TinyRadarNN: Combining Spatial and Temporal Convolutional Neural Networks for Embedded Gesture Recognition with Short Range Radars

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Abstract—This work proposes a low-power high-accuracy embedded hand-gesture recognition algorithm targeting battery-operated wearable devices using low power short-range RADAR sensors. A 2D Convolutional Neural Network (CNN) using range frequency Doppler features is combined with a Temporal Convolutional Neural Network (TCN) for time sequence prediction. The final algorithm has a model size of only 46 thousand parameters, yielding a memory footprint of only 92 KB. Two datasets containing 11 challenging hand gestures performed by 26 different people have been recorded containing a total of 20,210 gesture instances. On the 11 hand gesture dataset, accuracies of 86.6% (26 users) and 92.4% (single user) have been achieved, which are comparable to the state-of-the-art, which achieves 87% (10 users) and 94% (single user), while using a TCN-based network that is 7500x smaller than the state-of-the-art. Furthermore, the gesture recognition classifier has been implemented on Parallel Ultra-Low Power Processor, demonstrating that real-time prediction is feasible with only 21 mW of power consumption for the full TCN sequence prediction network.

Index Terms—gesture recognition, machine learning, internet of things, ultra-low power

I. INTRODUCTION

Human-computer Interface (HCI) systems provide a plethora of attractive application scenarios with a wide array of solutions, strategies, and technologies [1]. Traditionally, the approaches for recording human gestures are based on image data or direct measurements of movement, i.e. using motion sensors. [2], [3] The main types of sensors used in literature are image-based and motion-based, using cameras with or without depth perception, force-sensitive resistors, capacitive elements or accelerometers to measure the movement of the subject directly. [4] While these approaches have been shown to work well in controlled settings, robustness remains a challenge in real-world application scenarios. Image-based approaches have to deal with well-known environmental challenges like subject occlusion and variability in brightness, contrast, exposure and other parameters. [5] Another drawback of image-based solutions is the comparatively high power consumption, with popular sensors like the Kinect sensors having power consumptions of 2.25 W (v1) and 15 W (v2) respectively. [6] Wearable systems using motion-based sensing are much less affected by environmental variability and typically use significantly less power, but are more difficult to adapt to differences in user physique and behaviour. Approaches based on Wi-Fi have also been studied, but are generally restricted to coarse or full-body gestures, due to the low spatial resolution and susceptibility to electromagnetic interference and multi-path reflections. [7]–[10] On single subjects, however, they have been shown to achieve high accuracy. [3], [11]

A very promising novel sensing technology for hand gesture recognition is based on high frequency and short-range pulsed RADAR sensors. [12] RADAR technology can leverage the advantages of image-based recognition without being exposed to the same disadvantages in environmental variability. The electromagnetic RADAR waves can propagate through matter, such that it can potentially record responses even if placed behind clothing. Furthermore, recently proposed designs based on novel sensor implementations can fit within a low power budget. [12], [13] Battery-operated Internet of Things (IoT) and wearable devices typically host an ARM Cortex-M or RISC-V based microcontroller (MCU), which can achieve power consumption in the order of Milliwatts and computational speeds in the order of hundreds of MOPS/s. [14], [15] Fitting within these limited computational resources to run machine learning algorithms is a fascinating challenge for industrial and academic researchers. [16] Recently, several research efforts have started to focus on specialized hardware to run machine learning algorithms, and in particular neural networks on power-constrained devices. [16]–[18] Parallel architectures leveraging near-threshold operation and multi-core clusters, enabling significant increases in energy efficiency, have been explored in recent years with different application workloads [19] and low-power systems [20].

The main state-of-the-art approaches to machine learning-based time-sequence modelling for gesture recognition are Hidden Markov Models (HMM) [21] and Long Short-Term Memory (LSTM) [22] networks, which both use an internal state to model the temporal evolution of the signal. In recent years especially, Artificial Neural Networks (ANN) have seen a rapid increase in popularity, with most recent works relying on LSTM-based approaches. [23], [24] On the processing side, previous work has shown the potential of RADAR signals for use with machine learning algorithms to classify static as well as dynamic hand gestures. [13] The recently proposed RADAR sensing platform Soli, jointly developed by Infineon and Google, has been studied in different works, most prominently by Wang et al. [25]. They propose an LSTM model that
achieves an accuracy of above 90% over 11 classes. However, the memory requirements of the model exceed 600 MB, which is several orders of magnitude more than what is feasible with any low-power edge device using a microcontroller.

In contrast to the state-based modelling of the input signal, Temporal Convolutional Neural Networks (TCN) are stateless in the sense that their computation model does not depend on the input. This means that they can compute sequential outputs in parallel, unlike LSTMs or HMMs. Furthermore, since they only use stateless layers, TCNs use significantly less memory for buffering feature maps compared to LSTMs, defusing the memory bottleneck on embedded platforms. TCN have increasingly been adopted in many application scenarios where the classification of data is heavily linked to its temporal properties, for example, biomedical data or audio data.

This paper proposes a novel embedded, highly accurate temporal convolutional neural network architecture, optimized for low-power microcontrollers. The proposed model achieves both a memory footprint of less than 100 KB, as well as achieving a per-sequence inference accuracy of around 86.6% for 11 challenging gesture classes, trained on a multi-user dataset, and 92.4% for a single-user dataset. This work exploits novel, low-power short-range A1 RADAR sensors from Acconeer\cite{acconeer_products} to acquire two rich and diverse datasets, one for a single user and one for a total of 26 users, each containing 11 gestures. Further, we leverage a multi-core RISC-V based embedded processor taking advantage of the emerging parallel ultra-low power (PULP) computing paradigm to enable the execution of complex algorithmic flows on power-constrained devices, targeting wearable devices especially.

We show that highly-accurate, real-time hand gesture recognition within a power budget of around 120 mW, including the sensor and processing consumption, is possible with the proposed sensor and computing platform. Experimental evaluation with a working prototype demonstrated both the power consumption and the high accuracy and are presented in the paper.

The main contribution of this paper can be summarized as follow:

- Design and implementation of a TCN network architecture optimized for low-power hand gesture recognition on microcontrollers, achieving state-of-the-art accuracy with a total memory footprint of less than 512 KB.
- Recording of an open-source gesture recognition dataset featuring 11 challenging, fine-grained hand gestures recorded with the low-power Acconeer A1 pulsed RADAR sensor to provide a baseline dataset for future research.
- Implementation of the proposed model in a novel parallel RISC-V based microcontroller that has 8 specialized parallel cores for processing and 512 KB of on-chip memory.

The novel, power-optimized architecture of the processors enables a full-system power consumption below 100 mW in full active mode.

- Evaluation of the benefits of the algorithm in terms of accuracy, energy efficiency and inference speed, showing that the system uses orders of magnitude less for real-time prediction compared to the state-of-the-art.

II. RELATED WORKS

Hand gesture recognition is a widely investigated field. However, it is difficult to put all the research into context, as there are many different categories of hand gestures, which vary in complexity. Also, depending on the number of modelled gestures, the sensor used and how well diversified the studied dataset is, accuracies vary greatly. An important distinction can be made between coarse gestures, where parts or all of the arm are included in the gesture like hand waving and pointing with a finger (and the full arm) into a certain direction, as opposed to fine-grained hand gestures, where only the hand or part of it are in motion.

A. Image-based gesture recognition

One of the well-studied data sources for state-of-the-art gesture recognition tasks are 2D-RGB and RGB-D images and videos. Works by Wan et al., Wu et al. and Calin use Hidden Markov Models to model time-sequence progression in RGB-D image-based data. One work by Varol et al. focusing on RGB video has employed 3D-CNNs, similar to the work by Ji et al. where the third dimension corresponds to the time axis. While this approach works very well for their application scenario, the input feature map includes the full-frame time sequence for each layer, which is very memory intensive. A very recent work by Koller et al. shows the potential of combining Convolutional Neural Networks (CNN) with LSTM and HMM for continuous sign language recognition with weakly supervised training.

B. RADAR-based gesture recognition

Some research has been conducted to utilise RADAR systems or radio signals to predict hand gestures. The approaches vary in terms of the application scenario, as well as accuracy and power efficiency. Different models without explicit sequence modelling have been employed in the past, a sample of which is discussed here. Kim et al. use pulsed radio signals to determine static hand gestures by analysing the differences between reflected waveforms with the help of a 1D CNN. Accuracies of over 90% are achieved for American Sign Language (ASL) hand signs using a CNN and micro-Doppler signatures. Kellogg et al. use an ultra-low-power approach by building a system, which classifies simple, coarse hand gestures such as Push, Pull, Flick, Pinch and Zoom In & Out by utilising ambient, already existing RF signals, such as TV signals, or signals from an RFID reader. With their analog gesture-encoding prototype they use only 5.85 µW of power for 15 gesture recognitions per minute yielding an accuracy of 94.4% for 8 coarse hand-gestures.

\footnote{1https://www.acconeer.com/products}
convolutional neural networks to classify ten hand-gestures using micro-doppler signatures from a pulsed RADAR. Their offline prediction algorithm reaches an accuracy of 85.6% on a single participant. [37] Using a similar approach based on micro-doppler signatures and a Frequency-Modulated Continuous Wave (FMCW) RADAR, Sun et al. showed that inference accuracy of over 90% on a nine gesture dataset recorded from a stationary RADAR for driving-related gestures is possible. [38]

Different works have used combinations of LSTM cells or Hidden Markov Models combined with different pre-processing strategies and convolutional layers to classify both coarse- and fine-grained gestures with the help of time-sequence modelling. Hazra et al. present a FMCW-based system which is trained to recognize eight gestures, reaching an accuracy of over 94%. [39] Targetting embedded, low-power applications, Lien et al. developed a high-frequency short-range RADAR specifically for the purpose of hand-gesture recognition, called soli. They implement a neural network to classify four hand gestures. Their final implementation uses a random forest classifier on those features with an optional bayesian filter of the random forest output. They use four micro-gestures, which they call “virtual button” (pinch index), “virtual slider” (sliding with index finger over thumb), “horizontal swipe” and “vertical swipe”. On those four gestures, they achieve a per-sample accuracy of 78.22% and a per-sequence accuracy of 92.10% for the bayesian filtered random forest output. [12] Choi et al. used the soli sensor and a self-recorded 10 gesture dataset featuring ten participants to train an LSTM-based neural network. They achieve an accuracy of over 98% using a GPU for inference computation. [40] Using the soli sensor, Wang et al. propose a machine learning model to infer the hand motions contained in the RADAR signal, based on an ANN network containing both convolutional layers and LSTM cells. They use a fine-grained eleven gesture dataset recorded using the soli sensor. While their approach shows high accuracy of 87.17%, their proposed model uses more than 600 MB of memory which is several orders of magnitude more than most low-power microcontrollers offer. Moreover, the Soli sensors are consuming more than 300 mW of power, which will drain any reasonably sized battery for a wearable device in a few minutes of use [25].

While it has been shown that TCN can outperform LSTM for action segmentation tasks, both in terms of accuracy and inference speed [26], [41], the use of TCN for gesture recognition remains a relatively unexplored field of research. However, one work by Luo et al. indicates that classical 2D-TCNs can perform equally well and even outperform approaches based on LSTM cells and HMM for gesture recognition tasks. [42]

This paper presents a combination of TCN and CNN models to improve energy efficiency, reduce memory requirements and maximize the accuracy of gesture recognition using sensor data from a short-range RADAR. The hardware implementation and the benefits of the combination of TCN have briefly been discussed in the authors’ previous work. [13]

In this paper, we significantly extend the contribution of the previous work by fully discussing the model architecture and comparing it against other state-of-the-art gesture recognition algorithms, showing that the proposed TCN-based model performs significantly better in terms of accuracy per operation than the state-of-the-art LSTM-based approach. We further evaluate in-depth the selection of features starting from the raw sensor data. To the best of the authors’ knowledge, there is no previous work that evaluates the use of TCNs for embedded, real-time hand-gesture recognition.

III. BACKGROUND

A. Range Frequency Doppler Map

Feature maps based on the Fourier transform of the time axis, like the Range Frequency Doppler Map (RFDM), similarly to micro-Doppler signatures, have been proven to be effective for machine learning applications in previous research on gesture recognition. [37]–[40], [43] It relies on the Doppler effect, which quantifies the shift of frequency in a signal that is reflected from a moving object. This shift of the frequency is correlated to the velocity of the object in the direction of the sensor. In order to detect changes in velocity, the I/Q signal is Fourier transformed into the frequency space, where changes in frequency can be observed. In order to detect the movement of objects in front of the sensor, multiple sweeps (i.e. time steps) are joined together and the time signal is Fourier transformed for each range point. As the sampled signal from each sweep $S(t, r)$ is time and range discrete the Discrete Fourier Transform (DFT) is used. The $i$–th row vector $S^{(i)}(f, r)$ of the RFDM can be calculated according to the following equation:

$$S^{(i)}(f, r) = \sum_{t=0}^{T} S(t, r) e^{-\frac{2\pi if}{T}}$$

Where $T$ is the total number of sample points per recorded distance point. In this work, only the absolute values of this function are considered.

B. Temporal Convolutional Networks

Temporal Convolutional Networks are a modelling approach for time series using dilated convolutional neural networks, proposed by Lea et al. [41], which has been used for a multitude of tasks, but very prominently in speech modelling [44], [45] and general human action recognition [46]. The basis of TCN are causal, dilated convolutions. Causal refers to the fact that for the prediction of any time step no future inputs are considered. Thus, the support pixel of the kernel is always chosen to be the last pixel. This is needed in a real-time prediction scenario, as in that case only the current and past data values are available at prediction time. The idea of TCNs is to use convolutional kernels and stretch them out (i.e. to use dilation), such that the size of the receptive field of the kernel...
increases. By increasing the dilation factor for consecutive layers the receptive field can be increased rapidly and very long effective memory of the network can be achieved. Figure 1 shows the data flow of the TCN as used in this work.

\[ \Delta d \text{ of the Acconeer sensor amounts to } 0.483 \text{ mm, which corresponds to a time-of-flight of } 1.6 \text{ ns.} \]

B. Dataset Specification and Acquisition

To train and evaluate the sensor for hand gesture recognition, two datasets were gathered in this work: One 5-gesture dataset and two 11-gesture datasets. The 11-gesture dataset features the same gestures as Wang et al. [25] and the 5-gesture dataset uses a subset of the same 11 gestures, consisting of the "Finger Slide", "Slow Swipe", "Push", "Pull" and "Palm Tilt" gestures. Using the same gestures allows us to have an effective comparison. All eleven gestures are depicted in figure 2.

The 11-gesture dataset uses two Acconeer sensors with a sweep rate of 160 Hz each, while the 5-gesture dataset uses a single sensor with a sweep rate of 256 Hz. Participants were shown figure 2, the approximate height at which to perform the gesture, but were given minimal instructions on how to perform the gestures.

The 11-gesture dataset contains a total of 45 recording sessions of 26 different individuals, out of which 20 recordings are recorded from the same person to evaluate single-user accuracy, while the other 25 recordings are each recorded from different individuals. Subsets of the 11-gesture dataset are used to evaluate single user (SU) performance and multi-user (MU) performance. For the single-user dataset, the aforementioned 20 recordings from one single individual are used. For the multi-user dataset, one recording of the same individual is merged with the remaining 25 recordings of different individuals, which results in a dataset of 26 recordings of 26 different individuals. Thus, the multi-user and single-user datasets overlap by one recording of one individual.

A complete overview of the dataset parameters can be found in table I.

\[ \text{The 5G and 11G datasets and code for feature extraction are available for research purposes at https://tinyradar.ethz.ch} \]
### TABLE I: Overview of the parameters used to record the dataset

| Parameters          | 5-G | 11-G (SU) | 11-G (MU) |
|---------------------|-----|-----------|-----------|
| Sweep frequency     | 250 Hz | 160 Hz | 160 Hz |
| Sensors             | 1   | 2         | 2         |
| Gestures            | 5   | 11        | 11        |
| Recording length    | 3 s | ≤ 3 s     | ≤ 3 s     |
| # of different people | 1 | 1         | 26        |
| Instances per Session | 50 | 7         | 7         |
| Sessions per recording | 10 | 5         | 5         |
| Recordings          | 1   | 20        | 26        |
| Instances per gesture | 500 | 710      | 910       |
| Instances per person | 2500 | 7700     | 35        |
| Total Instances     | 2500 | 7700     | 10010     |
| Sweep ranges        | 10 - 30 cm | 7 - 30 cm | 7 - 30 cm |
| Sensor modules used | XR111 | XR112 | XR112 |

V. ENERGY-EFFICIENT AND HIGH ACCURACY GESTURE RECOGNITION ALGORITHM

One of the major contributions of this paper is the proposal of a model to accurately classify hand gestures recorded with a short-range RADAR sensor. The proposed model enables the reduction of memory and computational resources, which pose the biggest challenge for the deployment of a model for small embedded devices such as microcontrollers.

The constraints for peak memory use and throughput in this work were chosen to work with microcontrollers like the ARM Cortex-M7 series and RISC-V based devices with a power budget in the order of tens of Milliwatts. These microprocessors are very memory-constrained, usually offering below 512 KB of memory, and achieve optimal operating conditions when using 8-Bit quantization for the activations and 16- or 8-Bit quantization for the weights. \[47\]

A. Preprocessing

Since the dataset consists of periodic samples of distance sweep vectors, we chose to use the well-known approach of stacking a number $TW$ of sweep vectors into one feature map window of raw data, which is called a frame. For the proposed network, the number of sweep vectors was chosen to be 32. This corresponds to a total time resolution of 200 ms per frame for 11-G datasets and 125 ms for the 5-G dataset. These frames are then processed by normalizing them and computing their Range-Frequency Doppler Map (RFDM). While the 2D range-frequency spectrum contains a real and an imaginary component, only the absolute value of each bin is used, since the phase component of the spectral representation, while having the same number of values as the magnitude, did not add any significant improvement to the overall inference accuracy.

B. Neural Network Design

For the 11-G dataset, the input feature map size is $(492, 32, 2)$ values, as each sensor contributes one channel, the number of time steps considered are 32 and the number of range points per sweep is 492. Even when compressing each value to 8 Bit, the total required buffer memory for each frame amounts to 246 KB. For successful time-sequence modelling, the information of multiple frames needs to be stored and processed. Using the raw frame for multiple time steps would lead to buffer space requirements in the order of megabytes, which is not available in commercial microcontrollers.

To solve this issue, the proposed model is based on a combination of a 2D CNN and a 1D TCN, which are designed to separate the spatial-temporal modelling problem into two parts, a short-term and spatial modelling problem, which captures little temporal information and can be solved on the level of individual frames, and a sequence modelling problem which can be solved on the level of extracted features from the first network. As we will show, this approach leads to significantly smaller networks in comparison to state-of-the-art temporal modelling approaches without significant loss in accuracy. The overall data flow is depicted in figure 3.

C. Spatial and Short-Term Temporal Modelling

Spatial and short-term temporal modelling in this work can be seen as the task of extracting spatial and short-term temporal information from a single frame of RADAR data into a 1D feature vector containing spatial features that can be accurately classified with a sequence modelling algorithm. This approach compresses each frame by a factor of 82x, which allows the extracted features to be stored on the low-memory microcontrollers for multiple time steps, which is required for accurate time-sequence prediction.

The proposed network for spatial feature extraction is depicted in figure 4.
Since the width direction of the data frames corresponds to the spatial dimension, i.e. the distance from the sensor and the height direction corresponds to the temporal dimension of the frame, the frame width is considerably greater than the frame height. Since the distance sampling is chosen to be very fine-grained, wide kernels are used, both for pooling and convolutions.

The layer parameters are shown in table II.

| Layer           | Input       | Output      | Kernel | Padding |
|-----------------|-------------|-------------|--------|---------|
| 2D Conv         | 32x492x2    | 32x492x16   | 3x5    | Same    |
| Max Pooling     | 32x492x16   | 10x98x16    | 3x5    | Valid   |
| 2D Conv         | 10x98x16    | 10x98x32    | 3x5    | Same    |
| Max Pooling     | 10x98x32    | 3x19x32     | 3x5    | Valid   |
| 1D Conv         | 3x19x32     | 3x19x64     | 1x7    | Same    |
| Max Pooling     | 3x19x64     | 3x2x64      | 1x7    | Valid   |
| Flatten         | 3x2x64      | 384         | -      | -       |

TABLE II: Layer architecture of the 2D CNN

The total required buffer memory size for inference for algorithms using a static allocation of memory is given by the maximum of the sum of the buffer space required for the input and output feature map of any layer. For the proposed network, the total required buffer size is reached in the first layer and amounts to $(492 \cdot 32 \cdot 2 + 98 \cdot 10 \cdot 16) \cdot 8$ Bit = 368 KB.

### D. Long-Term Temporal Modelling

The features computed by the 2D CNN are processed further with a TCN. The TCN uses an exponentially increasing dilation factor to combine features from different time steps into a single feature vector which can then be passed to a classifier consisting of fully-connected layers. For the proposed network, five time steps are considered by the TCN, i.e. five consecutive output feature vectors of the 2D CNN are used as the input of the TCN. This corresponds to a total effective time window of 1 s for the 11-G datasets and 0.625 s for the 5-G dataset.

The overall TCN structure, taking into account the exponential dilation steps, is depicted in figure 1.

In this work, each TCN filter in the TCN is made up of residual blocks, each consisting of one depthwise convolution layer followed by a ReLU activation, the result of which is then added to the original input. This is slightly different from the original definition of residual blocks in Lea et al. [41], as normalization layers, dropout layers and one depthwise convolutional layer are removed to save memory space and execution time. A graphical comparison of the residual blocks as proposed by Lea et al. and as used in this work can be seen in figures 5a and 5b.

| Layer           | Input       | Output      | Kernel | Dilation |
|-----------------|-------------|-------------|--------|----------|
| Causal 1D Conv  | 5x384       | 5x32        | 1      | -        |
| Causal 1D Conv  | 5x32        | 5x32        | 2      | 1        |
| Adding Layer    | 5x32        | 5x32        | -      | -        |
| Causal 1D Conv  | 5x32        | 5x32        | 2      | 2        |
| Adding Layer    | 5x32        | 5x32        | -      | -        |
| Causal 1D Conv  | 5x32        | 5x32        | 2      | 4        |
| Adding Layer    | 5x32        | 5x32        | -      | -        |
| Fully connected | 5x32        | 5x64        | -      | -        |
| Fully connected | 5x64        | 5x32        | -      | -        |
| Fully connected | 5x32        | 5x11        | -      | -        |

TABLE III: Overview of the layer structure in the TCN

### E. Training Setup

Both the 2D CNN as well as the TCN were implemented using the Keras/Tensorflow framework. The RFDM features were extracted from the dataset and saved before training. Both network parts were trained together, using a batch size of 128 for a total of 100 epochs. The optimizer chosen for training is Adam [49]. Both 5-fold cross-validation (CV5) and leave-one-user-out cross-validation (LOOCV) training runs were performed and are shown in the results section.

### VI. Results and Discussion

We evaluated the final model and its implementation on embedded hardware in terms of power consumption and inference performance on a system-scale. In particular, we present the test setup and the evaluation of the proposed model in terms of accuracy, memory and computational requirements in the first subsections, comparing different features and processing alternatives, while we present an evaluation of the implementation on a novel RISC-V based parallel processor in a later subsection.
A. Experimental Setup

The GAP8 from Greenwaves Technologies is an off-the-shelf RISC-V based multicore embedded microcontroller developed for IoT applications. At its core, the GAP8 features one RISC-V microcontroller and an octa-core RISC-V processor cluster with support for specialized DSP instructions, derived from the PULP open-source project. The GAP8 memory architecture features two levels of on-chip memory hierarchy, containing 512 KB of L2 memory and 64 KB of L1 memory.

Figure 6 shows the hardware test setup, using evaluation boards for the GAP8 and A111 RADAR sensor, connected with an ARM Cortex-M4 evaluation board, which is used to broadcast the data to both a connected PC and the GAP8.

The trained model was deployed onto the GAP8 with the AutoTiler tool which generates C Code optimized for parallel execution of the model on the hardware platform.

B. Accuracy of the Algorithm

The inference accuracy of the algorithm can be discussed both in terms of per-frame accuracy, i.e. considering every frame for only one time step or in terms of per-sequence accuracy, i.e. the prediction for each frame taking into account the prediction for the individual frame at all time steps. To fairly compare results on the same dataset and frame definition, the per-frame metric is preferable, since it allows to accurately compare different approaches and the impact of sequence modelling versus single-frame processing. For fair comparison to other datasets and frame definitions, the per-sequence accuracy is used to compare to other research.

C. Evaluation of Pre-Processing Methods

To increase classification performance, different pre-extracted features were evaluated in combination with the features extracted by the convolutional neural network. The pre-extracted features are the signal energy, both for the Signal-over-Range (SOR) as well as the Signal-over-Time (SOT), the signal variation for the SOR and SOT and the centre of mass, which measures the intensity of the signal over the range of the sensor. An important consideration for embedded systems is the size of the feature maps since memory is the most common bottleneck for neural network implementations on microcontrollers and similar devices. An overview of the number of values per feature with respect to the number of sampling windows $TW$ and the number of range points $RP$ can be found in table V.

| Feature            | Data Format | 5-G       | 11-G      |
|--------------------|-------------|-----------|-----------|
| Raw I/Q Signal     | TW x RP x 2 | 26496     | 62976     |
| Signal Variation 2D| (TW-1) x RP x 2 | 25668 | 61008     |
| RFDM               | TW x RP    | 13248     | 31488     |
| Signal Energy SOR  | RP         | 414       | 492       |
| Signal Energy SOT  | TW         | 32        | 32        |
| Signal Variation SOR| RP     | 414       | 492       |
| Signal Variation SOT| TW     | 32        | 32        |
| Centre of mass     | TW x 3     | 96        | 96        |

TABLE V: Overview of the size of different input features

Due to the splitting of the data into windows containing both spatial and temporal information, an evaluation of the preprocessing and pre-extracted feature performance using the 2D-CNN and a fully-connected layer to estimate the feature quality can be given. Using this setup, the per-frame training accuracy results in table VI were achieved.

| Feature Combination | 5-G SU-CV5 | 11-G MU-CV5 |
|---------------------|------------|-------------|
| Raw I/Q Signal      | 90.35%     | 69.09%      |
| Signal Variation 2D | 89.93%     | 65.32%      |
| RFDM                | 91.08%     | 69.37%      |
| Signal Energy SOR & SOT | 70.25% | 51.90%      |
| Signal Energy SOR   | 65.67%     | 49.95%      |
| Signal Energy SOT   | 64.40%     | 40.72%      |
| Signal Variation SOR| 38.10%     | 17.92%      |
| Signal Variation SOT| 20.92%     | 10.57%      |
| Centre of mass      | 47.56%     | 33.81%      |

TABLE VI: Overview of the per-frame performance of different features for the 2D-CNN

The RFDM features provide the best baseline in terms of pre-processed feature maps, both in terms of memory
efficiency as well as classification performance. The raw data shows similar performance as the RFDM in the case of a single-frame model, which makes it important to consider, as using the raw data needs no pre-processing, while all other features do. However, the required energy to calculate the RFDM features is around 34x less than what is used for one inference of the 2D-CNN, so the impact of pre-processing on energy efficiency is negligible. To further increase the accuracy, combinations of the RFDM with signal energy, variation and centre of mass were also studied. The per-frame performance of the RFDM features combined with other features can be seen in table VII.

| Feature Combination                  | 5-G SU-CV5 | 11-G MU-CV5 |
|-------------------------------------|------------|-------------|
| RFDM baseline                       | 91.08%     | 69.37%      |
| RFDM & signal variation 2D          | 91.05%     | 71.93%      |
| RFDM & signal energy SOR            | 91.08%     | 69.16%      |
| RFDM & centre of mass               | 91.34%     | 70.35%      |
| RFDM & signal variation SOT         | 76.93%     | 59.33%      |
| RFDM & signal energy SOT            | 91.20%     | 70.33%      |

TABLE VII: Overview of the 2D-CNN per-frame network performance with combined features

As can be seen in the graph, the classification accuracy plateaus after 32 TCN filters. The averaged per-frame accuracy for different selections of features using 32 TCN filters and five time steps can be seen in table VIII.

| Feature Combination                  | 5-G SU-CV5 | 11-G MU-CV5 |
|-------------------------------------|------------|-------------|
| Raw I/Q Signal                      | 91.90%     | 76.91%      |
| RFDM                                | 93.83%     | 81.52%      |
| RFDM & signal variation 2D          | 92.75%     | 78.84%      |
| RFDM & signal energy SOR            | 93.22%     | 80.92%      |
| RFDM & centre of mass               | 91.81%     | 78.45%      |
| RFDM & signal energy SOT            | 93.38%     | 78.99%      |

TABLE VIII: Overview of the averaged per-frame accuracy of the whole network with combined features

Again, as already seen in the evaluation of pre-processing methods, the added features do not increase accuracy by a significant margin, which substantiates the choice not to add them for the proposed network.

D. Hyperparameter Tuning of the TCN

The performance of the network with the added TCN was evaluated against the performance of the 2D CNN alone. As explained in section V-D, the number of TCN filters is independent of the rest of the network and can be tuned to fit the constraints of the application and target hardware. To find the optimal operating point for the number of filters, the correlation between the number of filters and the increase in accuracy was evaluated for the 11 gesture dataset and is shown in figure 7.

![Fig. 7: Classification performance vs. number of TCN filters on the 11-G dataset, using 5-fold cross-validation (blue) and leave-one-out cross-validation (grey)](image)

As previously discussed in the evaluation of the pre-processing methods, adding manually extracted features does not positively impact the overall accuracy of the network.

Further, for all combinations of features, especially with respect to the 11 gesture multi-user dataset, the TCN improves the per-frame accuracy of the overall network by a significant margin.

E. Comparison to LSTM-based Networks

The proposed model’s time-sequence modelling network using custom TCN layers was also evaluated against a modelling approach based on LSTMs as proposed by Schmidhuber et al. [22] and a network using standard TCN layers.

The performance for all three alternatives was evaluated using the same number of filters and time steps. The per-frame test accuracies for 32 and 128 filters are shown in table IX.

| Time steps | 5    | 10   | 20   |
|------------|------|------|------|
| LSTM, 32 filters | 79.24% | 79.69% | 80.71% |
| LSTM, 128 filters | 79.29% | 80.23% | 81.77% |
| Original TCN, 32 filters | 80.50% | 80.46% | 81.49% |
| Original TCN, 128 filters | 80.55% | 80.26% | 82.09% |
| Proposed TCN, 32 filters | 80.13% | 80.17% | 81.45% |
| Proposed TCN, 128 filters | 80.79% | 81.32% | 82.79% |

TABLE IX: Per-frame test accuracy of the whole network for different sequence modelling approaches using 32 filters

The number of time steps beyond five does not significantly increase the inference performance of the network neither for the TCN version nor for the LSTM version. Besides accuracy, the focus for embedded deployment is always on network size. Table X shows the number of parameters for 32 and 128 filters. Note that the number of time steps does not impact the number of parameters.

| Filters     | 32  | 64  | 96  | 128 |
|-------------|-----|-----|-----|-----|
| LSTM        | 25.4k | 99.8k | 223.5k | 396.3k |
| Original TCN | 12.4k | 49.6k | 111.2k | 197.4k |
| Proposed TCN | 6.2k  | 24.8k | 55.6k  | 98.7k  |

TABLE X: Number of parameters required for sequence modelling using LSTM vs. TCN broken down by number of filters

The number of parameters for the TCN-based implementations is much lower than the number of parameters required for...
the LSTM-based implementations. Considering the superior accuracy achieved with the TCN-based implementations, the TCN models perform better by all evaluated metrics. Furthermore, using the proposed TCN variant, the number of parameters for the sequence modelling part can be reduced by a factor of 4x compared to LSTM-based variants.

F. Experimental Results

The proposed algorithm, as explained in section V, was implemented and evaluated on a GAPUino evaluation board and power measurements were taken for both the microcontroller as well as the RADAR sensor. The overall number of weights of the model is split between the 2D CNN, requiring 22,368 weights and the TCN, requiring 22,917 weights. Using 16-Bit quantization and considering the implementation overheads, the network requires just under 92 KB on the GAP8. In terms of operations, the 2D CNN dominates the overall algorithm, taking up more than 99% of the overall computations, which total around 42 MOps per inference, taking a total of 5.8 M/Cycles per inference on the GAP8.

An overview of the energy consumption with respect to operating frequency is given in figure 8.

![Energy efficiency of the algorithm vs. cluster frequency](image)

Fig. 8: Energy efficiency of the algorithm vs. cluster frequency

For the system to work in real-time at 5Hz prediction rate, including the sampling of the RADAR sensor and execution of the algorithm, the cluster frequency should be chosen to be at least 100 MHz. This leads to an average power consumption of 21 mW of the GAP8 microcontroller measured during 2 inference/sleep cycles, with peak power consumption of 98mW while running the inference. An overall breakdown of operations, energy and cycles per inference at a clock frequency of 100 MHz using 8 cores is shown in table XI.

| Algorithm step | Energy per Frame | Cycles | MACs |
|----------------|------------------|--------|------|
| FFT            | 0.12 mJ          | 176 \cdot 10^3 | -    |
| 2D CNN         | 4.07 mJ          | 5100 \cdot 10^3 | 20470 \cdot 10^3 |
| TCN            | 0.32 mJ          | 458 \cdot 10^3  | 256 \cdot 10^3  |
| Dense          | 0.006 mJ         | 86 \cdot 10^3   | 22 \cdot 10^3   |
| Full Network   | 4.52 mJ          | 5820 \cdot 10^3 | 20750 \cdot 10^3 |

TABLE XI: Energy breakdown of the algorithm on GAP8 at 100 MHz

To consider the overall system performance, the power consumption of the RADAR sensor has to be taken into account. Measuring the power consumption of the development board used in this work results in an upper bound, shown in table XII.

| Sweep frequency | Power consumption | Samples |
|-----------------|-------------------|---------|
| 100 Hz          | 89 mW             | 300     |
| 160 Hz          | 95 mW             | 480     |
| 256 Hz          | 144 mW            | 768     |

TABLE XII: Power consumption of the RADAR sensor development board at different sweep frequencies

Taking into account the power consumption for the RADAR sensors, we arrive at a system-level power consumption of around 200 mW when using two RADAR sensors at 160 Hz, and 115 mW when using one RADAR sensor at 160 Hz.

G. Comparison to Previous Work

A direct comparison of this work is most fairly possible with previous work in Wang et al. since this work uses the same set of gestures and evaluation metrics. In table XIII we compare our results with those reported by Wang et al. All accuracies are reported per-sequence, as the definition of frames is different.

| Metric                          | Interacting with Soli | This work |
|---------------------------------|-----------------------|-----------|
| Model size                      | 689 MB                | 91 KB     |
| Single sensor power consumption | 300 mW                | 95 mW     |
| Total sensor power consumption  | 300 mW                | 190 mW    |
| Network inference power         | -                     | 21 mW     |
| 11-G SU Accuracy               | 94.5%                 | 92.39%    |
| 11-G MU-CV5 Accuracy           | 86.4%                 | 78.85%    |
| 11-G MU-LOOCV Accuracy         | 88.27%                | 78.85%    |
| Number of different users       | 10                    | 26        |

TABLE XIII: Comparison of the proposed implementation with previous work

The direct comparison shows that our proposed network performs comparably accurately, if slightly worse, in all but leave-one-subject-out cross-validation, to the network proposed by [25]. The drop from 5-fold cross-validation to leave-one-out cross-validation points to problems with overfitting, which should be addressed by future work. Nonetheless, our network size is smaller by a factor of 7500x and our power consumption is lower by several orders of magnitudes, as we use a GPU for inference, which operates at tens to hundreds of Watts of power consumption.

VII. CONCLUSION

This work presented a high-accuracy and low-power hand-gesture recognition model combining a TCN and CNN model to achieve accuracy and low memory footprint. The model targets data processing with short-range RADAR. The paper proposed also a hand-gesture recognition system that uses low-power RADAR sensors from Acconeer combined with a GAP8 Parallel Ultra-Low-Power processor and can be battery operated. Two large datasets with 11 challenging hand-gestures performed by 26 different people containing a total of 20,210 gesture instances were recorded, on which the proposed algorithm reaches an accuracy of up to 92.4%. The model size is only 92 kB and the implementation in GAP8 shows that live-prediction is feasible with a power consumption of the prediction network of only 21 mW. The results show
the effectiveness and potential of RADAR-based hand-gesture recognition for embedded devices, as well as the network design, using the TCN approach.

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