PERACTIV: Personalized Activity Monitoring - Ask My Hands

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Abstract. Medication adherence is a major problem in the healthcare industry: it has a major impact on an individual's health and is a major expense on the healthcare system. We note that much of human activity involves using our hands, often in conjunction with objects. Camera-based wearables for tracking human activities have sparked a lot of attention in the past few years. These technologies have the potential to track human behavior anytime, any place. This paper proposes a paradigm for medication adherence employing innovative wrist-worn camera technology. We discuss how the device was built, various experiments to demonstrate feasibility and how the device could be deployed to detect the micro-activities involved in pill taking so as to ensure medication adherence.

Keywords: Wearables · Wrist-worn camera · Micro-activty detection · Medication adherence · Pill taking

1 Introduction

Human activity recognition has been an active field for more than a decade. Recent advancements in machine learning and deep learning have spurred an explosion in human activity recognition wearable technologies [45]. Wearables have been used in both consumer-facing and non-consumer-facing applications for human activity recognition such as pose estimation, health monitoring, entertainment, fall detection, etc. [2,22]. Capturing human motion provides insights into activities that are being performed.

Humans use their hands to perform a majority of actions and often involve their hands to manipulate different objects and environments. We utilize our hands at a subconscious level, so we don't deliberately reflect on or regulate the movement of our hands. Thus, observing the movement of the wrist, palm, and fingers, and how they manipulate objects in the immediate environment can

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provide information to decipher human activity. In this paper, we introduce a new paradigm for monitoring the movements of palms and fingers, and explore the activity of pill taking in the setting of medication adherence.

Although pill taking is an important daily activity, it has been estimated that only 25% to 50% of patients correctly and consistently take their medications. In the U.S., in the order of 125,000 people die annually from non-adherence to medical prescription [50]. It is estimated that failure to take medicines as prescribed costs the healthcare system about \$100–\$300 billion annually [44]. Aids such as pillboxes marked with the days of the week do help; however, they leave responsibilities to the patient and do not address forgetfulness, incorrect ingestion, dropped or misplaced medication. This paper introduces a method to monitor medication adherence for pills using a wrist-worn camera device.

We structure this paper as follows. Section 2 reviews various exocentric and egocentric camera technologies for human activity recognition and the relevant research in the field of wrist-worn technologies. In Sect. 3, we detail a wrist-worn camera-based wearable technology for human activity understanding and its potential applications. The activity of pill taking and the proposed approach are discussed in Sect. 4. Section 5 provides our conclusions and suggestions for future work.

2 Related Work

2.1 Human Activity Understanding

There has been an increased interest in understanding human behavior using exocentric and egocentric sensors in the recent decade. Conventionally, activity monitoring is done with inertial sensors, such as accelerometers, gyroscopes, magnetometers, etc. These sensors in wearable smart wristbands and smartphones provide a means to keep track of people's daily and fitness activities by auto-logging different activities such as sitting, standing, lying down, climbing floors, cycling, running, swimming, walking, jogging, or the like. Although these inertial sensors can observe simple activities of daily living, they do not measure all aspects of motion that are important to understanding the behavior of humans. For example, traditional human activity monitoring systems may use accelerometers solely to capture movement and posture changes. Still, they do not account for body orientation changes, environmental information, and nearby objects, which substantially impact the body motion; also, inertial sensors are subjected to erroneous data. Substantial integration drift due to the errors such as time-variant sensor biases and measurement noise [30].

Understanding the finer details of human motion in certain activities such as manipulating objects, daily living activities, and sports could improve human activity recognition. The need to deeply understand human behavior has prompted the move to camera-based technologies and traditional vision-based approaches. Human action recognition using temporal images was first introduced in Yamato et al. [46]. The primary goal is to analyze a video to identify the actions taking place. Traditional approaches to action recognition rely on object detection, pose detection, dense trajectories, or structural information. In the last ten years, significant progress has been made in deep learning-based computer vision approaches for monitoring the physical and physiological aspects of human activities to better understand tasks we perform. Camera-based technologies can be broken down into two classes, *exocentric* and *egocentric*, characterized by their viewpoints. In exocentric, viewpoints (third-person view) of both the subject and the actions are captured. In egocentric, (first-person view) the camera is placed on the subject with only parts of their anatomy being visible [1].

An extensively studied example of the exocentric class is "fall detection" for seniors wherein different camera-based devices such as Microsoft Kinect [4,37,48], RGB [17,49], 3D cameras [23,38], and thermal cameras [36] have been investigated. A second example is the use of motion sensing input devices such as the Microsoft Kinect, Playstation II Eyetoy, and Nintendo Wii in applications such as VirtualGym [19], and other Exergames [10,35,47] to motivate physical activity among seniors and promote a non-sedentary lifestyle.

Egocentric or body-mounted video cameras come in different flavors and support the monitoring of varying activity. Head-mounted cameras have been proposed for finding missing objects [41], and when mounted on glasses, for hand segmentation [3]. Body-mounted cameras have been used for lifelogging [7], for location detection [13], for gait analysis when worn on shoes, obstacle detection, and context recognition [20].

We are particularly interested in exploiting wrist-mounted cameras which focus on the fingers and hands. We use our hands, in particular, to touch, displace, hold onto and manipulate objects as we perform different activities. Our hands are continuously moving; therefore, monitoring the hand movements and interactions of the hand with other objects in the environment is vital for understanding how different actions are performed.

Hand Pose estimation is the process of predicting the position of the hand and different joints in a 3D space and has become an important area of study with the emergence of Virtual Reality, Mixed Reality, and Augmented Reality [6].

Digits [14] is a wrist-worn sensor that uses an Infrared line projector and Infrared camera to understand the 3D pose of the hand with the help of kinematic models in eyes-free interaction with mobile devices and gaming. Finger occlusions and rapid motions still pose significant challenges to the accuracy of such methods [11].

The first mention of a wrist-worn camera technology to identify gestures was in [43], where a video camera was worn on the ventral side of the wrist to observe discrete changes in movements of three fingers from a rest position. Other researchers have implemented similar wrist-worn cameras for keystroke detection [39], and activity detection [26]. WristCam [43] uses a video camera worn on the ventral side that is used to observe discrete changes in movements of three fingers from a rest position to identify seven variations of the finger gestures and one rest position. Keystroke detection was performed using a very similar setup by

[18]. WristSense [26] is a wrist-worn device equipped with an accelerometer, microphones, and a camera. The sensor data is sent to a Bluetooth-enabled smartphone. Traceband [16] uses a wist-worn camera with proximity sensors to find missing items. The camera captures frames for 5 s at up to 10 frames per second. This paper aims to solve the problem of locating daily used objects in both young and the elderly due to absentmindedness or perceptual issues.

3 Wrist-Camera Technology

We propose PERACTIV - **Per**sonalized **Activ**ity Monitoring, a wrist-worn lightweight, low-cost, scalable, unobtrusive, and easy-to-use wearable technology that tracks the movements of the hand and fingers and generates a video stream of the activities performed and the immediate environment. In the simplest embodiment, this wearable device comprises a printed circuit board, camera, housing, and wrist cuff as seen in Fig. 1.

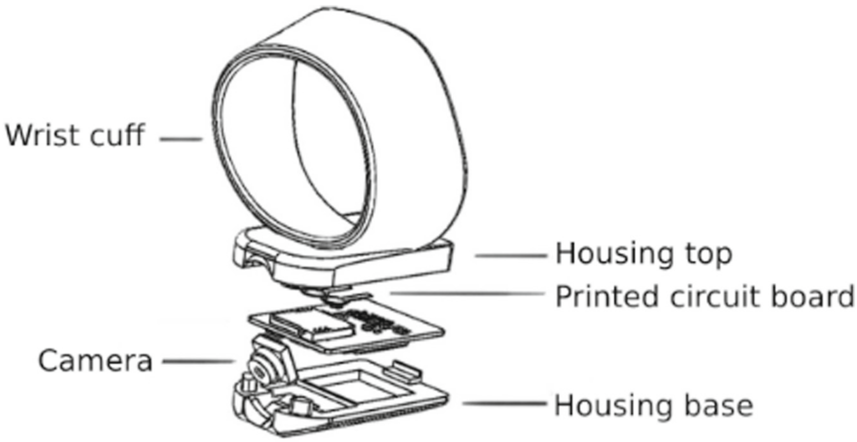

Fig. 1. PERACTIV device.

Figure 2 depicts the wrist-mounted vision-based device with a camera aimed at the user's hand and fingers (hand-centric view) to capture the user's nuanced interactions with their surroundings. The ventral side of the wrist is an ideal location for this wearable camera because it provides a detailed view of the palm and fingers, which we use for fine interactions with different objects. This location effectively captures the panoramic views of the locale along with the fingers and palm. Wrist-mounted cameras provide the ability to more consistently observe movements of the hand and its interactions while not having to detect and track the hands [9].

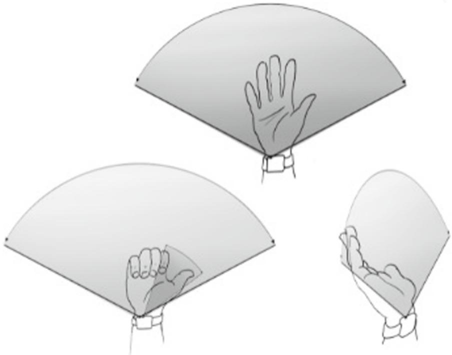

Fig. 2. Illustration of the wrist-worn device's placement and the field of views from different viewpoints.

3.1 Design

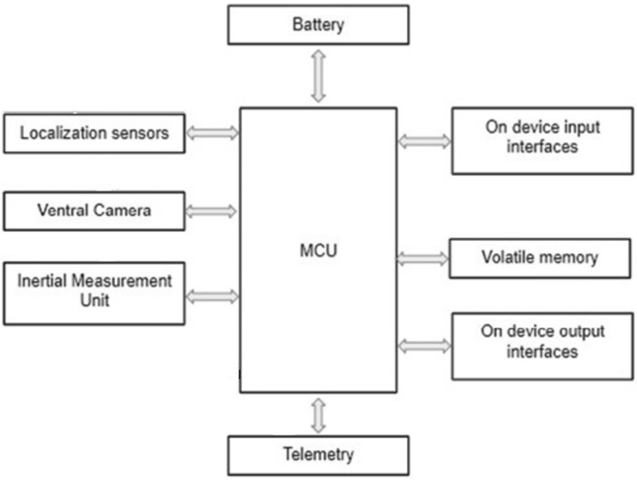

Fig. 3. Structural components of the PERACTIV device.

The structural components of the wrist-worn device are comprised of a micro-controller unit, various sensory modules such as the camera, IMU, etc., along with other essential components such as a battery, memory, on-board storage, expandable storage, and telemetry in terms of WiFi and Bluetooth adapters. This can be seen the Fig. 3. The current iteration of the device is built using a Raspberry Pi Zero W kit, a Raspberry Pi Camera Module, an MPU-9250, and a battery.

The micro-controller unit handles on-device user interactions through the on-board input and output interfaces. It connects to all the sensory modules and communicates with a mobile application executable by a mobile phone or other mobile devices through the telemetry unit.

The device tracks the movements of the wrist, hands, and fingers while also producing a video feed of the hand and fingers as well as their immediate surroundings. The wrist-worn camera device can be equipped with Near-Field Communication (NFC), Bluetooth beacons, GPS, pressure sensors, and many other sensors to increase functionality and use cases.

The final product, as illustrated in Fig. 4 would be part of a smartwatch which includes a miniature camera on the ventral side embedded into the wrist strap. This smart device can be used to monitor and track the environment and the movements of the palm and fingers during object interactions.

Fig. 4. PERACTIV device as a Smartwatch.

3.2 Experiments

Different experiments and literature have supported and helped our design process immensely. We developed multiple prototypes for testing the most simple and useful configuration of the device, as seen in Fig. 5. These experiments have helped to identify the possible placement of the camera on the wrist, the angle, and the type of camera used.

Fig. 5. An array of PERACTIV prototypes.

Ventral and Dorsal Placement of Wrist Ccamera: The goal of this experiment is to find the best possible placement of the camera on the wrist that is completely unobtrusive, and does not interfere in any way with the movements of the hands and fingers but also gives a clear view of the interactions of the hands within the environment. From this experiment, we learned that cameras placed on the ventral and dorsal sides of the wrist, as seen in Fig. 6, are the two best locations.

Fig. 6. Camera placed on both Ventral (left) and Dorsal (right) side of the wrist.

The immediate surroundings are captured by one video camera on the dorsal side of the wrist, while the fingers, hand, and object of interest are captured by the second video camera on the ventral side of the wrist. For most cases, the ventral side of the wrist is an ideal location for a wearable camera because it provides a thorough view of the palm and fingers, which we employ for fine object contact.

Understanding Different Motions of the Wrist: The wrist's normal functional range of motion has to be tested with the device. The range of motions from the wrist for wrist flexion to extension are between 38° and 40°; wrist radial and ulnar deviation is between 28° and 38°; and forearm pronation and supination is between 13° and 53° [31].

These movements in Fig. 7 were verified with different participants. The participants identified no discomfort in the actions performed, and the device was able to capture the motion performed.

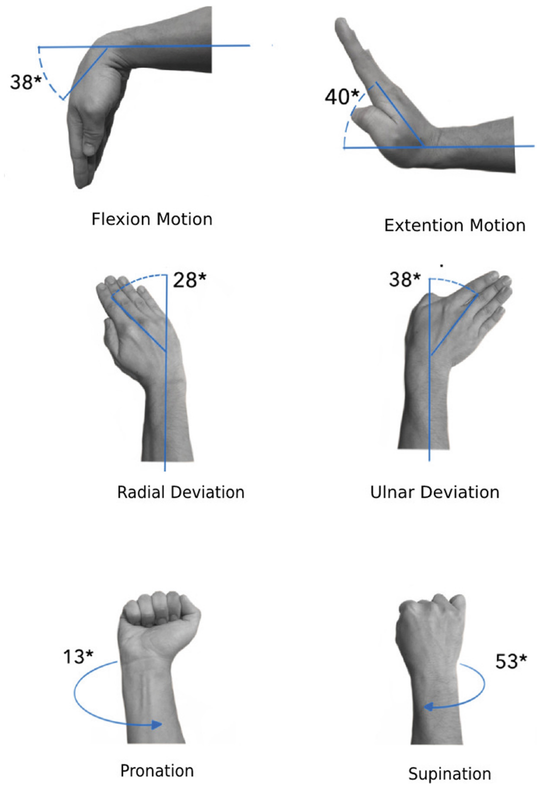

Fig. 7. Wrist motions.

Understanding Interactions with Different Kinds of Objects: Hands are often in motion; however, we are only interested in a subset of these motions that are relevant to the action of interest. Reaching towards an object is a basic motion that all people perform. Typically, depending on the object of interest, an individual makes these motions in a stereotypical manner; for example, little objects such as pills are pinched between the thumb and index, whereas large objects such as a set of keys utilize both the palms and fingers as seen in Fig. 8.

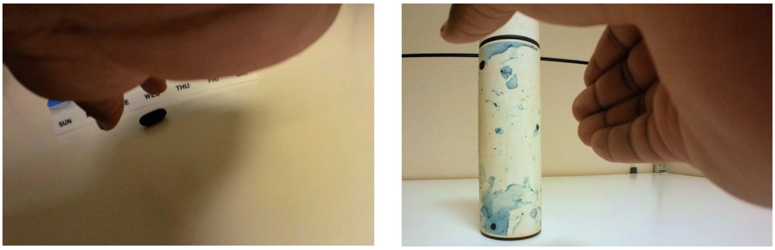

Fig. 8. The hand approaching a tiny object (left) and approaching a large object (right).

The fingers take varied positions when the hand contacts, grasps, displaces, or manipulates an object. The pattern of hand position and motion is determined by the object, and it varies from person to person. We tested the device with participants holding different objects to understand the various grasps as mentioned in [5]: Cylindrical grasp, Tip grasp, Hook or Snap grasp, Palmar grasp, Spherical and Lateral grasp.

Along with exploring the different grasps, we wanted to understand the activities performed. This study was then extended to investigate grips in sports. Interviews were conducted with Power Lifting, Weight Lifting, Rock Climbing, Boxing, Golf, and Lacrosse athletes and sports professionals. This provided us with a comprehensive insight into different holds and grips in sports. Especially in rock climbing, there exist different types of grips for each type of rock. These include the jug, sloper, undercut, crimp, and pinch. Capturing and identifying these grips is a difficult task, but the device is capable of capturing grasps from simple everyday tasks.

Understanding Occlusion by Palm and Visibility of Fingers: A silhouette study was performed to understand the occlusion caused by the Thenar and Hypothenar eminences of the hand. The results from this study, as seen in Fig. 9, helped us understand that sometimes the view of the fingers is occluded by the eminences. Following this study, we also moved the camera away from the wrist and pointed it towards the thumb and index finger to improve visibility and reduce occlusion.

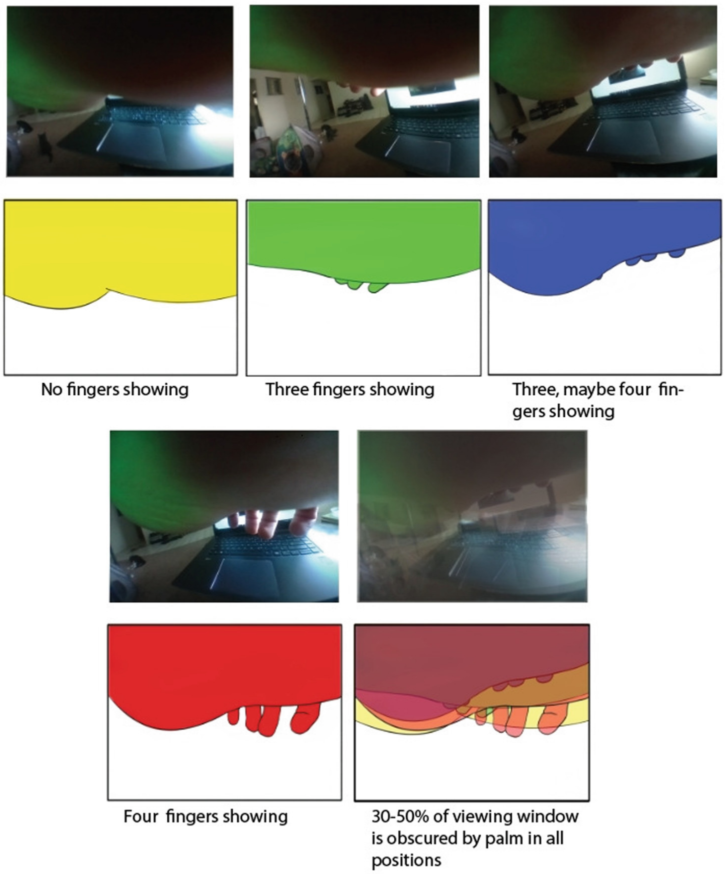

Fig. 9. Visibility of the fingers while approaching objects under obstruction from thenar and hypothenar eminences.

3.3 Applications

Based on all our experiments and interviews, we have identified various applications for this device. The wide array of sensors on the device can be used with various applications such as tracking everyday objects, health and fitness tracking, elderly care, aids for the vision-impaired, gesture-based interfaces, sports, education, and Virtual Reality, Mixed Reality, and Augmented Reality gaming. The device can leverage modern machine learning and deep learning techniques for objects, locales, and activities identification. The technology has significant potential to lead to a new class of products and associated services centered on monitoring human activity associated with the hand. A wide array of additional sensors such as NFC readers can be added to the device to improve the functionality in various applications.

In Elderly Care, which is the focus of this paper, the system could be trained and customized using show and tell techniques to track personal items such as pills, keys, glasses, credit cards, etc. This can also be extended as a stand-alone device for individuals to track daily objects and monitor day-to-day activities. With voice or playback on a display device, an interactive Q&A system can then respond helpfully to a variety of user questions such as, "Where did I leave my glasses?" and "Did I take my medication this morning?". This can also be expanded to missing object detection and pill detection for medication adherence, as seen in Figs. 10 and 11, respectively.

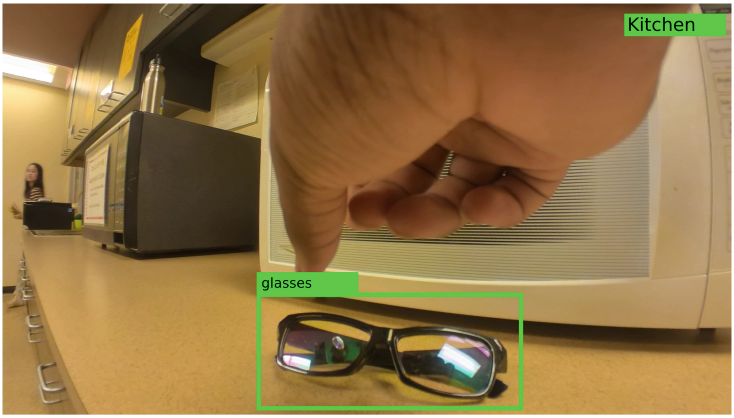

Fig. 10. Missing object identification and localization.

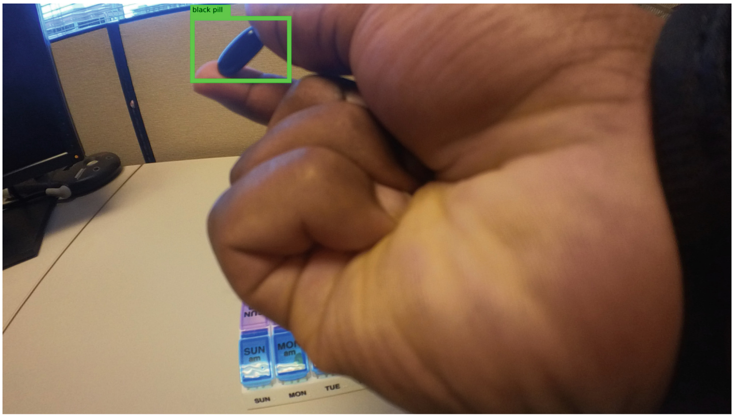

Fig. 11. Pill detection.

4 Pill Taking Activity

As previously discussed, failure to take prescribed medications is anticipated to cost the healthcare system between \$100 and \$300 billion each year [44]. Many studies have been performed to try and reduce the medication non-adherence issue. Some studies involve drug therapy education alone; however, the efficacy and effectiveness of education alone on a long-term basis is poor [12]. Automated pill dispensing systems such as Philips Lifeline Medication Dispenser [25], Hero [21], Pria [34], MedaCube [28], e-Pill MedSmart Voice [29] are programmable devices used to dispense the right pills, determine the right pill amount and at the right time. However, these are quite costly, difficult to use, immobile [15], and often prone to mechanical failures [42]. They also do not ensure the pill has been ingested. The medication can be dropped or misplaced after it has been dispensed. Using the PERACTIV device, we investigated the activity of pill-taking to better understand the process, its hurdles, pain points, and worries individuals have with pill taking. To interpret human action involving hands and objects, we must simultaneously monitor the hand and its surroundings.

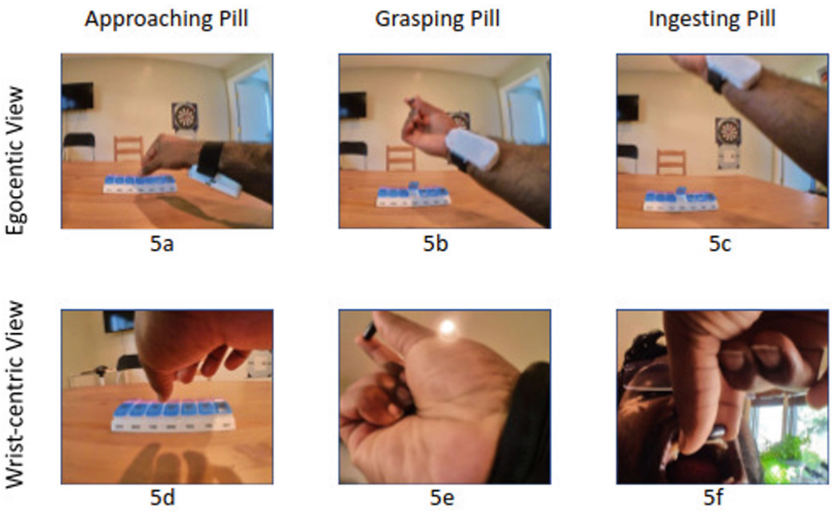

Fig. 12. Comparing egocentric and wrist-centric view for pill taking.

Research in computer vision for predicting and detecting human activities has been carried out using exocentric views (cameras placed within the environment) [27] or egocentric views (cameras placed on the body) [33]. This device provides a new paradigm with wrist-centric views. We use the videos of patients taking medication using a wrist-worn camera put on the dominant hand. The dataset is comprised of videos with successful and unsuccessful attempts for the activity of pill taking.

As seen in Fig. 12, the wrist-centric placement enables a clearer view of the movement of the fingers (i.e., opening, closing, manipulating) and their interactions with the medication as compared to an egocentric view. The pill is always visible and can be tracked until it reaches the mouth. This ensures detection of weather the medication has been successfully ingested, and also, the reason why the medication may not be ingested.

The occlusion of objects due to the user's hands and fingers makes object detection a difficult task in various contexts and environments despite advances in object detection algorithms and techniques using the wrist-mounted camera technology [32]. In many cases, we see that the fingers may completely or partially enclose the object, causing complete object occlusion or providing only partial views of an object. In Fig. 13, we can see the pill is completely occluded by the fingers. A fine-grained pill-taking analysis is a challenging task since people have different styles and ways of taking medication, different pillboxes, different medications, and also, different situations such as standing, sitting, indoors, and outdoors with different lighting.

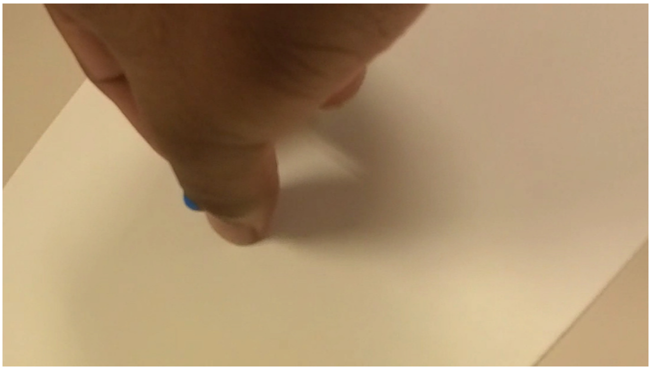

Fig. 13. Finger occlusion.

Our approach is based on insights into how individuals grasp objects. The visual system's task is to find and identify the object and then guide the hand in its approach to the object subconsciously. From a behavioral point of view, i.e., as it appears to the outside observer, the hand moves autonomously without any mental effort towards the object and changes its pose as it approaches the object. When it is within touching distance, the fingers and the hand have assume a pose, ready to grasp the object, where fine control depends upon one's sense of touch. We propose a model involving the identification of finer activities, in which the movement and actions are broken down into manageable granular actions, which we call micro-activities.

In the case of pill-taking, one possible decomposition is: (i) moving towards a pill, (ii) grasping the pill, (iii) moving with the pill in hand and, finally, (iv) releasing the pill into the open mouth. If these micro-activities are identified with high confidence levels, then we may conclude that the individual has successfully completed the process of taking the pill. An example of successful completion of the pill-taking activity is shown in Fig. 14.

This approach will not only help to identify success or failure in taking medication, but will also identify the fault or reason for failing in the activity of pill taking. These may include situations where the pillbox may contain incorrect pills, the individual might drop a pill, the individual might interrupt the process to take food or a drink, etc.

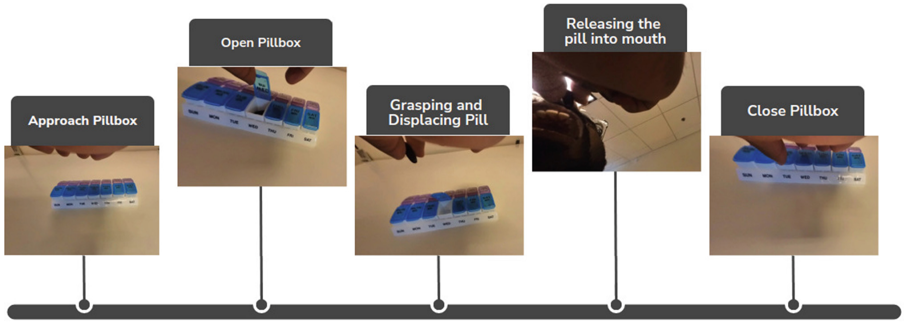

Fig. 14. Micro-activities involved in taking medication captured by the PERACTIV device.

We propose to apply deep neural network models to detect these micro-activities. Standard Convolution Neural Networks (CNN) treat frames independently by extracting features from single images and might miss temporal and Spatio-temporal dependencies. Deep neural networks using spatio-temporal filtering approaches such as 3DCNNs [40] and TwoStream-Inflated 3DCNNs [8] capture temporal information and can be trained to detect micro-activities. We propose to develop a probabilistic inference model that can string together the detected micro-activities to infer the success or failure of pill taking.

The micro-activities, as seen in Fig. 14, can have different lengths, spatial and temporal dependencies, and object interactions. In the instance of pill-taking, these may be the use of different pills and pillboxes, different styles of taking a pill, e.g., use of the fingers to pickup the pill or use of the palm, on the other hand, to place the pill, pill taking while sitting or standing, and in different environments such as indoors or outdoors. A common neural network model will to incapable of detecting micro-activities of all the users. We intend to train a base model with data from all the users and apply transfer learning to adapt a base model to the data of each user to create a customized pill activity recognition system for every user.

5 Conclusion

Medical adherence is very complicated; through our interviews and background research, we have identified the different ways and settings that medication can be administered. Medication may be administered orally as liquids, pills, tablets, or chewable tablets, by injection into a vein, sprayed into the nose, applied to the skin, and many more. To add to the complexity, the medication can be taken while standing or sitting, using various pillboxes, in different locations and lighting conditions, and the arm, hand and fingers movements vary significantly from person to person.

The fine-grained pill-taking analysis is a challenging task. Based on our findings, we plan to collect and publish a wrist-worn camera dataset for the activity of pill taking involving various scenarios and styles, examine how we can enhance the activity of pill taking by augmenting the data through adding additional variations to the data, and work on identifying algorithms for this data.

The proposed research aims to help individuals with varying cognitive deficits living alone or in nursing homes. The results of this research will also enhance our understanding of both the utility and impact of intelligent, wrist-centric wrist wearables on senior activities of daily living, quality of life, and independence.

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