Two-Stream Convolution Augmented Transformer for Human Activity Recognition

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Abstract

Recognition of human activities is an important task due to its far-reaching applications such as healthcare system, context-aware applications, and security monitoring. Recently, WiFi based human activity recognition (HAR) is becoming ubiquitous due to its non-invasiveness. Existing WiFi-based HAR methods regard WiFi signals as a temporal sequence of channel state information (CSI), and employ deep sequential models (e.g., RNN, LSTM) to automatically capture channel-over-time features. Although being remarkably effective, they suffer from two major drawbacks. Firstly, the granularity of a single temporal point is blindly elementary for representing meaningful CSI patterns. Secondly, the time-over-channel features are also important, and could be a natural data augmentation. To address the drawbacks, we propose a novel Two-stream Convolution Augmented Human Activity Transformer (THAT) model. Our model proposes to utilize a two-stream structure to capture both time-over-channel and channel-over-time features, and use the multi-scale convolution augmented transformer to capture range-based patterns. Extensive experiments on four real experiment datasets demonstrate that our model outperforms state-of-the-art models in terms of both effectiveness and efficiency \(^1\).

Introduction

Human activity recognition (HAR) aims to recognize various human activities such as walking, sitting, falling down, etc. It is widely used in many fields such as healthcare system (Zheng et al. 2017; Jobanputra, Bavishi, and Doshi 2019), smart building solutions (Pu et al. 2013), and Internet of Things (IoT) applications. For examples, elderly people monitoring (Jobanputra, Bavishi, and Doshi 2019), energy-efficiency system for smart buildings (Pu et al. 2013), daily activity recognition for robot-assisted living (Zhu and Sheng 2011). Other applications include fall detection (Wang, Wu, and Ni 2017), security monitoring (Zheng et al. 2017), rescue systems (Grzonka et al. 2010), etc.

Due to its importance, numerous research efforts are devoted to HAR in recent years, mostly rely on various sensors or dedicated devices, such as cameras (Aggarwal and Ryoो

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1\(^*\)Code: https://github.com/windofshadow/THAT

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tions share some common drawbacks, which hinder them from further performance improvement, as listed below:

i) **Order-unawareness.** Spatial models such as CNN simply treat CSI data as an image and use two-dimensional kernels to extract spatial patterns. However, different from images where semantics of both dimensions are identical (i.e., refers to spatial positions), for CSI data, the meanings of the two dimensions are completely different (i.e., refers to temporal time-stamp and channel state, respectively). Simply treating them equally will yield inferior features. Moreover, CNN is hard to effectively distinguishing order-sensitive activities such as sit-down and stand up.

ii) **Neglect the temporal features extracted along the channel dimension (time-over-channel).** Sequential models such as RNN and LSTM regard CSI data as a temporal sequence. They are aware of orders and able to capture channel features extracted along the temporal dimension (channel-over-time). Unfortunately, they neglect the time-over-channel features, which are shown to be effective in distinguishing actions with similar motions but different body postures, such as sit down and lie down, since the time-over-channel features are more sensitive to density changes as different channel frequency has different penetration on human bodies.

iii) **Granularity is too small.** Existing models take every point as the meaningful unit to generate features. The point-level granularity is too small to see the whole picture, since a meaningful pattern usually appears in a continuous range rather than a single point due to the continuity of CSI data.

To address the above issues, we propose a sophisticated yet highly effective Two-stream Convolution Augmented Human Activity Transformer (THAT) model to exert the advances of deep learning techniques on HAR tasks. Our model presents a two-tower structure, each tower is in charge of the channel stream or the temporal stream to extract both time-over-channel and channel-over-time features. The core component of our model is the Multi-scale Convolution Augmented Transformer (MCAT), which adopts a residual-connected multi-head self-attention to effectively generate hidden representations and a multi-scale convolution block to capture range-based patterns. To make the model be order-sensitive, we propose a Gaussian range encoding to preserve the positional information of the CSI data. Besides, owing to the parallel nature of self-attention and convolution, our model is also very time-efficient. The experimental results show that the proposed model not only achieves a very high accuracy (above 98.7%), but also is 1.83–3.37× faster than state-of-the-art sequential models.

### Related Work

CSI based human sensing methods mainly rely on data-driven approaches to learn the complex relationship between wireless signals and human action (Wang et al. 2019). Traditional schemes for CSI-based activity recognition firstly extract discriminative and representative features from multiple domains and then feed the extracted features into machine learning models to predict certain activities as a multi-class classification problem. Some of the popular techniques are support vector machines (SVMs) (Wang et al. 2016), hidden markov model (HMM) (Wang et al. 2015), and k-nearest neighbor algorithm (kNN) (Ali et al. 2015).

However, handcrafted solutions in previous works require expert-knowledge and are labor-intensive and time-consuming. Recently, deep architectures contribute to the significant advancement in the fields of computer vision, natural language processing, data analysis and so on. Some researchers propose to use deep learning approaches, which are able to save that labor-intensive and time-consuming feature exploration procedure. Yousefi et al. proposed a deep learning approach, i.e., LSTM, which could hold temporal state information of activities and help in extraction of implicit features for similar activities (Yousefi et al. 2017). Chen et al. argued that the conventional LSTM can only process the CSI measurements in the forward direction, which may lead to some informative features loss (Chen et al. 2018). Based on that, they proposed an attention based bidirectional long short-term memory (ABLSTM) approach for human activity recognition using WiFi CSI. In (Shi et al. 2019), discriminative features for different human activities were extracted by LSTM with RNN and then were inputted to a softmax classifier for activity recognition. Gao
et al.] developed a CSI-based sparse auto-encoder (SAE) network for device free wireless localization and activity recognition (Gao et al. 2017). Ma et al. (Ma et al. 2018) proposed a deep learning framework based on convolutional neural network (CNN) for sign gesture recognition using CSI, which achieved higher accuracy and efficiency than the non-deep-learning baselines.

Model

Model Overview

The architecture of our THAT model is summarized in Figure 2. From bottom to top, the first layer inputs the raw CSI data and pre-processes it into temporal and channel streams. The MCAT layer extracts discriminative features from the two-stream. Finally, the two-stream features are aggregated and fed it into the prediction layer for the final output. 

Input and Pre-processing Layer receives the raw CSI data as inputs and resized it into temporal stream and channel stream to be fed as the input of MCAT layer. The raw CSI data is a set of records \( \{ r_1, r_2, \ldots, r_n \} \). Each record \( r_i \) is a two-dimensional matrix, in which a cell \( v_{ic} \in r_i \) is a real value indicating the state value of channel \( c \) at time \( t \). To facilitate batch-processing, we perform a timing alignment of each record to make the size of each record identical, i.e., \( r_i \) has the same dimensionality as \( T \times C \). To be less memory-intensive, we shrink the size of temporal dimension \( T \) by preforming a mean-pooling on adjacent time slots. The temporal dimension first (with dimensionality \( T \times C \)) data is used as temporal stream. The channel dimension first (with dimensionality \( C \times T \)) data is used as channel stream, which could be readily fetched by a simple transpose operation.

MCAT Layer extracts discriminative features from the two-stream data. This layer manifests a two-tower structure. Each tower is a stack of \( H \)-layer (for temporal stream, and \( N \)-layer for channel stream) multi-scale convolution augmented transformers. The two towers separately extract channel-over-time features and time-over-channel features. Notably, if \( H = 0 \) or \( N = 0 \), the model is degenerated to a single-stream model.

Aggregation Layer receives features of the temporal stream and channel stream and aggregates them into fixed-length vectors via two separate Convolutional blocks (CNN). Then, temporal and channel vectors are concatenated to be fed as the input of the prediction layer.

Prediction Layer is a linear layer with a softmax operation to compute the probabilities over activity categories.

Multi-scale Convolution Augmented Transformer (MCAT)

MCAT consists of two sequentially stacked sub-layers: (1) a multi-head self-attention, and (2) a multi-scale CNN with an adaptive scale. Each of the two sub-layers is encompassed by a residual connection (He et al. 2016) (Add) and a layer normalization (Ba, Kiros, and Hinton 2016) (LayerNorm).

\[
\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V;
\]

where \( d_k \) is the queries and keys dimension, and \( \sqrt{d_k} \) is a scaling factor that enables smoother gradients. \( Q \in \mathbb{R}^{L \times d_k}, K \in \mathbb{R}^{L \times d_k}, \) and \( V \in \mathbb{R}^{L \times d_v} \) is queries, keys, and values, respectively. They are generated by letting the input \( X \in \mathbb{R}^{d_{in} \times d_k} \) go through three linear projections, namely,

\[
Q = XW_Q, K = XW_K, V = XW_V
\]

where \( W_Q \in \mathbb{R}^{d_{in} \times d_k}, W_K \in \mathbb{R}^{d_{in} \times d_k}, \) and \( W_V \in \mathbb{R}^{d_{in} \times d_v} \) are projection parameters. In order to jointly attend to information from different representation subspaces, the queries, keys and values are independently projected \( h \) times (called \( h \)-head) with different projection parameters, and the outputs of projections are concatenated and projected again to result the final output:

\[
\text{MultiHead}(Q, K, V) = [\text{head}_1; \ldots; \text{head}_h]W_O,
\]

where \( \text{head}_h = \text{Attention}(XW_Q^h, XW_K^h, XW_V^h) \), and \( W_O \in \mathbb{R}^{d_k \times d_o} \) is the final projection matrix.

To facilitate residual connections, all sub-layers in the MCAT, as well as the input layer, share identical dimension, i.e., \( d_{in} = h \times d_v = d_o \).
Multi-scale Convolutional Block with Adaptive Scale Attention  For HAR tasks, a single temporal point is too small to be informative. To capture features in a larger scope, we propose multi-scale convolutional blocks that use different kernel sizes and adaptively adjust between different scales by an adaptive scale attention mechanism.

Given a set of kernel sizes $J = j_1, j_2, ..., j_J$, each kernel size is related to a specific scale, e.g., a 30 kernel size enables the model to capture the pattern within a temporal range of 30 ms. The output of multiple convolutional blocks is $P = P_1, P_2, ..., P_J$, where $P_j \in \mathbb{R}^{L \times d_o}$ is the feature matrix regarding the $i$-th kernel size $j_i$. $P_i$ is defined as:

$$P_i = \text{ReLU}(\text{Dropout}(\text{BN}(\text{Conv}(W^{i}; X))))$$  \hspace{1cm} (4)

Eq. 4 consists of four cascaded operations: a convolution ($\text{Conv}(\cdot)$), a batch normalization ($\text{BN}(\cdot)$) (Ioffe and Szegedy 2015), a Dropout operation ($\text{Dropout}(\cdot)$) (Srivastava et al. 2014), and a ReLU unit. The core operation is $\text{Conv}(W^{i}; X)$, which receives the output features $X$ of the multi-head self-attention module along with learnable weights $W^{i} \in \mathbb{R}^{d_o \times j_i \times d_o}$. The $W^{i}$ consists of $d_o$ filters, and each filter has the size of $j_i \times d_o$, convolving $j_i$ adjacent positions. Notice that we use zero-padding to the two sides and each filter has the size of $30 \times d_o$, to make the resulting feature map have the same size as $L \times d_o$. Fig. 3 shows an example of using scales 1, 3, 7 to capture pattern within different ranges to yield three features vectors.

Notably, it is unwise to use all those features since some of them are either redundant or less informative. In order to adaptively ensemble features at different scales, we propose an adaptive scale attention mechanism, as shown in Fig. 3. Formally, the ensembled features $P^{ens}$ are defined as:

$$P^{ens} = \alpha P = \sum_i \alpha_i P_i,$$  \hspace{1cm} (5)

where $\alpha_i$ is an attention score of $P_i$ at scale $j_i$. $\alpha = \langle \alpha_1, \alpha_2, ..., \alpha_J \rangle$ is the vector of attention scores, which can be computed by:

$$\alpha = \text{softmax}(\text{FFN}(P)),$$  \hspace{1cm} (6)

where $\text{FFN}(\cdot)$ is a two-layer fully connected feed-forward neural network:

$$\text{FFN}(P) = \text{ReLU}(P \cdot W_1^T + b_1)W_2^T + b_2,$$  \hspace{1cm} (7)

where $W_1 \in d_h \times d_o$ and $W_2 \in 1 \times d_h$ are parameter matrices with a hidden dimension $d_h$, and $b_1$ and $b_2$ are biases.

Preserve Order Information by Gaussian Range Encoding  The order information is vitally important in identifying reverse actions such as sit down and stand up. Unfortunately, existing positional encodings methods, e.g., absolute encodings (Vaswani et al. 2017) or relative encodings (Shaw, Uszkoreit, and Vaswani 2018) are all defined on a single point: they assign a unique and highly-discriminative encoding for each single point. As we argued, a meaningful unit should be a range rather than a single point. Simply encoding each point will turn out to be a kind of noise, and lead to generally worse results. Thus, we wish to use range-based encodings instead.

To make the encoding be flexible to different start/end blank periods or subtle action speed changes, we propose a Gaussian range encoding that allows a position belonging to multiple ranges at the same time, and dynamically adjust proportions of different ranges during the training.

Without loss of generality, we assume there are $K$ different ranges, and use random variable $z_{ij}$ to denote the occurrence of position $i$ belonging to the $j$-th range. We assume $z_{ij}$ is drawn from a Gaussian distribution $\mathcal{N}(\mu^j, \sigma^j)$ (i.e., $z_{ij} \sim \mathcal{N}(\mu^j, \sigma^j)$) with probability $p^i_j$. As such, a position $i$ is a mixture of all $K$ ranges, and the distribution over ranges are $p_i = \langle p^i_1, p^i_2, ..., p^i_K \rangle_\zeta$, where $\zeta$ is a normalization factor. Given the values vector $v = \langle v_1, v_2, ..., v_K \rangle$, $v_j$ is the value of the $j$-th range. The expectation of position $i$ is $p_i \mu^T$.

All $\mu$, $\sigma$, and $v$ are unobserved hidden variables, and thus they cannot be directly estimated through maximum likelihood estimation (MLE). Fortunately, we can implicitly perform an expectation-maximization by neural networks’ back-propagation. We set $\mu$, $\sigma$, and $v$ as randomly initialized free parameters, and dynamically update them with the training of the whole THAT model.

Formally, let $\beta \in \mathbb{R}^{L \times K}$ be the normalized weights over $K$ Gaussian distributions, which is defined as

$$\beta = \text{softmax}(B),$$  \hspace{1cm} (8)

where $B \in \mathbb{R}^{L \times K}$ is a weight matrix, in which each cell $b_{ij}$ indicates the weight of the $j$-th Gaussian distributions for position $i$. $b_{ij}$ is formally defined as:

$$b_{ij} = \frac{(i - \mu^{(j)})^2}{2\sigma^{(j)}_2} - log(\sigma^{(j)}),$$  \hspace{1cm} (9)

Figure 4: An example of generating Gaussian range encoding for one of positions. The final Gaussian range encoding is the multiplication of the $K$ learnable range embeddings and normalized PDF vector of $K$ Gaussian distributions.
where $\mu^{(j)}$ and $\sigma^{(j)}$ are learnable parameters that indicate the mean and standard deviation for $j$-th Gaussian distributions, respectively.

Finally, the range-biased stream $X'$ is generated by adding the range encodings to the original stream $X$:

$$X' = X + \beta E,$$

(10)

where $E \in \mathbb{R}^{K \times d_m}$ is a set of learnable range encodings. We can see that $E$ corresponds to $v$, $\beta$ corresponds to $p_i$, which can be proved that it is equivalent to computing $L_1$-normalized $K$ univariate Gaussian probability density functions (PDFs).

Fig. 4 shows an illustrative example of the range encoding. For position 140, we can get the normalized PDF vector for $K$ different Gaussian distributions, and each element in the vector indicates the proportion of the corresponding range. The final encoding is the multiplication of the range embeddings and their corresponding proportions.

**Aggregation Layer**

Assume that the features extracted from temporal and channel streams have the size of $T \times d_t$ and $C \times d_c$, respectively. In order to be amenable for the prediction layer, it is necessary to aggregate the features into a small fixed length vector. The aggregation layer aggregates each feature matrix using a CNN with a max-pooling operation:

$$u^X = v(W^X, X) = \text{ReLU}(\text{Dropout}(\text{Pooling}(\text{Conv}(W^X, X)))),$$

(11)

where $v(\cdot)$ consists of four cascaded operations: a convolution, a 1-max-over-time pooling operation (Kim 2014), a Dropout operation, and a ReLU unit. The convolutional layer has $w$ kernel sizes and $l$ filters, and each filter has the size of $h \times d$ ($h$ denotes the kernel size). Further, we use a 1-max-pooling operation to select the largest value over the feature map of a particular kernel to capture the most important feature, and it also helps to shrink the feature size to the kernel number. The output vector $u^X$ has a fixed size $1 \times w l$.

The final feature vector $U \in \mathbb{R}^{1 \times (w^t + w^c)}$ is generated by concatenating the two output vectors:

$$U = [u^T; u^C].$$

(12)

The final feature vector $U$ is fed to the prediction layer to identify different activities.

**Loss Function**

The loss function $\mathcal{L}$ is a standard cross-entropy loss (CE-loss), which is defined as:

$$\mathcal{L} = - \sum_{i} y_i \log(f(\theta; <X_T; X_C>)),$$

(13)

where $y_i$ is the ground-truth label, and $f(\cdot)$ denotes the predicted distribution of the final prediction layer of THAT model. $X_T$ and $X_C$ are input temporal and channel streams. $|A|$ is the number of different activity categories.

### Experimental Evaluation

In this section, we evaluate the performance of the proposed THAT model on human activity recognition tasks, and demonstrate its superiority over state-of-the-art models.

#### Evaluation Datasets

We used four datasets for evaluation, i.e., Office Room, Activity Room, Meeting Room, and Activity+Meeting. The first dataset is publicly available, and the last three are collected by our prototype system. Each dataset is a set of CSI matrices along with their corresponding ground-truth labels. Their brief statistics are summarized in Table 1.

#### Experimental Settings and Evaluation Metrics

The strides of average pooling were set to 4 for temporal stream and 3 for channel stream. The number of Gaussian distributions was $K = 10$. The $\mu$s were evenly distributed among temporal dimension, namely, beginning from 25 and ending with 475 with the step 50. All $\sigma$s were set to 8. The number of stacks for temporal module was $H = 5$ and channel module was $N = 1$. The dimensionality $d_{in} = d_{k} = d_{c}$ was set to 90 and 500, the number of heads $h$ were set to 9 and 200, and $d_{c} = d_{c}/h$. The dropout rate was 0.1. For temporal module and channel module, the kernel sizes were $\{1, 3, 5\}$ and $\{1, 2, 3\}$, the hidden dimensions $d_{h}$ were 360 and 400. For temporal and channel module, the kernel numbers $w$ were set to 128 and 16, and the kernel sizes $l$ were set to $\{10, 40\}$ and $\{2, 4\}$. The dropout rate for this layer was set to 0.5.

The model was implemented using Pytorch 1.4 with Python 3.6, and trained on a Nvidia 1080Ti GPU. For optimization, we used Adam (Kingma and Ba 2014) with an initial learning rate 0.001. All weight parameters were initialized using Xavier (Glorot and Bengio 2010). All datasets adopt 8:1:1 train/dev/test split. The batch size was 16.

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Table 1: Statistics of the four evaluation datasets.

| Datasets        | # Rec. | # Activ. | Freq. | TX-RX Dist. |
|-----------------|--------|----------|------|-------------|
| Office Rm       | 140    | 7        | 1K Hz| 3m          |
| Activity Rm     | 600    | 6        | 500 Hz| 4.5m        |
| Meeting Rm      | 600    | 6        | 500 Hz| 2m          |
| Activ.+Meet.    | 1200   | 6        | 500 Hz| 4.5m/2m     |

Table 2: The recognition accuracy (%) comparison of THAT and baselines on the four evaluation datasets.

| Methods        | Office | Activity | Meeting | Activ.+Meet. |
|----------------|--------|----------|---------|--------------|
| S-RF           | 75.3   | 80       | 84.7    | 82.6         |
| S-HMM          | 79.7   | 75       | 83.4    | 80.5         |
| LSTM           | 91.4   | 89.7     | 90.6    | 90.1         |
| CNN            | 96.4   | 94.3     | 96.2    | 95.4         |
| AB-LSTM        | 97.1   | 95.6     | 96.8    | 95.9         |
| THAT           | 98.2   | 98.4     | 99.0    | 98.6         |
Follow the common practices, we achieve new state-of-the-art results on these datasets. Our model THAT excels all baselines significantly, the proportion of correctly recognized activities among all predictions) as the metric.

### Baselines

We compared with five state-of-the-art models: two feature-based models S-RF (Yousefi et al. 2017) and S-HMM (Wang et al. 2017), and three DL-based models CNN, LSTM (Yousefi et al. 2017), and ABLSTM (Chen et al. 2018).

### Main Results

Table 2 lists the recognition accuracy of the proposed THAT model compared with baselines on the four evaluation datasets. From Table 2, we can see that:

i) Our model THAT excels all baselines significantly, achieving new state-of-the-art results on these datasets. Our model outperforms the best previous model ABLSTM by 1.1 pts (percentage points), 2.8 pts, 2.2 pts, and 2.7 pts on the four datasets, respectively. This demonstrates our convolution augmented transformer and the two-stream structure do truly achieve a better performance on HAR tasks.

ii) The performance gaps between feature-based models (S-RF and S-HMM), and deep-neural models (LSTM, CNN, ABLSTM, and THAT) are huge. Among all the models, S-HMM has the worst performance (on average 79.65% accuracy), and S-RF is only slightly better than S-HMM (80.65%). For DL-based models, LSTM performs the worst since it suffers greatly from the long-range dependency problem. Being able to adaptively integrate hidden states by a attention mechanism, ABLSTM achieved a better results (around 6 pts) than traditional LSTM model and became the best among baselines. All DL-based models achieved at least 10 pts average improvements over feature-based models. Compared with the best feature-based model, our model achieved 18.6 pts, 18.4 pts, 14.3 pts, and 16 pts improvements. This is because deep-neural models are of high expressiveness, and can automatically and adaptively extract useful features from raw data.

iii) Our model performed equally well on different working scenarios. On the first three single-scenario datasets, the difference is only 0.6 pt. For hybrid-scenario dataset Activity+Meeting, the performance of THAT model is commendably good compared to that under single-scenario and excels other models significantly. This demonstrates the effectiveness of THAT on hybrid-scenario. Another observation is that other DL-based models (i.e., LSTM, CNN, and ABLSTM) perform slightly worse on Activity Room than other two. We believe it mainly caused by the TX-RX distance, which is larger than others in Activity Room (4.5m vs. 2m and 3m). It may weaken the received strength and entail more noise. Thus, our model is of high robustness against different working scenarios.

### Categorical Performance Comparison

Table 3 shows the categorical performance comparison between THAT and baselines on the four evaluation datasets. We can see that our model outperformed almost all base-

| Environment          | Methods | Lie down | Fall | Pick up | Run | Sit down | Stand up | Walk | Average |
|----------------------|---------|----------|------|---------|-----|----------|----------|------|---------|
| Office Room          | S-RF    | 65.1     | 82.2 | 85.5    | 83.8| 59.8     | 60.7     | 89.8 | 75.3    |
|                      | S-HMM   | 62.9     | 86.7 | 89.2    | 94.2| 73.4     | 59.9     | 92.0 | 79.8    |
|                      | LSTM    | 95.0     | 92.8 | 98.1    | 96.9| 82.4     | 82.2     | 93.4 | 91.6    |
|                      | CNN     | **97.4** | 97.5 | 98.0    | 98.5| 90.2     | 93.8     | **99.0** | 96.3    |
|                      | ABLSTM  | 96.4     | 98.9 | 97.6    | 97.8| 94.9     | 96.5     | 96.6 | 97.0    |
|                      | THAT    | 96.4     | 99.0 | 98.9    | 98.7| 97.4     | 99.9     | 98.4 | 98.4    |
| Activity Room        | S-RF    | 66.1     | 71.2 | 88.3    | 82.1| 81.4     | 87.1     | 88.8 | 80.0    |
|                      | S-HMM   | 36.8     | 47.9 | 92.7    | 90.8| 89.8     | 94.7     | 91.9 | 89.7    |
|                      | LSTM    | 88.1     | 81.8 | 90.6    | 90.9| 94.7     | 97.2     | 93.8 | 94.3    |
|                      | CNN     | 94.1     | 90.4 | 93.8    | 96.5| 95.5     | 96.5     | 97.9 | 95.6    |
|                      | ABLSTM  | 93.4     | 93.9 | 95.5    | 96.6| 96.5     | 96.5     | 97.9 | 95.6    |
|                      | THAT    | **98.8** | **97.9** | **96.7** | **98.7** | **97.4** | **98.7** | **98.9** | **98.4** |
| Meeting Room         | S-RF    | 66.1     | 88.7 | 81.1    | 82.1| 81.4     | 90.5     | 84.7 | 75.0    |
|                      | S-HMM   | 67.1     | 77.2 | 89.1    | 82.8| 90.6     | 93.6     | 83.4 | 83.4    |
|                      | LSTM    | 89.6     | 87.2 | 90.5    | 91.6| 93.7     | 90.7     | 90.6 | 90.6    |
|                      | CNN     | 96.2     | 92.2 | 95.8    | 98.4| 98.3     | 96.2     | 96.2 | 96.2    |
|                      | ABLSTM  | 96.5     | 98.2 | 97.1    | 98.5| 92.8     | 97.6     | 96.8 | 96.8    |
|                      | THAT    | **99.3** | **99.8** | **97.3** | **99.7** | **99.2** | **98.4** | **99.0** | **99.0** |
| Activity+Meeting     | S-RF    | 70.9     | 82.8 | 88.7    | 85.6| 81.7     | 85.9     | 82.6 | 82.6    |
|                      | S-HMM   | 50.9     | 66.8 | 88.7    | 88.8| 89.7     | 97.8     | 80.5 | 80.5    |
|                      | LSTM    | 78.8     | 91.9 | 96.9    | 92.1| 89.2     | 91.7     | 90.1 | 90.1    |
|                      | CNN     | 93.1     | 95.2 | 97.3    | 95.9| 97.1     | 93.6     | 95.4 | 95.4    |
|                      | ABLSTM  | 93.6     | 94.5 | 97.1    | 97.4| 97.4     | 95.8     | 97.1 | 95.9    |
|                      | THAT    | **99.0** | **99.2** | **99.4** | **99.6** | **97.6** | **98.7** | **98.4** | **98.6** |

Table 3: Categorical performance comparison on Office Room, Activity Room, Meeting Room, and Activity+Meeting datasets.
lines in identifying any activity on all the four datasets. This demonstrates our model is effective in capturing general patterns rather than just taking advantages of the “biases” of some specific activities.

Another observation is that, LSTM and CNN suffer more difficulties in recognizing reverse activities sit down and stand up because they need position or order information. Owing to involving an attention mechanism, ABLSTM has an improvement over LSTM. Our model performs significantly better than both scope-based model CNN (5.5 pts) which does not preserve positional information and sequential model ABLSTM (1.5 pts) that focuses on a fixed scale. This demonstrates our proposed Gaussian range encoding and multi-scale CNN block could preserve order information and are able to capture multi-scale features.

**Ablation Test**

We conducted an ablation study to evaluate the contributions of the proposed Gaussian range encoding, multi-scale CNN, and the two-stream structure. Table 4 represents the results. In each test, we ablated a specific component from the full model. Notably, we made two further tests by replacing the ablated component with an alternative component: the first used positional encoding proposed in (Vaswani et al. 2017) to replace our Gaussian range encoding (i.e., Gaussian Range Encoding (+ PE)), the second used a position-wise feed-forward neural network to replace our multi-scale CNN (i.e., Multi-scale CNN (+ PFFN)).

From Table 4, we can see that position/order information does help a better recognition. The ablation on Gaussian range encoding incurs roughly 0.5 pt accuracy decline. Interestingly, the results of using positional encoding PE (Vaswani et al. 2017) are even worse than without any positional encoding. This is caused by the over-positionality that the encodings assigned to each single position turn out to be an interference.

The ablation on multi-scale CNN incurs a 1.83 pts accuracy decline, compared with using PFFN, still 1 pt performance gap. This demonstrates the multi-scale pattern captured by the CNN is critical, especially on datasets (e.g., Office Room) that have a long time range.

Another observation is, compared with single-stream model, the two-stream structure could effectively improve the model performance. This indicates the two-stream could be complementary to improve the recognition accuracy. Among the two streams, the ablation on temporal module incurs a bigger decline, which is in accord with common sense that temporal features are more intuitive and important. From ablation test, we can conclude that all these components contribute significantly to the model performance.

**Empirical Efficiency**

To validate the time-efficiency of THAT, we show the empirical execution time on Activity Room dataset in Table 5.

From Table 5, we can see that all DL-based models (i.e., LSTM, CNN, ABLSTM, and THAT) are more time-consuming than traditional machine learning models (i.e., S-RF, S-HMM). Our THAT model (and CNN) has a better time-efficiency than sequential models LSTM and ABLSTM, since most of the computations (e.g., multi-head self-attention module, all convolution modules) can be computed in parallel. The high time costs in training phase would not be a big issue since it can be computed offline. In testing phase, our model is 3.37× faster than ABLSTM, 1.83× faster than LSTM, and competitive to CNN. The throughput rate of THAT is 32.58 Recs/Sec, indicating each record can be inferred within 4ms. Considering the window size of each record is 4 seconds, the time cost of our model could be fully ignored. This demonstrates our model is not only of high effectiveness, but also efficient enough for real-time WiFi-based human activity recognition.

**Conclusion**

In this paper, we propose a novel neural network for device-free HAR tasks. Our model extracts both time-over-channel and channel-over-time features, and uses Gaussian range encoding and a multi-scale convolution block to capture range patterns. The experimental results show that, compared with the best previous model ABLSTM, our model delivers an average 2.2 pts accuracy improvement, while being 1.83~3.37× faster.

| Model                  | Office Room | Activity Room | Meeting Room | Activity+Meeting |
|------------------------|-------------|---------------|--------------|------------------|
|                        | Accuracy Δ | Accuracy Δ    | Accuracy Δ   | Accuracy Δ       |
| THAT                   | 98.2        | 98.4          | 99.0         | 98.6             |
| - Gaussian Range Encoding | -0.4       | -0.5          | -0.5         | -0.4             |
| - Gaussian Range Encoding (+ PE) | -7.2       | -14.1         | -8.7         | -10.8            |
| - Multi-scale CNN      | 95.3        | 97.4          | 97.0         | 97.3             |
| - Multi-scale CNN (+ PFFN) | -3.0       | -1.2          | 98.1         | -0.9             |
| - Temporal Module      | 92.0        | 95.2          | 97.5         | 95.9             |
| - Channel Module       | 93.8        | 97.7          | 98.3         | 98.0             |

Table 4: Ablation study results compared with the full THAT model. The accuracy is shown in percentage (%).

| Models | Training (Sec) | Testing (Sec) | Recs/Sec |
|--------|----------------|---------------|----------|
| S-RF   | 6.09           | 0.016         | 31250    |
| S-HMM  | 0.029          | 0.22          | 2272.72  |
| LSTM   | 5168.86        | 4.39          | 113.9    |
| CNN    | 1474.76        | 1.12          | 446.43   |
| ABLSTM | 11352.82       | 6.77          | 73.86    |
| THAT   | 2996.75        | 1.55          | 332.58   |

Table 5: Empirical execution time on Activity Room dataset.
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