Enhancing Human activity modeling through Spatio-temporal neural nets for applications in assistive robotics

Geometric Media Lab

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This study explores the potential of enhancing wearable robotics by analyzing walking activity data from a number of subjects. The research team employs sophisticated algorithms to recognize distinct human activities, aiming to bridge the gap between human motion and robotic assistance. By decoding patterns within walking data, the project seeks to contribute significantly to the development of more intuitive and responsive wearable robotic systems.

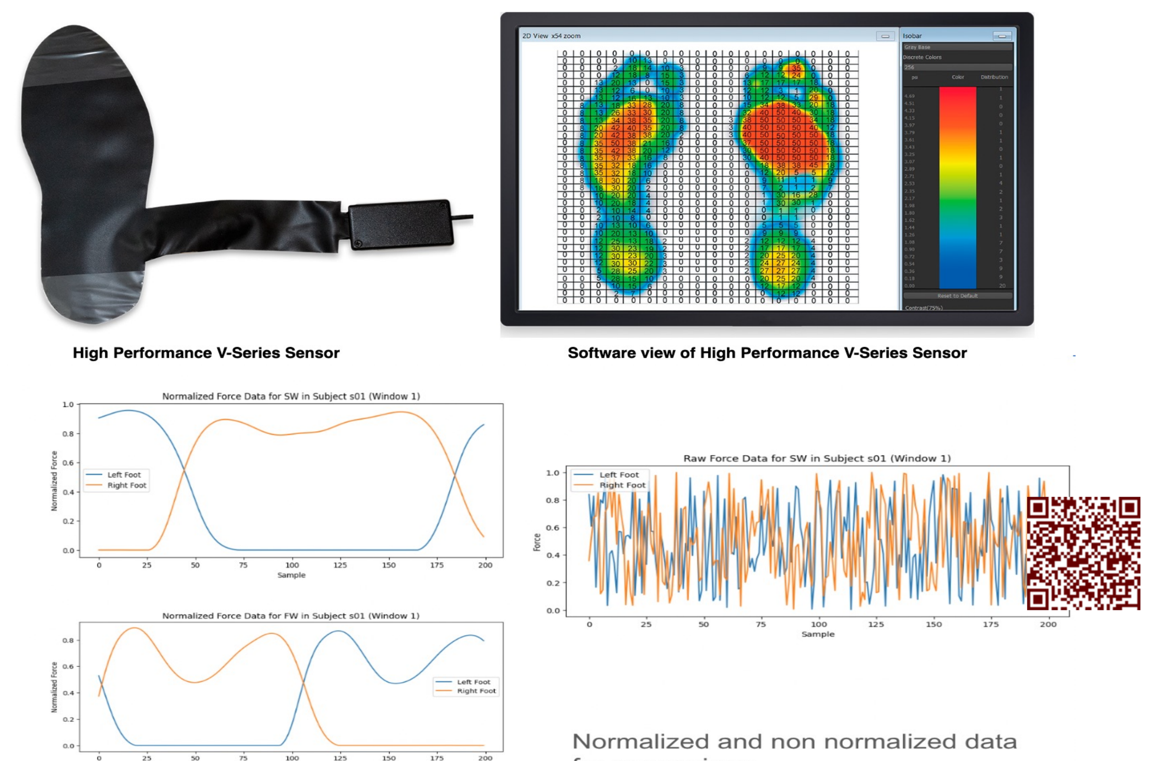
Activity Recognition Problem

In the realm of human activity recognition (HAR), the challenge lies in accurately identifying and classifying the type of activity being performed based on sensor data. This research focuses on a unique dataset collected from nine subjects performing four distinct activities: Slow Walking (SW), Fast Walking (FW), Normal Walking (W), and Running (RW). These activities were chosen to span a broad spectrum of human locomotion dynamics. The subjects walked on a treadmill while wearing a device embedded within the soles of their shoes, designed to measure the ground reaction forces (GRFs). These forces are pivotal in understanding the nuances of each activity, as they directly correlate with the biomechanical and physiological aspects of human movement. Recognizing these activities with high accuracy is crucial for applications ranging from sports science to rehabilitation and beyond.

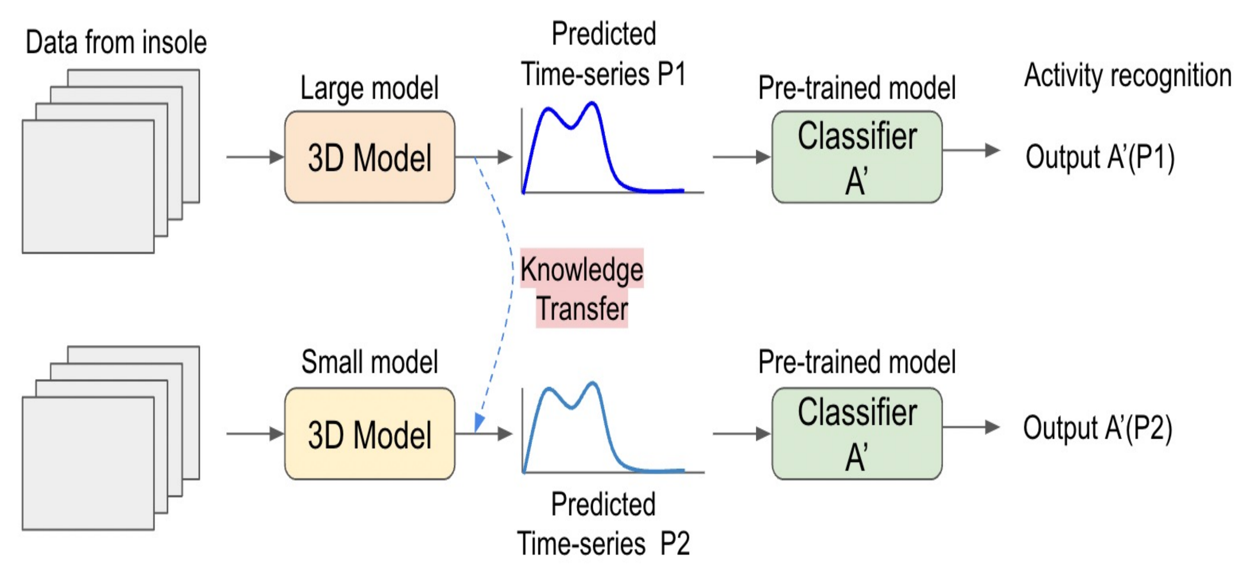
Dataset (w400)	Sbj 1	Sbj2	Sbj3	Sbj4	Sbj5	Sbj6	Sbj7	Sbj8	Sbj9	Total
SW	139	139	139	139	139	139	139	139	139	1251
W	0	0	139	139	139	139	139	139	139	973
RW	0	139	139	139	139	139	139	139	139	1112
FW	139	139	139	0	139	139	139	139	139	1112
Total	278	417	556	417	556	556	556	556	556	4448

Knowledge Distillation

Knowledge distillation is used to transfer insights from complex, pre-trained networks to smaller, more efficient models. In this method, a smaller "student" model learns to replicate the "teacher" model's output. The goal is to make the student model as effective as the larger model but with fewer computational demands. This is essential for use in devices with limited processing power, like wearable technology. By doing so, we ensure our models are both accurate and capable of real-time operation in such devices. Advantages include reduced model size and computational requirements, making the technology more accessible and practical for everyday applications.



Normalized and non normalized data for comparison.
Clear aspects defined in normalization



Future Work:

This research contributes to wearable human robotics, especially in developing assistive devices like exoskeletons and prosthetics. By accurately identifying walking activities and understanding ground reaction forces, we can improve these devices' design and functionality. Integrating our activity recognition algorithms into wearable robotics enables these devices to assist movement more naturally and efficiently. This advancement helps in rehabilitation, helping people recover from injuries or overcome mobility impairments, ultimately enhancing their quality of life.

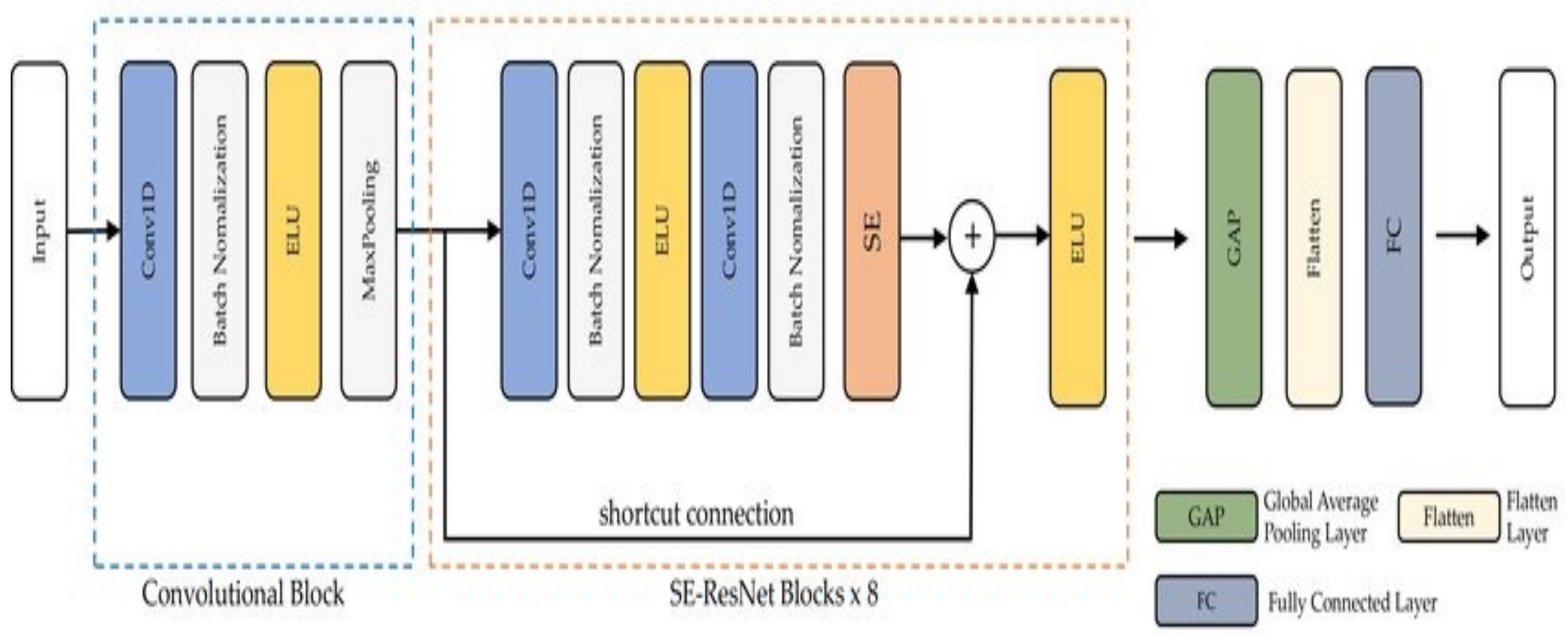
References:

1. A. R. Anwary, D. Arifoglu, M. Jones, M. Vassallo and H. Bouchachia, "Insole-based Real-time Gait Analysis: Feature Extraction and Classification," 2021 IEEE International Symposium on Inertial Sensors and Systems (INERTIAL), Kailua-Kona, HI, USA, 2021, pp. 1-4, doi: 10.1109/INERTIAL51137.2021.9430482. keywords: {Legged

2. Chatzaki C, Skaramagkas V, Tachos N, Christodoulakis G, Maniadi E, Kefalopoulou Z, Fotiadis DI, Tsiknakis M. The Smart-Insole Dataset: Gait Analysis Using Wearable Sensors with a Focus on Elderly and Parkinson's Patients. Sensors. 2021; 21(8):2821. https://doi.org/10.3390/s21082821

Neural Architecture for Insole Data Processing:

In this research, we use pre-trained ResNet models (e.g., ResNet-8, ResNet-20) for feature extraction and classification. ResNet's design helps avoid the vanishing gradient problem, making it possible to use deeper networks. We adapt these models to our task of recognizing activities from 1D time series data of ground reaction forces. Since the original ResNet models are designed for 2D data (images), we modify the convolutional neural networks (CNNs) to process 1D data. This adaptation involves adjusting the input layer to accept 1D time series inputs, allowing the models to effectively learn from and classify our specific type of data. This strategy speeds up training and improves the models' ability to generalize across different tasks by utilizing the complex features ResNet has learned from various datasets.



Accuracy (%)

ResNet 8

Dataset (w400)	Sbj 1	Sbj2	Sbj3	Sbj4	Sbj5	Sbj6	Sbj7	Sbj8	Sbj9	avg
Insole(m)	96.4029	91.1271	80.2158	80.295	67.9856	77.1583	66.7266	80.5755	50.8993	76.8207
GRF	99	97.3621	97.6619	80.3357	57.9137	94.2446	75.5396	87.9846	39.5683	81.0678

ResNet 20

Dataset (w400)	Sbj 1	Sbj2	Sbj3	Sbj4	Sbj5	Sbj6	Sbj7	Sbj8	Sbj9	avg
Insole(m)	91.0072	98.0815	66.9065	88.9688	70.1439	81.4748	79.6763	82.7338	64.2086	80.3557
GRF	100	99.5204	98.2014	91.1271	70.6835	98.2014	82.554	98.3813	61.8705	88.9488

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