

# Multi-channel Time Series Decomposition Network For Generalizable Sensor-Based Activity Recognition

Jianguo Pan, Zhengxin Hu, Lingdun Zhang, Xia Cai

**Abstract**—Sensor-based human activity recognition is important in daily scenarios such as smart healthcare and homes due to its non-intrusive privacy and low cost advantages, but the problem of out-of-domain generalization caused by differences in focusing individuals and operating environments can lead to significant accuracy degradation on cross-person behavior recognition due to the inconsistent distributions of training and test data. To address the above problems, this paper proposes a new method, Multi-channel Time Series Decomposition Network (MTSDNet). Firstly, MTSDNet decomposes the original signal into a combination of multiple polynomials and trigonometric functions by the trainable parameterized time series decomposition to learn the low-rank representation of the original signal for improving the extraterritorial generalization ability of the model. Then, the different components obtained by the decomposition are classified layer by layer and the layer attention is used to aggregate components to obtain the final classification result. Extensive evaluation on DSADS, OPPORTUNITY, PAMAP2, UCIHAR and UniMib public datasets shows the advantages in **classifying** accuracy and stability of our method compared with other competing strategies, including the state-of-the-art ones. And the visualization is conducted to reveal MTSDNet’s interpretability and layer-by-layer characteristics.

**Note to Practitioners**—This paper is motivated by solving the problem of decreased **classification** accuracy caused by differences in human activity, such as the differences in walking patterns between young and elderly people. Models trained on young people’s data are difficult to accurately recognize the activities of the elderly. This is a problem of domain generalization, where the distribution differences between training and testing data require the model’s ability to generalize across domains. We propose a model based on time series decomposition, which helps the model learn universal features and effectively improve its generalization ability. This method can be further extended to time series tasks with varying domain distributions.

**Index Terms**—Human activity recognition, Domain generalization, Time series analysis.

## I. INTRODUCTION

**H**UMAN activity recognition (HAR) is a research hotspot in the field of machine learning (ML) and pattern recognition for the goal of classifying the activities conducted by the participants with ML algorithms [1], which has been widely used in medical diagnostic monitoring [2], [3], human-computer interaction [4], [5], identity recognition [6], [7] and other fields. Compared with video or image-based HAR [8], [9], sensor-based HAR has more advantages in

cost and privacy. Traditional HAR method based on ML such as SVM [10], KNN [11] usually concentrates on feature engineering and needs to be redesigned when the recognition task changes. Recently, deep learning methods such as CNN, LSTM [12], DeepConvLSTM [13] and Transformer [14], can achieve higher **classification** accuracy and have gradually become the main methods for HAR tasks. These models work well when the data of training and test data has the similar or overlapping data distributions, which are achieved by splitting data of each participant into both training and test sets. Nevertheless, this approach proves unwieldy in real-world scenarios, prompting a more pragmatic alternative in the form of cross-person HAR, which entails segregating the data according to different volunteers. Specifically, in the sensor-based cross-person HAR, sensor data exhibits the variations in age, scene and etc., where the distribution of training and test sets fails to conform to the assumption of independent and identical distribution (I.I.D). For example, in the fall detection task, the data of the elderly is difficult to be collected which is often needs to be replaced by the data of the young for model learning. Similarly, in the conventional activity recognition task, the training set comprises data acquired from a controlled laboratory environment, whereas the test set comprises data from complex, real-world environments that exhibit higher levels of environmental noise and activity complexity, exceeding those encountered during training. Remarkably, when confronted with data derived from unobserved subjects, the researchers found that the model would experience a decrease in accuracy and identified some of the reasons as differences in hardware or wearing [15], [16].

To deal with the above discrepancies of data distribution, transfer learning, domain adaptation and domain generalization are presented in literature [17], [18]. Transfer learning method usually adopts two steps: training and fine-tuning, where the model is trained with multiple source domains and then is fine-tuned in order to adapt to the target domain. In the fine-tuning process, the auxiliary information of the target domain is more or less introduced [19], [20] to avoid negative transfer problems. When the data distribution of the target domain is known or unlabeled target domain data is provided, the models of domain adaptation can map the source domain and target domain to the subspace under the same distribution for reducing the domain differences. Most methods of domain adaptation are designed for image data and are incompatible with time series data [21], [22]. Meanwhile, if there are multiple target domains, transfer learning and

domain adaptation methods both need to be re-trained for each target domain. Domain generalization method focuses on obtaining invariant features or domain-independent features to ensure the generalization ability on invisible target domain and reduce the interference of domain-specific features [23], which does not require any additional information of target domain, compared with transfer learning and domain adaptation.

In this work, we focus on the cross-person sensor-based HAR and treat the data of different volunteers as a single domain. We investigate the error characteristics of sensor data and propose a new model called MTSDNet to hierarchically process the original signal based on the time series decomposition and the design in NBEATS method [24]. Each layer of MTSDNet consists of a decomposer and a classifier, where the decomposer is used to decompose the input signal into specific components and the classifier outputs the classification results of the components. MTSDNet expresses the original signal as a combination of multiple polynomials and trigonometric functions with trainable parameters. By using  $1 \times 1$  convolution instead of fully connected layers for parameter sharing, MTSDNet applies a single channel time series decomposition method to multi-channel temporal data. Meanwhile the normalization within a sliding window is employed at each layer to constrain the feature range for learning the low-rank representation of the original signal. Through these steps, MTSDNet transforms the original distribution into multiple distributions with different constraints so that the distribution of components in the same layer remains constant, while that of different layers varies. This structure allows the model to focus on the component with the smallest distribution difference and improve the model's generalization ability. Our experimental evaluations on DSADS, PAMAP2, OPPORTUNITY, UCIHAR and UniMib datasets validate that our model can outperform state-of-the-art methods with enhanced generalization ability and is suitable for practical HAR applications.

In sum, the main innovations of MTSDNet are as follows:

- 1) A novel decomposer structure including the normalization and denormalization within a sliding window to constrain the layer distribution is designed for classification, and the statistical information is integrated into the features through multi-view approach to recover the information lost during normalization.
- 2) A novel converter is presented that can directly convert the additive model of time series decomposition into multiplicative model to adapt to different signals.
- 3) A multi-channel time series decomposition structure is proposed, which replaces the fully connected layer with  $1 \times 1$  convolution to expand single-channel time series decomposition into multi-channel time series decomposition.

The proposed MTSDNet is shown in Figure 1. Input signal is decomposed into specific forms by MTSDNet. MTSDNet **classifies** each component separately and a layer attention is used to obtain the final result.

## II. RELATED WORK

Feature learning method for sensor-based HAR can roughly be grouped into two categories: classical machine learning and deep learning. The general processing steps of machine learning mainly consists of using statistical features or fourier transform for feature engineering and using KNN [25], XGBoost [26] and other algorithms for classification. Time series decomposition method, which takes a compositional perspective on time series data, is often used in conjunction with traditional ML methods for sensor-based HAR. Recently, this method has also been incorporated into deep learning approaches. In this regard, a novel recognition method based on online feature vector calculation and multi-way decomposition algorithm has been proposed [27]. FuzzyAct jointly classifies and detects human activities through Discrete Wavelet Transform (DWT) and Recurrent Neural Network (RNN) [28]. Distribution-Embedded Deep Neural Network (DDNN) integrates data features from multiple modalities and enhances the model's generalization ability by fusing spatial, temporal and statistical domain information [29]. DeepConvLSTM [13] effectively applies convolutional network and Long Short-Term Memory (LSTM) network to different sensor modes. Attention mechanism is introduced later for further enhancing the model's feature extraction ability [30]. **Dual Attention Network for multimodal human activity recognition (DanHAR) [31] blends channel and temporal attention on residual networks to improve feature representation ability. Triple cross-domain attention (Triple-Res) [32] establishes three attention branches to capture the cross features between sensor, time and channel dimension to improve the classification accuracy.** These methods are characterized by enhancing the model's feature extraction ability and improving generalization ability to some extent.

Looking at cross-person HAR from the perspective of domain generalization, many methods refer to the training and fine-tuning steps in transfer learning, which train on the source domain and fine-tune on the partial data from target domain. However, in sensor-based HAR tasks, due to the differences in the number and location of sensors, as well as the lack of sensor data, it is not feasible to simply employ transfer learning method. Domain-Adversarial Training of Neural Networks (DANN) achieves the error minimization of task classification and the error maximization of domain classification by adopting the methods of gradient reversal and multi-task learning, thereby forcing the model to focus only on the domain-irrelevant part during feature extraction [33]. Convolutional deep Domain Adaptation model for Time Series data (CoDATS) constructs a domain adaptive weakly supervised method and uses target domain data for domain adaptation to improve the model's accuracy [18]. Generalizable Independent Latent Excitation (GILE) adopts multi-task learning and source domain-independent architecture to separate volunteer-specific features and volunteer-independent features based on volunteer source labels so that only volunteer-independent features are used for **classification** to enhance cross-person generalization ability [17].

## III. METHOD

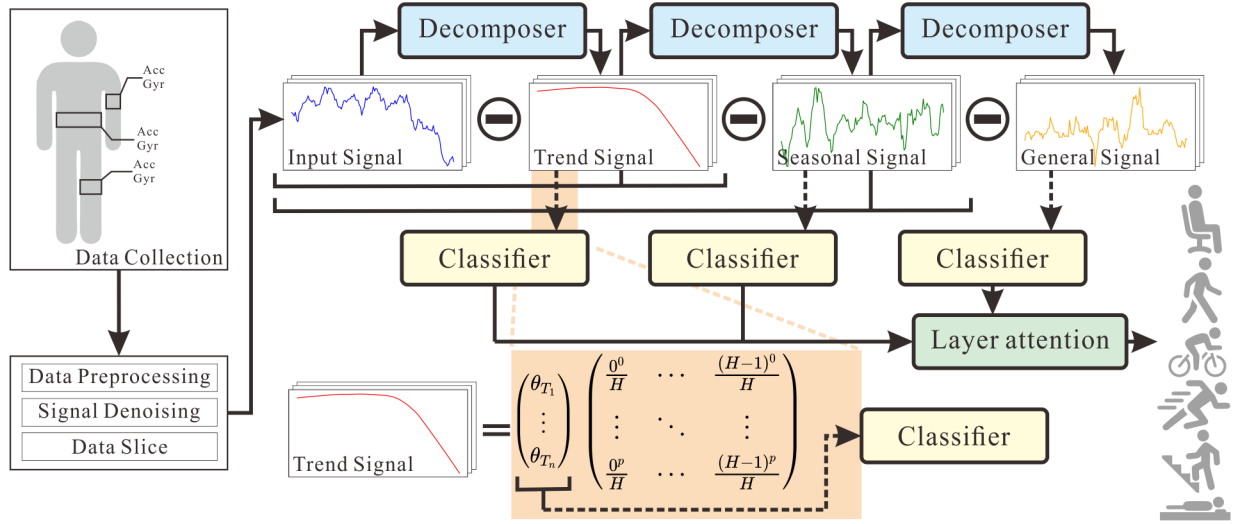


Fig. 1. Illustration of the proposed method. Firstly, data is collected through sensors such as accelerometers and gyroscopes. After data preprocessing, denoising and slicing, input data is decomposed into multiple components by decomposer. Each component can be considered as a multiplication combination of preterm coefficients and constraint terms. The orange part indicates that the classifier use the preterm coefficients of each component. Finally, MTSDNet integrates classification results using a layer attention. Here it adopts the structure of the model MTSDNet-A-tsg, which is an additive model and decompose the signal to one trend, one seasonal and one general component. More details can be found in Section III-C.

In this section, we will introduce how MTSDNet is designed. Meanwhile, we will explain why time series decomposition is introduced and how time series decomposition enhances domain generalization ability.

Introducing prior knowledge of specific tasks in model design can help improve model performance. CNN, LSTM, and PINN all take advantages of specific ways to extract prior knowledge. Unlike domain differences in image classification, domain differences in HAR are in terms of time. Therefore, MTSDNet use time series decomposition in order to make full use of the prior knowledge of time.

**Sensor-based human** activity recognition can be regarded as a time series classification task with **domain differences** or **distribution differences**. By analyzing the possible differences in human activities, we can get the following errors.

#### A. Error Analysis

Regarding the analysis of the sensor data used for cross-person HAR, it is found that the following factors are the main reasons for the distribution differences between different volunteers:

- 1) **Data bias**: arising from the wearing differences of the sensors in the same position and the variations in the three-axis direction caused by the sensor production, this bias is manifested in the original signal as static or background deviation. Taking the accelerometer as an example, the bias appears as variations in data direction and amplitude, contingent upon a variety of factors, including sensor placement, rotation, motion-induced displacement and so on.
- 2) Volunteer activity differences: mainly derived from the signal differences reflected on sensors under the amplitude, frequency and composite of dynamic actions between different volunteers, as well as signal differences

of complex actions on the sensors. This difference is manifested in the original signal as features such as the amplitude, frequency and periodicity of seasonal signals.

- 3) Secondary noise: mainly arising from the relative movement of sensors to the body caused by human motion when the sensors and the body are not tightly attached. The information collected by the sensors contains the movement of the sensors relative to the body in addition to the human motion, which is manifested as data bias changing over time in other original signal.

For the above, data bias is rarely singled out and addressed specifically. The work [16] explains the data bias problem caused by the sensor hardware, but does not consider the data bias problem caused by the fixed way of the sensor on human body.

**Domain differences in HAR** are different from those in other fields. Complex domain differences can be regarded as a stack of the errors mentioned above. A straightforward way is to deal with these differences separately so MTSDNet adopts time series decomposition. Time series decomposition can decouple features, so as the domain differences.

By using time series decomposition, specific domain differences **will** be limited to a certain term. For example, the data bias caused by wearing is only generated in the trend item. When there is only data bias, the utilized time decomposition can ensure that the seasonal and general terms are not disturbed. Even if the classification of trend term is incorrect due to domain differences, the other two terms still work independently in a correct way. Therefore, time series decomposition can enhance the domain generalization ability in HAR.

Time series decomposition is often implemented for time series prediction such as predicting geographic or financial data. In these tasks, different terms are either retained or discarded because of different requirements because time series

decomposition is good at keeping terms independent from each other. For example, the task attaching more importance to long-term trend needs to eliminate the effects of seasonal terms and residuals, vice versa.

In HAR, time series decomposition in MTSDNet focuses on trend term, seasonal term and general term.

**Trend terms** can capture static activity features and handle static biases. Seasonal terms can capture dynamic activity features and handle the features with different periodic patterns. Then the remaining signals are processed by general term, with residual signal left. In time series prediction, the remaining signals are often discarded. In HAR, however, the remaining signals processed by general term are still useful. For example, in fall detection, falling activities appear as sporadic signals on sensors, and the general term can better capture sporadic signals.

What's more, time series decomposition is also good for explicit feature alignment. Explicit feature alignment makes the feature distributions of multiple source domains as close as possible. By learning a time series decomposition, each layer of terms is fixed in the same feature space. In addition, sliding window normalization is able to ensure that each layer of terms obtains the same distribution, which further enhances domain generalization ability.

## B. Problem Statement

For cross-person HAR, we consider each volunteer as a domain which can be defined as a joint distribution  $\mathbb{P}^d(x, y)$  on  $\mathcal{X} \times \mathcal{Y}$ , where  $\mathcal{X}$ ,  $\mathcal{Y}$  and  $d \in \mathcal{D} = \{1, \dots, D\}$  denote activity instance space, activity class space and the index of source domain. The difference between the cross-person HAR and traditional HAR during modeling is the division way of training and test set. Training set can be defined as  $\{(X^d, y^d) \sim \mathbb{P}^d(x, y)_{d=i}^D\}$  and test set can be defined as  $\{(X^d, y^d) \sim \mathbb{P}^d(x, y)_{d=j}^D\}, \forall i \neq j \text{ where } i, j \in \mathcal{D}$ . In this task, training set and test set have the same activity class space. The goal of cross-person HAR is to train a generalizable model within training set, which is able to generalize well on test set and is unaffected by volunteer differences.

To simplify the task, a sliding window is used to divide the data into fixed-length sequence which can be defined as  $\{(F_k^t, y), F_k^t \in \mathbb{R}^{k \times t}\}$ . Here  $k$  is the number of sensor channels,  $t$  is the sliding window length,  $y$  is the activity label of the last moment in the sequence. Combined with Section III-A, the model decomposes the original data into multiple components, which can be expressed as either additive model or multiplicative model. For example, in the additive model shown as  $F_k^t = \sum_{i=1}^q p_i + I$ , where  $p_i \in \mathbb{R}^{k \times t}$  is the component,  $q$  means the number of components and  $I$  is the noise. After decomposition, each component is classified by the designed model and the final classification result can be obtained by a weighted sum of the outputs from different components. The result is shown as  $\hat{y} = \sum_{i=1}^q (w_i \times f_i(p_i))$ , where  $w_i$  is the weight and  $f_i$  is the classification model for each component.

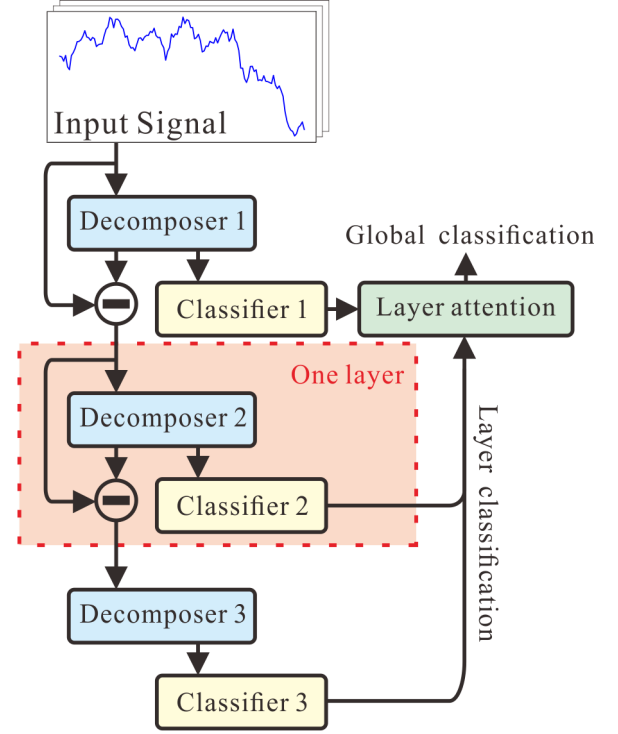


Fig. 2. The overall structure of proposed MTSDNet according to the additive model with three layers and no decomposition term output in the last layer. The model input is the sensor data divided into many sliding windows and the output is a weighted classification results of multiple layers.

## C. Overall Structure

The model framework of MTSDNet is shown in Figure 2, which is composed of multiple layers with each layer having one input and two outputs. The left output is the decomposed signal and the right is the classification output of the layer, where the classification outputs of different layers are aggregated into a final result through the layer attention mechanism. The input signal is processed by subtraction or division in the multi-layer block from top to bottom to form an additive or multiplicative model. Each layer consists of a decomposer and a classifier. The decomposer is used to extract specific term. The classifier uses a three-layer MLP implementation to classify specific term.

Each layer will receive a classification result, for which MTSDNet uses a layer attention to aggregate and obtain a final result. The layer attention is a saliency-based attention. In training, the attention weight of each layer is trained in a data-driven way. The attention weight obtained by training reflects the quantitative importance of time series decomposition features. The layer attention ensures that the sum of weights is 1 through softmax. When testing, MTSDNet uses the trained attention weight to aggregate multiple classification results.

In Figure 2, the symbol '-' shows additive model. Each layer consists of a decomposer and a classifier, which are responsible for time series decomposition and classification of component features, respectively. In light of the fact that traditional time series decomposition methods are characterized by both additive and multiplicative model, MTSDNet preserves consistency with these methods by adopting the



same designs. And this framework enables the decomposition of the original data into additive or multiplicative forms subject to the constraints of MTSDNet shown as following:

$$S_{original} = \sum_{i=1}^n T_i + \sum_{i=1}^m S_i + \sum_{i=1}^o G_i + I \quad (1)$$

$$S_{original} = \prod_{i=1}^n T_i \times \prod_{i=1}^m S_i \times \prod_{i=1}^o G_i \times I \quad (2)$$

where  $S_{original}$  is the original time series signal.  $T$ ,  $S$ ,  $G$  and  $I$  are the trend, seasonal, general and noise items.  $n$ ,  $m$ ,  $o$  are the number of  $T$ ,  $S$ ,  $G$ , which means the original signal can be decomposed into a combination of  $n$  trend terms,  $m$  periodic terms, and  $o$  general terms. The polynomial constraint and trigonometric function constraint are used for trend and seasonal items, respectively. The general item consists of two  $1 \times 1$  convolutional layers without any constraint. The remaining part after the completion of time series decomposition is  $I$ , which is not used for classification. The items of  $T$ ,  $S$  and  $G$  can be decomposed step by step with multiple layers.

Polynomial constraint and trigonometric constraint can be considered as nested functions with time matrix  $Z$  as the independent variable. Time matrix  $Z$  is used to express the time dimension.  $Z$  is defined as follows:

$$Z = \begin{bmatrix} 0 & \dots & \frac{(H-1)}{H} \end{bmatrix} \quad (3)$$

Where  $H$  is the length of the sliding window. The  $T$  trend uses the following polynomial constraint:

$$T_i = \theta_T T' \quad (4)$$

$$T' = F_T(Z) = \begin{bmatrix} 1 \\ Z \\ Z^2 \\ \vdots \\ Z^p \end{bmatrix} = \begin{bmatrix} 1 & \dots & 1 \\ \frac{0}{H} & 1 & \dots & \frac{H-1}{H} \\ \frac{0}{H} & \frac{0}{H} & 2 & \dots & \frac{H-1}{H}^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{0}{H} & \frac{0}{H} & \dots & \frac{H-1}{H}^p \end{bmatrix} \quad (5)$$

Where  $T'$  is a matrix representing polynomial constraints,  $\theta_T$  is the feature generated through trend decomposer and  $p$  is the order of polynomials, respectively.  $F_T(Z)$  indicates that the polynomial function acts on each element of  $Z$  matrix.  $F_T(Z)$  is equivalent to using  $Z$  as the independent variable for  $p$ -order polynomial expansion. Polynomial constraints are expressed in matrix form and the decomposition form of the signal is obtained by matrix multiplication with the computed high-dimensional features. This is equivalent to restricting the trend item to a specific structured polynomial function and allowing the model to learn the coefficients of each polynomial term. The  $S$  trend item uses the following trigonometric constraint:

$$S_i = \theta_S S' \quad (6)$$

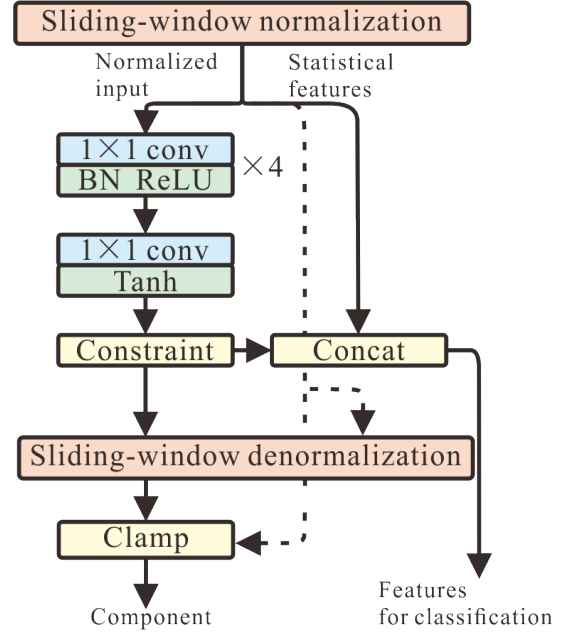


Fig. 3. The illustration of decomposer structure with one input and two outputs. The left and right sides output the decomposition term and classification results, respectively. The dashed line indicates that the data is used as parameter for the function instead of function input.

$$S' = F_S(Z) = \begin{bmatrix} \cos(2\pi \times 0 \times Z) \\ \cos(2\pi \times (\frac{H}{2} - 1) \times Z) \\ \vdots \\ \cos(2\pi \times (\frac{H}{p} - 1) \times Z) \\ \sin(2\pi \times 0 \times Z) \\ \sin(2\pi \times (\frac{H}{2} - 1) \times Z) \\ \vdots \\ \sin(2\pi \times (\frac{H}{p} - 1) \times Z) \end{bmatrix} \quad (7)$$

Where  $S'$  is a trigonometric constraint expressed in matrix form, and  $\theta_S$  is the feature generated through seasonal decomposer.  $F_S(Z)$  indicates that the trigonometric function acts on each element of  $Z$  matrix.  $F_S(Z)$  is equivalent to using  $Z$  as the independent variable for  $p$ -order trigonometric expansion.

Similar to the polynomial function constraint, trigonometric function constraint can also be expressed as a restriction on the seasonal term, which is a combination of specific trigonometric functions with coefficients that are learned during the training process.

By the above construction using  $T'$  and  $S'$ , the decomposer can decompose input signal into the product of coefficient matrix and temporal characteristic matrix to express the temporal characteristics of the input signal. According to the constraint property, the input signal will have a high coefficient on part of features, while the rest of coefficients are close to zero, thus constituting a low-rank feature.

#### D. Decomposer Structure

The decomposer is composed of a sliding window normalization and denormalization module, a statistical eigenmodel fusion module, a constraint control module and a distribution

clamping module. Sliding window normalization and distribution clamping modules are used to control the distribution of components. Constraint control module is used to match specific construction like  $T'$  or  $S'$ . Denormalization module is used to restore the original distribution. The structure of the decomposer is illustrated in Figure 3. The flow of the decomposer is described as following steps, with the solid line representing data utilized as features and the dashed line indicating data utilized for parameter input.

- 1) The input signal of current layer is normalized within a sliding window where the statistical information (minimum, mean, maximum and variance) can be obtained. In addition, a fixed bias of  $1e^{-5}$  is added to the variance in case of zero variance.
- 2) Four  $1 \times 1$  convolutional layers, batch normalization (BN) and ReLU are employed for channel-by-channel information extraction with weight sharing. Then a  $1 \times 1$  convolutional layer is used to obtain the fixed-size features with Tanh activation function, which is multiplied with the constraint term in order to extract the signal.
- 3) The extracted components in the time domain are obtained through multiplying the high-dimensional features by the constraint terms, and then the statistical information within the sliding window is used for denormalization. Subsequently, the signal is corrected according to the additive or multiplicative model of the time series decomposition. Finally, the minimum and maximum values from the statistical information are employed for clamping. The range of the signal for the additive model is limited to 1.1 times the range of the input data, while the multiplicative model is constrained to a range of (0.5, 2). The range clamping for the additive model is specifically calculated as follows:

$$D_{out} = clamp(\min(D_{in}) - C \times |\min(D_{in})|, \max(D_{in}) + C \times |\max(D_{in})|, D_{in}) \quad (8)$$

where  $D_{in}$  and  $D_{out}$  are the input and output feature of the clamp module, respectively.  $C$  is constraint weights to control the range of component. In additive model, the value of  $C$  is set to 0.1. The clamp module can restrict the data within a specific range.

- 4) The classifier of the model is constructed by three-layer MultiLayer Perceptron (MLP). Considering that the normalization in the first step can lose statistical information of input features, such as mean and variance, which contains behaviorally relevant features and should not be ignored, both high-dimensional features and statistical features are concatenated together as the inputs of classifier for the classification.

Through the above steps, MTSDNet is finally designed based on the framework of additive model. Then we further propose that MTSDNet can be transformed into a multiplicative one to fully utilize input signals using the following expression:

$$D_* = Relu(D_+) + \left( \frac{1}{Relu((-1) \times D_+) + 1} \right) \quad (9)$$

where  $D_+$  is the feature extracted from MTSDNet under the additive model, and  $D_*$  is the transformed features for multiplicative model. This operation is located between sliding-window denormalization and clamp.

## IV. EXPERIMENTS

### A. Experimental Environment

All of the experiments are conducted on a sever containing NVIDIA GeForce RTX 3080 with pytorch-lightning and pytorch, which also are executed with the same training hyperparameters, including a batch-size of 512, a learning rate of  $3e^{-3}$ , 20 training epochs and 10 repetitions of each model with random seeds. We follow the assessment approach of domain generalization during the experiments. Specifically, the data from different volunteers is treated as the different domains and the data is divided into the training and test set using single-domain or multi-domain splitting method. The mean and variance of accuracy under 10 training sessions are adopted as evaluation metrics.

For the comparison of experimental results, a variety of traditional methods including LSTM, GRU and three-layer MLP, as well as DeepConvLSTM and Transformer are provided. **DanHAR and Triple-Res focus on patial-temporal dependencies of multimodal sensing data, mainly using attention to improve classification accuracy. DanHAR and Triple-Res achieved SOTA on different datasets.** DANN and GILE are selected for comparing model performance under domain generalization. Although DANN is proposed as a domain adaptation method, it is changed as a domain generalization method to uses the labels between different source domains as auxiliary targets for unifying measurement in this work. GILE uses 2 and 0.5 as loss hyperparameters in multi-task learning.

### B. Experimental Dataset

Five HAR benchmark datasets are used for the experimental evaluation in this paper, including the DSADS [34], PAMAP2 [35], OPPORTUNITY [36], UCIHAR [37] and UniMib [38] datasets. The parameters associated with each dataset involved in the experiments are listed in Table I.

The 'Part' in the paper contains either one or several volunteers generated from dataset by different volunteer splitting methods. For example, 'Part2' means the second part of volunteer data is taken as test set while the rest part is used as training set and then experiment is conducted for 10 times with random seeds. In addition, the experiments focus on gesture recognition task of OPPORTUNITY dataset and fall detection task of UniMib dataset. The 9th volunteer on PAMAP2 dataset and the 29th and 30th volunteers on UCIHAR dataset are only used for training due to limited data on corresponding volunteers. MTSDNet can be designed several structural versions, such as MTSDNet-A-stg, MTSDNet-M-g3 or MTSDNet-A-t3s3g3, where A and M mean MTSDNet is based on additive and multiplicative model, respectively. t3s3g3 means that the decomposition structure of the model is 3 trend blocks, 3 seasonal blocks and 3 general blocks. If no number is attached to the letter, it means one block. In this paper, we refer to the feature order obtained by traditional

TABLE I  
THE PARAMETER SUMMARY OF INVOLVED PUBLIC DATASETS

Parameters	UCIHAR	PAMAP2	DSADS	OPPORTUNITY	UniMib
Volunteer Num	30	9	8	4	30
Sensor Channel Num	9	54	45	113	3
Activity Num	6	18	19	18	2
Preprocessing	Standard	Standard	Standard	MinMax	Standard
Length	128	128	32	64	151
Stride	32	32	28	32	151
Split	1-7,8-14,15-21,22-28	1,2,3,4,5,6,7,8	1,2,3,4,5,6,7,8	1,2,3,4	1-10,11-20,21-30
Label-unbalance	Null	Null	Null	Weighted CE LOSS	Null

TABLE II  
COMPARISON OF **CLASSIFICATION** ACCURACY ACHIEVED BY VARIOUS METHODS ON FIVE DATASETS. THE BEST RESULT ON EACH DATASET IS HIGHLIGHTED IN BOLD.

Methods	UCIHAR	PAMAP2	DSADS	OPPORTUNITY	UniMib
GRU	91.79	64.96	81.87	44.07	94.85
LSTM	90.97	64.65	81.23	21.87	89.48
MLP	90.52	64.61	79.47	68.50	96.29
Transformer	90.57	66.20	84.29	47.47	95.77
DeepConvLSTM	92.16	69.86	85.02	54.73	94.94
MTSDNet-A-tsg	91.67	71.92	91.28	<b>78.63</b>	<b>98.92</b>
MTSDNet-A-t3s3g3	91.70	<b>73.34</b>	<b>92.16</b>	78.14	98.85
MTSDNet-M-tsg	92.32	72.91	91.28	78.30	98.81
MTSDNet-M-t3s3g3	<b>92.42</b>	72.50	90.90	74.58	98.74
DANN	89.29	63.30	81.30	55.49	94.75
GILE	92.26	72.37	87.49	58.32	97.00
DanHAR	91.6	71.73	89.46	70.12	97.26
Triple-Res	91.93	71.69	86.85	73.20	96.70

time series decomposition and choose 4 versions of MTSDNet: MTSDNet-A-tsg, MTSDNet-M-tsg, MTSDNet-A-t3s3g3 and MTSDNet-M-t3s3g3, to highlight the differences between the additive and multiplicative models and show the effect of different stacked ways.

### C. Experimental results

The contrast accuracy results achieved by different methods are listed in Table II, which are the average classification accuracy through traversing all Parts as the test set on five datasets.

As shown in Table II, MTSDNet and GILE achieve better accuracy compared with other methods, where the average accuracy of MTSDNet surpasses all existing practice on all datasets and GILE is ranked the 2nd on UCIHAR and PAMAP2. DanHAR ranked 2nd on DSADS and UniMib. Triple-Res ranked 2nd on OPPORTUNITY. On UCIHAR and PAMAP2 datasets, the gap of average accuracy between MTSDNet and GILE is small within 1% or less. Compared with the second highest accuracy methods, MTSDNet has improved about 0.2% on UCIHAR, 1% on PAMAP2, 2.7% on DSADS, 5.4% on OPPORTUNITY and 1.66% on UniMib. In addition, when using a higher stacked decomposition model, the accuracy of multi-layer stacked MTSDNet-A-t3s3g3 is generally improved compared to the MTSDNet-A-tsg model, while this phenomenon is not reflected in MTSDNet-M-t3s3g3.

DANN method is less effective than MLP when the target domain is not visible for the model, which shows that DANN is not suitable for domain generalization because negative transfer phenomenon occurred in this method. As for the

multi-layer stacking of MTSDNet, it is shown that for the additive model, the multi-layer stacking can achieve higher accuracy in some cases, and even if the accuracy is not improved, the decrease of its accuracy is smaller. For the multiplicative model, the accuracy decreases and only on the UCIHAR dataset, MTSDNet-M-t3s3g3 is superior.

Table III shows the trainable parameters of multiple models on five datasets. The parameters of MTSDNet-tsg is approximately equal to LSTM and it can exclude the improvement of accuracy caused by the increase in model size. This also indicates that the improvement in MTSDNet accuracy does not come from the increase in parameters. MTSDNet-A-tsg can achieve better classification accuracy with relatively reasonable model parameters.

In Table IV, the average training time of MTSDNet-A-tsg is second only to MLP, GRU, LSTM, and DANN. MTSDNet-A-t3s3g3 with higher stacking are closer in training time to the slowest method. DANN can be approximately equivalent to MLP.

In the comparison of traditional methods, DanHAR and Triple-Res, which design new attention module for HAR tasks, have significant advantages. However, the shortcomings of these two models lie in their size and time requirements. DanHAR has the largest size among all models and can reach about 24 times the size of MTSDNet-A-tsg on OPPORTUNITY. Overall, MTSDNet can balance model size and operational efficiency while ensuring the highest average accuracy.

For detailed experimental results, violin plots are provided for the DSADS and UniMib datasets to highlight the best and worst cases on each domain as shown in Figure 4 and Figure 5, which present the distribution of classification accuracy

TABLE III  
COMPARISON OF PARAMETERS ACHIEVED BY VARIOUS METHODS ON FIVE DATASETS.

Methods	UCIHAR	PAMAP2	DSADS	OPPORTUNITY	UniMib
GRU	54.1K	65.4K	69.7K	95.6K	51.3K
LSTM	71.9K	86.7K	92.1K	126K	68.4K
MLP	165K	608K	203K	945K	75.4K
Transformer	437K	467K	434K	453K	422K
DeepConvLSTM	86.8K	222K	222K	518K	49.4K
MTSDNet-A-tsg	51.4K	83.2K	75.4K	159K	64.7K
MTSDNet-A-t3s3g3	154K	249K	226K	479K	145K
DANN	216K	659K	255K	996K	126K
GILE	225K	282K	264K	415K	221K
DanHAR	334K	1.9M	784K	3.8M	155K
Triple-Res	193K	723K	562K	1.7M	133K

TABLE IV  
COMPARISON OF AVERAGE TRAINING TIME FOR ONE EPOCH ACHIEVED BY VARIOUS METHODS ON FIVE DATASETS.

Methods	UCIHAR	PAMAP2	DSADS	OPPORTUNITY	UniMib
GRU	53.89	194.06	64.78	70.78	46.39
LSTM	52.27	200.37	64.16	70.26	48.19
MLP	51.18	148.06	62.09	71.93	43.84
Transformer	67.75	540.87	98.48	90.50	69.36
DeepConvLSTM	62.58	569.10	116.81	133.90	59.61
MTSDNet-A-tsg	56.98	332.42	103.41	93.88	49.82
MTSDNet-A-t3s3g3	71.80	618.49	158.12	125.14	62.27
DANN	50.76	180.90	74.30	73.26	45.77
GILE	61.21	385.34	115.01	100.90	57.26
DanHAR	57.59	697.33	94.64	178.15	47.77
Triple-Res	58.24	697.16	117.57	196.13	50.34

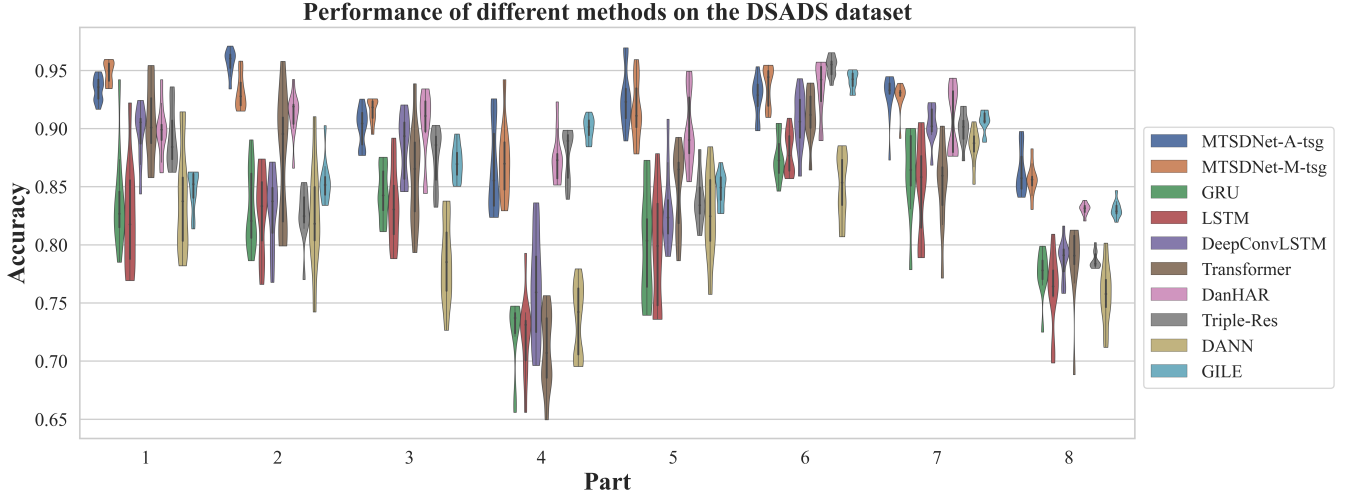


Fig. 4. Violin plot of accuracy distribution on the DSADS dataset. MTSDNet shown in blue and orange achieves higher accuracy than other baselines on almost all Parts.

obtained after 10 different random seed for training. Violin plots are represented with equal width in order to highlight view. Compared with the histogram error lines, the violin plots can not only show the average and variance accuracy of the model, but also show the specific distribution characteristics.

The violin plots can demonstrate the stability and robustness of each baseline model, Figure 5 can highlight MTSDNet's stability more clearly. The stability of accuracy can be indicated by the length of the color band. The length of color band is equivalent to the range of accuracy. The robustness of the model can be judged by focusing on different volunteer divisions. A model with good robustness should exhibit

consistent advantages across all partitions. In Figure 4 Part 4, Models such as GRU and LSTM show significant accuracy degradation. This indicates that its robustness is poor and it is difficult to classify correctly among some volunteers. As shown in Figure 4 and Figure 5, MTSDNet exhibits relatively good stability and robustness in all volunteer partitioning.

In Figure 4, it can be clearly seen that the range between MTSDNet and GILE is smaller than models such as LSTM and Transformer. Some models, such as Transformer in Part3, have almost the same optimal accuracy as MTSDNet-A-tsg, but the worst accuracy is reduced by 15%. In Part2, Part4 and Part8, there is a distinct accuracy gap between different



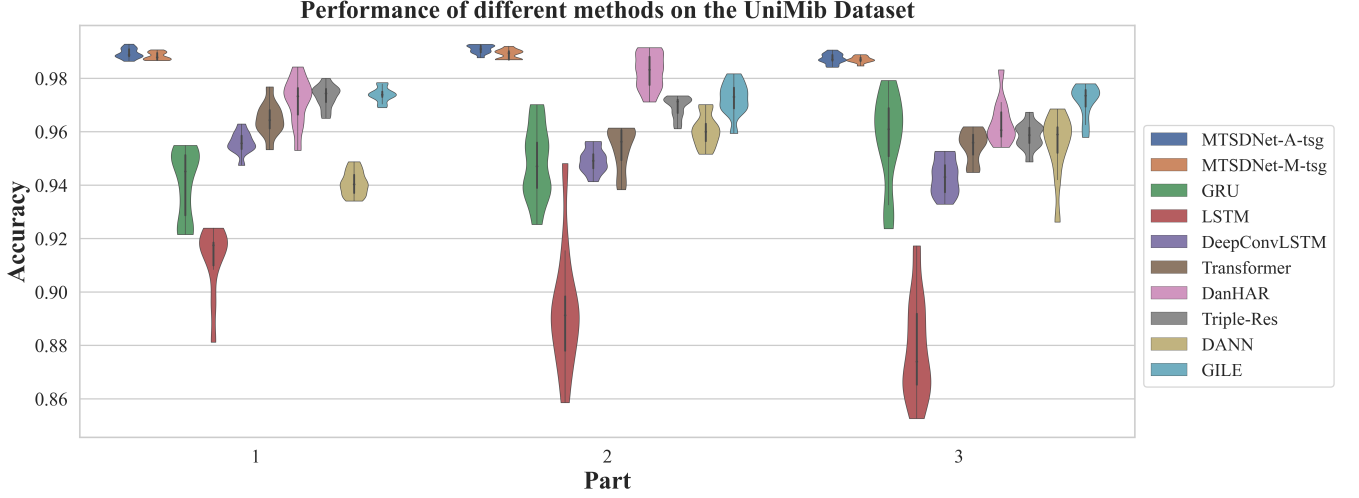


Fig. 5. Violin plot of accuracy distribution of UniMib dataset. MTSDNet shown in blue and orange achieves higher accuracy than other baselines on 3 parts and also has higher stability.

TABLE V  
THE ABLATION EXPERIMENT ON FIVE DATASETS

Method	UCIHAR	PAMAP2	DSADS	OPPORTUNITY	UniMib
MTSDNet-A-tsg	<b>91.67</b>	<b>71.92</b>	<b>91.28</b>	<b>78.63</b>	<b>98.92</b>
MTSDNet-A-tsg-nostat	86.97	69.60	80.33	74.27	96.90
MTSDNet-A-t3s3g3	<b>91.70</b>	<b>73.34</b>	<b>92.16</b>	<b>78.14</b>	<b>98.85</b>
MTSDNet-A-t3s3g3-nostat	88.95	69.82	80.27	75.86	97.02
MTSDNet-M-tsg	<b>92.32</b>	<b>72.91</b>	<b>91.28</b>	<b>78.30</b>	<b>98.81</b>
MTSDNet-M-tsg-nostat	89.41	70.06	87.98	74.23	97.06
MTSDNet-M-t3s3g3	<b>92.42</b>	<b>72.50</b>	<b>90.90</b>	74.58	<b>98.74</b>
MTSDNet-M-t3s3g3-nostat	91.37	69.52	89.10	<b>77.35</b>	97.32

models. MTSDNet, DanHAR and GILE are significantly better than other models. MTSDNet and DanHAR have good robustness under all partitions.

The UniMib dataset contains four tasks, and our experiment mainly focuses on the binary classification of fall detection. As seen from Figure 5, all methods can achieve an accuracy of over 90% in this task. Importantly, MTSDNet not only has the best average accuracy and minimum variance, but also achieves an accuracy of nearly 99%, which is much higher than other methods that generally have the accuracy of around 95%. The stability of MTSDNet is also significantly better than others. The accuracy range of MTSDNet is less than 0.5%, while the LSTM range can reach 8%.

Overall, MTSDNet has shown the improvements of **classification** accuracy and stability in most cross-person HAR datasets, especially on the OPPORTUNITY and UniMib datasets. And the difference of **classification** accuracy and stability between the additive model and the multiplicative model is small. The additive model can be applied to almost all situations. The selection between additive and multiplicative models should be based on the data characteristics, which is similar to the traditional time series decomposition method.

#### D. Ablation Experiment and Visualization

We further conducted the ablation experiments on whether to use statistical features. The suffix of '-nostat' shown in Table V indicates that the statistical features are not used

in the models. The experiments focus on MTSDNet-A-tsg and MTSDNet-M-tsg, which are the most simplified form of MTSDNet. According to the results in Table V, the use of statistical features has a significant impact on the **classification** accuracy, which indicates that the normalization of the sliding window can lose the features in the original signal. Therefore, during the construction of MTSDNet, the fusion of statistical features is indispensable. In addition, when statistical features are not used, the multiplicative model has a greater advantage than the additive model.

TABLE VI  
THE WEIGHT OF MTSDNET-A-TSG AND MTSDNET-A-TSG-NOSTAT IN THE ATTENTION LAYER.

DATASET	MODEL	T	S	G
UCIHAR	MTSDNet-A-tsg	0.48	0.25	0.26
	MTSDNet-A-tsg-nostat	0.40	0.25	0.35
PAMAP2	MTSDNet-A-tsg	0.58	0.20	0.21
	MTSDNet-A-tsg-nostat	0.31	0.33	0.35
DSADS	MTSDNet-A-tsg	0.62	0.21	0.17
	MTSDNet-A-tsg-nostat	0.44	0.27	0.28
UniMib	MTSDNet-A-tsg	0.32	0.28	0.39
	MTSDNet-A-tsg-nostat	0.37	0.27	0.34
OPPORTUNITY	MTSDNet-A-tsg	0.46	0.34	0.20
	MTSDNet-A-tsg-nostat	0.34	0.36	0.29

In order to further investigate the preference of MTSDNet for statistical features, the feature values of layer attention are analyzed and the results are presented in Table VI. MTSDNet-

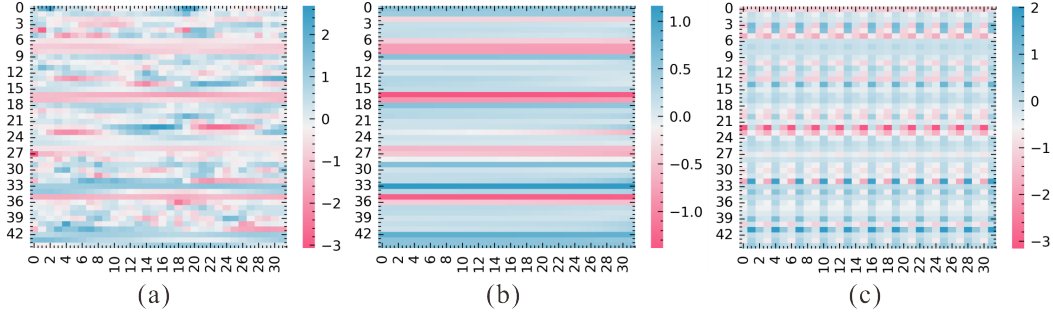


Fig. 6. The time series of a sample from DSADS dataset is decomposed into multiple components for the visualization of MTSDNet-A-tsg model. (a) Original signal. (b) Trend component. (c) Seasonal component.

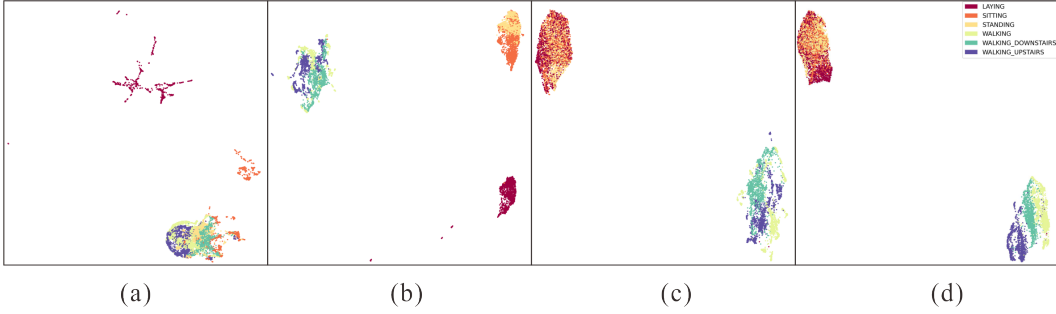


Fig. 7. Visualization of high-dimensional features from UCIHAR dataset using UMAP for MTSDNet-A-tsg model. (a) Original signal. (b) Trend component. (c) Seasonal component. (d) General component.

A-tsg is used for the convenience of experimental comparison. As seen from Table VI, when using statistical features, the layer attention of the first layer has significantly improved on most datasets. On PAMAP2, DSADS and OPPORTUNITY datasets with significant differences in individual activity, the attention weights are increased by 0.1 to 0.2, respectively. This indicates that compared to structures without statistical features, the model attaches more importance to the statistical information of original signal for final classification. On the UCIHAR and UniMib datasets with little difference in individual activity, the increase of weight value is not significant in the first layer attention. The mentioned phenomenon suggests that in the presence of substantial volunteer variability, statistical features of the original signal exhibit stronger generalization capabilities compared to other feature types. This aligns with traditional practices of feature engineering during the feature design. Conversely, when inter-volunteer differences are relatively minor, the statistical properties of the original signal may not receive sufficient consideration.

In addition, we visualize the extracted signals from time series decomposition and the characteristics of decomposition signals at different layers to show the interpretability and distribution differences of MTSDNet-A-tsg model at each layer. Figure 6 shows the time series decomposition visualization of a single sample on the DSADS dataset. From Figure 6 (b) and (c), the signal extracted by decomposer has a low-rank characteristic. Trend term in Figure 6 (b) can be approximated as the mean value extracted to the input signal. The polynomial constraint has high coefficients only on the constant term, with the rest of the coefficients close to zero. Seasonal term in

Figure 6 (c) has a clear preference for a certain frequency and it can be seen that seasonal term is biased towards high-frequency signals. We believe that there may be two reasons: firstly, the size of sliding window currently used is difficult to extract low-frequency signals; Secondly, similar to traditional time series decomposition methods, when the periodicity of the original signal is not remarkable, the seasonal term is easily extracted from high-frequency signals. Owing to the insignificant effect of high-frequency signals on classification, the model has assigned lower weights to seasonal layer, as shown in Table VI.

Furthermore, by adopting the UMAP [39] method, we visualize the high-dimensional features in different decomposition layers of MTSDNet-A-tsg model for input data. Figure 7 and Figure 8 are the visualization results on the UCIHAR and PAMAP2 datasets. The reason for using UCIHAR and PAMAP2 datasets is that UCIHAR dataset has weak differences in distribution while PAMAP2 dataset is just the opposite, thus making the visualization diverse. The visualization is repainted with different colors for every activity. UMAP can effectively reflect the correlation between data and represent it by the distance between data points. UMAP can even exhibit periodic characteristics of data by visualizing it as linear or circular shapes, which can be seen in Figure 8 (a). The visualization of high-dimensional features from UCIHAR dataset using UMAP for MTSDNet-A-tsg model is shown in Figure 7, which indicates that the trend term effectively separates static activities (laying, sitting, standing), while the seasonal term and general term are almost identical from static activities and focus more on the division of dynamic activi-

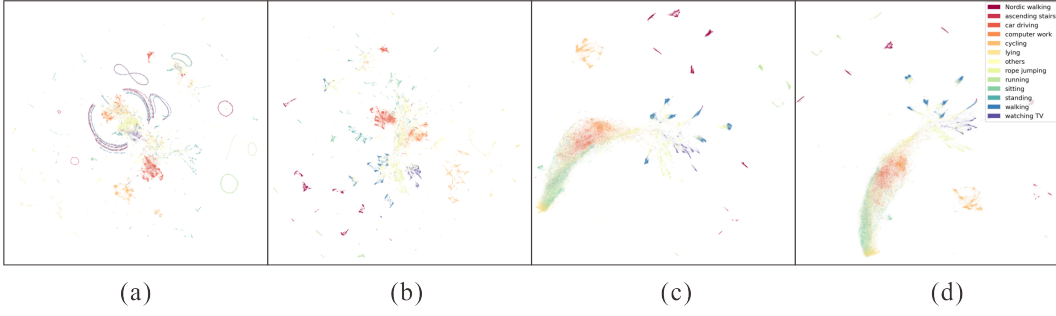


Fig. 8. Visualization of high-dimensional features from PAMAP2 dataset using UMAP for MTSDNet-A-tsg model. (a) Original signal. (b) Trend component. (c) Seasonal component. (d) General component.

ties (walking, upstairs, downstairs). This means that different levels of attention gain diversity in the focused features. The distribution difference on the UCIHAR dataset is small, so from the visualization we can see that the same activity from different volunteers are clustered in one group.

PAMAP2 dataset has a significant difference of data distribution, as shown in Figure 8, which is relatively scattered and chaotic. From Figure 8 (a) to Figure 8 (c), the scattered points are clustered into fewer and more dense clusters. For activities such as going up and down stairs, standing and sitting, it shows that there are obvious distribution states of multiple clusters, which correspond to different volunteers performing the same activity. As shown in Figure 8 (c) and Figure 8 (d), the differences in some activities are eliminated, and multiple volunteers either gather together in the form of point clouds (green, yellow and orange) or are in adjacent areas (crimson, blue and purple) with the form of multiple clusters. From the global positions of the clusters, the features obtained from time series decomposition alleviate differences among volunteers and highlight different activities.

The visual structure of seasonal and general terms as shown in Figure 7 (c,d) and Figure 8 (c,d) is very similar, implying that the extracted features are homogeneous. But there are slight differences in the global structure and the distance arrangement between some clusters has changed. The above results are consistent with the general cognition, which reflects the reliability of the constructed model. Furthermore, it can be observed that the clusters of general terms exhibit a higher degree of spatial clustering in comparison to seasonal terms.

In addition, there was no significant difference between MTSDNet-A and MTSDNet-M in all the experiments mentioned above. This lack of differentiation can be attributed to the absence of multiplicative interference in HAR, rendering MTSDNet-M, based on multiplicative models, without evident advantages. In time series signals with additive interference, both can express signal characteristics well, and MTSDNet-A is suitable for most tasks.

Overall, by decomposing the original signal into multiple components, we can find remarkable clustering in the visualization results, indicating the difference reduction between volunteers and simultaneously emphasizing their behavioral patterns. The clustering degree of visualization suggests that trend term displays greater structural variability in contrast with both seasonal term and general term, thus demonstrating

more notable discriminatory power of its feature extraction. In other words, the characteristic structures of the seasonal and general terms are more homogeneous.

## V. CONCLUSION

This study analyzes the signal characteristics of sensor-based cross-person HAR tasks and investigates domain-specific features called data bias and volunteer activity differences. To process components separately, this work presents MTSDNet, a novel sensor data-based method for cross-person HAR task with the ability of time series decomposition. MTSDNet decomposes the original signal into low-rank representations of polynomials and trigonometric functions, enabling the model to learn more generalized features and enhancing its domain generalization ability. MTSDNet does not require additional information and is suitable for the **classification** of new domain. **Compared with the second highest accuracy methods, MTSDNet has improved about 0.2% on UCIHAR, 1% on PAMAP2, 2.7% on DSADS, 5.4% on OPPORTUNITY and 1.66% on UniMib, respectively and performs good stability in most cases.**

In addition, the visualization demonstrates that MTSDNet extracts differentiated features through time series decomposition, which indirectly reflects the effectiveness and interpretability of time series decomposition in domain generalization. By the idea of decomposing original signal into multiple components to reduce distribution differences, the performance of domain generalization is effectively improved, which can also extend to other applications including remote sensing images, where spatio-temporal disparities caused by the factors like fog, season and lighting introduce the data bias.

## ACKNOWLEDGEMENTS

This work was supported in part by the National Natural Science Foundation of China under Grant 61802258, in part by the Natural Science Foundation of Shanghai under Grant 20ZR1455600 and the National Key Research and Development Program of China under Grant 2022YFB4501704. In addition, the authors would like to express the sincere appreciation for the support provided by Shanghai Engineering Research Center of Intelligent Education and Bigdata as well as Research Base of Online Education for Shanghai Middle and Primary Schools.

## REFERENCES

- [1] Z. Sun, Q. Ke, H. Rahmani, M. Bennamoun, G. Wang, and J. Liu, "Human Action Recognition From Various Data Modalities: A Review," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 3, pp. 3200–3225, 2023.
- [2] L. Bibbò, R. Carotenuto, and F. Della Corte, "An Overview of Indoor Localization System for Human Activity Recognition (HAR) in Healthcare," *Sensors*, vol. 22, no. 21, 2022.
- [3] F. Serpush, M. B. Menhaj, B. Masoumi, and B. Karasfi, "Wearable Sensor-Based Human Activity Recognition in the Smart Healthcare System," *Computational Intelligence and Neuroscience*, vol. 2022, p. 1391906, 2022.
- [4] A. A. Malibari, J. S. Alzahrani, A. Qahmash, M. Maray, M. Alghamdi, R. Alshahrani, A. Mohamed, and A. M. Hilal, "Quantum Water Strider Algorithm with Hybrid-Deep-Learning-Based Activity Recognition for Human-Computer Interaction," *Applied Sciences*, vol. 12, no. 14, 2022.
- [5] P. Gong, C. Wang, and L. Zhang, "MMG-HCI: A Non-contact Non-intrusive Real-Time Intelligent Human-Computer Interaction System," in *Artificial Intelligence*, L. Fang, Y. Chen, G. Zhai, J. Wang, R. Wang, and W. Dong, Eds. Cham: Springer International Publishing, 2021, pp. 158–167.
- [6] F. Luo, S. Khan, Y. Huang, and K. Wu, "Activity-Based Person Identification Using Multimodal Wearable Sensor Data," *IEEE Internet of Things Journal*, vol. 10, no. 2, pp. 1711–1723, 2023.
- [7] S. Mekrucksavanich and A. Jitpattanakul, "Biometric User Identification Based on Human Activity Recognition Using Wearable Sensors: An Experiment Using Deep Learning Models," *Electronics*, vol. 10, no. 3, 2021.
- [8] R. Poppe, "A survey on vision-based human action recognition," *Image and Vision Computing*, vol. 28, no. 6, pp. 976–990, 2010.
- [9] M. Lu, Y. Hu, and X. Lu, "Driver action recognition using deformable and dilated faster R-CNN with optimized region proposals," *Applied Intelligence*, vol. 50, no. 4, pp. 1100–1111, 2020.
- [10] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "Training computationally efficient smartphone-based human activity recognition models," in *Artificial Neural Networks and Machine Learning – ICANN 2013*, V. Mladenov, P. Koprinkova-Hristova, G. Palm, A. E. P. Villa, B. Appollini, and N. Kasabov, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 426–433.
- [11] M. A. Awan, Z. Guangbin, C.-G. Kim, and S.-D. Kim, "Human Activity Recognition in WSN: A Comparative Study," *International Journal of Networked and Distributed Computing*, vol. 2, pp. 221–230, 2014.
- [12] N. Y. Hammerla, S. Halloran, and T. Plötz, "Deep, convolutional, and recurrent models for human activity recognition using wearables," *arXiv preprint arXiv:1604.08880*, 2016.
- [13] F. J. Ordóñez and D. Roggen, "Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition," *Sensors*, vol. 16, no. 1, 2016.
- [14] I. Dirgová Luptáková, M. Kubovčík, and J. Pospíchal, "Wearable Sensor-Based Human Activity Recognition with Transformer Model," *Sensors*, vol. 22, no. 5, 2022.
- [15] G. M. Weiss, K. Yoneda, and T. Hayajneh, "Smartphone and Smartwatch-Based Biometrics Using Activities of Daily Living," *IEEE Access*, vol. 7, pp. 133 190–133 202, 2019.
- [16] A. Stisen, H. Blunck, S. Bhattacharya, T. S. Prentow, M. B. Kjærgaard, A. Dey, T. Sonne, and M. M. Jensen, "Smart Devices Are Different: Assessing and Mitigating Mobile Sensing Heterogeneities for Activity Recognition," in *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*, ser. SenSys '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 127–140.
- [17] H. Qian, S. J. Pan, and C. Miao, "Latent Independent Excitation for Generalizable Sensor-based Cross-Person Activity Recognition," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, no. 13, pp. 11 921–11 929, May 2021.
- [18] G. Wilson, J. R. Doppa, and D. J. Cook, "Multi-Source Deep Domain Adaptation with Weak Supervision for Time-Series Sensor Data," in *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, ser. KDD '20. New York, NY, USA: Association for Computing Machinery, 2020, p. 1768–1778.
- [19] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345–1359, 2010.
- [20] J. Wang, Y. Chen, L. Hu, X. Peng, and P. S. Yu, "Stratified Transfer Learning for Cross-domain Activity Recognition," in *2018 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2018, pp. 1–10.
- [21] M. Wang and W. Deng, "Deep visual domain adaptation: A survey," *Neurocomputing*, vol. 312, pp. 135–153, 2018.
- [22] S. Sun, H. Shi, and Y. Wu, "A survey of multi-source domain adaptation," *Information Fusion*, vol. 24, pp. 84–92, 2015.
- [23] K. Zhou, Z. Liu, Y. Qiao, T. Xiang, and C. C. Loy, "Domain Generalization: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 4, pp. 4396–4415, 2023.
- [24] B. N. Oreshkin, D. Carpo, N. Chapados, and Y. Bengio, "N-BEATS: Neural basis expansion analysis for interpretable time series forecasting," *arXiv preprint arXiv:1905.10437*, 2019.
- [25] S. Sani, N. Wiratunga, and S. Massie, "Learning deep features for kNN-based human activity recognition." CEUR Workshop Proceedings, 2017, pp. 95–103, cOMPLETED – OpenAIR and coversheet to be updated with new information listed below 7/6/2018 LM – SelfBACK project 13/11/2017 LM – Proceedings to be published on <http://ceur-ws.org/> website 1/9/2017 LM – Info from contact 31/8/2017 LM ADDITIONAL INFORMATION: Sani, Sadiq – Panel B.
- [26] W. Zhang, X. Zhao, and Z. Li, "A Comprehensive Study of Smartphone-Based Indoor Activity Recognition via Xgboost," *IEEE Access*, vol. 7, pp. 80 027–80 042, 2019.
- [27] M. Abbas and R. L. B. Jeannès, "Exploiting Local Temporal Characteristics via Multinomial Decomposition Algorithm for Real-Time Activity Recognition," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.
- [28] F. A. Dharejo, M. Zawish, Y. Zhou, S. Davy, K. Dev, S. A. Khowaja, Y. Fu, and N. M. F. Qureshi, "FuzzyAct: A Fuzzy-Based Framework for Temporal Activity Recognition in IoT Applications Using RNN and 3D-DWT," *IEEE Transactions on Fuzzy Systems*, vol. 30, no. 11, pp. 4578–4592, 2022.
- [29] H. Qian, S. J. Pan, B. Da, and C. Miao, "A Novel Distribution-Embedded Neural Network for Sensor-Based Activity Recognition," in *International Joint Conference on Artificial Intelligence*, vol. 2019, Conference Proceedings, pp. 5614–5620.
- [30] S. P. Singh, M. K. Sharma, A. Lay-Ekuakille, D. Gangwar, and S. Gupta, "Deep ConvLSTM With Self-Attention for Human Activity Decoding Using Wearable Sensors," *IEEE Sensors Journal*, vol. 21, no. 6, pp. 8575–8582, 2021.
- [31] W. Gao, L. Zhang, Q. Teng, J. He, and H. Wu, "Danhar: Dual attention network for multimodal human activity recognition using wearable sensors," *Applied Soft Computing*, vol. 111, p. 107728, 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1568494621006499>
- [32] Y. Tang, L. Zhang, Q. Teng, F. Min, and A. Song, "Triple cross-domain attention on human activity recognition using wearable sensors," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 6, no. 5, pp. 1167–1176, 2022.
- [33] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. March, and V. Lempitsky, "Domain-adversarial training of neural networks," *Journal of Machine Learning Research*, vol. 17, no. 59, pp. 1–35, 2016.
- [34] B. Barshan and M. C. Yüsek, "Recognizing Daily and Sports Activities in Two Open Source Machine Learning Environments Using Body-Worn Sensor Units," *The Computer Journal*, vol. 57, no. 11, pp. 1649–1667, 2014.
- [35] A. Reiss and D. Stricker, "Introducing a New Benchmarked Dataset for Activity Monitoring," in *2012 16th International Symposium on Wearable Computers*, 2012, pp. 108–109.
- [36] D. Roggen, A. Calatroni, M. Rossi, T. Holleczer, K. Förster, G. Tröster, P. Lukowicz, D. Bannach, G. Pirk, A. Ferscha, J. Doppler, C. Holzmann, M. Kurz, G. Holl, R. Chavarriaga, H. Sagha, H. Bayati, M. Creatura, and J. d. R. Millán, "Collecting complex activity datasets in highly rich networked sensor environments," in *2010 Seventh International Conference on Networked Sensing Systems (INSS)*, 2010, pp. 233–240.
- [37] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "A public domain dataset for human activity recognition using smartphones," in *Esann*, vol. 3, Conference Proceedings, p. 3.
- [38] D. Micucci, M. Mobilio, and P. Napoletano, "UniMiB SHAR: A Dataset for Human Activity Recognition Using Acceleration Data from Smartphones," *Applied Sciences*, vol. 7, no. 10, 2017.
- [39] L. McInnes, J. Healy, and J. Melville, "Umap: Uniform manifold approximation and projection for dimension reduction," *arXiv preprint arXiv:1802.03426*, 2018.