Mobile and Ubiquitous Computing- Active Radar

Samuel Scheele
Georgia Institute of Technology
scheele@gatech.edu

Davina Wooley
Georgia Institute of Technology
davinawooley@gatech.edu

Yilun Cai
Georgia Institute of Technology
derolawrence@gatech.edu

Prajwal Mavinkere Revanna
Georgia Institute of Technology
prajwalmr@gatech.edu

ACM Reference Format:
Samuel Scheele, Davina Wooley, Yilun Cai, and Prajwal Mavinkere Revanna. 2020. Mobile and Ubiquitous Computing- Active Radar. In *Proceedings of* . ACM, New York, NY, USA, 3 pages.

1 INTRODUCTION

Gesture recognition is a mode of human-computer interaction in which humans use the movement of their body as input to the computer. These systems help users to interact more naturally with computers than is possible using the keyboard and mouse as inputs. In this paper, we propose a active RADAR system capable of capturing human body language, i.e., gestures, detect the associated task and perform that task. We are using a RADAR system as it provides better anonymity as compared to similar camera based systems. We aim to create a user friendly gesture detection system based on radar which in the future can be on par with existing camera based systems while creating less privacy concerns to the user.

The application of such gesture recognition system can be in any active feedback system such as thermostat, TV, a monitor, IOT devices and it can also act as an extra input option to touch based products. Hand gestures can be used to perform small tasks like changing the TV channel, turning on or dimming the lights, increasing volume on devices, varying the temperature of the house using the thermostat, etc. Such radar systems can also be added to VR and AR devices to get more depth data and also capture accurate movement of the wearer.

2 AUTHOR KEYWORDS

Radar, Machine Learning, Ubiquitous Computing, Multiuser Detection, Privacy, Human Computer Interaction, Graphical User Interface, Gesture Detection

3 PREVIOUS AND RELATED WORKS

Gesture recognition is a method that allows computers to take human gestures as input by capturing it, interpret it and execute associated commands. These gestures basically involve a large or small physical movement, which will be used to interpret the underlying commands. Gestures vary from broad gestures like an uppercut to small gestures like a head tilt. Gesture recognition is used in a wide variety of areas like gaming, AR, sign language interpretation, smart devices, etc.

A good amount of research has been done in gesture recognition. Most of these revolve around either using a camera or a RADAR for capturing the gestures. Microsoft's Kinect is one of the most used camera systems because of its ability to capture 3D data, basically depth information. The works of Zhengyou Zhang[15], Ciricirelli[3], Y. Gu[5] and Z Ren[11] explores the advances in depth cameras such as Kinect and provides different approaches for kinect based gesture detection for humans as well as robots. Hani Karam's work[6] uses a depth camera to detect finger clicks. Miron[10] uses a stereo camera system instead of a depth camera and utilizes simulation of movement to detect hand gestures. Ben Jmaa[1] used a RGB-D camera which records depth along with RGB.

Cameras have high privacy concerns as it records the person realtime. Users are concerned with them being recorded as it makes them more public. RADAR is used to alleviate such privacy concerns as it only captures signals. Google's Soli[8] shows a method to develop a radar-based sensor specific to gesture tracking. Google Pixel 4 and 4 XL adopted this sensor to do simple tasks like pause songs, next/previous songs, call Google Assistant, etc. Jiajun Zhang[13], Zhang[14] and Tenglong[4] showcase gesture recognition using different kinds of radars such as Doppler-based radar and FMCW radar. Ahmet Gunduz[7], Jiajun Zhang[13] and Sun[12] explore the use of convolutional neural networks for gesture identification. Neural networks help achieve better accuracy and faster computation.

Our work is a radar based gesture detection system aimed to replace camera based systems which record the user to identify the gesture and creates privacy concerns to the user. We are using a low range radar chip to capture only the hand movement. And since we are only recording the signals, unless tagged, the data recorded cannot be mapped to a particular user.

4 METHODOLOGY AND RESULTS

4.1 Technical Approach

The radar antenna board chosen for this project was the TI IWR6843ISK. The antenna board was chosen primarily for its power output of 12 dBm, which gives it a higher effective range than many radar chips, and its frequency bandwidth of 60-64 GHz, which is higher than many applications (WiFi, which is commonly used for gesture recognition, as in SignFi [9], operates in the 2.4G GHz - 5 GHz bands). The high frequency means that the radar has less ability to penetrate obstacles, which makes it better at detecting human extremities (which aren't particularly radar reflective). However, the noise of the radar output at its sampling rate made it difficult

ACM ISBN …$

to do gesture recognition using only point clouds. Therefore, our team chose to use only the velocities obtained by doppler radar to recognize gestures. Code for reading data from the radar device and using it to identify gestures was written in MATLAB.

Our team's goal was to identify circular gestures. Though different gestures of a specific shape can be distinguished from one another by their frequency, phase, and direction, we chose to differentiate only by frequency. This choice was mediated by the limitations of doppler radar (namely: it only provides the component of velocity parallel to the antenna-object axis - projecting 2D data into a single dimension) and the limitations of MATLAB (which is unsuitable for real-time applications). Despite its limitations, this choice creates a highly flexible system, because the orientation of the radar becomes less important to its function. For a trajectory in some 2D plane $[x, y]^T = f(t)$, where the radar is taken to be at the origin, the doppler velocity measured at time T is

$$V_d = -|\dot{f}(T)|\cos(\Theta_{\dot{f}(T),f(T)})$$

Where r is the position vector of the radar. In the case of circular motion, V_d is a sinusoid with the same frequency as the motion and some phase shift that varies with user location and orientation relative to the antenna. Though the orientation has some effect on the observed frequency of the motion, this effect is small as long as the angle between $\dot{f}$ and $r - f(t)$, the axis from the user's hand to the radar device, is close to 0 or π (the magnitude of the angle's cosine is large). This can be accomplished by installing the radar in a ceiling, as people naturally gesture in planes containing the z-axis (up/down axis). Changing the relative position of a person relative to the radar corresponds to a phase shift in V_d, but the frequency remains approximately the same, making it an ideal feature for recognition.

The program waits to get at least one period of sinusoidal data and then analyzes it to extract a frequency. After extracting frequency data from doppler inputs, the program checks historical doppler data for the last 30 frames (3 seconds at our sampling rate of 10 Hz) to see how well the frequency hypothesis matches historical data. However, history which doesn't show oscillating motion of some kind is disregarded. This method provides a good balance between activation time and stability - an option can be selected in less than 1 second, but switching between options takes up to 3 seconds to confirm.

4.2 User Study

The user study was based off of PathSync[2]. PathSync is a gesture technique built on rhythmic path mimicry. The goal for the participants was to follow a blue dot's path using their hand/finger and the radar was capturing the participant's hand motion. The participants were shown two windows, both having one dot moving around a circular path. We instructed the participant to use their hand and draw circles in the air, replicating the dot's path(mimicry).

The dot on the left window moved at a slower speed than the dot on the right window. We instructed the users to follow the left window first. The radar system would identify when the matches(becomes in-sync) with the dot's path and speed. The dot would change color from blue to green when the user achieves sync. The participants were to told to sync their movement to that of the left or the right window's dot path on our cue. We recorded the time it took from which the participant received the cue for a particular window to the point they achieved sync with the particular dot's path. The participant's were given 8 total cues to switch between the windows, so each participant ended with 8 time stamps. After the study, the participants were provided with a survey regarding the study. It was based off the NASA TLX method.

4.3 User Study Results

The user study was conducted with 22 participants with each participant told to switch between the windows 8 times. On average it took 3 seconds with a standard deviation of 1.3 seconds from the time the participant were told to switch to when the RADAR recognised the switch. The average times of individual participants varied from 2.36 to 4.425 seconds. The fastest recognition of a switch was 1 second and the slowest was 8.5 seconds. On average the participants did better in the 2nd half clocking 2.8 over 3.18 seconds clocked in the 1st half. We think this is because the participants get some form of muscle memory of the two dot motions.

When asked regarding satisfaction with their 41% said they were moderately satisfied and 41% said they were neither satisfied nor dissatisfied. 94% of the participants said they faced little to no impact of pace on their accuracy or performance. 60% said they were neither irritated or relaxed during the study. 100% of the participants said that they found the interface to be either easy or very easy. 87% of the users said the study was well paced. 73% of participants said that they found little to no time pressure due to the pace of the study. 82% of participants said that they did not find the interaction with the system physically demanding. When asked about the physical activity needed for the study, 86% said they need little to none of it. 86% of the participants found the study simple.

5 DISCUSSION

The main intent of active radar is to build an active gesture recognition system which is more privacy friendly than camera based systems. The user study explored the feasibility and adaptability of a user to such devices. Based on participant feedback, it was evident that most of them found this system to be simple, less physical, easy interface and less stressful. Based on the study, it is also evident that the participants became faster as they used the gesture more and more. Since, we use a relatively small range radar, the signal range was limited, whereas in a camera system, it can be wider. During the study, during some switches between dot paths, by vision it looked the user switched some seconds before the radar identified it.

Another issue that occurred during the study was that, due to the presence of only two actions for the participant, very few times, the participants switched before getting the cue to switch. This led to a very quick recognition in such cases. One participant pointed that, since the study task had no constraint on which hand to use to draw the gesture, they could use one hand for the left window's dot motion, and another for the right, achieve better muscle memory and switch faster.

6 FUTURE WORK

Neural Networks can be incorporated in the system to achieve better accuracy which would lead to quicker identification of gestures.

This would also help design a more user-custom gesture system, since the network would learn the imperfections when the user performs gestures, making it faster.

The radar system should be incorporated should be tested with a simple active system such as thermostats or ovens. Gestures can be designed to do cross device tasks. For example, a clockwise gesture would increase the temperature in both devices. Additional gestures should be designed to identify between the device to which the user did the task for. If a universal radar system is designed which can cover the whole house, based on the signal, the radar can calculate the position of the user relative to the active device to adopt the gesture to that device.

The study was very limited with respect to gestures, tasks, users and range. It needs to be redesigned with more gestures, cross device gestures and tasks. More gestures helps alleviate the error that might have been caused when the participants switched before the instruction. To understand the range and timing requirements for real time use, a study should be done with participants performing gesture tasks, in front of both a radar and a camera system. The study sample must be large with over 1000 users in a wider age demographic over a longer period of time to achieve more robust results.

7 CONCLUSION

In this paper, we have introduced a a mimicry based system for gesture detection using a radar. We have demonstrated the ease, responsiveness, less physically taxing and simplicity of the radar gesture detection system with a small group of 23 users who used our system to mimic two dot motions.

With the implementation of active feedback, change in color of the dot being followed, the users felt more comfortable knowing that they were following the motion correctly. We have demonstrated is a legitimate alternative to camera based gesture detection systems which is more privacy friendly as it only records the gesture motion.

REFERENCES

[1] Ahmed Ben Jmaa, Walid Mahdi, Yousra Ben Jemaa, and Abdelmajid Ben Hamadou. 2016. A New Approach For Hand Gestures Recognition Based on Depth Map Captured by RGB-D Camera. *Computacion y Sistemas* 20 (12 2016), 709–721. https://doi.org/10.13053/CyS-20-4-2390

[2] Marcus Carter, Eduardo Velloso, John Downs, Abigail Sellen, Kenton O'Hara, and Frank Vetere. 2016. PathSync: Multi-User Gestural Interaction with Touchless Rhythmic Path Mimicry. (2016), 3415–3427. https://doi.org/10.1145/2858036.2858284

[3] Grazia Cicirelli, Carmela Attolico, Cataldo Guaragnella, and T. D'Orazio. 2015. A Kinect-based Gesture Recognition Approach for a Natural Human Robot Interface. *International Journal of Advanced Robotic Systems* 12 (03 2015). https://doi.org/10.5772/59974

[4] Tenglong Fan, Chao Ma, Zhitao Gu, Qinyi Lv, Jialong Chen, Dexin Ye, Jiangtao Huangfu, Yongzhi Sun, Changzhi Li, and Lixin Ran. 2016. Wireless Hand Gesture Recognition Based on Continuous-Wave Doppler Radar Sensors. *IEEE Transactions on Microwave Theory and Techniques* 64 (10 2016). https://doi.org/10.1109/TMTT.2016.2610427

[5] Y. Gu, H. Do, Y. Ou, and W. Sheng. 2012. Human gesture recognition through a Kinect sensor. (2012), 1379–1384.

[6] Hani Karam and Jiro Tanaka. 2015. Finger Click Detection Using a Depth Camera. *Procedia Manufacturing* 3 (2015), 5381 – 5388. https://doi.org/10.1016/j.promfg.2015.07.653 6th International Conference on Applied Human Factors and Ergonomics (AHFE 2015) and the Affiliated Conferences, AHFE 2015.

[7] Okan Köpüklü, Ahmet Gunduz, Neslihan Kose, and Gerhard Rigoll. 2019. Real-time Hand Gesture Detection and Classification Using Convolutional Neural Networks. *CoRR* abs/1901.10323 (2019). arXiv:1901.10323 http://arxiv.org/abs/1901.10323

[8] Jaime Lien, Nicholas Gillian, M. Emre Karagozler, Patrick Amihood, Carsten Schwesig, Erik Olson, Hakim Raja, and Ivan Poupyrev. 2016. Soli: Ubiquitous Gesture Sensing with Millimeter Wave Radar. *ACM Trans. Graph.* 35, 4, Article 142 (July 2016), 19 pages. https://doi.org/10.1145/2897824.2925953

[9] Yongsen Ma, Gang Zhou, Shuangquan Wang, Hongyang Zhao, and Woosub Jung. 2018. SignFi: Sign Language Recognition Using WiFi. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 1, Article 23 (March 2018), 21 pages. https://doi.org/10.1145/3191755

[10] C. Miron, A. Păsărică, D. Arotăriţei, H. Costin, R. G. Bozomitu, and C. Rotariu. 2017. Hand gesture detection using a stereo camera system and simulation of movement. (2017), 297–300. https://doi.org/10.1109/ATEE.2017.7905134

[11] Z. Ren, J. Meng, and J. Yuan. 2011. Depth camera based hand gesture recognition and its applications in Human-Computer-Interaction. (2011), 1–5. https://doi.org/10.1109/ICICS.2011.6173545

[12] J. Sun, T. Ji, S. Zhang, J. Yang, and G. Ji. 2018. Research on the Hand Gesture Recognition Based on Deep Learning. (2018), 1–4. https://doi.org/10.1109/ISAPE.2018.8634348

[13] Jiajun Zhang, Jinkun Tao, Jiangtao Huangfu, and Zhiguo Shi. 2017. Doppler-Radar Based Hand Gesture Recognition System Using Convolutional Neural Networks. (2017). arXiv:1711.02254 [cs.CV]

[14] X. zhang, Q. Wu, and D. Zhao. 2018. Dynamic Hand Gesture Recognition Using FMCW Radar Sensor for Driving Assistance. (2018), 1–6. https://doi.org/10.1109/WCSP.2018.8555642

[15] Zhengyou Zhang. 2012. Microsoft Kinect Sensor and Its Effect. *IEEE MultiMedia* 19, 2 (April 2012), 4–10. https://doi.org/10.1109/MMUL.2012.24