Male, M. Hehn, M. W. Mueller, J. S. Willmann, F. Gramazio, M. Kohler, and R. D'Andrea,

"The flight assembled architecture installation: Cooperative construction with flying machines," *IEEE Control Systems Magazine*, vol. 34, no. 4, pp. 46–64, 2014.

[18] P. Urbanová, M. Jurda, T. Vojtíšek, and J. Krajsa, "Using drone-mounted cameras for on-site body documentation: 3d mapping and active survey," *Forensic science international*, vol. 281, pp. 52–62, 2017.

[19] A. Georgiou, P. Masters, S. Johnson, and L. Feetham, "Uav-assisted real-time evidence detection in outdoor crime scene investigations," *Journal of forensic sciences*, vol. 67, no. 3, pp. 1221–1232, 2022.

[20] M. Cooney, L. M. W. Klasén, and F. Alonso-Fernandez, "Designing robots to help women," in *14th Scandinavian Conference on Artificial Intelligence (SCAI 2024): AI for a better society, June 10-11, 2024, Jönköping, Sweden*. IEEE, 2024, pp. 168–177.

[21] A. Bucknell and T. Bassindale, "An investigation into the effect of surveillance drones on textile evidence at crime scenes," *Science & justice*, vol. 57, no. 5, pp. 373–375, 2017.

[22] Z. Rymansaib, B. Thomas, A. A. Treloar, B. Metcalfe, P. Wilson, and A. Hunter, "A prototype autonomous robot for underwater crime scene investigation and emergency response," *Journal of field robotics*, vol. 40, no. 5, pp. 983–1002, 2023.

[23] P. Araujo, J. Fontinele, and L. Oliveira, "Multi-perspective object detection for remote criminal analysis using drones," *IEEE Geoscience and Remote Sensing Letters*, vol. 17, no. 7, pp. 1283–1286, 2019.

[24] M. Butt, N. Glas, J. Monsuur, R. Stoop, and A. de Keijzer, "Application of yolov8 and detectron2 for bullet hole detection and score calculation from shooting cards," *AI*, vol. 5, no. 1, pp. 72–90, 2023.

[25] T. Nandhini and K. Thinakaran, "Detection of crime scene objects using deep learning techniques," in *2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*. IEEE, 2023, pp. 357–361.

[26] U. Buck, S. Naether, B. Räss, C. Jackowski, and M. J. Thali, "Accident or homicide–virtual crime scene reconstruction using 3d methods," *Forensic science international*, vol. 225, no. 1-3, pp. 75–84, 2013.

[27] M. Esposito, F. Sessa, G. Cocimano, P. Zuccarello, S. Roccuzzo, and M. Salerno, "Advances in technologies in crime scene investigation. diagnostics 2023, 13, 3169. h ps," *doi. org/10.3390/diagnostics13203169 Academic Editor: Hiroshi Ikegaya Received*, vol. 15, 2023.

[28] G. Galanakis, X. Zabulis, T. Evdaimon, S.-E. Fikenscher, S. Allertseder, T. Tsikrika, and S. Vrochidis, "A study of 3d digitisation modalities for crime scene investigation," *Forensic sciences*, vol. 1, no. 2, pp. 56–85, 2021.

[29] E. Liscio, P. Bozek, H. Guryn, and Q. Le, "Observations and 3d analysis of controlled cast-off stains," *Journal of Forensic Sciences*, vol. 65, no. 4, pp. 1128–1140, 2020.

[30] E.-T. Lin, T. DeBat, and J. A. Speir, "A simulated crime scene footwear impression database for teaching and research purposes," *Journal of Forensic Sciences*, vol. 67, no. 2, pp. 726–734, 2022.

[31] Y. Wu, X. Wang, and T. Zhang, "Crime scene shoeprint retrieval using hybrid features and neighboring images," *Information*, vol. 10, no. 2, p. 45, 2019.

[32] D. R. Bailey Kong, James Supancic and C. Fowlkes, "Fine-grained forensic matching," in *Proceedings of the British Machine Vision Conference (BMVC)*, G. B. Tae-Kyun Kim, Stefanos Zafeiriou and K. Mikolajczyk, Eds. BMVA Press, September 2017, pp. 188.1–188.12. [Online]. Available: https://bmva-archive.org.uk/bmvc/2017/papers/paper188/index.html

[33] A. R. Weber and I. K. Lednev, "Crime clock–analytical studies for approximating time since deposition of bloodstains," *Forensic Chemistry*, vol. 19, p. 100248, 2020.

[34] T. Bergman, M. Klöden, J. Dreßler, and D. Labudde, "Automatic classification of bloodstains with deep learning methods," *KI-Künstliche Intelligenz*, vol. 36, no. 2, pp. 135–141, 2022.

[35] A. Norton, G. Turk, B. Bacon, J. Gerth, and P. Sweeney, "Animation of fracture by physical modeling," *The visual computer*, vol. 7, pp. 210–219, 1991.

[36] R. Matsumoto, H. Nakayama, T. Harada, and Y. Kuniyoshi, "Journalist robot: Robot system making news articles from real world," in *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2007, pp. 1234–1241.

[37] C. F. Yeong, A. Melendez-Calderon, R. Gassert, and E. Burdet, "Reachman: a personal robot to train reaching and manipulation," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2009, pp. 4080–4085.