Combining electrocardiogram signal with Accelerometer signals for Human Activity Recognition using Convolution neural network

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Abstract. As the environment getting polluted, people are suffering with different medical problems also people are causes about their health as well. Considering this in the mind, Body sensor based human activity recognition attracting researcher towards this direction. A fusion of electrocardiogram signals and accelerometer signals processed through convolution neural network is proposed in this paper. Accelerometer placed at different location of the human body are fused with the electrocardiogram signals, generated through the ECG sensors placed at the chest of the human body. These fused signal are processed through convolution neural network to automatically detect the features and finally apply softmax for classification of the activities. We choose mHEALTH dataset for the experiment and achieve 98.91% validation accuracy.

Keywords: Fusion, Convolution neural network, Human activity recognition, ECG signals, Accelerometer signal.

1. Introduction
Research based on body sensor have become popular because of its low computation cost. Many of the emerging areas like entertainment, security, wellness and health-care are using body sensor approaches. Human behaviour and actions can be recognized using body sensors. they can be used to recognize human various poses and behaviour more accurately Hence, these sensors can improve the people’s living and help to monitor their daily activities. Thus, body sensors seem to be quite impressive to help in revolutionizing our life similar to personal computers [1]. Accelerometer generate tri-axis data which change with the change in the position. Electrocardiogram signals can easily distinguish the activates like walking, running and jogging because it will show different shape for each activity. Combining electrocardiogram signals with the accelerometer data will boost up the accuracy in data while performing activities. A model based on the combined data of Accelerometer and Electrocardiogram is proposed in this paper. Accelerometer placed at the ankle and chest are combine with the signal generated through the electrocardiogram.

2. Literature review
Human activities have inherent translation characteristics in that different people perform the same kind of activity in different ways. In recent years, several CNN-based human activity recognition methods have been proposed.

A basic fusion scheme was used by Song et al. [3], in which data generated by the accelerometer transform into a magnitude vector. Another way of fusion used by Gu et al. [4] to form a single 1D vector by using the time serial signals of different modalities and use a denoising autoencoder to learn robust representations. Guo et al. [5] proposed a multilayer perceptron model for each modality and combine them with assign collective weight. Laput et al. [6] combined the time frequency feature and CNN for fine-grained hand activity sensing system. Ha et al. [7] proposed a 1D CNNs for different modalities to learn modality-specific temporal characteristics. Liu et al. [8] processed the accelerometer and Gyroscope data and analyse the performance of machine learning algorithm and finally applied CNN. Lee et al. [9] proposed a one-dimensional convolutional neural network in which they calculate the magnitude of the tri-axis data of accelerometer captured by their research team. They recorded three activities walking.

A Sequential information based deep recurrent neural network was proposed in Md. Zia et al. [10]. Multiple sensor data was fused and apply KPCA, and at last, RNN is trained for classifying the activity.

3. Proposed model
In this section, a fusion of electrocardiogram signal with Accelerometer signals is proposed. Signal generated through accelerometer placed at the chest and ankle are combine with the electrocardiogram signals and input to the convolution neural network. Graphical representation of the model is present in the figure 1. Each convolution layer of model is trained in a similar way and the individual unit is shown as Figure 1. To down sample, the feature map, average pooling is used. At the end softmax layer is used for the classification of the activates.

![Proposed model](image)

Sensor data was first divided into time series segments of same size. We select the window size 4 with one fourth overlapping. Data is divided in 25% validation and 75% training. mHEALTH [2] dataset is chosen for the experiment which capture the body motion for ten volunteers. Total 12 activates performed by the 10 volunteers which are mentioned in the table 1. Although 3 accelerometers, 2mentometer, 2 gyro meter and 2 electrocardiogram sensors are placed at various location on the body of volunteers but, we consider only accelerometer place at the chest and ankle and one electrocardiogram data for the experiment.

| Table 1: Activities performed in mHEALTH dataset |
|   | Activity                      |
|---|-------------------------------|
| 1 | Standing still               |
| 2 | Sitting and relaxing         |
| 3 | Lying down                   |
| 4 | Walking                      |
| 5 | Climbing stairs              |
| 6 | Waist bends forward          |
| 7 | Frontal elevation of arms    |
| 8 | Knees bending                |
| 9 | Cycling                      |
|10 | Jogging                      |
|11 | Running                      |
|12 | Jumping front and back       |

4. Result analysis and discussion

This section discussed the result of the proposed model. We choose mHEALTH dataset for the experiment. Proposed model achieve 98.90% accuracy. Figure 2 shows the accuracy of the model per epoch and shown remarkable training and validation accuracy.
Figure 3: Confusion matrix

It is observed from figure 3 that the model had better performance and achieved 100% accuracy for sitting, cycling, front elevation, knee band, lying down and waist band forward and bit confused for running with jogging. Model achieve 99% accuracy for standing still, walking and climbing stairs.

Table 2: Precision, Recall and F-Score

| Activity               | mHEALTH |       |       | F-Score |
|------------------------|---------|-------|-------|---------|
| Jogging                | Precision | Recall | F-Score |
| Running                | 0.97     | 0.93  | 0.95  |
| Sitting                | 0.98     | 1.00  | 0.99  |
| Standing Still         | 1.00     | 0.99  | 1.00  |
| Walking                | 1.00     | 0.90  | 1.00  |
| Climbing Stairs        | 1.00     | 0.99  | 1.00  |
| Cycling                | 1.00     | 1.00  | 1.00  |
| Frontal elevation arm  | 1.00     | 1.00  | 1.00  |
| Jump front back        | 1.00     | 0.98  | 0.99  |
| Knees band             | 1.00     | 1.00  | 1.00  |
| Lying down             | 0.99     | 1.00  | 1.00  |
| Waist band forward     | 1.00     | 1.00  | 1.00  |
| Macro Avg.             | 0.99     | 0.99  | 0.99  |
| Weighted Avg.          | 0.99     | 0.99  | 0.99  |

We also analyze the precision, recall and f-score. Macro average and weighted average, both are 0.99.

\[
\text{Precision} = \frac{TP}{(TP+FP)} \tag{1}
\]

\[
\text{Recall} = \frac{TP}{(TP+FN)} \tag{2}
\]
$$F - Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100$$ (3)

Where
- TP -> True positive instances
- FP-> False Positive instances
- TN-> True Negative Instances

5. Conclusion

We presented the recognition of human activity using deep learning technique by combining the accelerometer sensor with electrocardiogram signals placed at multiple location of human body. The proposed model tested on mHEALTH dataset and achieve 98.91% accuracy result. Results specified that the proposed network can distinguish similar actions with different velocity. In future, some more fusion techniques can be used by combining different modality signals

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