



ARL-TR-9443 • APR 2022



# **Soldier State Estimation: Modelling and Analysis (Summary Technical Report, Oct 2020–Sep 2021)**

**by Mark Dennison and Michael H Lee**

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# **Soldier State Estimation: Modelling and Analysis (Summary Technical Report, Oct 2020–Sep 2021)**

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**REPORT DOCUMENTATION PAGE**

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<b>1. REPORT DATE (DD-MM-YYYY)</b> April 2022			<b>2. REPORT TYPE</b> Summary Technical Report		<b>3. DATES COVERED (From - To)</b> October 2020–September 2021	
<b>4. TITLE AND SUBTITLE</b> Soldier State Estimation: Modelling and Analysis (Summary Technical Report, Oct 2020–Sep 2021)					<b>5a. CONTRACT NUMBER</b>	
					<b>5b. GRANT NUMBER</b>	
					<b>5c. PROGRAM ELEMENT NUMBER</b>	
<b>6. AUTHOR(S)</b> Mark Dennison and Michael H Lee					<b>5d. PROJECT NUMBER</b>	
					<b>5e. TASK NUMBER</b>	
					<b>5f. WORK UNIT NUMBER</b>	
<b>7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)</b> DEVCOM Army Research Laboratory ATTN: FCDD-RLC-IB Aberdeen Proving Ground, MD 21005					<b>8. PERFORMING ORGANIZATION REPORT NUMBER</b>  ARL-TR-9443	
<b>9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)</b>					<b>10. SPONSOR/MONITOR'S ACRONYM(S)</b>	
					<b>11. SPONSOR/MONITOR'S REPORT NUMBER(S)</b>	
<b>12. DISTRIBUTION/AVAILABILITY STATEMENT</b> Approved for public release: distribution unlimited.						
<b>13. SUPPLEMENTARY NOTES</b> ORCID ID: Mark Dennison, 0000-0001-9780-0511						
<b>14. ABSTRACT</b> Enabling leaders with the ability to make decisive actions in high-operational tempo environments is key to achieving decision-superiority. Under stressful battlefield conditions with little-to-no time for communication, it is critical to acquire relevant tactical information quickly to inform decision-making. A potential augmentation to tactical information systems is access to real-time analytics on a unit's operating status and emergent behaviors inferred from Soldier-worn or embedded sensors on their kit. Automatic human activity recognition (HAR) has been greatly achievable in recent years thanks to advancements in algorithms and ubiquitous low-cost—yet powerful—processors, hardware, and sensors. This work utilized weapon-born sensor measurement acquisition, processing, and HAR approaches to demonstrate Soldier state estimation in a target acquisition and tracking experiment. The Soldier states that were classified included whether the Soldier was at rest, tracking a target, transitioning between potential targets, or firing a shot at the target. We implemented Multivariate Time Series Classification using the “SKTime” toolkit for this work and discuss the performance from various classification methods. We also discuss a framework for efficient transference of this information to other tactical information systems on the network.						
<b>15. SUBJECT TERMS</b> STR, Humans in Complex Systems, Military Information Sciences, AI/ML, AITR, Soldier lethality						
<b>16. SECURITY CLASSIFICATION OF:</b>			<b>17. LIMITATION OF ABSTRACT</b>  UU	<b>18. NUMBER OF PAGES</b>  12	<b>19a. NAME OF RESPONSIBLE PERSON</b> Mark Dennison	
<b>a. REPORT</b> Unclassified	<b>b. ABSTRACT</b> Unclassified	<b>c. THIS PAGE</b> Unclassified			<b>19b. TELEPHONE NUMBER (Include area code)</b> (562) 290-9437	

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## Executive Summary

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The US Army Futures Command's Soldier Lethality (SL) Cross-Functional Team (CFT) is investigating novel methods for augmenting dismounted infantry through a combination of head-borne and weapon-borne capabilities. Per direction from SL-CFT, US Army Combat Capabilities Development Command (DEVCOM) Army Research Laboratory researchers explored techniques for enhancing aided target-recognition capabilities as part of the Army's next generation Intelligent Squad Weapon Program.

Complex decisions involving potential targets in a hostile environment must be made by dismounted Soldiers to maintain tactical superiority. These decisions can be powerful information for artificial intelligence (AI) technologies, such as AI-enabled fires or command and control decision aids. For example, a Soldier firing a weapon is a clear indication that a hostile target is in the area. However, a Soldier tracking a potential target through the environment and then lowering their weapon is an ambiguous, implicit indication that the target was of interest, but ultimately was deemed by the Soldier to not be an immediate threat. In a close-combat setting, implicitly labelled data associated with a Soldier's state (e.g., electro-optical video, position location information, or fires actions) can be used to input decision-making aids to derive realistic battlefield context. However, a more thorough examination of these actions is needed. Furthermore, the emergent non-communicative behaviors from individual Soldiers aggregated across a squad can enhance tactical situational awareness. Despite their potential for tactical impact, these state estimations or behavioral indicators are often not obtained in an immediately usable form.

DEVCOM Army Research Laboratory (ARL) researchers investigated an approach to dismounted Soldier state estimation through opportunistic sensing—a way to collect and infer critical real-world data without needing explicit action from the human. Data were continuously obtained to interpret Soldier behavior while directly interacting with their weapon via normal use to track and engage both moving and stationary targets. The approach for Soldier-weapon behavior classification used in this effort was primarily derived from human activity recognition (HAR) research. However, the experimental paradigms frequently used in eye-tracking literature to link eye movement and cognitive reasoning were mirrored in this work to increase ecological validity of behavioral outcomes. Specifically, a goal of a subset of eye-tracking research is to collect and interpret eye-movement events related to overt visual attention (i.e., fixation, saccade, and pursuit), which can reveal cognitive processes and objective content about the

environment.\* During combat, Soldiers may dwell their aim on a static target (fixation), quickly transition aim point when new, have potential targets pop up (saccade), or track their aim point as a potential target moves (smooth pursuit).

Currently, head-mounted eye-tracking technologies are being developed for combat use. However, the noise in the gaze data related to calibration errors makes it difficult to use these data effectively. A more salient solution may be present in the interactions between Soldiers and their weapons, which this effort performed using traditional HAR techniques. The primary method for performing HAR is to collect time-series data using inertial measurement units on a person as they perform some physical activity. Machine-learning techniques are then used to train classification models to predict actions based on data signals. This methodology can be extended to include classification of the motion of objects as humans interact with them. In this case, the motion profile of the weapon is obtained opportunistically while a close-combat Soldier interacts with potential threats, which provides a window into the complex decisions these Soldiers make in such environments.

A comprehensive analysis of this evaluation has been documented and published in the paper: *Modeling and Analysis of Motion Data from Dynamic Soldier State Estimation to Enable Situational Understanding*.<sup>†</sup>

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\* Kiefer P, Giannopoulos I, Raubal M, Duchowski A. Eye tracking for spatial research: cognition, computation, challenges. *Spatial Cognition and Computation*. 2017;17(1-2):1–19.

† Lee M, Tweedell A, Dennison M, Sabbagh P, Conroy J, Trout T, Freeman J, Lance B. Modeling and analysis of motion data from dynamic Soldier state estimation to enable situational understanding. *SPIE DCS XR for MDO*; 2022.

# **1. Introduction and Overview of Evaluations and Results**

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## **1.1 Soldier Data Collection and Model Research and Development**

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A new data collection effort was necessary because labeled data critical to performing supervised machine learning were not available at the onset of this project. Eight US Army Soldiers that were marksmanship-qualified with the M4 platform participated in a data collection event at Aberdeen Proving Ground (APG). During the collection, the Soldiers performed different shooting scenarios. These scenarios included target static fixation, transitioning from one target to another, tracking a moving target, and no action with weapon lowered. Twenty trials of each scenario were performed for a total of 80 trials; however, the order of scenario presentation was randomized to prevent the Soldiers from predicting target locations or subsequent behaviors. The participants were also not informed which scenario would be presented prior to any individual trials. Participants discharged one round from their M4 per targeting trial and were told to prioritize accuracy over speed when engaging a target. For each trial, participants were given hit-or-miss performance feedback.

Linear acceleration and angular velocity measurements were recorded continuously onto a laptop and processed offline. The multi-variate time-series feature vectors were the x-, y-, z-axis linear acceleration and the x-, y-, z-axis angular velocity of the M4. Researchers manually segmented the data representing different behavioral classes: static (Soldier has weapon shouldered and is actively aiming at center target, which is stationary), tracking (Soldier is slewing weapon smoothly in time with moving target), transition (Soldier is sharply slewing to new target), weapon raise (Soldier is raising the weapon into a high-ready and shouldered position), shot (recoil profile from weapon discharge), and no activity (nonevents or when Soldier is not actively shouldering or aiming the weapon).

Once data were appropriately segmented, a 1-s window was slid across with 50% overlap between windows. These 1-s windowed data segments were used as labeled training and testing data for classification. The following algorithms were trained to classify Soldier aiming behaviors during the experiment: Random Forest (15 estimators) and Ridge Regression Discriminator with L2 penalty. A stratified 10-fold cross-validation strategy was used to assess classification performance. The Python machine-learning modules “sklearn” and “sktime” were used for model training and evaluation. For each fold of the cross validation, 10% of the data was held out for testing while 90% were used to train the model. The average accuracy across the 10-fold cross validation for the Random Forest Classifier was 95.10%,

with an average training and testing time of 115.13 and 4.17 s, respectively. The Ridge Regression Classifier exhibited slightly lower accuracy at 94.60%, with an average training and testing time of 1115.39 and 1.48 s, respectively.

## **1.2 Military Information System Integration**

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DEVCOM ARL researchers developed a proof-of-concept architecture to integrate these Soldier state estimation algorithms with external military information systems (MIS) over a research network. Such MIS include the Android Tactical Assault Kit (ATAK) and the cross-reality common operating picture (XR-COP). The data pipeline involves sending weapon sensor data via robot operating system messages to a listener application on a laptop that subscribes to relevant data topics, such as inertial measurement unit or magnetometer feeds. These feeds are binned into approximately 1-s segments. The segments are then packaged as AURORA application data and sent over a network using the AURORA proxy to another laptop that unwraps the application data to provide the raw segmented data. These data are then processed by the classifier and a class label is assigned approximately every 1-s as a string type. The string with the class label is then sent back over the network where it can be consumed by a system like ATAK or the XR-COP. Further research and development may occur to optimize this process and expand the message formatting of the data to enable interoperability with a wider range of military systems.

## **2. Conclusions**

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The successful discrimination of Soldier–weapon interactions through the classifiers developed in this effort demonstrates the feasibility of garnering tactical behaviors with no additional actions needed by the weapon holder. These classified behaviors—raising the weapon, dwelling on a static target, and tracking moving targets—represent conscious choices that may serve as useful information to the Soldier’s fire team, squad, and/or higher echelons. However, the dynamics defining how this state information should be conveyed with the multitude of information systems deployed across a battlefield is an open research question to be explored in future efforts.

## List of Symbols, Abbreviations, and Acronyms

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AI	artificial intelligence
APG	Aberdeen Proving Ground
ARL	Army Research Laboratory
ATAK	Android Tactical Assault Kit
CFT	Cross-Functional Team
DEVCOM	US Army Combat Capabilities Development Command
HAR	human activity recognition
MIS	military information systems
SL	Soldier Lethality
XR-COP	cross-reality common operating picture

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