C-HAR: Compressive Measurement-Based Human Activity Recognition

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***Abstract*—In this paper we present C-HAR, a low-cost, low-complexity, compressive measurement-based human activity recognition framework for embedded devices, capable of simultaneously filtering and acquiring the sensor readings of a smartwatch's accelerometer and gyroscope at sub-Nyquist rates. A software simulation of the full system obtains an accuracy of 92.0% and 88.0% for the accelerometer-based and gyroscope-based systems respectively, obtained at a 5 Hz sample rate. A microcontroller implementation of the system's back-end obtains an accuracy of 90.3% and 87.1% for the accelerometer-based and gyroscope-based systems respectively with a runtime over twice as fast as that of a comparable baseline system.**

***Index Terms*—human activity recognition, compressive sensing, wearable sensors**

I. Introduction

We are currently witnessing an explosion in the adoption of smartwatches and their associated technologies. Market analysis conducted by [1] shows that the global smartwatch market volume is predicted to reach 230.3 million units by 2026, with the adoption rate growing across all demographics. This has led to a situation in which an ever-increasing number of people carry sensors on their wrists (a part of human anatomy with multiple axes of movement) for extended periods of time, significantly increasing the viability and scope of human activity recognition (HAR) systems.

Battery life and system autonomy are crucial factors in many HAR systems, especially those found in safety-critical applications where usage and adoption need to be as consistent and as uninterrupted as possible, and smartwatch-based HAR is no exception. We refer to this particular subcategory of HAR which focuses on maximizing system efficiency while presenting performance metrics comparable to regular, non-lightweight, alternatives as "lightweight HAR", where lightweight means "low-cost, low-complexity".

Lightweight HAR sees extensive use in medical applications in particular for two key reasons. The first reason is that low-cost, low-complexity systems can be worn for longer periods of time without needing to be recharged, increasing the device usage rate among the subjects. This is made clear in [2] where the authors found that 27% of participants in a medical trial stopped using their wearable sensing devices due to difficulties ensuring they remained powered and operational. The second reason is that more computationally complex systems often transmit information from a sensor or sensors worn by subjects to a local or cloud computing node for processing and storage, which significantly increases the risk of a subject's personal information being intercepted and misused by an ill-intentioned third party. This has a significant impact on the adoption rate of wearable HAR device-based healthcare, as highlighted in [3], where the authors found that a significant set of users in a medical devices trial did not feel comfortable letting their personal information be transmitted to a remote location for processing. Lightweight systems capable of performing processing and classification on-device can help overcome both these limitations. Moreover, the possibility of real-time on-device processing and classification offers significant advantages in a number of different HAR applications: the absence of transmission overheads due to communicating with the cloud would be particularly advantageous in safety-critical [4] or nudge-based systems [5], for instance.

There is a considerable existing body of research focusing on smartwatch-based HAR, but it is important to note that not all smartwatch-based systems are intrinsically lightweight: certain approaches either require the use of significant amounts of data to operate (such as the system proposed in [6] which obtains a large amount of sensor data and sends it via Bluetooth Low Energy (BLE) to a smartphone for off-device processing), or make use of larger-scale, more complex classifiers to identify the various activities (such as the approach presented in [7] in which the authors perform classification using off-device large-scale artificial neural networks (ANNs)). The cost, complexity, and off-device processing requirements of these systems make them unsuited for use in safety- and privacy-critical applications.

In this paper, we present a method to reduce the amount of data required to classify a range of daily human activities using smartwatches, while maintaining an accuracy comparable to existing approaches. By doing so, we hope to lower the system memory requirements by reducing the classifier model size, input data storage requirements, and overall computational costs associated with traditional HAR systems; the end goal being to design a lightweight HAR framework capable of operating on embedded devices in real-time, with the classification procedure performed entirely on-device. Our proposed approach further reduces overall system cost and complexity

doi: 10.1109/PerComWorkshops56833.2023.10150315

by simultaneously acquiring and filtering input signals, removing the need for an additional preprocessing stage.

We achieve this using a compressive sensing- (CS) inspired method first presented in our previous work [8], in which input signals are simultaneously filtered and sampled at sub-Nyquist rates by using spectrally shaped bipolar demodulating signals. We name the compressive measurement-based human activity recognition approach proposed in this paper C-HAR accordingly.

Furthermore, we implement the feature extraction and classification processes of the proposed system on a microcontroller (MCU). The small form factor and limited computational resources of a typical MCU make it a suitable stand-in for a smartwatch, and deploying our proposed system on such a platform will serve to prove its viability as a lightweight smartwatch-focused HAR framework.

Our main contributions can be summarized as follows:

- We put forward an approach to simultaneously filter and sample 3-axis sensor readings at sub-Nyquist rates using Markov chain-generated spectrally shaped bipolar sequence; we tailor the choice of bipolar sequences to both the sensor, and the individual sensor axis. Our proposed system's sample rate is 4 times lower than that of comparable typical systems using a "sample-then-filter" approach.
- We use our proposed system to perform on-device multi-class classification, obtaining accuracy similar to existing binary classification systems. The on-device runtime of our proposed system is over twice as fast as that of a comparable baseline system.
- We present an MCU implementation of the system's feature extraction and classification processes, demonstrating its viability as a smartwatch-compatible lightweight sensing architecture.

The remainder of this paper is structured as follows: we begin in Section II by examining the existing literature, in Section III we describe the system design process, and how we deal with the input data particular to our application, in Section IV we evaluate our proposed system to gauge it's viability as a lightweight HAR framework, and discuss the obtained results in Section V. In Section VI we cover the process of implementing C-HAR on an MCU, and finally conclude the paper and discuss potential directions for future work in Section VII.

II. Related Work

There is a range of existing research focusing on CS-based lightweight wrist-worn HAR systems, which while ostensibly similar to our proposed C-HAR approach vary significantly in certain aspects. The authors of [9] leverage CS in a healthcare monitoring application to reduce the minimum required transmission power between sensors placed on patients and a central processing computer. While this system uses CS to acquire input signals at sub-Nyquist rates, it differs majorly from our proposed system as it recovers the original signal from the compressive measurements before performing classification.

In [10], the authors present a compressive measurement-based stroke detection system which bypasses the CS reconstruction process entirely, and performs classification using the information contained in the measurements prior to reconstruction. While this approach is similar to the one put forward in our work, there are two key differences between the two. The first difference is the way in which the compressive-measurements are processed: in our proposed method, the input signal is filtered during the sampling process, rather than being filtered post-sampling. The second difference is the number of class labels: our proposed method performs multiclass classification, and the system outlined in [10] performs binary anomaly detection classification.

The authors of [11] present a low-power compressive sensing-inspired sub-Nyquist sensing device. The system employs non-uniform wavelet sampling (NUWS) to obtain a set of features directly from an electrocardiogram (ECG) signal, which are then used to detect cardiac arrhythmia. Again, this approach is similar to our proposed C-HAR approach, however this system does not process or filter the compressive measurements before classification, and similarly to the approach described previously in [10], only performs binary anomaly detection classification.

More generally, there is a large body of existing research focusing on MCU-based HAR. The authors of [12] present a framework which makes use of traditional accelerometer and gyroscope sensor information in conjunction with a wearable stretch sensor placed on a subject's leg to obtain data from multiple sensing modalities. This information is presented to an MCU-based deep neural network (DNN), whose performance can be improved through user feedback. This feedback however, is provided through a smartphone application which also calculates and transmits the necessary weight and bias changes of the DNN, and so it cannot be said that the full system is entirely contained on an MCU. In contrast to the systems outlined above which all use supervised learning methods to perform classification, the authors of [13] propose an unsupervised learning approach using a combination of convolutional neural networks (CNNs) and self-organizing maps for use in lightweight embedded device-based HAR applications.

III. System Design

A. System Overview

An overview of our proposed C-HAR system is shown in Figure 1 and is made up of three sections: *Random Demodulator*, *Spectral Shaper* (split into 3 *subshapers*), and *Feature Extraction and Classification*.

Three-dimensional input signals drawn from the sensor readings of a smartwatch's onboard accelerometer and gyroscope sensors are simultaneously filtered and sampled at a sub-Nyquist rate in the *Random Demodulator* section using a Markov chain-generated spectrally shaped bipolar pseudo-random sequence *prs* created by the *Spectral Shaper* section. Features are then extracted from the acquired samples and used to detect and identify a range of daily human activities in the *Feature Extraction and Classification* section. In this paper we refer to the 3-dimensional input signal as $s(t)$, with each dimension corresponding to a different sensor axis, and refer to the *subsignals* corresponding to each axis as $x(t)$, $y(t)$, $z(t)$.

In the following sections, we first give a brief overview of the theory underpinning our C-HAR system, which is based on the results of our previous work presented in [8], before explaining the operation of the different C-HAR system components in more detail.

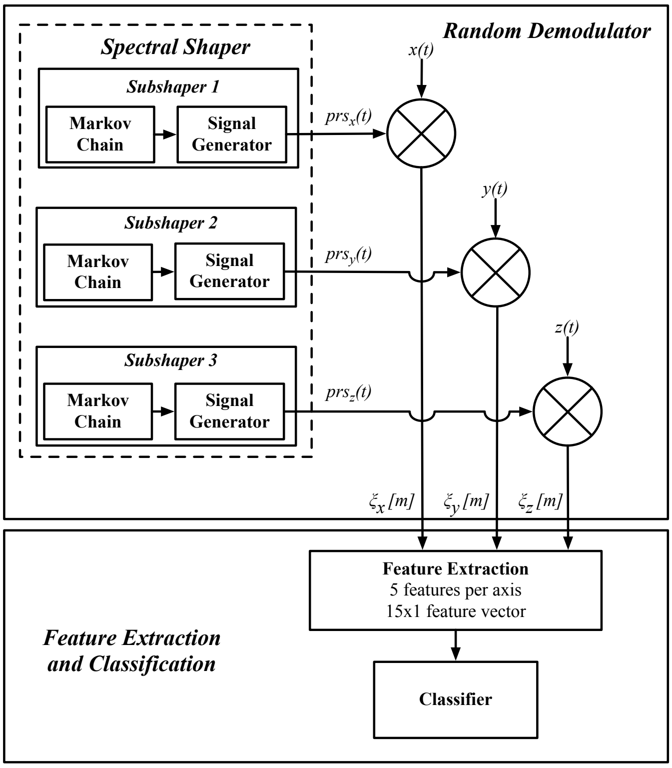


Fig. 1: C-HAR system overview: the $x(t)$, $y(t)$, $z(t)$ *subsignals* of the input signal $s(t)$ are combined with suitable $prs_x(t)$, $prs_y(t)$, and $prs_z(t)$ signals, before being acquired at sub-Nyquist rates. Features are extracted from the resulting $\xi_x[m]$, $\xi_y[m]$, $\xi_z[m]$ measurements and used as inputs to a classifier.

B. Compressive Measurement Processing

The most computationally intensive step in the entire CS procedure is the reconstruction process. In our proposed C-HAR system, we significantly reduce the computational requirements by bypassing the reconstruction process and performing classification based on information extracted directly from a set of compressive measurements ξ.

If we consider ξ as samples from which features can be extracted, then it follows that appropriate preprocessing of the compressive measurements can improve the performance of any associated supervised learning approaches. Typically, preprocessing is performed once the ξ measurements are obtained and is ordinarily modeled as a sequence of matrix operations on an input matrix or vector such as in [14] or [15]. While this approach can lead to precise filtering and processing, it often requires knowledge, and thus on-system storage of $\mathbf{\Theta}$, the reconstruction matrix used in the recovery process, which places minimum requirements on the memory and computational capabilities of the hardware on which the processing occurs.

We propose a solution to this problem in our previous work [8] where we present a simultaneous sub-Nyquist sampling and filtering framework based on the random demodulator (RD) architecture [16]. We showed that the frequency spectrum of the pseudorandom bipolar spreading sequence $prs(t)$ has a direct effect on the frequency spectrum of the reconstructed signal $\hat{s}(t)$. Thus, with prior knowledge of spectral locations of interest in the input signal, using tailored bipolar sequences during the demodulation process allowed us to attenuate and amplify frequency content at these specific locations, improving subsequent classification accuracy. The bipolar sequences were generated using either single or combined dual Markov chains, whose frequency-domain representations are determined by the chains' lengths (2- or 4- state) and transition probabilities p_1 and p_2. This ensured that the resulting $\mathbf{\Theta}$ matrix adhered to the strict criteria restricted isometry properties (RIP) outlined in CS theory [17], thereby allowing the $\xi[m]$ measurements to be considered as a reduced-dimensionality representation of the input signal. The simultaneous sub-Nyquist sampling and filtering of smartwatch sensor signals presented in this paper is performed using a modified version of this framework.

C. Random Demodulator

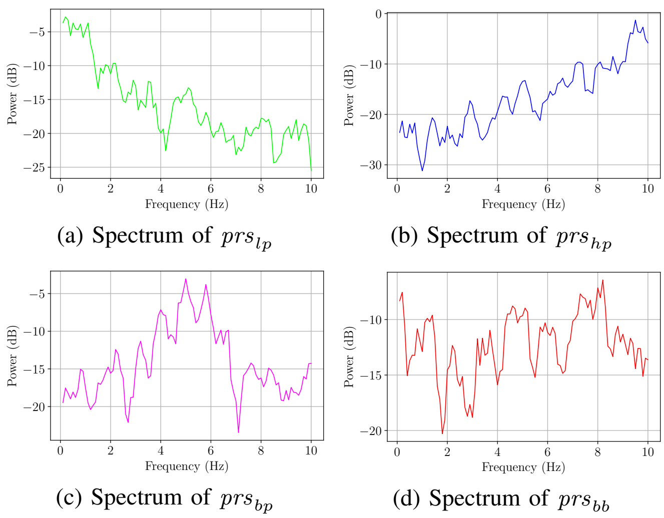
The *Random Demodulator* section acquires the 3-dimensional input signals at sub-Nyquist sample rate R, and is made up of a signal generator, a mixer, a low-pass filter (LPF), and an analogue-to-digital-converter (ADC). The compressive measurements obtained from each of the $x(t)$, $y(t)$, and $z(t)$ *subsignals* are referred to as $\xi_x[m]$, $\xi_y[m]$, and $\xi_z[m]$ respectively. In our proposed C-HAR system, the *prs* used to demodulate the input signals are generated in the *Spectral Shaper* section.

D. Spectral Shaper

The *Spectral Shaper* section consists of 3 *subshapers*, each of which is made up of a signal generator and Markov chain block. They are used to produce bipolar sequences designed in such a way as to amplify or attenuate specific frequency information in an input signal $s(t)$, with each of the 3 *subshapers* producing a *prs* which modulates the respective individual $x(t)$, $y(t)$, $z(t)$ *subsignals* of $s(t)$. As we will see in Section IV-A, in our application we are faced with 18 different activities recorded using 2 different sensors over 3 axes, resulting in a total of 108 different signals. Given that it is not possible to individually match each and every $x(t)$, $y(t)$, $z(t)$ with a suitable $prs_x(t)$, $prs_y(t)$, and $prs_z(t)$, we create a set of four predefined "filter" sequences, whose spectra match the frequency responses of commonly used filter types, using the approach discussed in Section III-B: a low-pass sequence, a band-pass sequence, a high-pass sequence, and a broadband sequence referred to as prs_{lp}, prs_{bp}, prs_{hp},

TABLE I: Filter prs Parameters

prs	Number of Chains	p_1	p_2	Length of 1^{st} Chain	Length of 2^{nd} Chain
prs_{lp}	Single	0.85	-	2	-
prs_{bp}	Dual	0.9	0.9	2	4
prs_{hp}	Single	0.1	-	4	-
prs_{bb}	Single	0.5	-	2	-



(a) Spectrum of prs_{lp}

(b) Spectrum of prs_{hp}

(c) Spectrum of prs_{bp}

(d) Spectrum of prs_{bb}

Fig. 2: Spectra of “filter sequence” prs signals.

and prs_{bb} respectively. The optimal prs for each axis in our C-HAR system is determined empirically prior to operating and evaluating the system. The spectra of the “filter” sequences are shown in Figure 2, and the parameters used to generate them are shown in Table I.

E. Feature Extraction and Classification

The *Feature Extraction and Classification* section consists of a feature extraction block and a classifier block. We extract a set of 5 features from the $\xi_x[m]$, $\xi_y[m]$, $\xi_z[m]$ measurements of both sensors, for a total of 15:

- *mean*
- *standard deviation*
- *median*
- *largest absolute value*
- *interquartile range*

for $\xi_x[m]$, $\xi_y[m]$, $\xi_z[m]$

In the classifier block, these extracted features are used as inputs to a multiclass classifier to identify the activities performed by the subjects. We use a random forest (RF) classifier, often employed in HAR applications due to its suitability for multiclass classification, minimal preprocessing requirements (no input data rescaling required), and good outlier tolerance. The RF is implemented using the *scikit-learn* library [18].

IV. Evaluation

A. Input Data

The data used in our proposed system comes from the WISDM dataset [19]. The dataset contains the 3-dimensional sensor data of the accelerometers and gyroscopes, sampled at a rate of 20 Hz, of smartphones and smartwatches worn and carried by a set of 51 subjects, who each performed one of 18 different activities for a duration of 3 minutes. The 18 activities can be split into 3 categories: “Non Hand-Oriented”, “Hand-Oriented (General)”, and “Hand-Oriented (Eating)”.

We perform a number of preprocessing steps before using the dataset in our proposed system. The first step is to discard all the data collected by smartphones, retaining only the data collected by smartwatches. The second step is to remove the data of any subjects who did not perform all 18 activities, bringing the number of subjects down from 51 to 43. The final step is to split the sensor data by subject and by activity into non-overlapping windows of length t_w. In addition to the raw sensor data, the WISDM dataset includes a range of precalculated features extracted from $10s$ windows of the raw time-series data, thus for the sake of consistency and future comparison of results, we set the time window for activities in our system as $t_w = 10s$.

This leaves us with a total of 9300 segments with an average of 216 segments per subject for the accelerometer data, and a total of 9192 segments with an average of 213 segments per subject for the gyroscope data. Because the sampling rates of the two sensors are not synchronized, we consider the accelerometer and gyroscope readings separately, rather than as a single, combined sensor reading. For illustrative purposes, we show the average frequency-domain representation of a single example activity from each of the 3 categories (namely, “Walking”, “Typing”, and “Eating Pasta”) in Figure 3.

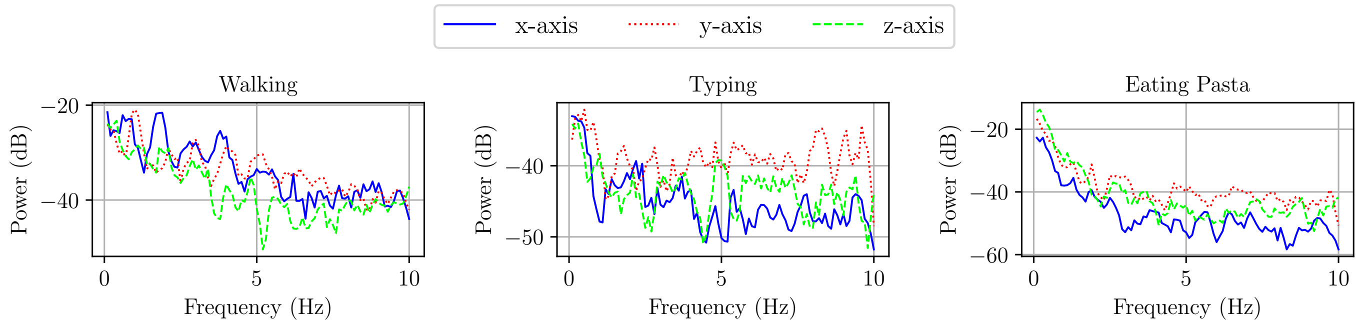
B. Iterative Multiclass Classification

Accurately classifying 18 different activities involves extensive input signal preprocessing or the use of a consequentially larger classifier, both of which require significantly more computational power than what is found in current lightweight approaches. Therefore, given that the activities present in our dataset are split into 3 categories, we evaluate our C-HAR system using iterative 3-class classification as this enables us to effectively and fairly evaluate system performance under the current computational constraints.

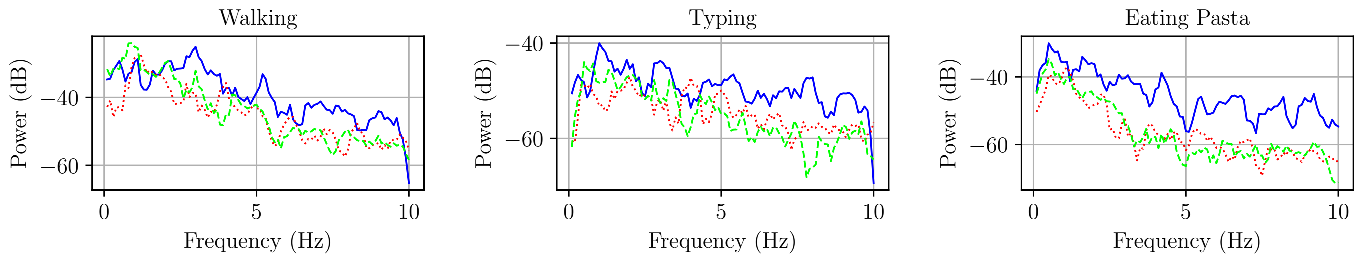
Thus, evaluation is performed by iteratively drawing one activity from each of the 3 categories (“Non Hand-Oriented”, “Hand-Oriented (General)”, and “Hand-Oriented (Eating)”) in turn, performing multiclass classification on every possible 3-activity combination, for a total of 210 combinations and averaging the final results. All other simulation parameters are summarized in Table II. System performance is evaluated using the accuracy metric.

C. Feature Extraction and Classification

We evaluate the classification performance of C-HAR using *leave-one-subject-out* cross-validation: we set each one of the 43 feature sets (where each set corresponds to a different test subject, and contains the 15 features presented in Section III-E) as the testing set, and the combined 42 remaining feature sets act as the training set. This process is performed 43 times in total, with each of the feature sets acting as the testing set in turn.



(a) Average accelerometer frequency domain plots by axis.



(b) Average gyroscope frequency domain plots by axis.

Fig. 3: Average frequency domain plots of the a) accelerometer and b) gyroscope sensor readings by axis for “Walking”, “Typing”, and “Eating Pasta’ activities.

TABLE II: Simulated C-HAR System Parameters

Nyquist Rate W		20 Hz
ADC Rate R		5 Hz
Bit Depth B		12 bits
Signal Length (Time) T_s		$10s$
Signal Length (Samples) N		200
Number of Compressive Measurements M		50
$prs_x(t)$	Accelerometer	prs_{lp}
	Gyroscope	prs_{lp}
$prs_y(t)$	Accelerometer	prs_{hp}
	Gyroscope	prs_{bp}
$prs_z(t)$	Accelerometer	prs_{hp}
	Gyroscope	prs_{lp}

We set the RF parameters n_estimators $=$ 1000 and min_samples_leaf $=$ 3, and leave the other parameters as default. Both the training and testing sets are balanced using random undersampling prior to classification, and the results obtained from each of the 43 runs are averaged to obtain the system accuracy. Finally, to account for any potential discrepancies caused by inherent randomness in the classification process, we perform the full classification process 10 times and average the obtained results.

V. Results and Discussion

Table III displays the final system classification accuracy, obtained by averaging the accuracies of each of the individual 210 3-class groups, for both sensors. Also displayed are the accuracies of other systems against which we can compare C-HAR, which can be split into two categories:

TABLE III: C-HAR Compared to Baseline Approaches and Existing Systems

System	Accuracy	Sample Rate	Classification
C-HAR (Accelerometer)	92.0%	5 Hz	3-class
C-HAR (Gyroscope)	88.0%	5 Hz	3-class
Baseline (Accelerometer)	93.4%	20 Hz	3-class
Baseline (Gyroscope)	90.1%	20 Hz	3-class
[10]	91.0%	10 Hz	Binary
[11]	98.9%	360 Hz	Binary

- **Baseline Approaches:** The first category consists of accelerometer- and gyroscope-based baseline approaches, designed to mimic the operation of C-HAR using a typical “sample-then-filter” methodology. The $x(t)$, $y(t)$, $z(t)$ *subsignals* of both sensors are acquired at the Nyquist rate $W = 20$ Hz before being filtered by a separate filter whose frequency response matches that of the corresponding prs_x, prs_y, and prs_z bipolar sequences. The filters used are 6^{th} order Butterworth filters, and the cutoff frequencies are set as 5 Hz for the high-pass and low-pass filters, and as 2.5 Hz and 7.5 Hz for the band-pass filter. We can see that for both sensors, C-HAR obtains a comparable accuracy to the baseline systems, for a back-end sample rate $R = \frac{W}{4} = 5$ Hz.
- **Existing Systems:** The second category consists of existing lightweight CS-based systems [10] and [11], both of which are healthcare-focused ECG-based systems. We can see that while the accuracies of the two systems and C-HAR (in particular the accelerometer-based version) are similar, C-HAR operates at a lower sample

rate, and performs 3-class classification, while the other systems only perform binary classification. It is important, however, to bear in mind the differences in the applications these systems are deployed in, and thus the signals obtained and identified: C-HAR looks to acquire and classify relatively low-noise onboard sensor signals, whilst the other two systems are looking to obtain and identify significantly noisier ECG signals. It is reasonable to assume that the relative noise levels of the signals, along with other factors, have an effect on the accuracy performance of the different systems.

VI. Microcontroller Implementation

A. General Approach

The first step in the MCU implementation of C-HAR is to select a suitable device. We choose the Teensy 4.1 board[1] for our implementation as it has a good cost-to-memory ratio, and a large amount of total available memory.

The compressive measurements $\xi[m]$ are generated in the manner described in Section III, and are saved on an SD card from which they are sequentially loaded into the MCU for feature extraction. The previously trained classifiers used in C-HAR are ported from their software implementations onto the MCU using the *emlearn* library [20].

The system parameters used in this MCU implementation are the same as used in Section IV, displayed in Table II. Given the considerable lengths of the model training, model porting, and $\xi[m]$ measurement loading process, in our initial evaluation of C-HAR's MCU implementation we use a reduced-sized dataset for the sake of time and practicality. This reduced-size dataset consists of 14 of the original 43 subjects chosen at random, performing a single activity from each of the 3 categories. We choose as 3-activity combination the 3 activities shown in Figure 3 ("Walking", "Typing", and "Eating Pasta").

B. Feature Extraction and Classification

We load the $\xi[m]$ measurements for both sensors and for each axis onto the MCU, and extract the same features as described in Section III-E. We visually confirm that the features extracted by the MCU are identical to the features extracted in the software implementation of C-HAR by outputting them to the Teensy IDE's serial monitor.

The classifier used is a smaller ported version of the RF classifier trained in the system's software implementation. We set the RF parameters as $\mathrm{n\_estimators} = 100$ and $\mathrm{min\_samples\_leaf} = 3$ respectively, and leave the other parameters as default. As in Section IV-C, evaluation is performed using *leave-one-subject-out* cross-validation.

C. Results and Discussion

The MCU implementation of C-HAR obtains an accuracy of 90.3% for the accelerometer-based system and 87.1% for the gyroscope-based system. These results are similar to the simulation accuracies of 92.0% for the accelerometer-based system and 88.0% for the gyroscope-based system presented in Section V. Despite the reduction in model size from $\mathrm{n\_estimators} = 1000$ to $\mathrm{n\_estimators} = 100$, the system's accuracy performance remains stable.

We quantify the improvements to computational efficiency by comparing the runtimes of C-HAR's feature extraction and classification processes to those of a non-compressive measurement-based baseline approach (as previously described in Section V). The runtime results averaged across both sensors are shown in Table IV. We can see that C-HAR runs more than twice as fast as the baseline approach, illustrating the computational advantages presented by our proposed method. We speculate that the difference in measured runtime between the C-HAR and baseline classification processes is due to a lack of timer resolution at such short time intervals, and that a more precise timer would show the measured values to be close to identical.

These results help prove the viability of C-HAR as a lightweight, embedded-device compatible framework. It is important to note, however, that the MCU implementation of C-HAR was evaluated using a reduced-size version of the dataset, and that system performance may vary if confronted with the entire original dataset.

TABLE IV: C-HAR MCU Implementation Runtime Results

Process	C-HAR	Baseline
Feature Extraction	50.4 ms	118 ms
Classification	0.257 ms	0.413 ms
Total	50.7 ms	119 ms

VII. Conclusion

In this paper we presented C-HAR, a lightweight sub-Nyquist compressive measurement-based human activity recognition system, capable of classifying a range of daily human activities using data obtained from the sensor readings of a smartwatch's onboard accelerometer and gyroscope. When compared to traditional "sample-then-filter" baseline approaches, C-HAR obtains a similar accuracy for a sampling rate 4 times lower. When compared to existing CS-based lightweight HAR systems, C-HAR obtains a similar accuracy for a lower sample rate, and performs multiclass rather than binary classification. The back-end feature extraction and classification processes of C-HAR can be implemented on an MCU, where they run over twice as fast as those of a comparable baseline system, and do not require communication with an external device such as a smartphone or server to process or classify data. We hope that the results presented in this paper will help drive the adoption of smartwatch-based and wearable sensors by both extending system autonomy and alleviating privacy concerns. Future work involves fine-tuning our bipolar sequence-based preprocessing and classification approaches to increase the number of classes our system is able to detect, increasing the number of different applications it can be deployed in.

Acknowledgment

This work was supported in part by JSPS KAKENHI Grant Numbers JP22K18652 and JP18H03233, and in part by the

[1]https://www.pjrc.com/store/teensy41.html

Cooperative Research Project Program of the Research Institute of Electrical Communication (RIEC), Tohoku University.

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