

Designing Efficient and Customizable Radar-based Gesture Interfaces

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ABSTRACT

Radar sensors have many advantages compared to traditional vision-based sensors for gesture recognition. They work in poor lighting and weather conditions, come with less privacy concerns than vision-based sensors, and can be integrated into everyday objects. However, due to the size and complexity of radar data, most radar-based systems rely on deep-learning techniques for gesture recognition. These systems take time to train and make it challenging to support quick customization by the user, such as changing the gesture set of an application. In this thesis, we want to investigate whether we can create efficient and customizable radar-based gesture interfaces, by reducing the size of raw radar data and relying on simple template matching algorithms for gesture recognition. We have already implemented a pipeline that handles these steps and tested its performance on a dataset of 20 gestures performed by three participants in front of a cheap, off-the-shelf FMCW radar. The next steps include developing a software environment for testing recognition techniques on radar gestures, optimizing our pipeline for real-time gesture recognition, and investigating two new use cases: environments where the radar is obstructed by some materials (wood, glass, and PVC) and breathing patterns recognition.

CCS CONCEPTS

• **Human-centered computing** → **Gestural input**; **Graphical user interfaces**; *Interactive systems and tools*; • **Computing methodologies** → *Model development and analysis*; • **Software and its engineering** → Runtime environments; • **Hardware** → Radio frequency and wireless interconnect.

KEYWORDS

Gesture-based interfaces, Mid-air gestural interaction, Radar-based interaction

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1 INTRODUCTION

Gesture-based interfaces can act as a more natural and intuitive interaction method for users [4]. Past research focused mainly on 2D gestures and proposed many simple and efficient algorithms for 2D gesture recognition, such as the $-family of recognizers [11]. However, technology improvements have shifted the focus to 3D gestures in the last decade, as sensors became increasingly accessible and their precision increased. The move from 2D to 3D provides more freedom to developers in the design of gestural interfaces. New interaction methods become possible, such as breathing patterns and mid-air motion involving one or many parts of the body (*e.g.*, hands, legs, head, or tongue) or even objects.

However, the type of sensor used by a system limits the range of supported gestures and the contexts in which they can be reliably recognized. For example, IMU-equipped devices (*e.g.*, smart gloves, rings, and watches) are relatively inexpensive and allow developers to support many users that interact simultaneously while moving around without affecting the quality of motion tracking. Yet, because these devices are worn by the user, they are more intrusive, have limited ability to distinguish between the motion of different body parts, and require specific attention in some contexts, such as public spaces, to prevent theft and limit the spread of diseases caused by improperly cleaned devices. Vision-based sensors are now a relatively mature technology for gesture sensing. They are cheap (*e.g.*, the Leap Motion Controller, or LMC, costs around 100$) and can accurately track body parts from one or more user(s). However, they are sensitive to occlusion and lighting conditions, and may raise some privacy concerns because of their camera(s). As such, they may be better suited to private indoor spaces than storefronts and other public spaces. Radar-based systems may provide an alternative to vision-based sensors in challenging environments, thanks to their insensitivity to varying lighting and weather conditions [14], and where where privacy is deemed important by end-users. Cheap radar systems can be hidden behind surfaces (*e.g.*, a wall or a door), integrated nearly seamlessly into everyday objects (*e.g.*, a smartphone [8], a TV, or a desk [2]), and even worn by the user [13]. On the other hand, they are not as mature as vision-based techniques. The lack of development tools supporting radar sensors and the high complexity of radar data hinder the development of radar gesture-based applications. While the industry is starting to move towards a standardization of radar data format for general purpose applications (https://www.cta.tech/Resources/Standards/Ripple), most research papers still rely on a wide variety of radar sensors which are rarely directly compatible with each other.

In this thesis, we want to investigate the feasibility of radar-based gesture interaction by: (1) exploring and determining the space of

3D gestures that are acceptable both from an end-user and a system perspective, (2) defining and testing a model-based approach to reduce raw radar signals into fewer, physically-meaningful properties for gesture recognition, (3) developing a software environment for testing radar-based gesture interaction. To achieve this objective in a realistic and focused way, we pose the following working hypotheses: (H1) we rely one inexpensive and off-the-shelf radar sensor, the Walabot, for motion sensing; (H2) we focus on hand gestures and breathing patterns performed by one user at a time; and (H3) the gesture set of an application should be customizable in real-time by the user. Our website https://sites.uclouvain.be/ingenious/ features relevant material, such as videos, datasets, and software tools.

2 RESEARCH METHODS

Our research methodology consists of the following stages:

SLR of radar-based gesture interaction and recognition techniques (Fig. 1a). Radar-based gesture recognition is a hot research topic, which results in many publications on the subject being published each year. Although some surveys have already targeted radar-based gesture recognition [1, 3], we believe that there is a need for an SLR that encompasses the recognition techniques, radar systems, as well as the types of gestures and applications covered by each work. For this SLR, we follow Liberati *et al.*'s approach [7] and use PRISMA diagrams to represent the process.

Elicitation of radar-based gestures (Fig. 1b). Gesture Elicitation Studies (GESs) [12] help identify the gestures preferred by users to perform various actions (called "referents") in specific contexts of use. Many works evaluate the performance of their system on non user-defined gestures, which may not represent actual usage scenarios. By conducting a GES, we intend to identify user-defined gestures that are both accurately recognized and highly relevant to our context of use (*i.e.*,, a Walabot that converts hand motion into commands to control IoT devices).

Acquisition of radar-based gestures in various contexts (Fig. 1c). Good datasets are key to training gesture recognition algorithms. Based on our GESs, we will acquire relevant radar gestures in various contexts and make them available to the scientific community. Participants will be selected to cover a wide range of physical characteristics (*e.g.*, hand surface, height, weight, gender). Our datasets should cover mid-air hand gestures for controlling IoT devices, as well as breathing patterns. Mid-air hand gestures will be performed with and without materials (*e.g.*, wood, glass, PVC) between the user and the radar system, to investigate the impact of obstruction on gesture recognition. In some cases, gestures may be recorded with multiple devices simultaneously (*e.g.*, LMC and radar) to provide a point of comparison.

Development of an environment for radar-based gesture recognition (Fig. 1d). Our environment consists of two parts: (1) a pipeline that cleans up the radar signal and reduces it to two physically meaningful dimensions (hand-radar distance and relative permittivity) in real time, simultaneously reducing data size, increasing execution speed, and facilitating the data interpretation; and (2) a software environment for the testing of recognition techniques on (radar) gesture data. In the future, this environment may be extended to assist in the development of gesture-based interfaces.

Evaluation of algorithms for radar gesture recognition. This evaluation has two objectives: (1) identify the most accurately recognized gestures in specific contexts of use (environment, radar system, recognizer); and (2) configure the gesture recognition system to achieve the best compromise between accuracy, training time, and execution time. Coupled with GESs, such evaluations facilitate the design of intuitive and effective (radar) gestural interfaces. We will evaluate template-matching algorithms on our datasets in user-dependent and user-independent scenarios.

3 STATUS OF THE RESEARCH

3.1 Current Status

We have completed an SLR of radar-based gesture recognition, in which 118 relevant papers were identified (Fig. 1). For each paper, we noted the algorithm(s) and radar system(s) used for gesture recognition, as well as the type of application, evaluation, and gestures. Very few of the gesture sets featured in the papers were publicly available. Based on the work of Lambot *et al.* [5, 6], we also developed a pipeline for offline processing of the radar signal that extracts from the signal the distance between the hand and the radar and the relative permittivity of the medium defined by the hand [9]. The former informs on the position of the hand in space and the latter provides information on the hand pose. We created two radar gesture datasets. The first consists of 16 gestures recorded from one user with three sensors (Walabot, horn antenna, and LMC) while the second dataset extends the first with four new gesture classes and samples from more users recorded with two sensors (Walabot and LMC). Finally, we tested the pipeline in user-(in)dependent scenarios with Jackknife [10], a popular template matching algorithm for gesture recognition. It performed well in the user-dependent scenario, but relatively poorly in the user-independent scenario, suggesting that some form of normalization with respect to the users could provide some benefits.

3.2 Next Steps

We are working on a tool for comparing gesture recognition techniques on radar datasets. It will enable developers to create gesture sets that can be accurately recognized and select the best performing gesture recognition algorithm(s), thus advancing towards more qualitative gesture interaction. This tool could be extended to further assist developers in the design and implementation of (radar) gesture interfaces. We are also improving the pipeline to normalize data with respect to users and achieve real-time performance through optimizations (*e.g.*, pruning, multi-threading, data dimension reduction) and compromises (*e.g.*, lower framerate and precision). We will apply our pipeline to two new contexts for gesture interaction: hand gestures through materials (wood, glass, PVC) and breathing patterns. The former is a natural extension of our previous work with use cases such as interactive store fronts and smart furniture (*e.g.*, desks, doors). Similarly, radar-based breathing pattern recognition has applications in healthcare (*e.g.*, breathing exercises supervision) and as a non-intrusive interaction method for people with disabilities (*e.g.*, tetraplegia). We defined a procedure for recording a new dataset involving around 40 participants that will encompass these two contexts. Finally, we want to identify other interactive applications that could benefit from or require using our approach to radar sensing.

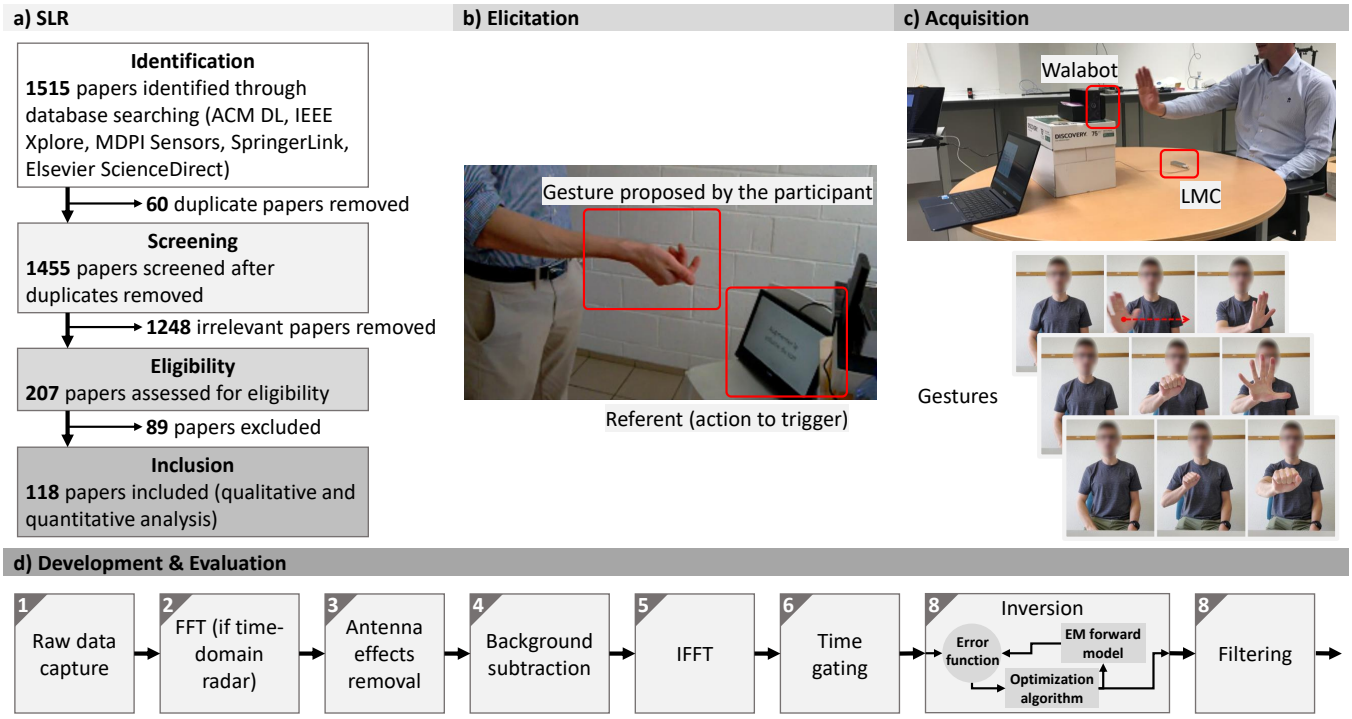


Figure 1: Summary of the research methodology.

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