Demo Abstract: Human Activity Detection with Loose-Fitting Smart Jacket

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ABSTRACT

We demonstrate a human activity detection with casual loose-fitting smart garment system. By employing a new type of highly sensitive, stretchable, optical transparent and low-cost strain sensor and a deep learning model enabled by CNN-LSTM, the loose-fitting jacket is able to recognize 5 activities with 90.9% accuracy when the system is trained with the user data, and 73.5% accuracy when an unseen user wears the smart jacket, which is comparable with tight-fitting smart garment system. In the demonstration, we will showcase activity recognition of three activities: walk, sit, and stand.

KEYWORDS

Smart garment, deep learning, CNN-LSTM, piezo-resistive strain sensor, posture detection

1 INTRODUCTION

Electronics miniaturization and advancements in textile technology have enabled integration of various types of sensors into textiles and fabrics ushering in an era of E-Textiles or so called *smart garments*. Posture or activity detection via smart garments has become a hot topic of research in recent years [2, 4–6, 9, 11]. A fundamental challenge facing smart-garment-based posture detection is the high level of sensor signal noise caused due to the movement of the garment relative to the skin. The problem can be largely addressed by tight fitting of the garment, which is why the current smart garment products focus on socks, undergarments, gloves, and tight-fitting cuts for shirts and pants. However, for the smart garment industry to really take off, accurate activities detection solutions must be devised for the casual loose-fitting garments as well.

Facing this challenge, we developed a smart garment system by attach four piezo-resistive strain sensors on a casual loose-fitting jacket. Thanks to newly-designed transparent, low-cost and highly sensitive mircocracks-based strain sensors and a deep neural network, the loose-fitting jacket is able to recognize 5 activities with 90.9% accuracy when the system is trained with the user data, and 73.5% accuracy when an unseen user wears the smart jacket.

In this demonstration, we will showcase the activity detection on both participants with trained data and unseen participants with 3 activities: walk, sit and stand.

2 TECHNICAL DETAILS

The processing pipeline of the smart garment system is shown in Figure 1. The sensing unit for comprised of piezoresistive sensor, amplifying circuit and data logger as shown in Figure 2. A newly-

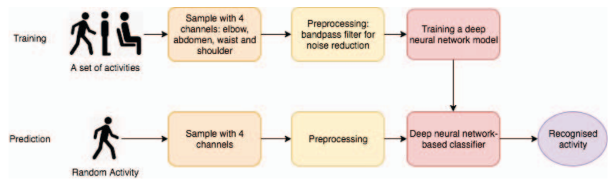

Figure 1: The processing pipeline of the smart garment system.

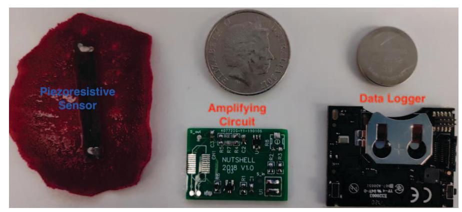

Figure 2: A sensing unit.

developed stretchable and wearable piezo-resistive strain sensors based on flexible and conductive polymer nanocomposites were mounted onto loose-fitting cloths. It features stretchable, transparent, low-cost and high sensitivity. The sensitivity between the stretched length and corresponding resistance changes can be computed to be 306 $k\Omega/mm$, which is approximately 150 times more sensitive than the sensor used in previous works [9].

We use the SensorTag manufactured by Texas Instruments[1] to capture the strain measurements from the sensor. The data logger SensorTag features a Cortex-M4 microcontroller, and a 2.4 GHz low power radio transceiver that supports both Bluetooth Low Energy and IEEE 802.15.4.To log the resistance changes of strain sensors, we designed and implemented an amplification circuit to convert the resistance changes into voltage changes. The stretch levels can be thereby captured by a 12-bit on-board Analog-to-Digital Converter (ADC) of the SensorTag within its dynamic ranges. The sampling rate for the ADC is 128 Hz. Finally, the ADC voltage readings will be stored in the on-board flash memory of the SensorTag for off-line analysis.

We selected two joint locations, shoulder and elbow, as well as two non-joint locations, waist and abdomen, and attached our sensing units onto a L size jacket for male as shown in Figure 3.

We implemented three signal pre-processing algorithms for E-Jacket: synchronization, noise filtering, and segmentation. All sensing units attached on the smart garment are synchronized using

[1]SensorTag: http://www.ti.com/ww/en/wireless_connectivity/sensortag2015 /index.html

978-1-7281-5497-8/20/$31.00 ©2020 IEEE
DOI 10.1109/IPSN48710.2020.000-6

Figure 3: Smart garment prototype with 4 sensor locations.

a time-slotted channel hopping-based (TSCH) [3] time synchronization mechanism. After raw signal captured, we firstly apply a Butterworth band pass filter with cut off frequency from 0.5 Hz to 10 Hz to remove irrelevant energy, as the useful human motion usually lies below 10 Hz [8]. We then apply sliding windows with 50% overlapping and the size of 4 seconds to segment strain signals.

Our deep learning model is a combination of a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) recurrent network (CNN-LSTM) [1, 10], which generally fits a human activity recognition task.

The structure of the CNN-LSTM model is depicted in Figure 4. We reshape input data from the 1d sequence to 2d matrix before feeding them to the model. Firstly, we employ a two 1d-convolutional layers on the input data so that we can extract robust features. A max pooling layer is applied to extract the most important features from the output feature map of the convoluational layers. The flatten layer reshapes the feature map from max pooling layer to a 1d vector which can be considered as a 1d time series data. The last two layers are fully connected layers. We implement the ReLu activation in the second last fully connected layer, and Softmax activation in the last fully connected layer, which will output the class labels. We insert two dropout layers after the second convolutional layer and the LSTM layer respectively. The dropout rate is empirically selected to be 0.5, which means that 50% of input units will be set to be zeros.

3 DEMONSTRATION

In this demonstration, we will only showcase the prediction of three activities: sit, stand, and walk, with smart garment system in Figure 1[2]. The training will be done with three participants before the demonstration. At least one participant out of three will attend the demonstration session. The demonstration with this participant will showcase the activity recognition when a user trains the smart garment system before use. Random participants will be invited to wear the smart garment to showcase the activity recognition when a new user uses the smart garment system without training. Apparently, the first case is expected to have higher accuracy than the second case.

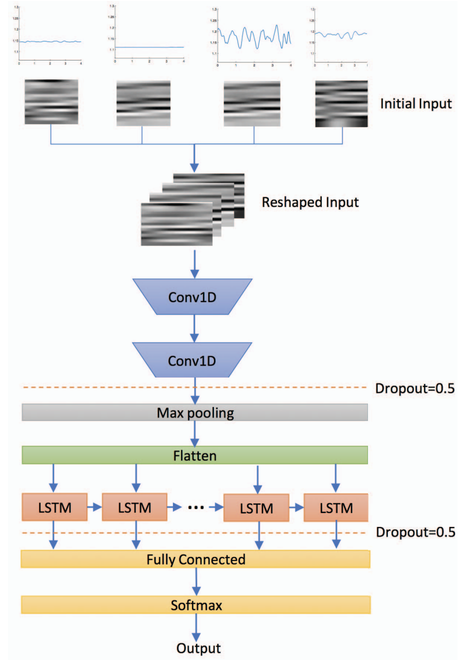

Figure 4: The CNN-LSTM model structure of E-Jacket.

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[2] Ethical approval has been granted by the corresponding organization (Approval Number HC190407)