RFID Sensing and Analytics to Improve Team Training

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ABSTRACT

Law enforcement and military operators are intensively trained and evaluated on their taskwork skills during room clearing procedures (e.g., speed of room entry, firing position, firing accuracy; Salas et al., 2008). As these teams become experts in executing their procedures, teamwork skills and processes (e.g., team coordination, backup behaviors, shared situational awareness) become critical factors in their ultimate performance and error avoidance (Salas et al., 2001). Extant research has demonstrated how various unobtrusive sensors can be used to evaluate teamwork skills and processes (Dubrow et al., 2017). For example, data collected from Radio Frequency Identification (RFID) tags, such as physical location, proximity to team members, speed, and orientation can be used as proxy measures for shared situational awareness, effort, and coordination (Feese et al., 2013, 2014; Kranzfelder et al., 2011). The current paper provides a technology demonstration of how unobtrusive RFID data collection, coupled with visualizations, analytics, and live video feeds, can be used to help improve teamwork training in expert teams. Lab data of individuals replicating publicly available standard operating procedures for room clearing in a shoot house are used to show how instructors may use the system during teamwork training sessions to help accomplish training objectives. Metrics such as physical distribution of Operators, entry speed, and orientation are used as proxies for teamwork states and processes including coordination, effort, and shared situational awareness (Feese et al., 2014; Kranzfelder et al., 2011). The paper demonstrates how data collected from RFID tags and cameras can be used to provide immediate replay of metrics, visualizations, and video to show changing Operator locations and orientations to augment current instructor training methods to meet teamwork training objectives.

ABOUT THE AUTHORS

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INTRODUCTION

Law enforcement and military operators are intensively trained and evaluated on their taskwork skills during room clearing procedures (e.g., speed of room entry, firing position, and firing accuracy; Salas et al., 2008). As these teams become experts in executing their procedures, teamwork skills and processes (e.g., team coordination, backup behaviors, and shared situational awareness) become critical factors in their performance and error avoidance (Salas et al., 2001). Thus, crew resource management (CRM) training was created to help teams improve their coordination and adaptation as a group (Kozlowski & Ilgen, 2006). CRM is meant to train teams on how to monitor their performance and provide backup behaviors by supporting their team members in complex situations (Hamilton, 2009). These teamwork skills are especially important for teams working to complete physical tasks such as room clearing that rely on fast-paced responses resulting in limited opportunity to rely on verbal communication.

While CRM trainings have been developed for various contexts and industries, including law enforcement and military operations, the ability to measure the improvement of teamwork following these trainings is limited. First, measures of teamwork capabilities are typically captured via surveys, observations, interviews, and qualitative analysis of video and audio. Many of these measures are cumbersome to collect, resource intensive, and require time consuming and in-depth analysis to make use of the data. Additionally, the limitations to the reliability of self-report data are exacerbated in training environments where team members cannot be stopped in the middle of their work to answer survey questions or provide verbal interview responses.

Until recently, observations and surveys have been the primary tools used to understand team performance (Rosen et al., 2014). However, research has begun to demonstrate how various unobtrusive sensors can be used to evaluate teamwork skills and processes (Dubrow et al., 2017). For example, data collected from radio frequency identification (RFID) tags, such as physical location, proximity to team members, speed, and orientation can be used as proxy measures for shared situational awareness, effort, and coordination (Feese et al., 2013, 2014; Kranzfelder et al., 2011). Luciano and colleagues (2018) argued that three types of teamwork activity can be collected unobtrusively: behaviors, physiological responds, and words. For the purposes of the current paper, we focus on behaviors of Operators in room clearing contexts. Behaviors in this context can include movement (e.g., speed), room position, and proximity, which can be representative of team coordination (Luciano et al., 2018; Vorin, 2015).

Utilizing Unobtrusive Measurement During Training

Data collected unobtrusively from wearable and environmental sensors is still primarily used for research purposes and is rarely in the hands of instructors to use for training in real-time or during after action reviews (Dubrow et al., 2017). The current paper provides a technology demonstration for a potential training decision aid that can be used to help instructors understand the meaning of data being collected in real-time during room clearing exercises.

In many contexts, room clearing operations included, there are too many variables at play to provide an objective overall score of teamwork. Dozens of standard operating procedures (SOPs) are used by Operators to respond to different types of environments, based on the number of rooms, doors, threats, and unknowns in their environment. Additionally, there is a complex order of operations used to prioritize different types of threats that Operators may discover once they enter a building or room. Thus, a training tool for instructors should consider the context and the relevant SOPs that Operators are meant to follow in each scenario to make the data captured about Operator behaviors optimally meaningful.

For the current study, the most critical team outcomes (i.e., performance and safety) are dependent on whether SOPs are correctly followed. For example, whether Operators moved to the correct positions can be indicative of situational awareness, and the speed and movement synchronicity of Operators often represents strong team coordination (Dubrow et al., 2017). The proposed system highlights key metrics of interest to detect abnormalities in behavior that might demonstrate a lack of adherence to SOPs. With such a system, instructors will not need to rely on their memory to find the correct time stamps in video recordings to review. Instead, the system can draw instructor attention to timestamps of interest, and instructors can use the information as an aid to provide a deeper level of analysis and provide qualitative instruction for how Operators can improve their teamwork in similar scenarios during future runs.

Lab data of individuals replicating publicly available SOPs for room clearing in a shoot house are used to show how instructors may use RFID-based data analytics during teamwork training sessions to help accomplish training objectives (i.e., the goals and metrics set for each specific training). Specifically, we demonstrate how data collected from RFID tags can be used to provide immediate replay of metrics, visualizations, and video to show changing operator locations and orientations to augment current instructor training methods to meet teamwork training objectives.

Limitations and Considerations for Unobtrusive Measurement

Unobtrusive metrics provide large amounts of quantitative data related to behaviors of interest during teamwork training exercises. While these metrics have several advantages of more traditional data collection methods such as surveys and observations, they are not without their limitations. Most importantly, unobtrusive metrics are only proxies for the teamwork constructs of interest (Dubrow et al., 2017). In other words, while movement patterns may correlate with situational awareness, movement is not equal to situational awareness. Thus, it is critical to determine the constructs of interest, behavioral indicators, and alternative explanations for those behaviors before conducting a training exercise using unobtrusive data (Dubrow & Bannan, 2019).

Orvis and colleagues (2013) published the RADSM (Rational Approach to Developing Systems-based Measures) approach to ensure that developed sensor-based measures of team behaviors are logically related to constructs of interest. RADSM is meant to be used in circumstances where team behaviors leave behind traces of information that can be picked up by physical sensors and used to understand team states and processes (Orvis et al., 2013). In addition to providing more objective information than self-report surveys, RFID sensor data can provide cues that are indicative of different constructs, depending on the construct. For example, while proximity is often used as a measure for coordination (Dubrow et al., 2017; Feese et al., 2014), there are some circumstances in which proximity could negatively affect coordination, depending on the SOP. For example, proximity could be a threat to safety in some circumstances. Thus, it is important to align sensor-based cues with constructs of interests a priori using the RADSM method (Dubrow et al., 2017; Dubrow & Bannan, 2019).

When determining alternative explanations for sensor-based measures, context should be carefully considered. The same behavior can be representative of different constructs, depending on the situation. For example, if an instructor is shown that a team's speed slowed down, and the system suggests that this action is negative for team performance, the instructor may be led astray in how to train the team based on this data without considering context. Slowing down before moving to the next piece of work can represent poor coordination or a lack of shared situational awareness, causing the team to stall because they are unprepared for how to collaborate on their next set of actions. However, teams might also slow down between tasks because the next piece of work is especially complex and requires collaborative planning and decision making before the team can move forward. Thus, the same behaviors can be indicative of both weak and strong teamwork.

Luciano and colleagues (2018) point out that system design should be considerate of which analytics may cause the most confusion or lead to misinterpretation without additional context. For the current study, the RADSM approach was utilized to determine constructs of interest and indicators of those constructs. Additionally, six scenarios are used to demonstrate how the data can show the difference between good teamwork behaviors (i.e., SOPs are correctly followed) and poor teamwork behaviors (i.e., SOPs are incorrectly followed).

METHODS AND RESULTS

RADSM Approach

Methods for developing the design for the current study began with utilizing the RADSM approach to creating system-based measure of teamwork behavior (Orvis et al., 2013). The first step in the RADSM process is to identify the context and the constructs of interest in the environment. Methods for the current study were created based on publicly available SOPs for room clearing in a shoot house. Two SOPs were used: Scenario 1 is based on a corner-fed room entry and Scenario 2 is based on a center-fed room entry. Core components of each scenario were identified, including the number of Operators, the correct stack order for room entry, stopping location for each Operator to engage a target and/or scan the room, and the order in which Operators are meant to leave the room. General indicators of performance were also identified, including speed, safety, and total room coverage.

To demonstrate the utility of a system that can unobtrusively sense and highlight Operator and team behaviors in room clearing contexts, four participants gathered to implement each SOP scenario as written, plus two alternatives to each scenario that are used as examples for detecting anomalies to behavior that may be indicative of constructs of interest, including performance, safety, coordination, effort, and adherence to SOPs. Stack order, position in room, speed, and safety were manipulated for the study to highlight different levels of the constructs of interest (e.g., low and high safety; low and high coordination).

The second step of the RADSM approach is to develop construct indicators. For the current study, the research team drew from the academic literature on unobtrusive metrics of team behavior as well as publicly available SOPs for room clearance tactics and safety metrics. Indicators of performance include adherence to SOPs, speed of room entry (Feese et al., 2013), and speed to stopping location. Instances of flagging (i.e., pointing a weapon directly at another Operator) are indicative of breaches to safety (Shoot House Instructor Course, 2018). Amount, intensity, and variability of physical activity are indicative of effort (Feese et al., 2013). For the current study, the intensity of physical activity at room entry and when leaving the room are the most important indicators of effort. Additionally, movement along the wall, total entry time, and how team members enter the room (e.g., from what position, in what order) are important performance metrics in this domain (Vatral et al., 2022).

Teamwork constructs of interest include team coordination and team situational awareness. Both spatial activity alignment and team member proximity are indicative of coordination (Feese et al., 2014). Finally, when all Operators move to the correct locations according to their SOPs, the team likely has a shared situational awareness (Kranzfelder et al., 2011). Team situational awareness can also be indicated by showing that the team has engaged all of the targets in a room and fully clears all of the areas within a room.

The third step of RADSM is to identify system-based information, based on the data that are available. In the current study, we utilize information that can be derived from RFID sensor data to identify and measure indicators of interest. The fourth step is to develop measures and the components of those measures. The current analyses utilize location paths, movement locations relative to teammates, contextualized SOPs, and target locations to capture situational awareness and performance. Additionally, speed (e.g., acceleration when entering a room, stopping to engage a target) are used to show adherence to SOPs. For example, one Operator's role is often to wait until all other Operators have left the room before leaving their position. The fifth step of RADSM is to instantiate these measures, which were collected using RFID sensors and post processing for data analytics and visualization.

The final step of RADSM is to validate the measures for the constructs of interest. For the current study, measures were validated against video and the SOP scenarios used to ensure data accuracy. Future validation will include working with subject matter experts to ensure that there are not alternative explanations for the measures and what they might indicate outside of the constructs of interest. Instructor and observer ratings can also be used to compare qualitative metrics with the RFID metrics captured.

Equipment

Each of the four participants was equipped with a helmet with an RFID sensor attached to the top. Additionally, each participant had a simulated weapon with an RFID sensor attached to capture the orientation of the weapon. The room in which data collection took place was equipped with two overhead cameras and 12 RFID receivers.

Scenario 1: Corner-Fed Room Clearing

Scenario 1 was adapted from room clearing techniques for a corner-fed room (i.e., door is in the corner of the room) from the Department of the Army Training for Urban Operations handbook (Department of the Army, 2008). The correct SOP begins with Operator 1 entering the room first and engaging the target in the lower right corner of the room. Operator 2 turns left upon entry to engage the second target in the far corner. Operator 3 follows behind Operator 1, careful to avoid flagging, while Operator 4 covers the door and does not enter the room. After the targets are cleared, Operators 1 and 3 leave the room together, and Operator 2 waits for all teammates to exit the room before following.

Two incorrect versions of the SOP were purposely used for Scenario 1. In the first incorrect scenario, Operator 3 waits ten seconds before very slowly following behind Operator 1, slowing down the entire team clearing. Operator 4 goes into the room with Operator 3 and fails to cover the door. In the second incorrect scenario, Operator 2 does not wait for the rest of the team to leave the room before following them.

Data Analysis

Two data streams were used to demonstrate different constructs for the current study. First, 3-dimensional position was collected at 10 Hz from the RFID tag mounted on each Operator's helmet and gun. From this data stream, room entry time, room entry speed, the time and distance to the "stopping" (firing) position, the distance off the strong wall (i.e., the wall with the door) at firing position (Vatral et al., 2022), the distance between operators, and the total time spent in the room was calculated. Second, information about each tag's 3-dimentional orientation, represented as a quaternion, was collected at 10 Hz and used to calculate Euler angles (roll, pitch, and yaw in degrees). Position was low pass filtered using a 6^{th} order Butterworth filter with a cutoff frequency of 0.66 Hz.

Scenario 1 SOP Manipulations and Data Demonstrations

Several elements of the data demonstrate how the SOP was followed in the first instance of Scenario 1 (i.e., "S1 - Correct SOP"). First, each Operator was meant to enter the room and approach a certain location. It is assumed there are no hostiles nor any dangerous materials in the environment. Figure 1a) shows the correct movement paths and stopping locations for the Operators. For the purposes of this study, team performance is operationalized as alignment with the SOPs. Dotted lines in the Figure indicate the separation between Operators. As expected, Table 1 shows that Operator 2, who had the farthest distance to the stopping position was in the room for the longest amount of time, and Operator 3, who had the least distance to travel, stopped in the shortest amount of time. The timestamps in Table 1 show that the Operators entered in the correct order; such alignment of spatial activity indicates good team coordination (Feese et al., 2014). Figure 1b) shows the speed of each Operator over time and how all Operators accelerated simultaneously and stopped at approximately the same time to engage targets. The consistent amount, and early high intensity of physical activity, indicates the team demonstrated high effort and were highly effective (Feese et al., 2013; Olguin et al., 2009).

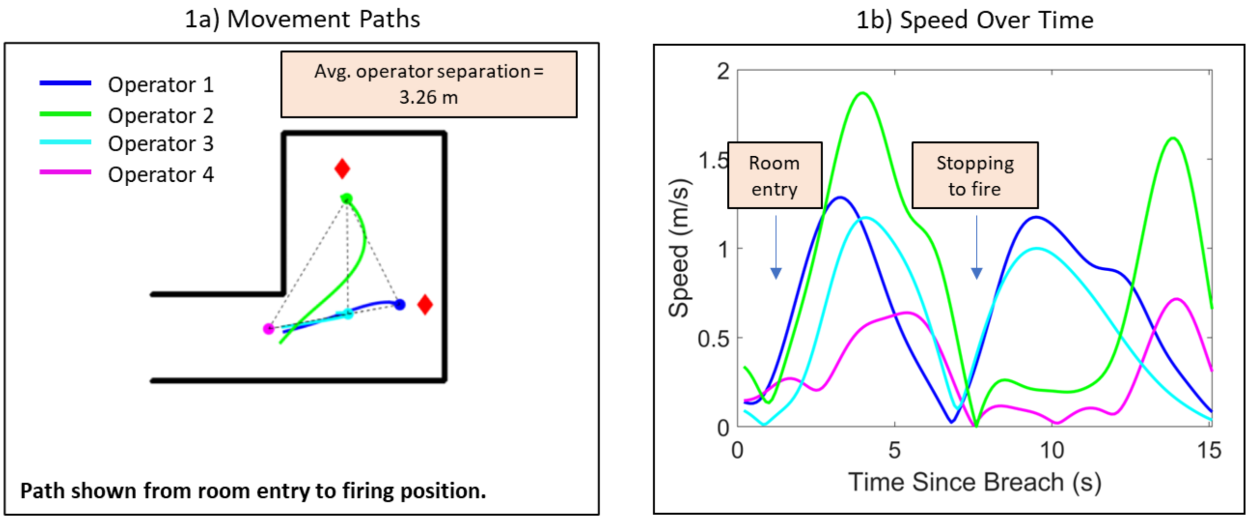

Figure 1. Scenario 1 – Correct SOP

The first incorrect version of Scenario 1 (i.e., "S1 - Incorrect SOP #1") started with Operator 3 entering the room late and very slowly, followed by Operator 4. The data show that Operators 3 and 4 entered the room about ten seconds after Operators 1 and 2 (Figure 2b; Table 1 entry times). Such misalignment of spatial activity indicates a lack of coordination between team members (Feese et al., 2014). Additionally, a comparison between the correct version of Scenario 1 and the first incorrect version shows a large difference in the total time of each run. The total time spent in the room for the correct SOP is about 10 seconds shorter than for the first incorrect SOP run because Operators 1 and 2 had to wait for Operators 3 and 4 to enter before they could lead. The slow entry and movement of Operator 3 led to low performance for the entire team (Feese et al., 2013). Finally, Operator 4 entered the room instead of covering the door. The incorrect position of Operator 4 shown in Figure 2a) indicates a lack of situational awareness (Kranzfelder et al., 2011).

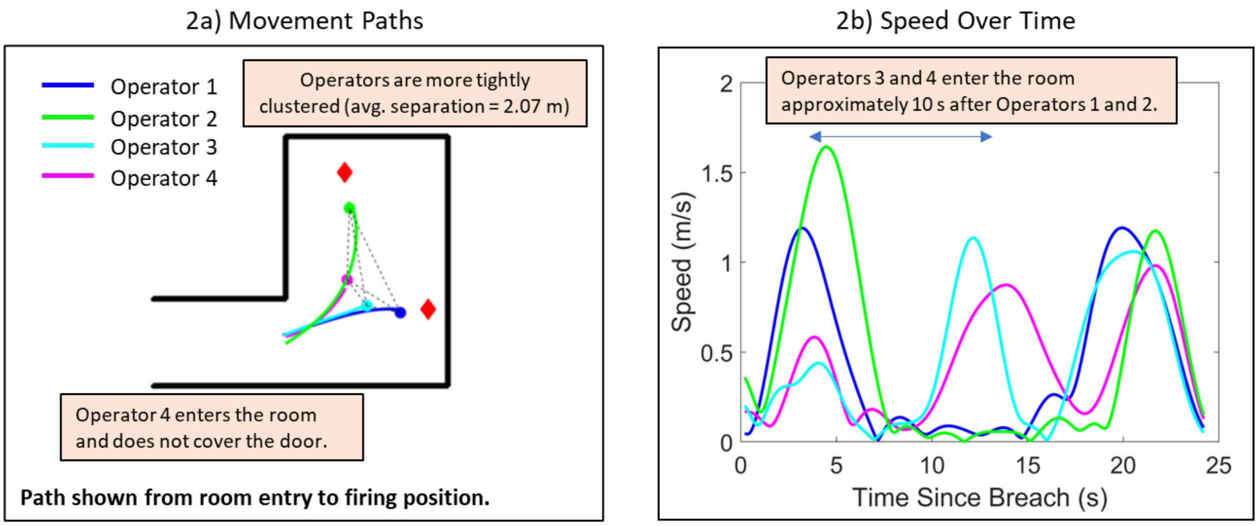

Figure 2. Scenario 1 – Incorrect SOP #1

During the second incorrect version of Scenario 1 (i.e., "S1 - Incorrect SOP #2"), Operator 2 travels to an incorrect location in the room and does not engage, or ever face, the target (see Figure 3a). Operator 2 likely lacked situational awareness when entering the room (Kranzfelder et al., 2011). There was also a safety breach during Incorrect SOP #2 during which Operator 3 flagged Operator 1. The cone shown in Figure 3a) shows this flagging instance. Operator 2 also fails to follow the SOP in this scenario by leaving the firing position first instead of being the last team member to leave. Figure 3b) shows Operator 2 accelerating before the other team members, demonstrating misalignment in spatial activity and therefore low coordination (Feese et al., 2014).

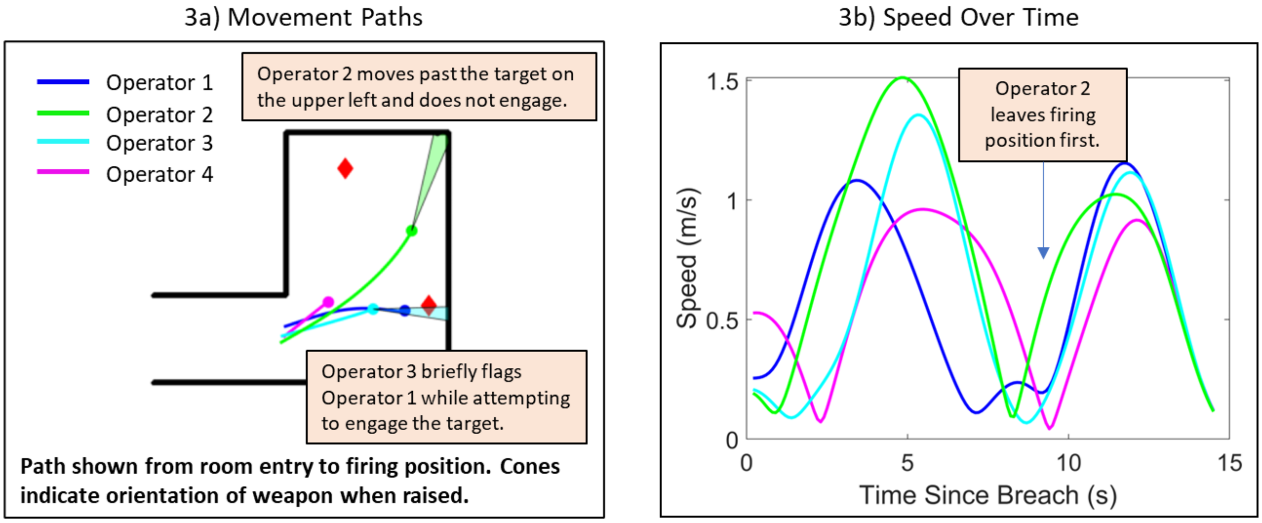

Figure 3. Scenario 1 – Incorrect SOP #2

Table 1. Scenario 1 Operator Movement Metrics

Movement Metric	Scenario	Operator 1	Operator 2	Operator 3	Operator 4
Entry Time (MM:SS)	Correct SOP	00:00	00:00	00:02	N/A - Covered Door
	Incorrect SOP #1	00:00	00:01	00:09	00:11
	Incorrect SOP #2	00:00	00:02	00:03	00:05
Time to Stopping Position	Correct SOP	4.3 s	5.5 s	2.5 s	N/A - Covered Door
	Incorrect SOP #1	4.9 s	5.2 s	3.3 s	3.8 s
	Incorrect SOP #2	5.8 s	3.3 s	3.6 s	2.7 s
Distance to Stopping Position	Correct SOP	3.9 m	6.7 m	2.1 m	N/A - Covered Door
	Incorrect SOP #1	3.8 m	6.1 m	2.7 m	2.8 m
	Incorrect SOP #2	4.7 m	4.4 m	3.1 m	1.8 m
Total Time in Room	Correct SOP	9.4 s	12.3 s	5.6 s	N/A - Covered Door
	Incorrect SOP #1	19.0 s	21.2 s	9.1 s	10.2 s
	Incorrect SOP #2	11.7 s	11.2 s	7.8 s	5.4 s

Scenario 2: Center-Fed Room Clearing

Scenario 2 was adapted from a room clearing procedure from a center-fed room (i.e., door is in the center of the room) based on the Urban Combat Skills handbook from GlobalSecurity.org (Global Security, 2000). During Scenario 2, the correct SOP was for Operator 1 to enter from the left side of the door and travel to the lower right corner without stopping. Operator 2 completes the opposite action by entering from the right and traveling to the lower left corner. Operator 3 follows to the right behind Operator 1, and Operator 4 follows to the left behind Operator 2. All four Operators are meant to stay close to a strong wall and scan the rest of the room completely, without flagging each other. It is assumed there are no hostiles nor any dangerous materials in the environment. Two incorrect versions of the SOP were used for Scenario 2. In the first incorrect scenario, Operator 4 moves too far off the strong wall, and Operator 2 stops the room scan too soon, causing the team to fail to scan the entire room. For the second incorrect scenario, Operator 1 flagged Operator 4. Additionally, Operators 3 and 4 swap positions, and Operator 4 moves very slowly.

Scenario 2 SOP Manipulations and Data Demonstrations

The correct SOP for Scenario 2 (i.e., "S2 - Correct SOP") began with Operators 1 and 3 entering the room from the left and turning to the right corner while Operators 2 and 4 traveled in the opposite direction. All four Operators entered the room in the correct positions (Figure 4a) and their speed over time was relatively synchronized, with high acceleration, followed by stopping to engage the target, ending with a final acceleration to leave the room (Figure 4b). These alignments of SOPs were indicative of strong team performance. The timestamps for room entry shown in Table 2 also indicate that the team was well coordinated since they entered in the correct stack order (Feese et al., 2014).

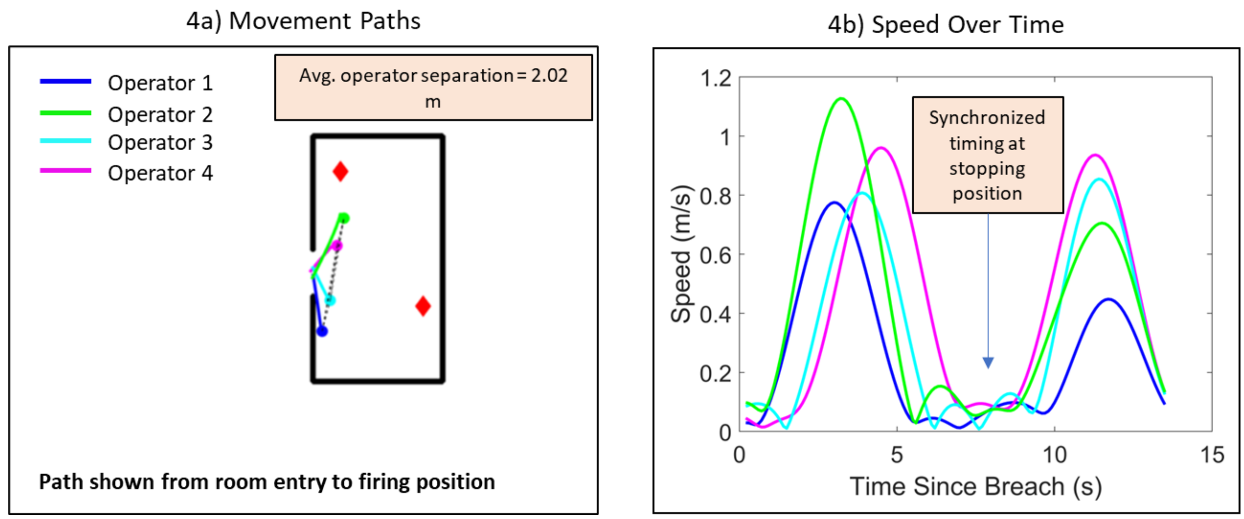

Figure 4. Scenario 2 – Correct SOP

The first incorrect run of Scenario 2 (i.e., "S2 - Incorrect SOP #1") began with Operator 4 moving to the incorrect position to approach the upper right target directly, instead of moving to the lower left of the room (Figure 5a). By doing so, Operator 4 risked being flagged by Operator 3 during room scanning. Operator 4's movement misalignment with the SOP is indicative of low performance and poor safety. Additionally, Operator 4 moved far off the strong wall to engage the upper right target (Figure 5b; Table 2), creating a higher than intended average separation between the teammates. A lack of proximity between teammates, especially when in contradiction with an SOP, is indicative of both low effectiveness (Olguin et al., 2009) and a lack of team coordination (Feese et al., 2014).

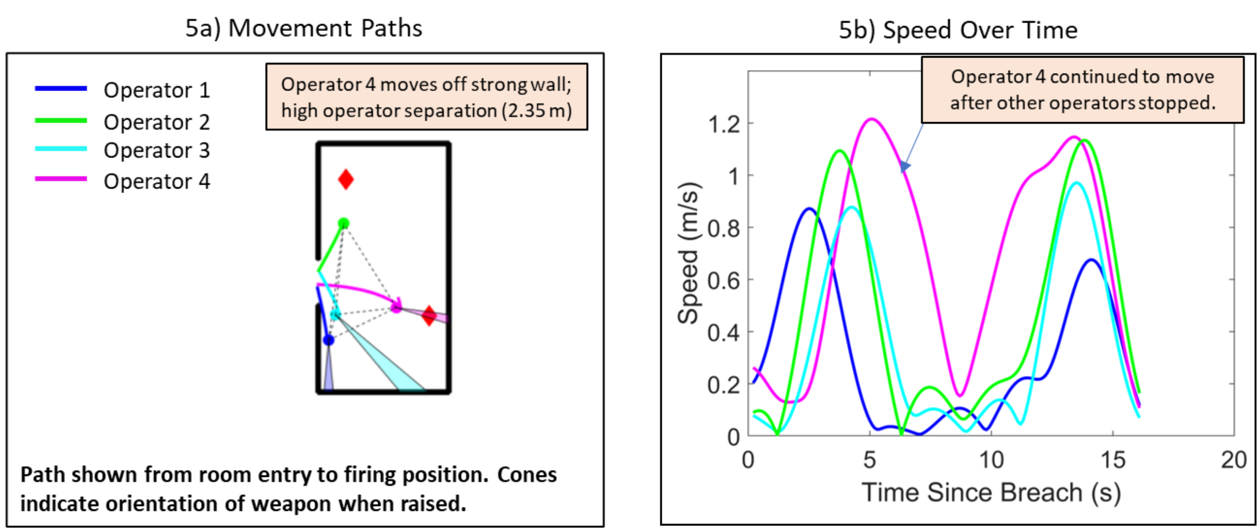

Figure 5. Scenario 2 – Incorrect SOP #1

During the second incorrect run of Scenario 2 (i.e., S2 - Incorrect SOP #2”), Operator 2 committed a safety breach by crossing his weapon over Operator 4 while scanning the room in the incorrect direction (Figure 6a). Additionally, Operator 3 and Operator 4 switched positions compared to the SOP. The misalignment with the SOP led to low performance before Operator 4 moved into position very slowly (Figure 6b). The low intensity of physical activity indicates low effort and low effectiveness (Feese et al., 2013; Olguin et al., 2009).

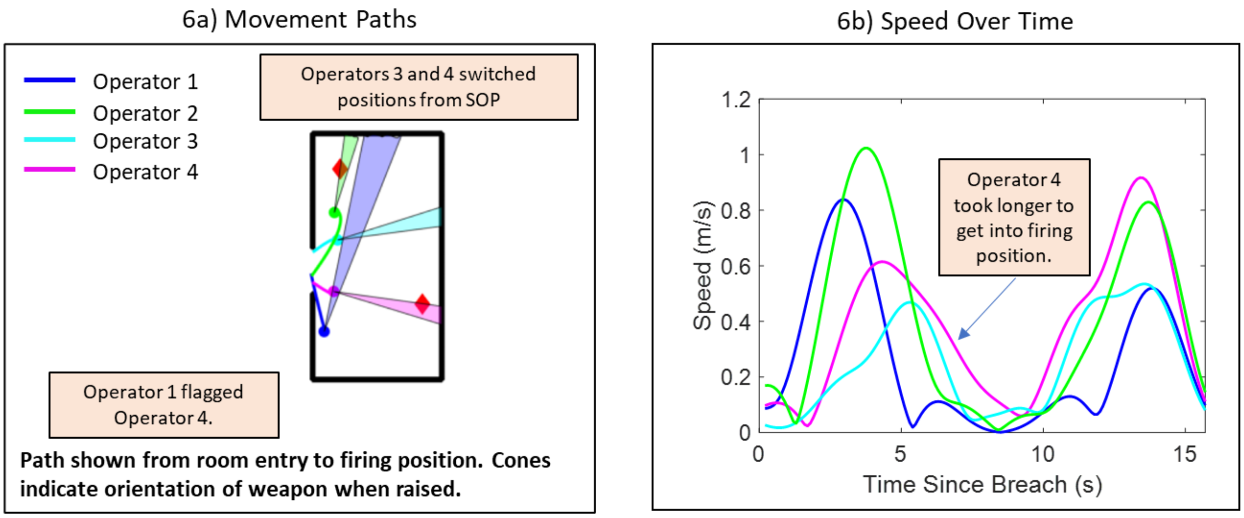

Figure 6. Scenario 2 – Incorrect SOP #2

Table 2. Scenario 2 Operator Movement Metrics

Movement Metric	Scenario	Operator 1	Operator 2	Operator 3	Operator 4
Entry Time (MM:SS)	Correct SOP	00:00	00:01	00:02	00:03
	Incorrect SOP #1	00:00	00:01	00:02	00:03
	Incorrect SOP #2	00:00	00:04	00:03	00:04
Time to Stopping Position	Correct SOP	4.9 s	4.7 s	3.3 s	3.3 s
	Incorrect SOP #1	5.0 s	4.2 s	4.9 s	2.9 s
	Incorrect SOP #2	4.8 s	4.4 s	2.4 s	2.3 s
Distance to Stopping Position	Correct SOP	2.2 m	2.3 m	1.7 m	1.6 m
	Incorrect SOP #1	2.3 m	2.1 m	2.4 m	2.7 m
	Incorrect SOP #2	2.4 m	2.5 m	1.1 m	0.9 m
Total Time in Room	Correct SOP	11.5 s	10.2 s	7.9 s	6.0 s
	Incorrect SOP #1	14.1 s	11.3 s	9.1 s	7.7 s
	Incorrect SOP #2	13.7 s	11.6 s	8.0 s	6.0 s
Distance off Strong Wall at Firing Position	Correct SOP	0.2m	0.8m	0.4m	0.6m
	Incorrect SOP #1	0.2m	0.7m	0.4m	2.2m
	Incorrect SOP #2	0.3m	0.6m	0.7m	0.6m

DISCUSSION

Operator movement paths show how each individual enters the room, where they stop, where they were in relation to targets, and what parts of the room they faced based on the orientation of their weapons. Operator movement paths also provide team-level information, such as the relative distance from the strong wall and the average separation of the Operators during each run. Instances of flagging can also be seen when the orientation of one Operator's weapon covers another Operator. The examples of movement paths shown in the current paper represent a summary of the time Operators spent in the room. Instructors can utilize access to real-time video and data visualization replay of movement patterns, stopping locations, and orientation. Viewing this information side-by-side with video could allow instructors to identify key moments to review with students. Additionally, a system could potentially detect momentary anomalies in the movement paths (e.g., an Operator moving to the incorrect location in relation to an SOP; instances of flagging). Summary metrics such as the amount of the room covered by Operator scanning could also be captured.

Graphs of speed over time show synchronized (or asynchronized) movement of team members at room entry, stopping locations when targets are engaged, and acceleration when leaving the room. High performers can be identified by looking at the fastest Operator to enter the room. Additionally, instructors can easily see how quickly the entire team entered the room, and who was the fastest (or slowest) to arrive at their stopping location. Anomalies such as situations in which one Operator continues moving long after others have stopped moving or delayed room entry could be highlighted by a system to help instructors identify which parts of a video recording to review for further analysis. Typically, teams should aim to have synchronized movement patterns for effective coordination (Feese et al., 2013), but this may change depending on the SOP. These graphs can be used to facilitate individual and team learning during after action reviews by allowing operators to see their performance compared to what is expected when following an SOP.

Finally, Operator movement metrics can be used to show a variety of taskwork and teamwork behaviors. First, room entry time can be used to determine stack order, and to compare stack order to an SOP, as well as to identify the synchronicity in team member movements. Entry speed is often indicative of performance (Feese et al., 2013). Time to stopping position and distance to stopping position can be used to understand how Operators are working relative to one another. For example, instructors can be alerted if there is a negative correlation between time and distance to stopping position, which may indicate that an Operator incorrectly slowed down before reaching their stopping location. Video could then be reviewed to better understand why that Operator slowed down, and whether their reason for slowing down was justifiable for the situation or whether their actions should be modified in the future. Total time in the room can be used as a speed measure of performance for the time it took to clear the room. Finally, the distance off the strong wall at the firing position can be used to understand coordination and alignment between team members. Distance off the strong wall is most relevant during scenarios where room clearing procedures require Operators to stand close to the wall, even if there is a threat somewhere else in the room.

Table 3 summarizes the constructs of interest (e.g., performance, effort, coordination), indicators (e.g., alignment with SOPs, intensity of physical activity, spatial alignment of team members), and demonstrative examples of such constructs and indicators from the data collected in the current study (e.g., Operators following the correct paths, high speeds at room entry, and team members entering rooms in the correct order). Each of these examples shows how existing research on metrics of team behavior can be used by instructors during training events when they have access to near real-time data that can detect indicators of strong performance as well as anomalies that require further review. When combined with video, these data can be used to help improve instructors' abilities to provide feedback to their students and update their trainings to teach the teamwork and taskwork skills needed for optimal team performance.

Table 3. Summary of Constructs of Interest and Data Demonstrations

Scenario	Construct of Interest	Indicators	Data Demonstration	References
Correct SOPs	High Performance	Alignment with SOP	Figure 1a) and Figure 4a) Team follows correct paths and stopping locations	Department of the Army, 2008
	High Effort	Amount and intensity of physical activity	Figure 1b) and Figure 4a) Speed highest at room entry; Operator speed synchronization	Feese et al., 2013; Olguin et al., 2009
	High Coordination	Spatial activity alignment	Table 1) and Table 2) Operators enters in correct stack order	Feese et al., 2014

Scenario	Construct of Interest	Indicators	Data Demonstration	References
Incorrect SOPs	Low Performance	Slow speed	Table 1) Incorrect SOP total time team in room is about ten seconds longer than in the Correct SOP run	Feese et al., 2013
	Low Effort	Low intensity of physical activity	Figure 3b) O4 moves into position too slowly	Feese et al., 2013; Olguin et al., 2009
	Low Coordination	Spatial activity misalignment; lack of team member proximity	Figure 2b): O3 and O4 enter ten seconds after O1 and O2; Figure 5a) O4 moves too far off strong wall relative to teammates, and not in accordance with SOP	Feese et al., 2014
	Low Situational Awareness	Incorrect positions	Figure 3a) O2 moves to the incorrect position and does not face target; O4 enters room instead of covering the door and Figure 6a) O3 and O4 are in opposite positions compared to SOP	Kranzfelder et al., 2011
	Low Safety	Flagging (crossing weapon over teammate)	Figure 3a) Orientation shows O3's weapon crosses over O1 and Figure 5a) O2 orientation shows flagging O4	Shoot House Instructor Course, 2018

Note. O1 = Operator 1, O2 = Operator 2, etc. SOP = Standard Operating Procedure. Flagging = Crossing weapon over a teammate.

Key Takeaways

1) Not All Measures Should be Used for Scoring

Unobtrusive measurement of Operator and team behavior collected from RFID during room clearing exercises can help instructors better understand team performance and processes based on proxy indicators of constructs of interest. Some measures, such as measures of safety (e.g., instances of flagging) and performance (e.g., following SOPs for stack order and stopping locations, acceleration at room entry) are consistently indicative of behaviors of interest and can potentially be used for scoring individual and team performance.

Other measures, such as proximity of team members and spatial activity alignment of team members, can often be used as a proxy for constructs of interest such as coordination and shared situational awareness, but can also be indicative of other events. For example, while team members should maintain their proximity when they are supposed to be aligned against the strong wall, there are other circumstances in which proximity is not needed from a team. Therefore, it is important to (a) align data indicators with SOPs and (b) use data to indicate which video should be reviewed later.

2) Data Accuracy

Each RFID tag needs to "see" multiple receivers for its position to be accurately triangulated in three dimensions. In areas where multiple operators are in close proximity to each other (e.g., a hallway), or areas where the tag is only visible to a handful of receivers (e.g., a corner, or doorway), occlusion can limit positional accuracy. In addition, since the distance from a tag to each receiver is based on the radio signal's time of flight, reflections off metal walls or other obstacles can also affect positional accuracy, especially where occlusion is also a problem. High-frequency noise (on order of cm) can be filtered out in real-time with a low pass filter. Larger artifacts (on order of m) need to be identified in post-processing and removed before metrics are calculated.

3) Several Metrics Demonstrated Rely on SOP Context

Several of the metrics discussed in this paper are dependent on specific SOP contexts. For example, the metrics related to moving to the correct locations in a room, distance from the strong wall, and the number of targets engaged are dependent on the context of the room and the SOP the team is following. While SOPs can sometimes be hard coded in a system for reference, instructors may want to focus on the metrics that are most often indicative of team performance, regardless of the SOP. These include metrics such as speed and safety.

Future work is also needed to automatically capture room context to identify which SOPs should be applied and to limit the confusion caused by metrics that the system may highlight as positive or negative behavior (Luciano et al., 2018). Complexity measures could be developed based on the features of rooms being cleared, including whether the entry is corner-fed or center-fed and how many threats are in the room in order to make metrics more meaningful. Instructors often make minor changes to scenarios throughout a training event, and being able to automatically detect those changes can help instructors better understand their Operators' performance data. Future iterations of similar systems should integrate both SOPs and threat prioritization based on different types of complexities, including the number of targets, unknowns, and doors in a room.

4) More Complex Metrics Should Be Developed

Several new metrics can be developed to provide a better understanding of general team performance, coordination, and situational awareness, that is not dependent on hard coding contextualized SOPs. First, orientation can be used to capture the percentage of the room scanned by Operators, including the extent to which Operators overlapped in their scanning. Visualizations can be used to show how the room is scanned over time and to highlight areas that are missed. These visualizations can be used to show team progress throughout the run and can be used to evaluate quality of both teamwork and taskwork behaviors (Vatral et al., 2022). Additionally, RFID data analytics can show the time it takes for a team to reach its next piece of work when the team is clearing multiple rooms in the same run. The time of moving from room to room can be as important as room clearing time in any individual room. A time to next piece of work metric could help instructors identify slowdowns that may be due to a lack of coordination or shared situational awareness of what task needs to be completed next, and how it should be completed.

CONCLUSION

The current study builds on the existing literature regarding unobtrusive measures of team behaviors by introducing an example of a data capturing, analysis, and visualization system that can help instructors improve their team training. Metrics derived from an operator's position and speed can be used to identify when SOPs are, and are not, followed correctly. They can also show indicators of safety, team coordination, effort, coordination, and situational awareness. Overall, instructors and data analytic system developers should be careful to consider alternative explanations for analytics, as there are often cases when the same metric (e.g., slow speed) could be indicative of both low and high coordination or performance.

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