Space Sign Language for Spacewalks: Sign Profiling and Edge Computing Approach

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***Abstract*—Long journeys for space exploration demand innovative solutions to address hazards where conventional communication systems may fail due to electromagnetic (EM) disruptions or environmental extremes. Effective search and rescue strategies are vital for spacewalks and unforeseen EM instability. We propose a research direction involving ad-hoc, direct communication protocols to enhance survivability under harsh space conditions. It provides a pathway for real-time communication that is perceptible to humans, computationally efficient, and resilient to EM interference. Furthermore, it can take advantage of upcoming advancements in wearable sensors and non-terrestrial edge computing. Our proposed methods include sign profiling via analysis of visual cues from sign language for the deaf. Profiles can be achieved by detecting critical pose landmarks through a body area network of wearable sensors. We also recommend an embedded artificial intelligence approach using edge computing to achieve real-time performance with small size, weight, power and cost. Our work may lead to new developments in spacesuit design and new search and rescue practices. We also propose related research problems concerning variations in sign languages across communities to foster seamless spoken and unspoken exchanges.**

***Index Terms*—BAN, Wireless, Space communication, Extreme, Edge computing, Embedded artificial intelligence, Sign Language, Machine Learning**

I. Introduction

As outlined by NASA [1], future long-duration space missions encounter five primary risks: space radiation, isolation and confinement, distance from Earth, gravity (and the lack of it), and closed or hostile environments. Under these extreme conditions, existing communications methods depend on portable transceivers capable of transmitting and receiving signals. These are either integrated into spacesuits or harbored in their space-based modules. Such devices typically operate in the ultra-high frequency spectrum. However, challenges such as signal interference, latency fluctuations, and ambient noise persist, exacerbated by cosmic radiation and solar activity, which can impair radio communications. Space environments may also have higher background noise levels, affecting signal clarity and quality. During spacewalks, electromagnetic (EM) disruptions may cause communications outages, necessitating alternative methods for interaction especially for critical search and rescue operations. Historically, pre-electromagnetic communication relied on mechanical, auditory, visual, or tactile techniques. Nevertheless, adapting these to space emergencies reveals significant constraints. Acoustic methods depend on sound-conductive media such as liquids or thick gases, rendering them ineffective in the Moon's vacuum, where sound cannot travel through the atmosphere-less environment. Utilizing vibrations through lunar soil is similarly unreliable due to inconsistent density and structure. Visual cues offer the potential for close-range signalling and are commonly used terrestrially. Augmenting these with mechanical or kinetic enhancements could broaden their reach. Nonetheless, traditional optical and mechanical signals demand unobstructed visibility and stable illumination, making them vulnerable to lunar dust, shadows, and other environmental variables. Emerging advances in sensor and material science can be used to create physical markers that emit laser or thermal signatures, paired with detectors spanning visible and non-visible spectra—open new avenues for refining visual cue-based systems, prompting deeper investigation into their application for space communication. Furthermore, in non-terrestrial networks, we observed the emergence of edge computing methods i.e., processing data near the source and before further processing at the computing center of the computing networks. Similarly, there have been significant recent advances in embedded artificial intelligence (EAI) [2], machine learning accelerators (MLA) [3]. EAI refers to integrating intelligence directly into hardware devices [2], whereas MLA are systems specialized for the high speed execution of machine learning tasks. Both approaches need to minimize the transmission period and power consumption for spacewalk tasks. In extreme conditions where non-verbal communication is a necessity, analyzing and transcribing Space Sign Language (SSL) [4] requires the latency to be similar to current terrestrial standards. According to the International Telecommunication Union (ITU) [5], this has a maximum value of 150 ms before quality becomes compromised.

Body area network (BAN) architectures are a promising approach to achieve communications in space and extreme environments [4]. This work will benefit from improvements in sensor fusion techniques and can open new research directions for human interaction during spacewalks and other electromagnetic (EM) outage situations.

In this work, we propose that combining EAI methods and

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BAN architectures form appropriate steps in utilizing manual modalities and visual cues in SSL. This work extends our preliminary work [4] that proposed a framework for developing a Non-Verbal Communication (NVC) system, suitable for space environments. The main objectives of this work include:

- Elaborating a systematic analysis of sign language poses for communication during spacewalks and EM outages.
- Analyzing results for identifying critical landmarks in sign language poses and compiling an initial dictionary of signs.
- A thorough review of Body Area Network architecture and communication protocols for future development.

These contributions aim to define a framework for enhancing communication reliability and adaptability in extreme space conditions.

II. Related Works

Space-borne edge computing enables intelligent, personalized, and distributed on-demand services, offering a distributed computer experience with virtually zero latency. Traditional computing systems, such as Central Processing Units (CPUs), are designed for general-purpose tasks, handling sequential instructions efficiently. However, current AI computations, such as deep learning (neural networks) often utilize advanced parallel processing capabilities, coupled with a specialization in vector/matrix processing [6]–[8]. There are a few example configurations and designations such as Google's 'Tensor Processing Unit (TPU)' [9], Apple's 'Neural Engine' [10], or 'Neural Processing Unit (NPU)' [11], [12]. Furthermore, non-terrestrial networks could provide extensive coverage and support numerous *Internet-of-Things* devices, making them suitable for various applications [13].

Advanced substances for upcoming spacesuits have been engineered to satisfy needs like non-flammability, heat insulation, and wear resistance. Developments in fire service and military uses have presented encouraging materials such as aerogels for thermal protection and intelligent fabrics embedding sensors for health tracking and energy collection [14]. The Extravehicular Mobility Unit (EMU) is the outfit worn during spacewalks, crafted for prolonged reuse with advanced versions created for future missions [14].

Investigations into nonverbal communication (NVC) reveal that people can detect various traits from nonverbal signals [15]. Creating and interpreting NVC are shaped by elements like personal characteristics, emotional conditions, and social abilities [15]. The study highlighted the importance of NVC across multiple fields.

Sign languages and physical gestures allow swift and effective transmission of basic directives without spoken interaction. Hand-based elements express meaning via motions, while non-manual markers (NMS), such as facial looks and head actions, offer added context, emotional depth, or stress [16]. Progress in computer vision has supported conversion between sign languages and spoken terms, vital for addressing exhaustion and tension during long space assignments [17], [18]. Standardized signs lessen mental effort, providing a less demanding communication option for astronauts in distress. Continuing our existing work to analyze sign languages using a body area network approach [4], we can further apply our method of network analysis [19] to keypoints of a pose to propose a new way for sign profiling.

III. Proposed Method

A. Multi-stage Framework and Relevant Research Areas

Figure 1 shows a phased approach to yield a fully functional NVC practice for spacewalk in extreme conditions to accommodate current advances in computing and sensing technologies. The initial phase focuses on designing an encoding instrument and user interface, integrating computer vision and linguistic analysis to establish design specifications and identify critical landmarks for routine operations and emergency contexts. Next phases will expand the system's lexical scope.

In later stages, we will define fundamental parameters for a Body Area Network (BAN) of sensors and actuators. These unconventional nodes will be engineered to facilitate efficient communication between astronauts in the space environment. Consequently, new BAN-to-BAN communication protocols will be developed and studied. The criteria for those stages are finding designs that are efficiently, robust and could support a real-time and reliable communication. The final stage would be focus on manufacturing and human training strategies to adopt SSL in applications.

1) Machine Learning for Sign Feature Extractions: To extract basic sign features, we can analyze visual data using pose extraction methods [20] [21]. A set of 136 keypoints is calculated and filtered using anthropometric constraints from NASA-STD-3001 [22], informing the standardization of a Space Sign Language- SSL [4]. Drawing parallels with International Sign Language (ISL), SSL employs contextual and visual elements, adapting signs from established languages such as Auslan, ASL, BSL, and LSF [16] for spacesuit compatibility through exaggerated gestures and sensor augmentation. Coordinates of a popular set of 136 *keypoints* are calculated with confidence probabilities. Outliers can be removed by applying the anthropometric survey range from the recent NASA-STD-3001 standard [22].

To build sign profiles, we can extract more advanced features using our feature engineering methods such as described in our prior research [23]. For example, for gait detection via wearable sensors, we aim to continuously monitor time-series data from sensors and detect 'anomalies' [24]. We also can apply our network analysis to time series data presented in the previous work [19] to compare the contribution role of different nodes in a network of sensors.

We calculate information to find the network of interaction. Each data channel is considered as a node of a network. The relationship between two nodes is represented as a *link* between two nodes and the *weight* of the link is the strength of the relationship. The weight was computed by pairwise spectral coherence C_{xy} between the two data windows of nodes x and y. C_{xy} is calculated by the Fourier transform (the Welch method [25] Eq. 1) between two EEG channels

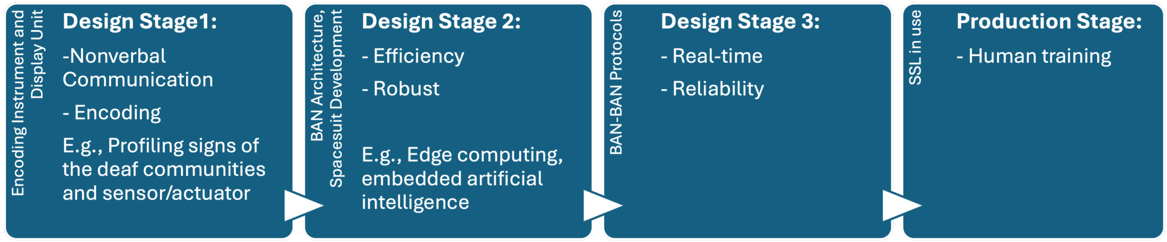
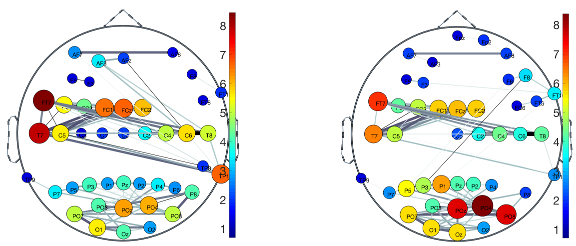


Fig. 1. Multi-stage framework for developing a BAN system for NonVerbal Communication (NVC).



(a) $p = 5\%$, open eyes (b) $p = 5\%$, close eyes

Fig. 2. Example of network analysis in our previous work [19] for 64 sensors at a head. Parameter p for preserved links with largest weights. The network behaviors are compared between different action of a signer such as open and close eyes when $p = 5\%$. Color and size of each node are up to the number of connections. Links are weighted in the grayscale.

across time windows (size of $2.5s$ sliding each second) in the frequency range of 30–90 Hz (so-called *gamma* band).

$$C_{xy}(\omega) = \frac{P_{xy}(\omega)}{\sqrt{P_{xx}(\omega).P_{yy}(\omega)}} \tag{1}$$

where ω is frequency, $P_{xx}(\omega)$ is the power spectrum of signal x, $P_{yy}(\omega)$ is the power spectrum of signal y, and $P_{xy}(\omega)$ is the cross-power spectrum for signals x and y. When $P_{xx}(\omega) = 0$ or $P_{yy}(\omega) = 0$, then also $P_{xy}(\omega) = 0$ and we assume that $C_{xy}(\omega)$ is zero. The power and cross spectra are estimated by the Fourier transform. In the continuous domain, let $\mathfrak{F}_x(\omega)$ and $\overline{\mathfrak{F}_x(\omega)}$, denote the Fourier transform and its conjugate of signal x, respectively, i.e. $\mathfrak{F}_x(\omega) = \int_{-\infty}^{+\infty} x(t).e^{-j\omega t}dt$.

After that, the network interactions are represented by a three-dimension matrix of which one dimension is for time windows and the others are for a connectivity matrix, C. Leading interactions can be found by applying a threshold p $(0 < p < 1)$. Links with small weights represent weak relationships can be ignored. For example we can set all weak links including self-node connections were assigned with weight of 0.

Due to the scope of this work, we will present further this method in upcoming reports. We illustrate in Fig.2 one example from our previous work [19]. We analyzed a small network of 64 sensors surrounding a head. We used the proportion parameter p for preserved links with largest weights. The network behaviors are compared between different action of a signer such as open and close eyes when $p = 5\%$. Insights from such analysis can be transferred to the next task of linguistics and standardizing signs for spacewalks.

2) Linguistics Aspects: The concept of SSL is similar to International Sign Language (ISL), a practical communication tool for deaf communities in international contexts, such as the World Federation of the Deaf Congress or educational settings. ISL, though not fully standardized, depends on context and visual cues, while national sign languages like American Sign Language (ASL), British Sign Language (BSL), French Sign Language (LSF), and Australian Sign Language (Auslan) [16]—each with distinct grammar and vocabulary—prevail in daily use. As deaf individuals enter diverse professions, new signs emerge within prominent signing communities, akin to spoken language evolution, with widely adopted signs likely meeting IPA standards. For our initial experiments, we utilized Auslan to pinpoint key landmarks and signing profiles, with plans to explore BSL, ASL, and LSF in subsequent phases.

Designing SSL signs involves constraints tailored to bulky spacesuits. Proposed signs simplify deaf community originals, using fewer, distinct gestures for ease of execution in suits, with exaggerated movements to boost visibility. Tools, like thermal imaging and actuators, address challenges from distance, dust, or darkness. Standardizing nonverbal elements may introduce novel signs, necessitating psychological studies to assess interpersonal accuracy via trials akin to [15].

B. Sign Profiling

1) Data Sources: We demonstrate the process of developing core SSL signs by collating isolated signs from video recordings of our local sign language. These recordings have been cleaned and well-annotated by Auslan expert users in the published dataset named Auslan Daily [17]. The dataset includes two themes of daily vocabulary: conversations and news from sources such as Sally and Possum, and ABC News with Auslan.

We establish a set of glosses that cover the most common and crucial concepts needed in space. First, we identify primary areas of communication, including safety protocols, equipment operation, emergency procedures, and social interactions. We based our vocabulary list on 100 common tasks and scenarios for emergencies provided by the Deaf Connect organization in Australia.

2) Analysis of Languages: Analysis of Auslan sources reveals that, in conversations, approximately 600 of 2,500 words appear over 10 times, while in news contexts, about 2,000 words exceed 10,000 occurrences, reflecting gloss reuse and contextual reliance for simplification.

This article has been accepted for publication in IEEE Journal of Radio Frequency Identification. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JRFID.2025.3645790

For each Auslan video, we examined signer poses and gestures per frame, employing deep learning neural networks for computer vision to extract 136 keypoints with confidence probability scores. We utilized the top-down approach [21] and reserving bottom-up [20]. Due to manuscript limitations, we only report on the top-down approach here and will present comparisons in another work. Preprocessing involved feature engineering steps. Assigning positive x and y coordinates for spatial positioning relative to the origin. Outliers were filtered using NASA-STD-3001/3000 anthropometric ranges [22], with findings applicable to SSL linguistics and standardization.

Exhaustive subset searches for landmark selection are computationally infeasible; thus, we applied a hard threshold (e.g., ¿0.5) to probability scores or used advanced search algorithms [23]. Here, we introduce a filtering method based on intrinsic data measures, ranking landmark importance via mutual information [23], independent of classifier performance.

For SSL design, we adopted an asymmetric keypoint representation: facial features, capturing non-manual emotional expressions, were scaled to twice their size, while hand gestures (manual modalities) retained standard scaling. Arms, body, and legs were reduced to half size. Post-pose detection, the neck midpoint and shoulders were set as the new origin.

3) BAN Architecture and SSL Encoding: Pose data derived from deep learning models were benchmarked against NASA body size guidelines [22]. Head length per individual in each frame served as a normalization factor to ensure subject-independent consistency. The *keypoint* map, depicted with tailored scaling across body regions, is presented in Fig.3. Outliers, as defined by the guidelines, had their estimated values substituted with those from the prior frame.

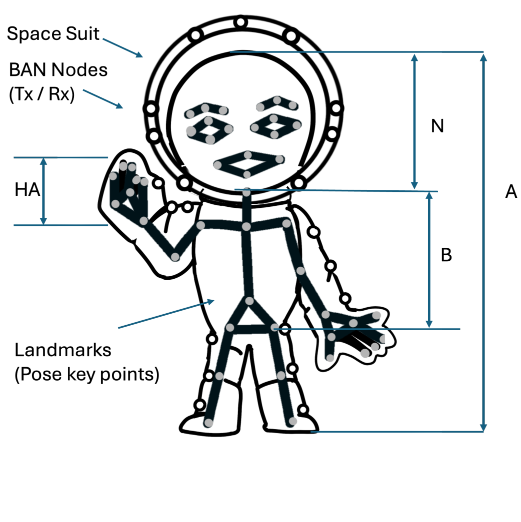


Fig. 3. BAN architecture design: Nodes embedded on the EMU spacesuit surface include sensors or stimulus sources. Main anthropometric measurements are: N (head length), HA (hand length), A (height), B (vertical trunk length), and C (crotch height).

We collected significant movements of the landmarks in each recording. These movements were ranked according to their standard deviation (std) relative to a quartile percentage threshold. We selected the top 85% quartile group of movements, ensuring they provided sufficient representation of the sign. These profiles were then built for further examination with a set of vocabulary of interest. Nodes of the BAN are sensors and stimulus generators that could be situated on the EMU spacesuit. The BAN is an integrated network of intelligent, extremely low-power, tiny nodes. It operates as a data hub or gateway and provides a user interface for viewing and managing BAN applications on the spot.

Sensor fusion techniques can complement wearable sensors such as visible range or thermal cameras and accelerometers to create a body area network (BAN). This approach is similar to existing work [26], which addressed extreme scenarios where optical, auditory, and telecommunication capabilities were mostly impaired. Rescue robots use radar and laser fusion to track the legs of rescuers, interpret human behavior, reason based on it, and deduce their own actions accordingly.

Regarding the appropriate BAN size, our review of pose analysis indicates that the number of key points in a pose can range from 17 to 136, as proposed in [20], [21]. To visualize a scene involving a person and a group of others, we assessed 18 nodes per person. These nodes are selected from a larger pool of 136 candidates extracted by deep learning models. The selection process ranks and chooses a shortlist of 18 highly important landmarks per pose.

C. Communication Protocols

Specific BAN-BAN protocol settings depend on the availability of advanced materials utilized in each BAN node. However, within the scope of this work, a general workflow is depicted in Fig. 4. We anticipate that, with advances in speech-to-text and brain-computer interface research, the terminal modules will be able to convert conventional signals, such as voice and thought commands, into nonverbal communication (NVC) signals. Thus, if the electromagnetic (EM) outage occurs only outside the EMU spacesuit and the BAN continues to function with EM inside the EMU, the sender and receiver may not need to manually interpret and execute NVC signals. Fig. 4 includes both voice and pose signals at the sender's encoding module, while a conventional display unit, such as the one on the helmet visor (shown in the inset of Fig. 4), is also equipped at the receiver's decoding module. The transmitter block in Fig. 4 generates stimuli that are then sensed by the receiver. The locations of these emitters are arranged in a specific configuration (e.g., as depicted in Fig. 3), which is learned from the sign profiling for the NVC encoding process shown in Fig. 1.

D. SSL Signer and Emergency-call Operator Communication

We propose a bidirectional communication loop that lets a signer initiate and sustain an emergency call with a human operator. An EDGE device colocated with the user performs all time-critical perception and language tasks, while a backend "automated emergency call system" assists with call setup and routing (Fig. 5 and Fig. 6). The end-to-end signaling and the

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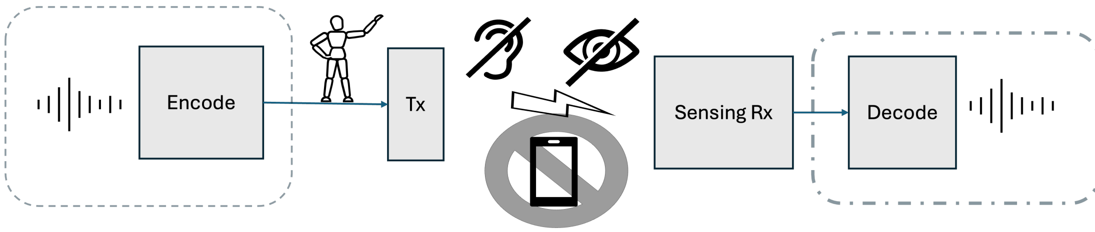

Fig. 4. Example of BAN-to-BAN communication flow. Extreme communication conditions outside the EMU include EM outage, impaired hearing, and obstructed visibility. Each side of the communication can convert between conventional signals and NVC signals, provided that the EM outage does not affect the interior of the EMU. Details of the BAN architecture are shown in Fig. 3.

human–machine interfaces depicted in the figures guided the system design.

The EDGE device runs a two-stage pipeline: (i) frame-level pose/hand-shape extraction and temporal modeling to produce a gloss sequence; (ii) intent parsing that maps the sequence to call intents (e.g., "medical help," "fire," "unsafe person present") and short semantic summaries. All processing is performed locally to minimize latency and preserve privacy. Firstly, the EDGE device initiates the emergency call and automatically voices a concise, structured sentence summarizing the detected intent, user identifier (if available), and live status. The same pipeline continues to update the operator with short voiced statements as new frames/telemetry arrive (Fig. 6). Then, human operator speech is captured on the call, transcribed, and semantically simplified by the automated call system, then transmitted to the EDGE device. Locally, the message is rendered as signer-facing instructions—either via a signing avatar on the user display or as icon-and-text prompts—so the user receives step-by-step guidance ("apply pressure," "move to a safe area," etc.). The loop is continuous: new operator prompts are reflected to the user; new user signs are understood and summarized back to the operator.

E. Edge Computing with Embedded Artificial Intelligence

We review current state-of-the-art EAI models and evaluate with benchmarks in ML inference applications. Several projects provide benchmarks such as Dawnbench [27], Geekbench AI [28], TPCx-AI [29]. These benchmarks provide valuable insights into the performance and efficiency of various ML inference systems, helping us identify solutions that align with the needs for real-time, energy-efficient communication.

In this work, we used the benchmark of MLPerf [11]. This suite evaluates the performance of different ML tasks under the same setting conditions for each test. MLPerf is part of a larger effort by MLCommons [30], a group focused on advancing machine learning technology. Within the scope of early investigation stage, our analysis focus solely on the data provided by MLCommons to assess the performance and efficiency of ML inference systems. Note that MLPerf has categorized systems by their scale, such as datacenters or embedded systems. The latter's metrics are bench-marked by 'MLPerf Tiny' [31]. MLPerf Tiny is a specialized benchmark within the MLPerf suite, designed to evaluate the performance of machine learning systems specifically for small-scale or embedded environments. This benchmark targets systems with limited resources, such as those found in wearable devices or edge computing applications, which fit SSL-related tasks. MLPerf not only simplifies the process of replicating its benchmarks across various settings, ensuring consistent testing conditions, but it also actively collects and publishes the results of these benchmarks from a wide range of systems [32], [33].

By analyzing these benchmark results, we aimed to understand how well existing edge computing systems can handle the demands of real-time sign language processing in space environments. To analyze the performance of various systems, we gathered data from the MLPerf Tiny benchmark, focusing on systems that had both latency and energy consumption metrics available.

IV. Experiment Results

A. Encoding Instrument and Display Unit

During a spacewalk, though SSL relies on signals transmitted via BANs, the signer can be equipped with a display unit within line of sight. A torso-mounted display module can facilitate interaction, allowing crew members to perceive signals from this visual board. This module is useful to aid SSL signers in training or as a tool in space and can be positioned on the spacesuit's front, back, and helmet visor for transmitting and receiving content if needed.

In that case, a grid-based display resembling Braille, can be used with high-contrast squares for pattern recognition and raised or flat surfaces for tactile binary feedback [4]. It may support from 360 to 1,500 characters. If the pose is displayed, the BAN transmitter grid should be ¡24 $\times$ 24 nodes.

B. Sign Profiling

A three-dimensional profile enhances the depiction of *keypoint* motion during signing. Fig.11 exemplifies this for "Push" fingerspelling, enabling comparisons across events by different signers or the same signer over time. Patterns along the temporal axis are discernible in Fig.11.

Fig. 7 illustrates the re-centering of the plane's origin to a body-centric framework. Coordinates of *keypoints* are captured within a frame, with *high-profile keypoints* annotated in the legend. These are defined by a threshold of 85% of the maximum standard deviation of *keypoint* displacements along the horizontal and vertical axes (x, y). Temporal variations in x and y are mapped in Fig.9, while polar coordinate representations, depicting changes in radius and rotation, are shown in

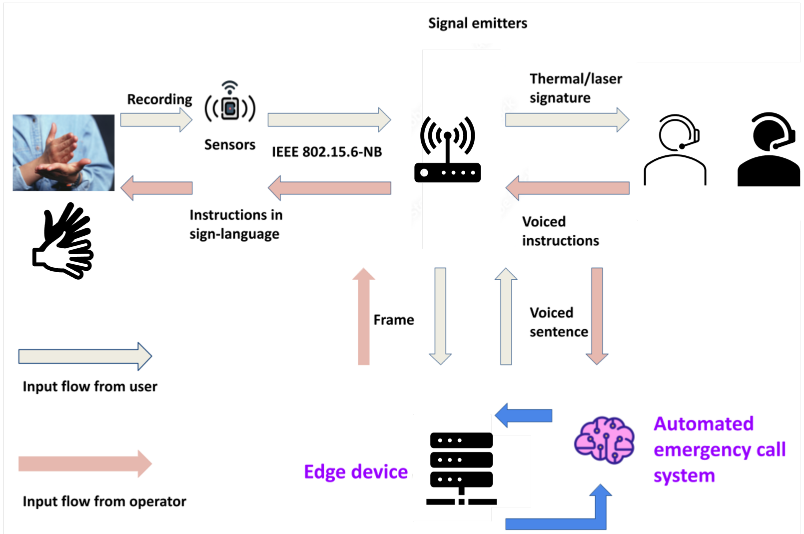

Fig. 5. Example of two-way communication between an SSL signer and an operator during an emergency call: signer → EDGE (SSL understanding) → operator (voiced summaries) and operator → automated system → EDGE (transcribed/simplified) → signer (sign/visual instructions), enabling natural, rapid interaction during emergencies.

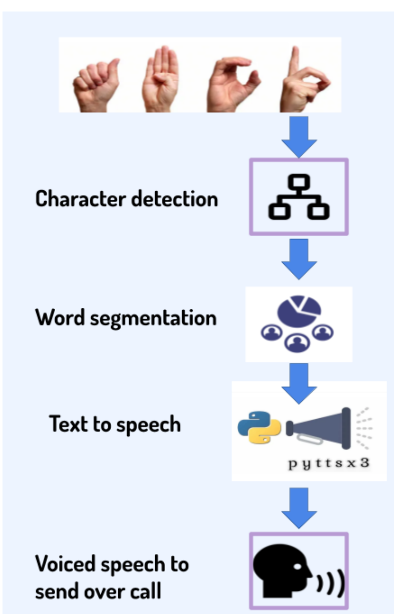

Fig. 6. Example of translating signs and voice between an SSL signer and an operator during an emergency call as shown in Fig. 5.

Fig.10. Bar charts in Fig. 10 also display *high-profile keypoint* profiles—rotation angles (degrees) and radial distances from the body center during finger-spelling of "Push."

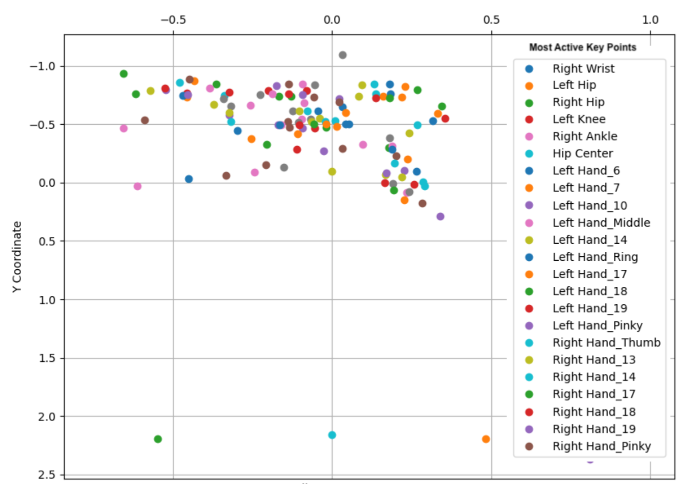

Fig. 7. Result of re-centering the coordinate origin depicted in a frame. Legend area: *High-profile keypoints* that fall within the top 15% of standard deviation values for changes in the spatial dimensions of the horizontal and vertical axes (x, y) during the finger-spelling of the word "Push".

Furthermore, a three-dimensional profile can help to provide a full description of a *keypoint* movement during a signing action. Fig. 11 presents examples of the same finger-spelling for the word "Push". We can compare this action across

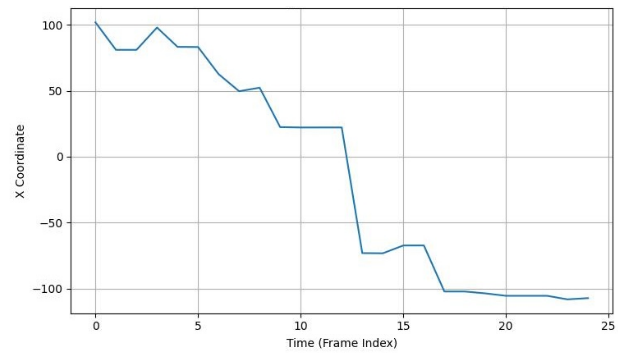

Fig. 8. Changes in x across the time dimension for the right elbow during the finger-spelling of the word "Push".

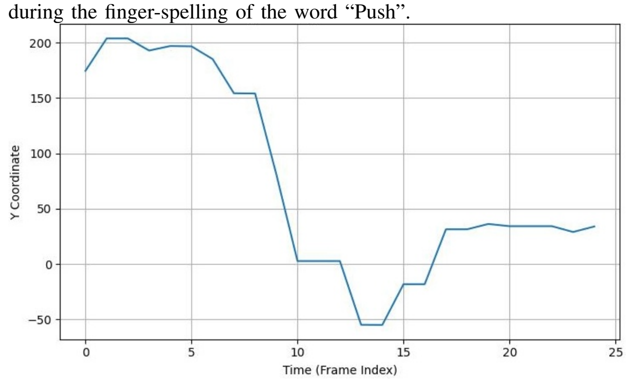

Fig. 9. Changes in y across the time dimension for the right elbow during the finger-spelling of the word "Push".

different events performed by different signers or the same signer at different times. In Fig. 11, we can observe patterns in the profile across the time axis.

These are illustration of finger-spelling of Auslan based on English languages. Besides this, we also analyzed signs that are not finger-spelling type. These are more challenging due to the variation of different nations and people with different signing style. Therefore, to prepare for the next phases, we ran through the whole dataset collated. We completed profiling an initial *vocabulary* list of about one hundred of common words in the relevant context of extreme condition search and rescue context for further SSL development. All the profiles are made available online at our public cloud storage folder.

C. BAN-to-Edge Communication Algorithm

This work considers wireless methods for communication within Body Area Networks (BANs). Similar to existing computing units on space suits, sensor nodes in space suits are expected to operate in orbit for extended periods. However, radiation hardening and redundancy measures can significantly increase cost, size, and power consumption. For instance, current power-efficient radiation-hardened units, such as the Honeywell HG1700 [34], typically consume around 5–8 watts. According to NASA spacesuit maintenance practices [35], the Extravehicular Mobility Unit (EMU) is refurbished every six years or after 25 spacewalks, whichever comes first.

To demonstrate the concept of exchanging emergency calls between an astronaut and a system operator (as shown in Fig. 5 and Fig. 6), the algorithm's functions can first be validated using current wireless technology standards, as illustrated in Fig. 12. The IEEE 802.15.6 standard [36] defines wireless BAN (WBAN) communication protocols that support extremely low-power devices with data rates up to 10 Mbps. Other protocols, such as Zigbee (IEEE 802.15.4 [37]), serve as robust backup options to add redundancy to the WBAN.

In the event of electromagnetic (EM) failure due to loss of signal, such as from solar particle events or regions of extreme interference, it is reasonable to assume that wireless communication for WBANs—which also relies on EM transmission—could be rendered unusable. As a further level of fallback, optical cable signaling can be considered, effectively transforming a wireless BAN into a wired BAN using low-profile optical cables. These ultra-fine fiber optics are widely used to control drones in military applications where signal interference is constant and ordnance requires constant guidance for precise engagement. These polymer-based cables can be as thin as 0.9–2 mm (including a protective shell), durable enough to stretch dozens of kilometers, with virtually negligible weight while providing bandwidth in the gigabits-per-second range, depending on the manufacturer. Within the wired BAN network, these cables can ensure uninterrupted communication between all components, using any internal network architecture such as SpaceCAN [38](Fig. 12), which can be easily integrated into existing space systems. SpaceCAN is promoted as a more reliable alternative to common buses like I2C for space missions, with prototypes demonstrating its robustness. For detailed specifications, refer to the LibreCube documentation [39] and other references.

D. Embedded Artificial Intelligence Evaluation

We evaluate the feasibility of edge computing with EAI for SSL encoding scenario using data collected and published by MLPerf [40]. We compiled this data from v0.5 to v1.2 of MLPerf Tiny to ensure a heavy computing load. All the steps and data processing methods used in this analysis are replicable and can be found in an online repository [41].

We used Visual Wake Words (VWW) and Image Classification (IC) as our primary ML applications for evaluation. These applications were selected because they are closely aligned with the tasks involved in SSL encoding. VWW involves detecting specific visual cues in realtime [31], similar to identifying sign language gestures. Meanwhile, IC requires recognizing and categorizing visual data [31], close to interpreting different sign language poses.

Figure 13 illustrates the performance of various systems in terms of latency and energy consumption for ML inference using the MLPerf Tiny benchmark with the MobileNetV1 0.25x model [42], used in VWW applications. Systems closer to the bottom-left corner are ideal for real-time, energy-constrained applications. The plot helps identify trade-offs between latency and energy consumption, aiding in the selection of optimal hardware and software configurations for specific use cases. Meanwhile, Figure 14 shows the results from executing the ResNet-V1 model [43] for IC purposes.

Figures 13 and 14 show that a few systems are now capable of achieving a latency of less than 150 ms. This indicates

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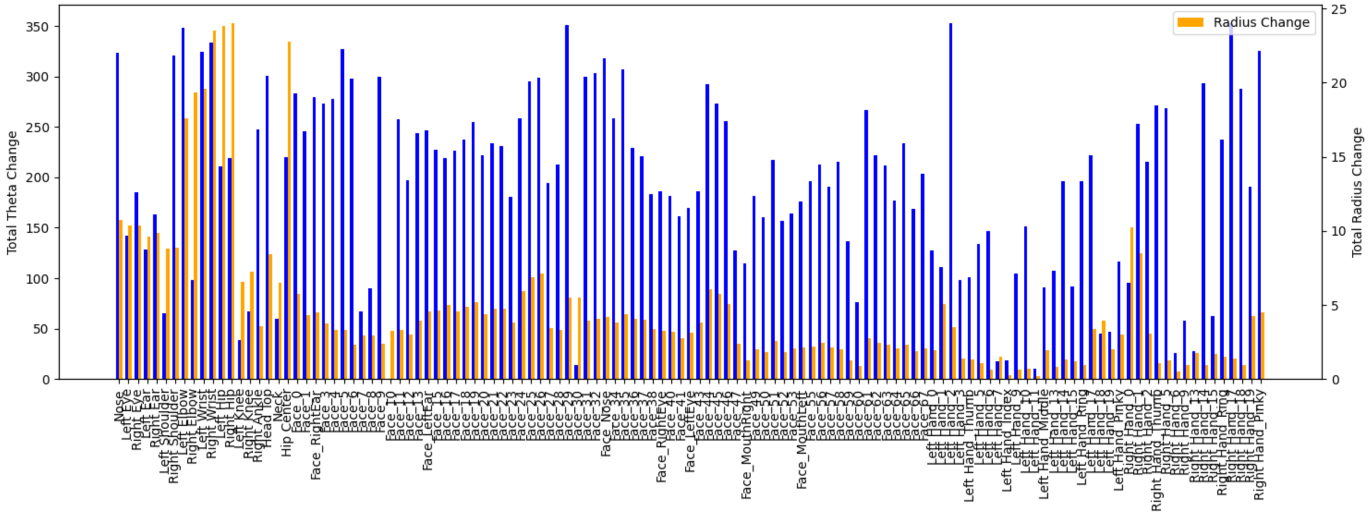

Fig. 10. Profiles of *high-profile keypoints* in terms of rotation angles (degrees) and radius from the body center during the finger-spelling of the word "Push".

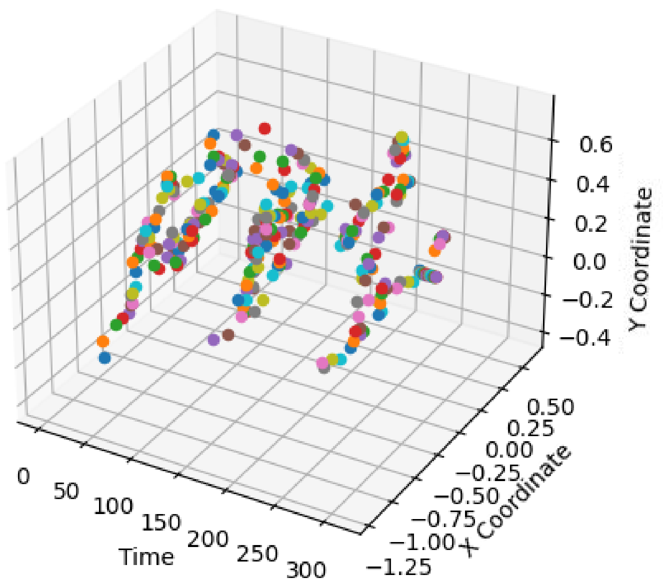

Fig. 11. Three-dimensional trajectory of the right-hand wrist during the finger-spelling of the sign "Push".

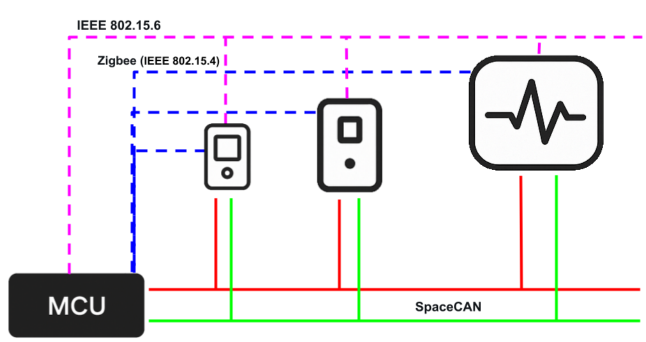

Fig. 12. Emergency call functions can be first validated using our current daily wireless technology standards.

that such performance is possible with recent off-the-shelf implementations.

V. Discussion

In summary, this work presents a process for developing a non-verbal communication system to be used in space-walks or emergency electromagnetic (EM) outage scenarios. By integrating machine learning, sign languages, and wireless technologies, the future of communication in space and extreme environments could become more intuitive, adaptive, and efficient, thereby enhancing collaboration and interaction among astronauts and support teams.

Numerous tasks can be conducted in parallel to develop a core vocabulary set utilizing state-of-the-art computer vision technology as well as linguistic and psychological experiments. The body area network (BAN) architecture and specific protocols for communication between users (BAN-BAN) rely heavily on the availability of advanced materials and sensor/actuator technologies.

We have demonstrated that fundamental steps can be taken to achieve initial development milestones. This research direction highlights the advantages of using generative models to unify sign languages across various nations, such as the United States, the United Kingdom, France, China, and Vietnam. It could also foster culturally neutral practices that can be learned from a comprehensive collection of sign languages.

Future work will include developing more sign profiles for SSL as well as refining the BAN architecture and protocols. The highest priority should be to identify robust keypoints for SSL and to develop a complete SSL definition and dictionary. The BAN technology can utilize advances in laser and thermal sensor technologies and these could be explored further.

Current progress in sign-to-spoken translation further enhances this effort by expanding the core vocabulary set for SSL. However, we should note that SSL should be specifically designed for space-related gestures that must be tested under space-equivalent conditions, such as in zero-gravity simulators, and integrated into actual extravehicular mobility units. Thus,

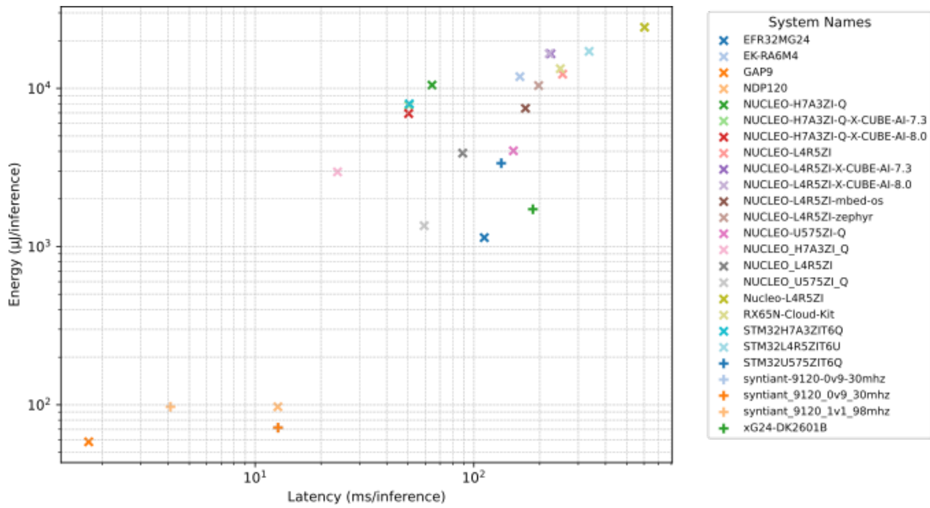

Fig. 13. Performance of various systems in terms of latency and energy consumption for ML inference using the MLPerf Tiny benchmark with the MobileNetV1 0.25x model [42], used in Visual Wake Words applications

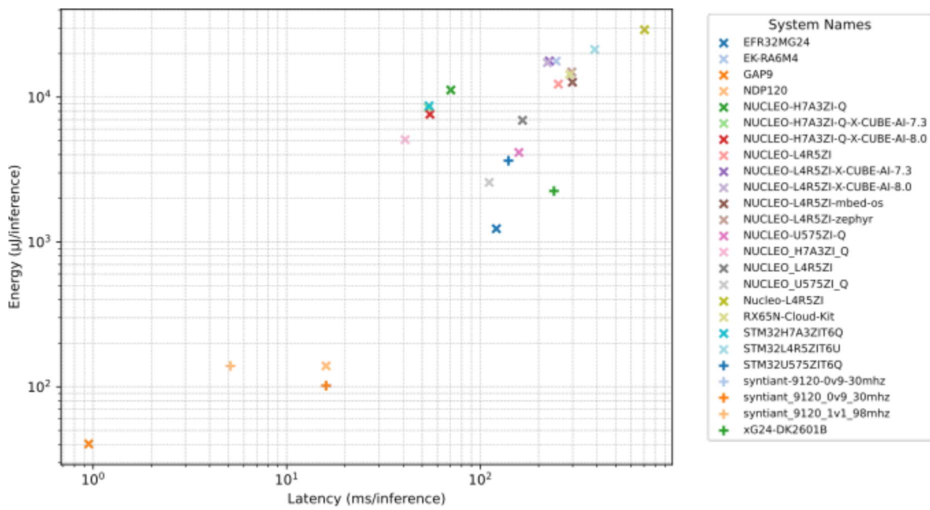

Fig. 14. Performance of various systems in terms of latency and energy consumption for ML inference using the MLPerf Tiny benchmark with the ResNet-V1 model [43] for Image Classification (IC) applications

exploring diverse sign language databases from deaf communities may not be sufficient; we may also need to incorporate other encoding resources to create SSL cues.

Regarding the edge computing with EAI, our benchmark evaluation shows that a latency of less than the ITU recommended for human communication of 150 ms achieved. Notably, systems like Syntiant's NDP9120 (released in 2022) [44] and Greenwave's GAP9 (released in 2023) [45] demonstrate that the state-of-the-art hardware is beginning to meet these demands. This progress suggests significant potential for real-time, energy-efficient computing in demanding environments.

Moreover, Field-Programmable Gate Arrays (FPGAs) or Application-Specific Integrated Circuits (ASICs) could offer even lower latency. Thus, we could further research on using these energy consumption systems under our scenarios of constrained conditions.

Future works can explore other sources of benchmarks, such as DawnBench [27] or GeekbenchML [28], to provide additional insights into the performance of various ML inference systems. We should test further models that accurately reflects the unique requirements of Space Sign Language applications. SSL encoding characteristics could be significantly different from those of IC or VWW to make a real difference in expected performance of those same systems.

Moreover, challenges and considerations, such as data privacy and security, require attention. The non-verbal communication system is as vulnerable to breaches as our usual verbal communication and needs protection from unauthorized access by third parties.

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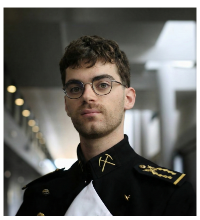
BIOGRAPHIES

Thuy T. Pham (Member, IEEE) earned her Ph.D degree in Electrical and Information Engineering at The University of Sydney, NSW, Australia. Her passion for signal processing started at The University of Arizona, USA with her MSc in Electrical and Computer Engineering in 2010, where she built her background on Neuroscience, Robotics, Digital Signal and Image Processing. She received the Australian Prime Minister Award and Norman I. Price Scholarship for her PhD study. She has been held visiting scholar appointments and collaborated with world-leading medical and physiology groups. She is currently an academic with the School of Electrical and Data Engineering, University of Technology Sydney (UTS), Australia. Dr. Pham's current research interests include radio frequency identification (RFID), low-power embedded systems, Internet of Things (IoT), and applied machine learning for sensing systems. She has authored and coauthored numerous peer-reviewed journal and conference papers in these areas. She is an active member of IEEE and regularly serves as a reviewer for leading IEEE journals and conferences.



Lucien Gheerbrant began his academic journey at École des Mines de Saint-Étienne (France), where he pursued a Master of Engineering in Microelectronics and Computer Science. During his studies, he took the opportunity to expand his expertise through a international dual degree program, earning a second Master of Engineering in Electronics and Telecommunications from the University of Technology Sydney (UTS, Australia). He graduated from both institutions in 2025 and was recognised on the Dean's List at UTS for his academic excellence.

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