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Using Wearable Sensors to Enhance Communication in the US Army

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14. ABSTRACT
Efficient communication in the military is essential for the success of wars and safety of Soldiers. Many current means of communication present in the military are outdated (e.g., radio), require Soldiers to turn from their line of sight to receive the hand signals, or require sufficient waiting periods to receive the message. The group devised an innovative approach to address this challenge through a nonverbal hand communication system. The device consists of three main components: an inertial measurement unit (IMU) glove for tracking and transmitting hand signals, heads-up display glasses for receiving incoming messages, and a commander's app for sending and receiving signals. The objective was to focus on the proof of concept that IMU gloves can generate and process hand signals for transmission. Using Rokoko smart gloves, we successfully tracked static hand signals from numbers zero to nine. The files were exported, converted, and then inputted in MATLAB for data analysis. Each hand signal comprised 88 unique quaternion points spanned across the hand and onto the arm, recorded at 30 fps. Five individuals (three female, two male) participated in recording the hand signals from zero to nine. Quaternion data for each number and individual were initialized and inputted into a machine-learning algorithm. The algorithm successfully identified numbers based on finger angle orientations and displayed the designated signal. The machine model achieved 99.9% classification accuracy with one false positive and negative. These findings demonstrate the success of the proof of concept and hold promise for a nonverbal communication device.

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1. Introduction

1.1 Problem Statement

The goal of this project was to identify a critical issue within military command and control operations and devise an innovative solution that leverages physiological monitoring to enhance operational effectiveness, efficiency, or safety.

1.2 Approach

An initial literature search was conducted to understand the various military practices, available technology, and common challenges faced in the military. In addition, the project team engaged in conducting numerous personal interviews with individuals who had direct experience with command and control and physiological monitoring. These interviews included past and present Soldiers, commanders, and military researchers who were asked to share their experiences and provide insights on how a novel sensor could address common problems. Their perspectives provided valuable insight into the challenges encountered in the military.

1.3 Background

Our team compiled literature and interviews to identify the most relevant problems. One of the significant problems noted in the military is the outdated and inefficient communication methods currently in use. Military communication follows a PACE system, where each phrase becomes progressively more urgent to grab attention in case of danger. PACE is an acronym for primary, alternate, contingency, and emergency, representing the assigned order of communication methods.[1] The primary method is the standard and most efficient form of communication between Soldiers and commanders, but it relies on outdated technology such as radio and walkie-talkies. This puts Soldiers at increased risk, especially in stealth environments such as clearing houses, where feedback from commanders and other Soldiers is not readily accessible through verbal forms of communication.

An alternate form of communication between nearby Soldiers is often conducted via hand signals. Soldier uses specific hand signals that are relayed up the battle formation to convey the current situation and the next course of action. This nonverbal communication process presents issues, as battle formation can span over a quarter of a mile, requiring substantial time to ensure every Soldier receives the messages, making it impractical in fast-paced situations.

Soldiers also employ this method when dispersed throughout the woods with an assigned point man serving as focal point for message distribution. However, this approach requires Soldiers to physically turn to receive signals, diverting their attention from potential threats. This action compromises their position and ultimately increases risk for both Soldiers and squad, reducing situational awareness and hindering overall operational effectiveness.

Military tracking refers to the process of monitoring and assessing movement, activities, and status of military personnel, vehicles, or targets. Currently, military tracking is often conducted using physical objects and maps, where status is represented by color such as red, amber, or green to indicate various conditions or readiness levels. However, this approach is time-consuming and hinders real-time tracking capabilities.

Ultimately there was a common consensus that a new communication system is essential. This system must streamline communication, reducing both time and effort required to transmit messages between Soldiers and commanders. It should enhance Soldiers' effectiveness by either providing additional information or accomplishing tasks more efficiently. For example, updating the military tracking to real-time data provides commanders with the ability to make quicker informed decisions, thereby optimizing performance of their Soldiers.

1.4 Technology

In addition to uncovering problems within the military, our team sought out available technologies available to address these issues. Augmented reality with integration of gaze detection has potential to develop impactful novel capabilities. Gaze detection involves tracking eye movements to uncover valuable information, including visual surroundings, human behavior, and cognition (e.g., fatigue).[2] Augmented reality integrates real-world and virtual objects to enhance perception and interactions with the surroundings through technology.[3] Military technology can be significantly advanced by combining these two systems allowing for numerous possibilities. One advancement could involve the identification of hot and blind spots. Hot spots would be locations where Soldiers consistently focus their gaze, helping to identify unusual areas that may require further examination. Blind spots would represent areas Soldiers have not yet analyzed, potentially indicating areas of threat that could go unnoticed.

Eventually, the goal would be for commanders to receive transmitted augmented reality data that integrates the real and virtual worlds. This capability would enable remote observation from far distances, aiding in the identification of specific objects and determination of the safest routes for operation.

1.5 Invention

Our team integrated all the knowledge together to develop a nonverbal/non-line-of-sight hand communication device. This innovative sensor focuses on communication between Soldiers and commanders in battle formation, stealth environments, and areas where direct line of sight is not always feasible. The device will consist of two components: a Soldier interface and a commander interface.

The design for our proposed nonverbal gesture-based communication tool consists of three main components: gesture recognition technology, the Soldier interface, and the commander interface. Gesture recognition is the fundamental backbone, enabling the system to interpret and understand hand signals made by users. Previous research explored the use of gesture recognition systems in different settings including robotics, American sign language, and many other uses, but identified several challenges.[4,5] These included variation in brightness affecting accuracy, difficulties with changes in rotation, and issues caused by shadows and illumination.[6,7] The goal for the device is to allow gesture recognition in all lightening conditions and to support dynamic, nonstatic hand gestures for military use. The Soldier interface should ideally be intuitive and easy to use, serving as the conduit through which vital signals are transmitted silently and without line of sight. The commander interface provides a comprehensive overview of the hand signals being relayed by multiple Soldiers. This capability would help commanders make informed decisions based on real-time information and mitigate the limitations of current communication tactics. The central focus of this project was using gesture data to achieve hand signal recognition, with the overarching objective of integrating this component into the Soldier and commander interfaces envisioned for future development.

2. Methods

Rokoko Smart Gloves[8] were used to acquire hand position and orientation, modeling the envisioned future technology of sensors embedded in military-grade gloves. The glove design and movability are depicted in Fig. 1. As users move their hands, the gloves transmit data to the software, which models the gestures in real time rotating about the elbow joint. The gloves integrate inertial measurement unit (IMU) sensors alongside electromagnetic field (EMF) sensors for comprehensive motion tracking.[8] These sensors include accelerometers, gyroscopes, and magnetometers. The EMF sensors use small coils positioned on the gloves to create a local magnetic field, enhancing tracking accuracy through sophisticated algorithms.[8] This combination of IMU and EMF sensors ensures high-quality hardware tracking and provides precise finger positioning data.

Fig. 1 Standard design of Rokoko smart gloves worn by users to collect gesture data[8]

Rokoko Studio[9] was used for motion capture visualization and hand signal recording. The studio software connects to Rokoko Smart Gloves via Wi-Fi and syncs movement with a virtual character that remains still from the elbow up.[2] The Rokoko Studio[9] streamlines the recording and storage of hand signal motion files to export data for analysis. An example of this is shown in Fig. 2.

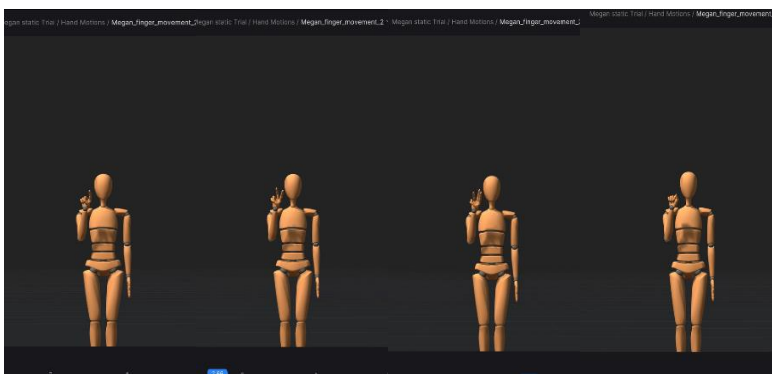

Fig. 2 Rokoko studio application for various hand signals. Full video is available on team's GitHub.[10]

Recordings are exported as a Biovision Hierarchy (BVH) 3D object files and then converted to Javascript Object Notation (JSON) format using the third-party app Filestar.[11] The conversion process ensures that the gesture data is compatible with integration into MATLAB for further processing and analysis. The JSON file version of the recordings describes the hierarchical structure of a skeletal model and contains meaningful data pertaining to the hands and fingers. The hierarchy starts at the "Spine" bone and descends to the fingers. Each node in the hierarchy represents a segment of the body, with transformations specifying their position and orientation relative to their parent node. For instance, the hierarchy includes nodes such as "RightShoulder," "RightArm "RightForeArm," and "RightHand," representing the segments of the right arm leading up to the hand. Further down, there are nodes for individual fingers, such as "RightFinger1Metacarpal," “RightFinger1Proximal,” and “Right Finger1Distal,” detailing the segments of the thumb (Finger 1). This hierarchical structure offers a thorough depiction of the hand and finger anatomy, further detailed in Fig. 3. The transformation within each node specifies translations and rotations, determining the position and orientation of each segment in reference to the previous segment.

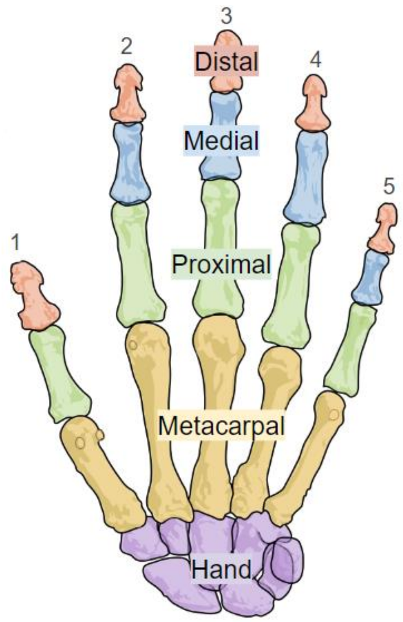

Fig. 3 Labeling of hand and finger segments. Finger numbering starts at the thumb and progresses toward the pinky.[12]

The gesture data contains a total of 22 segments pertaining to the arm, forearm, hand, and fingers with corresponding quaternion data. Each segment is listed below for the right hand in Table 1. A quaternion is a four-dimensional unit vector in the form [ω, x, y, z]. These values are derived from the transformation between nodes at each time point, recorded at 30 fps. Quaternions were initially converted to Euler angles for the medial finger joints, providing a starting point for visualization and analysis. However, to maintain precision and accuracy in subsequent recognition techniques, raw quaternion data was used throughout.

Table 1 List of all data segments used to describe hand gestures

1	Right Arm
2	Right Forearm
3	Right Hand
4	Right Finger 1 Metacarpal
5	Right Finger 1 Proximal
6	Right Finger 1 Distal
7	Right Finger 5 Metacarpal
8	Right Finger 5 Proximal
9	Right Finger 5 Medial
10	Right Finger 5 Distal
11	Right Finger 4 Metacarpal
12	Right Finger 4 Proximal
13	Right Finger 4 Medial
14	Right Finger 4 Distal
15	Right Finger 3 Metacarpal
16	Right Finger 3 Proximal
17	Right Finger 3 Medial
18	Right Finger 3 Distal
19	Right Finger 2 Metacarpal
20	Right Finger 2 Proximal
21	Right Finger 2 Medial
22	Right Finger 2 Distal

A total of 10 pilot recordings were collected from individuals, each approximately 2 s in duration. The protocol consisted of holding a static number hand signal ranging from zero to nine according to the graphic in Fig. 4 from the US Army training circular for visual signals.[13]

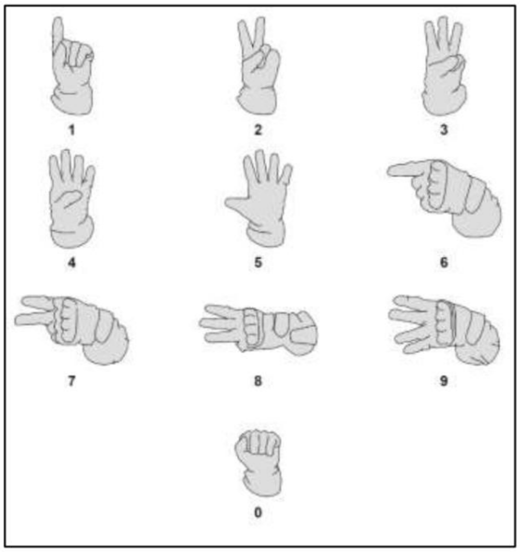

Fig. 4 Guide to numerical hand signals zero to nine. Reprinted from Headquarters, Department of the Army.[13]

The smart gloves captured the gesture data corresponding to each number, providing a comprehensive dataset of diverse hand measurements for classification training. This dataset was analyzed using the MATLAB Classification Learner app, a tool designed to train models for classifying data using supervised machine-learning techniques.[14] Quaternion values acted as predictors with the hand signal number serving as the response variable. After processing through a fine decision tree, the resulting trained model was exported for further use.

This trained model achieved accurate prediction of numerical hand signals with a prediction output for each time point of a recording. A specialized function was used to distinguish between held signals and noise resulting from transitions between hand positions. This function identifies blocks of repetitive data, enabling the differentiation of genuine signals and temporary fluctuations. It also provides the ability to decipher sequences of digits communicated through hand signals like "one-zero-one" and multiple-digit numbers like "twenty-seven." This capability enables the interpretation of complex numerical sequences conveyed through single-digit hand signals.

Once the system could handle static hand signals and sequences, the capability to decipher certain dynamic hand signals was pursued. A new library of moving hand signals was collected from individuals' hand movements. These signals included the hand and arm motions commonly used by the US Army[8] to communicate the commands "rally point," "move up," and "column formation" as depicted in Fig. 5.

Fig. 5 Guide to certain hand signals that require motion according to the US Army. Reprinted from Coleman's Military Surplus.[15]

An update to the data processing file included calculation of angular velocity from quaternion data at each time point. The magnitude of each angular velocity vector was calculated and included in the labeled training data with corresponding quaternion data. This training data matrix for dynamic signals was labeled with numeric responses for compatibility with machine learning, where the number "10" indicates "rally point," "11" indicates "move up," and "12" indicates "column formation." A new model was trained separately from the classifier for static hand signals zero to nine. This capability enables the interpretation of dynamic hand signals that rely on motion to convey a message, demonstrating the potential for integrating additional signaling techniques.

The trained classification models were ultimately used to test and validate the effectiveness of the system, demonstrating the feasibility of the concept. An assortment of test data was collected by recording separate trials of static number signals and sequences as well as dynamic hand signals that were not included in the training data. These recordings were exported from Rokoko Studio[9] as BVH 3D object files and converted to JSON files. All data processing capabilities were compiled into one MATLAB script file for ease. All available script files appear in the team's GitHub.[10] The program prompts selection of a JSON file where the user can choose the test data recording. This file is then loaded and decoded in MATLAB. The quaternion data for the right hand, arm, and fingers are extracted and used to compute angular velocity magnitudes. To determine the correct trained model (static zero to nine or dynamic), the average of angular velocity magnitudes across all time points is compared against distinct threshold values. If the average angular velocity is low, this indicates minimal hand movement, so the file is processed through the static trained model to determine number predictions at each time point. The output is then blocked by repetition to recognize a singular number or a sequence of numbers. If the average angular velocity is high, then the data is processed through the dynamic trained model, which outputs the assigned numerical label of the moving hand signals. This value is then converted back to the command that it represents.

3. Results

For the classification of static hand gestures representing numbers zero to nine, the model achieved an impressive accuracy rate of 99.9%. This was validated using a confusion matrix (Fig. 6), which shows the model's ability to correctly identify each numeral with minimal errors. The model was trained with 5-fold cross-validation using a fine decision tree algorithm. The training set included 2382 observations, 88 predictors, and 10 response classes. The near-perfect accuracy indicates the model's robustness in distinguishing between different numerical gestures. The classification model for dynamic gestures, which includes commands such as "rally point," "move up," and "column formation," achieved an accuracy rate of 100%. This was validated through another confusion matrix (Fig. 7), showing perfect classification with no misclassifications. The model was trained with 5-fold cross-validation using a fine decision tree algorithm, with a training set comprising 237 observations, 110 predictors, and three response classes. The perfect accuracy highlights the effectiveness of the model in recognizing dynamic hand signals used in military operations.

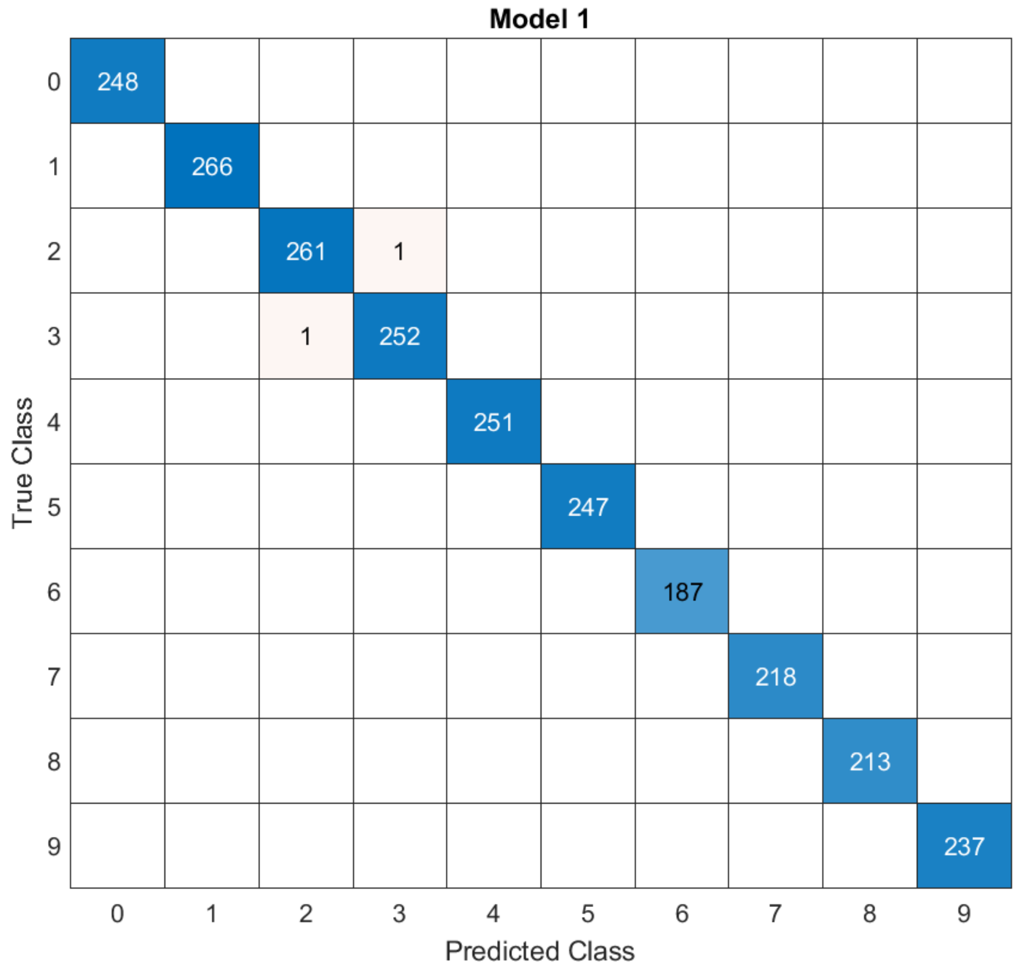

Fig. 6 Confusion matrix for zero to nine classifier

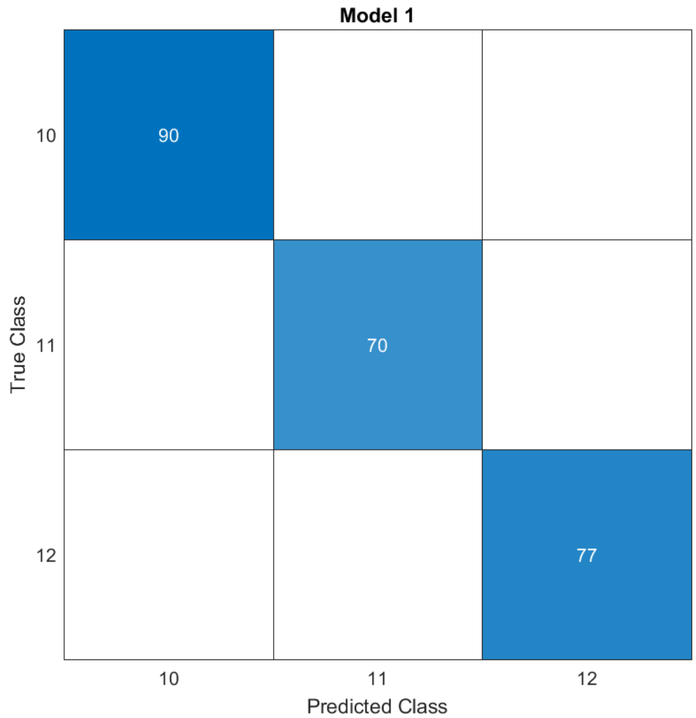

Fig. 7 Confusion matrix for dynamic signal classifier

In addition to individual gesture recognition, our system demonstrated the ability to recognize and correctly interpret sequences of numerical inputs for which it was not explicitly trained. For instance, during a trial where the individuals performed the gestures seven, zero, two, and one in sequence, the trained model accurately recognized and outputted the sequence as 7 0 2 1. This capability is critical for real-world applications where Soldiers might need to convey complex information using a series of gestures. The system's ability to accurately process sequential inputs demonstrates its potential for use in various communication scenarios, such as relaying counts, coordinates, or coded messages.

To visualize and validate the functionality of our gesture recognition system, we developed a MATLAB app that processes and displays the recognized hand signals. The app provides a user-friendly interface where users can load hand signals, which then are processed using our machine-learning algorithms. This app, while basic in its presentation, offers viewers a more intuitive understanding of our system's functionality compared to raw code. It acts as a bridge between the technical intricacies of our algorithms and the practical application of gesture recognition in a military context. This sample design serves as a fundamental proof of concept, highlighting the robustness of our gesture recognition algorithm and the efficacy of postprocessing techniques in deciphering and responding to predefined gestures. While this app serves as a demonstration tool for this presentation, it will not be a part of the final prototype, as the heads-up display will be the designated interface to display the signals in real time.

Upon initiating the app, users are prompted to load a hand signal, which is then processed using our MATLAB-based coding process. The output, associated with the recognized hand signal, is then displayed for the user, showcasing the system's ability to interpret gestures and generate appropriate responses (Fig. 8).

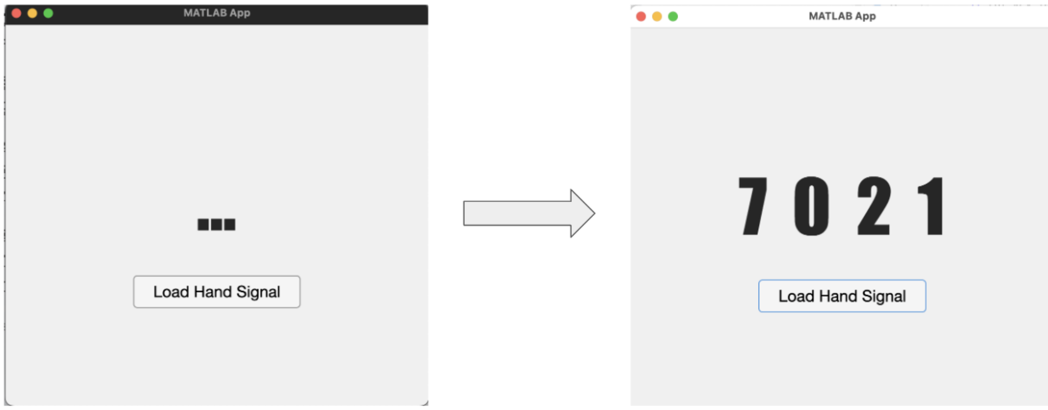

Fig. 8 Loading of hand signal on MATLAB app and associated signal response

4. Discussion

Transitioning from this preliminary stage to our final prototype, we envision a comprehensive system comprising three key components: wearable smart gloves, a heads-up display (HUD) visor interfacing with the Soldier, and a commander interface app. A final prototype will evolve to incorporate live streaming capabilities, enabling real-time processing of hand signals regardless of environmental conditions. This advancement will empower Soldiers with instantaneous communication, facilitating swift decision-making and response coordination on the battlefield.

The smart gloves, equipped with sensors to track hand, wrist, and finger movements, will serve as the primary input device for Soldiers and the cornerstone of our communication system. Their design ensures comfort and reliability, allowing Soldiers to communicate effortlessly in dynamic battlefield environments. These gloves will seamlessly capture and transmit gestures to the HUD visor as well as the commander interface app, where communication signals will be displayed for the wearer or user, respectively.

The HUD visor, designed to overlay visual information onto the Soldier's field of view, will provide intuitive and unobtrusive communication, enhancing situational awareness without distracting from the mission at hand. Displayed communication signals will provide Soldiers with vital insights into enhanced situational awareness such as troop movements, enemy encounters, and strategic directives, which will empower them to make informed decisions in real time.

Simultaneously, the commander interface app will enable commanding officers to receive and transmit communication signals to Soldiers within their brigade. This app, accessible from offsite locations, will leverage advanced networking capabilities to relay commands and gather real-time updates from the field. Commanders can issue directives, gather intelligence, and assess the battlefield's evolving dynamics with unprecedented efficiency, facilitating rapid response coordination and mission execution. By bridging the gap between command and frontline units, our system ensures streamlined communication and enhanced operational effectiveness.

In a military context, these components would revolutionize communication and coordination on the battlefield. Sections 5 and 6 present two compelling examples of real-world scenarios where our communication system addresses critical military needs, validated through our collaboration with the US Army.

5. Scenario 1: Commander's Situational Awareness

In a dynamic battlefield environment, situational awareness is crucial for effective decision-making and mission success. The nonverbal gesture-based communication system (NGCS) provides a practical solution to enhance a commander's understanding of the operational landscape. This system enables commanders, who often oversee multiple squads simultaneously, to gather real-time information about enemy encounters from a remote location. Through this system, a commander can initiate a query to a squad leader requesting details on the number and location of enemy forces encountered by the unit. The squad leader, equipped with our system's smart gloves, responds promptly with the appropriate hand signals to represent the encountered threat levels. These signals are processed in real time and transmitted back to the commander (Fig. 9).

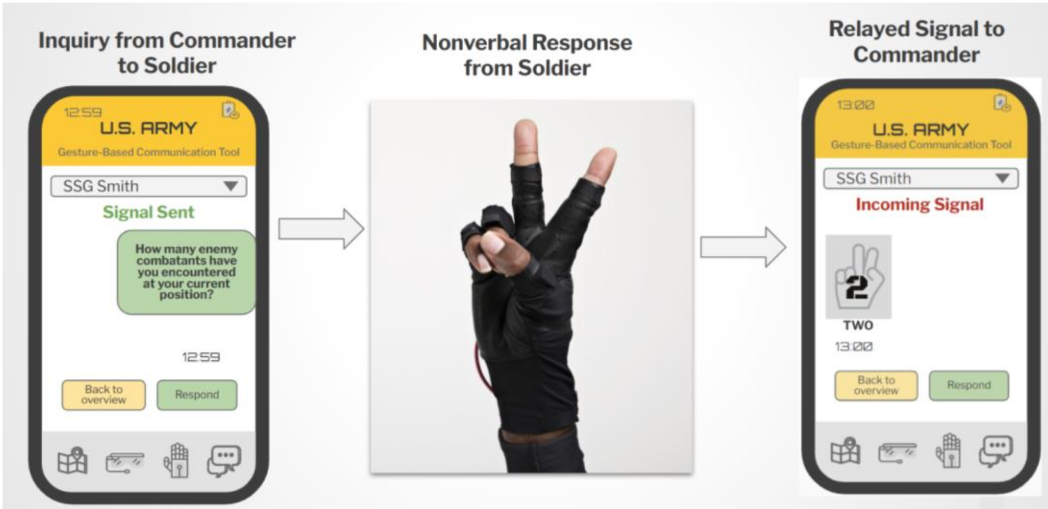

Fig. 9 Input and relay side of scenario 1: commander's situational awareness

This allows the commander to instantaneously gain a comprehensive understanding of the tactical situation, enabling more informed decision-making regarding troop movements, reinforcements, or strategic maneuvers (Fig. 10).

Fig. 10 Response/commander decision side of scenario 1: commander's situational awareness

6. Scenario 2: Stealth Mission Coordination

In covert operations, maintaining stealth and coordination are crucial for mission success and safety. NGCS offers a discreet and efficient communication method that supports seamless coordination among team members while maintaining operational security. For instance, during nighttime stealth missions, a squad led by a point man might encounter an enemy patrol or threat. In such a scenario, swift and silent communication is essential to avoid detection and maintain the element of surprise. With our system, the point man, equipped with IMU gloves, initiates a silent signal to halt the squad's advance upon sighting the enemy. This signal is detected by the HUD visors worn by each team member, instantly halting their movements without the need for verbal commands or a direct line of sight to the individual giving the commands (Fig. 11).

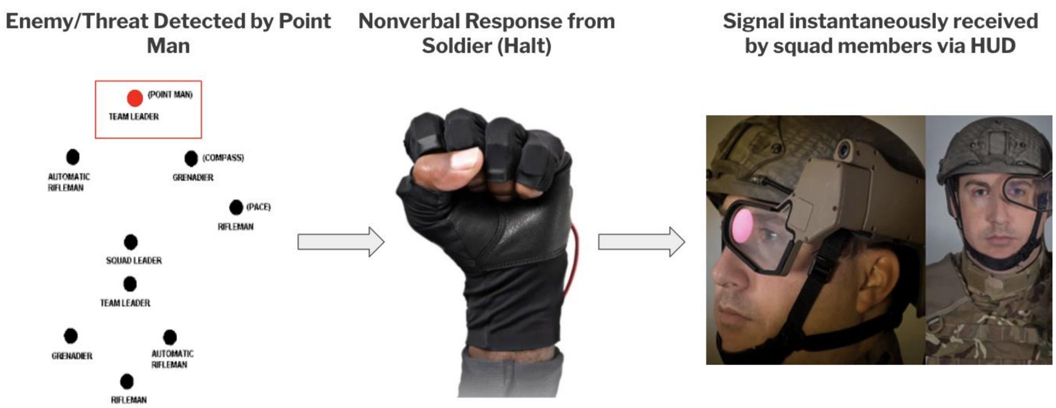

Fig. 11 Outline of scenario 2: stealth mission coordination

The squad maintains position, ready to react to any developments without alerting the enemy to their presence. The communication system enables precise and stealthy navigation through hazardous terrains, demonstrating its potential to enhance operational effectiveness and survivability in covert missions.

To ensure its reliability and effectiveness in real-world scenarios, further refinement and testing of our prototype will be essential to ensure its reliability and effectiveness in real-world military scenarios. Continued collaboration with military stakeholders and technology experts will be crucial to identifying opportunities for future enhancements and applications of our sensor-based communication system.

7. Conclusion

Overall, our work represents a significant step toward advancing military communication capabilities and enhancing the effectiveness of modern warfare strategies. The development of our nonverbal gesture-based communication system has demonstrated the potential for innovative sensor-based solutions to address the limitations of current military communication methods. The preliminary results, including high classification accuracy and the successful recognition of sequential numerical inputs, underscore the feasibility and reliability of our approach.

The MATLAB app prototype provides an intuitive and effective means of visualizing the system’s performance, serving as a critical proof of concept that bridges the gap between technical development and practical application. As technology continues to evolve, the potential for sensor-based solutions to revolutionize military communication will continue to grow. These advancements promise to enhance situational awareness, streamline decision-making processes, and improve coordination on the battlefield.

The integration of cutting-edge sensor technologies and machine-learning algorithms has the potential to transform how Soldiers and commanders interact, ultimately enhancing the effectiveness of military operations. Future developments and refinements will further solidify the role of sensor-based communication solutions in modern warfare strategies, significantly enhancing military capabilities.

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List of Symbols, Abbreviations, and Acronyms

3D	three-dimensional
BVH	Biovision Hierarchy
EMF	electromagnetic field
HUD	heads-up display
IMU	inertial measurement unit
JSON	Javascript Object Notation
NGCS	nonverbal gesture-based communication system
PACE	primary, alternate, contingency, and emergency

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