Future Directions for Intelligent Human Machine Collaboration and Application in Defense

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Abstract

Autonomous systems have seen tremendous progress since the last decade and have the potential to become transformative military technologies in the coming few years. Future intelligence, surveillance and target acquisition systems would generate much larger volumes of real-time data which would be nearly impossible to process with human mental capacity. Machines would be challenged by the uncertainty and ambiguity in such unstructured data leading to difficulty in decision making. It must be understood that human operators would eventually be task saturated handling the unmanned systems and thus, there is a pressing need to utilize AI to free up human mental capacity in a flexible and adaptable way. This paper articulates how effective integration of soldiers, robots and artificial intelligence may contribute to future military advantage and warfighting systems. A cognitive analysis framework is presented to analyse the need for explicit allocation of cognitive responsibilities between the team members to achieve specific objectives while understanding the trade-off between performance and cognitive overload. A case study is presented to highlight the importance of flexible human robot interaction and demonstrate the impact of human robot collaboration in defence scenario. The paper enunciates key challenges for future ground forces for developing competent human-machine teams.

Keywords

BCI, Cognition, HMT, HRI, Intelligent systems, Shared Mental Model

I. Introduction

In this age of artificial intelligence, new technologies continue to automate the more routine tasks and the need exists to make ever faster decisions than ordinary humans can process. The automation of many tasks currently performed by soldiers would potentially augment the soldier capabilities and provide additional gains in performance and reductions in threats. This motivates to understand that the future trends in technology and warfare would conform to scenarios where human and machine coexist, collaborate with AI and complement each other resulting in increased productivity. Human and machine teaming (HMT) is paramount for future battlefield where tens of thousands of robots would be employed. Coordinated teams of heterogeneous unmanned systems would work in concert with human executing desired missions. Human machine teams have a competitive advantage when a task is so complex or complicated that it exceeds the cognitive capabilities or skill sets of either one. The adoption of AI in human machine teams seeks to achieve performance gains and error reduction. A comparison of human and machine cognitive processes and their relative merits reveals the ways in which complimentary attributes can combine to deliver robust team capabilities.

A team task can leverage the distributed perception, concentration, intellect, and experience of multiple members and, if correctly executed, can apply the entire effort to the task [1]. The communication of the common goal, sharing information about the environment, identifying capacity to complete tasks within the team, and the aggregation of the completed tasks are all examples of places where teams have an overhead coordination task. Human-machine interfaces play a central role of communication for team effectiveness through information transfer, task monitoring, and situational awareness, reinforcing relationships, and affirming predictable behaviour.

Implementation of a unique human machine team where members coordinate in decision-making in dynamic environments needs to be accomplished in response to an expanding demand to employ machines as teammates of humans instead of as agents that operate independently of humans. In order to enhance the system with social functions tailored to the specific context a social intelligence layer between the autonomous systems and human team members needs to be realized [2]. This may be accomplished through a coactive design model [3] based on an abstract interface between the robot and the human teammates that facilitates OPD (observability, predictability, directability) and provides a framework for designing user interfaces that enable a robot to serve as a teammate in a joint activity.

In order to achieve this kind of dynamic collaboration, bidirectional cognitive interactions between human and robot would be paramount along with explicit allocation of cognitive functions and responsibilities between them to achieve specific objectives while considering the balance between performance and cognitive overload. Cognition is the practice of gaining knowledge through experience and thought and is the complex mental ability that makes communication, decision-making, reasoning, problem-solving, and other complex mental processes possible [4]. Human cognition relates to processing information about the environment to develop situation awareness. Humans and machines each have unique cognitive capabilities and limitations and it becomes important to consider the cognitive attributes as machines have certain characteristics that make them more capable of certain tasks. Moreover, the use of AI has the potential to accelerate decision-making for warfare beyond current process timelines that are encumbered by human cognition limitations. It is apparent that in future humans would be unable to process the unprecedented volume of data fast enough to defeat AI opponents, thus, pairing machines and human would enhance each other's strengths by exploiting the unique capabilities of each to facilitate future combat.

A thorough understanding of human cognitive load is vital to achieving effective human machine teams and prevent the use of machine teammates from degrading human performance. It represents the load imposed on the working memory during performance of a cognitive task and identifying the factors that contribute to cognitive load is important for understanding how cognitive overload occurs. High levels of cognitive load are linked to increased learning time and increased error rates and, therefore, poor performance [5]. Measuring cognitive load directly is difficult because cognition occurs in the mind of the individual. There are three broad approaches to measuring cognitive load: subjective, physiological, and task/performance based. Subjective techniques require the individual to reflect on how much mental effort they felt they expended to complete a task. Physiological evaluation techniques rely on measuring physical changes in an individual that are attributed to increased mental effort or arousal state, such as changes in heart rate and eye activity. Performance-based methods measure the performance when primary tasks are performed by an individual or both primary and secondary tasks are executed concurrently. Robust and real time multimodal cognitive load measurement collects signals from various sensors and input devices to assess the cognitive burden during task. A framework needs to be established that relates task, individual and environmental characteristics to cognitive load and task performance, as well as the methods for measuring cognitive load.

Cognitive load theory states that during learning information is stored in the working memory before it can be processed and passed to long term memory [6]. Humans' process information in the context of the environment and this situation awareness is a significant input to decision-making. Gaining and maintaining situation awareness is a task that requires an individual to allocate attention and working memory capacity. Perception involves sensing information about the status, behaviors, and dynamic aspects of components in the environment that are relevant to the individual and their objectives. Achieving this level of situation awareness places a significant burden on working memory, as the human must not only keep their comprehension of the current environment state updated, but also employ rules to develop the future state from the current state, as well as formulate the appropriate action to achieve the desired future state.

How situation awareness occurs in a team environment depends on how similarly team members view a given situation. To achieve a high level of shared situational awareness, teams must perceive and comprehend the current situation similarly and must project the same future state. To accomplish this, team members must convey perceived environmental information to other team members who have not perceived the information. Shared mental models (SMMs) among team members may reduce the need to communicate every piece of environmental information to team members who require the SA generating information [7]. In the military context, gaining and maintaining situational awareness is not an end in itself but a means to make informed choices that alter the future state of reality. The paper highlights the possibilities and challenges for teaming intelligent machines with humans to cooperatively perform tasks in complex dynamic environments. Section 2 discusses the techniques of human robot teaming in existing global and defense scenarios. Section 3 presents a cognitive analysis framework supported by a case study to explain human robot interaction in a typical defense scenario. Various research challenges to realizing effective human robot coordination are briefly presented in Section 4 and finally, we conclude the paper by highlighting potential risks in achieving effective teaming and deliberate on promising research opportunities that can address these risks and challenges.

II. Related Work

There are many situations where robots are expected to work with people to achieve a common goal by performing joint actions. Medicine, sports teams, non-profit business units, corporates as well as military organisations are some of the areas where multiple agents work together to take advantage of the skills and expertise of individuals and perform a task in concert. For most part of the last century, intelligent machines have been employed as tools and not teammates. Robotic assistants, self-driving cars and chatbots have been developed for various domains and applications and these technologies extend human capabilities but possess inadequate cognitive and communicative abilities to function as a trustworthy teammate. Despite considerable technological advances, numerous challenges exist to achieve fully autonomous machines that can handle high risk and complex operations including critical battlefield environments.

Recent advances in artificial intelligence and machine learning have given way for development of systems where intelligent machines team with humans in limited contexts. Intelligent teammates must possess awareness and understanding of current goals and actions, the ability to produce adaptable responses to hypothetically defined needs, and the capacity to gain from and adapt to evolving surroundings. Over the last ten years, research in psychology, neuroscience and technological advances have led to insights to understand these behaviours through varied experiments across domains. In military training, autonomous AI systems have been used to populate the battlefield with friendly and enemy units and also simulated as co-pilots [8] which involve interaction with a human during task execution.

Understanding of human capabilities is necessary to understand and design flexible, intelligent systems that optimally interact with humans. The behaviour of a person acting alone is very different from when they coordinate in a group. This includes the behaviour and interaction of people in a group, understanding intentions of each other and coordinate to perform a joint action [9]. Also, it must be understood that in group interactions, the activities of every member influences the behaviour of others and robots and humans need to share a common physical space. As discussed below, significant work has been done to build policies for robots to share a space with humans and most of it has focused on building models from human demonstration.

A. Proximate Human Robot Teaming for Anticipatory Action Planning

Development of the capacity for humans to supervise and task large robot teams and interact with robotic teammates sharing common physical space is an important task. Human motion trajectories were gathered by Ben Amor et al. [10] as Dynamic Movement Primitives (DMP) from a human-human task and demonstrated human robot joint activities using Interaction Primitives. Collaborative planning based on MDP to anticipate a person's future actions to plan appropriate actions for a robot to perform collaborative tasks in a shared environment by modelling human kinematics and intent has been developed by Koppula, Jain, and Saxena [11]. Their results suggested that this approach performed better than various baseline methods for collaborative planning. A framework has been presented by [12] to allow a human and a robot to perform a manipulation task together in close proximity by generating a prediction of occupancy of human workspace and motion planner to generate robot trajectories. Anticipation algorithms for higher level group behaviours have been studied by Iqbal, Rack, and Riek [13] where robots perceive real time human behavior , anticipate future course of actions, and produce their own movements. Various other models of human demonstration and anticipatory action planning exist where robots avoid collisions to efficiently collaborate with people.

B. Integrated Cognition for Collaborative Actions

Group cognition is the ability to relate to other member's intents, decisions and beliefs. In case of teams, aspects of planning, decision-making, idea generation, creativity, problem-solving play a vital role and group cognition helps to maintain a common understanding among agents. It is a critical factor to achieve collaboration and emerges in interaction when the group members involved, humans or machines, share knowledge and objectives and also dynamically update their understanding for better joint performance [14]. Chaski is a collaborative system where a robot can schedule its action and adapt to the human teammate to minimize the human's idle time through shared planning [15], [16]. Significant research has been done on building cognitive models for robots to identify one's mental sates and confirm the reception and interpretation of objectives. Hoffman and Breazel [17] have presented a hierarchical goal-oriented task execution system that integrates human verbal and nonverbal actions, as well as robot nonverbal actions to support collaborative activity in human robot groups. Affects on group coordination in a heterogeneous human-robot team has been investigated by Iqbal and Riek [18] and indicate that robot behaviour and number play a major role in group coordination dynamics. Additionally, various real world applications such as consumer online choice behaviour also focus on specific cognitive domains such as attention, memory, decision making etc. [19]. Intent recognition [20], cognitive artificial intelligence [21] and human level problem solving [22] are some of the other areas which have seen growing interest in group cognition.

C. Human Robot interaction and shared knowledge base

To achieve effective human machine collaboration information needs to be shared between them through interaction which not only includes language, but also gestures, and even interpretation of emotion expression. Few research communities are exploring ways to accomplish this while not overloading the human's capacity to learn and solve such problems. Many researchers use verbal and nonverbal signals including eye gaze, head orientation, gesture etc. for a seamless interactive environment. A state of the art approach wherein a small humanoid robot hands over objects in a public space using relationship between non-verbal signals (eye gaze) and arm extension has been developed by Shi et al. [23]. Gesture and emotion expression are also an active area of research. According to [24], focus on subtle aspects of language such as indirect, non-literal speech may account for the listener's beliefs and desires. Grigore et al. [25] introduced a higher level cognitive layer to model joint actions into human robot interactions to improve success rate of robot to human handover task by incorporating eye gaze and head orientation into the robot's decision making. In order to monitor each other's performance and have a shared understanding of the task, shared knowledge bases and models need to be designed that can facilitate productive thinking. An Open knowledge database to equip intelligent agents with knowledge about entities, concepts, and relationships in the world has been explored in [26] where future states are predicted using data structures and representations. One such model has been presented by [27] where they have represented SMMs using alternative representations. In [28], McNeese et al. have explored how human factors are affected while teaming with a synthetic teammate where they have compared teams in an unmanned aerial system context. It is understood that due to ubiquitous nature of AI this would continue to remain an open area of research as unrestricted natural language comprehension continues to be beyond AI capabilities.

D. Explicit behaviour analysis using learning from demonstration

Robots that learn from demonstration can observe human motion using their sensors and replicate the similar actions as humans. This type of imitation can be identified by observing, representing and reproducing an action and enables robots to take optimal actions in unstructured environments. As a result, imitation learning consists of recognizing the human conduct and strategies for organising the motor-control system for mimicking learning abilities [29]. Significant work has been carried out for identifying robotic assembly tasks by human demonstration [30]. Depending on the requirements of the problem, supervised, reinforced or unsupervised learning technique may be employed to solve the problems of robot learning. A survey on grasp sysnthesis has been presented by Bohg et al. [31] that includes a taxonomy of imitation learning methods used in that specific area. Though, majority of the work is focused on supervised learning experiments, unsupervised learning may also be accelerated using biologically inspired predictive learning [32]. The effect of imitation learning by a robot on human robot teaming using head gestures while interaction has been studied by Riek et al. [33], [34], [35]. Their studies explore head gesture mimicking along with the effect of cooperative gestures performed by a humanoid robot in a teaming scenario. Nikolaidis et al. [36] propose a two -phase framework to fit a robot's collaborative policy with a human collaborator using Inverse Reinforcement Learning model with Mixed Observability MDP. The efficiency of learning in AI systems can be enhanced by incorporating curiosity and active learning by reinforcing acquisition of information in the face of uncertainty [37]. Going forward, it would become particularly important to develop robots that autonomously generate questions in order to fill knowledge gaps about the external world and generalise this learning to other tasks.

E. HMT in Defence

Military organizations around the world are already studying the changing character of war based on prevailing trends to inform their planning. Human robot teams can have broad application across military organizations as better teamwork, improved communication interfaces and improved usability and reliability for applications would reduce the number of humans needed to operate a system. The installation of large numbers of advanced sensors on devices, extensive communication links, and a growing flow of information are driving the use of AI in the military and offer the potential for effective human machine teaming and human augmentation. The military are readily prepared to adopt robotics and AI technologies to boost individual and team performance, enable new operating concepts and increasing adaptability of systems to new situations for military deployment. The latest achievement of the military is the XQ-58 valkyrie drone designed and developed by Kratos Defence & Security Solutions for United States Air Force [38]. It is a low cost, stealth unmanned combat aerial vehicle for deployment in ISR and long range missions as an escort to a manned fighter aircraft. Guardium UGV is a semi autonomous unmanned ground system for perimeter security and equips the soldier with a robust tool kit for route proving and logistics support and provides comprehensive situational awareness [39]. Lockheed Martin's [40] Squad Mission Support System (SMSS) is another UGV system which is able to follow a person through goals that are sent using a map. The user can interact with the SMSS using a handheld device with a touchscreen, several buttons, and a joystick. The Squad X project of DARPA uses autonomous robots, aerial drones and android tablets to survey and study the environmental factors and present this information to soldiers on the ground for taking better decisions [41]. An important step in the advancement of autonomous weapon system was made by the possibility that groups of small robots could act together under human direction. Advanced swarm behaviors during complex combat scenarios like cooperative decision-making and self-healing have been demonstrated by Perdix micro drones [42]. The UK government is also working on network enabled drones equipped for confounding and overpowering the enemy [43]. These systems empower humans to make better decisions faster by steering towards a novel approach of autonomous aircraft piloting and maneuvering.

F. Brain Computer Interface

A number of defence applications are being explored for BCI and brain activated devices are beginning to revolutionize. Electro-encephalography (EEG), invasive direct connections and electro-corticography (ECoG) are the universally accepted techniques for mind reading and control. Sensors are used by machines to integrate neural activity patterns and behavioral observations, in order to infer the human's intentions and cognitive states. Chavarriaga et al. [44] explore how Brain Machine Interface provides enhanced interaction during driving a vehicle by taking into account environmental information, user's actions and physiological signals, as well as their cognitive states inferred from EEG. Neuralink is a BCI venture wherein device is proposed to be implanted in the human brain with the intent of helping human beings and potentially improve memory by allowing for more direct interfacing by reading huge data and transmitting amplified signals from the brain [45]. It is a merger of biological and digital intelligence which could be used by humans to improve themselves and has the potential to replace cumbersome devices currently used as brain-machine interfaces. Cyberdyne Hybrid Assistive Limb suit (HAL) is a suit developed to detect brain signals where the wearer only needs to think about a particular movement and the suit reads and deciphers wearer's intent [46]. It is the world's first cyborg which improves, supports and enhances bodily functions and is a perfect illustration of man, machine and information fusion. Though these devices could be dangerous due to their invasive nature but the promising future predicted for BCI has encouraged research community investigating the generation of hands-free applications and increase the accuracy of existing human computer Interfaces.

G. Adaptive HMT

Humans team with autonomous vehicles to manage multiple roles and missions in complex environments. Systems (human or automated) that do not understand their human collaborator suffer from decreased safety, efficiency, and rates of adoption. It becomes very important to evaluate the adoption and performance of human collaborators with new technology. The strengths and weaknesses of both the human and machine need to be understood along with a better insight for the human to understand the machine and also for the machine to understand the human. Search and rescue, hazardous area assessment dynamic path planning are some of the complex real world situations in the defence sector and are characterised by environment uncertainty, communication limitations, indecision, adversarial behaviour and high dimensional domain. This calls for a robust human AI collaboration system that can capture human preferences, co adapt and share tasks with humans over time. As shown in fig. 1, a real world human multi-robot team collaboration task would typically consist of an intelligent agent which provides advice for a human operator engaged in multi-robot supervision and control and thus, enhances operators' performance. The agent acts as a collaborator between the human operator and a robot or a team of robots operating simultaneously.

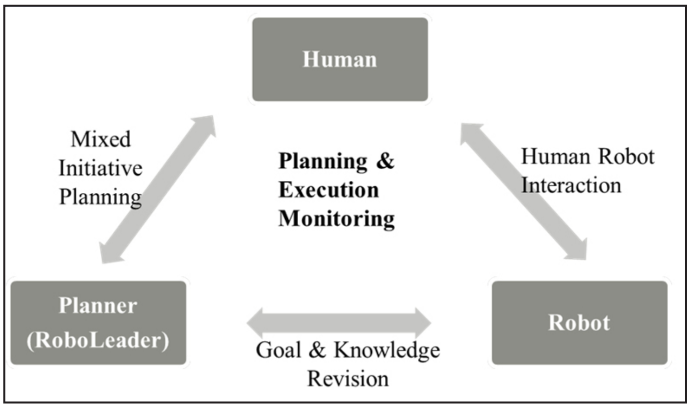

Fig. 1: Interaction in Human robot scenario (Derived from [47])

For a particular scenario, teaming must consider the type of robot as there exist various types of robots with varying capacities. Human robot interaction works towards the development of a natural interface between human and machine. The plans generated by the intelligent agent are received by the human operators and these human agent shared plans anticipate and suggest actions for human aware task planning called mixed initiative planning. These shared plans are used for action monitoring and execution control between the group of robots and the intelligent agent. The goal may be specified incompletely in a complex dynamic scenario and hence, robot must be equipped to handle the user's changing goals using goal and knowledge revision models. Myers [48], [49] work on advisable planning provides an iterative feedback process that incorporates behavior and performance by allowing humans to provide recommendations in natural language. With developments in automation, cognitive modelling and machine learning, HMT should be adaptive where human can mediate machine operations for task reallocation, resource redirection and incorporate learning methods (supervised, unsupervised, reinforcement) to learn human preferences and priorities and continuously improve human machine team performance [50]. For a seamless interface, it should incorporate human level interaction and planning in a human robot environment with a centralised knowledge base. One of the key implications of this paradigm shift is that the machines need not be constantly supervised by the humans. As a result, the machine would have greater autonomy and increased shared awareness would be critical to ensure that the human and machine stay apprised of each other's state. A human behaviour model that is aware of human capabilities, provides a personalized, optimized autonomous agent that contributes to changing context, dynamic functional allocation and human availability would facilitate effective HMT. The next section presents key elements of an HMT architectural framework in the context of surveillance and navigation in military situations and further describes human robot interaction for specific tasks in defence environments through a case study.

III. Cognitive Analysis Framework for HMT in Defence

Scenario: A reconnaissance HMT scenario where teams of heterogeneous unmanned systems (UAVs and UGVs) collaborate for goal setting and course of action selection is shown in fig. 2. This type of collaborative navigation would enhance obstacle avoidance planning and traversability of UGV in unknown environments. In another scenario, a human machine team would consist of a human operating a robotic surveillance system at remote and border areas. Intelligent agents would be able to assess extensive data, challenge human bias, and recognize patterns that humans may not comprehend. The focus would be on designing optimally hybrid teams of humans and intelligent machines executing team goals by coordinating communication and task distribution to optimise team performance. HMT would be influenced by agent cognition, interface design, functional allocation and effective performance in highly unstructured and dynamic situations.

The following are key elements of our human machine collaborative framework:

A. Cognitive Factor Analysis

This involves real-time cognitive load measurement with the dynamic fusion of multimodalities to understand the task and classify the cognition in task including task's cognitive complexity and cognitive environment.

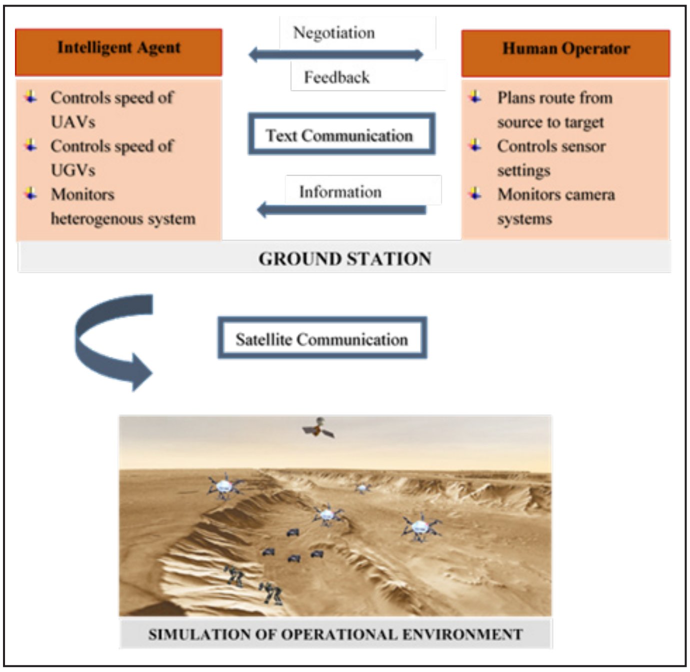

Fig. 2: A typical HMT Defence Scenario

Estimation of cognitive load is one of the fundamental tasks in human learning scenarios. Surveys based on subjective and psychometric scales may be used to distinguish between categories of cognitive load. Physiological measures of cognitive load include electroencephalography (EEG), heart rate, electromyogram (EMG), eye movements and pupil dilation during real time learning and related cognitive tasks. Being implicit and continuous, these psychophysiological measures are sensitive to different cognitive process and offer objectivity in cognitive load assessment. In case of complex task scenarios, influences of augmented reality assistance and 3D virtual reality demonstrations may facilitate efficient performance by measuring and interactively adjusting displays based on operator's cognitive load level. New technologies and devices for cognitive load measurement like big data analytics for group experiences of cognitive load, longitudinal tracking to construct cognitive profile for a single subject, and experience-based cognitive load studies may be explored for better cognitive load measurement.

B. Team Design

The scenario discussed sketches complex situations in which human and machine teammates need to cooperate with each other while analysing a situation, communicate and take suitable action. Designing cognitive agents that can exploit partner's cognitive load would enhance performance in human-centred teamwork. It is difficult to determine the cognitively optimal number of human and machine agents for a particular task executed in an environment and hence, a worthy division of roles and responsibilities among machines and humans is also critical.

This is a problem because humans and machines each have unique cognitive capabilities and limitations, and failure to consider these cognitive attributes could lead to poor mission performance. Team composition guides the analysis of task functional allocation and team composition. Any combination of agents, other than identical machine agent teams, provides cognitive diversity that can add value when performing complex or ambiguous tasks.

C. Team Collaboration

Team coordination activities include dynamic distribution and functional allocation of tasks and subtasks, integration of completed subtasks, information sharing processes, teammate monitoring, task progress evaluation, error management, and all are necessary for the team to realize the performance benefits of operating as a collaborative group. Teams coordinate their activities more effectively and achieve better overall task performance when team members share one or more common goals and interact socially i.e when members develop a shared mental model (SMM). Shared Mental Models would help in maintaining consistency by resolving conflicts due to differing perceptions, different knowledge states and asynchronous information and track task progress in terms of goals and sub-goals achieved. An implementation of SMM ontology that consists of a) data representations that capture state information about the team, tasks, and environment, as well as task-relevant knowledge that is shared among team members; and b) computational processes that create and maintain the data representations needs to be designed.

As a result, SMMs integrated into cognitive robotic architectures would greatly enhance the performance of mixed human-robot teams while supporting domain independence, generalizability and scalability thereby, providing robot behaviour adaptation by updating and synchronising SMM state information. This integration needs to allow the robot to (1) directly observe humans to estimate their current performance fluctuations, (2) track human's progress toward their assigned goals, (3) determine the human's current task focus using performance estimates, goal assignments and progress, (4) estimate the human's cognitive workload based on task focus, (5) predict the implications of modified task assignments using performance estimates and current task focus, and (6) adapt its behaviour based on the measurements and predictions.

Consequently, the cognitive impact of integrating autonomous systems needs to be studied and examined in order to gain profound understanding of the cognitive and decision-making implications for autonomous systems integration and to improve task performance by optimising the cognitive abilities of human-machine teams.

D. Case Study

Human robot collaboration for real world application calls for studying the interaction of people and robots while understanding how people perceive different types and behaviors of robots. In this section, we present a case study to demonstrate HRI using spoken dialogs for a typical human machine teaming scenario in defense which involves task sharing, goal management etc.

1. Task Description

In this case study we would be focusing on the teaming task where robot is autonomously searching for suspected objects in some area and the human operator parallely monitors the entire area for potential objects/threats and guides the robot to search for the missed detections by giving various speech commands. The human operator is equipped with a laptop for monitoring, planning, and decision-making. The laptop is equipped with a smart dashboard and wireless connection to sensors, robot, video cameras and LiDAR. The human may act as a monitor who intervenes infrequently to redirect resources to new regions or regions where threat is suspected, or revise a goal based on intelligence from higher authorities or may perform the role of a supervisory controller who issues high level commands that are carried out by machine agents if he perceives the agents to be confused or not behaving as expected. The user interface comprises of two monitors: one is a situation awareness display for monitoring status of individual surveillance areas for suspected objects, and real-time views based on updates from the cameras; and the other provides detailed information on sensors, motion, location, cameras, etc. and monitors execution status of actions taken by the operator using the User Interface (UI).

The failure of the human robot team to detect a potential threat/object could be harmful and kill many lives and thus, the task criticality is high. In a teaming task, robot can take many forms. The robot being deployed in this scenario is neither anthropomorphic nor zoomorphic, but functional i.e. its appearance would be related to its function. It's a UGV and performs navigation, obstacle avoidance, object detection, and is also capable to pick objects using a gripper. It is equipped with a touchscreen and speakers for interaction with humans. Cameras and sensors are mounted on the robot for gesture recognition and object tracking. A gripper is also attached for performing object manipulation. The task would involve one human operator and one intelligent unmanned robot (may be increased to two if the area to be searched is large). In case two robots are deployed, they would be of the same type (homogenous) so that they are able to communicate through a single interface naturally.

Fig. 3 shows the level of shared interaction between the human and robot(s). In both the cases, the humans and robots need HRI awareness so they have knowledge of each other's commands needed to direct their activities. In the first case, one human operator gives commands to one robot, which sends sensor information back to the human. In the second case, one operator is directing two robots that work independently. The operator might want to direct the robots in two different directions of a hazardous land to obtain as much information about the environment as quickly as possible.

2. Interaction Roles

Roles that a human may take when interacting with a robot may be operator, supervisor, teammate etc. [51]. One or more of these values may be assigned to the human in any scenario. In our task, the human would essentially play a supervisory role of monitoring the behavior of a robot and issues high level commands, but does not need to directly control it. It may tell the unmanned vehicle where it should move and then the vehicle plans and carries out its task.

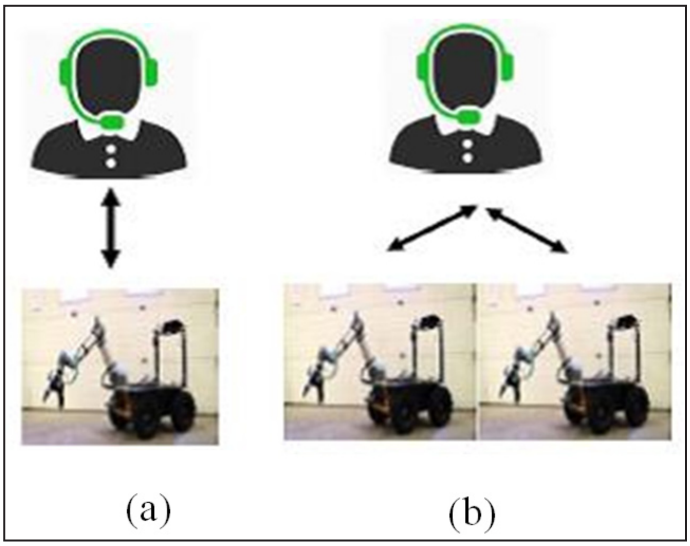

Fig. 3: Two Possible Combinations of Human Robot Teams for Given Scenario; (a) one Human one Robot; (b) one Human Multi Robot

In abnormal situations where it is necessary to change robot's undesirable behavior, human may take the role of an operator who intervenes only when needed to revise goals or redirect assets (i.e., resources) based on available external intelligence. The robot monitors regions for suspected objects by performing path planning and obstacle avoidance, detects objects, alerts the human of potential threat locations, supports human operator's planning and execution monitoring, and adapts surveillance pattern based on human operator's directions.

3. Autonomy level of the system

The autonomy level of a system depends upon the amount of intervention by the human operator. A system where a robot can carry complete task on its own is said to have full autonomy. Whereas systems are said to have shared control where human intervention takes place for robot control and they have the potential to move up or down the autonomy scale. There may be instances, such as a missed object, where human may take over control and handle the situation. In our system, the low level navigation tasks such as path planning and obstacle avoidance would be handled by the unmanned vehicle while the human operator would be responsible for high level directional commands.

Time and space taxonomy are imperative elements of human robot interaction [52]. In the current task, robots operate in a synchronous mode with the human but occupy different space (non-collocated) than humans as they operate in areas that are too dangerous for humans.It is very important to consider the type of information that is provided to operators for decision support. The information about available sensors, the type of sensor fusion and pre-processing are essential for designing the interface for HRI for efficient decision making [52]. The unmanned vehicle would have camera and LIDAR sensors to navigate and build a map of its environment and eventually detect objects and the data available from these sensors would be measured in the user interface and would determine how the amount of decision support affects the operator's performance.

4. Software Architecture of navigation and behaviour subsystem

Our system is based on a three layer architecture as shown in fig. 4. The raw sensor data goes to the processing layer which handles the localisation of robot and generates a map of the environment (SLAM). The path planning generates safe and efficient paths to a destination selected by the control layer. This layer is responsible for behaviour selection and control like speech recognition, object recognition, obstacle avoidance, and skills that control the camera and the gripper. The global path is sent to execution layer where these waypoints are transformed to motor commands.

5. HRI using task based spoken dialogs

One of the most essential part of human social exchanges is interactions in natural language dialogues. As a result, developing capabilities of natural language processing (NLP) in robotic architectures is critical to facilitate dialog based natural interaction in future robots [53]. In our case study we focus on task-based spoken dialogs, though many other different forms of dialogs may also be possible.

During human-robot interaction, speech signals are processed and generated on an off-board PC, which is connected to the mobile robot through wireless Ethernet/LAN and a radio modem. The robot accepts voice inputs from a human operator.

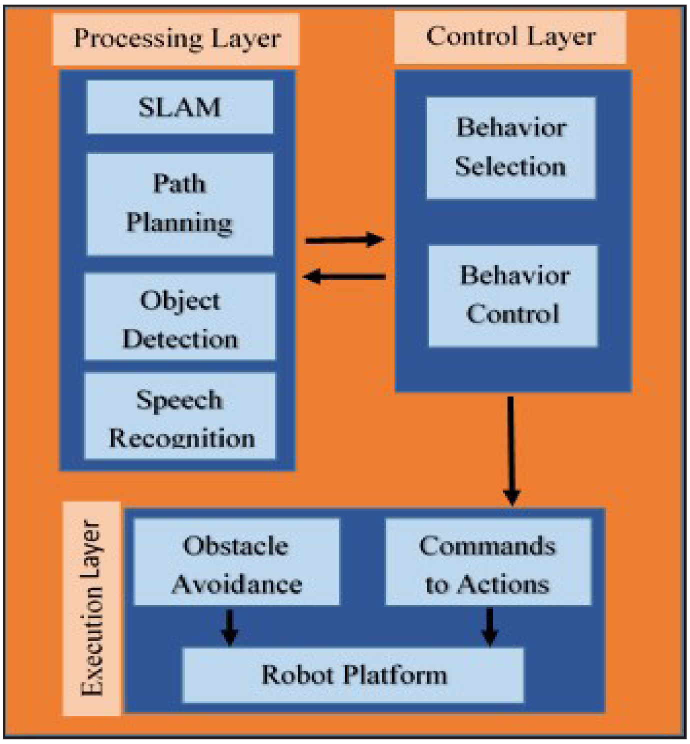

Fig. 4: Layers of Software Architecture

The system currently implements a one-one human-robot ratio, i.e., one operator interacting with one robot. There are two modes of interaction between the operator and the robot: local and remote. In the local mode, the robot and the operator are within visual proximity of each other. The operator wears a headset that consists of one headphone and one microphone and communicates with the robot through speech. The operator's speech engine runs on the offboard computer connected to the robot's computer through the radio modem. The operator can also follow the robot by carrying a laptop with the speech recognition engine installed on it. In the remote mode, neither the operator nor the robot is within visual proximity of the other. The operator wears a head mounted display and relies on the video feed from the robot's camera depending on the working range i.e., the distance at which the robot can send and receive signals to and from the operator. Let us consider an example dialog between the operator and robot-

Operator: What objects can you see?
Robot: Box, dustbin, mine,
Operator: What can you do with mine?
Robot: I can detect it, pick it and dump it.
Operator: Can you see a box?
Robot: No
Operator: Turn left twenty degrees
Robot: Ok
Operator: Can you see a box?
Robot: Yes
Operator: Bring the box
Robot: I see two boxes. Big and small. Which box should I bring?
Operator: Big
Robot: Ok

A key idea is for the robot and the operator to arrive at mutual understanding with respect to a specific activity by sharing a common set of goals. Since the operator knows the robot's goals, he or she can adjust language inputs to suit the robot's level of understanding and since the robot knows the goals likely to be referenced by the operator, the robot's dialogue is based on language recognition instead of language understanding [54]. Speech is processed by a speech recognition engine using several grammars that can be defined statically at design time or dynamically as the application is running [55]. The robot cognizes the world in terms of objects and actions. Both objects and actions are referenced by language and referenced actions become objectives pursued by the robot. The speech input along with grammar goes as input to the speech engine and is broken into symbols or tokens. These tokens are fed to a semantic network which provides unified access to vision and action through language and shapes the robot's interaction with the environment. Each node in the semantic network represents a goal, object or an action and the root node points to the final objective to be achieved.

The complete process of processing speech commands for our system and converting into actions is illustrated below for a command:

Command : Bring the big box
Objective :- (bring-obj)
Token sequence (bring-verb-slot obj-slot).
Grammar:-
Action:- Get, bring, fetch
Object:- Box, mine, dustbin
Features:- big, small

To activate the target objective, an input must first activate its verb slot and then its object slot. The token 'bring', the first token in the operator's command, is activated, which, in turn, activates bring-verb. With the verb slot activated, the token sequence is advanced one token to the right and becomes (obj). The tokens obtained from "the big box" activate (obj) and as soon as box is activated, the object models for big box are brought into the robot's memory. After (obj) is activated, the token sequence becomes empty, thus activating the target. When the objective is activated, an instance of (bring-obj), is created. In addition, the target objective is sent to the execution layer of the system. During execution, object detection module is also enabled. The system captures the image, detects the big box and saves the following into the system memory: (detected-obj box), (dist- 2) (score-.75). This means that the system detected a box 2 meters away from the robot, with a matching score of .75. The execution layer then signals the robot to navigate to the object and pick up the box with the gripper. This type of operator-robot engagement through spoken language also facilitates introspection and instruction based learning where the speech is regarded as misunderstood if the input does not refer to any goal.

IV. Research Challenges

The implementation of the identified framework would require a better understanding of human intelligence and successful human machine learning and collaboration. The differences between human intelligence and artificial intelligence need to be taken into account. AI lacks the ability to apply common sense and knowledge transfer from one area to another [56]. On the other side, humans are inefficient in storing and processing large amounts of information. The robots need to be more proficient in their sensing and communication abilities in order to allow machines to perform larger and more complex roles and serve as mentors for humans or human robot teams. Another important aspect of an effective team is shared understanding of the demands of the context, the capabilities and preferences of the other team members for the benefit of the team. An effective teamwork requires a common ground, integration of motivation toward team versus individual objects and most importantly trust among teammates [57]. This section describes the key challenges for human machine teaming.

Communication is an obvious enabler for effective teaming and not only includes language but nonverbal behaviour like gestures and emotions. Automated speech recognition, comprehension and gestures recognition are active areas of research but focus on unrestricted natural language comprehension such as indirect and non-literal speech is beyond current AI capabilities. Real world experiments for anticipating teammate's intent and predicting behaviour need to be designed for establishing a common ground. It also calls for research on how information can be discovered, exchanged and understood among multiple connected smart technologies and humans. Experimental research has mostly been restricted to laboratory settings and it would be imperative to develop paradigms to understand natural language in real world scenarios in order to cope with uncertainty and complexity of the real world.

There is a considerable potential to be gained in developing shared human machine models to mutually communicate their capabilities, goals, and intentions. This cannot be achieved without a standard language and dynamic feedback mechanism that effectively conveys intent between the team members and improves observability, predictability and trust for a given task. Both humans and machines often have different embodiments and capabilities that may affect the role they play in a team. Understanding the aspects of the human mind is vital for the machine to build a comprehensive model of the human based on context and situation. The impact of a machine teammate on a human also needs to be studied and explored so as to not overload the human and make machines easier to work with. How to construct and dynamically model human and machine's internal state and intentions for effective teaming remains an open question for the research community.

Progress in AI competences suggests that effective collaboration between machine and humans would require machines with capabilities of complex problem solving, planning and learning from past experiences to find a reasonable solution for emerging problems. AR and VR have the ability to add information to the physical world and would influence communication and presentation abilities. Moreover, human intelligence would be augmented with cognitive technologies like natural language processing which would bring about a paradigm shift in the way teams reason, judge, decide and manage associations. Cognitive needs would differ across tasks and teaming scenarios and a clear understanding of the specific capabilities required by a machine to function as an effective teammate in the relevant task and environment is critical. A research agenda needs to be formulated to understand the essential facets and concepts to design machine teammates for collaborative environment. Real time sensing of the environment and teammates is often noisy and incomplete which makes it difficult for machines to perceive human's actions, infer team goals and act on cooperative tasks [58]. Machine teammates need to dynamically learn from the environment through imitation, demonstration and interactive task learning to improve task performance and better anticipate the goals, beliefs and human interactions. Continued research on integrated cognitive architectures (knowledge from cognitive science, AI and cognitive neuroscience) such as ACT-R and Soar for modelling human behaviour and controlling robots have the potential to understand the functional structure of the mind to aid in perceptual processing and develop a common model of cognition throughout different types of tasks [59]. These research gaps need to be addressed to ensure machines sustainably supplement human collaboration and facilitate constructive processes and outcomes for both individuals and organisations.

In the defence scenario, the primary concern of HMT is effective integration of human and machine tasks to optimise the efficiency of critical missions like military surveillance, threat neutralization, and national security. Identification and designing of common metrics that facilitates a well organised HMT is crucial to steer this field forward. This would confirm consistent and repeatable outcomes with high accuracy and demonstrate effective teaming. This could be achieved by establishing, defining and evaluating benchmarks of HMT components i.e human, machine and team for specific application areas based on various subjective, objective and functional metrics [60-61]. Various researchers have proposed a set of common metrics to measure the performance of interaction but with certain limitations [62-63]. Research in this direction would aid in preparation of an HMT metric toolkit to expand the practical applicability horizon of this field and reap the benefits of the enormous efforts that are being invested in human machine teaming.

V. Conclusion

Novel combination of human machine teams would generate a paradigm shift in the character of war and the reality of military operations would become more diverse, complex and highly contextualized. Machines would make it possible to analyse the dynamic warfare in real time and take quick and optimal decisions while reducing risks to soldiers by providing exquisite ISR (Intelligence, surveillance, reconnaissance) that is critical to aerial, ground and space domains. Complex adaptive system and swarm optimisation would enable self-organised swarms to be used in future conflict. Immersive user interfaces like augmented reality paired with A.I. technologies would improve soldier situational awareness dramatically and aid our soldiers to navigate, and guide through difficult tasks that would otherwise be beyond their skill level. These may be employed in UGVs, UAVs, tanks or armoured vehicles to undertake a huge range of simulations to teach awareness, build skills, and provide valuable experience and thereby, transform and enhance a soldier's lethality by making him more aware, accurate and swift in decision making. The paper discusses the importance of team cognition, HRI, shared mental models and presents insights for designing approaches to optimised human-machine teams to establish a better understanding of Defence's future requirements. One of the intended effects of teaming soldiers and machines is to relieve soldiers of the mundane tasks, however, there are potential risks involved in this collaboration. HMT systems may benefit from a design that includes mutual understanding and a trust factor for AI that informs the interaction with humans. Well- designed interfaces between HMT teammates lower the burden of cognitive load and improve team situational awareness dramatically and aid in navigation, visual identification of critical targets and guidance through difficult tasks that would otherwise be unattainable. AR/VR interfaces would allow the possibility to explore and experiment on human subject cognition and rapidly iterate without waiting for the physical delivery of advanced robotic systems by tailoring the experimental environment. There is a need to develop NLP based agent communication languages and interaction protocols that would allow both humans and machines to convey, perceive, and interpret standardized language and symbolism. Standardized language and data models are important not only in planning but also avoid communication and situational awareness errors thereby, providing a seamless human robot interaction that reduces the cognitive load of both agent types that results from coordination. Overcoming these barriers and challenges would accelerate progress and yield breakthroughs in multidisciplinary research applications of human machine teaming.

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