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Review

Dynamical biomarkers in teams and other multiagent systems

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ABSTRACT

Effective team behavior in high-performance environments such as in sport and the military requires individual team members to efficiently perceive the unfolding task events, predict the actions and action intents of the other team members, and plan and execute their own actions to simultaneously accomplish individual and collective goals. To enhance team performance through effective cooperation, it is crucial to measure the situation awareness and dynamics of each team member and how they collectively impact the team's functioning. Further, to be practically useful for real-life settings, such measures must be easily obtainable from existing sensors. This paper presents several methodologies that can be used on positional and movement acceleration data of team members to quantify and/or predict team performance, assess situation awareness, and to help identify task-relevant information to support individual decision-making. Given the limited reporting of these methods within military cohorts, these methodologies are described using examples from team sports and teams training in virtual environments, with discussion as to how they can be applied to real-world military teams.

1. Introduction

Effective team behavior in high-performance environments such as in sports and the military requires that team members reciprocally coordinate their actions with respect to each other and changing task demands. This requires that individual team members efficiently perceive the unfolding task events, predict the actions and action intents of the other team members, and plan and execute their own actions to simultaneously accomplish individual and collective goals.[1,2] When individuals are performing independent tasks that collectively contribute to the achievement of a common, joint goal, it is referred to as cooperation. To understand the complex behavioral demands of cooperation relevant to effective team performance, it is therefore necessary to quantify the dynamics and situation awareness of individual team members and how these collectively contribute to the team's performance. The aim of this paper is to highlight various time series-based methods of measuring team dynamics and situation awareness and the analytical frameworks that can be applied to investigate team performance and cooperation in various task contexts. Specifically, these methodologies analyze situational awareness via visual perception, movements of body segments (e.g., head and torso), or positional data of personnel and entire teams during team-based tasks using either basic spatio-temporal measures of each individual's activity (e.g., positions, velocities, and head orientations), or measures that capture the complexity of human movement (e.g., detrended fluctuation analysis and complexity matching). Further, we describe how explainable-AI techniques have been used to elucidate the perceptual features individuals use during team performance to facilitate decision-making. Finally, this review highlights collective measures like cluster phase analysis and network analysis, and how they can be used to describe team behavior and performance in real world settings.

The significance of this research summary is that, depending on the task complexity, availability of data, and the objectives of the analyses, researchers can use one or a combination of these methods to predict the success of individuals and teams, identify the markers of successful team performance, decision making, and situational awareness, or to structure skill learning paradigms. The methods discussed in this review were presented as part of an expert panel at the "2022 Defence

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Biomarker Symposium – Biomarkers of Performance and Injury in the Warfighter: Inside and Out". Therefore, we note that this is not an exhaustive list or a systematic review of various methodologies that can be used to measure team performance and we encourage the readers to refer to these articles 3–6 for more detailed reviews of various methods of measuring team performance and situational awareness.

2. Measuring situation awareness

Situation awareness can be defined as an individual's understanding of 'what is going on around them'[7] and how exactly it is established by individuals working within teams has been a rich topic for research.[8] When engaged in team tasks, team situation awareness also includes each individual's understanding of the roles each member will adopt, and how to appropriately coordinate their actions. Within the teamwork literature, there is a tradition of assessing situation awareness during a task exercise with the use of debriefing questionnaires to identify the extent to which team members were aware of task-relevant items.[9] However, this is not possible for real-world analyses as it interrupts the ongoing team dynamics and would be dangerous in military contexts.

Therefore, in-situ measurements such as monitoring visual search behaviors are one modality that can be implemented to assess situation awareness in such environments. The role of visual perception in establishing situation awareness is undisputed. For example, in Endsley's three-level framework,[10] 'perception of elements in current situation', is the first level for providing an agent's overall situation awareness (see also Boyd's observe–orient–decide–act [OODA] loop[11]). In the team sports domain, eye movements are commonly used to identify attentional behaviors. However, the relationship between visual search behaviors and domain-specific expertise has been a topic of debate within team sports. For example, both fewer fixations for a longer duration[12] and more fixations for a shorter duration[13] have been attributed to more expert footballers. Despite this contradiction, some researchers have argued that differences in eye movements can signal differences in player expertise,[14] while others emphasize that these findings are an artifact of the fact that eye movements are strongly influenced by task constraints.[15,16]

2.1. Measuring situation awareness from positional data

In real-world team environments that require whole body environment interactions and where tracking eye movements can be practically difficult, head and body positions as a measure of situation awareness, via visual exploration, can be a better measure of competence and performance.[16,17] Taking an eye-in-head-on-body approach, this also allows for the use of more robust sensors in a real-world setting.[17] Using this approach, head and body-mounted inertial measurement units (IMUs) and global positioning system (GPS) sensors have been used to measure physical performance and visual scanning in real-world scenarios. For example, in representative football (soccer) games, it was found that certain aspects of visual scanning behaviors, in particular exploration frequency (i.e., the number of head movements/scans - about the longitudinal axis - in a certain time-period) and exploration excursion (i.e., the angular distance - about the longitudinal axis - of the movement) are linked to a player's situation awareness (i.e., speed of decision-making and performance outcomes, such as passing decisions and passing success).[17,18] Further, even when players are fatigued, visual scanning behaviors remain unaffected.[19]

Within military contexts, simple wearable sensors such as IMUs can be embedded into personnel kits and simple data-analytic measures, such as visual scanning frequency and excursion mentioned above, can provide an estimate of situation awareness. This is expected to especially be the case in conflict situations such as close combat and special forces, where both the head and body frequently rotate to monitor their surroundings. While IMUs have been used within military contexts to test target acquisition/aiming and warfighter performance during a bounding rush[20] and wearable GPS devices (also containing IMUs) have also been worn during field-based section attacks,[21] there are further applications for these technologies toward quantifying military team behaviors and performance. For the context of firing a weapon on the move, IMUs are expected to provide a better and practical solution than systems such as head-worn eye trackers.

2.2. Measuring situation awareness via fluctuations in player movement

Although useful, summary-level measures such as mean frequency and angular excursion of head scanning behaviors may mask potentially useful information when assessing situation awareness within team contexts, specifically the structure of which these values change across time. Previous work has theorized that the structure of variation in such signals can provide valuable information about the organization of the underlying cognitive system.[22] One method to capture this structure is detrended fluctuation analysis (DFA).[23]

DFA involves linearly detrending a signal at various window sizes, averaging the residual variance across windows of a similar length, and then plotting the resultant value on a log–log plot for each window size. The slope of the resulting best-fit line provides an estimate for how variability is structured across time (where the slope is represented as DFA_{α}). Unstructured, time-independent variability results in slope values ≈ 0.5. Slope values < 0.50 are indicative of an anti-persistent signal that is reactive to previous inputs (e.g., such as tapping to a metronome[24]). Slope values > 0.50 and approaching 1.00 indicate persistence in the variability of the time series (i.e., positive [negative] deviations are more likely to follow positive [negative] deviations). A slope of 1.00 indicates fractal structure (i.e., pink noise) and is a signature of adaptive behavior.[25]

The value of DFA_{α} is sensitive to experimental manipulation and is theorized to reflect an interaction between individual agency and control, with constraints provided by the environment and task context.[26,27] Tasks which exhibit strong external constraints (e.g., unpredictable stimulus onset[26]) produce behavior fluctuations which are random/time-independent. When the constraints from the environment are lessened, such as through greater control during skill development,[28] behavior fluctuations become more interdependent which reflects greater coupling between the agent and their environment. DFA_{α} can be understood as reflecting a scale that balances external, environment and task constraints, with internal, individual constraints.

Of relevance here is that increases in the fractal structure (i.e., DFA_{α}) are hypothesized to relate to increases in individual situation awareness. A recent study by Nalepka et al.[29] evaluated the efficacy of using DFA to gage the situation awareness of personnel within a team-based game involving the search and retrieval of items scattered throughout a large virtual environment. The study included experimental manipulations designed to facilitate or hinder team members' ability to develop situation awareness, either by obfuscating their vision with environmental fog, or by presenting team members with a head-up display (HUD) which provided veridical information about the task environment. The results demonstrated that task conditions that made it easier for teams to develop situation awareness (e.g., no fog, access to a HUD) were associated with increases to DFA_{α}, applied to team members' displacement and head scanning behaviors. Further, DFA_{α} was also shown to increase over multiple sessions as teams developed expertise with the task.

Not only can DFA be applied to individual time series data, but it can also be used to quantify the level of coordination within a team. An approach to measure the extent to which teams are coordinated is to consider the extent to which the structure of their behavior is correlated during ongoing task performance. The coordination of behavior structure, referred to as "complexity matching", hypothesizes that the exchange of information between two coupled systems is maximized when their behavior complexities are similar and thus can be used as a predictor of team success.[30] Indeed, when applied to the dataset from 29, three-person teams who had veridical information about where their teammates were located with the HUD exhibited greater complexity matching, quantified as a smaller difference in DFA_{α} values, than when they did not have this information.

The use of positional and acceleration data, either via GPS sensors or IMUs can be leveraged to extract useful metrics that correlate with the development and maintenance of situation awareness of individuals which can be used in conjunction of other data streams, such as audio communication. Although these measures have been explored here using team sports and multiplayer video gaming, their relevance are expected to translate to military contexts involving tactical operation. For measures such as DFA, for example, a data sampling rate of 5 Hz would require about 2 min of data collection for an estimate of situation awareness to be obtainable. Additionally, measuring the degree of complexity matching may provide an estimate on the ability for team members to communicate and coordinate their actions effectively.

3. Discerning perceptual features for decision-making using explainable-AI techniques

In addition to tracking the behaviors of individuals in team settings, one might also wish to better identify the informational features that team members use that support their decision-making process. This can also include uncovering what information best supports optimal task performance, and what features differentiate expert from non-expert performance. In contrast to practical reasoning or deliberative decision-making activities, where individuals extensively evaluate all possibilities to determine optimal behaviors, the action decisions of individuals during dynamic team behavior are typically emergent and highly context dependent.[2] Moreover, team members rapidly and spontaneously adapt their actions to achieve task goals as successfully as possible,[31] with little conscious concern for what is optimal. Coherent with research on naturalistic decision-making,[32] the effectiveness of such action decisions is therefore a function of an actor's situational awareness,[33] with task expertise reflecting the trained attunement of an actor to information that best specifies which action possibilities might ensure task success.[34] It is these characteristics, however, that make predicting and understanding human action decisions during team activities so challenging.[35] This includes identifying what task information supports effective action decisions.[36–38]

Recently, Auletta et al.[39] have provided evidence suggesting that these challenges can be addressed using cutting-edge Supervised Machine Learning (SML), Long-Short Term Memory (LSTM) artificial neural networks, and explainable-AI (Artificial Intelligence) techniques. Specifically, the authors demonstrated how SML trained LSTM networks can not only be trained to predict the action decisions of individuals during team activity, but that an analysis of the resultant models using the explainable-AI technique, SHapley Additive exPlanation (SHAP),[40] can also identify and differentiate the sources of information that underlie the action decisions of expert and non-expert actors. In this study, target selection decisions were modeled from data of expert and novice pairs playing a simulated, fast paced shepherding game.[41] For this task, pairs of players controlled virtual herder agents to corral a herd of four virtual targets, dispersed around a game field. The recorded performance data was then used to train a LSTM network, via SML, to predict the *future* target selection decisions of players. Following model development and validation, the resultant LSTM models were then analyzed using the explainable-AI technique SHAP to identify the different sources of task information that defined the action decisions of expert and novice players.

The analyses demonstrated that using task information sequences of 1 s in duration, LSTM models were successfully able to predict the target selection decisions of both expert and novice players at an average accuracy above 95 %. Moreover, accurate target predictions could be made between 640 ms to 2.4 s prior to player decisions being enacted or observable within the state input sequence. Another key finding was that the LSTM models were expertise specific; when the expertise level of the training and test data was mismatched, prediction performance dropped to near chance levels. Perhaps most importantly, the SHAP analysis revealed that this specificity was because experts better relied on a richer set of informational features (e.g., the location of their teammate; the direction of movement of targets) compared to novices. Together, as one would expect, the results demonstrated that experts were more attuned to the collective state of the task environment, including when and what task actions were better enacted by themselves or their co-actor.

Relevant to military contexts, where decision making expertise is not just required in close-combat situations but also in remote warfare,[42] it is vital to understand the informational features that are a characteristic of expert decision makers. Advanced AI and explainable-AI techniques have the potential to distinguish between experts and novices based on the perceptual processes used by individuals instead of just end performance measures. Additionally, these insights can be used to design training interventions to facilitate decision-making via the perceptual learning of identified features that are associated with expertise.

4. Capturing group-level behavior and coordination

Geospatial data has been used within military research to analyze tasks such as simulated aerial combat[43] and simulated combat of dismounted personnel.[21] However, while such tasks require the coordination of multiple individuals, there are no reports, to our knowledge, of military geospatial data being used to investigate the coordination of the teams, although this may be due to such information remaining classified. Comparatively within team sports, researchers have also used positional data of all players on a team to capture cooperative behaviors. Firstly, time series of positional coordinates (longitude and latitude or X and Y coordinates in some simulation settings) are recorded for each individual. After aligning the time series of coordinates for each individual, simple measures, such as team centroid and the dispersion of team members around it, can be derived from team members' positional data which can be further used to analyze coordination of movements between the two and investigate coordinating behaviors between teams.[44] Analyses such as these have obvious applications toward military tasks (e.g., to determine the coordination between dismounted personnel or fighter pilots during various tasks), although it should be noted that a limitation of these measures is that they can often fail to encapsulate the individual team member contributions. One of the methods that overcomes this limitation is cluster phase analysis (CPA)[45] which quantifies the magnitude and patterning of the movement synchrony that can occur between the movements of a group of individuals. Indeed, synchronicity in individual behavior not only increases group affiliation but is also a marker of better performance in achieving joint goals.[46] Furthermore, synchronicity is not just limited to physical measures but also extends to neuro-physiological signals and has been associated with better problem-solving ability.[47] In the context of team sports, CPA can be used to quantify the geospatial relations between players, or subgroups of players within teams[48] based on how players attack or defend together, and how these behaviors are influenced by contextual circumstances.[49–51] This has clear implications for investigating the coordination of military personnel in the field who must also attack or defend as a collective unit such as during a section attack.

Of relevance here is the recent study by Novak et al.[49] that has shown how measures of speed, player spacing, and synchrony (CPA) of movements between individual team members can be used to describe collective team behaviors during various phases of an elite rugby match. Specifically, GPS data was obtained for players during 26 team-match observations of the 2018–2019 Super Rugby season and players were classified as Forwards (positions 1–8) and Backs (positions 9–15), and the speed, spacing, and CPA were calculated for each phase. Two classification models (multinomial mixed effects regression) were developed to test the efficacy of the metrics i.e., player speed, spacing, and synchrony in classifying phases of play: 1) objective (i.e., classifying according to the method of gaining possession) and 2) coach-led (i.e., classifying as structured attack, structured defense, unstructured attack, or unstructured defense). While the coach-led classification system resulted in somewhat poor accuracy (43.4 % (95 % CI: 40.1–46.7 %)), likely due to the generalized nature of the subjective system, the objective system achieved 71.4 % (95 % CI: 63.0–78.9 %) accuracy. As such, it appears that such metrics derived from wearable GPS devices can be used to classify some activity types and therefore determine when a team transitions from one state of behavior to another. Given that many team-based military tasks are complex and performed in remote settings, wearable technology combined with such analyses may present an avenue to improve analysis of team performances such as during after action reviews.

Despite the potential usefulness of positional analysis, it may not be possible or feasible to collect positional data in some settings e.g., where satellite connection is poor or where devices cannot be readily recharged. In these cases (or indeed as a supplement to positional analysis), concepts from network science can be applied, where nodes in the network can represent the individuals in a team and the links to quantify their interactive behaviors with other members.[52] In team sports, game footage can be used, in which the coordination of team members can be quantified from the passing decisions between players of the same team. The data relating to passing decisions can be quantified as an adjacency matrix in which the player's name and/or position of the passer is captured, along with the player's name and/or position of the receiver for every passing interaction throughout a match. This is then used to draw a weighted and directed network graph, where each node represents a player, and the links (edges) represent the direction (i.e., who passes to whom) and weight (i.e., how often do two players pass to one another) of the passing interactions. Once a graph is developed, its topography can be used to describe cooperative behaviors at three different levels: the collective level, integrative, and individual level. For researchers studying cooperation in team sports, the collective and integrative levels are most relevant. Cooperative behaviors at the collective level consist of measures computed at the team-level, while the integrative level is measured at the individual level, but relative to the team. Some collective and integrative measures used by researchers studying cooperative passing networks include the density (i.e., the number of reciprocal passes between players), closeness (i.e., the extent to which a player belongs to the shortest path length to every other node in the network), or betweenness (i.e., the number of times a node lies on the shortest path between two other nodes). The latter can be measured both at the integrative as well as collective levels, by averaging the closeness and betweenness for each player in a team. Cooperative passing behaviors quantified using metrics like the ones above have been associated with win probabilities[53] and scoring[54] in football as well as field position profiles in rugby union[55] among adult professionals. However, they appear to be unrelated to playing level in youth association footballers.[56]

Although described using a team sport example, network science concepts can be applied to any number of modalities to describe team-level interactions and can inform the design of communication networks to maximize performance,[57] having clear relevance in understanding the coordination dynamics of organizations such as the military from tactical action to command-and-control (C2).

5. Discussion

The methods highlighted in this article are only a small sample of the methods that can be employed to study social and team dynamics (e.g.,[58,59]) in humans, as well as human-autonomous teams (e.g.,[60]). These approaches highlight that there is a richness of information that can be obtained from behavioral time series data and that this information can be employed to infer cognitive control and performance. Furthermore, depending on the availability of data recording techniques and by applying analytical methods of varying levels of complexity, different levels of information can be identified, and corresponding measures can be derived. For instance, to quantify the situation awareness of team members, depending on the time length of the events or trials, one might use simpler visual exploratory action identified from the frequency of the head orientation data for shorter trials' or for longer trials' DFA computed on a time series consisting of changes in the heading directions of the team members. Both methodologies, applied in the right circumstances, can result in measures of individual and team situation awareness that are correlated with team performance. In addition to these behavioral measures, the use of explainable-AI provides a data-driven method to discern differences in decision-making ability as a function of expertise. This knowledge can facilitate the development of targeted training exercises to facilitate perceptual training to improve performance. Although the examples used in this review stem from our expertise in sport and computer-mediated team coordination, the methods and tools presented here can also be leveraged in demanding contexts such as those found in the military. To conclude, these approaches help move the field to better understand (e.g., via explainable AI techniques), track (e.g., via situation awareness measures like DFA) adaptive individual behavior, and provide a description (e.g., via team-level measures such as CPA or network-based measures) of team-level phenomena.

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Confirmation of ethical compliance

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Declaration of interest statement

All authors have no conflicts of interest to declare.

Transparency declaration

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