Activity Classification in Independent Living Environment with JINS MEME Eyewear

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***Abstract* — The number of older adults relative to the total world population is rising rapidly, resulting in an increased burden on the healthcare system. Older adults with complex needs are often limited in their ability to perform basic daily activities, and may require task-specific supports. Continuous health-monitoring systems have the potential to enhance one's quality of life and help older adults live safely in their homes. The ability to recognize people's activities in their homes can potentially enable context-specific and timely involvement of automated assisted living systems, caretakers and clinicians, who can take provide suitable adaptive care. With the advent of miniaturized sensing technology, which can be wearable, it is now possible to collect and store data on different aspects of human movement under realistic independent living conditions.**

In our most recent Smart Condo™ study, twenty-six participants were recruited to spend one two-hour session in the one-bedroom living environment, either alone or in pairs, and to perform a scripted protocol of activities of daily living. Twelve of these participants were asked to wear JINS MEME, a commercial smart eyewear device, which collected electrooculography, accelerometer and gyroscope data throughout their sessions. In this paper, we describe our method for offline classification of the participants' activities based on the collected data. We show that this method yields equal or better results with more diverse activities than other approaches involving multiple wearable devices, more restrictive wearable devices or a combination of wearable devices and environment-based sensors. The results demonstrate the suitability of JINS MEME for recognition of activities of daily living and identify some limitations associated with the current model of the device.

I. Introduction

Due to rising life expectancy and declining fertility rates in many countries, the population of older adults relative to the total population is increasing rapidly. The number of people aged 65 years and over in the world is expected to rise from 602 million in 2015 to 1.51 billion in 2050 [1]. Placement in a care facility, especially when it occurs against an individual's wishes, has been associated with negative effects such as depression, social isolation, and greater dependency on others for self-care tasks [2]. Older adults typically prefer to stay in their homes rather than enter a healthcare institution, even when they need specialized care. For example, in a survey undertaken in the United States, 30% of those over 65 years stated they would "rather die" than enter a nursing home [2].

This rise in the population of older adults has also led to an increased burden on the healthcare system, as the health of elderly persons deteriorates with age. In the United States, the prevalence of multiple chronic conditions in older adults exceeds 60%. According to the American Geriatrics Society, complex needs are chronic conditions that frequently require services from different healthcare practitioners in multiple settings including frequent hospitalizations [3]. Older adults with complex needs are often limited in their ability to perform basic daily activities, due to physical, mental and psychosocial challenges requiring complex continuing care [4]. Continuous health monitoring systems, such as those found in smart home environments, can enable older adults to live independently at home longer and reduce their reliance on caregivers, and can support caregivers to provide better care. These technologies have the potential to provide a cost-efficient approach to enhance one's quality of life and help older adults live safely in their homes [4]. The recognition and classification of activities of daily living can provide an important context for caretakers, clinicians and assisted living systems to plan suitable methods of providing adaptive care.

With the advent of miniaturized sensing technology, which can be wearable, it is now possible to collect and store data on different aspects of a person's movement [5]. This technology has the potential to be used in automated activity profiling systems, which can produce a continuous record of activity patterns over extended periods of time. Such activity profiling systems rely on classification algorithms for effectively interpreting the data emitted from wearable sensors to identify different activities [5]. The vast majority of activity classification systems have used inertial sensors such as accelerometers and gyroscopes [5]. Activity classification has also been performed using with electrooculography (EOG) sensors [6]. Inertial sensors are also often used in combination with external sensors placed in a smart home environment [7, 8] or with other wearable sensors [9, 10, 11, 12] in order to recognize a greater diversity of activities.

The Smart Condo™ is a smart home environment at the University of Alberta, conceived as a space for conducting research and training professionals on how to support older adults, including those with physical and cognitive disabilities, to live independently longer [13]. JINS MEME is an eyewear device that hides sensors – three EOG electrodes, an accelerometer and a gyroscope – in the form of traditional eyeglasses, used and marketed as a tool in a variety of applications from fitness tracking, to monitoring of alertness while working or driving. The device is designed to be cosmetically suitable and non-restrictive to the user's activities [14]. The device transmits data to a computer wirelessly via Bluetooth.

In this paper, we use data from the JINS MEME to classify the activities of twelve healthy participants. Each of these participants wore the JINS MEME glasses and performed a protocol of activities of daily living in the the Smart Condo™. Video footage collected through cameras installed on the ceiling of the condo was used to determine the ground truth. Machine-learning algorithms were used to classify participant activities using this data.

This study aims to develop a method of accurately classifying activities of daily living that is practical to set up and non-restrictive to the user's movements and social interactions. The study investigates the benefits and limitations of using the JINS MEME glasses for activity recognition, and identifies techniques and practices in signal processing and machine learning that are most suitable for activity classification using data from this device. This work makes the following contributions.

1. We examine the use of the sensors embedded within JINS MEME as a source of data to be used in the classification of activities of daily living. We show that this data can be used to accurately classify motion-based and visual-based activities.
2. We develop a method for calculating information about eye and head movements, in addition to basic characteristics of EOG and motion signals, to be used as attributes in the classification process.
3. We demonstrate techniques for mitigating the problem of imbalanced classes, often associated with activity recognition in daily living [15].

The remainder of this paper is organized as follows. In Section II, related work concerning the JINS MEME device and activity recognition with wearable sensors is summarized. In Section III, we outline the methods of data collection and signal processing, and discuss the limitations of the device. In Section IV, we summarize the process of activity classification and determine the effectiveness of pre-processing techniques. In Section IV, we present our results and compare them to the results of other literature Section V concludes the paper and discusses future work.

II. Related Work

The development of wearable and nearable technology to sense physiological signals has made it possible to collect and store information on different aspects of a person's movement and activity throughout the day [5]. These sensor devices have provided an opportunity for researchers to conduct studies that are more reflective of real word applications compared to studies conducted in highly controlled environments.

Researchers have investigated the use of wearable sensors in combination with environment-based sensors for activity classification. In contrast to single-sensor systems, using wearable inertial sensors to collect information about a person's behaviour, in combination with sensors embedded into a living environment to collect information about a person's location [7] or their use of specific objects [8], allows researchers to improve the detection of behavioural changes.

The effectiveness of wearable sensors in collecting data for activity classification has also been studied by using wearable sensors in combination with other wearable sensors. While this use of additional wearable sensors has been used to increase the accuracy of inertial sensors in collecting data for classifying postures and motion-based activities [9, 10], studies have also combined sensors the with the aim of classifying a more diverse variety of activities of daily living [11, 12]. The use of multiple sensors embedded within a wrist-worn device similar to a watch has been proposed with the goal of increasing user acceptance [10, 11].

Studies have also proposed the use of inertial sensors embedded within smartphones for activity classification systems. It has been suggested that their widespread usage, long battery life and non-obstructive nature will lead to increased acceptance among potential users [16, 17]. Past research has achieved high accuracy in the classification of motion-based activities using smartphones placed in the user's hand [16], pocket [16, 17] and belt case [18]. A drawback of activity classification systems that use sensors within smartphones is that they are limited to situations where the smartphone remains in the same position relative to the user [19].

Although the vast majority of activity classification systems have used inertial sensors such as accelerometers and gyroscopes [5], studies have also proposed the use of wearable devices with an infrared proximity sensor [20] and EOG [6] to address the limitation of inertial sensors to detecting motion-based activities and the limitation of environment-based sensors to detecting location and basic activities. These sensors detect information on blinks to be used in the classification of visual-based activities like reading, writing and watching videos rather than motion-based activities. While the infrared proximity sensor allows the detection of blink rate, EOG allows additional information to be drawn from eye movements including the duration and amplitude of blinks [6].

The present study proposes the use of JINS MEME, an eyewear device with inertial sensors and electrodes that detect EOG. This combination of sensors will collect information that could allow for the detection of a variety of motion-based *and* visual-based activities of daily living. The sensors are embedded within a traditional glasses frame that can be outfitted with prescription lenses, thereby increasing the chance of user acceptance among elderly individuals who are likely to already require corrective eyewear. The device also has the advantage of remaining in the same position relative to the user, since glasses are typically only worn in one manner. Previous research has used JINS MEME eyewear to accurately classify visual-based tasks [21], drowsiness state during driving [22] and control mode according to Hollnagel dynamic cognition model [23].

Activity profiling systems are also dependent on classification algorithms to interpret data from wearable sensor data and identify different activities [5]. Past research has performed activity classification using support vector machine (SVM) [6, 7, 11, 16, 18], decision tree [8, 9, 10, 16, 18], K-nearest neighbour [12, 16, 17, 18, 19], C4.5 [12, 20] and Naïve Bayes [16] algorithms.

III. Experimental Design, Data Collection and Signal Processing

Twenty-six participants were recruited to spend one two-hour shift, either alone or in pairs (7 pairs), in the Smart Condo™. The participants were asked to follow a scripted sequence of activities, i.e., an activity protocol. Video footage was used to determine the ground truth of participant activities.

Twelve of these participants wore the JINS MEME eyewear. In this paper, we investigate the use of the data collected from the EOG and inertial sensors in the JINS MEME glasses for the classification of activities of daily living.

A. The Activities

Within the broad goal of supporting older individuals to live independently longer, this study aims to classify a range of activities of daily living (ADLs) associated with independent living. Similarly to [11], we define two main types of ADLs.

Basic ADLs (BADLs) are activities which are necessary for self-care, while instrumental ADLs (IADLs) are activities that require slightly more complex skills and are important for independent living.

The Barthel Index [24] is a scale used in standard practice to measure performance in BADLs and ability to live independently. The Barthel Index uses ten variables to describe activities and mobility. Our activity protocol includes six out of the ten variables included in the Barthel Index: bathing, dressing, feeding, grooming, toilet use and walking. Wheelchair transfer, bowel control and bladder control were excluded because this study included healthy participants only. Stair ascension and descension were also excluded because the Smart Condo™ includes only one floor. IADLs include cooking, exercise/stretching, low and high intensity housework, typing/writing and watching television. In total, twelve ADLs are included in this study. A list of ADLs and their descriptions are shown in Table I.

TABLE I. Activities of daily living included in this study

Activity	**Description**
BADLs (Basic Activities of Daily Living)	
Bathing	Sitting down in the shower and pretending to bathe
Dressing	Donning and doffing clothing
Feeding	Eating food and taking medication
Grooming	Washing hands and using sink
Toilet Use	Sitting down on the toilet, retrieving toilet paper, flushing
Walking	Walking on level floor
IADLs (Instrumental Activities of Daily Living)	
Cooking	Preparing a meal using kitchen appliances
Exercise	Stretching
Housework (Low Intensity)	Setting the table and washing dishes
Housework (High Intensity)	Sweeping with a broom, loading the laundry machine and ironing
Typing/Writing	Using a tablet to type and play games
Watching TV	Sitting down and watching TV

The activity protocol was designed to simulate typical daily-living activities. Therefore, the tasks were performed for realistic amounts of time rather than equal amounts of time. Participants performed these tasks while wearing the JINS MEME eyewear. No participant-specific calibration or adjustments were made to the device.

B. Sensor-Data Collection

The JINS MEME eyewear collects EOG and motion data at 100 Hz, which it transmits via Bluetooth to a nearly computer. Three dry electrodes housed within the bridge and nosepads of the glasses collect EOG signals in the horizontal and vertical dimensions. An accelerometer and a gyroscope, housed within one of the arms of the glasses, collect motion data. Figure 1 shows an image of the JINS MEME eyewear.

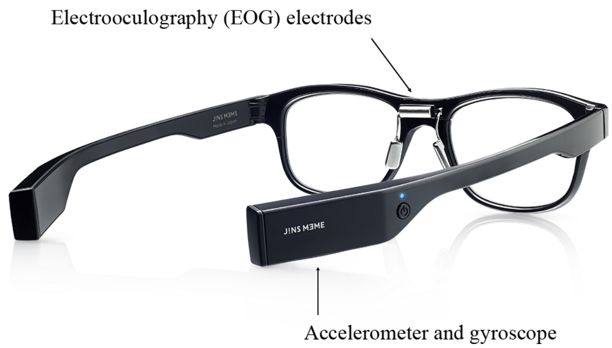

Fig. 1. The JINS MEME eyewear and embedded sensors [25]

Because only three electrodes are used, rather than the more conventional use of five electrodes, the EOG signal is calculated in a bipolar method rather than a monopolar method [14]. This means that the signal collected represents the velocity of eye movements rather than eye position.

While JINS MEME includes an accelerometer and gyroscope, it does not include a magnetometer. This means that the angular position of the inertial sensor along the user's Euler angles cannot be determined without drift about the longitudinal axis. Instead, the angular velocity of the inertial sensor along the user's Euler angles is determined, by combining the accelerometer and gyroscope data and correcting for an offset of the sensor position relative to the head position of the user.

The Smart Condo™ includes multiple video cameras that record footage simultaneously. This video footage was used to determine the ground truth of participant activities to synchronize with the data.

C. Attribute Extraction

The data collected from JINS MEME is emitted to a collecting computer in the main room of the Smart Condo™, including a timestamp for each data point. This timestamp was used to synchronize the data with the video collected from the Smart Condo™ since it was found that certain activities and certain locations in the condo caused the device to temporarily lose connection with the computer receiving the data, resulting in periods of data outage.

The raw sensor data was analyzed to extract signal attributes. To calculate these attributes over the time-dependent signal, the incoming data is sliced into windows; the data in each window is analyzed as a unit, and one set of attributes is computed corresponding to each analysis window.

Previous research has found that a window length of 5.6 seconds is most appropriate for activity recognition in living environments, as it is either optimal or near optimal for many attributes, and also allows for posture recognition [26]. Furthermore, for potential automated applications in real-time, a window length of 5.6 seconds is also short enough to enable timely intervention, since a potentially risky activity would be recognized almost as soon as it occurs and the decision to intervene is triggered. The same research also conceded that a disadvantage of such a short analysis window is lower performance on activities with high motion variability, since these activities can be performed in different ways depending on the situation [26]. Previous research has found that overlapping the windows is important in order to handle transitions more accurately [29].

In our study, we have adopted an analysis window of 5.6 seconds and a sliding increment of 1 second for an overlap of 4.6 seconds. As we have already discussed, data outages occurred when the subject was further away for the receiving computer. These outages caused some analysis windows to contain less than the anticipated 560 data points (5.6 seconds of data at 100 Hz). Windows with at least 60% of this number (336 data points) underwent an initial ***interpolation*** step to bring their number of data points to the expected 560 before attributes were extracted from the data within those windows.

D. Signal Characteristic Attributes

The attributes calculated in this study include characteristics of the raw signal, emitted by the JINS device, identified by previous research on activity classification using accelerometers [26]. Attributes were calculated in both the time domain and the frequency domain: previous research using accelerometer data has identified a relationship between the mean of the accelerometer signal in the time domain and the subject's movement intensity [27], while activities with a similar energy intensity can be identified in the frequency domain by the period of the accelerometer signal [28]. While [26] only extracted this set attributes from the three axes of accelerometer data, we extracted these attributes from (a) accelerometer data, (b) three Euler angles of the angular-velocity data, calculated as discussed above, and (c) three dimensions of EOG data (vertical, horizontal, reference).

Low-pass filters and bandpass filters were used in the calculation of many of these signal characteristic attributes. A ***low-pass filter*** was used to eliminate most of the signal noise generated by dynamic human motion while preserving the information generated by static human motion or posture information [26]. A ***bandpass filter*** was applied to eliminate the static signal components containing reference information related to posture about the orientation of the sensor [26].

E. Higher Order Attributes

In addition to the above attributes calculated from signal characteristics, we also analyzed the JINS signal to extract higher-order attributes, related to blinks, horizontal and vertical saccades, and head movements about Euler angles. A ***moving average*** over a duration of 0.05 seconds was applied to the EOG and head angular-velocity data to remove signal noise and maintain the overall form of physical movements.

Previous research in the identification of eye movements from EOG data used the derivative of the EOG signal to classify the presence of an eye movement as a blink or a saccade [30]. Since the raw data from JINS MEME already represents eye-movement velocity, rather than position as indicated in conventional EOG, the raw EOG signal from JINS MEME may be used in the same manner as the first derivative in [30]. This relationship is clarified in Table II.

TABLE II. EOG SIGNAL FROM JINS MEME AND CONVENTIONAL SETUP

EOG Setup	**Raw Signal**	**First Derivative**
Conventional	Eye position	Eye velocity
JINS MEME	Eye velocity	Eye acceleration

For the initial detection of eye movement, we used the first derivative (eye acceleration) of the EOG signal from JINS MEME rather than the raw signal under the rationale that the difference between steady periods of no eye movement and peaks during eye movement was more pronounced. In the first derivative of the EOG signal, all eye movements are characterized by a local maximum and local minimum. The direction of an eye movement in either the vertical or horizontal dimension can be determined by whether the local maximum leads (positive direction) or lags (negative direction) the local minimum.

Since blinks and upward and downward saccades occur in the same vertical dimension of the EOG signal, there is a need to determine whether an eye movement in this dimension is a blink or a saccade. Eye movements in the horizontal dimension are assumed to be saccades because blinks do not have a significant effect on the signal in this dimension. Blinks typically cause the raw signal to develop local maxima followed immediately by pronounced local minima as shown in Figure 2. Upward saccades cause the raw EOG signal to develop local maxima followed by a gradual decrease to zero, while downward saccades cause the signal to develop local minima followed by a gradual increase to zero as shown in Figure 3.

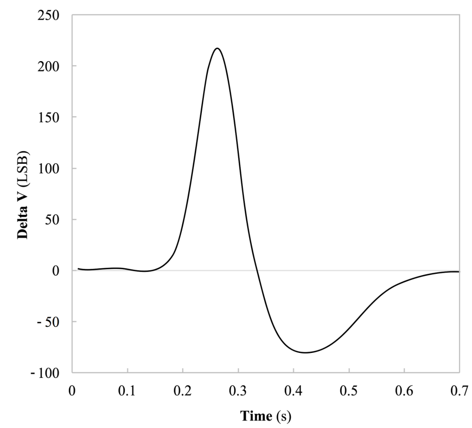

Fig. 2. The effect of a blink on EOG signal in the vertical dimension as detected by JINS MEME.

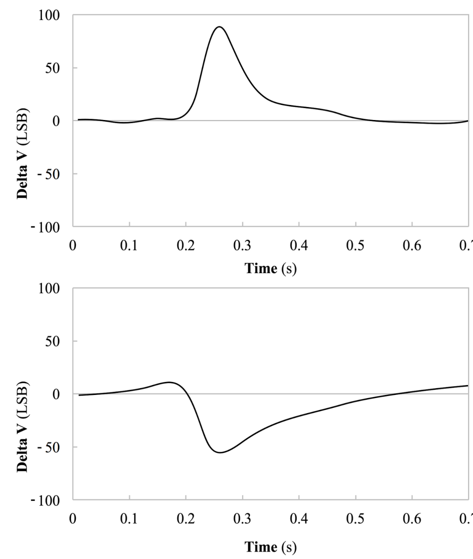

Fig. 3. The effect of an (top) upward and (bottom) downward saccade on EOG signal in the vertical dimension as detected by JINS MEME.

While downward saccades can be identified from the fact that the local minima occur before the local maxima in the derivative of the signal, there remains a need to distinguish between blinks and upward saccades. Reference [30] defined a variable, D_v, to distinguish between blinks and saccades based on the differences in fundamental form of the EOG signal between these eye movements. The calculation for this variable is shown in equation (1).

$$D_v = max - min - | max + min | . \tag{1}$$

Using equation (1) on eye movements detected in the EOG signal, we expect that D_v for blinks would be large due to the somewhat symmetrical form of the signal. D_v for upward saccades would be close to zero as the minimum is much less pronounced, i.e. the value of *min* in equation (1) would be a value close to zero. We determined a threshold of D_v for distinguishing between blinks and upward saccades based on trial tests with the JINS MEME eyewear. Baseline drift and static noise during eye movements was removed by subtracting an offset value from local maxima and minima. The offset value was determined by calculating the mean signal value during the time between 0.07 and 0.02 seconds before the start of the detected movement.

We used a similar approach to detect physical head movements about Euler angles using data calculated from accelerometer and gyroscope signals, as discussed above. The derivative of the signal along each angle was used to detect head movements along that angle and determine the direction of those movements.

The average amplitude, duration, and number of eye movements were calculated for left and right saccades, blinks, and upward and downward saccades. The same properties were calculated for head movements in both directions along each Euler angle. These properties of eye and head movements were used as higher-order attributes for each analysis window. Baseline drift and static noise were eliminated in the calculation of amplitude for eye and head movements as discussed above. Peak-to-peak amplitude was used as the amplitude for blinks.

JINS MEME uses dry electrodes that merely contact the user's skin, rather than conventional gel electrodes that adhere to the skin surface. Because of this, the EOG signal tends to exhibit large peaks during facial movements or adjustments of the eyewear that interfere with this contact. Such peaks are significantly larger than those observed during regular eye movements. We calculated the percentage of time covered by these peaks (when they were above a certain threshold) as a measure of contact interference and included this as an attribute for each analysis window. These peaks were ignored in the detection of eye movements.

IV. Evaluation Methodology

In order to evaluate the usefulness of information extracted above, we used four machine-learning algorithms to learn four classifiers correspondingly based on a subset of our data collected through the JINS MEME eyewear, which we then applied to the remaining data to evaluate the accuracy of each of the classifiers through cross-validation.

A. Class Balancing

Our activity protocol simulates a typical independent living scenario, with some activities (such as typing/writing and exercise/stretching) performed for longer durations than others (such as grooming and toilet use). This difference implies that the classification process must address the class-imbalance problem. This is a phenomenon where uneven instances of classes in training data cause classification results to be less favourable for classes with a smaller number of instances (minority classes). Imbalanced classes can negatively affect the outcomes of activity classification, since many machine-learning algorithms assume a balanced distribution of classes. Due to this assumption, they roughly equate misclassification costs for each class and perform poorly in predicting the minority classes [31, 32]. The implication for our study is that the accuracy of the classifier will be low for activities that occur during a smaller number of analysis windows when included in a data set with other activities that have a far greater number of windows. To mitigate this risk, activities with fewer than 50 analysis windows, i.e., grooming and toilet use, were removed from our evaluation.

For the ten remaining activities, a technique called SMOTE (Synthetic Minority Over-sampling Technique) was used to counteract the class-imbalance problem. SMOTE uses an algorithm to constructs new data based on existing data in order to increase the amount of data in underrepresented minority classes while avoiding overfitting [33]. Similarly to [34], the maximum number of samples generated using SMOTE per class was limited to 1,000 as another caution against overfitting the data.

B. Classification

IBk is a K-nearest neighbor classifier that has been shown to be accurate in activity recognition for ubiquitous sensor environments such as the Smart Condo™ [35]. K-nearest neighbor classifiers have been proven to yield classification accuracies greater than 90% for activity classification [12, 16, 17, 18, 19].

C4.5 is a nonparametric classifier that is efficient in dealing with large, complicated datasets without imposing a complicated parametric structure [36]. This rule-learning scheme induces an initial rule set and then refines it through global optimization where individual rules are discarded. PART is an algorithm that infers rules by repeatedly generating partial C4.5 decision trees and avoids the postprocessing stage that results in slow performance under the C4.5 method [37]. C4.5 classifiers have been shown to yield classification accuracies over 80% for activity classification [12, 20].

Random Forest is a decision tree classifier that requires little data pre-processing without normalization of attributes. This algorithm does not require attribute selection and is resistant to overfitting [9]. Past research using JINS MEME for real-time detection of drowsiness during driving used Random Forest for classification with 80% accuracy [22].

Sequential Minimal Optimization (SMO) is a simple algorithm designed to quickly solve the SVM quadratic programming problem by decomposing it into smaller subproblems [38]. Past research involving the use of wearable sensors for activity classification has suggested that SVM is an accurate classifier [6, 7, 11, 16, 18].

Classification of the activities according to the attributes was performed in Weka using the four classifiers (IBk, PART, Random Forest, and SMO). While 10-fold cross-validation is a standard way of measuring the error rate of a learning scheme on a particular dataset [39], research on the effect of reduction in cross-validation intervals has indicated that decreasing the number of folds to 5 reduces computation time by half with no loss of power [40]. This suggests that performing cross-validation with 5 folds, instead of 10, may allow the classification to be applied to larger data sets. Due to the large amount of data involved in this study, 5-fold cross validation was performed for each participant.

V. Results

A. Classification Accuracy

Of the four algorithms tested, the most accurate classification results were obtained using the Random Forest algorithm. Figure 4 shows the classification accuracy by activity using Random Forest, with and without applying SMOTE.

After using SMOTE to balance the classes, the classification accuracy improved for all of the activities except typing/writing. For most participants, this activity was performed for the longest amount of time and therefore had more analysis windows. The decrease in classification accuracy of typing/writing could be an indication of the elimination of bias in favour of the majority class. It could also be due to slight overfitting of other classes after applying SMOTE.

Table III reports the classification accuracy and precision of each activity in our study. Bathing and dressing, activities that involve a high amount of movement, have the highest classification accuracy. Typing/writing and exercise/stretching, activities that involve considerably less movement, have the lowest classification accuracy. These results may indicate that the proposed method is more effective at detecting motion-based activities than visual-based activities.

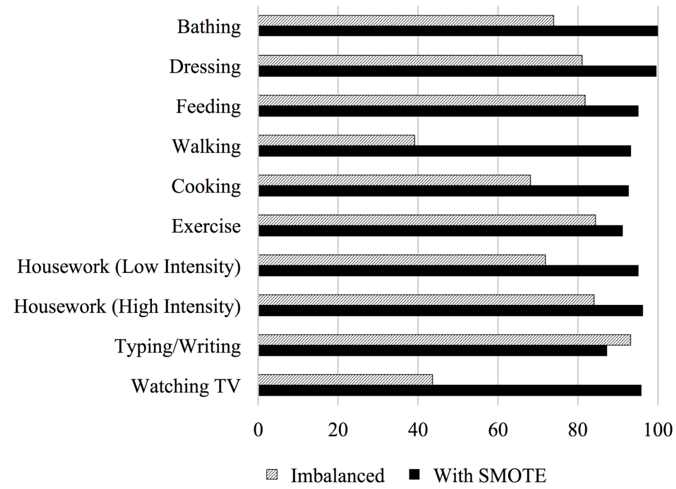

Fig. 4. Effect of SMOTE (Synthetic Minority Over-sampling Technique) on classification accuracy

TABLE III. Accuracy and precision by activity

Activity	**Accuracy (Recall)**	**Precision**
Bathing	100.00%	97.97%
Dressing	99.49%	98.50%
Feeding	95.08%	93.09%
Walking	93.25%	92.79%
Cooking	92.57%	93.49%
Exercise/Stretching	91.17%	90.11%
Housework (Low Intensity)	95.12%	92.15%
Housework (High Intensity)	96.12%	94.73%
Typing/Writing	87.15%	93.97%
Watching TV	95.80%	92.48%
Overall	93.03%	–

Table IV summarizes the overall final results of the present analysis and compares them to the results reported by relevant previous research. Compared to the publications included in the table, our method is able to classify the highest number of activities and maintains a high overall classification rate. These results suggest that the JINS MEME eyewear and Random Forest classifier can be used to reasonably classify activities in independent living environments. The non-obstructive nature and convenient setup of the proposed method may increase user acceptance.

TABLE IV. Accuracy between proposed method and related work

Year: Author(s)	Sensor Type(s) W = Wearable, E = Environment-based	# of Subjects	# of Activities	Types of Activities M = Motion-based, V = Visual-based	Accuracy
2017: Our method	W (Head): Electrooculography, Accelerometer, Gyroscope	12	10	M: Bathing, Dressing, Feeding Walking, Cooking, Exercise, Housework (Low and High Intensity) V: Typing/Writing, Watching TV	**93.03%**
2017: Pavey et al. [9]	W (Wrist): Accelerometer W (Thigh): Accelerometer	21	4	M: Sedentary, Stationary, Walk, Run	90.30%
2014: Ishimaru et al. [20]	W (Head): Accelerometer, Infrared Proximity Sensor	8	5	M: Sawing V: Watching Video, Reading, Solving Puzzle, Talking	82.00%
2013: Chernbumroong et al. [11]	W (Wrist): Accelerometer Gyroscope, Magnetometer, Altimeter, Temperature Sensor	12	9	M: Brush Teeth, Dressing, Feeding, Ironing, Sleeping, Sweeping, Walking, Washing Dishes V: Watching TV	90.23%
2012: Ayu et al. [16]	Smartphone: Accelerometer	1	5	M: Jogging, Jumping, Sitting, Standing, Walking	98.00%
2011: Bulling et al. [6]	W (Body & Head): Electrooculography	8	6	V: Copying Text, Reading, Handwriting, Watching Video, Browsing Internet, Null	70.50%
2010: Das et al. [19]	Smartphone: Accelerometer	1	7	M: Idle, Walking, Running, Jumping, Ascending Stairs, Descending Stairs, Phone Detached	93.00%
2010: Fleury et al. [7]	W (Arm): Accelerometer, Magnetometer E: Infrared Presence Location Sensors, Door Contacts, Temperature Sensors, Hygrometry Sensors, Microphones	1	7	M: Sleeping, Cooking/Eating, Dressing, Resting, Hygiene, Bowel Movement, Communication	86.20%
2010: Lau & David [17]	Smartphone: Accelerometer	1	5	M: Walking, Standing, Sitting, Ascending Stairs, Descending Stairs	99.27%
2010: Hong et al. [8]	W (Arm): Accelerometer W (Waist): Accelerometer W (Leg): Accelerometer E: RFID Sensors	15	10	M: None, Cutting, Brushing Teeth, Taking Picture, Shaking Hands, Wiping with Cloth, Putting on an Umbrella, Jumping Rope, Vacuuming, Pushing Shopping Cart, Applying Skin Conditioner	94.69%
2009: Maguire & Frisby [12]	W (Thigh): Accelerometer, Heart Monitor	6	8	M: Standing, Brushing Teeth, Ascending Stairs, Descending Stairs, Walking, Running, Vacuuming, Situps	90.07%
2009: Prekopcsák et al. [18]	Smartphone: Accelerometer	1	10	M: Walking, Running, Working (Sitting), Cooking, Vacuuming, Stairs, Elevator, Riding Bus, Lying Down V: Watching TV	95.77%
2006: Maurer et al. [10]	W (Wrist): Accelerometer, Temperature Sensor, Light Sensor, Microphone	1	6	M: Running, Walking, Standing, Sitting, Ascending Stairs, Descending Stairs	92.80%

VI. Conclusions

In this paper we report on a study designed to examine the potential of an off-the-shelf eyewear device, JINS MEME, as a means of sensing and accurately recognizing activities of daily living. Wearable sensors are frequently awkward or require a special process to use, which often makes people resist or forget to use them. JINS MEME's convenient packaging of sensors – EOG electrodes, accelerometer and gyroscope – in eyewear, which many older adults already have to wear, can potentially offer a practical method of activity recognition to help older adults living independently longer,

We conducted our study on data collected from twelve healthy adults who performed activities of daily living in the Smart Condo™, an independent living suite, while wearing JINS MEME. Video footage was used to determine when participants performed which activities. A set of attributes – including signal characteristics and higher order properties of blinks, saccades and head movements – was extracted from the collected data, calculated over 5.6-second windows. The resulting data set was further processed to eliminate infrequent classes (i.e., activities) and to balance the number of data points of the remaining imbalanced classes (with SMOTE).

Several machine-learning algorithms were used to classify each participant's activities offline using cross-validation; the Random Forest classifier resulted in the highest classification accuracy. The results indicate the removal of bias in favour of windows with many windows of processed data, but may suggest a slight reversal of this bias in favour of minority classes (activities with many windows of data generated using SMOTE). Data with a more balanced distribution among activities is needed for comparison in order to determine if overfitting occurred or if bias persists.

Overall, our method is capable of classifying the data collected with 93.03% accuracy for ten activities of daily living. These results are comparable to the best results achieved in past research using wearable sensors for activity classification, with the advantage that JINS MEME is non-restrictive to users and does not require calibration.

Admittedly, there are some challenges to using the JINS MEME device. The Bluetooth signal used to transmit data from the device to a computer was much less effective when participants were not in the same room as the computer. This resulted in a loss of data from activities performed in other rooms. A stronger Bluetooth signal would be needed to make this device effective for use in a variety of living environments. As well, the inclusion of an accelerometer and gyroscope without the inclusion of a magnetometer prevents the accurate determination of the angular position of the user's head without drift. The inclusion of a magnetometer would increase the effectiveness of the other inertial sensors.

In the future, we plan to conduct a follow-up experiment, in which we will include training activities where participants perform the protocol activities for short but equal amounts of time. This would mimic the user-specific training that may be necessary for the setup of the proposed method in living environments, remove the problem of imbalanced classes, and allow the proposed method, including the use of SMOTE, to be validated in classifying the protocol activities based on the training data only. Future analysis could also involve experiments for each sensor type in the JINS MEME device (EOG, accelerometer, gyroscope) in order to identify the most effective features for classifying each activity and evaluate the suitability of each of these sensors for activity classification to determine how appropriate the device is for these purposes.

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