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Feasibility Test of Activity Index Summary Metric in Human Hand Activity Recognition*

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Abstract: Activity monitoring is a technique for assessing the physical activity that a person undertakes over some time. Activity Index (AI) is a metric that summarizes the raw measurements from tri-axial accelerometers, often used for measuring physical activity. Our research compared the Activity Index for different activity groups and hand usage [1]. We also tested this metric as a classification feature, and how different data acquisition and segmentation parameter configurations influence classification accuracy. Data acquisition was done with a previously developed system that includes a smartwatch on each wrist and a smartphone placed in the subject's pocket; raw data from smartwatch accelerometers was used for the analysis. We calculated the Activity Index for labeled data segments and used ANOVA1 statistical test with Bonferroni correction. Significant differences were found between cases of hand usage (left, right, none, both). In the next analysis phase, the Activity Index was used as the classification feature with three supervised machine learning algorithms – Support Vector Machine, k-Nearest Neighbors, and Random Forest. The best accuracy (measured by F1 score) of classifying hand usage was achieved by using the Random Forest algorithm, 50 Hz sampling frequency, and a window of 10 s without overlap for AI calculation, and it was 97%. On the other hand, the classification of activity groups had a low accuracy, which indicated that a specific activity group can't be identified by using only one simple feature.

Keywords: Activity index, Accelerometry, Smartwatches, ANOVA1, Classification, Machine learning, Random Forest.

1 Introduction

Activity monitoring is a technique used for the objective and quantitative assessment of the physical activity that the person undertakes over some time. Devices used for activity monitoring are often based on accelerometers which measure the acceleration of the body part to which they are attached.

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Accelerometers are used to infer features about metabolic energy expenditure, movement (such as gait velocity, posture angle, etc.) as well as fall detection in smart systems. For stated purposes, accelerometers sensitive to changes in acceleration due to gravity or body movements are used [2].

Possible health applications of activity monitoring include various types of rehabilitation, fall detection [3], medicine intake tracking [4], providing help to dementia patients [5], as well as tracking the degree to which the upper-limb myoelectric prostheses users use their artificial limb [6]. All these applications require an integrated system to acquire, store, process, and classify the relevant data.

Platforms used for activity monitoring are often structured so that they have two main components: sensors for movement quantification, and mobile or immovable stations that collect and distribute data to the final destination using different communication protocols (Bluetooth, WiFi, ZigBee…) [7].

Smart devices nowadays are convenient to use as a platform for activity tracking since they have great computational abilities, high-speed connectivity, adequate storage, and a variety of sensors for data logging (i.e., accelerometers, gyroscopes, magnetometers).

Smartwatches are comfortable to wear and make continuous data acquisition during a longer period feasible since the inbuilt battery can be periodically recharged [8]. Besides the convenience, smartwatches fulfill the requirement that the activity tracking devices need to be lightweight, unobtrusive, and have a reasonable price [9]. Since smartwatches lack the computational resources for simultaneous data acquisition and processing, a smartphone is needed in every configuration, preferably for data sensing and processing, not only storage [10–11]. Various research in activity recognition has been done using a smartphone, which is usually carried in the pocket, and it has been shown that using a smartphone alone is not feasible in cases when the subject's movement includes hand usage only (opening a bottle, drinking water…) [8].

Raw sensor data is the output of the smart platform, based on which the summary metrics that describe activities are calculated over user-defined (overlapping) epochs. These metrics are obtained using custom software made for providing input for specific activity classifiers [12].

Feature extraction is used to describe subjects' daily activities using activity discrimination measures such as acceleration, or spectral entropy. Features are usually extracted from raw data by calculating summary metrics. There is a growing need for an explicit, open-source, and reproducible summary metric based on raw accelerometry data. Most of the existing metrics do not have a publicly accessible formula and have no straightforward interpretation. Often used metrics are Activity Count (AC) [12], or umbrella term used to describe different proprietary metrics – Activity Intensity [13], Euclidian Norm, and many more.

Activity Index (AI) is a metric proposed in [13], based on accelerometry, and it has proved to be easy to interpret and implement. It is estimated using standard deviation of the raw signal relative to the resting standard deviation. In [12], it was shown that AI has superior performance over other features, which is why it is considered in this paper, specifically because it was observed that often there is no improvement in classification accuracy when a great number of features are used [14]. Even if feature number doesn't necessarily influence classification accuracy, different research has shown that except for number & sensor placement, as well as acquisition parameters (like sampling frequency) [10] and segmentation parameters (window size and overlap percent) [22] also influence it.

One of the use-case scenarios important for this paper is tracking arm usage in patients with upper limb myoelectric prostheses. Those users can often find prostheses difficult or unintuitive to control; this can lead to passive use of the device or rejection, which can then have adverse effects on the contralateral limb due to overuse. Despite the research conducted to improve myoelectric prostheses, no aspect can be singled out for improvement [15], which is why there is a need to know how often and in which way myoelectric prostheses users use the artificial limb in activities of daily living, to streamline their development and tailor them to the actual needs of prosthetic users. Activity Index has the potential to broaden our knowledge on prostheses usage.

Our first hypothesis is that there is a significant difference in the AI values for active and passive/ no hand usage, as well as between different activity groups. This served as a classification feature testing step. The second hypothesis is that it is possible to build a classifier to include with the smart system, in order to make it more natural and comfortable to use, while aiming at higher classification accuracy with fewer features. This could possibly enable some new important conclusions on prostheses usage to be drawn.

This paper is organized as follows: Section 2 covers the hardware and software used for data acquisition, as well as the classification process, Section 3 contains the results, and Section 4 discusses the obtained results and provides a conclusion.

2 Materials and methods

2.1 Sensors and measurements

In order to obtain the data needed to calculate the selected summary metric (AI), a smart system proposed and validated in [16] was used. This system consists of two smartwatches (TicWatch, Mobvoi), and a smartphone (Samsung Galaxy A20e). Both smartwatches and smartphone are equipped with a three-axis accelerometer, three-axis gyroscope, and pedometer, while only smartphone is equipped with a magnetometer. Sensor Logger application was used for data logging, storing, and transfer, since it has three modules: one for PC, smartphone, and smartwatch. Data from smartwatches is stored in the smartphone, from which it can be transferred to a PC via USB or wirelessly.

2.2 System placement, tracked postures, and hand movements

Nine healthy right-handed participants, five male, and four female (mean ± SD, age: 24.78 ± 2.57, height: 175.89 ± 8.36, body mass: 73.56 ± 11.76) participated in the experiment. Each participant signed a written informed consent prior to the experiment.

Two smartwatches were placed on the participant, one on each wrist. The smartphone was placed in the participant's right pocket of the trousers. Participants were given instructions to perform a set of 32 different activities, without specific constraints, except those defined by the protocol, such as the order of activities and their duration (each activity was performed over the time of 70 s).

To obtain a good variety of upper limb activities or lack thereof, the tasks had to be relatable (done in daily life) and natural. Outer task variety was present, meaning that the protocol covered different elementary arm movements, such as reaching, rotating, lifting, and wrist flexion. Inner task variability was provided through a variety of executions (used to express task complexity, too).

Participants were given loose instructions on how to perform each activity, hence a certain degree of variance was allowed. The predefined order and duration of activities enabled proper labeling of the smartwatch data since there was no option to label it in real-time.

2.3 Data acquisition and preparation

Data acquisition was done in a laboratory environment, over a period of one hour per participant (including preparation time). The laboratory included 6 m of walking space and all the necessary requisites.

To make sure all the smartwatch sensors started measuring, the data logging application was started 5 minutes before the experiment, and its starting and ending times were noted.

Smartwatches were logging the data continuously with a sampling frequency of 20 Hz, which was a trade-off between battery life and activity spectrum that could be acquired [17]. Their data was saved to the smartphone and then transferred to a PC for further processing, where it was converted to a .csv format for easier use. After acquiring the data, it was labeled with a total of 32 activities for the left and right smartwatch separately, since for purpose of this paper, the smartphone was not considered (it mainly serves to classify posture [18]).

Table 1

Activities done during the experiment.
The Second column contains activity group, the third column notes the used hand and posture, and the fourth column represents the active hand for each activity.

ID	Activity group	Activity	Active hands(s)
1	Walking	Walking	Both
2		Glass in the right hand	Left
3		Glass in the left hand	Right
4	Sitting	Sitting	None
5		Glass in the right hand	None
6		Glass in the left hand	None
7	Standing	Standing	None
8		Glass in the right hand	None
9		Glass in the left hand	None
10	Grasping	Right hand, standing	Right
11		Left hand, standing	Left
12		Both hands, standing	Both
13		Right hand, sitting	Right
14		Left hand, sitting	Left
15		Both hands, sitting	Both
16	Pouring	Right hand, standing	Right
17		Left hand, standing	Left
18		Right hand, sitting	Right
19		Left hand, sitting	Left
20	Drinking	Right hand, standing	Right
21		Left hand, standing	Left
22		Both hands, standing	Both
23		Right hand, sitting	Right
24		Left hand, sitting	Left
25		Both hands, sitting	Both
26	Opening and closing cupboard	Right hand, standing	Right
27		Left hand, standing	Left
28		Both hands, standing	Both
29	Opening and closing bottle	Right hand, standing	Right
30		Left hand, standing	Left
31		Right hand, sitting	Right
32		Left hand, sitting	Left

2.4 Activity Index

Activity Index (AI) is a summary metric proposed in [12], based on the variability of raw acceleration signals in short epochs, which removes gravity and provides a summary measure of movement intensity. The standard deviation captures the magnitude of signal oscillation, so it can detect the change in oscillation frequency. In other words, AI represents device acceleration variability in absence of system noise. It is expressed in $\mathrm{m/s^2}$ and calculated based on (1), where for the participant $I, \sigma_{im}^2(t;H)$ $(m=1,2,3)$ represents accelerometer variance on axis *m*, over a window size *H*, with a beginning at time point *t*.

$$AI_i^{ABS}(t;H)=\sqrt{\max\left(\frac{1}{3}\left\{\sum_{m=1}^{3}\sigma_{im}^2(t;H)-\bar{\sigma}_i^2\right\},0\right)}\,. \tag{1}$$

System noise variance $\bar{\sigma}_i^2=\bar{\sigma}_{i1}^2+\bar{\sigma}_{i2}^2+\bar{\sigma}_{i3}^2$ is used for normalization of variability sum depends on the device, and it can be calculated using raw accelerometry data over idle device time.

Since there were 70 s of acquired data for each activity, the first and last 5 s were removed, and the remaining 60 s were used for AI calculation. Extracted segments were filtered with a *highpass* filter with a cutoff frequency at 0.5 Hz, to remove offset (DC component), often used to recognize posture.

2.5 Data processing and analysis

In order to analyze the sampling frequency influence on classification accuracy, collected data was also upsampled from 20 Hz to 50 Hz. AI was then calculated over a window of 1 s, 2 s, 5 s, and 10 s with 50 % overlap, and without overlapping [19], for both sampling frequencies. Data processing was implemented in Matlab R2019b (Mathworks Inc., Natick, USA).

First analysis was done to determine if there is any statistically significant difference between summary AI values (a sum of left- and right-hand AIs) in cases when either left, right, both, or no hands were used. In this case, AIs calculated at 20 Hz, with a window of 1 s and without overlapping were used. ANOVA1 statistical test with Bonferroni correction was used since the data normality was determined using the Lilliefors test (a Kolmogorov-Smirnov test modification) [20].

The second analysis was done based on groups of studied hand activities (defined in **Table 1**, second column). For instance, see **Table 1** – activity group “Drinking” for the left hand contains activities 21, 22, 24, and 25, since in every activity in this group the left hand is used in the same way. This principle was used to form activity groups for both hands. The goal was to determine if there is a statistically significant difference between AI values of different activity groups, for both left and right hand. Since not all data groups had normal distribution, every two groups were compared using the Wilcoxon Rank-Sum test [21].

2.6 Data classification

AI calculated in each data segmentation parameters configuration was used as a classification feature after the statistical analysis and normalization phase. The first analysis feature vector included left hand AI, right hand AI, and summary AI and they were used to classify unimanual activity of the left hand, the unimanual activity of the right hand, bimanual activity, and lack of hand activity (hand usage). The second analysis feature vector was identical to the first one, except it was used to classify 7 activity groups: walking, grasping, pouring, drinking, opening and closing the bottle, opening and closing the cupboard, and no activity - all the activities during which the specific hand wasn't active, including sitting and standing (**Table 1**, second column).

Three supervised machine learning algorithms were used – Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Random Forest (RF). Supervised ML algorithms use labeled data for their training.

SVM is an algorithm used for both classification and regression problems. It is based on finding the optimal hyperplane for dividing data into two classes. Support vectors are the points closest to the hyperplane and are considered to be the critical points. Depending on the problem's complexity and class separability, hyperplanes can be of a higher dimension. Data is mapped to a higher dimension by kernelling until a hyperplane that separates them into classes is formed.

The main tuning SVM parameter is the kernel, which maps the training set into a specific feature space, and can be linear, polynomial, radial, etc. The choice of the kernel and its parameters greatly influences the SVM performance.

kNN is a simple non-parametric classification algorithm based on distance (e.g., Euclidian) calculated between the sample that needs to be classified and the training set samples, which are sorted based on the said distance to the new sample, and then the new sample is assigned to the class with most of the k nearest samples. The performance of this algorithm is directly influenced by the tuning parameter k, which is highly data-dependent.

Random Forest is also used for both regression and classification problems. This algorithm works by constructing multiple decision trees, and the new samples' class is chosen by majority decision, hence the tuning parameter is the number of trees, and the number of features considered in each iteration.

Classification models were created for both left and right hand, using *'mlr'* and *'caret'* packages in R Studio. Data was divided using an 80:20 ratio for the training and testing set. Classifiers were trained and tuned using the training set. The performance of classifiers was tested on the test set while using 5-fold cross-validation.

To evaluate the classifier performance, the F1-score measure was used. F1-score is a harmonic mean of precision and recall and takes a value from 0 to 1, where values closer to 1 signify that the classifier has better performance. Fm is a mean of F1 for all the classes; it is used to score the general classifier performance. The presented results represent averaged left- and right-hand results.

3 Results

3.1 Statistical test results

Fig. 1 shows a mean value of AIs, with standard deviation, for each activity, for both hands. There is a notable visual difference between cases when the hand is used and the cases when the hand is not used (e.g., activity 7 vs. activity 28, sitting and opening and closing the cupboard with both hands). Furthermore, four hand usages were compared: left, right, both, and no hand usage. Mean values with standard deviation for summary AI in four different cases can be seen in Fig. 2.

There is no statistically significant difference between the summary AI for cases when either the left or right hand is active, which is expected since the same activities were done for both hands.

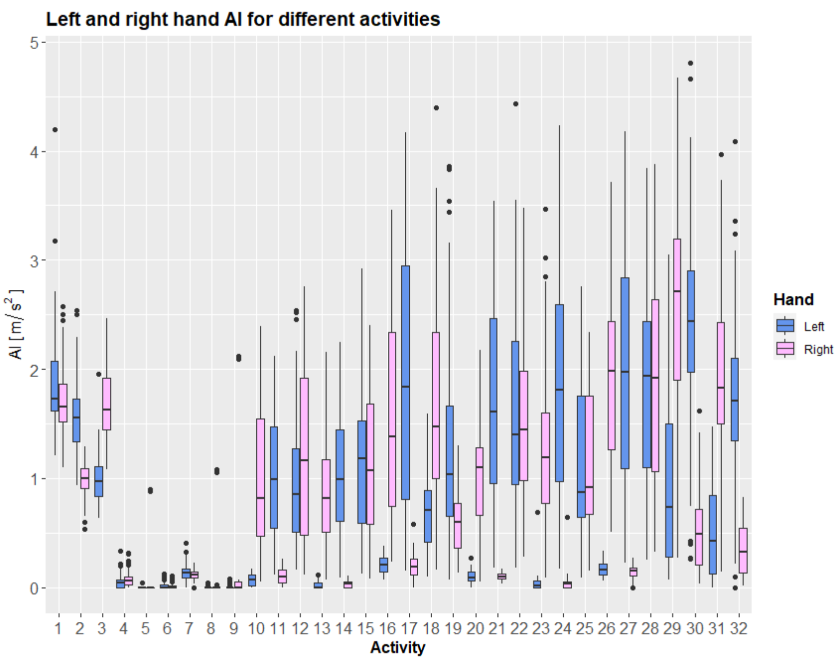

Fig. 1 – *Activity index of each of 32 activities for left and right hand. Graphs report the mean and the standard deviation over all three subjects. Higher mean values indicate a higher level of activity, while lower mean value indicates a lower level of activity.*

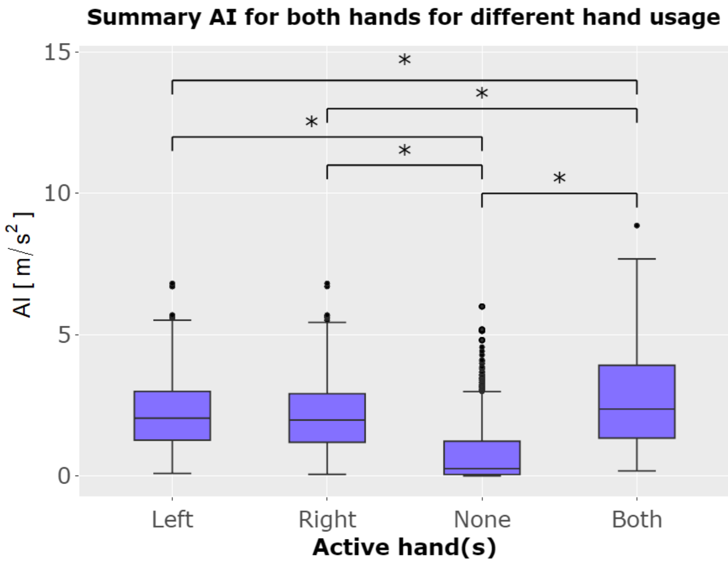

Fig. 2 – *Mean values with standard deviation for summary AI of four hand usages: left, right, none, and both* (**, $p < 0.01$).

On the other hand, there is a statistically significant difference between every other pair of cases, which is also expected since the summary AI almost doubles in case of both hands usage and is closer to zero in case of no hand usage.

The second analysis results can be seen in Figs. 3 and 4. The resulting matrixes were obtained by comparing the calculated Wilcoxon rank-sum test p-values with a threshold of statistical significance ($p < 0.05$). For values that were smaller than the threshold, 1 was noted in the matrix, and for those greater than the threshold, 0 was noted. This kind of representation shows which activity groups are different with a statistical significance.

For the left hand, pouring and drinking were determined to be similar based on the statistical test, along with walking. Opening the cupboard was found to be similar for both left and right hand. Since all the subjects were right-handed, there is a possibility that doing a task with a non-dominant hand resulted in more activities being similar, since AI is based on movement oscillations. Greater sample size could possibly give more information on these cases.

3.2 Classification results

In the case of the hand usage classification, for each data segmentation parameter configuration, the F1 score was above 75%. Best classification performances occurred in configurations with a window size of 5 or 10 s, with or without overlapping, for 20 or 50 Hz. RF classifier had the greatest F1 score of 97%, when 50 Hz, 10 s, no overlapping configuration was used.

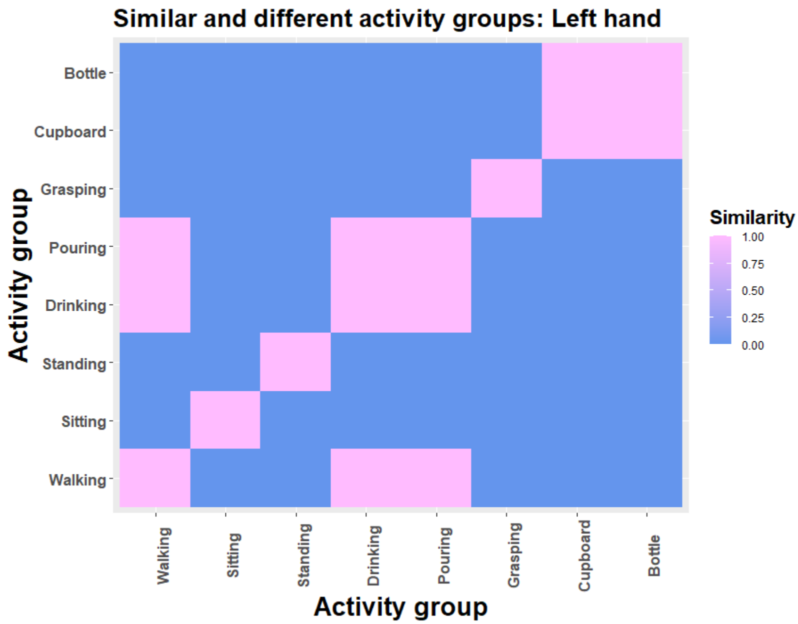

Fig. 3 – *Similar and different activity groups matrix for the left hand.*

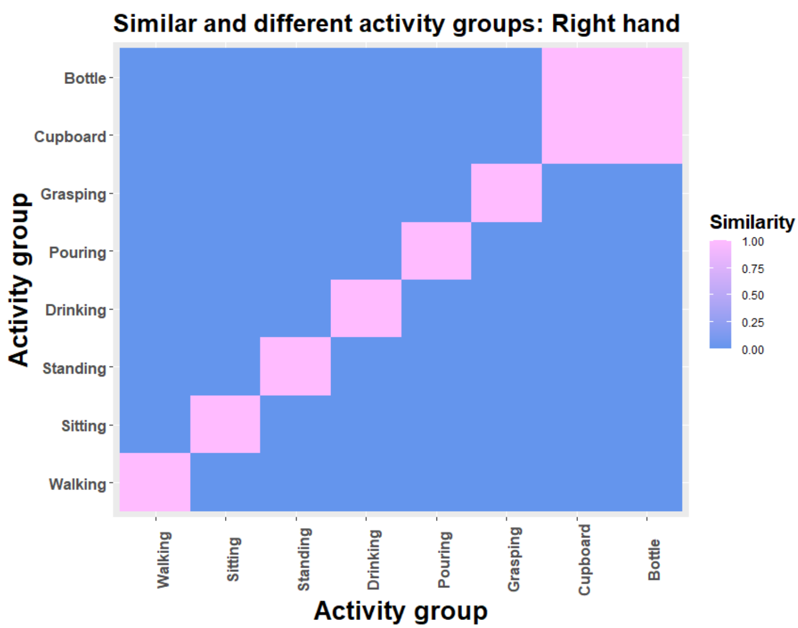

Fig. 4 – *Similar and different activity groups matrix for the right hand.*

Fig. 5 shows that classification error occurs rarely, but when it does, it can be justified. In case when no activity is classified as right-hand activity, the subject could have scratched their hand, or adjusted their hair, sleeves, etc. When a bimanual activity is classified as a unimanual activity, we can assume that one of the hands wasn't active enough. Regardless of the noted misclassifications, high classification accuracy is a clear indicator that it is possible to identify hand usage by using one or technically two features.

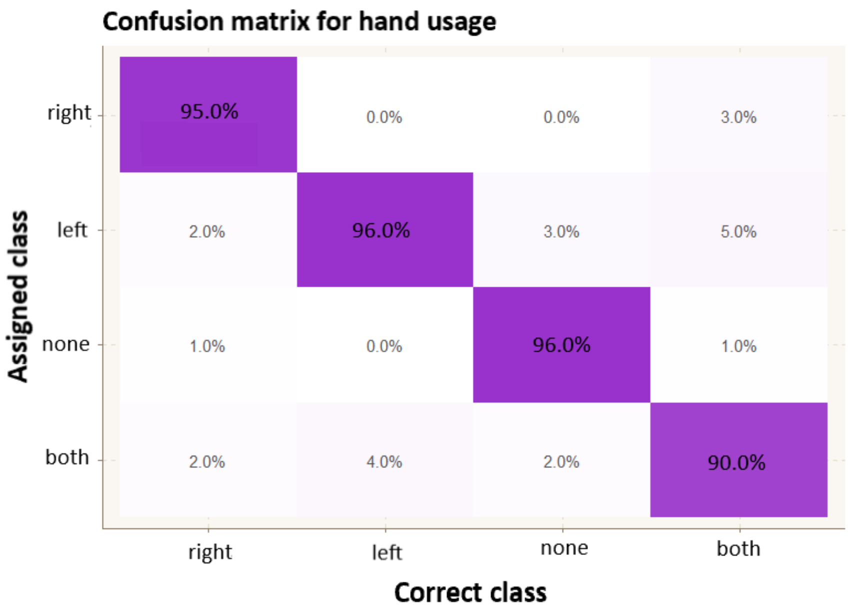

Fig. 5 – *Confusion matrix for hand usage – unimanual, bimanual, and no activity.*

As was expected, classifying activity groups using only one feature turned out to be a more challenging task. For each data segmentation parameters configuration, and for every classifier, the F1 score was below 70%. If we ignore the low accuracy, the best performance (F1 = 63%) was still achieved when 50 Hz, 10 s, no overlapping configuration was used, but with the SVM classifier. A low F1 score in all the configurations is a clear indicator that it is not possible to identify a specific activity group using only one or technically two features.

6 Conclusion

In this paper, we have tested the feasibility of a new summary metric in human hand activity recognition – Activity Index, and how it can enable better hand usage and activity group discrimination.

Statistical test results suggested that AI could have great potential as a classifier input. We concluded that by combining the summary AI and AI of the left and right hand, the information on a number of hands used and their side could be obtained. Other than that, we found a statistically significant difference between at least six activity groups of the dominant hand (walking, sitting, standing, grasping, opening and closing the cupboard, and opening and closing the bottle). The results suggest that six activity groups could potentially be discriminated by using only one classification feature. These results agree with those from Bai et al. [12] in terms of AI performance and enable a better understanding of AI performance in the case of wrist-worn accelerometers.

Results of the two classification procedures that were performed with AI and summary AI as the input features indicate that this summary metric can be used to classify hand usage, but it does not provide an accurate enough classification of the activity groups.

Further work would include an attempt to achieve a higher activity group classification accuracy, by adding as few simple features as possible, besides the AI. These steps could enable lower computational complexity, leading to an online implementation of hand activity classification while lowering the battery consumption.

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