Sentiment Analysis Based Human-Machine Teaming Dynamics Modelling for Improved Situational Awareness in Simulation Environments

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Abstract— Introduction of sentiment analysis, AI and machine learning (ML) based modeling of human-machine interactions can act as an excellent guide to assess the current strengths and weaknesses of human teams in a given paradigm and recommend targeted areas for improvement in team performance dynamics and situational awareness. This case study is conducted on human-machine interaction data from a team-based fire-fighting simulation environment. The primary goal of this research is to conduct sentiment analysis and ML on team communication data to gain deeper understanding of how teams behave and respond in stressful scenarios, how the levels of individual and team situational awareness influence the team dynamics, decision-making capabilities, and in turn impact the team performance (high vs. low) in the context of fireextinguishing tasks. The AI/ML analysis of the relationship between the team performance variables and situational awareness scores reveal contributing factors that were the best predictors for team performance.

Keywords—, AI, ML, Human Computer interaction, human Performance modelling, Human-Machine Interface and Communications, Sentiment Analysis, Situational Awareness

I. INTRODUCTION

Team dynamic behaviors can be described as the process of how groups and individuals act and react to changing or dynamic circumstances [1]. In general, situation awareness (SA) encompasses how individual team members perceive relevant elements in their environment to a specific time and place, how they comprehend the meaning of the elements and the projection of how these will unfold in the near future [1]. Team situation awareness (TSA) can thus be described as the degree to which every team member holds SA required for their task responsibilities. High levels of TSA are achieved through effective team interaction (i.e., team communication and coordination), In this study, we explore AI/ML prediction and sentiment analysis to understand the interplays between team and individual member behaviors (team dynamics) and their relationship with TSA to enhance teamwork and improve human-AI system interaction performance [1-3].

II. DATA COLLECTION AND SIMULATION ENVIRONMENT

We studied team communication and system interaction data from 42 teams with four members each during the course of a fire-rescue simulation operation which consisted of simulated Bryan Mesmer Department of ISEEM The University of Alabama in Huntsville Huntsville, AL, United States bryan.mesmer@uah.edu Sampson Gholston Department of ISEEM The University of Alabama in Huntsville Huntsville, AL, United States gholsts@uah.edu

forest and building fire eruption scenarios that are similar to typical fire incident exercises encountered in the real-world. The anonymous team members were seated in front of independent workstations, where they received role and taskspecific information prior to the simulation exercise. Teams engaged in a training simulation (simulation 0.0) followed by two fire-rescue operation simulations (simulation 1.0 and 3.0). Simulation 2.0 was an in between team discussion session. All simulations were 15 minutes each. The goal of simulation was to protect forest and housing from fire and reduce fire eruptions. Team members had access to information regarding their system capabilities, windspeed and direction, chat window, performance scores as well as full visibility of the simulation environment that included terrain, housing, forest and water towers to refill the system's water tank. Each team member was assigned their own fire response system, either a fire engine or helicopter. Teams were able to send and receive information through the chat window in text-based form at any given point throughout the simulation. At the end of each simulation, teams were presented a performance score based on the percent of forest and housing saved from fire. The team chat logs and TSA levels demonstrated during the simulation were captured from the team communication data for analysis.

TABLE I. TSA LEVELS AND EXAMPLES

Code #	Team Situation Awareness	Definition	Examples
3	Perception	Info about team factors and their current state such as condition, modes, action.	"My water tank is empty"
4	Comprehension	Info about task related occurrences within the team that help members understand team relations, team events and places.	"Our fire engines seem to be slower than our helicopters"
5	Projection	Info about possible future actions of their own team.	"We will have to split up areas"
6	Action	Action of team members in regards to own team.	"Fill up your water tank"

Table I, and II gives the TSA categories, team dynamics data collected and extracted from team communication (chat logs) using sentiment analysis throughout the simulations (0.0-3.0). These features are then subject to supervised learning using AI/ML techniques for team performance prediction.

TABLE II. TEAM DYNAMICS AND TSA FEATURES

#	Team Dynamics and TSA Features	
1	Average team member interactions	
2	Average Player 1 (team member) interactions	
3	Average Player 2 interactions	
4	Average Player 3 interactions	
5	Average Player 4 interactions	
6	Player 1 SA Average	
7	Player 2 SA Average	
8	Player 3 SA Average	
9	Player 4 SA Average	
10	Number of team member interactions with TSA score 3	
11	Number of team member interactions with TSA score 4	
12	Number of team member interactions with TSA score 5	
13	Number of team member interactions with TSA score 6	

III. EXPERIMENTAL RESULTS

We performed sentiment analysis on the team chat log data to visualize the team and individual member's sentiments throughout the simulations. The valence aware dictionary for sentiment reasoning (VADER) model in the NLTK package was used to analyze the chat logs and designate a sentiment intensity score as neutral (e.g. TSA level 3), positive (e.g. TSA level 6), negative (irrelevant response to task). These sentiment scores captured complex nuances in varied TSA levels and to derive additional features for AI/ML models.

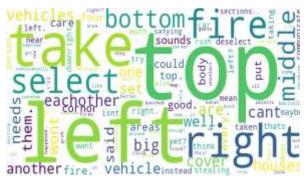


Fig. 1. Word cloud generated from team communication logs that demonstrate high TSA scores. Note directional statements (action- verbs).

Fig. 1. depicts the word cloud extracted using sentiment analysis on the team communication data logs of all teams to visualize the most frequently occurring words corresponding to TSA level 6 (action, positive sentiment) and TSA level 3 (facts, passive/neutral sentiments), respectively. It was also noted that high performance teams on an average demonstrated active and engaging communication dialogues.

To further understand the relationship between team dynamics, TSA, human (team) system interactions and team performance, feature selection using analysis of variance (ANOVA) was conducted on the dataset. Here the important team dynamics features correspond to the highest F-values as depicted in Fig 2. The features 6, 7, and 9 corresponds to the individual team member SA scores. This emphasizes that individual player's SA had a strong impact on the overall team success and high-performance team dynamics.

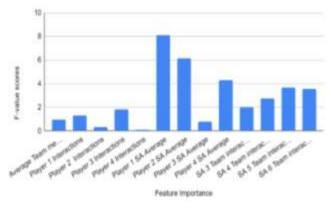


Fig. 2. Team Dynamics analysis using ANOVA-based feature selection

We then conducted team performance prediction based on the identified important team dynamics features using AI/ML techniques, namely, decision tree, random forest, support vector machines (SVM), and multilayer perceptron (MLP). The motivation here is to understand the contribution of team dynamics features that enables enhanced prediction of team performance. We randomly selected 50% of team dynamics data as training set and the remaining 50% was used for testing, since this split yielded the optimum results. From Fig. 3. it can be observed that both random forest and SVM classifiers gave the highest team performance prediction accuracy of 85.71% over other AI/ML methods.

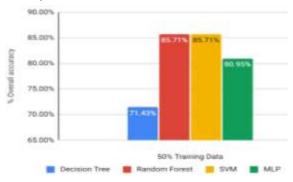


Fig. 3. Classification accuracy for AI/ML methods using 50% training data

IV. CONCLUSION

This research corroborates that the AI/ML techniques have great potential to identify key areas of human-system interaction design improvements to enhance team dynamics and boost the overall team performance.

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