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Detection Technology for Killshot Analysis

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Abstract: Marksmanship is a critical aspect of special operations training, but many of the current methods for evaluating marksmanship are based on outdated manual processes. Between each shot iteration, soldiers must walk to their respective targets and analyze their groupings, often recording the results in paper notebooks. This process does not support immediate analytic feedback or long-term analysis of marksmanship which severely limits coaching effectiveness and shooter evaluation. The proposed solution, Detection Technology for Killshot Analysis (DTKA), monitors a target for gunshots and stores the results in a remote database. The results of this research are intended to facilitate immediate on-range marksmanship feedback as well as provide the necessary data for long-term marksmanship analysis within the special operations community.

Keywords: Gunshot Detection, Automation, Marksmanship Analysis, Machine Vision, Marksmanship Coaching

1. Introduction

In special operations training, efficient and accurate marksmanship is essential to building a ready and lethal force. The current training process is characterized by individual coaching and evaluation with any data collection coming from manual paper processes. Automating the detection of gunshots on targets will provide opportunities for instant feedback and provide better data for shooter evaluation over time. A systematic approach to marksmanship analysis can improve the Army's shooting range capabilities, providing a tool for the Army's most precious and lethal asset, its soldiers.

This paper outlines the capabilities of the proposed system solution for automated gunshot detection, Detection Technology for Killshot Analysis (DTKA). The authors will first discuss the existing technology in this problem space and its effectiveness in providing accurate gunshot analysis. Next, they will describe their proposed system and its functions before showing some example output. Finally, this paper will discuss the challenges faced when developing the system and provide a road map for future research to address this critical problem.

2. Problem Statement

Special operations marksmanship training currently gathers little data from operators. In many cases, the only time that marksmanship accuracy and effectiveness are measured is in formal testing or qualification. Most marksmanship training involves non-coached range time which provides little feedback to the shooter. Even coached range time does not produce artifacts and the tracking of shooter improvement is left to the subjectivity of the busy shooting coaches. Automating gunshot detection on training ranges would provide assessors with valuable information about an individual's marksmanship progression.

This project plans to address two main areas of marksmanship training: testing/evaluation and training/improvement. Automating gunshot detection supports both of these goals. Current marksmanship evaluations show only snapshots of a shooter's abilities, but automating gunshot detection would allow assessors to see data on every shot that a soldier takes. This would support long-term analysis of shooter improvement and would give a more holistic view of a shooter's true ability. Additionally, automated gunshot detection provides an opportunity to provide shooters with instant feedback on their marksmanship including the potential for automated coaching.

3. Current Process

The marksmanship coaching and evaluation used by the special operations community is largely a manual process. The conventional Army's method of marksmanship training includes a three-phase, crawl-walk-run, series. The initial crawl phase includes understanding the principles of marksmanship in a classroom setting. The walk phase consists of training aids, devices, simulators, and simulations (TADSS) and group-and-zero in a live fire setting. The run phase includes qualifications and other live fire exercises (U.S. Department of the Army, 2019). Due to the mission set and high operation tempo of the special operations community, their training focus mimics accelerated versions of phases 2 and 3. Higher volumes of on-range marksmanship training, rather than the use of simulation, give the client a greater need for automated feedback than other units within the Army.

Following initial qualifications, marksmanship training is less structured with regard to long-term assessment. In the special operations community, marksmanship coaches are used to assist in marksmanship training by visually observing the shooter and the target. This system leaves room for bias, human error, and inefficiencies. Moreover, there are not enough coaches to provide feedback for every shooter during every training opportunity.

There are commercial systems available that provide automated gunshot detection, but they are not suitable for this specific application. According to the USA Shooting at the Olympic Training Center in Colorado Springs, the precision air rifle team uses a system called Megalink, a system developed by a company in Norway (*Information from Brent McPherson, USA Shooting*, n.d.). This system houses a membrane on a small target in a fixed location. The team shoots air rifles exclusively, which do not damage the target and membrane and allow gunshots to be registered based on impact. This is a functional system for air rifles at a dedicated range but is not adaptable to varied ammunition types in an outdoor environment. Additionally, target flexibility is important to this client, as their range types vary and not all targets are in fixed locations.

Simulation technology also exists within the marksmanship training space. Simulations are able to provide large amounts of data and feedback to shooters and it is already used in some parts of the Army. However, the sponsor of this research focuses on dynamic live fire environments for training and is looking for a system adaptable to those settings. Future technology may bring simulation closer to reality, but even the most advanced systems are not realistic enough for their training needs.

4. Literature Review

After researching the possibilities and capabilities of marksmanship analysis, it appears that many marksmanship analysis solutions rely on simulation. This approach is discussed in a short review of related simulation literature. While similar units may be more open to simulation as an alternative to live fire, as mentioned, the research sponsor is not interested in simulation technology for their marksmanship training. Instead, the proposed solution will leverage existing tools in the machine vision field, specifically the OpenCV library, which will be discussed in a review of relevant research in machine vision.

4.1. Simulation

There are two main types of simulation technology used in military marksmanship training, the Engagement Skills Trainer (EST) and the Intelligent Tutoring System (ITS). The EST is a computer-operated simulator that provides the shooter with an opportunity to engage visual targets with simulated weapons that physically replicate shooting actual weapons with respect to noise and recoil (Crowley, Hallmark, Shanley, & Sollinger, 2014). ITS, on the other hand, is a method of ensuring reliable, individualized, and targeted instructional feedback (Goldberg, Amburn, Brawner, & Westphal, 2014). Two additional simulation training systems that the authors reviewed are the Laser Marksmanship Training System (LMTS) and the Multipurpose Arcade Combat Simulator (MACS). The LMTS provides a portable simulation alternative, while otherwise providing similar feedback data on performance. MACS is a computer-based weapon trainer system that provides diagnostic feedback to shooters as they shoot on scaled ranges displayed through a computer screen (Goldberg et al., 2014). Each of these simulation tools offers potential training value, yet the benefits of simulation are limited in comparison to what active feedback on a physical range could offer.

4.2. Machine Vision

Modern machine vision, as defined by the SAS Institute, processes digital images from cameras, videos, and deep learning models (*Computer Vision: What it is and Why it Matters*, 2023). Through this processing, computers are able to

”identify and classify objects – and then react to what they see” (*Computer Vision: What it is and Why it Matters*, 2023). To the team’s knowledge, technology for image change detection has not been implemented to detect impacts on a target at a shooting range.

This project leverages OpenCV and the associated Python package (Bradski, 2000). OpenCV is an open-source machine vision library with robust functionality to support simple image recognition tasks, but also supports advanced methodologies such as the MIT/Yale RoCycle robot that automatically sorts recycling (Zhang, Zhang, Li, & Zhang, 2020). Though it is a robust library, this project relies on simple OpenCV image processing functions including difference detection, changing color encoding, blurring, and detecting contours (Kulhary, 2022).

5. Methodology

Figure 1 shows the high-level methodology for DTKA. After a gunshot is fired and hits the target, the camera detects a change which triggers code that looks for a new hole in the target. If a shot is detected, the coordinates of the center of the resulting bullet hole are saved to a CSV file along with a time stamp and the identity of the shooter (if provided). The data can then be offloaded manually or wirelessly using the included WiFi module. The remainder of this section will describe the hardware and software that comprise DTKA in more detail.

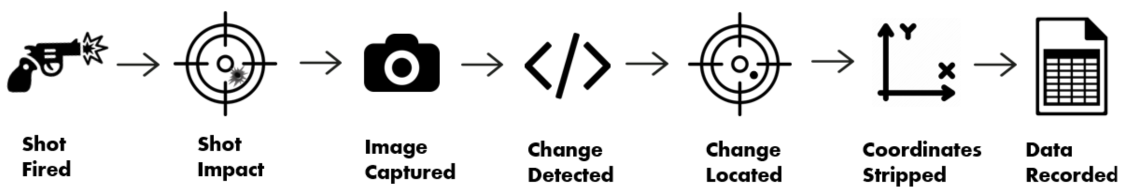

Figure 1: Icon Methodology

5.1. Hardware

The DTKA hardware, shown in Figure 2, includes a plastic ammunition can that houses components including a RaspberryPi, a touchscreen display, a camera, a battery, and a pair of adjustable telescoping legs. The camera has a zoom lens and manual adjustments for exposure and brightness. It also has a USB interface that is directly connected to the RaspberryPi. Independent telescoping legs allow for stable setup in varied terrain and they stow securely to the side of the system for transportation. The RaspberryPi is the main controller for DTKA and it is operated using a touchscreen.

(a) Unassembled Hardware (b) Compiled Hardware

Figure 2: DTKA Assembly

5.2. Software

There are two main software functions built into DTKA: set-up and data collection. During set-up, a user uses the touchscreen to start the process at which point a live video with a crosshair showing the exact center is displayed. The user positions DTKA such that the crosshair is at the center of their target and presses the touch screen again. At this point, the data collection begins.

During the data collection phase, DTKA monitors a constant stream of images for changes. DTKA detects changes by saving an original image and then comparing incoming images to the original. All incoming images are converted to grayscale before the absolute difference between the images is computed. Grayscale images correspond to 480 row, 640 column matrices with cell values ranging from 0 to 255. During testing, the researchers found that an absolute difference greater than 5 between two matrices is sufficient to catch any shots on target, but this parameter can be tuned for the desired sensitivity.

After a change is detected, DTKA finds the difference between the two image matrices and searches for contours. Contours are closed geometric shapes that appear in an image and can be identified using functions such as 'findcountours' within OpenCV (OpenCV, 2023). Shots on a target create closed circles which are easily identified as contours, but it is important to pre-process the images to account for possible noise caused by things like shadows or minor wind disturbances. To account for visual noise, the researchers first blur the differenced image, then apply a threshold for the minimum difference that should be considered by the contour search algorithm before finally running the contour search. As with the absolute difference parameter, the blur and threshold parameters can be tuned to a desired sensitivity but the authors found 10 to be a suitable value for both in their testing scenarios.

Once contours are detected, the system finds the center point of each (it is possible that rapid-fire will out-pace the gunshot detection speed so the system allows for multiple shots to appear at any time step) and logs it along with a timestamp and the identity of the shooter (if provided). Throughout testing, shot data is logged in a CSV and then manually offloaded from the device, but this data can also be pushed from the device in real time over a WiFi connection to an external database.

All of the code described in this section is available in a public Github repository that the authors will continue to update as they make changes: https://github.com/iankloo/ditka. This code is provided as Government off-the-shelf (GOTS) software as it was developed with Army funding.

6. Results

Researchers tested DTKA in several environments including a military training range as shown in Figure 3. The researchers found that their methodology was generally functional, but the real-world environment provided several complications.

(a) On-Range Setup

(b) DTKA in Action

Figure 3: Data Collection and Testing

Figure 4 shows the DTKA software as tested in a sterile lab setting (left) and on real-world data (right). In the sterile case, the code functions perfectly and provides accurate coordinates for each shot on the theoretical target. In practice, however, the authors found that real-world conditions can create false positives. The case shown on the right side of Figure 4 shows one example of a false positive caused by wind blowing the target on the left side. The software identified that the images were different and found a contour on the left side of the target and registered a gunshot that does not exist.

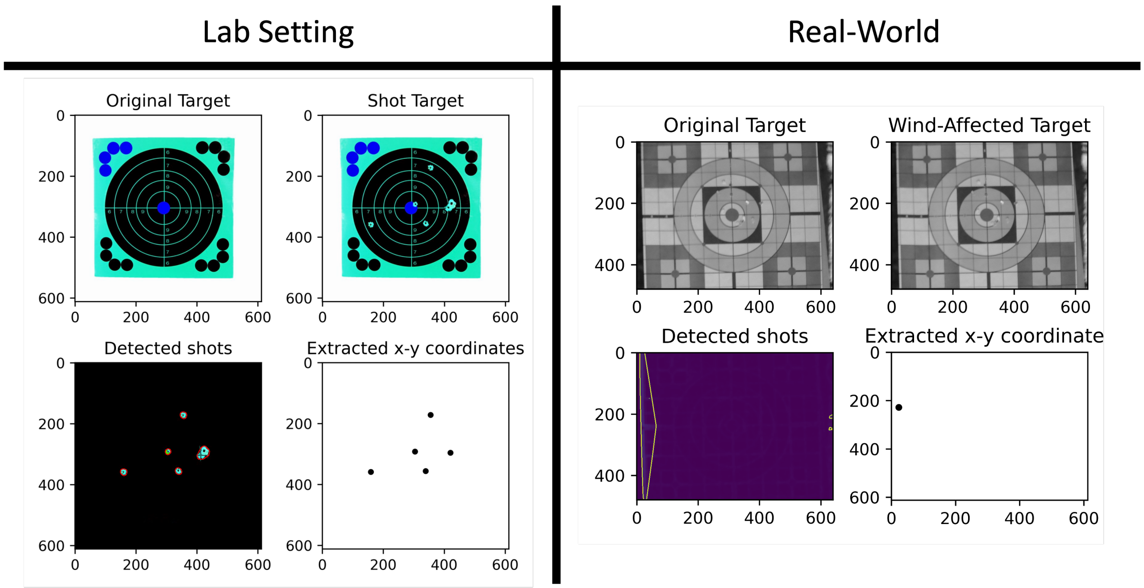

Figure 4: Gunshot extraction applied to sterile lab and real-world data. The real-world example shows how wind disturbance can result in false shots being recorded on the target.

7. Discussion

In its current state, DTKA detects gunshots in both a sterile lab environment and real-world settings; however, the team also encountered false positives in their real-world testing (as shown in Figure 4). Uncontrollable variables like changes in light (e.g., shadows and cloud movement) and wind create significant obstacles for the methodology as it relies on visual change detection to detect potential gunshots. Fortunately, most visual noise from things like wind does not create closed contours, so they do not generate false positive shots; however, Figure 4 shows an example of a noise event causing a detected contour. The team is currently experimenting with new software modifications to limit false positives including size limits on detected contours (bullet holes will have fairly uniform sizes), alternative image preprocessing pipelines (e.g., dramatically increasing contrast before comparing images) (*Contour Detection using OpenCV (Python/C++*, 2023), and creating boundaries around the targets through contour boundary detection (OpenCV, 2023). Ultimately, researchers will need to generate more real-world data sets to help them test and refine the software and correct for more potential sources of error.

While the authors plan to continue to make software improvements in their gunshot detection code, DTKA is entirely functional in terms of hardware and change detection. With minor improvements to the gunshot detection code, DTKA could serve as a fully functional GOTS prototype.

8. Future Work

As highlighted in the previous section, the most pressing need for future development is the gunshot detection code. Specifically, it will be important to ensure DTKA can reliably detect shots in a variety of shooting environments. The authors recommend using the DTKA hardware to create sets of images on a variety of real ranges that can be used to test any software solution for false negatives/positives.

In addition to software improvements, DTKA's hardware could also benefit from additional development. The authors recommend adding a set of clearly-labeled physical buttons to replace the touchscreen functionality such that a person with no prior knowledge could operate the platform. After developing the interface, the system should be evaluated for usability using the Systems Usability Scale (SUS) (Clark et al., 2021).

Future work should also examine the possibility of a multi-device solution to the gunshot detection problem. Specifically, the authors hypothesize that an on-weapon sensor that detects recoil could communicate with the camera fast enough to trigger it to look for a new shot on the target. This would eliminate the need to tune the absolute difference parameter and would reduce the need for the software to deal with images without new shots.

Finally, after DTKA is able to reliably detect and log shots on targets, it will be important to use the resulting data to help aid marksmanship training. Historical records of shooting performance will be easy to implement in assessment pipelines. Perhaps more interesting, the authors suggest working with marksmanship coaches to determine how DTKA could provide real-time feedback to shooters. In conjunction with a device on the weapon, it may be possible to train a classifier to identify likely shooter errors based on the location of shots on the target.

9. Conclusion

The special operations community has a persistent need to generate high-quality marksmen, but their current training processes are needlessly reliant on manual processes that fail to generate the high-quality data needed to train and assess their soldiers. This paper presents a fully functional prototype, DTKA, that can be used to detect and log shots on a target in a fully automated capacity. While there is still a need for both software and hardware development before DTKA is ready to be fielded, this study solved many of the initial problems with the system and provided a road map for future development. Improving DTKA and ultimately providing a complete gunshot detection system would provide significant benefit to the Army as a whole.

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