Data Analytics from Body Worn Cameras to Improve De-escalation Skills for Well-being and Safety for All

FINAL REPORT

August 2023

UNIVERSITY OF MARYLAND 1856
MARYLAND CRIME RESEARCH AND INNOVATION CENTER

About MCRIC

This document was prepared by the Maryland Crime Research and Innovation Center (MCRIC) at the University of Maryland. The Maryland Crime Research and Innovation Center engages in research to inform local, state, and national crime reduction strategy and policy through data-driven scholarship by conducting rigorous interdisciplinary basic and applied research, developing and evaluating innovative criminal justice strategies aimed at reducing crime in the state, leveraging cross-agency networks to foster data integration, and actively engaging in translational science through wide and varied dissemination of research. MCRIC leverages the broad range of expertise at the University of Maryland to engage in innovative research and interdisciplinary projects to enhance community safety and inform data-driven decision making. MCRIC works with a variety of partners including communities and community-based organizations, police and practitioners, lawmakers, academic peers, and industry, to promote data sharing, exchange knowledge and best practices, and develop new approaches.

About the Project

This is the final report for the Data Analytics from Body Worn Cameras project aimed at assessing the feasibility of automated analytics of body worn camera footage to classify and differentiate uniformed officers and civilians. This research was funded by the Maryland Governor's Office of Crime Prevention, Youth, and Victim Services (GOCPYVS), Police Accountability, Community and Transparency program. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the views or policies of the GOCPYVS, or the University of Maryland.

Contributors

Dr. Kiminori Nakamura – Principal Investigator
Assistant Research Professor, Department of Criminology and Criminal Justice, University of Maryland

Dr. Shuvra Bhattacharyya – Co-Principal Investigator
Professor, Department of Electrical and Computer Engineering, University of Maryland

Dr. Benjamin Riggan – Co-Principal Investigator
Assistant Professor, Department of Electrical and Computer Engineering, University of Nebraska-Lincoln

Dr. Bianca Bersani – Program Manager
Associate Professor, Department of Criminology and Criminal Justice, University of Maryland

Research Assistants

Can Dilaver
Department of Electrical and Computer Engineering, University of Nebraska-Lincoln

Yujunrong Ma
Department of Electrical and Computer Engineering, University of Maryland

Xiaowen Qi – Research Assistant
Department of Electrical and Computer Engineering, University of Maryland

Introduction

While most police-civilian encounters do not involve serious use of force or result in violence, those that have resulted in violence and fatalities in recent years have provoked public outcry and call for robust reforms. One of the most widespread recommendations to reduce the frequency and severity of use of force is the adoption of de-escalation policies and training (International Association of Chiefs of Police, 2020; President's Task Force on 21st Century Policing, 2015). While recent research has provided promising evidence (Engel et al., 2022; Goh, 2021), there are still serious limitations on the current evidence-base on de-escalation techniques, including core knowledge such as the lack of clear definitions and standards for effective de-escalation techniques (Engel, McManus, and Herold, 2020; Engel, McManus, and Isaza, 2020).

The use of body-worn cameras (BWCs) has rapidly diffused across the United States in the last decade (Hyland, 2018; Lum et al., 2019). Given that our current understanding of de-escalation techniques is largely based on self-reporting, rather than actual behavior, the actual officer behavior and interactions with civilians captured through BWCs provide an unprecedented opportunity to collect data on police-civilian interactions and also the opportunity for improved officer training on decision making (Engel et al., 2019).

The existing methodology of extracting and coding police body-worn camera footage is limited in scale and applicability as it is largely manual and relies on human coders (Makin et al., 2021; Sytsma et al., 2021; Terrill, Zimmerman, and Somers, 2023; Voigt et al., 2017; Willits and Makin, 2018). Furthermore, even before videos can be shared with researchers or released to the public, portions of the videos may need to be manually redacted to ensure privacy of the public and/or officers. Rapidly increasing volume of body-worn camera footage data, combined with advancement in both computing capabilities and algorithmic development, make automated analysis of BWC recording data a potentially transformative research endeavor with important implications for policing practices.

The long-term aim of this project is to leverage our research expertise in video data analytics and law enforcement operations and policy to detect and identify escalation patterns and sequences and de-escalation techniques in BWC footage data to enhance the safety and well-being of both officers and the public. The detection and identification of escalation patterns and de-escalation techniques from BWC footages requires addressing the following problems: 1) image/video enhancement and stabilization; 2) person detection; 3) officer or civilian classification; and 4) activity recognition (individual and between persons).

In supporting our long-term aim, in the near-term, the current pilot study conducts feasibility assessments to determine benefits and potential challenges of analyzing BWC data. As part of this pilot study, our primary objectives are: 1) to establish a testbed for collecting BWC video data; 2) to develop and assess face detection and redaction capabilities; and 3) to assess the ability for BWC video analytics to automatically differentiate uniformed officers from civilians.

In the following sections, we first provide the status of the Institutional Review Board (IRB) pertaining to the associated research objectives. We next present the details pertaining to the testbed and the associated data that was collected. We then provide the details pertaining to the algorithms that have been developed and assessed as part of this pilot study. We conclude with lessons learned and the next steps for our future efforts.

Institutional Review Board (IRB)

While one aspect of this project (the testbed) did not involve human subjects, the use of a secondary data source—the BWCFace dataset (Almadan, Krishnan, and Rattani, 2020) from the Wichita State University—containing data of BWC-recorded human subjects warranted a review of the dataset and the steps to ensure appropriate measures to protect consenting subjects' information. Therefore, the UMD and UNL research teams submitted all detailed information about this pilot study, including the non-human subject research components, to obtain the necessary IRB approvals to perform the proposed work. The IRB applications from both institutions were approved without significant delays. The approval letters are attached in Appendix 1.

Development of Testbed and Associated Data

Equipment

With prior experience with data collection activities and subject matter expertise with optics and computer vision, the UNL team has provided support to UMD with the equipment, planning, and execution of the testbed. To establish the testbed, the following items have been purchased:

- CammPro BWCs,
- LED Lighting kit,
- Male & Female Mannequins.

The CammPro BWC was selected due to its technical specifications that can closely simulate the Axon 3 BWC (Table 1), which is used by most law enforcement agencies in the U.S. This choice of BWC was intended to reduce differences between the testbed environment and operational conditions, while serving as a less costly alternative. The testbed offers the advantages of controllable lighting (using the lighting kit) and conditions, such as jitter of the BWCs. Two mannequins (one male and one female) were included to help mitigate any potential gender bias.

Table 1. The comparison between Axon 3 and CammPro BWCs

	Axon 3	CammPro
Video Resolution	1080p	1296p[1]
Field of View (FOV)	140 degrees	140 degrees
Video Format	MPEG-4[2]	H.264[3]

[1] Camera setting can be changed to acquire 1080p videos.

[2] MPEG-4 (specifically MPEG-4 Part 2) is a popular video/audio coding standard.

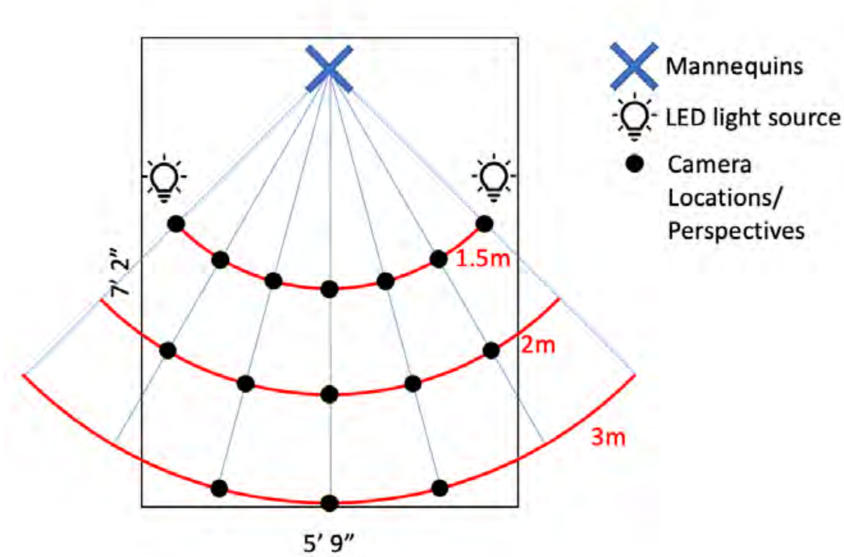
[3] H.264 (specifically MPEG-4 Part 10) is another popular video coding standard, which has a higher compression rate over MPEG-4 while maintaining the quality.

Testbed Layout and Data Collection Plan

The testbed layout for data collection is shown in Figure 1. There are many covariates to adjust for the testbed conditions, including viewing angles and distances, number of mannequins (or persons) in the field of view (FOV), mannequin (or person) positioning, lighting variations, jitter, and clutter. Based on the layout in Figure 1, there are up to 15 BWC positions available in the testbed, and the testbed can easily be adapted for additional viewing angles or distances (as the equipment is very mobile). The testbed can incorporate one or two mannequins in the FOV and each mannequin is moveable and can be arranged in any number of natural articulated positions (e.g., arms by side, forward facing, profile view, etc.).

The LED lighting kit offers 12 different levels of brightness, and the BWC can be used under stationary, walking, or jogging conditions to offer varying degrees of motion blur (jitter) and with varying degrees of clutter in the FOV. Therefore, the testbed is extremely versatile in its ability to capture a wide range of video data from BWCs.

Figure 1. Testbed layout with varying viewing angles and standoff distances



BWC Data Collection

Using the testbed, a large sample of testbed data was collected during two different sessions. The data include over 800 videos with lengths of 3-10 seconds[4] from stationary, walking, jogging, and outdoor conditions. The data also capture varying lighting intensities and perspectives. Sample "civilian" style images from a few different lighting conditions are shown in Figure 2. The inclusion of dark civilian clothing was intended to allow models to differentiate blue or dark colored clothing with officer uniforms. Sample "officer" style images for both male and female officers are shown in Figure 3.

[4] At 30 frames per second, this results in 90–300 video frames (i.e., images) from a single video.

Figure 2. Sample civilian style images over varying lighting conditions (left to right) and distances (top and bottom)

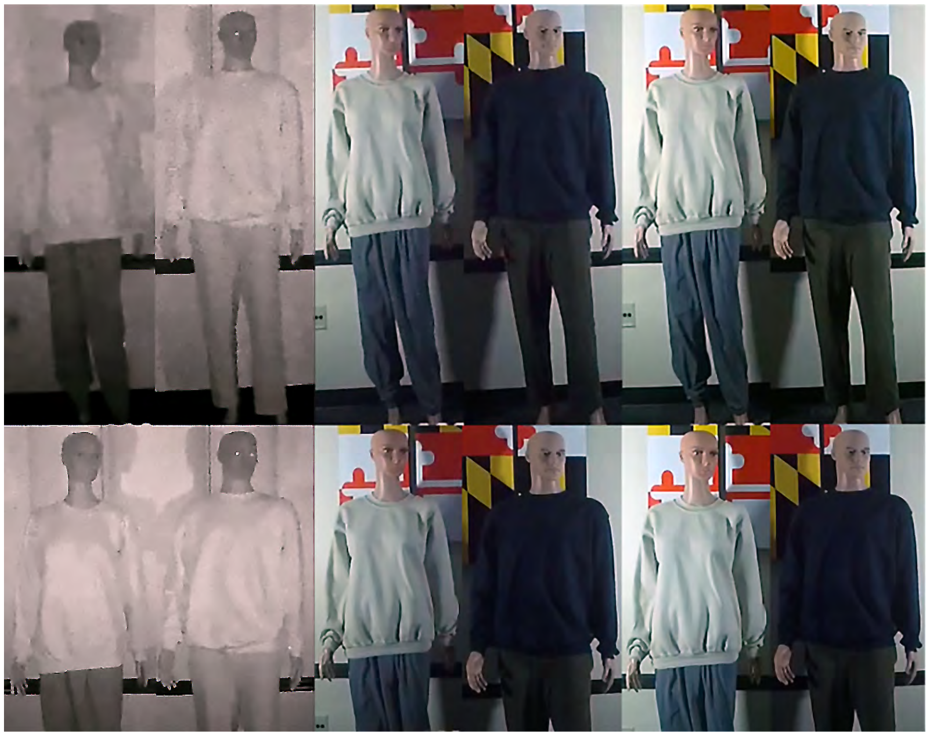
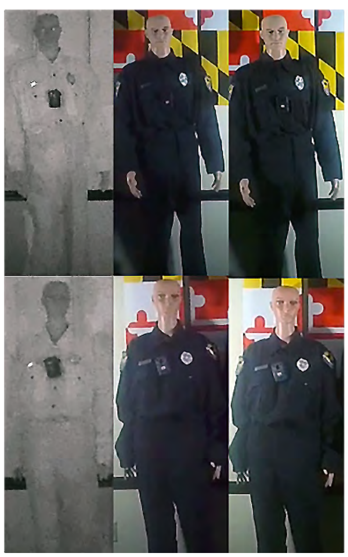


Figure 3. Left: Male (top row) and female (bottom row) officer style images over varying lighting conditions indoors. Right: Image acquired from natural outdoor lighting



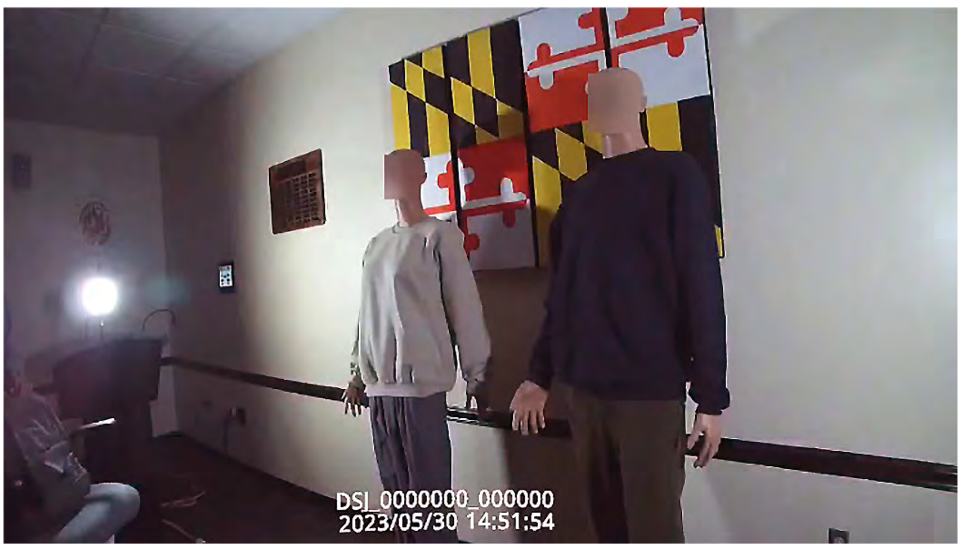
Pilot Study BWC Algorithms and Analysis

As part of the pilot study, we explored preliminary analysis using various computer vision algorithms for BWCs, including face detection and obfuscation, face recognition, and officer versus civilian classification.

Face Detection and Obfuscation

We considered several face detection models, including MTCNN (Zhang et al., 2016), YOLO (Redmon et al., 2016), and RetinaFace (Deng et al., 2020). Overall, our findings suggest that MTCNN is the slowest and may not be the best option for near real-time applications but can be used for offline analytics. Both MTCNN and YOLO tend to perform better on large objects/faces. Both MTCNN and RetinaFace are specifically designed for face detection – meaning they would need to be significantly modified to work on other types of objects. We used the face detectors on the testbed data to demonstrate the ability to obfuscate faces. Sample results are shown in Figure 4.

Figure 4. Sample results of automatic face detection and obfuscation from the testbed



Face Recognition

Using the BWCFace dataset, we experimented with vision transformers to study the effect of these methods to identify patterns in BWC imagery for facial recognition. While the potential advantage of vision transformers is their ability to relate spatially distant patterns (unlike convolutional neural networks), it is also known that they often require significantly more data to achieve better representational power. First, we initially experimented with shifted patch tokenization (Lee, Lee, and Song, 2020). This method excluded self-tokens and applied learnable parameter to the softmax function, which works by locally forcing each token to focus more on tokens with large relation to itself. As shown in Figure 6, this approach works well when trained only on natural daylight conditions from BWCFace but generalizes poorly to indoor lighting conditions. This is probably due to insufficient data and diversity.

Secondly, using vision transformer tools by Gosthipaty and Paul (2022), we considered the mean attention over different vision transformer blocks, as shown in Figure 7. This provides useful insight into the effectivness of each transformer block.

Lastly, we used the models by Steiner et al. (2022) and achieved validation accuracy of 96.45% after 25 epochs. This demonstrates that with the correct model and appropriate algorithm training, it is possible for vision transformers architectures to achieve robust face recognition results across significant lighting variations using images from BWCs.

Figure 6. Left: training and validation accuracy using only daylight BWCFace data. Right: training and validation accuracy when training on daylight conditions but evaluating on indoor lighting conditions from the BWCFace dataset.

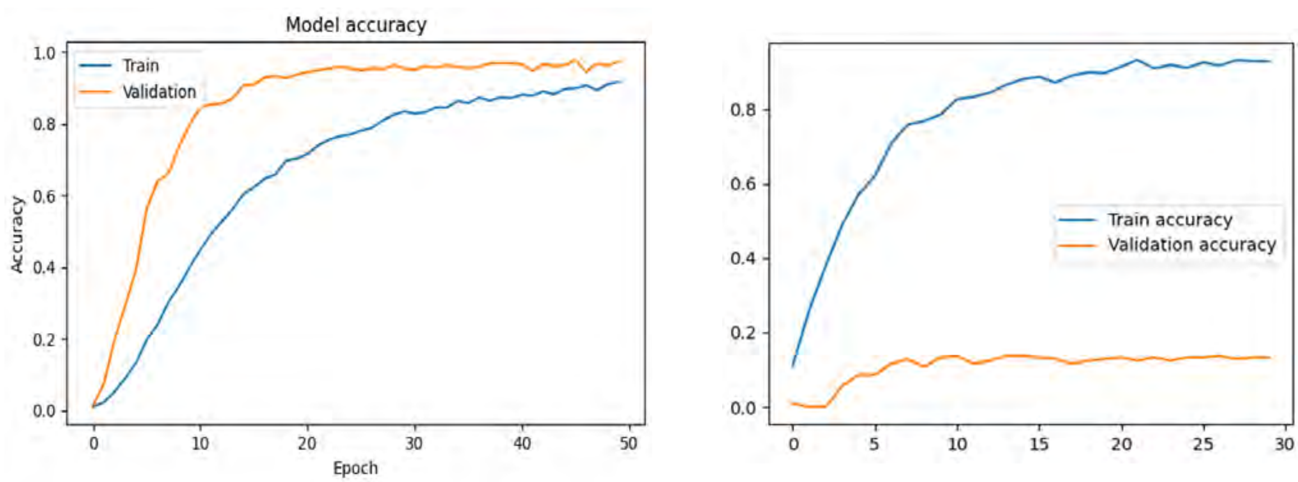
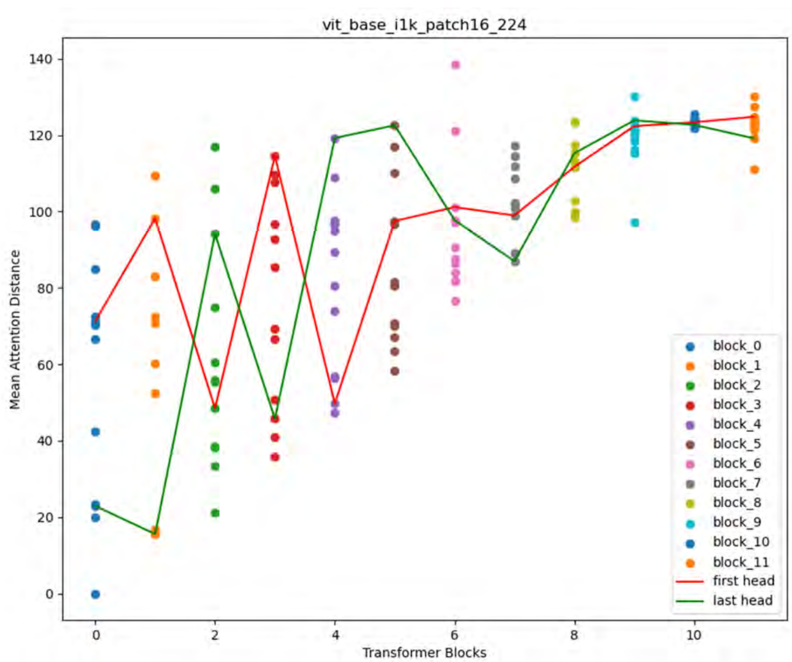


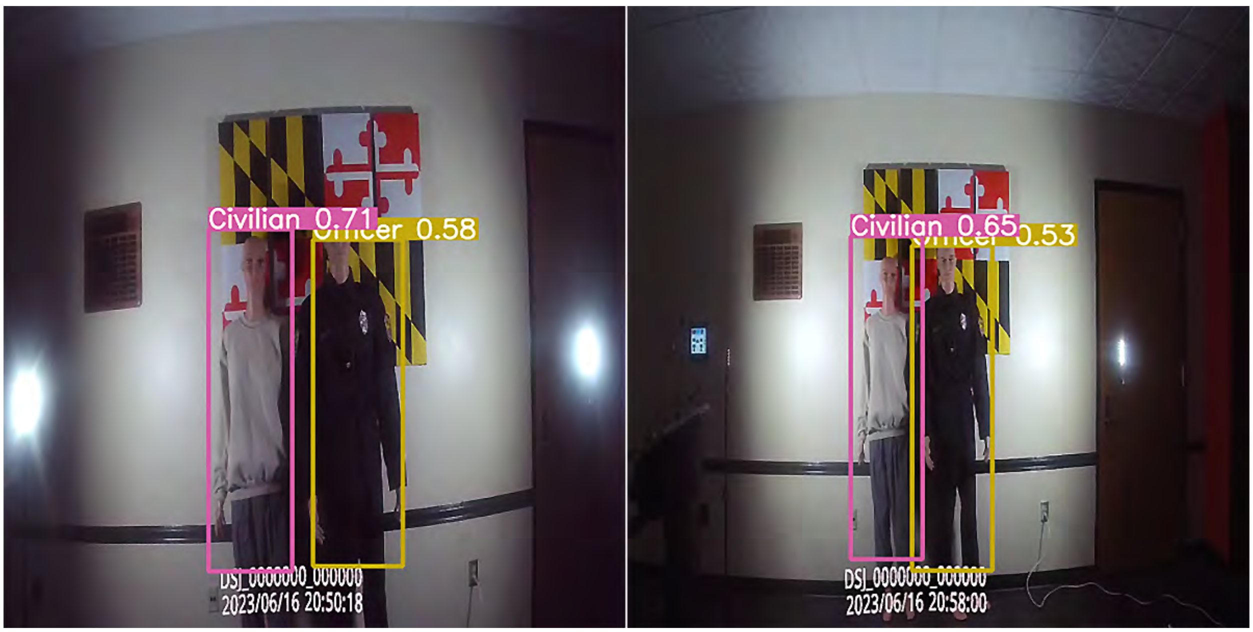
Figure 7. The mean attention tends to increase as function of increasing transformer blocks. Also, the variance of the mean attention is reduced.



Officer versus Civilian Classification

For this pilot study, we used YOLOv5 person detector to detect and classify each mannequin as either an officer or a civilian. While this approach was not perfect, sometimes confusing civilians with officers in similar-colored clothing, Figure 8 shows a more typical output when the civilian clothing is more distinct from that of an officer. Despite the currently lower performance with similar-colored clothing, the results show significant promise moving forward. For example, in the testbed images, distinguishing features of officers include their badges/shields and the BWCs that they wear on their chest. We believe that with more testbed data and variety, the models will learn to better identify these features for better discriminability.

Figure 8. Correct classifications of both officer and civilian using testbed data from multiple perspectives



Lessons Learned and Next Steps

The current pilot study provides a significant step toward BWC data analytics. Increasing use of BWCs among law enforcement agencies and resulting increases in the amount of BWC data suggest that leveraging such data for analytical solutions in public safety domains is due. While scholarly attention to BWC data has been increasing and producing informative findings, the research base is still in infancy and its methods to process BWC data for analysis have been largely manual and not at scale. In this pilot study, we focused on developing algorithmic capabilities to automatically detect faces of officers and or civilians in BWC data and redact them, if necessary, for privacy considerations. Such capabilities can facilitate data sharing with more law enforcement agencies and provide increasing opportunities for researcher-practitioner partnerships and to develop analytical solutions for pressing public safety needs. Among public safety needs that can benefit from BWC data analytics, our long-term efforts focus on escalation and de-escalation patterns detection in BWC-captured interactions with law enforcement officers and civilians. Within the short project duration of 3 months, the current pilot study has established a testbed, generated valuable BWC data, and developed and tested algorithms to detect and obscure faces, differentiate uniformed officers from civilians under various conditions. We also learned that algorithmic solutions could be sensitive to some of the BWC conditions we controlled, including lighting, and larger and more diverse data would help improve algorithms to discriminate officer and civilians in similar clothing.

Given the progress in data processing capabilities, our next steps focus on developing algorithmic capabilities to identify, detect, and predict escalation and de-escalation patterns using BWC data. Existent research points to considerable potential for early detection and prevention of escalation (e.g., Rho et al., 2023). Machine learning research on activity/action recognition has been advancing models to automatically detect human physical activities in a variety of applications, such as health care and education (Pareek and Thakkar, 2021; Ramasamy Ramamurthy and Roy, 2018). Importantly, there has also been increasing effort to detect violence in surveillance camera videos (Cheng et al., 2021). Video-based activity recognition can identify potential motion components of escalation patterns, including walking, running, rushing, and jumping based on graph convolutional network (GCN) methods as well as a PoseConv3D framework (Duan et al., 2022) for skeleton-based action recognition that tracks key points or joints of a human body. In addition to video data, audio data could also help detect escalation with acoustic and lexical features of speech (Zhou et al., 2021) and by capturing emotional arousal that is typically associated with escalation (Lefter et al., 2022). Recent studies extract both visual as well as audio features and fuse them as multimodal input for activity recognition (Wu et al., 2020; Ye, et al., 2021). There are other areas of activity recognition research that are relevant to escalation and de-escalation detection with BWC data, such as improving reliability of the detection in BWC videos that are collected real-time from multiple perspectives (e.g., Yao et al., 2021). In summary, the newly acquired capabilities from this pilot project strategically position our future research to leverage rapidly expanding activity recognition research to help develop BWC-driven public safety solutions.

References

Almadan, Ali, Anoop Krishnan, and Ajita Rattani, "BWCFace: Open-set Face Recognition using Body-worn Camera," *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, Miami, FL, USA, 2020, pp. 1036-1043, doi: 10.1109/ICMLA51294.2020.00168.

Cheng, Ming, Kunjing, Cai, and Ming Li. RWF-2000: an open large scale video database for violence detection, *2020 25th International Conference on Pattern Recognition (ICPR)*. IEEE, 2021: 4183-4190.

Duan, Haodong, Yue Zhao, Kai Chen, Dahua Lin, and Bo Dai. Revisiting skeleton-based action recognition, *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022: 2969-2978.

Engel, Robin S., Nicholas Corsaro, Gabrielle T Isaza, and Hannah D McManus. Assessing the impact of de-escalation training on police behavior: Reducing police use of force in the Louisville, KY Metro Police Department. *Criminology & Public Policy*, 21:199-233, 2022.

Engel, Robin S., Hannah D McManus, and Tamara D Herold. Does de-escalation training work? a systematic review and call for evidence in police use-of-force reform. *Criminology & Public Policy*, 19(3):721-759, 2020.

Engel, Robin S., Hannah D McManus, and Gabrielle T Isaza. Moving beyond "best practice": Experiences in police reform and a call for evidence to reduce officer-involved shootings. *The ANNALS of the American Academy of Political and Social Science*, 687(1):146-165, 2020.

Engel, Robin S., Robert E Worden, Nicholas Corsaro, Hannah D McManus, Danielle Reynolds, Hannah Cochran, Gabrielle T Isaza, and Jennifer Calnon Cherkauskas. *The Power to Arrest*. Springer, 2019.

Fan Hehe, Xin Yu X, Yuhang Ding Y, Yi Yang, and Mohan Kankanhalli. Pstnet: Point spatio-temporal convolution on point cloud sequences. *arXiv* preprint arXiv:2205.13713, 2022.

Gosthipaty, Aritra Roy and Sayak Paul. 2022. https://github.com/sayakpaul/probing-vits

Hyland, Shelley. *Body-worn cameras in law enforcement agencies*, 2016. US Department of Justice, Office of Justice Programs, Bureau of Justice, 2018.

International Association of Chiefs of Police. National consensus policy on use of force, 2017. President's Task Force on 21st Century Policing. *Final report of the president's task force on 21st century policing*, 2015.

Jiankang Deng, Jia Guo, Yuxiang Zhou, Jinke Yu, Irene Kotsia, and Stefanos Zafeiriou, "RetinaFace: Single-Shot Multi-Level Face Localization in the Wild", *CVPR* 2020.

Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi, "You Only Look Once: Unified, Real-Time Object Detection", *CVPR* 2016.

Kaipeng Zhang, Zhanpeng Zhang, Zhifeng Li, and Yu Qiao, "Joint Face Detection and Alignment Using Multi-task Cascaded Convolutional Networks", *IEEE Signal Processing Letters*, 2016.

Lee, Seunghoon, Seunghyun. Lee, and Byung C. Song. "Improving Vision Transformers to Learn Small-Size Dataset From Scratch," in *IEEE Access*, vol. 10, pp. 123212-123224, 2022, doi: 10.1109/ACCESS.2022.3224044.

Lefter, Lulia, Alice Baird, Lukas Stappen, and Björn W. Schuller. A Cross-Corpus Speech-Based Analysis of Escalating Negative Interactions. *Frontier in Computer Science*, vol.4, 2022.

Li Sian Goh. Did de-escalation successfully reduce serious use of force in Camden County, New Jersey? a synthetic control analysis of force outcomes. *Criminology & Public Policy*, 2021.

Lum, Cynthia, Megan Stoltz, Christopher S Koper, and J Amber Scherer. Research on body-worn cameras: What we know, what we need to know. *Criminology & Public Policy*, 18(1):93-118, 2019.

Makin, David A., Dale W Willits, and Rachael Brooks. Systematic social event modeling: a methodology for analyzing body-worn camera footage. *International Journal of Social Research Methodology*, 24(2):163-176, 2021.

Pareek, Preksha, and Ankit Thakkar. "A survey on video-based human action recognition: recent updates, datasets, challenges, and applications." *Artificial Intelligence Review* 54 (2021): 2259-2322.

Ramasamy Ramamurthy, Sreenivasan, and Nirmalya Roy. "Recent trends in machine learning for human activity recognition—A survey." *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 8.4 (2018): e1254.

Rho, Eugenia, Maggie Harrington M., Yuyang Zhong Y., Reid Pryzant R., Nicholas P. Camp, Dan Jurafsky, Jennifer L. Eberhardt. Escalated police stops of Black men are linguistically and psychologically distinct in their earliest moments. *PNAS*, vol.120, no.23, 2023.

Steiner, Andreas, Alexander. Kolesnikov, Xiaohua Zhai, Ross Wightman, Jakob Uszkoreit, and Lucas Beyer. "How to train your ViT? Data, Augmentation, and Regularization in Vision Transformers," *Transactions on Machine Learning Research*, 2022.

Sytsma, Victoria A., Eric L Piza, Vijay F Chillar, and Leigh S Grossman. Measuring procedural justice policy adherence during use of force events: The body-worn camera as a performance monitoring tool. *Criminal Justice Policy Review*, page 08874034211021894, 2021.

Terrill, William, Laura Zimmerman, and Logan J. Somers. Applying video-based systematic social observation to police use of force encounters: An assessment of de-escalation and escalation within the context of proportionality and incrementalism. *Justice Quarterly*, DOI: 10.1080/07418825.2023.2222819, 2023.

Voigt, Rob, Nicholas P Camp, Vinodkumar Prabhakaran, William L Hamilton, Rebecca C Hetey, Camilla M Griffiths, David Jurgens, Dan Jurafsky, and Jennifer L Eberhardt. Language from police body camera footage shows racial disparities in officer respect. *Proceedings of the National Academy of Sciences*, 114(25):6521-6526, 2017.

Willits, Dale W. and David A Makin. Show me what happened: Analyzing use of force through analysis of body-worn camera footage. *Journal of Research in Crime and Delinquency*, 55(1):51-77, 2018.

Wu, Peng, Jing Liu J, Yujia Shi Y, Yujia Sun, Fangtao Shao, Zhaoyang Wu, and Zhiwi Yang. Not only look, but also listen: Learning multimodal violence detection under weak supervision, *Computer Vision–ECCV 2020*: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXX 16. Springer International Publishing, 2020: 322-339.

Yao, Chuang, Su Xiaoyan, Wang Xuehua, Xinyi Kang, Jun Zhang J, Jiankang Ren. Motion direction inconsistency-based fight detection for multiview surveillance videos. *Wireless Communications and Mobile Computing*, 2021.

Ye, Liang, Tong Liu T, Tian Han T, Hany Ferdinando H, Tapio Seppänen T, and Esko Alasaarela. Campus violence detection based on artificial intelligent interpretation of surveillance video sequences. *Remote Sensing* 13(4):1–17, 2021.

Zhou, Peipei, Qinghai Ding Q, Haibo Luo H, and Xinglin Hou. Violent interaction detection in video based on deep learning. *Journal of physics: conference series*, vol. 844, no. 1. IOP Publishing, 2017, p. 012044.

Zhou, Ziang, Yanze Xu, and Ming Li. Detecting Escalation Level from Speech with Transfer Learning and Acoustic-Lexical Information Fusion. *arXiv* preprint arXiv:2104.06004. 2021 Apr 13.

Appendix 1: IRB Approval Letters

Official Approval Letter for IRB project #22868 - New Project Form

May 10, 2023

Benjamin Riggan
Department of Electrical and Computer Engineering
NH 411B UNL NE 685880511

IRB Number: 20230522868EP
Project ID: 22868
Project Title: IRB - Data Analytics from Body Worn Cameras to Improve De-escalation Skills for Well-being and Safety for All

Dear Benjamin:

This letter is to officially notify you of the approval of your project by the Institutional Review Board (IRB) for the Protection of Human Subjects. It is the Board's opinion that you have provided adequate safeguards for the rights and welfare of the participants in this study based on the information provided. Your proposal is in compliance with this institution's Federal Wide Assurance 00002258 and the DHHS Regulations for the Protection of Human Subjects under the 2018 Requirements at 45 CFR 46.

o Review conducted using expedited review category(ies) 6 & 7 at 45 CFR 46.110
o Date of Approval: 05/10/2023
o Date of Expedited review: 05/10/2023
o Date of Acceptance of Revisions: N/A
o Funding (Grant congruency, OSP Project/Form ID and Funding Sponsor Award Number, if applicable): UNL receives a subaward from the University of Maryland. OSP project #55182, OSP form #148908. grant congruency review conducted by RW.
o Consent waiver: consent at 45 CFR 46.116(f)(3)(i-iv)
o Review of specific regulatory criteria (contingent on funding source): 45 CFR 46
o Subpart B, C or D review: N/A

You are authorized to implement this study as of the Date of Final Approval: 05/10/2023 and upon submission of a fully executed data use agreement.

We wish to remind you that the principal investigator is responsible for reporting to this Board any of the following events within 48 hours of the event:
* Any serious event (including on-site and off-site adverse events, injuries, side effects, deaths, or other problems) which in the opinion of the local investigator was unanticipated, involved risk to subjects or others, and was possibly related to the research procedures;
* Any serious accidental or unintentional change to the IRB-approved protocol that involves risk or has the potential to recur;
* Any protocol violation or protocol deviation
* An incarceration of a research participant in a protocol that was not approved to include prisoners
* Any knowledge of adverse audits or enforcement actions required by Sponsors
* Any publication in the literature, safety monitoring report, interim result or other finding that indicates an unexpected change to the risk/benefit ratio of the research;
* Any breach in confidentiality or compromise in data privacy related to the subject or others; or
* Any complaint of a subject that indicates an unanticipated risk or that cannot be resolved by the research staff.

Any changes to the project, including reduction of procedures, must be submitted and approved prior to implementation. A change request form must be submitted to initiate the review of a modification.

For projects which continue beyond one year from the starting date, an annual update of the project will be required by informing the IRB of the status of the study. The investigator must also advise the Board when this study is finished or discontinued by completing the Final Report form via NUgrant.

If you have any questions, please contact the IRB office at 402-472-6965.

Sincerely,

Rachel Wenzl, CIP
for the IRB

University of Nebraska-Lincoln Office of Research and Economic Development
nugrant.unl.edu

NUgrant

UNIVERSITY OF MARYLAND

INSTITUTIONAL REVIEW BOARD

1204 Marie Mount Hall
College Park, MD 20742-5125
TEL 301.405.4212
FAX 301.314.1475
irb@umd.edu
www.umresearch.umd.edu/IRB

DATE:	July 10, 2023
TO:	Kiminori Nakamura
FROM:	University of Maryland College Park (UMCP) IRB
PROJECT TITLE:	[2023418-1] Body Worn Camera Data Analytics Pilot
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	July 10, 2023
REVIEW CATEGORY:	Exemption category # 45CFR46.104(d)(4)(ii).

Thank you for your submission of New Project materials for this project. The University of Maryland College Park (UMCP) IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will retain a copy of this correspondence within our records.

If you have any questions, please contact the IRB Office at 301-405-4212 or irb@umd.edu. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within University of Maryland College Park (UMCP) IRB's records.

MARYLAND CRIME RESEARCH AND INNOVATION CENTER

Maryland Crime Research and Innovation Center
University of Maryland
2220 Samuel J. LeFrak Hall
7251 Preinkert Drive
College Park, MD 20742

301-405-4699 | mcric-contact@umd.edu | go.umd.edu/mcric