A Deep Learning Framework for Activity Recognition and Joint Motion Tracking in the Home Environment

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Summary

This study introduces a remote mobility monitoring system that employs wearable technologies in the home environment. Ten participants performed 19 daily tasks while joint angles were calculated from IMUs (Inertial Measurement Units), and spatial location was tracked. A hybrid deep learning model classified tasks with 78.1% accuracy using a single IMU on the right forearm, and 86.9% accuracy with two IMUs placed on the left upper arm and right forearm. Additionally, three-dimensional angles of five joints were predicted and validated during various upper- and lower-limb activities.

Introduction

Mobility and joint function significantly contribute to health and quality of life. Aging-related declines in mobility, along with altered joint kinematics, are linked to reduced quality of life, increased disability, and higher morbidity and mortality rates [1]. Wearable technologies offer a solution for monitoring daily activities in the home setting, enabling applications such as remote rehabilitation, fall prevention, and long-term disease management [2]. Current frameworks for remote monitoring of daily activities often fail to quantify joint angles and classify a broad range of movements accurately. The aim of this study was to develop a remote monitoring system for physical activity and joint mobility that utilizes a minimal number of wearable devices and is applicable to a wide range of daily tasks performed by adults in home environments.

Methods

Ten healthy subjects (6 female and 4 male, age: 27.7±1.8 years) were recruited. Data collection was conducted inside a furnished apartment with five living areas: a kitchen, living room, study, bathroom and bedroom. Participants were instructed to perform 19 upper and lower limb tasks of daily living in random order, such as tooth brushing, hair combing, sit-to-stand and stand-to-sit, lying on a bed, and walking. Twelve IMUs were placed on body segments of each subject and joint angles were measured [3]. An ultra-wideband (UWB) system was used to track the real-time indoor spatial location of each participant as they moved within the home. A hybrid deep learning model combining Convolutional Neural Networks and Long Short-Term Memory networks was developed to classify the 19 activities using subject location data and data from all twelve IMUs as well as i) one, and ii) two IMUs. The optimal combinations of one and two sensors, and model hyperparameters, were derived using Bayesian optimization. A previously trained set of generative adversarial networks was employed to predict humerothoracic and elbow angles using sensors on the forearm, upper arm and thorax. The same process was repeated to generate hip, knee, and ankle angles using sensors on the sacrum, thigh, shank, and foot.

Results and Discussion

Using all twelve sensors, the 19 activities of daily living were classified with 96.9% accuracy. When combining spatial location data with a single IMU, the IMU placed on the right forearm achieved the highest classification accuracy (78.1%). When using two IMUs, the combination of the left upper arm and right forearm generated the highest task classification accuracy (86.9%) (Figure 1). The lowest root mean square error (RMSE) between the model predicted and measured humerothoracic angles across 11 upper limb tasks were achieved using the sensor on the right upper arm. These were 11.6°, 7.8°, and 9.3° for plane of elevation, elevation, and axial rotation, respectively. For the elbow, the combination of forearm and thorax sensors produced the lowest RMSE (below 9.9° for flexion and pronation). Deploying two sensors on the thigh and shank resulted in RMSE values below 5.7° for hip and knee flexion and ankle dorsiflexion across six lower limb activities. When using a single sensor, the thigh sensor represented the lowest RMSE, with values below 9.2° in the sagittal plane, and less than 5.5° in frontal and transverse planes for all three lower limb joints.

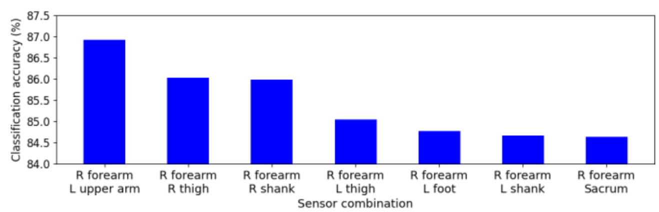

Figure 1: Best two-sensor combinations for classification of all 19 tasks; R: right, L: left.

Conclusions

This study presented a deep neural network model for advanced mobility measurement in home settings. The model classified 19 activities with 87% accuracy using spatial location data and just two IMUs. Upper- and lower-limb joint angles were estimated using one or two IMU sensors with close agreement with angles directly derived from IMUs. The predictions, however, were highly dependent on the number and placement of sensors. The forearm and thigh were the most beneficial segments for both task classification and angle measurement. The proposed framework offers a versatile solution for remote monitoring and rehabilitation systems.

References

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