Leveraging Activity Recognition to Enable Protective Behavior Detection in Continuous Data

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ABSTRACT
Protective behavior exhibited by people with chronic pain (CP) during physical activities is the key to understanding their physical and emotional states. Existing automatic protective behavior detection (PBD) methods depend on pre-segmentation of activity instances as they expect situations where activity types are predefined. However, during everyday management, people pass from one activity to another, and support should be delivered continuously and personalized to the activity type and presence of protective behavior. Hence, to facilitate ubiquitous CP management, it becomes critical to enable accurate PBD over continuous data. In this paper, we propose to integrate automatic human activity recognition (HAR) with PBD via a novel hierarchical HAR-PBD architecture comprising GC-LSTM networks, and alleviate the class imbalances therein using a CFCC loss function. Through in-depth evaluation of the approach using a CP patients’ dataset, we show that the leveraging of HAR, GC-LSTM networks and the CFCC loss function leads to clear increase in PBD performance against the state-of-the-art (macro F1 score of 0.81 vs. 0.66 and PR-AUC of 0.60 vs. 0.44). We conclude by discussing possible use cases of the HAR-PBD architecture in the context of CP management and other situations. We also discuss the current limitations and ways forward.

CCS CONCEPTS
• Applied computing → Life and medical sciences; • Computing methodologies → Machine learning.

KEYWORDS
Chronic pain, protective behavior, activity recognition, deep learning, continuous data.

1 Introduction
Chronic pain is a prevalent condition in ~30.7% of adults in the US [1]. People with chronic musculoskeletal pain (a common type of chronic pain) exhibit protective behavior (guarding, hesitation, the use of support, abrupt motion and rubbing) during physical activity [33], providing important information about their physical and emotional states and ability to manage their condition [34, 35]. In clinical rehabilitation, physiotherapists respond to this behavior by adjusting their feedback and the management strategies they advise [5]. This tailored support is critical to incrementally build patients’ self-efficacy and maintain their
engagement in physical activity [36]. However, such support is expensive and available to few people with CP. In addition, behavior in the clinic [68] is a narrow sample of the physical and psychological capabilities required for everyday physical functioning. Maintaining self-management is hard and people often disengage, thereby losing valued activities including social involvement [34]. To prevent disengagement, observation and personalized support need to extend beyond the clinical context [37].

Ubiquitous sensing and computing technology offer new opportunities to provide such support to people with CP. Patients describe technology capable of protective behavior detection (PBD) as a ‘second pair of eyes’, increasing their awareness and helping application of pain management strategies learned in the clinic [62]. In [79], patients and physiotherapists discussed how such technology could help patients to better control activity pacing and breathing when protective behavior is detected. The technology may also, e.g. replicate physiotherapists’ advice on chair height if the patient has difficulties sitting down or standing up. These studies also show that awareness of habitual protective behavior can help reduce it (e.g., reminding the person to bend the trunk as they stand up from a chair). In addition to providing personalized feedback, such technology can be adopted to evaluate the effect of clinical interventions [65].

The first step in building a ubiquitous technology to help people with CP in their everyday lives is to enable continuous PBD during diverse functional activities. To date, the focus has been on PBD in specific exercises where the activity being performed is known in advance. Interesting PBD results are only achieved within pre-segmented activity instances [25, 40, 64]. However, pre-segmentation is not feasible for everyday (functional) activities. In this paper, we aim to address these problems by approaching continuous PBD with continuous recognition of the activity (HAR) in process. We propose a novel hierarchical architecture, where the activity type when recognized is continuously leveraged to build activity-informed input for concurrent PBD.

To investigate the efficacy of our approach, we use the fully-annotated EmoPain dataset [32] that comprises full-body movement data (18 IMUs) captured from CP and healthy participants during sequences of movements reflecting everyday activities. We refer to these as Activities-of-Interest (AoIs) since they were chosen by physiotherapists as particularly demanding for people with CP and likely to trigger protective behavior. While this dataset was not collected in the wild, participants performed each activity without instruction, and transitions between AoIs created further noise typical of in-the-wild data collection. During transition periods, participants could rest according to their needs or enjoy casual movement such as stretching, walking and self-preparations. An illustration of a complete activity sequence of one CP participant with the protective behavior annotation is shown in Figure 1. Evaluation shows that the activity information noticeably improves the PBD performance in such continuous data, achieving macro F1 score of 0.73 and PR-AUC of 0.52 in comparison with the baseline method without such information (macro F1 score of 0.66 and PR-AUC of 0.44). By alleviating class imbalances with a CFCC loss function, PBD performance is further improved, achieving macro F1 score of 0.81 and PR-AUC of 0.60. Our contributions are four-fold:

1. For the first time, continuous detection of protective behavior is studied using full data sequences of CP patients. Previously, continuous PBD was only established on pre-segmented activity instances;
2. A novel hierarchical HAR-PBD architecture is designed to leverage the activity recognition to enable detection of protective behavior (i.e., movement behavior driven by emotional variables) in continuous data sequences. Protective behavior was investigated without leveraging its activity background;
3. Graph Convolution (GC) and Long Short-Term Memory (LSTM) layers are combined to model the body-worn IMUs data for PBD, while in the past only CNNs and LSTMs were applied. Although the concept of combining GC and LSTM exists in computer vision-based studies, it is adopted for the first time to show advantage of graph representation in the context of emotional behavior across activities. A loss function referred to as CFCC loss is also employed to alleviate class imbalances of continuous data;
4. Comprehensive experiments and analyses using data collected from both CP and healthy participants. Various training strategies of the proposed hierarchical architecture are explored, and an analysis of simulating fewer IMUs demonstrates the applicability and efficacy of our method on smaller sensor sets.
2 Background and Related Works

Our proposed hierarchical HAR-PBD architecture comprises two main modules: one for activity recognition and another for protective behavior detection. Here we summarize the literature related to pain-, fear- and anxiety-induced movement behavior detection and human activity recognition.

2.1 Affective movement behavior detection

Pain, fear and anxiety are expressed not only by the face, but also by altered body movements [2, 80]. The automatic detection of affective bodily expressions is a growing area of research in the affective computing community [3, 74]. While bodily expressions of emotion were previously studied in isolation, the focus is now on real-life data. Due to the technical challenges, most studies still use static situations (e.g. during a consultation interview with a therapist [6]) or the type of activity is constant throughout (e.g. the detection of pain and anxiety in game-based physical rehabilitation [71, 78]). Bodily expression is also used to inform healthcare applications, e.g. for detection of depression [6], oral hygiene [7] and perinatal assessment for stroke [8]. Typically, these scenarios only require the tracking of few body parts without fine-grained analysis of full-body movement.

Automatic detection of continuous affective behavior across different daily activities is still rare. For example, [4] explored the detection of bodily expressions of reflective thinking in the context of diverse full-body mathematical games. While this study developed activity-independent models over continuous data sequences, their proposed LSTM-based architecture needs to be trained on pre-segmented affective events (e.g. when the child expresses the states of interest vs. other states). Recently, studies very relevant to ours have attempted to detect protective behavior across different activities. On the EmoPain dataset [32], researchers have shown that the use of LSTM-based architectures facilitates activity-independent PBD with improved performances. Interesting results are seen in [40] and [64], where the stacked-LSTM network and body attention network (BANet) were proposed to conduct traversal and local processing of body movement data respectively. Although the model is activity-independent and functions across different activity types, continuous detection was constrained only within pre-segmented AoIs. The relationship between the type of activity and protective behavior is not leveraged in the modeling. The attention mechanism used in BANet only focuses on identifying the most relevant body segments but does not directly leverage such relationship.

As such, how to enable continuous PBD along a sequence of activities remains an open challenge. The high variability of protective behavior across people exhibited within the same activity type [64] also calls for a better approach to extract useful information from the full-body configuration data.

2.2 Human activity recognition

The modeling of body movement has gone through extensive development in the context of human activity recognition (HAR). The majority of HAR research focuses on classifying the type of activity a person is engaged in by using wearable sensor data [9-16] or skeleton data collected via visual motion-capture (MoCap) systems [17, 18]. The preference for wearable sensors vs. visual systems rests on the limits to mobility imposed by the application.
HAR with vision- and sensor-based data has evolved quickly in the past few years, especially for data processing. Initially, data was processed in a traversal manner, where acceleration, orientation or joint positional coordinates were treated as temporal multi-dimensional sequences. As a result, efforts were dedicated to feature engineering [38, 39] and basic neural networks [9-11] e.g. LSTM networks [61], to address the temporal aspects of body movement data. Later, various studies started to exploit the spatial configuration of the sensor/joint network. For instance, several data representations consider the relative relationships between sensors/joints [41-43], with network architectures designed to enable local processing of movement dynamics [12, 13, 44-46, 64]. Performance improvements achieved by these methods suggest that body configuration is important for activity recognition. More recently, the re-introduction of graph convolution network (GCN) [54, 55] offers a new method for HAR. One reason for the successful use of GCN on vision-based skeleton data [17, 18, 24, 47-49] is that the human body can be naturally presented as a non-directed graph. Graph representation helps a model learn the biomechanical relationships between body segments without imposing knowledge about the specific activities of interest. Noticeable improvements are seen on several benchmark datasets (e.g. NUS RGB+ [19] and Kinetics [20]), achieved by using GCNs.

Whilst the concept of body configuration is very much leveraged in vision-based HAR systems, enabled by the full-body capture therein, this is not the case for ubiquitous sensor-based HAR or movement behavior detection. The sensor-based HAR literature has focused on using a small set of sensors to classify activity, with each study examining specific activities [15] or benchmark datasets [21-23]. Using a small network of sensors also increases applicability and reduces cost in real-life deployment. However, as in the case of CP rehabilitation, critical information may not be in the movement of the main body segments involved, but in other body parts recruited to protect the body [33-36]. For example, Olugbade et al. [37] show the importance of head stiffness to indicate protective behavior during sit-to-stand-to-sit and reach-forward, although head movement is not needed to perform such activities. Psychology studies in chronic pain point to the importance of assessing movement quality, not just activity quantity. As a result, use of full-body movement data (as in the EmoPain dataset) rather than of a small set of sensors, to detect protective behavior across activities, is based on three arguments: i) full-body movement data is needed to capture detailed movement behavior of multiple body parts for PBD across activities; ii) patients and clinicians see benefits and opportunities that such sensing technology offers, and are open to using it [65]; iii) full-body sensing is becoming more convenient as wearable sensors are becoming smaller and integrated into clothes [76]. Moreover, we evaluate the efficacy of our method on small sensor sets at the end of this paper.

The advantage of using GCN in HAR, the need to model a large set of sensors, and the importance of local information for PBD all suggest the importance of exploring the use of GCN in the context of protective behavior. It also brings together research on HAR and PBD (or in general emotional movement behavior detection) that have surprisingly evolved separately, despite clearly representing activity and emotional bodily expression that co-occur in everyday life, each altering the other. To the best of our knowledge, only one paper has investigated the use of GCN in bodily affective expressions [49], but considers just one task (gait) and acted emotional expressions, a much simpler (stereotypical) problem to address. As such, they explored GCN alone and do not need to address the variety of activity and class imbalances of continuous data. In this paper, we aim to use the proposed hierarchical architecture to answer the questions: is HAR beneficial to PBD in continuous data and how can these two modules be connected? For each module of our proposed architecture, graph convolution is employed to model the movement data captured by multiple IMUs per timestep. Given the previous success of LSTM in capturing the temporal pattern of protective behavior [40, 64], LSTM layers are added to model the temporal dynamics.

3 The Hierarchical HAR-PBD Architecture and CFCC Loss
A novel hierarchical architecture combining PBD and HAR modeling is proposed to enable PBD over continuous data sequences of activities. An overview of this architecture is presented in Figure 2. Both the HAR and PBD modules receive consecutive frames extracted with a sliding-window from the data sequence collected with 18 IMUs as the input. For HAR module the activity type label is used for training, whereas for PBD the protective behavior label (absence and presence) is used. In addition, the first module (HAR) aims
to recognize the type of activity being performed and pass such information to the second module (PBD) that recognizes the presence or absence of protective behavior. For our main experiments, the HAR module is pre-trained with activity labels on the same folds of data during each round of LOSO validation used for PBD, and the model with the weight achieving the highest activity recognition accuracy is saved. The frozen HAR module with such pre-trained weight loaded is used in the hierarchical architecture, where its activity classification output is concatenated with the same original input frame and passed to train and test the PBD module using labels of protective behavior. We use this frozen (optimal) HAR module to better understand the benefit of using the proposed hierarchical HAR-PBD architecture. Further analyses using non-frozen HAR module are reported at the end of the paper. To the best of our knowledge, this is the first implementation to leverage the output of HAR to enable another simultaneous task on the same data input.

Both modules in our proposed architecture use a similar network comprising graph convolution and LSTM layers. The graph convolution method is used to model the body configuration information collected from 18 IMUs. Following its success in recent vision-based HAR literature, we aim to explore the contribution of graph convolution in PBD given the large variety in protective behavior exhibited by people with CP when performing each AoI. Meanwhile, LSTM is used to learn the temporal dynamics across graphs corresponding to the body movement at different timesteps, critical for both HAR and PBD (e.g. hesitation slows down movements, and fear of pain or perceived pain lead to difference in timing of body-part engagement for the same activity).

### 3.1 The HAR and PBD module with GC-LSTM

There is a variety of implementations of graph convolution for vision-based skeleton data. Some have altered the graph convolution itself to facilitate a spatial-temporal operation [17, 47-49]. Others connect the GCN and LSTM via extra layers [18] or integrate graph convolution within the gates of each LSTM unit [24] to enable a recurrent computation across time. The performance of these approaches fluctuates on vision-based HAR benchmarks [19, 20], and they have been never applied in the context of emotional bodily behavior across different activities. For both the HAR and PBD module in our proposed architecture, a network integrating GC and LSTM is used, referred to as HAR/PBD GC-LSTM. There are three considerations for the design of HAR/PBD GC-LSTM:

1. The limited size of the EmoPain dataset in comparison with popular vision-based HAR benchmarks [19, 20] that have been used to evaluate GCNs, making it more difficult to directly adopt more complex existing implementations.
2. The need to verify if the graph representation is indeed capable of improving the detection of protective behavior, which requires removing unnecessary components, e.g. attention mechanisms.
3. The aim to connect the HAR module with the PBD module, which requires the GC-LSTM network to tolerate the fusion of activity information and movement data at input level.
In this paper, we focus on a conceptually-simple implementation that builds cascade connection between the GC and LSTM as the basic component in our proposed architecture. Such implementation is able to show the advantage of using a graph representation to model data from multiple IMUs towards the joint objective of HAR and PBD, and further facilitates a hierarchical connection between the two modules.

3.2 Graph input

As provided in the EmoPain dataset [32], at each timestep, 3D coordinates of 22 body joints were calculated from the raw data of 18 IMUs stored in a Biovision Hierarchy (BVH) format. A wearable motion capture suit named Animazoo IGS-190 comprising 18 IMUs was used for the data collection. As contained in the BVH file, the metadata includes the skeleton proportion of the participant (e.g. the length of limbs) and position on the body each sensor was attached. Using a Matlab MoCap toolbox [70], the approximate position of 22 body joints in the 3D space was estimated based on the metadata, the gyroscope and accelerometer data. It is important to note that such transformation brings no prior knowledge of specific activities. It only reflects the definite position of each body joint in the 3D space. An illustration of such transformation from IMUs to positional triplets of body joints forming the graph input is shown in Figure 3.

3.3 Graph notation

A body-like graph is built to arrange each of the 22 joints to be a node connected naturally in the graph to the other joints, as shown in Figure 3 (c). We denote the graph as \( G = (V, E) \), with a node set \( V(t, i) = \{v_t \mid t = 1, \ldots, T; i = 1, \ldots, N \} \) representing the \( N \) nodes of a graph at a timestep \( t \) within a graph sequence of length \( T \), and an edge set \( E \) represents the edges connecting the nodes in this graph. In our case, \( N = 22 \) is in accord with the 22 body joints characterizing the EmoPain dataset, while only the intra-skeleton edge (representing the connection of body joints) is considered with \( E \{i, j\} = \{(v_{ti}, v_{tj}) \mid (i, j) \in B\} \), where \( B \) is the set of naturally connected nodes (joints) of the human body graph. Since in this work independent LSTM layers are used to learn the temporal dynamics across graphs at different timesteps, the inter-skeleton edge (usually represents the temporal dynamics) connecting consecutive graphs is not leveraged. An adjacency matrix \( A \in \{0,1\}^{N \times N} \) is used to identify the edge \( E \) between nodes, where \( A_{ij} = 1 \) for the connected \( i \)-th and \( j \)-th nodes and 0 for disconnected ones. \( A \) stays the same for all the tasks in this work. In other words, the basic configuration of a graph is independent of time and participants, while the relative relationship between different body parts in different activities is learned during training. The identity matrix is \( I_N \), a diagonal matrix that represents the self-connection of each node in the graph. With the adjacency matrix \( A \) and identity matrix \( I_N \), the natural human body configuration is represented by matrices that can be processed by neural networks. The feature of each node in a graph at timestep \( t \) is stored in feature matrix \( X^G_t \in \mathbb{R}^{N \times 3} \). For each node in the input graph, the raw feature is the coordinates of the respective body joint, denoted as \( X^G_t(v_{ti}) = \)

![Figure 3: The illustration of (a) the placement of 18 IMUs, (b) the calculation of 22 sets of positional triplets, and (c) the built graph input at a single timestep, where each node represents a human body joint. The blue contour marks the neighbor set (receptive field) of the centered node in green.](image)
\[ [x_{ti}, y_{ti}, z_{ti}] \]. The neighbor set of a node \( v_{ti} \) is denoted as \( \mathcal{N}(v_{ti}) = \{ v_{tj} \mid d(v_{ti}, v_{tj}) \leq D \} \), with distance function \( d(v_{ti}, v_{tj}) \) accounting for the number of edges in the shortest path traveling from \( v_{ti} \) to \( v_{tj} \) and threshold \( D \) defining the size of the neighbor set. In our work, following previous studies using GCNs for action analysis [17, 18, 24, 47-49], we set \( D = 1 \) to adopt the 1-neighbor set of each node.

### 3.4 Graph convolution

Basically, a graph convolution comprises two parts, one defines the way to sample data from the input graph and the other concerns assigning learnable weight to the sampled data. It should be noted that a higher-level knowledge about the subset of body parts relevant to specific activities is not manually provided in the network. Therefore, only low-level rules like sampling and weighting are defined in the graph convolution, which allows the network to develop its own understanding about the body movement. In our case, the graph convolution needs to conduct sampling on the full-body graph comprising 22 nodes.

Using the adjacency matrix \( \tilde{A} \) and identity matrix \( I_N \), we follow the forward-passing formula presented in [63] and the GC used in this work can be implemented as

\[
\mathbf{f}_{\text{out}}^{\text{GC}} = \tilde{\mathbf{A}}^{-\frac{1}{2}} \mathbf{A} \mathbf{A}^{-\frac{1}{2}} \mathbf{f}_{\text{in}}^{\text{GC}} \mathbf{W},
\]

where \( \tilde{A} = A + I_N \) represents the inter- and self-connection of each node, and \( \tilde{A}_{ij} = \sum_j \tilde{A}_{ij} \) is a diagonal degree matrix of \( \tilde{A} \). Since \( \tilde{A} \) is a positive diagonal matrix, the entries of its reciprocal square root \( \tilde{A}^{-\frac{1}{2}} \) are the reciprocals of the positive square roots of the respective entries of \( \tilde{A} \). Each diagonal value in the degree matrix \( \tilde{A} \) counts the number of edges connecting the respective node in the graph described by \( \tilde{A} \). Such transformation from \( \mathbf{A} \) to \( \tilde{\mathbf{A}} \) is in accord with our choice of distance-partitioning [17], where each neighbor set is divided into two subsets for weight assignment, namely the center node (I) and the neighbor nodes (A). \( \mathbf{f}_{\text{in}}^{\text{GC}} \) is the input feature matrix, and \( \mathbf{f}_{\text{in}}^{\text{GC}} = \mathbf{X}_t^I \) at the first layer of input level. \( \mathbf{W} \) is the layer-wise weight matrix. Please refer to the appendix section for a more detailed description about graph convolution.

### 3.5 Cascade connection of graph convolution and LSTM

Here, we describe how the GCN and LSTM layers are connected, as used in both the HAR and PBD modules of our hierarchical architecture. For each module, the input to a single unit in the first LSTM layer is the concatenation of the graph convolution output from all the nodes in the graph \( G \) at timestep \( t \), denoted by \( f_{\text{out}}^{\text{GC}}(\mathbf{X}_t^I) = [f_{\text{out}}^{\text{GC}}(v_{t1}), ..., f_{\text{out}}^{\text{GC}}(v_{tn})]^{\top} \). We want to investigate whether GCN improves the PBD performance or not, so the GCN and LSTM should not be integrated completely. For the adopted forward-processing LSTM layer, the computation at each LSTM unit is repeated to process the information across graphs from the first timestep to the last. As each LSTM unit at a timestep \( t \) receives the output from a graph convolution, we call such connection a cascade connection between the graph convolution and LSTM. Such conceptually-simple design involving the graph convolution only as a way to learn representations enables us to empirically study its impact on PBD performances. In comparison, others conducted the graph convolution within the gates of each LSTM unit [24] or used extra computational blocks between the GC and LSTM layers (e.g. fully-connected layers used in [18], pooling and attention mechanism applied in [28]).

### 3.6 Hierarchical connection of HAR and PBD modules

Up until this point, the GC-LSTM network used in each module of our proposed architecture has been defined. Here, we describe how to connect the HAR and PBD module. In each module, a fully-connected softmax layer is further added to the GC-LSTM network for the classification purpose. Let the probability toward each class of the current input frame to be \( \mathbf{P} = [p_1, ..., p_K] \) with \( K \) denoting the number of classes and \( \mathbf{Y} \) to be the one-hot prediction. \( K \) is 6, including the 5 AOs and transition activity class for the HAR module, and is 2 for protective and non-protective behavior of the PBD module. In our proposed architecture, to provide activity-informed input from HAR to PBD, a node-wise concatenation is conducted where the one-hot activity label \( \mathbf{Y}^{\text{HAR}} \) is added to the input matrix \( \mathbf{X}_t^I(v_{ti}) = [x_{ti}, y_{ti}, z_{ti}] \) of each node in the graph input for PBD per timestep (see Figure 2). Namely, for the PBD module, activity-informed input feature matrix at
a node $v_{t}\in$ a single graph is $X^{G\_PBD}_{t}(u_{t}) = [X^{G}_{t}(v_{t}), \mathbf{Y}^{\_HAR}]$. Since the raw graph input fed to the PBD module is joined by the output of the HAR module, we call such a **hierarchical connection** between the two.

### 3.7 Addressing class imbalances with CFCC Loss

A problem with non-acted movement datasets is class imbalance (e.g. datasets for HAR [21–23]). In the case of the EmoPain dataset, protective behavior is sparsely spread within the Aols of each data sequence, while it is generally absent during transition activities (see Figure 1). Specifically, on average the Aols represent only 31.71% of a participant’s data sequence, with the rest being transition activities. Furthermore, on average, samples labelled as protective behavior represent only 21.09% of a participant’s data sequence, with the rest labelled as non-protective. Typical approaches used to address class imbalance include: i) data re-sampling for each class, where samples are either duplicated from the less-represented class or randomly sampled from the majority class [27]; ii) loss re-weighting, e.g. setting higher weights for the less-represented class and lower weights for the majority class [26]. Unfortunately, these methods require manual interferences with data samples that could also harm the training of a model [60].

In our work, we propose to use a loss function that alleviates class imbalance during training. Normally, for the supervised learning of our modules, the following **categorical** cross-entropy loss (CCE) [66] is used

$$ L_{\text{categorical}}(P, Y) = -Y \log(P), $$

where $P = [p_1, ..., p_K]$ is the classified probability distribution of an input frame over the $K$ classes, and $Y$ is the respective one-hot categorical ground truth label with $Y(k) = 1$ only for the ground truth class $k$. During training, the loss computed for each frame is added up to be the total loss for the model to reduce. Such function tends to put more attention on decreasing the loss in the majority class and ignores the (mis)classification of the less-represented classes (e.g. the Aols classes in the HAR or the protective behavior class in the PBD task).

To address this problem, we took inspiration from the research on automatic object detection. In the object detection domain, a binary class imbalance is caused by the smaller area covered by the object-of-interest and the larger objectless background. Two main approaches proposed in this direction are the focal loss [59] and the class-balanced term [60]. Based on binary cross-entropy loss function [66], focal loss [59] applies a sample-wise factor function adjusting the loss weight for a sample based on its classification difficulty (defined by the classified probability towards the ground truth class). The Focal Loss (FL) together with binary cross-entropy (CE) can be written as

$$ \text{FL}(p, y) = (1 - p)^{\gamma} L_{\text{binary}}(p, y) = -(1 - p)^{\gamma} (y \log(p) + (1 - y) \log(1 - p)), $$

where $p$ is the classified probability toward the positive class of the current data sample, $y$ is the binary ground truth indicator with 1 for the positive class and 0 for the negative class. As we can see, the factor $(1 - p)^{\gamma}$ with tunable hyper-parameter $\gamma \geq 0$ is added to the original binary cross-entropy loss. The intuition is to reduce the loss computed from data samples that are well-classified, while the threshold for judging whether a data sample is well-classified or not needs to be adapted given different datasets and is controlled by $\gamma$. The increase of $\gamma$ will reduce the threshold, then data samples with comparatively lower classification probabilities toward the ground truth would be treated as the well-classified. In [60], the authors further revised the vanilla cross-entropy loss by adding a class-wise loss weight to each class based on the so-called effective number of samples within it. For the class $c$, the effective number of samples is denoted as $E_{n_c} = \frac{1 - p_c}{1 - p}$, with a hyper-parameter $\beta$ controlling how fast the effective sample number $E_{n_c}$ grows when the actual number of samples $n_c$ increases. The class-balanced term then used in their study is the reciprocal of $E_{n_c}$ written as

$$ \frac{1}{E_{n_c}} = \frac{1 - \beta}{1 - \beta n_c} $$

Unlike the binary imbalance caused by the object area and its useless background, in the HAR module, class imbalances exist among the 6 categories of activity, while in PBD both protective and non-protective classes share the same importance. Therefore, to adapt the focal loss and class-balanced term to our scenario, we replace the CE with CCE to combine the Equation 2-4 as
\[ CFCC(P, Y) = -\frac{1 - \beta}{1 - \beta^n_k}(1 - YP)^n_k \log(P), \]

where \( n_k \) is the number of samples of ground truth class \( k \) for the current input data frame. This revised function, referred to as Class-balanced Focal Categorical Cross-entropy (CFCC) loss function, will be used in our study. To the best of our knowledge, this is the first time for such a combination to be used for the computation of multi-class categorical cross-entropy loss in HAR and PBD. With CFCC loss, we aim to alleviate the class imbalance during training and also to understand its importance in comparison with the other components of our architecture. The code for Section 3 will be released.

4 Dataset, Validation and Metrics

In this section, we describe more details about the EmoPain dataset, the validation and metrics used.

4.1 The EmoPain dataset

The EmoPain dataset [32] used in this study contains movement data collected from 18 IMUs from 12 healthy and 18 CP participants. The placement of IMUs is illustrated in Figure 3(a). Four wireless surface EMG sensors (sEMG) were also used and placed on the high and lower back of a participant to capture the muscle activity. In this paper, we focus on the IMUs data and leave the exploration of muscle activity data for future works. As part of the EmoPain dataset, the annotation of protective behavior was provided by four domain-expert raters, including 2 physiotherapists and 2 clinical psychologists. Each expert rater independently inspected the on-site video of each CP participant that was collected in synchrony with the wearable sensor data, and marked the timesteps where each period of protective behavior started and ended. The healthy participants were assumed to show no protective behavior despite may have their own idiosyncrasies.

A sequence of five functional activities was designed by physiotherapists, comprising one-leg-stand, reach-forward, stand-to-sit, sit-to-stand and bend-down. These activities were selected to reflect the physical and psychological capabilities necessary for carrying out everyday functioning, e.g. a person may need to reach forward to take an object placed on the far-end of a table, or bend down to load the wash machine. Avatar examples of a healthy and CP participant extracted from the dataset are shown in Figure 4. The figure illustrates two strategies used by this CP participant as forms of protective behavior: i) avoidance of bending the trunk during reach-forward; ii) hesitation, trunk twisting and shoulder side inclination for arm support during stand-to-sit.

Each participant went through at least one trial of the activity sequence (~10 mins), while 5 healthy and 11 CP participants executed both the normal and difficult trials. As a result, in total we have 46 activity sequences from 30 participants. During the normal trial, participants were free to perform these activities without any constraint. In the difficult trial, they were required to start the activity under the instruction of experimenters and carry an extra 2Kg weight in each hand during reach-forward and bend-down to simulate carrying everyday objects (e.g. shopping bags as typically suggested by physiotherapists). Such difficulty is added to collect the movement of a participant under external pressure or needs. However, no instructions of how a movement should be performed were provided, to ensure participants performed the activity in their
own way as what they would do in real life. Between trials or even between activities, they were allowed to take break as needed and in the way they felt useful to relax or decrease muscle tension. The annotation of activity type was conducted manually by the EmoPain researchers, defining the starting and ending timesteps of each individual activity. In this study, we perform the following data preparations.

**Raw Data as Input.** Since the basic processing component of our proposed architecture operates on graphs that represent the configuration of the human body, the 3D coordinates of the 22 joints calculated from the IMUs are directly used. This differs from previous studies [25, 36, 37, 40, 64] on the same dataset, where low-level features as energies and angles between body segments were used. As described in Section 3.2, the approximate 3D joint coordinates were calculated from the BVH data returned by the motion capture suit (Animazoo IGS-190) using a Matlab MoCap toolbox [70]. The BVH data comprises the skeleton proportion, sensor placements, accelerometer and gyroscope data sequences produced by the system at 60Hz.

**Continuous Data Segmentation with Sliding-window.** Using a sliding window of 3s long and 50% overlapping ratio, each activity sequence of a complete trial of a participant is transformed into consecutive frames from the start of the first AoI to the end of the last AoI/transition activity. The window length and overlapping parameters are based on the evaluation studies reported in [25, 40]. As the IMUs were operating at 60Hz, each frame contains 180 timesteps (samples). At timestep $t$, we have an input graph $G_t = (V_t, E_t)$, represented by the input data matrix $X_t$, constant adjacency matrix $A \in \{0,1\}^{22 \times 22}$ and its identity matrix $I_{22}$, where $X_t = [x_{ti}, y_{ti}, z_{ti}], v_{ti} \in V_t$. These matrices only represent the graph structure and raw coordinate data of each joint. The graph structure simulating the human body includes the set of nodes and their connections, i.e., it is the same for all participants across all activities. The activity class ground truth, i.e. one-leg-stand, reach-forward, sit-to-stand, stand-to-sit, bend-down and the transition, of a frame is defined by applying majority-voting to the 180 samples within it. The protective behavior ground truth of a frame is decided by majority-voting across the 4 domain-expert raters in accord with [25, 40, 64], where a frame is labelled as protective behavior if at least 50% of the samples within it had been considered as protective behavior by at least two expert raters separately.

**Data Augmentation.** In order to address the limited size of EmoPain dataset, we apply a combined data augmentation approach that has shown clear improvement in performance in a previous work on the same dataset [25], namely Jittering and Cropping [77]. For jittering, the normal Gaussian noise is globally applied with standard deviations of 0.05 and 0.1 separately to the original data. For cropping, data samples at random timesteps and nodes are set to 0 with selection probabilities of 5% and 10% separately. These augmentations are also beneficial for simulating the real-life situations of signal noise and accidental data loss. Each single augmentation method would create two extra augmented data sets, which are only used in training. The original number of frames produced with the sliding-window segmentation from all participants is ~6200, while this number is increased to ~31K after the augmentation.

### 4.2 Validation, metrics and implementations

For all the experiments, a Leave-One-Subject-Out cross validation (LOSO) is applied, where both the normal and difficult trials are left out for a subject if conducted. For HAR, we report the accuracy (Acc) and macro F1-score (Mac.F1) to account for the performance of all classes [72]. For PBD, as this is a ‘binary’ task suffering from class imbalance, we additionally use the protective-class classification output acquired from all folds to plot Precision-Recall curves (PR curves) and report the Area under the Curve (PR-AUC) [73].

A search on number of layers, kernels and units for graph convolution and LSTM is conducted to identify the suitable hyper-parameter set for the HAR/PBD module separately: i) for HAR, we use one graph convolution layer with 26 convolution kernels, three LSTM layers with 24 hidden units of each and one fully-connected softmax layer with 6 nodes for output; ii) for PBD, we use three graph convolution layers with 16 convolution kernels of each, three LSTM layers with 24 hidden units of each and one fully-connected softmax layer with 2 nodes for output. If not mentioned, the default loss function used for all the methods is the vanilla
5 Results

The evaluation concerns several components of our proposed hierarchical HAR-PBD architecture, namely the contribution of graph convolution, CFCC loss and HAR to PBD performances. A visualization is also provided to analyze the errors of proposed methods. We conclude by evaluating different training strategies of the HAR-PBD architecture, and its performances under different sizes of the body graph configuration.

5.1 Contribution of GC to continuous PBD

The first aim of our evaluation is to understand the contribution of graph representation in comparison with other approaches to the PBD performance. Hence, we conduct a set of experiments using the PBD module alone, without the use of the entire hierarchical architecture and the CFCC loss. The evaluation is conducted against the stacked-LSTM [40] and BANet [64] with either i) joint angles and energies; or ii) 22 pairs of coordinates as input. Differently from their original studies [40, 64] that relied on the pre-segmentation of the body, we conduct a hyper-parameter search on $\gamma = \{0, 0.5, 1, 1.5, 2, 2.5\}$ and $\beta = \{0.9991, 0.9995, 0.9999\}$ for both tasks separately using the respective HAR or PBD module alone. We find $\gamma = 0.5, \beta = 0.9999$ to be the optimal for HAR and $\gamma = 2, \beta = 0.9999$ for PBD. Thereon, we compute the class-balanced term for each class of HAR and PBD. The Adam algorithm [67] is used as optimizer for all the models, while the learning rate is set to $5e^{-4}$ for the HAR module and $1e^{-3}$ for PBD module after another separate search on $lr = \{1e^{-5}, 5e^{-5}, 1e^{-4}, 5e^{-4}, 1e^{-3}, 5e^{-3}\}$. The OPTUNA framework [30] is used to conduct all the hyper-parameter tuning. The number of epochs is set to 100.

In the first experiment, we report the baseline results of stacked-LSTM [40] and BANet [64], which represent the state-of-the-art on the EmoPain dataset for PBD, even though in their original studies only pre-segmented activity instances were used. We report the results for these two methods using the input of either i) 13 joint angles plus 13 energies as were used in the original studies, and ii) the coordinates of 22 joints calculated from 18 IMUs as were used in our proposed method. For stacked-LSTM, at each timestep we merely concatenate the coordinates of 22 joints to form the input matrix with a dimension of $22 \times 3 = 66$. Accordingly, the input structure of BANet is adapted for 22 pairs of coordinates as shown in Figure 5. The hyper-parameters of the two models are also determined via a similar search as above.

| Methods                  | Acc | Mac.F1 | PR-AUC |
|--------------------------|-----|--------|--------|
| Stacked-LSTM (angle+energy) | 0.79 | 0.61 | 0.23   |
| BANet (angle+energy)     | 0.78 | 0.56 | 0.24   |
| Stacked-LSTM (coordinate) | 0.80 | 0.64 | 0.32   |
| BANet (coordinate)       | 0.79 | 0.63 | 0.27   |
| PBD GC-LSTM              | **0.82** | **0.66** | **0.44** |

Figure 5: a) the original BANet input structure; b) the adapted BANet input structure for raw coordinates.
activity instances, both methods are applied here over the full data sequences in a continuous manner. Results are reported in Table 1 with PR curves plotted in Figure 6 (left). As shown, the PBD GC-LSTM produces the best accuracy of 0.82, macro F1 score of 0.66 and PR-AUC of 0.44. The actual difference between these compared methods is the way the input data is processed, i.e., traversal concatenation (stacked-LSTM [40]), local processing (BANet [64]) and graph representation (PBD GC-LSTM). As such, the results suggest that the graph representation may indeed contribute to improving the continuous detection of protective behavior. Still, the below-chance-level (<0.5) results of PR-AUC of all methods demonstrate the difficulty of detection of protective behavior in continuous data sequence across various activities. This suggests the need to further improve continuous PBD with HAR and CFCC loss.

5.2 Contribution of CFCC loss and HAR

Through an ablation study, here we first investigate the contribution of the loss function alone in dealing with the imbalanced data for each module of our proposed architecture. We then use our proposed hierarchical HAR-PBD architecture to understand the impact of activity-class information produced by the HAR module. In particular, we aim to understand if recognizing the activity background has more impact on improving PBD in continuous data sequences, in comparison with the issue of class imbalances during training.

**Contribution of the CFCC Loss Function to Continuous HAR.** In our proposed hierarchical HAR-PBD architecture, the HAR GC-LSTM together with the CFCC loss function was firstly pre-trained on the same set of data using activity labels, then the weight achieving the best activity recognition performance was saved and frozen during the training of the entire architecture. For the training and testing of the hierarchical architecture, the HAR output was used as auxiliary information to contextualize the PBD. Therefore, the accuracy of the HAR module is important. Here, we report the performance of the HAR GC-LSTM alone with and without the CFCC loss function. The results are reported in Table 2, with confusion matrices shown in Figure 7. The CFCC loss leads to a higher macro F1 score (0.81 vs. 0.79) in the continuous HAR. Judging from the confusion matrices, the CFCC loss reduces the classification bias towards the most represented class (the transition activity), which resulted in a lower accuracy though (0.88 vs. 0.89). These results show the effectiveness of the CFCC loss for balancing multi-class categorical loss computation, which was not directly evaluated in the original studies [59, 60].

![Figure 6: PR curves of different learning methods (left), and PBD methods in the ablation study (right).](image)

| Methods                        | Acc | Mac.F1 |
|-------------------------------|-----|--------|
| HAR GC-LSTM                   | 0.89| 0.79   |
| HAR GC-LSTM with CFCC loss    | 0.88| 0.81   |

Table 2: HAR results of the ablation study
Contribution of the CFCC Loss Function to Continuous PBD. Here we investigate the contribution of the CFCC loss function to continuous PBD using the PBD GC-LSTM. The input to PBD GC-LSTM is the raw coordinate data without activity-class information. As we can see from the results in Table 3, the use of the CFCC loss function leads to ~5% macro F1 score improvement in continuous PBD (macro F1 score of 0.71 vs. 0.66). Confusion matrices shown in Figure 8 (a) (b) suggest that the adapted CFCC loss function does indeed help penalize the bias towards the more frequent class (non-protective class in this case) while improving the recognition of the less-represented one (protective class). However, the PR-AUC of 0.48 is still below chance level, suggesting that addressing class imbalance alone is not sufficient.

Contribution of Hierarchical HAR-PBD Architecture to Continuous PBD. For the training and testing of our proposed hierarchical HAR-PBD architecture, the HAR GC-LSTM within it is frozen and loaded with the optimal weights from its pre-training with CFCC loss. This is to keep the HAR performance constant and aid the understanding of the impact of continuously inferred activity information on continuous PBD. The results are reported in Table 3, with confusion matrix shown in Figure 8 (c). It is interesting to see that our proposed hierarchical HAR-PBD architecture using vanilla categorical cross-entropy loss achieved an improvement of ~2% with respect to the PBD GC-LSTM alone using CFCC loss function (macro F1 score of 0.73 vs. 0.71), while the PR-AUC of 0.52 achieved is also above chance level. Such result shows that the contextual information of activity type contributes to continuous PBD with our proposed hierarchical HAR-PBD architecture being a practical way to leverage such information. Furthermore, by adding the CFCC loss function to the PBD module of the hierarchical HAR-PBD architecture, higher macro F1 score of 0.81 and PR-AUC of 0.60 are achieved (confusion matrix shown in Figure 8 (d)). The PR curves for the PBD ablation experiment are plotted in Figure 6 (right).

Table 3: PBD results of the ablation study

| Methods                                         | Acc  | Mac.F1 | PR-AUC |
|-------------------------------------------------|------|--------|--------|
| PBD GC-LSTM                                     | 0.82 | 0.66   | 0.44   |
| PBD GC-LSTM with CFCC loss                      | 0.83 | 0.71   | 0.48   |
| Hierarchical HAR-PBD architecture                | 0.84 | 0.73   | 0.52   |
| Hierarchical HAR-PBD architecture with CFCC loss| 0.88 | 0.81   | 0.60   |
These results highlight that the contextual information of activity types played a higher role in improving PBD in continuous data, while adding a mechanism (CFCC loss in our case) to address the class imbalance problem led to a further-clear improvement. Such suggest that both the HAR and CFCC loss are necessary for continuous PBD despite one being more effective than the other.

5.3 Error analysis with visualization

To understand the temporal behavior of the two modules in the hierarchical HAR-PBD architecture, a visualized example of the model performances on the data sequence of one CP participant is shown in Figure 9. The upper two diagrams are the ground truth and recognition result of the HAR module respectively. As shown, on this long data sequence, our HAR GC-LSTM using the CFCC loss achieves good performance without any pre-localization and -segmentation of the AOIs. The lower five diagrams are the ground truth and results of the PBD module achieved by the four different methods respectively.

In the HAR result (upper part of figure 9), the errors are found to be: i) misclassification of one-leg-stand as transition activity (red rectangle in the left); ii) misclassification of transition activities as reach-forward and bend-down (red rectangles in the middle); iii) misclassification of bend-down as stand-to-sit (red rectangle in the right). We notice that most misclassified activities were possibly due to their similarity in execution given the use of protective behavior by this CP participant. For instance, the analysis of the on-site
video showed that the participant was unable to bend the trunk down and instead simply stretched both arms toward the ground, which is similar to the activity of reach-forward or transitions like standing still for rest.

We now compare the four PBD approaches (see M1-M4 in the lower part of Figure 9). Without the activity-class information and CFCC loss, the baseline PBD GC-LSTM (M1) misclassified most frames as the majority class of non-protective behavior. The use of CFCC loss (M2) and the activity-class information (M3) respectively enabled the model to detect more protective behavior frames. For this CP participant, M3 is shown to be more effective than M2 in terms of the detection at frame level during stand-to-sit, sit-to-stand and bend-down. The hierarchical HAR-PBD architecture with CFCC (M4) leads to the best result, especially for the detection at frame level during one-leg-stand. In the PBD result of the hierarchical architecture without CFCC loss (M3), the misclassified area marked by a red rectangle on the right side of the figure seems to be affected by the misclassification of a bend-down as stand-to-sit by the HAR module. Such error is corrected by using the CFCC loss function (M4). However, for the same approach (M4), the error marked by a red rectangle on the left side is likely to have been affected by the misclassification of one-leg-stand as transition activity by the HAR module.

These results suggest that i) misclassifications by the HAR module have a negative impact on PBD performance; ii) and this problem could be minimized by addressing the class imbalance with the CFCC loss in the PBD module. These support our concept of approaching continuous PBD by addressing the two technical issues together, namely the contextual information of activity type and the imbalanced presence of protective behavior. As the HAR module is challenged by the variety of protective behavior people use in performing an activity, it also becomes interesting to explore if the training of the PBD module may help improve the HAR performance when both are trained together. We discuss this in the next subsection.

5.4 Comparing training strategies for the hierarchical architecture

In the previous subsections, the HAR module used in hierarchical HAR-PBD architecture was pre-trained with the same training data using activity labels and frozen to adopt the model of optimal activity recognition performance. The aim was to understand the contribution of HAR to PBD across the different configurations. Here, we further explore the relationship between HAR and PBD modules by exploring joint-training strategies of the hierarchical architecture. In joint-training of the architecture, the HAR module would not be frozen but the activity labels would still be used to update it as the PBD module is trained. Meanwhile, the protective behavior labels of the same data input together with the output of HAR module are used for training the PBD module. Namely, we compare the following four strategies together with the use of CFCC loss:

1. **Joint HAR(CFCC)-PBD** and **Joint HAR-PBD(CFCC)**, where the HAR and PBD modules are initialized and trained together using activity and protective behavior labels respectively, with CFCC loss only added to either HAR or PBD module separately;

2. **Joint HAR-PBD with CFCC**, where the CFCC loss is added to both modules in joint training;

3. **Pre-trained Joint HAR(CFCC)-PBD** and **Pre-trained Joint HAR-PBD(CFCC)**, similar to (i) where the only difference is that the HAR module is first trained alone with activity labels to achieve the best activity recognition performance but then its training continues with the training of the PBD module;

4. **Pre-trained Joint HAR-PBD with CFCC**, where, after pre-training the HAR module to achieve the best HAR performance, the CFCC loss is added to both modules in the joint training.

For all these joint training strategies, the loss weights are set to $[1.0, 1.0]$ for both HAR and PBD modules. If the CFCC loss is not mentioned, the loss used for the respective module is the vanilla categorical cross-entropy loss. We also compare them with our proposed method used in previous sub-sections, here referred to as **Pre-trained HAR(Frozen)-PBD(CFCC)**, where the HAR module is first trained alone with activity labels and CFCC loss to achieve the best activity recognition performance per LOSO fold, then it is frozen with weights loaded and used in the hierarchical architecture for the training and testing of the PBD module. Results are reported in Table 4, with the PR curves for PBD results plotted in Figure 10 (left).

Without pre-training the HAR module, the best HAR (macro F1 score of 0.56) and PBD (macro F1 score of 0.74 and PR-AUC of 0.55) performances are achieved by the **joint HAR-PBD(CFCC)**. However, by adding CFCC loss to the HAR module alone (**joint HAR(CFCC)-PBD**), the performances are reduced notably for the HAR and slightly for PBD. One explanation could be that, the error passed back from the PBD module
harmed the HAR performance, especially when such error of PBD was not well handled e.g. without using the CFCC loss function. On the other hand, by adding the CFCC loss to both modules (joint HAR-PBD with CFCC), the HAR performance achieved (macro F1 score of 0.54) is comparable to joint HAR-PBD(CFCC) but the PBD performance is much lower (macro F1 score of 0.71 and PR-AUC of 0.45). Given the current hierarchical architecture, such results suggest that alleviating class imbalance in PBD has a stronger impact on the overall performance in joint training, while addressing it in HAR penalizes the PBD performance.

Rather than to start joint training from scratch, we further look into the uses of pre-training of the HAR module to reach an initial optimal activity recognition performance (macro F1 score of 0.81) before joint-training. A similar outcome as above is observed where the best performance is achieved by adding the CFCC loss to the PBD alone. Once again this proved the higher impact of alleviating the class imbalance of PBD, as the error passed back from the PBD module could harm the training of HAR module. In general, the results show that a pre-training of the HAR module improved the final performances of both HAR and PBD modules in comparison to the ones without it.

The performances achieved by the various joint-training strategies of the hierarchical architecture are still lower than the one by freezing the HAR module as used in previous sub-sections, for both HAR (macro F1 score of 0.81) and PBD (macro F1 score of 0.81 and PR-AUC of 0.60). It should be noted that this method is a two-stage process only in training and an end-to-end process in testing (inference). These results

Table 4: Results for different training strategies of the HAR-PBD architecture

| Training strategies                  | HAR       |            | PBD       |            |
|-------------------------------------|-----------|------------|-----------|------------|
|                                     | Acc  | Mac.F1 | Acc  | Mac.F1 | PR-AUC    |
| Joint HAR(CFCC)-PBD                | 0.62 | 0.42    | 0.85 | 0.70    | 0.54      |
| Joint HAR-PBD(CFCC)                | 0.76 | 0.56    | 0.84 | 0.74    | 0.55      |
| Joint HAR-PBD with CFCC            | 0.66 | 0.54    | 0.81 | 0.71    | 0.45      |
| Pre-trained Joint HAR(CFCC)-PBD    | 0.68 | 0.55    | 0.85 | 0.74    | 0.58      |
| Pre-trained Joint HAR-PBD(CFCC)    | 0.84 | 0.73    | 0.87 | 0.79    | 0.58      |
| Pre-trained Joint HAR-PBD with CFCC| 0.72 | 0.64    | 0.85 | 0.76    | 0.55      |
| Pre-trained HAR(Frozen)-PBD(CFCC)  | 0.88 | 0.81    | 0.88 | 0.81    | 0.60      |

Figure 10: PR curves of (left) proposed hierarchical architecture under different training strategies, (right) hierarchical HAR-PBD architecture with CFCC loss using input of different number of nodes.
highlight the importance of HAR performance to PBD and suggest that the error propagated from the PBD module during joint-training was not informative to guide how the HAR module should be refined. In other words, while our study shows that HAR improves PBD, the vice versa does not seem to hold, even though the activity is apparently altered when protective behavior is present.

### 5.5 Simulating fewer IMUs

Until this point, we have assumed all 18 IMUs to be available to enable the input of a full-body graph. In this experiment, we quantify the fluctuation in performance when fewer IMUs are available.

We simulate the limited availability of IMUs by removing nodes (containing the data of respective joints) from the full-body graph. According to the study on human observation of protective behavior [36], protective movement strategies are often visible on both sides of the body even if via different patterns. For example, a twisting of the trunk to reach for a chair may lead to a narrower angle between the arm and the trunk on one side but a compensatory larger angle between the other arm and the trunk. Therefore, a **one-side sensor set** of 14 nodes is created, where nodes number of 2-4 and 10-14 on the left limbs of the full-body graph are removed. Second, to simulate an even more compact sensor set, we further remove nodes number of 6, 8, 15, 17, 18, 20 and 21 from the one-side sensor set, resulting in a **smallest one-side sensor set** of 7 nodes. Additionally, from the full-body graph, we symmetrically remove nodes number of 3, 4, 6, 7, 8, 10-13, 15-18, 20 and 21 from both body sides to create a **smallest symmetric sensor set** with 7 nodes as well. The graph structures of these sensor sets still simulate human body connections, as shown in Figure 11. The hierarchical HAR-PBD architecture with CFCC loss is used here on the graph input extracted from each sensor set. For a fair comparison, we conducted another search to determine the suitable hyper-parameters under each condition, with the process detailed in Section 4.2. The HAR and PBD results of each sensor set are shown in Figure 12, with PR curves for the PBD results plotted in Figure 10 (right).

![Figure 11: Four graph structures used. The blue contour marks the neighbor set of each centered node in green.](image)

![Figure 12: HAR and PBD results of the hierarchical HAR-PBD architecture with CFCC loss using input of different number of nodes.](image)
Although the best PBD performance is obtained by using the default graph input of 22 nodes, competitive results are achieved using the one-side graphs with number of nodes reduced to 14 (macro F1 of 0.77 and PR-AUC of 0.55) and even 7 (macro F1 of 0.76 and PR-AUC of 0.53). These results are better than the ones achieved using the hierarchical architecture alone without CFCC loss on the full-body graph (macro F1 of 0.73 and PR-AUC of 0.52). On the other hand, given the same number of 7 nodes, the one-side sensor set created using human observations on protective behavior is more informative than the one following general practice of retaining nodes on both sides of the body (macro F1 of 0.75 and PR-AUC of 0.51). This shows advantage of using an observation-driven strategy in guiding the sensor-set reduction, in the context of PBD. Generally, it is empirically verified that the proposed hierarchical HAR-PBD architecture with CFCC loss leads to improvement even with small sensor sets. In order to improve the PBD performance under a smaller sensor set, efforts could be made on i) designing better graph structure, since in this work we merely employed the human-body connections; ii) further exploring the configurational pattern of body movement in the context of CP rehabilitation, given the performance achieved by one-side sensor sets.

6 Discussion

We discuss here our open challenge, current limitations and possible use cases of the proposed method.

6.1 The challenge and current limitations

The major challenge for the ubiquitous-computing research in chronic-pain rehabilitation is the lack of very large datasets. This is a problem we face as moving into real-world applications. The EmoPain dataset [32] comprises 18 CP and 12 healthy participants, the data collection and annotation of which took nearly a year to finish according to the authors. It is widely acknowledged that collecting data from patients is challenging given increasingly strict data protection regulations and privacy issues. In order to fully leverage the existing data for our model development, we followed the experience of previous studies [25, 40, 64] using data augmentations [77]. As wearable technology become easier to use in everyday scenario, we plan to conduct a long-term data collection in the future. Other limitations of this work with possible solutions for the next-step are summarized as follows:

**Dependence on Manual Annotation.** Our proposed architecture is a pure supervised-learning method relying on manual annotations, particularly domain-expert ratings of behavior. For expert annotation of protective behavior, labelling frames by majority voting can be problematic, possibly biasing the model in favor of one or two experts. In the next, one can treat this as a noisy-label problem, and model each expert’s annotation separately while gain better consensus through a multi-expert architecture [69]. On the other hand, the annotation of activity types is also challenging given the variety in performances between CP participants. In particular, discriminating the margin between activity-of-interest and transition is often difficult and may lead to the misclassification of transition toward AoIs, as shown in Section 5.3. We plan to follow recent progress on ambiguous activity annotation [31] to deal with such uncertainty in the next.

**Limited Improvement of Binary PBD to HAR.** Our experiment shows that the HAR module improves PBD, which is not for the vice versa. One reason could be the lack of granularity of protective behavior type in our study. In this paper, the five typical classes of protective behavior (guarding, hesitation, the use of support, abrupt motion and rubbing) [33] were pulled together and modelled as one unique class, given the limited number of instances per each type. If modelled separately, these may add more insight to the type of activity being performed, e.g. support is used more during bend-down or stand-to-sit. Hence, new data collection for similar applications should consider how to increase the number of instances per behavior type.

**The Use of Large IMUs Network.** For most experiments in this work, a set of 18 IMUs was assumed to be available to provide data of the full-body graph (22 joints). So many IMUs are not usually directly taped to the body, and we do not expect such to be the case when the system is deployed. In fact, ubiquitous motion capture suits that facilitate sensor wearability, e.g. the Animazoo IGS-190 [81] (used for the EmoPain dataset)
and Xsens MVN [82], have been around for a long time. Two examples of the user wearing the MoCap suit are shown in Figure 13. Both systems are integrated, wireless and consider users’ comfort. However, such motion capture systems are still expensive even though the IMU sensors are becoming cheaper, more accurate and wearable (e.g. invisible, washable or transferable between clothes [76]). Currently, it is out of the scope of this paper to develop the suit or integrate sensors into patients’ clothes. Still, it remains a research question for hardware developers and fashion designers. Progress in ubiquitous computing (as the one in our work) may lead to further advances in hardware development, a very active area e.g. the integration of multiple sensors in sport garments. Studies with clinicians and patients also show that such advancement is very desirable to manage the conditions [83, 84]. Hopefully, our research may further augment such wearable devices with PBD capabilities and extend applications to rehabilitation and clinical contexts. The original aim of this work is, with a large set of sensors, to research what is feasible and then explore how to improve it. Several studies have recently aimed to combine sparse IMUs or just accelerometers (less than 6 sensors) and visual clues [85, 86] to reconstruct full-body motion. Given the highest performance is achieved by using full-body graphs, we can follow this work to simulate full-body motion data using a smaller sensor set.

6.2 Future use cases

While the goal of our study was not to build a ubiquitous support system for pain management, our architecture is a key component of such a system: performance of continuous PBD is critical for effective support. It should be noted that contextualization provided by the HAR module not only leads to improved PBD performance but informs assessment of people with CP and customizes timely support for self-management. We discuss here the main use cases and further developments that can exploit our proposed HAR-PBD architecture to deliver new types of support and interventions in CP management and beyond.

**In-the-wild-informed Clinicals Rehabilitation.** Clinicians need to know about patients’ difficulties in everyday activity [68], beyond the safe environment of the clinic, and without reliance on self-reported behaviors (e.g., diaries) that are commonly used but of low reliability [29], since awareness of habitual protective behavior and their triggers is low [62]. A ubiquitous system, capable of recognizing activity context and continuously detecting protective behavior, can provide clinicians with better understanding of the patient’s activity difficulties, and of progress, which often varies across AoIs. Connected to GPS and time, the system could further contextualize the activity, with factors that add stress e.g. social pressure.

**Patient-oriented Ubiquitous Self-management.** Difficulty transferring movement strategies learned in the clinic to everyday life is common, because of the complexity of the real world (environment, social demands, variety of activities and responsibilities, etc.), and interference by emotional states [37]. In [29, 79], a ubiquitous system transforms real-time movements (of specific body parts) into sound (sonification) to increase awareness in people with chronic pain of their physical capabilities and facilitate the autonomous use of movement strategies beyond the clinic, responsive to need rather than permanently on. If integrated in
such ubiquitous system, our HAR-PBD architecture could help identify when advice is needed, e.g. when the frequency of protective behavior during specific activities rises above a certain level; it can also provide reminders of breathing and breaks. Taking breaks and relaxation are critical pacing strategies to avoid tension that could lead to setbacks and prolonged days in bed. During exercise, the system can provide dedicated suggestions or exercise plans based on the frequency of protective behavior detected.

**Beyond Chronic-pain Management to Next-stage Human Activity Analysis.** Beyond supporting the management of chronic pain, our proposed hierarchical architecture could be applied in a variety of contexts where ubiquitous HAR technology is being leveraged. For example, ubiquitous HAR technology is opening new platforms to aid workers in factory assembly lines [15], to support them in their workspace activities, e.g. to identify and help correct mistakes, to aid training and establish human-robot collaboration. Thereon, another interesting application is to promote workers’ wellbeing, such as in reducing mental or physical stress. Our architecture can be integrated into the system to leverage the HAR to detect cues of fatigue or pain. Such a system could help identify the need for a break, adjust working timetables, and thus minimize development of musculoskeletal problems, a common problem in manufacturing industries. In these contexts, the number of sensors could be reduced to fit the specific activities and relevant movements.

Another active area of application is in healthcare. For instance, in [8], limb movement was assessed to screen perinatal stroke in infants, while arm movement was continuously analyzed to track everyday rehabilitation in stroke patients [75]. For these, integration of our hierarchical architecture in the system could help establish the link between the type of activity/movement and the behavior category (e.g. good or poor rehabilitation engagement for [75] or even pain and anxiety). Such activity-aware functions could allow more in-depth understanding of the patient and generate opportunities for personalized support.

7 Conclusion
Ubiquitous technologies open new opportunities to support people with chronic pain during their everyday self-management. In this paper, we targeted PBD in continuous movement data as the critical first step. We proposed a hierarchical HAR-PBD architecture to recognize the varying context of activity to aid the simultaneous detection of protective behavior. An adapted CFCC loss was also used to alleviate the class imbalances during training. Our evaluation with data from real patients suggested that the activity type information is effective to aid PBD in continuous data, leading to a notable improvement over the baseline (macro F1 score of 0.73 and PR-AUC of 0.52 vs. macro F1 score of 0.66 and PR-AUC of 0.44), and is more impactful than just solving the class imbalances (macro F1 score of 0.71 and PR-AUC of 0.48). The best result was achieved by combining the hierarchical architecture with CFCC loss, with macro F1 score of 0.81 and PR-AUC of 0.60. Additionally, in Section 5.1, we verified that graph representation improves the PBD performance. In Section 5.4, we showed that it is feasible to jointly train the hierarchical HAR-PBD architecture. However, work is needed to gain mutual improvement between the HAR and PBD modules. In Section 5.5, we showed the applicability and efficacy of our method using fewer nodes/joints (macro F1 scores of 0.77 and 0.76 with 14- and 7-node data input respectively). In subsequent research, we hope to build on the findings of this paper to establish a ubiquitous CP management system, considering real-world scenarios and proper interactions between the user and system.
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A  APPENDIX

Following the derivation of GCN presented in [17], the GC used in this work can be written in detail as

\[ f_{out}^{GC}(v_{ti}) = \sum_{v_{tj} \in \mathcal{N}(v_{ti})} \frac{1}{Z_{ti}(v_{tj})} f_{in}^{GC}(p^{GC}(v_{ti}, v_{tj})) \cdot w^{GC}(l_{ti}(v_{tj})), \]

(1)

where graph-adapted sampling function is \( p^{GC}(v_{ti}, v_{tj}) = v_{tj} \) with \( d(v_{ti}, v_{tj}) \leq 1 \), the graph-adapted weight function is \( w^{GC}(v_{ti}, v_{tj}) = w(l_{ti}(v_{tj})) \) with \( l_{ti}(v_{tj}) = d(v_{ti}, v_{tj}) \) and \( w \) to be the trainable weight matrix, \( f_{in}^{GC} \) is the input feature of the sampled node set at current layer while \( f_{out}^{GC} \) is the output feature of the respective centered node \( v_{ti} \), and \( Z_{ti}(v_{tj}) = \text{card}\{l_{tk} = l_{ti}(v_{tj})\} \) is a normalization term representing the cardinality of the partitioned subsets in the neighbor set. The 1-neighbor set \( \mathcal{N}(v_{ti}) = \{v_{tj}|d(v_{ti}, v_{tj}) \leq 1\} \) is applied to be the receptive field of each node \( v_{ti} \), as depicted by the blue contour in Figure 3(c). Within the weight function, the partition function \( l_{ti}: \mathcal{N}(v_{ti}) \rightarrow \{0, \ldots, K - 1\} \) can be used under different strategies, while in our work the distance-partitioning strategy [17] is adopted that divides the 1-neighbor set \( \mathcal{N}(v_{ti}) \) into two subsets, namely the centered node \( v_{ti} \) and the remaining neighbor nodes \( v_{tj}|d(v_{ti}, v_{tj}) \leq 1 \). As a result, we have \( K = 2 \) subsets thus \( l_{ti}(v_{tj}) = d(v_{ti}, v_{tj}) \). By using the distance-partitioning strategy, \( Z_{ti}(v_{tj}) \) equals to the number of all the neighboring nodes \( v_{tj} \) within the same neighbor set because they are within the same subset as well.