Towards Deep Clustering of Human Activities from Wearables

Alireza Abedin  
The University of Adelaide  
alireza.abedin@adelaide.edu.au

Farbod Motlagh  
The University of Adelaide  
farbod.motlagh@student.adelaide.edu.au

Qinfeng Shi  
The University of Adelaide  
javen.shi@adelaide.edu.au

Hamid Rezatofighi  
The University of Adelaide  
hamid.rezatofighi@adelaide.edu.au

Damith Ranasinghe  
The University of Adelaide  
damith.ranasinghe@adelaide.edu.au

ABSTRACT

Our ability to exploit low-cost wearable sensing modalities for critical human behaviour and activity monitoring applications in health and wellness is reliant on supervised learning regimes; here, deep learning paradigms have proven extremely successful in learning activity representations from annotated data. However, the costly work of gathering and annotating sensory activity datasets is labor intensive, time consuming and not scalable to large volumes of data. While existing unsupervised remedies of deep clustering leverage network architectures and optimization objectives that are tailored for static image datasets, deep architectures to uncover cluster structures from raw sequence data captured by on-body sensors remains largely unexplored. In this paper, we develop an unsupervised end-to-end learning strategy for the fundamental problem of human activity recognition (HAR) from wearables. Through extensive experiments, including comparisons with existing methods, we show the effectiveness of our approach to jointly learn unsupervised representations for sensory data and generate cluster assignments with strong semantic correspondence to distinct human activities.

CCS CONCEPTS

• Human-centered computing → Ubiquitous computing: • Computing methodologies → Neural networks.

KEYWORDS

Activity Recognition; Deep learning; Clustering; Wearable Sensors

1 INTRODUCTION

Accurately and precisely understanding human activities is the basis for applications ranging from assessing our cognitive decline, physical and mental health to performance in sporting activities [10–13, 17, 24, 27, 32]. Increasing plethora of wearables are providing the opportunity to conveniently and at low-cost collect fine-grained physiological information to understand human activities. However, the premise for realizing the multitude of applications is our ability to build accurate and, often personalized, models for recognizing human activities from wearables.

Problem. Human activity recognition problems have relied predominantly on supervised learning regimes where deep learning paradigms are extremely successful in learning activity representations from annotated data. While the process of collection and annotation may be retrospective with vision based sensing modalities where visual inspections of, for example, video frames provides the basis for ground truth, the parallel task with wearables is nearly impossible. Moreover, such methods cannot be easily scaled to gather large datasets often necessary for deep neural networks (DNNs). In comparison to other domains, generating labelled data to benefit from supervised learning methods to build HAR applications in the absence of a reliable visualisation to establish ground truth is a unique HAR problem with wearable sensors.

Our Motivation. Although unsupervised methods provide avenues for learning from unlabelled data, investigations of unsupervised learning from wearable multi-channel time-series data remains dominantly limited to pre-training [3, 36] or unsupervised representation learning [6, 19]. Unsupervised alternatives without requiring any labels, such as deep clustering, exist for image data, however, these frameworks are tailored for still images and lack the inherent capability to learn representations and clusters from raw sequential data captured by wearables. Therefore, our motivation is to investigate and develop a deep clustering architecture that:

• Leverages the inherently sequential nature of sensory data.
• Learns clustering friendly representations of activity features in the multi-sensor and multi-channel input signals that offer separability of activity classes in the feature space.
• Promotes the formation of highly discriminative clusters with high semantic correspondence to human activities.

Our Contributions. In this study, we propose Deep Sensory Clustering—a deep clustering architecture that learns highly discriminative representations using self-supervision with reconstruction and future prediction tasks informed by feedback from a clustering objective to guide the network towards clustering-friendly representations.

The self-supervised tasks intend to incentivize the network to learn salient activity features that offer semantic separation in the feature space while simultaneously reducing the risk of collapsing clusters. Further, we augment the optimization objective with...
a clustering-oriented criterion to further refine the feature representations and gradually promote clustering-friendliness in the feature space. We validate our design concepts through extensive experiments; we summarize our key contributions below:

1. We develop an unsupervised deep learning network architecture for clustering human activities from raw sequences of wearable sensor data streams. Our approach, to the best of our knowledge, provides the first standalone, end-to-end, deep clustering method for raw sequential data from wearables.

2. Through a systematic experimental regime conducted on three diverse HAR benchmark datasets (UCI HAR, Skoda, MHEALTH), we demonstrate the effectiveness of our proposed approach. Further, we compare our method with closely related approaches, including traditional clustering methods.

## 2 RELATED WORKS

### Human Activity Recognition with Wearables

The superior performance of supervised deep neural networks in classification tasks has led to a shift towards the adoption of deep learning paradigms for recognizing human activities from raw wearable data [2, 20, 23, 30]. Researchers have explored CNNs [8, 33, 39–41], RNNs [15, 18], and a combination of convolutional and recurrent layers [1, 29, 31] to effectively model the temporal dependencies inherent in sequences captured with sensors. However, acquisition of labeled sensory data is labor-intensive and time-consuming. But, in the sequential sensor data domain, unsupervised learning has merely been investigated as a means for weight initialization [3, 19], unsupervised feature learning prior to supervised fine tuning with labels [6, 36] or clustering of handmade features [22], rather than a standalone end-to-end approach for exploiting cheaply accessible raw unlabelled data.

### Clustering with Deep Neural Networks

Recently, representation learning power of DNNs has been leveraged to achieve clustering-friendly representations and cluster assignments simultaneously for still image data; a shift towards Deep Clustering paradigms [28]. In this regard, the feature space for representing images is initialized using deep autoencoders and iteratively refined to obtain cluster assignments [25, 37]. Following similar ideas, Chen et al. [9] propose a locality preserving criteria to learn structure preserving image representations, and Dizaji et al. [14] encourage balanced cluster assignments during training. In another study, a CNN is trained with agglomerative clustering objective in a recurrent process [38]. Although these methods achieve impressive results for computer vision applications, existing deep clustering frameworks are tailored for still image datasets and suffer from their inability to exploit the sequential nature of wearable sensor data streams to learn representations and generate clusters of activities as substantiated in Section 4.1.

### 3 THE PROPOSED FRAMEWORK

We consider the problem of clustering a set of \( n \) unlabelled segments of sensory readings \( \{x_i\}_{i=1}^{n} \) into \( k \) clusters, each representing a semantic human activity category. These segments are obtained by applying a sliding window of fixed temporal duration \( \delta t \) over \( d \) sensor channels of recorded datastreams. We propose our unsupervised two-staged Deep Sensory Clustering framework illustrated in Fig. 1 for the problem and detail our approach in what follows.

### 3.1 Pretraining a Multi-Task Autoencoder

In order to facilitate learning clustering-friendly representations, we initialize the feature space by pretraining a recurrent autoencoder to accomplish auxiliary tasks in an unsupervised fashion. In accomplishing the delegated tasks, the network is forced to extract enriched representations from the multi-channel sensor sequences. Recurrent Encoder (\( \text{Enc}_0 \)). The encoder component of our network consumes a windowed excerpt of a raw multi-channel sensory sequence and learns a compact fixed length representation as a holistic summary of the input. In particular, we adopt a bi-directional GRU that reads through the partitioned sensory sequence \( x \) in both forward and backward directions and updates its internal hidden state in each time step according to the received input. The final hidden state obtained after scanning the entire input sequence is reduced in dimensionality through a fully connected layer. The resulting low-dimensional embedded feature, denoted by \( z \in \mathbb{R}^d \), encodes contextual activity information by modeling the temporal dependencies present in the input sequence of sensory measurements \( x \). We summarize the parameterized operations associated with encoding the input sequence \( x \) as \( z_i = \text{Enc}_0(x_i) \).

**Conditional Recurrent Decoders (\( \text{Dec}_i \)).** The decoder modules of the framework are structured symmetrically to the encoder component. First, a context vector is achieved by back projecting the embedded representation from the encoder into a higher-dimensional space such that it can be used to initialize the hidden states for the decoders. Two recurrent decoders then jointly exploit the generated context vector to accomplish different self-supervised tasks without requiring any manual supervision. Inspired by [34], we share the encoder network between decoders with two different expertise; one decoder is specialized to reconstruct the temporally inverted input sequence, while the other one learns to anticipate the future sensory measurements that should follow after, conditioned on the encoded input representation. Hence, the network has to not only learn a representation enriched with sufficient information to reproduce the input sequence, but also features that allow extrapolating future measurements. We sum up the parameterized decoding process as \( (\hat{y}_i^{\text{rec}}, \hat{y}_i^{\text{fut}}) = \text{Dec}_i(z_i) \), where \( \hat{y}_i^{\text{rec}} \) and \( \hat{y}_i^{\text{fut}} \) respectively denote the reconstructed and the anticipated sequences generated from the input \( x_i \) to satisfy the tasks.

**Pre-training Objective.** We pre-train the entire recurrent autoencoder with a joint objective function,

\[
L^{(i)}_{\text{AE}} = L^{(i)}_{\text{rec}} + L^{(i)}_{\text{fut}} = \|y_i^{\text{rec}} - \hat{y}_i^{\text{rec}}\|^2 + \|y_i^{\text{fut}} - \hat{y}_i^{\text{fut}}\|^2,
\]

where \( L_{\text{rec}} \) and \( L_{\text{fut}} \) denote the mean square error between each decoder’s generated output sequence (i.e., \( \hat{y}_i^{\text{rec}} \) and \( \hat{y}_i^{\text{fut}} \)) and the expected ground-truth target sequences (i.e., \( y_i^{\text{rec}} \) and \( y_i^{\text{fut}} \)). Once the training is complete and the discrepancy between the generated outputs and their corresponding target sequences is minimized, the optimal network parameters, i.e., \( (\theta^*, \phi^*) = \min_{\theta, \phi} \frac{1}{n} \sum_{i=1}^{n} L^{(i)}_{\text{AE}} \), serve as an initialization point for the second stage.
3.2 Representation Refinement with a Clustering Criterion

Once the autoencoder becomes proficient in accomplishing the auxiliary tasks, we expect the feature space to find a semantic orientation. We further extend our framework with a parameterized clustering network \( f_\omega(.) \) capable of estimating cluster assignment distributions and iteratively optimizing a clustering objective \( \mathcal{L}_C \) to refine the feature space and guide the network towards yielding clustering-friendly representations. In this paper, we incorporate Cluster Assignment Hardening [37] as a representative centroid-based approach for further refinement of the established feature space. During the refinement stage, both the clustering loss \( \mathcal{L}_C \) and the autoencoding objectives \( \mathcal{L}_{AE} \) are jointly incorporated to be optimized. Hence, the aggregated optimization criterion, for instance \( i \), is formulated as

\[
\mathcal{L}^{(i)} = \gamma \mathcal{L}^{(i)}_C + \mathcal{L}^{(i)}_{AE},
\]

where the coefficient \( \gamma \in [0, 1] \) controls contribution of the clustering objective. Notably, we chose not to discard the decoding tasks during the refinement step to preserve the local data structure and allow a smoother manipulation of the feature space without distorting the previously established one. Once the network parameters are optimized with respect to the global criterion, \( (\theta^*, \phi^*, \omega^*) = \min_{\theta, \phi, \omega} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}^{(i)} \) , the clustering network of our framework directly delivers cluster assignments \( w^{(i)} \) requiring a separate clustering algorithm to be run on the representations in a decoupled process. We describe the clustering criterion utilized next.

Cluster Assignment Hardening (CAH). This clustering objective leverages the similarities between the data representations and the cluster centroids as a kernel to compute soft cluster assignments. Placing emphasis on the high confidence assignments, it then purifies the clusters and forces the assignments to have stricter probabilities. To incorporate this method, our clustering network \( f_\omega(.) \) comprises a single layer which maintains the cluster centroids \( (\omega_j \in \mathbb{R})_{j=1}^{k} \) as tunable network parameters and generates assignment distributions \( q_i = f_\omega(z_i) \) for each instance \( i \). This layer follows the Student’s t-distribution to measure the similarity of embedded sequence representation \( z_i \in \mathbb{R}^k \) to the \( k \) cluster centroids and therefore, obtains the normalized similarities \( Q_i = (q_{ij})_{j=1}^{k} \),

\[
q_{ij} = \frac{(1 + \|z_i - \omega_j\|_{\phi}^2)^{-1}}{\sum_{j=1}^{k} (1 + \|z_i - \omega_j\|_{\phi}^2)^{-1}}.
\]

Through squaring this distribution and then normalizing it, an auxiliary target distribution \( P_i = (p_{ij})_{j=1}^{k} \) that leverages high confidence assignments is then defined to point the learning process towards stricter cluster assignments.

\[
p_{ij} = \frac{q_{ij}^2}{\sum_{j=1}^{k} q_{ij}^2}.
\]

Subsequently, the soft assignment distribution \( Q_i \) is iteratively purified through minimizing the Kullback-Leibler (KL) divergence between the soft labels and the auxiliary target distribution via training the network parameters, \( \mathcal{L}^{(i)}_C = KL(P_i||Q_i) = \sum_{j=1}^{k} p_{ij} \log \frac{p_{ij}}{q_{ij}} \).

This centroid-based approach requires the cluster centers to be initialized once at the beginning of the refinement stage. The initial centers are obtained by applying classical clustering algorithms on the acquired representations from the optimal pretrained parameters; i.e., \( \{z_i = \text{Enc}_{\theta^*}(x_i)\}_{i=1}^{n} \).

4 EXPERIMENTS

We ground our study by evaluating on three diverse HAR benchmark datasets: UCI HAR [4]; Skoda [35]; and MHEALTH [7] employing standard train and holdout test splits (as summarized in Table 1). Datasets are initially rescaled using per-channel normalization. After adopting the sliding window segmentation technique to partition the continuous data-streams, we consider the first 50% of sensory measurements in each segment to constitute the input sequences to our framework. Accordingly, the temporally inverted version of the input is used as the target sequence for the reconstruction task while the remaining sensory measurements are considered as the target sequence for the future prediction task.

**Network Architecture.** We leverage a 2-layer bi-directional GRU with 256 hidden units for the encoder. The decoders have an identical structure but utilize uni-directional connections. Considering the lower input dimension for UCI HAR compared with Skoda and MHEALTH datasets, we impose a bottleneck embedding dimension of 64 for the former and 256 for the latter in our autoencoders. The clustering network \( f_\omega(.) \) for integrating CAH uses a single layer that generates soft cluster assignments according to Eq. (3).

**Optimization Settings.** In mini-batches of size 256, the network parameters are updated using the ADAM optimizer with the initial learning rate set to \( 10^{-3} \) and decayed by a factor of 10 after 70 epochs. The network is pretrained for 100 epochs, and fine-tuned with the clustering objective until the cluster assignment changes.
between two consecutive epochs is less than 0.1%. The weighting coefficient γ is set to 0.1. All above parameters are held constant across all datasets to refrain from unrealistic parameter tuning.

4.1 Clustering

We base our evaluations for clustering on the two widely adopted metrics of unsupervised clustering accuracy (ACC) and Normalized Mutual Information (NMI) [28]. Our approach is compared against popular centroid-based k-means clustering [5] as well as representative hierarchical algorithms including agglomerative clustering with average linkage (AC-Average) [21], agglomerative clustering with complete linkage (AC-Complete) and Ward agglomerative clustering (AC-Ward). Further, we compare against end-to-end deep clustering methods proposed in [16, 37] for still images and show their inability to cater for the sequential nature of time-series data. Clustering Performance. In Table 2, we evaluate the clustering performance of the traditional baselines on both the: i) data space using raw input representations; ii) autoencoding space using the embedded features \( \{ z_i = \text{Enc}(x_i) \}_{i=1}^{n} \) attained by optimizing \( L_{AE} \) in the pretraining stage; and iii) compare with the end-to-end cluster assignments generated by deep clustering baselines and our proposed Deep Sensory Clustering. As required by the CAH objective, we report results over two different strategies to initialize the cluster centers only once before commencing the refinement stage: i) we run k-means clustering on the embedded features to obtain k centroids; and ii) we perform Ward clustering and use the mean representation of the obtained clusters as initial centers.

Our results demonstrate that our end-to-end approach not only outperforms traditional clustering algorithms applied on both input data and auto-encoding spaces, but also offers a large performance margin over representative deep clustering baselines proposed for image data. Without any manual supervision, our proposed unsupervised approach can directly deliver cluster assignments with high correspondence to activities of interest in the explored datasets; we can observe accuracy (ACC) performance of 78.79%, 52.9% and 57.19%, respectively on UCI HAR, Skoda and MHEALTH datasets. In addition, the consistent improvement of unsupervised metrics across all three HAR datasets using our proposed framework demonstrates its generalizability to different HAR problems.

Visualization. In Fig. 2, we illustrate: i) the evolution of the feature space towards the ultimate clustering-oriented embedding space achieved with our framework; and ii) the deep clustering baselines by visualizing the data representation for the sequences in UCI HAR using t-SNE [26]. For our framework, we show the original dataset \( (data\ space) \), the dataset embedded by the encoder after the pretraining stage (autoencoding space) and the final representations after optimizing for the aggregated objective function \( L \) in Eq. 2 (clustering-oriented space) with Ward initialization. We can observe that our framework discovers well-defined and clearly separated clusters of activity segments with strong correspondence to.

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Table 2: A quantitative comparison of clustering performance on three HAR benchmark datasets in accuracy (ACC) and NMI.

|Traditional Clustering on Input Data Space| UCI HAR Dataset| Skoda Dataset| MHEALTH Dataset|
|---|---|---|---|
|Train| Test Split| Train| Test Split| Train| Test Split|
|NMI| ACC| NMI| ACC| NMI| ACC|
|k-means| 44.28%| 45.62%| 49.71%| 48.37%| 54.06%| 49.71%|
|AC-Average| 4.61%| 14.34%| 5.95%| 14.34%| 6.23%| 14.03%|
|AC-Complete| 1.93%| 18.29%| 1.93%| 18.29%| 1.93%| 18.29%|
|AC-Ward| 53.85%| 45.48%| 53.85%| 45.48%| 53.85%| 45.48%|

|Traditional Clustering on Autoencoding Space| UCI HAR Dataset| Skoda Dataset| MHEALTH Dataset|
|---|---|---|---|
|Train| Test Split| Train| Test Split| Train| Test Split|
|NMI| ACC| NMI| ACC| NMI| ACC|
|k-means| 51.93%| 55.62%| 51.93%| 55.62%| 51.93%| 55.62%|
|AC-Average| 45.18%| 34.61%| 45.18%| 34.61%| 45.18%| 34.61%|
|AC-Complete| 40.66%| 43.67%| 40.66%| 43.67%| 40.66%| 43.67%|
|AC-Ward| 75.27%| 63.33%| 75.27%| 63.33%| 75.27%| 63.33%|

|End-to-End Deep Clustering| UCI HAR Dataset| Skoda Dataset| MHEALTH Dataset|
|---|---|---|---|
|Train| Test Split| Train| Test Split| Train| Test Split|
|ACC| 78.79%| 71.25%| 78.79%| 71.25%| 78.79%| 71.25%|
We tackle the hitherto unexplored problem of human action recognition from raw unlabelled multi-channel time-series data captured by wearables using a deep learning paradigm. To the best of our knowledge, ours is the first to investigate and develop a novel deep clustering architecture for HAR problems with raw sensor data. We demonstrate the effectiveness of the proposed approach across three diverse HAR benchmarks.

5 CONCLUSIONS

We tackle the hitherto unexplored problem of end-to-end clustering of human actions from raw unlabelled multi-channel time-series data captured by wearables using a deep learning paradigm. To the best of our knowledge, ours is the first to investigate and develop a novel deep clustering architecture for HAR problems with raw sensor data. We demonstrate the effectiveness of the proposed approach across three diverse HAR benchmarks.

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