17th International Conference on DEVELOPMENT AND APPLICATION SYSTEMS, Suceava, Romania, May 23-25, 2024

Smart Ring Gestures Recognition System Tailored to Serious Games Designed for Older People

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***Abstract*— The use of smart rings in the context of user interfaces designed for older people can bring significant benefits by fostering an intuitive user experience tailored to the needs and preferences of users. In this context, the contributions of this paper lie in the implementation of a smart ring gesture recognition system for serious game interfaces designed for older people. The proposed system comprises a training module responsible for gathering accelerometer raw data from smart rings and generating a classification model, and a recognition module tasked with predicting gestures and transmitting the labels to the user interface to execute the corresponding feedback.**

Keywords*— *smart rings, older people, serious games, gesture interaction, gesture recognition

I. Introduction

As the population ages, there is an increasing interest in leveraging technology to the preferences of older people [1]. At the intersection of new technologies and aging are a great diversity of possibilities for designing solutions that are appropriate to the unique needs of users. Serious games, for instance, offer dynamic engagement, triggering users mentally, physically, and emotionally, while also providing entertainment and cognitive stimulation [2], [3], [4], [5], [6], [7]. These games can range from puzzle games and quizzes to immersive virtual environments that allow users to explore new interaction techniques [8], [9]. Within serious games, users can encounter multiple input techniques to interact with the digital world starting from keyboard input to whole-body gestures and voice commands [3], [10], [11]. Related to body movements interaction, the Systematic Literature Review on serious games designed for older people conducted by Bilius et al. [12] uncovered a wide array of input devices that facilitate interaction, including Kinect [10], Balance Board [13], Motion Capture System [2], and Inertial Measurement Unit [5], [8], [14] (either integrated into tablets or smartphones [5], [14] or placed on knees or feet [8]).

As smart rings present limited adoption in previous research [12], [15], despite receiving positive feedback from older users [16], the goal of this paper is to introduce a gesture-based recognition system to streamline interactions between smart rings and serious game interfaces. Older people may have unique movement patterns due to factors such as physical limitations or needs, therefore, in the proposed implementation, we considered gesture customization based on user preferences. Specifically, the proposed system features a training module that collects accelerometer raw data gestures from the user's smart ring and generates a classification model, and a recognition module that predicts a gesture and then transmits it to the user interface. The interface will execute the corresponding action based on the gesture label returned by the recognition module.

This work was supported by a grant of the Ministry of Research, Innovation and Digitization, CCCDI- UEFISCDI, project number PN-III-P2-2.1-PTE-2021-0255, within PNCDI III.

In the following, Section II provides an overview of previous work related to serious games designed for older people and smart rings. Section III describes the system architecture of the gesture recognition system. Section IV presents the results of system evaluation using a public dataset, along with discussions on findings and future work. The paper ends with Section V dedicated to conclusions.

II. Related Work

Serious games designed for older people, spanning various technological platforms and immersive environments, offer customizable learning, accessible design, and social interaction, thereby increasing motivation and comfort with computer technologies and input techniques [3], [17]. According to the scientific literature, these games may involve a diversity of input techniques, including gestures such as taps, legs, hands, or whole-body movements [3], [4], [5].

In this regard, user-friendly devices (*e.g.*, Kinect, keyboard, touchscreen, balance board, AR/VR headset) can facilitate interactions, offering a wide range of alternatives and adjusting to fit a diverse group of users, in particular, older people and users with motor impairments [5], [18], [19], [20]. For example, Baranyi *et al.* [5] proposed a touchscreen application for rehabilitation that encompasses touch gestures with different levels of difficulty such as pinch, two finger movements, Suwicha *et al.* [10] explore five games designed to enhance the cognition of older people through body movements, leveraging Kinect for motion detection. Similarly, Billis *et al.* [13] introduced a game platform aimed at enhancing physical abilities, based on Wii Balance Board to collect body movements to interact with serious games. Exploring interactive input interactions in serious games blending traditional and contemporary input methods could leverage in creating a gaming experience tailored to all older people [4].

Smart ring devices have embedded sensors such as accelerometers, gyroscopes, and even small cameras providing the capacity to capture hand movements [21]. The data collected during these movements can then be used as input within serious games, providing a natural interaction during gameplay. In this context, Bilius and Vatavu [16] examined the preferences and perceptions of older people related to smart rings. Their findings uncovered a positive attitude among older people towards adopting smart rings for interaction with various smart systems, finding them efficient and useful for everyday use. In light of these conditions, in the following sections, we will describe a smart ring gesture recognition system designed for older people that can be used in serious game scenarios.

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Figure 1 Photographs of three commercial rings: Ring Zero (left), Litho (center), and NFC Omni Ring (right).

III. System Architecture

Serious games designed for older people can be controlled through mid-air gestures (such as drawing a circle, a square, or a line in the air) performed with the hand on which the ring is worn. In light of this aspect, below is described the software architecture of a gesture recognition system designed for smart rings. This system acknowledges that gestures are captured by the accelerometer embedded in the smart ring (see Figure 1), which is worn by the user on the index finger.

A. Description of the system architecture

In Figure 2, the block diagram of the application is presented. During the interaction, the Gesture Recognition System is waiting, ready to receive the raw data of the gestures captured by the user's smart ring through the Ring Interface.

The system operates via two distinct steps: Training Module and Recognition Module. The gestures are captured by Smart Ring and are transmitted through the Ring Interface to the software application, specifically the Gesture Recognition System. At this step, the accelerometer raw gestures are processed to ensure further accurate interpretation. In the Training Module, the user can add the preferred gestures including their labels, after being processed, into a database. Subsequently, the system will retrain with the new gestures generating an updated classification model that will be used for prediction. Following this, the user will receive Feedback regarding Training status. Mention that the database can contain gestures collected not only from the current user but also from other users who agreed to include their data in a public dataset. In the Recognition module, the gestures collected by Ring Interface are predicted using the classification model generated in the Training Module. This module will provide a gesture label that will perform the corresponding feedback on the user interface. For example, if the user performs a swipe to the left, an object on the user interface will move to the left, a swipe up performed in the air will access the next game, or a drawing of the X shape in the air will indicate stopping the current game.

To evaluate the smart ring gesture recognition system, we used a smart ring equipped with a Phidget MOT1100 [22] accelerometer that measures acceleration in three axes. To streamline gesture data collection in the database, we used the VINT Hub Phidget [22]. We chose Phidget Hub for its capacity to connect up to six accelerometers and its efficient integration into software applications. To connect the smart ring to the Ring Interface of the proposed gesture recognition system (see Figure 2), we used the `Phidget22` Python Package [23]; see Figure for the Python code reading data from the smart ring.

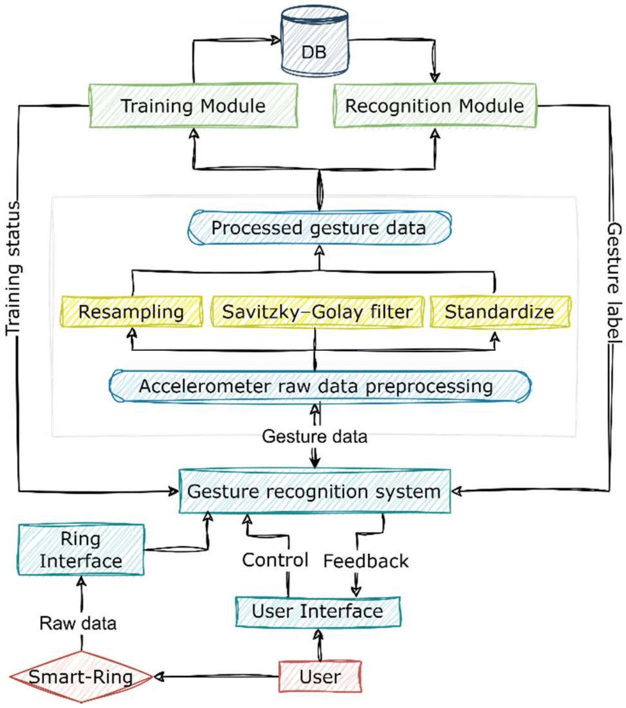

Figure 2 System architecture of the smart ring gesture recognition system.

```python
from Phidget22.Devices.Accelerometer import *
from Phidget22.Phidget import *

accelerometer = Accelerometer()
accelerometer.setOnAccelerationChangeHandler(
              onAccelerationChange)

def onAccelerationChange(accelerometer,
                         acceleration, timestamp):
    global reading_enabled
    if reading_enabled:
        listX.append(acceleration[0])
        listY.append(acceleration[1])
        listZ.append(acceleration[2])
```

Figure 3 Python code collecting data from Phidget accelerometer.

B. Gesture representation and recognition

In this paper, we used the gesture raw data read by the accelerometer sensor. Firstly, the collected data was resampled to ensure uniform length. The length, `avg` is equal to the average of all raw data lengths from the training dataset. A Savitzky–Golay filter was used to smooth noises in the data and then standardized to ensure consistency and comparability across different samples. The Savitzky–Golay filter was adopted from the Python SciPy package [24]; see Figure 4 for the Python code preparing the data for the Training and Recognition Module.

```
def prepareData(gesture, avg):
    lineG, lg = [], len(gesture[0])
    for i in gesture:
        lineG.append(np.array(
          np.interp(np.linspace(0, 1, avg),
          np.linspace(0, 1, lg), gesture[i])))
    lineG = savgol_filter(lineG, 20, 3)
    G = np.concatenate([np.array(lineG[0]).T,
          np.array(lineG[1]).T,
          np.array(lineG[2]).T])
    return G
```

Figure 4 Python code preparing raw data for training and predicting step.

Taking into consideration the potential increase of the database, we have implemented the writing of the classification model in a file. For this, we used the Pickle package in Python to serialize Python objects and save them to a binary file. This functionality enables the reload and reuse of the classification model without requiring retraining every time the user selects the Recognition Module. Mention that the classification algorithm used for training and predicting is the Extra Trees classifier [25]; see Section IV for more details.

IV. System Evaluation and Discussion

A. System Evaluation

To evaluate our system, we used the 6DMG dataset [26], which consists of 5615 gestures comprising 20 distinct gesture types collected from 28 participants. The gestures were collected using the accelerometer and gyroscope sensors embedded in Wiimote's [26]. The data collected from users have been gathered anonymously maintaining in this way confidentiality. For each motion gesture, in the database are stored timestamps, accelerations, angular speeds, positions, and orientations. We used 6DMG dataset due to its comprehensive coverage of motion gestures that can be performed with smart rings [21] being commonly used in interactive systems, including swipe motions (right, up, left, down, up-right, up-left, down-right, down-left), forth and back motion (poke-right, poke-up, poke-left, poke-down), V shape, X shape, circles (horizontal and vertical clockwise and counterclockwise) and wrist twisting (twist clockwise and twist counterclockwise) [26].

In the evaluation step, we computed the accuracy of accelerometer data from the 6DMG dataset [26]. We used five classifiers from the Scikit learn package [25] mentioned in Table 1. We have selected five variations of Extra Trees and SVM based on the top algorithms evaluated by Bilius *et al.* [27] on all raw data from the database 6DMG. The selection process [27] involved 5-fold cross-validation and grid search hyper-parameter optimization across various algorithms.

Table 1 Accuracy rates of recognition obtained through leave-one-gesture-out cross-validation procedure.

Classifier	Accuracy		Execution Time	
	Mean	***Std***[a]	***Train***	***Predict***
Extra Trees (50 estimators and 2 splits)	91.77%	3.37%	515.53 *ms*	3.69 *ms*
SVM[b] (ovr, rbf kernel)	90.49%	3.82%	521.19 *ms*	1.19 *ms*
Extra Trees (20 estimators and 2 splits)	89.44%	3.55%	282.77 *ms*	3.99 *ms*
SVM (ovr, linear kernel)	88.57%	3.98%	263.33 *ms*	1.04 *ms*
SVM[b] (ovr, linear kernel)	88.12%	3.89%	311.37 *ms*	1.99 *ms*

[a.] Standard deviation, [b.] Standardized data.

Table 1 lists the recognition accuracy rates obtained for the five classifiers using the cross-validation leave-one-gesture-out technique. The highest value, 91.77% (SD = 3.37%) was obtained for Extra Trees with 50 estimators and 2 splits. In Table 1 we also reported the execution time required for both training and prediction steps. For the experiments, we used Python 3.12.2 running on a machine under Windows 11 with 16 GB of memory.

B. Discussion and Future Work

Commercial smart rings come in a variety of shapes to address the diverse preferences and needs of users. Using the motion-sensing capabilities of smart rings in conjunction with older people holds the potential for immersive experiences, allowing users to control actions and make decisions through intuitive and natural hand gestures during gameplay. Additionally, the diverse form factors of smart rings fit individual preferences, ensuring inclusivity and accessibility for all users. In this context, according to [16], nine older users expressed a preference for using smart rings with various form factors, as indicated by high ratings on the Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Specifically, ratings for Litho, Omni, and Zero were overall over 5 (refer to Figure 1 for pictures of the smart rings form factors studied in [16]). These findings underscore their suitability for a wide range of usage scenarios, including gesture interaction. We refer to readers' [16] paper for empirical findings on smart ring technology from older people.

Given the variability in users' preferences, except for smart ring form factors, gesture sensitivity, recognition speed, and gesture-to-action mapping may vary significantly. To address these challenges, the proposed gesture recognition system facilitates customization by allowing users to define their gesture vocabulary and choose which function within the interface each gesture controls. An example would be an older user who finds it challenging to perform a clockwise circle gesture to start a game. Therefore, the user replaces the gesture with a double tap by adding the new gesture in the database using the Training Module. In future work we aim to complement the proposed system with a recommendation module for gesture vocabulary based on age-related symptoms reported by older users, addressing the needs of users who may find themselves in similar contexts [18], [19]. The smart ring gesture recognition system has been tested in the laboratory, and we aim to integrate it into a serious game user interface in real scenarios. As the scientific literature approaches various devices to control serious games [12], we aim to complement the following study with a comparison of smart rings against other technologies such as Kinect (*e.g.,* an exergame that uses physical movements to control games [10]), Motion Capture System (*e.g.,* used to control an exergame through physical movements [2]), and Inertial Measurement Unit (*e.g.,* IMU embedded in a smartphone which was used for a game controlled by different gestures consisting in phone manipulation such as rotation, touch, move [5]).

The smart ring gesture recognition system proposed in this paper has certain limitations. Particularly, during data collection, we have not fully ensured user security and confidentiality. In future work, we will consider ensuring both user security and confidentiality through several methods such as anonymization, secure data storage and communication, and ensuring ethical standards and procedures for research.

Beyond serious gaming, the proposed smart ring gesture recognition system holds potential for other applications. Drawing insights from [16], where nine participants aged between 61 and 69 (M = 64, SD = 2.8 years) reported their preferences regarding the devices and systems they would like to control during daily activities (*e.g.*, home appliances, such as vacuum cleaner, TV, or intercom), we predict more implementation possibilities for the proposed smart ring gesture recognition system.

V. CONCLUSIONS

In this paper, we proposed a gesture recognition system using accelerometer raw data collected from a smart ring. The recognition system comprises both training and recognition modules, therefore the system can continuously improve its accuracy and adaptability over time. By extending the gesture vocabulary based on user preferences, the system can support a wide range of serious gaming scenarios, from physical rehabilitation to skill learning.

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