Recognizing Activities of Daily Living Using Audio and IMU Data from Commodity Smartwatches

Yvette Espinoza
Department of ECE
Purdue University
Los Angeles, CA
yespinoz@purdue.edu

Cameron Johnson
Department of ECE
Purdue University
Asheville, NC
john3096@purdue.edu

Jahangir Mollah
Department of ECE
Purdue University
Seattle, WA
jmollah@purdue.edu

Abstract—Human activity recognition is applicable to health-care, but there are limitations on devices that can be used. The popularity of smart devices allow for comfort while also providing the data necessary to expand enable activity recognition. In this project, smartwatches will be used to recognize activities of daily living.

I. Introduction

Early research in activity detection aimed at finding differences in signal characteristics of the collected accelerometer data, and determining the ideal sensor placement. In [2], activities were grouped together into four categories by levels of physical activity, and sensors were placed throughout the body to determine the best location for each of the categories. Their results found each category performed best with a different sensor location. A sensor placed on the waist was best at detecting low level activities like eating, while a sensor on the chest or wrist was best at medium level activities like housework.

While different sensor placement based on an activity would be ideal for performance, it would not be practical for widespread use. An accelerometer by itself is not enough to determine an activity. More context is needed and different sensors on the body are an inconvenience for users. Human activity recognition is widely used in healthcare applications, with the elderly being a large part of the user demographics [4], to suit their needs the data collection would require an unobtrusive setup. To address the inconvenience of full body sensors and the need for context, [8] used a wrist-worn device equipped with an accelerometer and camera to recognize daily activities. The camera provided context for the activities, and the accelerometer provided characteristics of the body movement associated with different activities, both of which were used to train a model to predict the activity.

The advancement in smart devices, like smartwatches and conversational assistants, allow for more sensors in a user friendly device. Conversational assistants, like a Google Home, and smartwatches are used to train a model to recognize activities of daily living [1] [3].

A. Motivation

Audio monitoring can also be used to detect hazardous situations such as loud noises, falls, or emergencies. By integrating audio analysis into a smartwatch, users can be alerted to potential dangers in real-time, providing an added layer of safety.

Human activity recognition has potential applications that can be leveraged in healthcare, dietary monitoring, and weight management

We propose a research project, recognizing activities of daily living using the IMU and audio data from a commodity smartwatch. We will be following existing research performed in [3].

II. Methodology

Our process will involve conducting experiments wearing a smartwatch and performing a variety of basic activities such as writing, brushing teeth, and washing hands. We will record IMU data and audio data using the mic on the watch as input to a deep learning model which fuses the inertial data and acoustic data to determine the activity being performed, shown in Figure 1. Recognizing activities of daily living using inertial data has been the focus of a number of studies in the recent past, but fewer studies have included acoustic data in the model. We believe using both types will result in more accurate recognition. Some activities such as writing are more easily captured using inertial data while other activities such as cutting paper are more captured using acoustic data. Smart watches prove especially practical for recording both types of data because the mic is at close proximity to the hand which is often close to the activity being performed and the IMU records useful motion on the wrist as opposed to a smartphone in the pocket or strapped to the chest.

A. Hardware Setup

The authors of [3] used the same watch for all of their experiments. They used a Fossil Gen 4, Android Wear OS 2.21, Custom application collects data synchronously and stores locally on watch. Max inertial sensor samples at rate 50 Hz, acoustic sampled at 22.05 KHz. We will be using different watch manufacturers in our experiment to ensure generic compatibility.

B. Original Experimental Setup and Results

The paper that we follow conducted two generally different experiments. In the first experiment, an individual

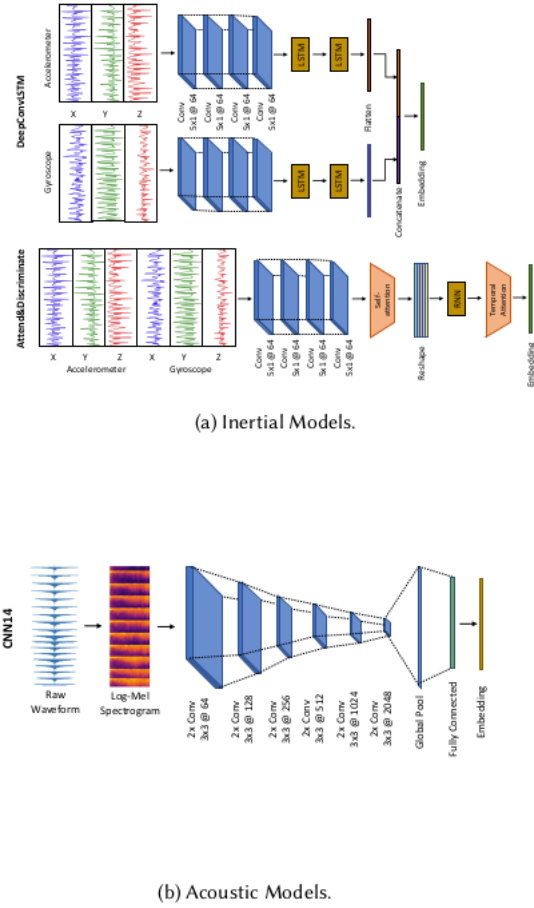(a) Inertial Models.

(b) Acoustic Models.

Fig. 1. Architecture of Inertial and Acoustic Models, provided by [3]

performs a series of activities for 30 seconds wearing a Fossil smartwatch which records inertial and acoustic data. There is a clear distinction between each activity and the watches are programmed to listen at frequent intervals. The authors implemented a variety of machine learning models to recognize the activity in this experiment with an accuracy of 94.3. The second experiment implements a less controlled, more realistic setting. One limitation of this paper was that their not controlled experiment had poor results due to noise and mislabeling of activities due to the setup. Since their experiment was not controlled, not all the activities they were interested in were performed, in some cases activities overlapped, and combined with a limited sample size resulted in misclassifications.

For our project we plan to expand our sample size and have a more controlled environment. We intend to focus on recognizing an activity on command, in a more controlled environment where we set rules to prevent the noise and mislabeling seen in the original paper.

C. Schedule

The project was divided into four phases. More details on due dates and deliverables for each phase are provided in Table I.

TABLE I
SCHEDULE

Phase	Activities	Due Date
Planning	- Identify existing research data - Identify available hardware - Plan for how to capture and store data - Identify how to process data - Identify machine learning classification models	March 18
Data Collection	- Capture and process raw data - Capture audio data at all times - Review existing research data - Get volunteers for experiments	April 1
Analysis	- Fuse data collected from different sources - Label data collected - Run the classification models - Analyze results	April 15
Finalize Report	- Write up final report - Create presentation	April 22

ACKNOWLEDGMENT

Paper we are implementing [3].

REFERENCES

[1] Rebecca Adaimi, Howard Yong, and Edison Thomaz. "Ok Google, What Am I Doing? Acoustic Activity Recognition Bounded by Conversational Assistant Interactions". In: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 5.1 (Mar. 2021). DOI: 10.1145/3448090. URL: https://doi.org/10.1145/3448090.

[2] Louis Atallah et al. "Sensor Positioning for Activity Recognition Using Wearable Accelerometers". In: *IEEE Transactions on Biomedical Circuits and Systems* 5.4 (2011), pp. 320–329. DOI: 10.1109/TBCAS.2011.2160540.

[3] Sarnab Bhattacharya, Rebecca Adaimi, and Edison Thomaz. "Leveraging Sound and Wrist Motion to Detect Activities of Daily Living with Commodity Smartwatches". In: 6.2 (July 2022). DOI: 10.1145/3534582. URL: https://doi.org/10.1145/3534582.

[4] Yi Chen et al. "Robust Activity Recognition for Aging Society". In: *IEEE Journal of Biomedical and Health Informatics* 22.6 (2018), pp. 1754–1764. DOI: 10.1109/JBHI.2018.2819182.

[5] Vassilis N. Ioannidis, Antonio G. Marques, and Georgios B. Giannakis. "Graph Neural Networks for Predicting Protein Functions". In: *2019 IEEE 8th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*. 2019, pp. 221–225. DOI: 10.1109/CAMSAP45676.2019.9022646.

[6] Dhruv Jain et al. "SoundWatch: Exploring Smartwatch-Based Deep Learning Approaches to Support Sound Awareness for Deaf and Hard of Hearing Users". In: ASSETS '20. Virtual Event, Greece: Association for Computing Machinery, 2020. ISBN: 9781450371032. DOI: 10.1145/3373625.3416991. URL: https://doi.org/10.1145/3373625.3416991.

[7] Haik Kalantarian and Majid Sarrafzadeh. "Audio-based detection and evaluation of eating behavior using the smartwatch platform". In: *Computers in biology and medicine* 65 (Oct. 2015), pp. 1–9. ISSN: 0010-4825. DOI: 10.1016/j.compbiomed.2015.07.013. URL: https://doi.org/10.1016/j.compbiomed.2015.07.013.

[8] Takuya Maekawa et al. "WristSense: Wrist-worn sensor device with camera for daily activity recognition". In: *2012 IEEE International Conference on Pervasive Computing and Communications Workshops*. 2012, pp. 510–512. DOI: 10.1109/PerComW.2012.6197551.

[9] Adria Mallol-Ragolta et al. "harAGE: A Novel Multimodal Smartwatch-based Dataset for Human Activity Recognition". In: *2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021)*. 2021, pp. 01–07. DOI: 10.1109/FG52635.2021.9666947.

[10] Shibo Zhang et al. "Deep Learning in Human Activity Recognition with Wearable Sensors: A Review on Advances". In: *Sensors* 22.4 (2022). ISSN: 1424-8220. DOI: 10.3390/s22041476. URL: https://www.mdpi.com/1424-8220/22/4/1476.