ARC-Net: Activity Recognition Through Capsules

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Abstract—Human Activity Recognition (HAR) is a challenging problem that needs advanced solutions than using handcrafted features to achieve a desirable performance. Deep learning has been proposed as a solution to obtain more accurate HAR systems being robust against noise. In this paper, we introduce ARC-Net and propose the utilization of capsules to fuse the information from multiple inertial measurement units (IMUs) to predict the activity performed by the subject. We hypothesize that this network will be able to tune out the unnecessary information and will be able to make more accurate decisions through the iterative mechanism embedded in capsule networks. We provide heatmaps of the priors, learned by the network, to visualize the utilization of each of the data sources by the trained network. By using the proposed network, we were able to increase the accuracy of the state-of-the-art approaches by 2%. Furthermore, we investigate the directionality of the confusion matrices of our results and discuss the specificity of the activities based on the provided data.

I. INTRODUCTION

In the human activity recognition field, the goal is to predict the activity of a human subject based on a window of measurements provided by the available sensors. These activities may range from lying to rope jumping. A wide variety of sensors such as accelerometer, gyroscope, magnetometer, force sensor, and light sensor may be used to classify the activity performed in that window of collected data. Even everyday devices such as smartphones and smartwatches may be used in order to obtain the required data for activity recognition. Due to availability and the low cost of the mentioned sensors, HAR is utilized in many areas such as design of exoskeletons [1] and more commonly, elderly care [2]. Furthermore, the collected data from HAR sensors may be collected and utilized to provide more personalized services through the monitored activities. For example, the data collected from body-worn sensors and the behavior extracted form this data can help increase security [3], provide more modern and reactive healthcare [2] and allow the creation of better user interfaces [4].

Deep learning has proven to be an adequate tool for recognizing patterns and extracting rich features that may be utilized to classify data [5]. Human activities may be classified based on the patterns that are seen in the input data. Therefore, rather than looking only at the measurements from individual data sources, we require our algorithm to view the input data on different levels and fuse the extracted features in such a way that the perceived patterns would be able to tell us about the activity being performed, e.g., to differentiate between walking and running, it would be misleading to only look at the data provided by a motion sensor located on the ankle of the subject and we would reach better performances by also using the data from subject’s forearm. This calls for a technique that is able to adequately fuse the information from every data source and use the said information to make a prediction about the activity.

In this paper, we propose using a single Convolutional Neural Network (CNN) as an encoder to extract the features from each of the IMUs and pass the said features to CapsNet [6] in order to fuse the extracted information and make a prediction about the activity of the subject. We will use two datasets to evaluate the performance and generalization of our approach. Moreover, a modified version of the network proposed in [7] will be used as our encoder which uses stage-based fusion to extract the necessary information. Our contributions are as follows:

• CapsNet is used to fuse the information obtained from each IMU
• Provide intuitive interpretations regarding the utilization of each of the IMUs based on the true label
• Provide comparisons to empirically examine the capability of capsules in rejecting corrupted modalities
• Our method outperforms the state-of-the-art deep learning based approaches

This paper is organized as follows: In Section 2, we go through various available classical and deep learning-based approaches to HAR alongside the current state-of-the-art (SOTA) approaches. In Section 3, we explain the proposed architecture and provide an introduction to capsules. In the last section, we present quantitative and qualitative evaluations of the proposed method against SOTA approaches and provide visualizations alongside corresponding discussions.

II. RELATED WORK

From an algorithmic point of view, approaches to HAR may be divided into three groups, namely, classical approaches that utilize preprocessing methods such as pose estimation, machine learning-based approaches that rely on hand-crafted features devised by an expert and deep learning-based methods that rely on gradient backpropagation in order to both extract features and perform classification. Deep learning based methods can be separated into multiple groups of architectures themselves. Each group utilizes a specific characteristic of an architecture to improve the accuracy of their predictions. This category of approaches may be divided further based on the
memory of past inputs [12]–[14], unsupervised methods [10], [11], non-recurrent methods [7], [15].

In [8], video sequences captured by a monocular camera are used to classify the activity of subjects. Optical flow alongside background extraction methods is used as features which are then passed to a support vector machine (SVM) to generate predictions. [9] uses decision trees to classify the activity of the subject based on features extracted from an accelerometer of a smartphone. Ten features such as phone position on the human body, user location, age and sensor readings are passed through a decision tree to make predictions. [10] uses activity sets rather than single label ground truth values to predict the potential activities in the corresponding window of measurements from IMUs. This work also uses unsupervised learning methods prior to supervised learning in their training process to achieve a more effective feature representation.

In [11], unsupervised learning methods are deployed where the number of activities is unknown. This is done by using clustering methods that operate on the frequency components of the measured acceleration and angular velocity values.

[12] proposes DeepConvLSTM which is an LSTM based network that utilizes a CNN to extract the features from inputs. Due to the usage of recurrent layers, this model falls into the category of memory-based networks. DeepConvLSTM aims to increase the performance of HAR systems by modeling temporal dependencies while using raw sensor data. In [13] various architecture choices are compared to reach a conclusion about the necessity of recurrence in HAR models. [14] uses variants of Recurrent Neural Networks (RNNs) to observe the cognitive decline by monitoring the daily activities of the subject, while [12]–[14] all use IMU measurements as network input.

[15] stacks IMU measurements from a smartphone and creates a window of measurements. These measurements are then passed through a CNN to predict the activity of the subject. This work aims to model the temporal connections between raw sensor measurements using the convolution operations that reside in CNNs. [7] also stacks the raw measurements from the available IMUs and uses convolutional layers to extract the features from said inputs. This work uses specific kernel sizes that allow the network to perform data fusion in multiple levels. Reference [7] also proposes that late sensor fusion is more effective due to the separate processing of each axis of sensor module in the initial layers. We base our encoder on this architecture with modifications to prevent loss of information during pooling layers. Moreover, we view HAR as a multimodal fusion problem. We use a single encoder to extract features from IMUs with no constraints on the position of the data source on subject’s body. Thereafter, we use mechanisms that fuse the collected information and predict the performed activity.

III. THE PROPOSED APPROACH

We propose using CapsNets to fuse the high dimensional features passed from an encoder. The general overview of our architecture is shown in Fig. 1. We stack a pre-specified number of measurements from each IMU and create a two-dimensional array where columns represent each measurement. These arrays are passed to a single CNN separately and the features corresponding to each of the IMUs are extracted. Then, primary capsules are formed by reshaping the output of the CNN and concatenating the extracted features from each of the encoders. The concatenated features are then passed through CapsNet to obtain a probability vector of the activities. These steps are elaborated in detail in Section 3.A and 3.B.

A. Encoder

In order to extract features from each of the IMUs, we use a CNN with varying kernel sizes at each layer similar to the architecture proposed in [7]. A modified version of this architecture is presented in Fig. 2. As it is seen in this figure, at the first layer of the encoder, we perform a 1-dimensional convolution operation that does not perform any fusion on the given inputs and mainly acts as a filter. In the next layer, a 2-dimensional convolution is applied to the features of the former layer. Due to the size of the kernel and the strides of this layer, each module of the IMU is processed separately and the features of the accelerometer and gyroscope are not fused in this layer. In the final layer, a kernel size of $(2 \times 15)$ convolves over the features of the second layer and fuses the information extracted from each of the modules. To be able to pass the extracted features to CapsNet, we will need to reshape these features as shown in Fig. 2.
B. CapsNet and Dynamic Routing

CapsNet [6] uses vectors of neurons (capsules) to represent the entities that may be present in the given input. Each capsule looks at a small window of the input and gives the probability of the existence of a specific pattern in the data. The magnitude of a capsule gives the probability of the existence of an entity and the orientation of the capsule in its high dimensional space defines the characteristics of that entity. The capsules in the first layer of the network, which are called primary capsules, are extracted through the encoder as shown in Fig. 2 CapsNet uses an iterative mechanism to dynamically route each of the lower layer capsules to the higher layer ones. Through this mechanism, the network is able to use the information about the existence of low level entities to decide about the presence of higher level ones. In our approach we only use one layer on top of the primary capsules in order to obtain predictions about the activity performed by the subject. Therefore, the higher level capsules will represent the activity that is potentially present in the given window of measurements. In other words, the routing mechanism will allow us to link the existence of specific patterns in each of the IMU measurements to the potential activity that is being performed by the subject.

By concatenating the primary capsules from each of the IMUs, we will have a feature map of size $12n \times 96$ where $n$ is the number of IMUs. As seen in Fig. 2 each primary capsule has 96 dimensions and 12 capsules are extracted from each of the IMUs. Assuming $U_i$ represents the $i^{th}$ lower layer capsule and $V_j$ is the $j^{th}$ higher layer capsule, Algorithm 1 describes the routing mechanism used in our approach for a number of iterations. The squash non-linearity is formulated as follows:

$$\text{squash}(\hat{V}_j) = \frac{\|\hat{V}_j\|^2}{1 + \|\hat{V}_j\|^2} \hat{V}_j$$

While, the softmax function is formulated as follows:

$$\text{softmax}(b) = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})}$$

Following [16], we added a soft updating rule with the coefficient $\eta$ in Algorithm 1 to prevent overrouting. Furthermore, we used the original loss function from [6] which is a margin loss that calculates a separate loss value for each of the predicted classes.

![Fig. 2. The architecture of the encoder.](image)

Algorithm 1: Dynamic routing algorithm

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initialize the log prior matrix $b$ and set $b_{ij} \leftarrow 0$
$U_{ij} \leftarrow U_iW_{ij}$
c_{ij} \leftarrow \text{softmax}(b)$
for $r$ iterations do
    $c_{ij} \leftarrow c_{ij} + \eta c_{ij}$
    $V_j \leftarrow \sum_{i} c_{ij}U_{ji}$
    $V_j \leftarrow \text{squash}(V_j)$
    $b_{ij} \leftarrow b_{ij} + V_j \cdot U_{ji}$
end
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IV. Experiments

The experiments were conducted using an NVIDIA Tesla P100 with 16 gigabytes of RAM and 3584 CUDA cores. We used the PyTorch framework to implement the proposed architecture and PyTorch lightning as an interface for reproducibility purposes.

A. Datasets

The proposed method was tested on the PAMAP2 [19] and RealWorld [20] HAR datasets. The validation set of the PAMAP2 dataset was used to tune the model hyperparameters. The quantitative results from each of the datasets were compared against the state of the art methods with the same preprocessing characteristics. We report our results against PerceptionNet [7], DeepConvLSTM [12] and CNN-EF [15] on the PAMAP2 dataset and to test the generalizability of our method, we also provide quantitative results for PerceptionNet [7] and DeepConvLSTM [12] alongside our method on the RealWorld dataset. To train the network and to infer the activity of each of the subjects from either dataset, we only use the IMU measurements, namely accelerometer and gyroscope.

1) RealWorld: This dataset contains measurements from 15 subjects (8 males and 7 females) with recorded data from the chest, forearm, head, shin, thigh, upper arm, and waist of each of the subjects. For each subject, this dataset provides measurements from GPS, IMU, gyroscope, light, sound level data and magnetic field sensors. The annotated activities from this dataset are climbing up and down the stairs, jumping, lying, standing, sitting and running. The data is not synchronized and is recorded at a frequency of 50Hz. After synchronizing the IMUs, we segment the data into windows...
of 128 measurements (2.56 seconds) with 60% overlap. We use the leave-one-subject-out approach to evaluate our method. Specifically, we use subjects 10 and 11 as validation and test subjects and the rest are used to train the network.

2) PAMAP2: The physical activity monitoring dataset consists of 18 different physical activities from 9 subjects (8 males and 1 female). Three Colibri wireless inertial measurement units were used to provide measurements alongside a heart rate monitor. This dataset contains IMU measurements from the chest, dominant wrist and dominant ankle at a frequency of 100Hz. We downsampled this dataset to 50Hz in order to match the frequency of the RealWorld dataset and stacked 128 measurements with the same overlapping that was used for the preprocessing stage of the RealWorld dataset. Similar to PerceptionNet, we chose a leave-one-subject-out approach to validate and test our model. Subjects 1 and 5 were chosen as test and validation sets, respectively.

B. Performance evaluation metrics

Due to an imbalance in the number of labels for both of the datasets, we chose the weighted $F_1$ score to report the quantitative results of our network. This score is formulated as below

$$wF_1 = \sum_c \frac{N_c}{N} \cdot \frac{2 \cdot \text{Precision}_c \cdot \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c}$$

(3)

Where $c$ represents each class, while $N$ is the total number of data and $N_c$ is the number of data with label $c$. Moreover, we report the precision, recall and accuracy values separately and compare our results against the state of the art methods.

We also provide the confusion matrix as a qualitative measure for both of the datasets. This matrix allows us to interpret how the model wrongly classifies each of the categories. In the provided matrices, the rows correspond to the actual labels while columns represent the predicted classes. We will also take a look at the directionality of this matrix and discuss how easy it is for a model to confuse one class with the other but not the other way around. This approach will allow us to get a look at the specificity of the classes.

V. RESULTS AND DISCUSSION

We used the Optuna [21] library to optimize the hyperparameters of the network. Due to a limited amount of computational power, we only used this library to search for iteration number($r$), soft-updating value($\eta$) and the initial learning rate. Twenty trials were conducted while each trial lasted 200 epochs. The best set of hyperparameters were chosen based on the average validation loss. Moreover, an exponential learning rate scheduler with a multiplicative factor equal to 0.98 was used to train the network on both datasets.

A. Results on PAMAP2

Loss margins were set to 0.95 and 0.05 for this dataset. Moreover, the iteration number and the soft updating coefficient were set to 3 and 0.1, respectively, while the training proceeded with a batch size of 64. The test accuracy of our model ranges from 89.18% to 90.51% across multiple training sessions of the same model and the best single epoch based on the validation loss achieves an accuracy score of 90.51% on the test set. Due to the observed variance in the performance of each model during training, we also formed a horizontal voting ensemble [22], based on epochs of a single model using the top validation scores but the metrics did not improve when using this ensemble. Table I provides a comparison between the obtained results of our model and the reported metrics from the state of the art models. As it can be seen in Table I the results from our model surpass the state of the art results on all metrics. The largest gap between ARC-Net and PerceptionNet can be seen in the precision achieved on the test results which is about 2.01%. Furthermore, a consistent improvement is seen on other metrics.

| Model          | Precision | Recall | wF1  | Accuracy |
|----------------|-----------|--------|------|----------|
| CNN-EF         | 85.51%    | 84.53% | 84.57% | 84.53%   |
| DeepConvLSTM   | 87.75%    | 86.78% | 86.83% | 86.78%   |
| PerceptionNet  | 89.76%    | 88.57% | 88.74% | 88.56%   |
| ARC-Net        | 91.77%    | 90.52% | 90.76% | 90.51%   |

![Confusion map of the test set on the PAMAP2 dataset](image)
Fig. 4. Confusion map of the test set on the RealWorld dataset

easily. Furthermore, lying, cycling, rope jumping and running have a precision of 100%. The precision of the ironing activity is low while having a high recall, specifically ironing has a recall of 100% while its precision is only 68.04%.

B. Results on RealWorld

The accuracy of our method on the test set ranges from 95.47% to 95.64% across multiple training sessions. We report our best epoch in Table II alongside a full comparison of our network against the state of the art methods. Due to the observed variance in the performance of the network during training, we also formed a horizontal voting ensemble based on the validation loss of each of the epochs of a single model. This way, we were able to increase the accuracy of our model to 95.92%. Same as the results achieved on PAMAP2, a consistent improvement of all the metrics is seen in Table II. Because of the relatively large number of sensors in this dataset, the number of iterations was increased to 7 while the soft updating coefficient was dropped to 0.01. By this means, the larger amount of iterations would allow the network to focus more on the routing of each primary capsule from each IMU to the high level capsules. Moreover, the smaller soft updating coefficient would prevent overrouting of the network.

C. Prior Matrix Visualization

The prior matrix denoted by \( b \) in the routing mechanism of CapsNet is a learnable parameter and is also responsible for setting the values that describe the model’s prior belief regarding the routing between two layers of capsules. Therefore, it is possible to extract the values of this matrix after training and visualize the routing between each pair of capsules. Based on Fig. 5 and Fig. 6, the routing that the network has come up with seems intuitive in activities such as the ones related to walking or climbing up and down the stairs where the network relies on the movement of the ankle or hand more than other modalities to make predictions. Moreover, correlations can be seen between the heatmaps of PAMAP2 and RealWorld for the same activities, e.g. the activity of lying relies on the measurements from the waist/chest when trained on either datasets. Based on Fig. 6, the addition of a thigh modality has allowed the standing and sitting activities to be more distinguishable with respect to PAMAP2. This has resulted in a substantial improvement in the directionality between the two classes in Fig. 4 with respect to Fig. 3.

Fig. 4. Confusion map of the test set on the RealWorld dataset

![Confusion Map](image)

Table II

| Activity       | Precision | Recall | \( \text{wF1 Score} \) | Accuracy |
|----------------|-----------|--------|------------------------|----------|
| DeepConvLSTM   | 92.83%    | 92.65% | 92.63%                 | 92.65%   |
| PerceptionNet  | 94.78%    | 94.20% | 94.27%                 | 94.20%   |
| ARC-Net        | 96.08%    | 95.64% | 95.67%                 | 95.64%   |

| Activity       | \( \Delta \text{wF1} \) | \( \Delta \text{Acc} \) |
|----------------|------------------------|------------------------|
| PerceptionNet  | 20.47%                 | 18.63%                 |
| ARC-Net        | 10.60%                 | 10.93%                 |

![Table II](image)

![Table III](image)

![Normalized Prior Matrix](image)

![Normalized Prior Matrix heatmap of the network trained on PAMAP2](image)
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Fig. 6. Normalized prior matrix heatmap of the network trained on RealWorld

D. Modality Corruption Test

One of the modalities was randomly corrupted by replacing its measurements with a zero matrix to simulate the potential case of modality failure during inference. The drops in the accuracy and weighted F1 scores of our method and PerceptionNet on the test sets of each dataset are reported in Table II. It can be seen that on both datasets, our approach is significantly more robust against modality corruptions compared to a CNN only approach.

VI. CONCLUSIONS

In this paper, we developed a method for human activity recognition that relies on CapsNet to fuse the information from multiple IMUs. We tested our approach on two datasets with varying sensor positions and compared our results against the SOTA. Our results surpassed that of SOTA by about 2% in accuracy and weighted F1 score. Moreover, the confusion matrices of the test set of each dataset were presented and specificity of the classes was investigated. Our approach allowed for the visualization of routing between modalities and activities. Through these visualizations, we were able to interpret the importance of each modality for correct classification of each activity. Finally, modality corruption was simulated by passing an array of zeros instead of one random modality during inference. Through this test, the capability of our method in noise rejection was shown. In our approach, it is possible to add extra modalities without a need for significant changes in the structure of the network which allows for easier transfer learning. Moreover, our encoder can be trained on data from various positions of the body to achieve a general feature extractor.

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