Operational Environment Recognition for Human-Robot Collaboration Based on Human Physiological Sensory Feedback

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Abstract

Effective human–robot collaboration requires awareness of the user's operational environment, particularly when the robot's own sensing is limited. This study investigates whether human physiological signals can be used to infer environmental sensory noise during collaborative tasks. Motion and muscle activation data were analysed using three feature extraction strategies—raw data, variational autoencoders, and handcrafted statistical features—combined with multiple classifiers. The results show that statistical features with Random Forest classification provide the most reliable recognition, with muscle activation signals offering greater discriminative power than kinematic data. Performance improved further when analyses focused on stabilised trials, reflecting consistent user adaptation. However, high inter-subject variability highlights the challenge of generalising across users. These findings demonstrate the feasibility of physiological-based environment recognition and support the development of adaptive robots that exploit human feedback to perceive environmental conditions beyond their own sensing.

Declaration of originality

I hereby confirm that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright statement

1 Introduction

1.1 Background and motivation

Human–robot collaboration (HRC) has become a central paradigm in assistive robotics, in which humans and robots jointly pursue shared goals through coordinated task execution and effective information exchange [1]. For assistive robots to deliver reliable and contextually appropriate support, they must be able to perceive and interpret their operational environment accurately. This requirement is particularly critical in unstructured or dynamic settings, such as healthcare, rehabilitation, or domestic environments, where conditions are often unpredictable [2]. Despite advances in sensing and perception, inferring environmental conditions remains challenging, especially when the environment cannot be directly or reliably accessed through the robot's sensors.

The human neuromuscular system, regulated by the central nervous system (CNS), continuously adapts to external conditions by modulating muscle activation and limb impedance, thereby shaping energy exchange with the environment [3], [4]. During physical interaction, humans naturally alter muscle activation strategies, such as co-activation or reciprocal activation, to optimise sensory integration and motor performance [5], [6]. These physiological responses encode rich information about environmental conditions. If accessed by robotic partners, such responses could serve as indirect indicators of environmental states, thereby complementing or substituting direct sensing modalities.

While most HRC research has focused on how robots adapt to human behaviour, less attention has been given to the inverse perspective: how human physiological signals during collaborative tasks can provide robots with critical insights into environmental variability. Understanding these adaptive responses opens the possibility of developing robots capable of inferring environmental conditions indirectly through human physiological feedback. Such an approach is particularly valuable when the robot's sensors are impaired or limited, or when the human possesses unique access to environmental information that the robot cannot measure directly.

This study addresses this gap by examining whether robots can infer environmental noise conditions—specifically, levels of visual and haptic noise—through analysis of human physiological signals collected during collaborative tasks. Building on prior experimental work on human impedance modulation in visuo-haptic perception, we utilise a dataset comprising human motion and electromyographic (EMG) signals under systematically varied feedback conditions [7]. This dataset provides a foundation for developing and evaluating machine learning approaches to environmental recognition grounded in human physiological adaptation.

1.2 Aims and objectives

The overarching aim of this study is to design and evaluate machine learning methods that reliably recognise environmental noise levels from human physiological signals in HRC tasks. The specific objectives are to:

1. Identify correlations between visual and haptic noise levels and human physiological adaptation patterns within impedance modulation datasets.
2. Develop a classifier pipeline that benchmarks raw data against variational autoencoder (VAE)-based feature extraction and statistically engineered features [8].
3. Assess the classification performance of different data modalities (motion only, EMG only, combined motion + EMG, and motion + EMG + torque), with the aim of determining the minimal sensor configuration required for robust inference.
4. Evaluate the generalisation capabilities of the proposed models across different subjects and noise conditions.

1.3 Statement of contributions

The contributions of this study are threefold:

1. A universal preprocessing pipeline for physiological data, presented in Section 3, which is applicable across a range of machine learning approaches.
2. A classifier training pipeline capable of reliably identifying environmental noise conditions across subjects, described in Section 3.
3. A comprehensive evaluation of different data modalities, with analysis of their relative importance and implications for the design of resource-constrained robotic systems.

2 Literature review

2.1 Human-Robot collaboration systems

Human–robot collaboration (HRC) has developed substantially from traditional industrial robotics, where humans and robots operated in segregated spaces, towards systems that enable close, real-time interaction in shared environments. Modern HRC emphasises mutual adaptation and communication, requiring robots to interpret both the human's state and the surrounding environment [1].

Various sensing modalities are employed in HRC systems, including vision, force/torque sensors, and wearable devices [9]. More recently, physiological signals such as EMG have attracted growing interest for their potential to provide insight into human state and intention [10]. HRC applications span manufacturing [1], healthcare [10], agriculture [11], and challenging domains such as deep-sea exploration [2], all of which involve variable environmental conditions that may compromise sensing reliability. While most research has focused on adapting robotic behaviour to human actions, this study investigates the complementary problem of inferring environmental conditions through human physiological adaptation.

2.2 Physiological signals as environmental sensors

Physiological signals, and in particular surface EMG, offer a direct measure of neuromuscular responses to environmental changes. EMG captures the electrical activity generated during muscle contractions, reflecting the CNS's continuous modulation of motor output [5]. Prior work has shown systematic adaptations in EMG under sensory perturbations, with muscle co-activation (KM) increasing in response to haptic noise and decreasing with visual noise [6]. Such findings support the notion that EMG may encode signatures of environmental uncertainty and noise.

Other physiological modalities, such as EEG, electrocardiography (ECG), and heart rate variability, have also been employed to infer cognitive or affective states relevant to HRC [9], [12]. However, EMG is particularly suited to environmental recognition because it directly reflects the neuromuscular adjustments made during physical interaction.

2.3 Machine learning for environmental recognition

Machine learning has transformed the analysis of complex physiological signals by enabling robust feature extraction and classification. Classical approaches rely on handcrafted features, including time-domain (e.g., mean absolute value, waveform length), frequency-domain (e.g., mean power, median frequency), and time–frequency representations (e.g., wavelet coefficients) [13]. More recent work employs deep learning methods, including CNNs and LSTMs, which learn features directly from raw data [14].

Variational autoencoders (VAEs) are particularly promising for physiological signal analysis, as they combine deep neural representation learning with probabilistic modelling [8]. By encoding data into

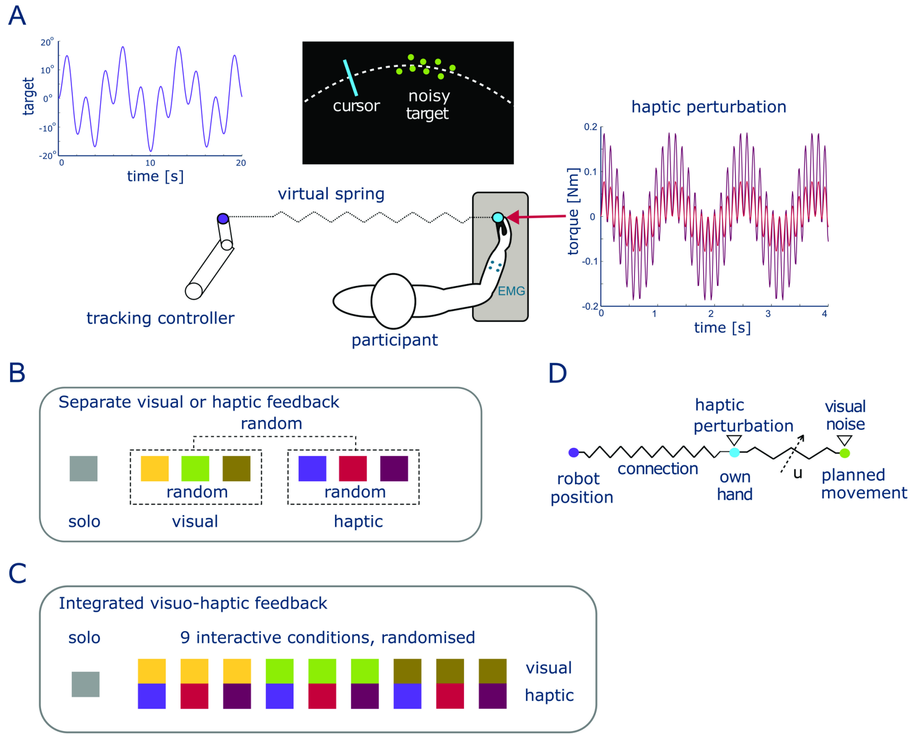


Fig. 1. Experiment setup and protocol. Figure adapted from Cheng, Shen, Ivanova, *et al.*, 2025. A: Participants were asked to track a randomly moving target with noisy visual feedback and in some conditions were connected to the human-like tracking controller of [15]. B,C: Experiment protocol of separate visual or haptic feedback experiment, with each block consisting of nine trials. The 13 participants received only visual/haptic feedback in random order and each with random noise level (B). Another 22 participants experienced nine integrated visual and haptic conditions presented in a random order (C). (D) illustrates the mechanical modelling scheme of the human-robot interaction with visual and haptic noise.

compressed latent variables, VAEs capture the essential structure of complex, high-dimensional signals such as EMG while suppressing irrelevant variability. This makes them well suited for applications requiring robust recognition under noisy conditions.

Although machine learning has been widely applied to activity and intention recognition [14], its use for environmental recognition from human physiological signals remains underexplored. This study directly addresses this gap by developing machine learning pipelines that infer environmental noise conditions from physiological responses observed during collaborative tracking tasks.

3 Methods

3.1 Data origin

3.1.1 Experimental setup

This study utilises data collected from previous experiments investigating human impedance modulation for visuo-haptic perception [6]. The experimental protocol was approved by the Research

Ethics Committee of Imperial College London (No. 15IC2470). Participants were seated on height-adjustable chairs with their dominant wrists attached to the handle of a Hi5 robotic interface. The Hi5 handle was driven by a current-controlled DC motor, instrumented with a differential encoder for wrist angle measurement and a torque sensor. Kinematic and force data were logged at 100 Hz. Surface electromyographic (EMG) activity from two antagonist wrist muscles (flexor carpi radialis, FCR; extensor carpi radialis longus, ECRL) was recorded using a medically certified 16-channel non-invasive EMG system at 100 Hz.

3.1.2 Experimental Task and Protocol

Participants performed a 20-second wrist flexion-extension tracking task, following a pseudo-random multi-sine target to minimize memorization. In solo trials, the robot applied no active torque. Otherwise, the wrist was coupled to the tracking controller via a compliant virtual spring producing torque. Three haptic noise conditions were tested: H0 (no additional noise), H1 (weak perturbation), and H2 (strong perturbation); and three visual conditions: V0 (sharp display) and two noisy displays V1/V2 in which the target was rendered as a cloud of eight dots with varying degrees of spatial dispersion.

The experimental protocol comprised nine familiarization (solo) trials followed by 20-second interaction trials. Two complementary cohorts were tested: a visual-only versus haptic-only cohort (13 naïve subjects, 6 female, 7 male; age 21-25, mean 22.5 ± 1.05; one left-handed) who each completed two randomized blocks (nine 20-second trials per condition), and a visuo-haptic cohort (22 naïve subjects, 12 female, 10 male; age 22-35, mean 24.1 ± 3.06; one ambidextrous), for which EMG analyses used 20 subjects due to incomplete EMG data from two participants. The nine visuo-haptic experimental blocks comprised all combinations of the three visual and three haptic noise levels presented in randomized order.

3.2 Data analysis

3.2.1 Data preprocessing

Raw EMG signals were high-pass filtered at 20 Hz (second-order Butterworth) to remove drift, full-wave rectified, and low-pass filtered (second-order Butterworth, 15 Hz cutoff) to obtain the EMG envelope used for subsequent analyses.

Initial tests revealed that the available dataset size was insufficient for variational autoencoders (VAEs) to effectively learn features from the complete 20-second data sequences. Therefore, for

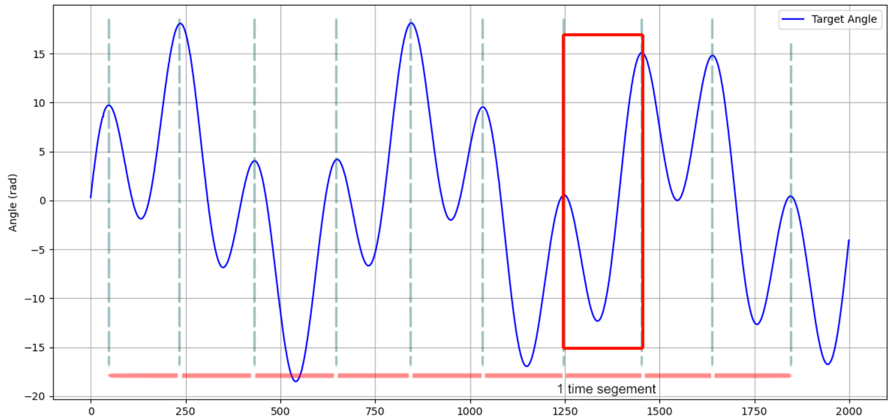


Fig. 2. Data segmentation: The peak timestamp of the target–time curve in each test instance was used as the segmentation point across all seven feature dimensions.

each test instance (unique combination of subject, trial, and condition), the corresponding time series of length 2000 was processed as follows to facilitate VAE learning (Fig. 2):

1. Identification of peak positions in the target-time curve for each test instance.
2. Data segmentation based on the identified peak time positions.
3. Interpolation to a fixed length of 250 samples per segment.

Data were standardised along the feature dimension to ensure consistent scaling across different modalities.

3.2.2 Feature extraction

Three distinct feature extraction approaches were implemented and compared to transform the raw time-series data into informative representations suitable for training machine learning classifiers.

1. Raw data baseline

   In the raw data baseline, the preprocessed but otherwise unmodified time-series data were used directly as classifier input. The complete dataset $\mathcal{D}$ comprised N samples (i.e., time segments obtained as 1 sample × 9 conditions × 9 trials for each subject), where each sample $\mathbf{X}_i$ corresponded to a single trial from a specific subject under a particular noise condition. The dataset was therefore constituted as:

$$\mathcal{D} = \{(\mathbf{X}_i, y_i)\}_{i=1}^{N} \tag{1}$$

The condition label $y_i \in 1, \ldots, 9$ mapped to the nine visuo–haptic combinations in the following order: {1:V0H0, 2:V0H1, 3:V0H2, 4:V1H0, 5:V1H1, 6:V1H2, 7:V2H0, 8:V2H1, 9:V2H2}. Each sample contained seven data channels, each represented as a 250-point vector after segmentation and interpolation. A single data sample $\mathbf{X}_i$ can be expressed as:

$$\mathbf{X}_i = [a_i, tg_i, ext_i, flex_i, km_i, kd_i, \tau_{m,i}] \tag{2}$$

where *a* is the vector of hand movement angles. *tg* is the vector of target angles for movement tracking. *ext* is the vector of extensor muscle activation, *flex* is the vector of flexor muscle activation. *km* is the vector of muscle co-contraction, defined as $\text{km}(j) = \min(|\text{ext}(j)|, |\text{flex}(j)|)$. *kd* is the vector of muscle reciprocal activation, defined as $\text{kd}(j) = \text{ext}(j) - \text{flex}(j)$. τ_m is the vector of motor torque generated in the handle.

This baseline served to evaluate whether classifiers could effectively learn discriminative patterns directly from raw temporal sequences without additional feature engineering.

2. VAE feature extraction

Three VAE architectures were designed to learn compressed, discriminative representations of the raw data (Fig. 3).

- *Primary architecture (independent VAEs)*

  Each data dimension was modelled by a separate VAE (Fig. 3a). The encoder $q_\phi(\mathbf{z}|\mathbf{x})$, implemented as a multi-layer perceptron following [8], mapped inputs $\mathbf{x}$ to a latent distribution $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$, and the decoder $p_\theta(\mathbf{x}|\mathbf{z})$ reconstructed the input. The model was trained by maximising the evidence lower bound (ELBO):

$$\mathcal{L}(\theta, \phi; \mathbf{x}) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})] - \beta D_{\text{KL}}(q_\phi(\mathbf{z}|\mathbf{x})||p_\theta(\mathbf{z})) \tag{3}$$

  where $\mathbb{E}$ denotes expectation, D_{KL} is the Kullback–Leibler divergence, $p(\mathbf{z})$ is the prior distribution, and β is a weighting coefficient. After training, the mean vector $\boldsymbol{\mu}_z$ of the latent distribution was extracted as the learned feature. Latent vectors across the seven feature dimensions were concatenated to form a combined feature matrix for classifier training.

- *Secondary architecture (conditional VAE with classifier head)*

  A conditional extension of the VAE was implemented by integrating a classification head, which predicted noise conditions directly from $\mathbf{z}$. The head comprised a linear layer projecting $\mathbf{z}$ to 32 features, a ReLU activation, and a final linear layer mapping to nine classes. The total loss combined reconstruction, divergence, and classification terms:

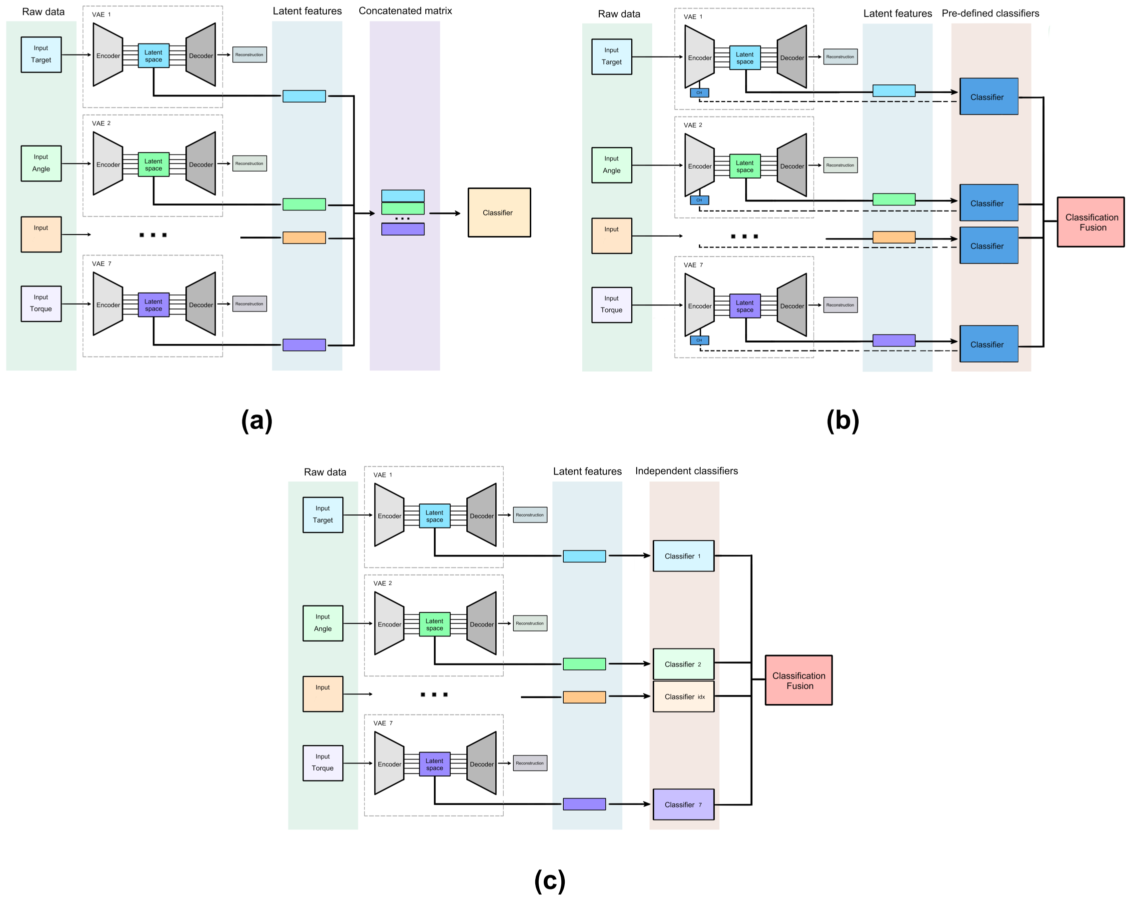


Fig. 3. Three VAE-based feature extraction architectures: (a) Standard model, where VAE-extracted features from all dimensions are concatenated for classification. (b) Classifier-heads model, where each VAE is trained jointly with a classification head, and predictions are fused for the final result. (c) Independent-classifier model, where each dimension is classified separately and results are fused.

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{ELBO}} + \lambda \mathcal{L}_{\text{CE}}(y, \hat{y}) \tag{4}$$

where $\mathcal{L}_{\text{CE}}$ is the cross-entropy loss and λ balances the two objectives.

Dimension-specific predictions were fused to form the final output. For both secondary and tertiary architectures, predictions from dimension-specific models were combined using:

– *Majority voting* selects the final label as the most frequently predicted class across all classifiers:

$$\hat{y}_{\text{final}} = \text{mode}\{\hat{y}_1, \ldots, \hat{y}_7\} \tag{5}$$

– *Weighted voting* incorporates classifier reliability by assigning weights w_i proportional to their validation accuracy. The final decision corresponds to the class with the highest weighted vote count:

$$\hat{y}_{\text{final}} = \arg\max_{c} \sum_{i=1}^{7} w_i \cdot \mathbb{I}(\hat{y}_i = c) \tag{6}$$

where $\mathbb{I}(\hat{y}_i = c)$ is an indicator function that equals 1 if classifier i predicts class c, and 0 otherwise.

– *Stacking* integrates probabilistic outputs. The posterior probability vectors $\mathbf{p}_i$ from each classifier are concatenated to form a meta-feature representation:

$$\mathbf{p}_{\text{meta}} = [\mathbf{p}_1, \ldots, \mathbf{p}_7] \tag{7}$$

which is then used as input to a higher-level meta-classifier.

The best-performing method on validation was selected for final testing.

- *Tertiary architecture (independent classifiers)*

  Instead of concatenating features, separate classifiers were trained for each dimension (Fig. 3c). The final decision was determined using the best-performing fusion scheme selected from (5), (6), and (7). This design evaluated whether certain modalities were particularly informative for specific noise conditions.

3. Statistical feature extraction

   The statistical feature extraction approach (“Advanced_stats”) followed established methodologies in motion analysis and EMG signal processing, generating handcrafted features from each modality.

   Motion features: Extracted from angle and target signals [16]–[18]:

   - *Velocity/time metrics:* maximum/average velocity, maximum/average acceleration, time to peak velocity.
   - *Accuracy metrics:* overshoot, arrival accuracy, normalised error, trajectory error, mean absolute error.
   - *Smoothness metrics:* mean jerk, jerk–velocity ratio, velocity shape, spectral arc length.

   EMG features: Following Abbaspour, Lindén, Gholamhosseini, *et al.* [19], although only a subset of features was implemented:

   - *Ext/Flex:* maximum, minimum, mean, median, standard deviation, area under curve, RMS, mean power, mean absolute value, waveform length, skewness, kurtosis, simple square integral, average amplitude change.

- *KM/KD:* maximum, minimum, mean, median, standard deviation, peak-to-peak, RMS.

Torque features: Maximum, minimum, mean, median, standard deviation, peak-to-peak, RMS, area under curve, skewness, kurtosis.

This handcrafted set provided a multi-faceted description of the physiological and biomechanical mechanisms underlying adaptation to variable noise conditions.

3.2.3 Feature processing

Two dataset variants were prepared for evaluation:

- *Full trials dataset:* all nine trials per condition–subject combination.
- *Stable trials dataset:* only the last four trials, assuming participants reached a stable adaptation state.

Both datasets were split into training (70%), validation (15%), and test (15%). Features were standardised using the training mean and standard deviation. The same parameters were applied to validation and test sets to avoid data leakage. All VAE training, feature extraction, and classification used these standardised datasets.

3.3 Classification methods

Classifier choice depended on the feature extraction approach.

For VAE features, which are typically low-dimensional and dense, we employed Support Vector Machines (SVM), Random Forests, Logistic Regression, K-Nearest Neighbors (KNN), Multi-Layer Perceptrons (MLP), and XGBoost.

For statistical features and raw data, we used SVM, Random Forests, Logistic Regression, and MLP. Additionally, Long Short-Term Memory (LSTM) networks were included for the raw baseline, as they are well-suited to modelling temporal dependencies in uncompressed time-series.

Classical machine learning models were implemented in scikit-learn (default parameters unless noted). Deep models (MLP) were implemented in PyTorch with three hidden layers (256, 128, 64 units), ReLU activations, batch normalisation, and dropout. Training used the Adam optimiser [20] with learning rate 0.001, batch size 64, and ReduceLROnPlateau scheduling. All classifiers were trained with the same data splits and evaluated using stratified k-fold cross-validation. Final performance was reported on the held-out test set.

Table 1. Performance comparison between full and stable trials (F1 scores)

Feature group	Model	Full trials	Stable trials	Difference
Kinematic	LogisticRegression	0.140	0.147	+0.007
EMG	MLP	0.426	0.595	+0.169
Kinematic+EMG	LogisticRegression	0.294	0.464	+0.170
Full (Kinematic+EMG+Torque)	MLP	0.612	0.649	+0.037

4 Results and discussion

4.1 Trial selection

The initial analysis compared model performance using all available trials versus only the last four stabilised trials per condition. This comparison was essential to assess whether participants' adaptation behaviour stabilised over time, thereby providing more consistent signals for environmental recognition.

Paired t-tests revealed significant differences ($p < 0.01$) between full and stable trials across all feature groups. Stable trials consistently yielded higher performance, with the largest improvements observed in EMG-based features (mean difference: +0.145, $t(6) = -18.37$, $p = 1.68 \times 10^{-6}$). This indicates that participants' adaptation patterns became more consistent and discriminative in later trials, reflecting a stabilised strategy for managing environmental noise. Consequently, all subsequent analyses employed the stable trials dataset.

4.2 Feature extraction

4.2.1 Raw features baseline

The raw features baseline yielded limited performance across classifiers using the full feature set (kinematic+EMG+torque). The best result was obtained by MLP (F1 = 0.471; Fig. 5a), whereas the LSTM performed poorly (F1 = 0.333), despite its suitability for time-series data. This suggests that while raw sequences contain relevant information, effective extraction methods are necessary for robust classification.

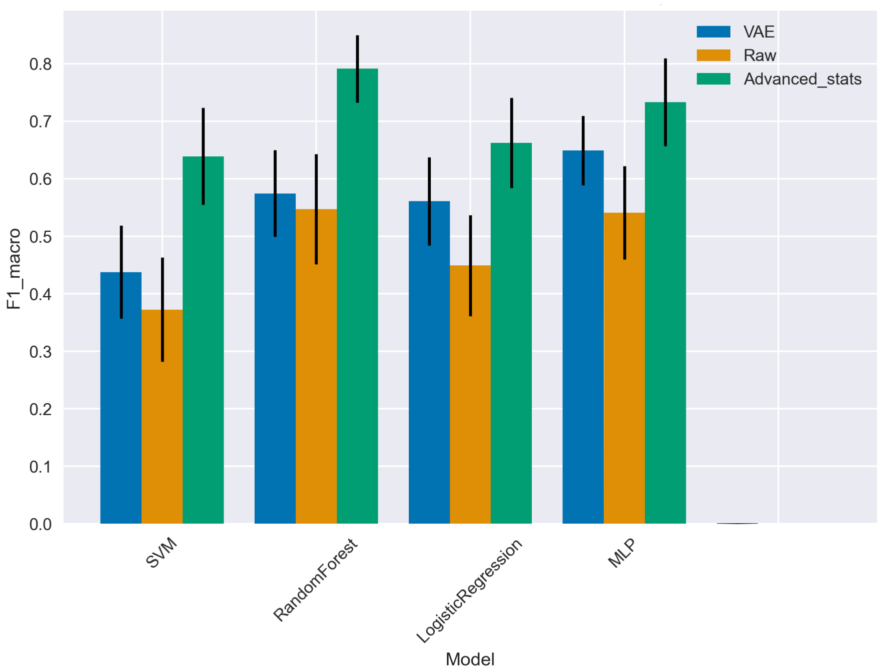
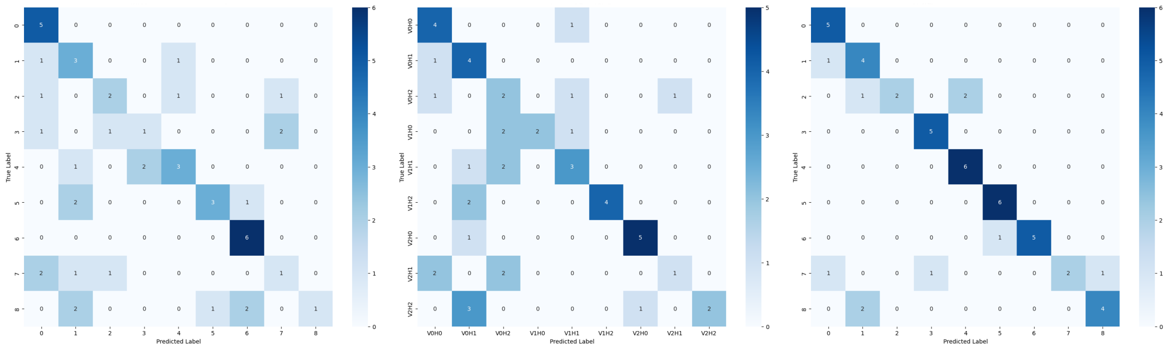


Fig. 4. Average F1 scores of three feature extraction methods across all feature groups under stable trials.



(a) (b) (c)

Fig. 5. Confusion matrices of feature extraction methods on the same subject (best F1 score): (a) raw features, MLP, F1 = 0.471; (b) VAE features, MLP, F1 = 0.546; (c) statistical features, RF, F1 = 0.774.

4.2.2 VAE features

Alternative VAE architectures (classifier heads and independent classifiers) produced inferior performance. Independent classifiers achieved a maximum dimension-specific accuracy of 34.7% (Flex and KD), while fusion methods yielded only 14.3–16.3%, well below the primary architecture. The standard VAE feature extraction approach significantly improved performance over raw features. The best model was MLP (F1 = 0.546), representing a 13.7% improvement (Fig. 5b).

Table 2. Contribution of feature modalities to classification performance (F1 scores)

Feature group	Best model	F1 score
Kinematic	MLP	0.180
EMG	MLP	0.613
Kinematic+EMG	MLP	0.565
Full (All modalities)	MLP	0.649

4.2.3 Statistical features (Advanced Stats)

The Advanced Stats approach provided the strongest performance across all feature groups and classifiers. RandomForest achieved the highest score (F1 = 0.774) with the full feature set (Fig. 5c), markedly surpassing VAE and raw feature methods. This indicates that expert-designed statistical features effectively capture the discriminative characteristics of physiological adaptation to environmental noise (Fig. 4).

4.3 Modality contribution

Analysis of feature groupings revealed substantial variation. EMG-based features consistently outperformed kinematic features, achieving 72.5% of the performance of the full set. This suggests that muscle activation patterns provide stronger discriminative information about environmental noise conditions than kinematics. The combination of kinematic and EMG features offered limited additional benefit, indicating redundancy or weak complementarity.

4.4 Generalisation

4.4.1 Cross-subject stability

The Advanced Stats method demonstrated superior stability across subjects, particularly for EMG and full feature sets. The lowest cross-subject standard deviation was observed with Advanced Stats and RandomForest ($\sigma = 0.058$), compared to VAE with MLP ($\sigma = 0.061$) and Raw with RandomForest ($\sigma = 0.096$) (Fig. 4).

4.4.2 Cross-subject effectiveness

Cross-subject tests revealed major challenges. Models trained on multiple subjects and tested on left-out subjects performed near chance level (best F1 = 0.065), highlighting strong subject-specific patterns in physiological responses and substantial intersubject variability.

Table 3. Cross-subject classification performance (F1 scores)

Model	Training subjects F1 score	Test subjects F1 score
SVM	0.326	0.039
RandomForest	0.923	0.025
LogisticRegression	0.185	0.065
MLP	0.116	0.045

4.5 Discussion

The findings demonstrate the feasibility of recognising environmental noise conditions from human physiological signals during human–robot collaboration. Several conclusions can be drawn.

First, stable trials yielded superior results, suggesting that consistent adaptation strategies emerge over time, particularly in EMG signals. Second, handcrafted statistical features outperformed both raw and VAE-derived representations, highlighting the enduring value of expert knowledge. Third, EMG signals provided stronger discriminative power than kinematic features, reflecting their closer link to human adaptation under uncertainty. Finally, cross-subject generalisation remained limited, underlining the individuality of physiological responses.

Confusion matrix analysis further clarified these results. Raw features showed the greatest confusion between conditions differing only in visual noise but sharing the same haptic level (e.g., V1H0 vs. V2H0). The VAE improved discrimination of visual noise levels but struggled with subtle haptic variations. Statistical features proved most robust, particularly in distinguishing high-noise conditions (V2H2). Nonetheless, all methods exhibited misclassification between V1H1 and V2H2, suggesting overlapping physiological responses to intermediate noise levels.

Limitations must also be acknowledged. The dataset was collected under controlled laboratory conditions, which may not generalise to real-world settings. The current noise classification represents a highly simplified model; extending it to more complex or realistic noise scenarios may further affect performance. In addition, the feature extraction methods were tailored to this dataset, and their effectiveness may vary across different tasks or signal modalities.

Overall, physiological-based environmental recognition appears most viable when models are personalised or trained on sufficiently diverse datasets. For assistive robotics, this capability could enable robots to infer environmental conditions indirectly from human adaptation, supporting more context-aware and resilient collaboration.

5 Conclusions and future work

5.1 Conclusions

This study demonstrates that human physiological signals, particularly EMG, contain valuable information for recognising environmental noise conditions in human–robot collaborative tasks. The main conclusions are:

1. Statistical feature extraction (Advanced Stats) with RandomForest achieved the strongest performance for environmental recognition.
2. EMG signals provided substantially more discriminative power than kinematic data, suggesting that muscle activation patterns directly reflect adaptation to uncertainty.
3. Stable trials (later trials post-adaptation) yielded significantly better recognition than full trial sets, confirming that consistent strategies develop over time.
4. Strong intersubject variability limits cross-subject generalisation, with models trained on one subject transferring poorly to others.

These results advance adaptive human–robot collaboration by enabling robots to infer environmental conditions from human adaptation strategies. Such capability may allow robots to perceive environmental factors not directly accessible to their own sensors.

5.2 Future work

Future research should address the following directions:

Hybrid Feature Extraction: Explore combinations of learned representations (e.g. VAEs) with handcrafted statistical features, either sequentially or through novel hybrid architectures.

Advanced Fusion Techniques: Develop more sophisticated fusion approaches, such as attention-based mechanisms, to dynamically weight modalities.

Multimodal Integration: Investigate integration of physiological-based recognition with robot sensor data to enhance robustness and contextual awareness.

References

[1] U. Othman and E. Yang, “Human–robot collaborations in smart manufacturing environments: Review and outlook,” *Sensors*, vol. 23, no. 12, p. 5663, 2023 (cited on pp. 7, 9).

[2] G. Brantner, *Human-Robot Collaboration in Challenging Environments*. Stanford University, 2018 (cited on pp. 7, 9).

[3] N. Hogan, “Impedance control: An approach to manipulation,” in *1984 American control conference*, IEEE, 1984, pp. 304–313 (cited on p. 7).

[4] E. Burdet *et al.*, “The central nervous system stabilizes unstable dynamics by learning optimal impedance,” *Nature*, vol. 414, no. 6862, pp. 446–449, 2001 (cited on p. 7).

[5] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, “Techniques of emg signal analysis: Detection, processing, classification and applications,” *Biological procedures online*, vol. 8, no. 1, pp. 11–35, 2006 (cited on pp. 7, 9).

[6] X. Cheng *et al.*, “Human impedance modulation to improve visuo-haptic perception,” *PLoS computational biology*, vol. 21, no. 5, e1013042, 2025 (cited on pp. 7, 9, 10).

[7] X. Cheng, “Human Impedance Modulation to Improve Visuo-Haptic PerceptionHuman Impedance Modulation to Improve Visuo-Haptic Perception,” Dec. 2024. DOI: `10.6084/m9.figshare.28029272.v2`. [Online]. Available: `https://figshare.com/articles/dataset/Human_Impedance_Modulation_to_Improve_Visuo-Haptic_Perception/28029272` (cited on p. 7).

[8] D. P. Kingma and M. Welling, “Auto-encoding variational bayes,” *arXiv preprint arXiv:1312.6114*, 2013 (cited on pp. 8, 9, 13).

[9] C. J. Lin and R. P. Lukodono, “Sustainable human–robot collaboration based on human intention classification,” *Sustainability*, vol. 13, no. 11, p. 5990, 2021 (cited on p. 9).

[10] M. Al-Ayyad *et al.*, “Electromyography monitoring systems in rehabilitation: A review of clinical applications, wearable devices and signal acquisition methodologies,” *Electronics*, vol. 12, no. 7, p. 1520, 2023 (cited on p. 9).

[11] V. Moysiadis *et al.*, “Human–robot interaction through dynamic movement recognition for agricultural environments,” *AgriEngineering*, vol. 6, no. 3, pp. 2494–2512, 2024 (cited on p. 9).

[12] A. Soni and K. Rawal, “A review on physiological signals: Heart rate variability and skin conductance,” in *Proceedings of First International Conference on Computing, Communications, and Cyber-Security (IC4S 2019)*, Springer, 2020, pp. 387–399 (cited on p. 9).

[13] R. H. Chowdhury *et al.*, “Surface electromyography signal processing and classification techniques,” *Sensors*, vol. 13, no. 9, pp. 12 431–12 466, 2013 (cited on p. 9).

[14] S. Kansal, S. Jha, and P. Samal, “Dl-dare: Deep learning-based different activity recognition for the human–robot interaction environment,” *Neural Computing and Applications*, vol. 35, no. 16, pp. 12 029–12 037, 2023 (cited on pp. 9, 10).

[15] A. Takagi *et al.*, “Physically interacting individuals estimate the partner’s goal to enhance their movements,” *Nature Human Behaviour*, vol. 1, no. 3, p. 0054, 2017 (cited on p. 10).

[16] M. Longhi *et al.*, “Instrumental indices for upper limb function assessment in stroke patients: A validation study,” *Journal of neuroengineering and rehabilitation*, vol. 13, no. 1, p. 52, 2016 (cited on p. 15).

[17] A. Merlo *et al.*, “Upper limb evaluation with robotic exoskeleton. normative values for indices of accuracy, speed and smoothness,” *NeuroRehabilitation*, vol. 33, no. 4, pp. 523–530, 2013 (cited on p. 15).

[18] S. Balasubramanian, A. Melendez-Calderon, and E. Burdet, “A robust and sensitive metric for quantifying movement smoothness,” *IEEE transactions on biomedical engineering*, vol. 59, no. 8, pp. 2126–2136, 2011 (cited on p. 15).

[19] S. Abbaspour *et al.*, “Evaluation of surface emg-based recognition algorithms for decoding hand movements,” *Medical & biological engineering & computing*, vol. 58, no. 1, pp. 83–100, 2020 (cited on p. 15).

[20] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” *arXiv preprint arXiv:1412.6980*, 2014 (cited on p. 16).

Appendices

A Project outline

Operational Environment Recognition for Human–Robot Collaboration Project Outline

By Shuyan Zhang

I. Introduction

Effective assistive robotics hinges upon a robot's capacity to comprehend the user's operational environment and adapt its assistance accordingly. In human–robot collaboration, variations in sensory feedback—particularly visual and haptic noise—directly influence human motor behaviour and muscle activation patterns. Prior experiments [1] have demonstrated that muscle co-activation increases under elevated haptic noise and diminishes when visual information is degraded, with concomitant changes in muscle stiffness reflecting these adaptations. This project proposes to leverage these empirically observed relationships to infer environmental conditions from human biosignals. By extracting salient features of human motion and electromyographic (EMG) data collected during collaborative tracking tasks, we aim to develop a machine learning classifier capable of predicting the user's sensory environment. The resultant recognition algorithm will form the basis for adaptive control strategies that tailor robotic assistance to user-specific environmental interactions, thereby optimising collaborative performance in complex or uncertain settings.

II. Scope of the Project

This project will develop an environmental-noise inference model utilising the Impedance Adaptation dataset, which comprises synchronised human motion kinematics and muscle activation signals recorded under varying visuo-haptic feedback conditions. The principal tasks are as follows:

1) Data preprocessing and feature engineering
2) Model development
    - Implement and compare several deep learning architectures, with a particular focus on the Variational Autoencoder (VAE) [2]framework.
    - Optimise hyperparameters for classifier performance.
3) Generalisation assessment
    - Evaluate the transferability of models trained on data from one subject to alternative subjects.

The project will not delve into the underlying neurophysiological mechanisms of muscle co-activation or the biological origins of the dataset; nor will it explore novel machine learning algorithms beyond those selected for comparative purposes. The primary deliverables will be the inference model itself and a comprehensive performance analysis, detailing classification accuracy, robustness to noise and cross-subject generalisation.

III. Motivation and Significance

Human motor behaviour is inextricably linked to perceptual input: when sensory feedback is noisy or incomplete, individuals adapt their muscle activation strategies to maintain task performance. In the context of human–robot interaction, a robot that can infer a user's perceptual state—specifically the levels of visual and haptic noise—could dynamically adjust its control parameters to provide more intuitive and efficient assistance. For instance, heightened haptic noise may prompt a robotic system to employ stiffer force-control modes, whereas impaired vision might lead to augmented haptic guidance. Such adaptive strategies not only improve task accuracy and user comfort but also foster greater trust and fluidity in collaborative scenarios. By extracting nuanced features from motion and EMG data, this project endeavours to bridge the perceptual gap between human and machine, enabling context-aware assistive robotics that responds in real time to environmental uncertainty.

IV. Aims and Objectives

The overarching aim is to create a reliable algorithm for recognising environmental noise models from human biosignals. Specific objectives include:

- **Objective 1:** Identify and extract key features from impedance adaptation datasets that correlate strongly with levels of visual and haptic noise.
- **Objective 2:** Design and implement a suite of deep learning classifiers—centred on a Variational Autoencoder architecture[2]—and benchmark their performance against conventional algorithms (e.g. support vector machines).
- **Objective 3:** Evaluate classification performance using distinct feature modalities (motion-only, EMG-only and fused motion + EMG) to identify the minimal sensor suite required for reliable environmental inference in resource-limited settings.
- **Objective 4:** Quantify the inference model's generalisation capabilities by testing across different subjects and noise profiles.
- **Objective 5:** Deliver a detailed evaluation report encompassing classification accuracy, confusion matrices, receiver operating characteristic (ROC) curves and computational efficiency metrics.

V. Methodology

A. Model Architecture and Training

We will implement a VAE [2] to learn a compact latent representation of the combined feature space. The encoder network compresses high-dimensional inputs into a probabilistic latent code, while the decoder reconstructs the original signals. A classification head appended to the latent space will predict discrete noise conditions. Comparative models—such as multilayer perceptrons and convolutional neural networks—will be trained using identical feature sets. Training will employ cross-entropy loss for classification and mean squared error for reconstruction, with an L_2 regularisation term to prevent overfitting.

B. Evaluation and Validation

Model performance will be assessed via k-fold cross-validation. Metrics will include classification accuracy and area under the ROC curve. To evaluate generalisation, models trained on one subject's data will be tested on data from alternative subjects, quantifying any performance degradation.

VI. Project Plan and Timeline

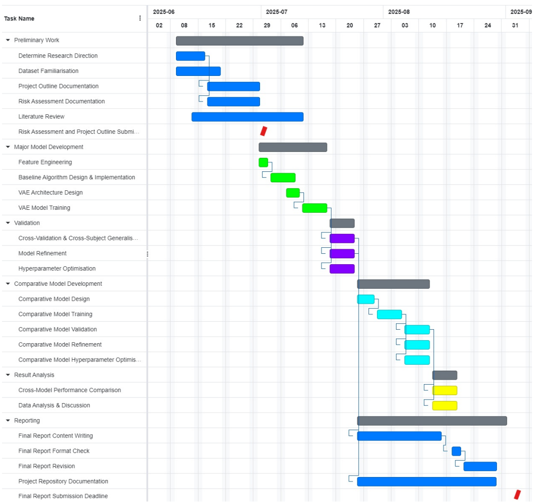


Fig. 1: Project Gantt Chart

1 illustrates task dependencies and milestones.

VII. Expected Outcomes

- A validated inference model capable of classifying environmental noise types from human kinematic and EMG data
- A thorough comparative analysis of deep learning versus classical machine learning approaches.
- Recommendations for integrating the recognition algorithm into adaptive robotic controllers, paving the way for future experimental validation in real-time human–robot collaboration scenarios.

VIII. Limitations and Exclusions

This project will not address:

- The design or optimisation of novel machine learning algorithms beyond those specified.
- In-depth biological or neurological investigations of muscle co-activation mechanisms.
- Real-time implementation or hardware integration; the focus remains on offline data analysis and algorithm development.

References

[1] X. Cheng, S. Shen, E. Ivanova, G. Carboni, A. Takagi, and E. Burdet, "Human impedance modulation to improve visuo-haptic perception," *PLoS computational biology*, vol. 21, no. 5, p. e1013042, 2025.

[2] D. P. Kingma, M. Welling *et al.*, "Auto-encoding variational bayes," 2013.

B Risk assessment

General Risk Assessment Form

Date: (1)	Assessed by: (2)	Checked / Validated* by: (3)	Location: (4)	Assessment ref no (5)	Review date: (6)
20/6/2025	Shuyan Zhang		Home (Square Gardens) and University of Manchester (Main Library, Nancy Rothwell Building and Alan Gilbert Learning Commons)		

Task / premises: (7)
Working from home and on campus, including working out of hours

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Working from home	Lone working	Shuyan Zhang Isolated,	1. Refer to the University Lone Working policy and guidance for more information 2. Refer to the new University Working at Home guidance 3. Refer to the new University Wellbeing Support website Participant is able to have regular direct contact with line manager and colleagues via phone, Teams, Zoom or email	Low	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Working from home	Poor posture, repetitive movements, eye strain, from long periods looking at DSE (display screen equipment)	Shuyan Zhang Back strain (due to poor posture). Repetitive Strain Injury (RSI) to upper limbs. Eye strain.	1. Refer to the DSE policy, guidance and poster for more information on how to set up your workstation properly 2. Complete DSE Self-Assessment for home working at least every 2 years but sooner if any changes or pain is experienced. 3. Complete Homeworking self-assessment checklist 4. Set up workstation to a comfortable position with good lighting and natural light where possible 5. Take regular breaks away from the screen 6. Regularly stretch arms, back, neck, wrists and hands to avoid repetitive strain injuries. Refer to seated exercises 7. Set up a desktop working space where possible and try to avoid working on a laptop without a docking station, separate keyboard or mouse 8. Small equipment purchases of up to £50 to assist with working from home, contact local administration for more details. 9. If experiencing ill-health issues contact local DSE assessor or local safety advisor who will perform a full DSE assessment. 10. Occupational health referral where issues cannot be resolved from full DSE assessment. 11. DSE users should have regular eye tests, follow guidance FSE run monthly DSE awareness sessions on Teams	Low	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Working from home	Stress / Wellbeing	Shuyan Zhang Psychosocial effects Work / Life imbalance Anxiety Poor performance Fatigue & Tiredness	1. Refer to Stress Prevention and Management toolkit for policies and guidance 2. Refer to new University guidance for Managing teams working from home 3. Refer to Seven rules of home working published by AMBS 4. Refer to Guidance for Managers and Guidance for Staff 5. Complete training Work Related Stress: Identification, Prevention & Management (Online) 6. The University Stress Assessment tool can be used to highlight the main factors for an individual that are recognised as having the potential to lead to work-related stress 7. Projects, work plans and objectives to be discussed and agreed with line manager regularly 8. Refer to full FSE Stress Risk Assessment 9. Regular contact meetings with manager and peers via Teams, Zoom, email and phone 10. Define working hours, set a start & close daily routine, and prioritise tasks.	Low	A
Use of electrical appliances	Misuse of electrical appliance, faulted electrical appliance.	Shuyan Zhang Electric shock, burns and fire	1. All office equipment used in accordance with the manufacturer's instructions 2. Visual checks before use to make sure equipment, cables and free from defects 3. University IT equipment brought home should already be PAT tested, small electrical items can be tested through the FSE I&F team 4. The domestic electrical supply and equipment owned by the employee is the responsibility of the employee to maintain 5. Liquid spills cleaned up immediately Defective plugs, cables and equipment should be taken out of use	Med	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Moving around the home office	Obstructions and trip hazards	Shuyan Zhang Slips, trips and falls causing physical injury	1. Floors and walkways kept clear of items, e.g. boxes, packaging, equipment etc 2. Furniture is arranged such that movement of people and equipment are not restricted 3. Make sure all areas have good level of lighting 4. Reasonable standards of housekeeping maintained 5. Trailing cables positioned neatly away from walkways Cabinet drawers and doors kept closed when not in use	Med	A
Working from home and on campus	Fire	Shuyan Zhang Risk of burns, smoke inhalation, asphyxiation	1. In the event of a fire evacuate out of the building and call the fire brigade on 999 2. All waste, including combustible waste, removed regularly 3. Heaters located away from combustible materials and switched off when not in use, don't leave heaters unattended 4. Avoid daisy chaining and do not overload extension leads 5. Please refer to fire brigade Home Fire Safety and Smoke Alarms	Med	A
Working from home and on campus	Manual handling	Shuyan Zhang Back pain bruises, sprains, strains, fractures.	1. Do not store large, heavy, fragile or cumbersome items at height (e.g. on high shelves or on top of cabinets/bookcases etc.) 2. Ensure there is a firm grip on the item whilst moving 3. Ensure trip hazards are removed on route from the front door to where the item is to be located.	Low	A
Working from home and on campus	Accident / Incidents	Shuyan Zhang Injuries from home working activities	1. If suffer an accident / incident whilst working at home in relation to your workstation, please report the event to your line manager and the School Safety Advisor and complete an accident / incident form. 2. Ensure you have adequate first aid supplies to treat minor injuries. Call 999 in an emergency. 3. All Campus Security staff are first aid trained. Security contact details are 0161-306-9966. This telephone number can be found on the back of staff/student ID cards. 4. AEDs/ Defibrillators are located throughout campus, please see map for nearest location	Low	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Working on campus	COVID infection through close contact or the contact with surfaces which may have been contaminated by previous users	Shuyan Zhang, other students, staff, visitors Infection of respiratory illness	1. COVID restrictions have ceased in the UK. 2. Face coverings and hand sanitisers remain available at main entrances of University buildings. 3. Refer to the latest University's COVID guidance, https://www.staffnet.manchester.ac.uk/campus-management	Med	A
Maintaining building security	Suspicious people/ activities in and around campus	Shuyan Zhang, other students, staff, visitors Difficulty in contacting help/assistance	1. If using a swipe card to access a building, do not allow anyone to tailgate 2. If seeing any suspicious activities in and around the premises, get yourself to a safe place and call Campus Security immediately on 0161 306 9966 3. Do not enter into any area unauthorised for your use, lone working or out-of-hours 4. Do not prop doors open When entering and exiting the building, keep to well-lit area and be extra vigilant of surroundings	Med	A
Use of office electrical equipment, both Personal and University Owned	Electric shocks Fire Damage to other electrical equipment Misuse of electrical appliance, faulted electrical appliance.	Shuyan Zhang Burns, Smoke inhalation,	1. Any damaged equipment should be taken out of service and either replace or repaired. 2. All equipment whether personal or UoM owned must comply with relevant standards such as the British Standard or EU standards. 3. All equipment should be used in accordance with the manufacturer's instructions. 4. Liquid spills near electrical equipment should be cleaned up immediately. 5. Extension cables should be avoided as much as possible. Daisy-chaining is not permitted. 6. Visual checks before use to make sure equipment, cables and free from defects Defective plugs, cables equipment etc. should be taken out of use and be reported for repair/replacement.	Low	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Use of display screen equipment Repetitive/prolonged use of equipment or tasks	Incorrect posture whilst using DSE Incorrect workstation set up Prolonged use without breaks Electrical hazards	Shuyan Zhang Musculoskeletal injuries/disabilities Limb disorders Eye strain Headaches Back pain Repetitive strain Fatigue Electric shock	1. Please refer to the DSE policy, guidance and poster for more information on how to set up your workstation properly 2. Complete DSE Self-Assessment for a Safety Advisor to review and report back with any recommendations or actions. 3. Seats should be stable and adjustable to provide comfort 4. Set up workstation to a comfortable position with good lighting and natural light where possible 5. Take regular breaks away from the screen. 6. Regularly stretch your arms, back, neck, wrists and hands to avoid repetitive strain injuries. Refer to workstation exercises here 7. Provision of adjustable equipment and furniture available following DSE assessment 8. Refer to use of electrical equipment. Any work of a repetitive nature must be subject to a separate risk assessment in consultation with a Safety Advisor	Low	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Work at Height	Falls Falling objects	Shuyan Zhang, other students, staff, visitors Users fall from ladders or other height or drop items which can injure others through direct impact or indirectly through damaging equipment	• Avoid storing items high up. All heavy objects should not be stored high up. • Users who are required to use steps, ladders or other access equipment must complete the working at height training course available through SLD TLCO500. • Following training, users must read sign and follow the specific working on ladders risk assessment • Any work at height that falls outside of the scope of the working at height training must be specifically risk assessed • Identified working at height equipment is inspected at least annually and records kept locally. • Pre-use visual checks must be done by the user every time especially if locking mechanisms are needed. Different types of working at height equipment e.g. access steps, ladders, foot stools, are available to allow users to choose the most appropriate for the task.	Low	A

Activity (8)	Hazard (9)	Who might be harmed and how (10)	Existing measures in place to control the risk (11)	Risk rating (12)	Result (13)
Working out of hours	Potential for lone-working Changes to the environment during evenings and weekends	Shuyan Zhang More vulnerable. Difficulty in contacting help/assistance	1. Out of hours working to be approved by line manager/ Academic Supervisor beforehand. 2. Minimise the duration and frequency of working out of hours. 3. Carry a charged up mobile phone on person at all times. 4. Be aware of out of hours safety protocols, including security contact telephone numbers, evacuation and first aid information. 5. General building and campus support will be reduced out of hours. 6. Inform someone beforehand of the planned lone working (time, location and duration). Set up a buddy system so you contact someone at regular intervals (within the building if possible or by telephone /emails/ Teams etc.) 7. Accompanied buddy is for high-risk activities = Work with another person in the same area in close proximity 8. Remote buddy is for low-risk activities = Regular contact with another person via visits, phone, texts or emails 9. SafeZone app can be set with a check-in timer during out of hours use. Should the timer not be switched off, security and/ or remote buddy will be alerted to call occupant. 10. In an emergency or if in need of first aid call Campus Security on 0161 3069966	Med	A

Notes to accompany General Risk Assessment Form

This form is recommended for use by Safety Services. It is strongly suggested that you use it for all new assessments, and when existing assessments are being substantially revised. However, its use is not compulsory. Providing the assessor addresses the same issues, alternative layouts may be used.

(1) **Date** : Insert date that assessment form is completed. The assessment must be valid on that day, and subsequent days, unless circumstances change and amendments are necessary.

(2) **Assessed by** : Insert the name and signature of the assessor. For assessments other than very simple ones, the assessor should have training in assessing risks (eg completed TLCO300 Principles of Risk Assessment E Learning) from the L&OD Training Catalogue or equivalent)

(3) **Checked / Validated* by** : delete one.

Checked by : Insert the name and signature of someone in a position to check that the assessment has been carried out by a competent person who can identify hazards and assess risk, and that the control measures are reasonable and in place. The checker will normally be a line manager, supervisor, principal investigator, etc. Checking will be appropriate for most risk assessments.

Validated by : Use this for higher risk scenarios, eg where complex calculations have to be validated by another "independent" person who is competent to do so, or where the control measure is a strict permit-to-work procedure requiring thorough preparation of a workplace. The validator should also have attended the University's risk assessment course or equivalent, and will probably be a chartered engineer or professional with expertise in the task being considered. Examples of where validation is required include designs for pressure vessels, load-bearing equipment, lifting equipment carrying personnel or items over populated areas, and similar situations.

(4) **Location** : insert details of the exact location, ie building, floor, room or laboratory etc. that the assessment covers If off-campus, provide information about expected location(s) or attach itinerary.

(5) **Assessment ref no** : use this to insert any local tracking references used by the school or administrative directorate.

(6) Review date : insert details of when the assessment will be reviewed as a matter of routine. This will usually be in 1 year's time, at the end of a short programme of work, or longer period if risks are known to be stable. Note that any assessment **must be reviewed if there are any significant changes – to the work activity, the vicinity, the people exposed to the risk, etc**

(7) **Task / premises** : insert the scope of the risk assessment, what it covers and where appropriate, what it doesn't cover. Include a brief summary of the task/activity/process being assessed, eg typical office activities such as filing, DSE work, lifting and moving small objects, use of miscellaneous electrical equipment. Or, research project [title] involving the use of typical laboratory hardware, including fume cupboards, hot plates, ovens, analysis equipment, flammable solvents, etc. NB ensure all the activities associated with the task are included eg preparation steps, maintenance tasks and waste disposal/clean up activity.

(8) **Activity** : use the column to describe each separate activity covered by the assessment. The number of rows is unlimited, although how many are used for one assessment will depend on how the task / premises is sub-divided. For laboratory work, activities in one particular lab or for one particular project might include: use of gas cylinders, use of fume cupboard, use of computer or other electrical equipment, use of lab ovens, hot plates or heaters, use of substances hazardous to health, etc

(9) **Hazard** : for each activity, think about and list the hazards that may cause harm as a result of the specific work you intend to do. Remember to consider hazards that are not immediately obvious. For example, use of a lathe will require identification of the machine hazards, but also identification of hazards associated with the use of cutting oils (dermatitis), poor lighting, slipping on oil leaks, repetitive actions, etc. The same activity might well have several hazards associated with it.

Assessment of simple chemical risks (eg use of cleaning chemicals in accordance with the instructions on the bottle) may be recorded here. More complex Chemical risk assessments eg for laboratory processes, can be recorded on a specific COSHH / Chemical risk assessment form.

(10) **Who might be harmed and how** : Think about all who may be harmed by each hazard and what that harm might be. List everyone who might be affected by the activity and specify groups particularly at risk. Remember those who are not immediately involved in the work, eg colleagues, cleaners, young persons on work experience, maintenance contractors, Estates personnel carrying out routine maintenance and other work. Remember also that the risks for different groups will vary. Eg someone who needs to repair a laser may need to expose the beam path more than a laser user would do. Vulnerable groups could include children on organised visits, pregnant/nursing mothers, or employees and students with known disabilities or health conditions, or those working alone (this is not a definitive list).

For each group, describe how harm might come about, eg an obstruction or wet patch on an exit route is a hazard that might cause a trip and fall; use of electrical equipment might give rise to a risk of electric shock; use of a ultraviolet light source could burn eyes or skin.

(11) **Existing measures in place to control the risk** : list all measures that are already in place to mitigate the risk. They should be considered in the following order of effectiveness; a combination of controls is usually required:

Eliminate the hazard completely
Substitute by using a less hazardous option
Engineering Controls to isolate people from the hazard eg work in a fume cupboard or use other local exhaust ventilation, ensure machines are guarded,
Administration Controls – eg training requirements, supervisory requirements, use of safe systems of work, signage, access control, reducing time spent at the task
Personal Protective Equipment (PPE) – specify exactly what type will be needed to control the risk
(see also University Arrangements Chapter 9 & associated guidance)

Many of these will have been implemented for other reasons, but should nevertheless be recognised as means of controlling risk. For example, restricting access to laboratories or machine rooms for security reasons also controls the risk of unauthorised and unskilled access to dangerous equipment. A standard operating procedure or local rules (eg for work with ionising radiation, lasers or biological hazards) will often address risks. Some specific hazards may require detailed assessments in accordance with specific legislation (eg COSHH, DSEAR, manual handling, DSE work). Where this is the case, and a detailed assessment has already been done in another format, the master risk assessment can simply cross-reference to other documentation. For example, the activity might be 'use of a carcinogen', the hazard might be 'exposure to hazardous substances', the existing control measures might all be listed in a COSHH assessment. Controls might also include use of qualified and/or experienced staff who are competent to carry out certain tasks; an action plan might include training requirements for other people who will be carrying out those tasks.

(12) **Risk Rating** : the simplest form of risk assessment is to rate the remaining risk as high, medium or low, depending on how likely the activity is to cause harm and how serious that harm might be.

The risk is **LOW** - if it is most unlikely that harm would arise under the controlled conditions listed, and even if exposure occurred, the injury would be slight.

The risk is **MEDIUM** - if it is more likely that harm might actually occur and the outcome could be more serious (eg some time off work, or a minor physical injury.

The risk is **HIGH** - if injury is likely to arise (eg there have been previous incidents, the situation "looks like an accident waiting to happen") and that injury might be serious (broken bones, trip to the hospital, loss of consciousness), or even a fatality.

Schools or Directorates may choose to use other rating systems. Typical amongst these are matrices (of 3x3, 4x4, 5x5 or even more complex) which require the assessor to select a numerical rating for both "likelihood that harm will arise" and "severity of that harm". These may give a spurious sense of accuracy and reliability – none are based on quantitative methods. There are methods of estimating risk quantitatively, and these may be appropriate for complex design of load bearing structures and the like.

Advice on methods of complex risk assessment is available from Safety Services. Whatever system of assessment is adopted, it is **essential** that the assessor has received suitable training and is familiar with the meaning of the terms (or numbers) used.

(13) **Result** : this stage of assessment is often overlooked, but is probably the most important. Assigning a number or rating to a risk does not mean that the risk is necessarily adequately controlled. The options for this column are:

T = trivial risk. Use for very low risk activities to show that you have correctly identified a hazard, but that in the particular circumstances, the risk is insignificant.

A = adequately controlled, no further action necessary. If your control measures lead you to conclude that the risk is low, and that all legislative requirements have been met (and University policies complied with), then insert A in this column.

N = not adequately controlled, actions required. Sometimes, particularly when setting up new procedures or adapting existing processes, the risk assessment might identify that the risk is high or medium when it is capable of being reduced by methods that are reasonably practicable. In these cases, an action plan is required. The plan should list the actions necessary, who they are to be carried out by, a date for completing the actions, and a signature box for the assessor to sign off that the action(s) has been satisfactorily completed. Some action plans will be complex documents; others may be one or two actions that can be completed with a short timescale.

U = unable to decide. Further information required. Use this designation if the assessor is unable to complete any of the boxes, for any reason. Sometimes, additional information can be obtained readily (eg from equipment or chemicals suppliers, specialist Safety advisors) but sometimes detailed and prolonged enquiries might be required. Eg is someone is moving a research programme from a research establishment overseas where health and safety legislation is very different from that in the UK.

For T and A results, the assessment is complete.
For N or U results, more work is required before the assessment can be signed off.

(14) **Action Plan**. Include details of any actions necessary in order to meet the requirements of the information in Section 11 'Existing measures in place to control the risk'. Identify someone who will be responsible for ensuring the action is taken and the date by which this should be completed. Put the date when the action has been completed in the final column.

C Additional experimental results

Due to space constraints in the main body of the paper, this appendix presents supplementary experimental results and analyses that provide further insight into the performance and characteristics of the environmental recognition system.

C.1 Correlation between tracking quality and recognition performance

This analysis examined whether individual participants' tracking performance was correlated with the environmental recognition performance of classifiers trained on their physiological data. Tracking quality was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Maximum Error during the tracking task, while recognition performance was measured by the best F1 score achieved by any classifier for each subject.

Analysis and discussion: The results indicate a complex relationship between tracking quality and recognition accuracy. No strong direct correlation was found between error-based tracking metrics (MSE, RMSE) and recognition performance (F1 score). However, participants with extremely poor tracking ability (e.g. Subject 12, MSE = 45.60) tended to achieve lower recognition accuracy, whereas others with moderate tracking errors were still able to reach high recognition performance (e.g. Subject 20, MSE = 19.62, F1 = 0.769).

Interestingly, the correlation coefficient between the target and actual trajectory exhibited a stronger positive relationship with recognition performance (mean correlation = 0.934 across subjects). This suggests that participants who maintained a consistent relationship with the target trajectory—even with substantial absolute error—produced more discriminative physiological signals for environmental recognition than those with inconsistent tracking behaviour.

C.2 Association between VAE training quality and classification performance

This analysis investigated whether the quality of variational autoencoder (VAE) training, measured by the test reconstruction loss, was associated with downstream classification performance in environmental recognition.

Analysis and discussion: The relationship between VAE test loss and classification performance was found to be weak and non-linear. The Pearson correlation coefficient between VAE test loss and best F1 score was -0.28, indicating only a slight tendency for lower reconstruction error to correspond with better classification performance; however, this relationship was not statistically significant ($p > 0.05$).

Moreover, some participants with relatively high reconstruction loss achieved strong classification results (e.g. Subject 4, loss = 58.29, F1 = 0.670), while others with comparatively low loss exhibited poorer performance (e.g. Subject 10, loss = 43.71, F1 = 0.549). This suggests that a VAE's capacity to reconstruct input signals accurately does not necessarily translate into the extraction of features that are most discriminative for classification.

The absence of a strong association implies that VAE representation learning and classification optimise different objectives. While VAEs seek compact latent representations suitable for reconstruction, the features that are most informative for environmental recognition may correspond to different signal properties. This finding supports the use of task-specific feature extraction methods (e.g. the Advanced Stats approach) rather than relying solely on unsupervised representation learning in this application.