Multi-Sensing Data Fusion for Human Activity Recognition based on Neuromorphic Computing

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***Abstract*—This paper proposes a multi-sensing Human Activity Recognition framework, which uses Neuromorphic computing to processing from Sensors and Radars of different type signals for data fusion and classification. At this point, Inertial Measurement Unit sensors and Universal Software-defined Radio Peripheral, and Radar devices are used to collect human activities signals separately. The feature extraction and selection process the sensors signal to dimension reduction without time factor by design an attention mechanism. And then, following Expectation-Maximization calculation to achieve a binary feature pattern that fits the discrete Hopfield neural network input. Depend on the Neuromorphic computing of associative memory function and similarity calculation to the neurons' feedback output. It finally achieves human activity recognition with one-shot learning. There are explores multi-sensing human activity recognition between limited dataset and ensures accuracy without dropping. The technique can be extended to include more hardware signal processing to the system.**

***Index Terms*—Data Fusion, Human Activity Recognition, Artificial Intelligence, Signal Processing**

I. INTRODUCTION

Nowadays, traditional machine learning (especially deep learning models) has achieved good results in the Human Activity Recognition (HAR) field, but it has also led to a large amount of training data collection overhead [1]. Although deep neural networks are good at learning from high-dimensional data, it causes problems such as huge demand for training samples, complex model structure and time-consuming training. On the other hand, deep learning completes the end-to-end calculation without the more cumbersome process of feature engineering. However, it loses the cognition of features, and there are challenges to know the importance of data features.

In order to handle limited sample data sets, neuromorphic computing has the advantage that it requires fewer training samples to achieve good recognition results compared to traditional machine learning [2]. It is based on the combination of feature engineering for the abstract expression on the object and the associative memory function of the Hopfield neural network, which achieves one-shot learning for human activity recognition. Feature Selection and feature extraction are two important sub-contents of Feature Engineering. Among them, feature extraction can find the attributes that represent the purpose from the data. Feature selection is to select the appropriate feature from the candidate features [3]. It can reduce the dimension of data, improve the model effect and optimize the model performance.

II. MATERIALS AND METHODS

In this work, we used multi-sensing hardware devices to collect human body movements, which including: 1, IMU sensor for Shimmer3, it contains Gyroscope, Accelerometer and Magnetometer. 2, Universal Software-defined Radio Peripheral (USRP) for X300 unit. 3, Radar for Walabot DIY model. First, the IMU sensor is worn on the wrist, and the three axes of the coordinate system of each sensor have the spatial coordinate information of X, Y and Z respectively. Then, the USRP and the Radar keep a distance of 2 meters from humans fixedly, and there are collect electromagnetic signals. In here, two activity has been collected, which are sitting down and standing up. The raw signal data of multiple sensors is shown in Figure 1.

Figure 2 shows the framework workflow from multi-sensing data to neuromorphic computing for human activity recognition. Furthermore, Algorithm 1 verifies the feasibility of the whole framework theoretically, and shows the specific calculation process of each step in the workflow. In order to facilitate the signal of different types of hardware to be free from interference in the calculation, feature extraction will be performed separately processing first. The data fusion is processed at the feature-level, which can avoid the loss of original information caused by different types of signals. Depend on the attention mechanism [4], the most important sub-features can be extracted from the fused feature-set. In order to make the Hopfield neural network get better processing results, the activity feature matrix is converted into the Binarized

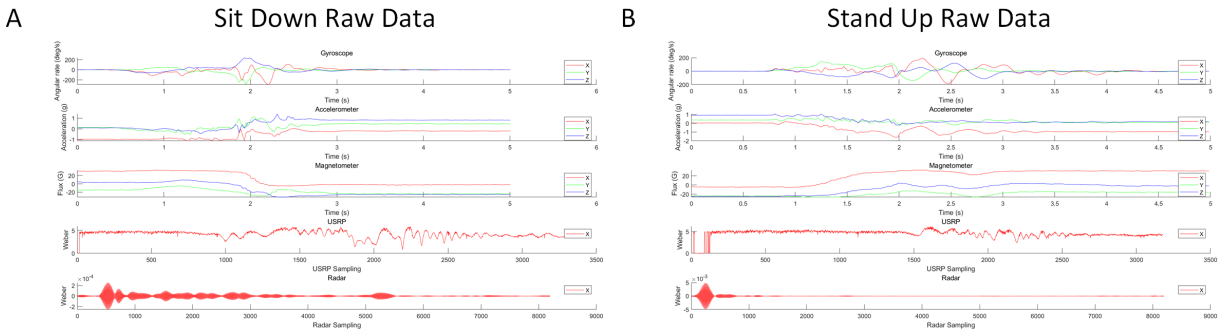

Fig. 1. The multi-sensing raw activity signal data.

feature template by Expectation-Maximization(EM) algorithm [5]. Finally, following the calculation of the similarity between the Hopfield neural network's output and feature template, the confidence of the activity classification can be achieved to complete human activity recognition.

Algorithm 1 Multi-Sensing Data for Human Activity Recognition.

Load Multi-Sensing Hardware data:
[Gx, Gy, Gz] = Gyroscope [:1, 2, 3]
[Ax, Ay, Az] = Accelerometer [:1, 2, 3]
[Mx, My, Mz] = Magnetometer [:1, 2, 3]
[Ux] = USRP data Matrix [:1]
[Rx] = Radar data Matrix [:1]
Require: :
Feature Extraction:
F_{IMU}(G,A,M) = (*f(Gx)*) +(*f(Gy)*) + (*f(Gz)*) + (*f(Ax)*) + (*f(Ay)*)+ (*f(Az)* + (*f(Mx)*)+ (*f(My)*)+ (*f(Mz)*);
F_{USRP}(U) = *f(Ux)*;
F_{Radar}(R) = *f(Rx)*;
Feature Selection:Attention Mechanism
F' = Sort F_1(G), F_1(A), F_1(M), F_1(U), F_1(R)
M = TopK(F') : K = 5x5
Binarization Matrix:Expectation-Maximization
B_M = EM(M)
E-Step: Expectation Calculation

$$Q_i\left(z^{(i)}\right) := p\left(z^{(i)}|x^{(i)};\theta\right) \tag{1}$$

M-Step: Maximization

$$\theta := argmax_\theta \sum_i \sum_{z^{(i)}} Q_i\left(z^{(i)}\right) In \frac{p\left(x^{(i)}, z^{(i)};;\theta\right)}{Q_i\left(z^{(i)}\right)} \tag{2}$$

Threshold value = t
for i = 0:24 **do** : out[n][i] = (M > t[i]) ? 0 : 1;
return **Matrix B_M(5:5)**;
HNN = Hopfield(B_M)
Out(Confidence) = Similarity(HNN-B_M)
return **Recognition Accuracy**;

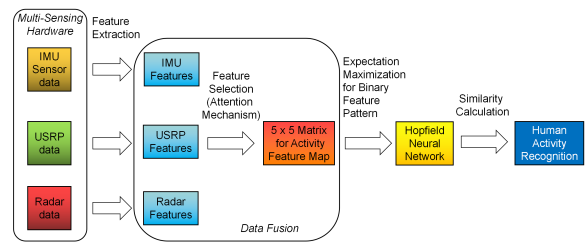

Fig. 2. The multi-sensing entire calculation workflow to human activity recognition.

III. CONCLUSION

This paper introduces a Neuromorphic Computing-based multi-sensing human activity recognition system that can easily and swiftly fuse multiple hardware signal data and is friendly to small datasets. This method not only addresses the problems of conventional machine learning for large training samples requirement effectively, but it also allows for better flexibility in fitting various types of hardware signals. The suggested technique has the potential to assist the different types of measurement devices to achieve system-level data fusion without affecting the accuracy of classification and recognition. In future, the feasibility of this computing architecture will be explored further to obtain scientific and experimental findings to verify the proposed theoretical method.

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