UDC 004.62

PHOTOPLETHYSMOGRAPHY AND ACCELEROMETER SENSOR SIGNALS FOR THE DETECTION OF PHYSICAL ACTIVITY

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Annotation. Wearable devices for monitoring human physiological parameters have become popular, and due to their low cost, the most common method of monitoring human information in such devices is the use of photoplethysmography (PPG) signals. Nevertheless, the accurate estimation of the PPG signal recorded from the subject's wrist during various physical exercises is often a challenging problem because the initial PPG signal is heavily corrupted by motion artifacts. Long Short Time Memory (LSTM) is built to recognize activities.

Keywords. Photoplethysmography, Accelerometer, LSTM.

Accurate estimation of the wrist-recorded PPG signal is often a difficult problem when the patient is wearing the wearable device during exercise, because the original PPG signal is strongly affected by motion artifacts (MAs), mainly due to the relative motion between the PPG springs and the skin of the wrist [1]. To reduce MAs, a number of signal processing techniques based on data from different types of sensors, especially ACC data, have proven to be very useful.

ACC provides information about the acceleration of the human body during motion. In smartphones and smartwatches, the integrated three-axis ACC is probably the most commonly used sensor for activity tracking. A combined approach to retrieve PPG and acceleration data is available directly on smartphones and smartwatches [2]. HAR can be viewed as a pattern recognition problem where machine learning techniques have been particularly successful. Several machine learning models have been developed for HAR. The main goal of this paper is to maintain the good performance of the RNN framework in terms of detection accuracy [3], and an RNN for human activity detection using four-dimensional ACC and PPG data has been developed.

PPG signals are continually captured during activities from the wrist using Maxim Integrated MAXREFDES100 device. To guarantee a perfect fit of the sensor unit to the skin surface, a specific weightlifting cuff, adjustable by tear-open closure, is used to hold the sensor in place by fully tightening the strap with a cable protruding from the back end of the strap. The PPG signal value is equivalent to the output of an ADC (Analog to Digital Converters) photodetector with a pulse width of 118 μs, a resolution of 16 bits and a full scale of 8192 nA, illuminated by a green LED (Light-Emitting Diode). The ACC signal values on the three axes correspond to MEMS (Micro-ElectroMechanical System) outputs with 10-bit resolution, left-aligned, and a scale of ±2 g.

For analysis, a recently published data set consisting of 105 PPG signals (15 per subject) and 105 corresponding triaxial ACC signals recorded at 400 Hz from seven different subjects was used. The seven adult subjects were three males and four females, ranging in age from 20 to 52 years, who performed five sets of resting, squatting, and stepping activities. The signals were recorded simultaneously and the dataset contains 210 audio clips with a total duration of 17,201 seconds.

The individual PPG signal values for the same subject are highly variable from series to series, and vary considerably over short periods of time within the same series. Normalization allows for better separation of the PPG signal from motion artifacts using the following equations:

$$\boxed{\mathrm{PPG_{cal}} = \frac{\mathrm{PPG} - \mu_{\mathrm{PPG}}}{\sigma}}, \tag{1}$$

$$\boxed{\mu_{\mathrm{PPG}} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{PPG}_i} \tag{2}$$

where $\boxed{\mathrm{PPG_{cal}}}$ is the calculated PPG data, $\boxed{\mathrm{PPG}_i}$ means PPG value of the i-th data.

The accelerometer is affected by the low noise level, the gravitational acceleration is in three spatial axes, so the data usually has some bias, remove it by subtracting the average from the data, the procedure gives a fine filtering of the signal with the following equation:

$$\mathrm{ACC_{cal}} = \mathrm{ACC} - \mu_{\mathrm{ACC}} \tag{3}$$

$$\mu_{\mathrm{ACC}} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{ACC}_i \tag{4}$$

where $\mathrm{ACC_{cal}}$ is the calculated ACC data, ACC_i means ACC value of the *i*-th data.

The network model used in the publication is shown in Figure 1. It is based on a widely used architecture for time-based sensor data and consists of a combination of fully connected layers and LSTM modules [4]. The input data has three acceleration axes, and PPG generates a four-dimensional timeline. The data is then transmitted to the network in a window, where the parameter is the time point size of one data window.

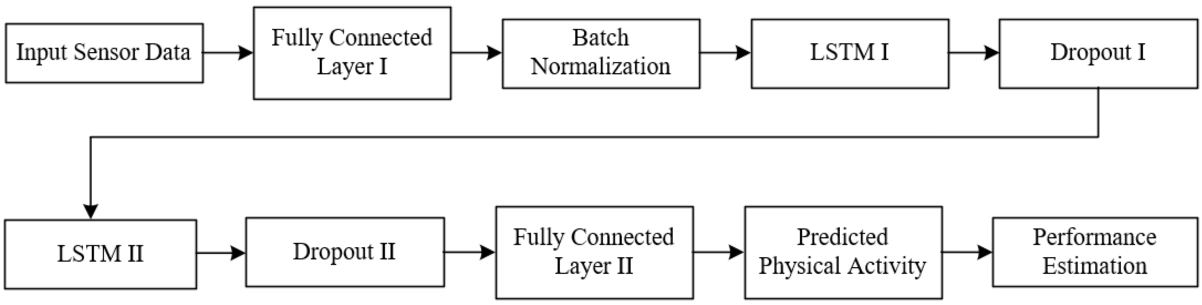

Figure 1-The network model for training dataset

The first layer is fully connected layer and aims to identify the relevant features in the input data. In this layer, the general neuron produces an output value y:

$$y = f\left(\left[w_1, w_2, \ldots, w_n\right]\left[x_1, x_2, \ldots, x_n\right]^T + b\right), \tag{5}$$

where the x_n inputs to the layer and the w_n neuron weights in association with each input, f is the activation function and b is the bias value.

The batch normalization layer, which normalizes the mean and standard deviation of the global data, operates on individual batches of data with training. Then, the recurrent neural network is represented at its core by two cascaded LSTM layers, with the LSTM followed by a dropout layer that randomly discards some of the inputs to reduce overfitting.

In the end, there is a fully connected layer of size 3 which, together with the sparse class cross-entropy loss function assigned to the network, classifies one of these three classes of layers. The loss function represents the error that must be minimized by the training process. The representation of the error varies upon the given function of the network allotted to it. For a categorical cross-entropy function $J(w)$, the error function is as follows:

$$J(w) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log y_i + (1-y_i)\log(1-y_i)], \tag{6}$$

where w is the set of model parameters, N is the number of input test features, y_i and y_i are the true and predicted classes respectively, expressed numerically.

The virgin PPG signal has been severely corrupted by MAs, mainly due to the relative motion between the PPG source and the wrist skin. In order to reduce MAs, the ACC data and PPG were integrated into four-dimensional data, which were processed and analyzed. In an investigation of Python based data analysis of PPG and ACC signals, the study completed the design of functions such as importing data and analysis of signals.

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