Eye tracking-based Sedentary Activity Recognition with Conventional Machine Learning Algorithms

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BACKGROUND

Eye tracking is "the process of measuring either the point of gaze or the motion of an eye relative to the head" [1].

Applications:
Analysing gaze signal has various benefits:
- Improving cognitive fitness [2].
- Monitoring the driver's activity [3].

Terminology:
- **Fixation:** maintaining the focus of your gaze at one point.
- **Saccade:** the rapid eye movement between fixation points.

RESEARCH QUESTIONS

1. How to design and implement **different feature extraction methods** for eye movement signals?
2. To achieve good recognition accuracy, what are **the best features** for training conventional machine learning algorithms.
3. What is the impact of different subjects on the recognition performance?

METHODOLOGY

Step 1: Data Preprocessing

Median filter with a sliding window of 500ms.

Normalization.

Step 2: Feature Extraction

Fixation filter [4]:
- Develop dynamic thresholds.
- Estimate fixations positions.

Low-level gaze features [5]:
- Fixation-based.
- Saccade-based.

Step 3: Feature Selection

mRMR (minimum-Redundancy Maximum-Relevance):
- Features strongly influencing the target variable.
- Correlation between previously selected features.

Step 4: Classification

Classifiers:
- Random Forest.
- SVM.
- k-NN.

Evaluation:
- Person-dependent.
- Person-independent.

RESULTS

Performance per activity

- The activities recognized most accurately are *read*, *interpret* and *watch*, Figure 1.
- The *write* activity is misclassified as the other software-related activities: *debug* and *interpret*.

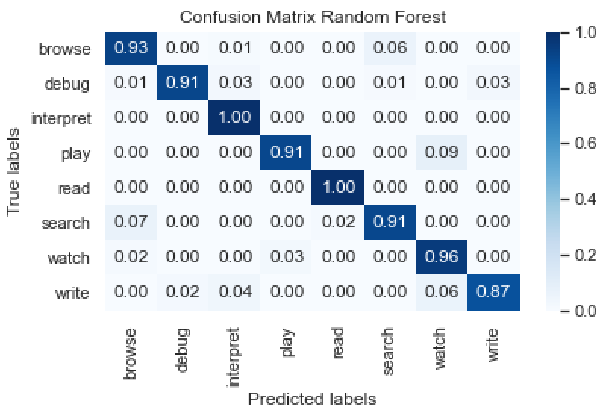

Figure 1: The confusion matrix of the Random Forest classifier.

Feature Importance

- The mRMR selects 18 features for the SVM classifier and 17 for the k-NN model, Table 1, out of 21 features in total.
- All saccade-based features are relevant for a correct classification, while only a subset of the fixation-based features are important.

Selected features by mRMR.	
Saccade-based	**Fixation-based**
sacc_right	fix_disp_area
sacc_down_right	fix_radius
sacc_down	fix_slope
sacc_down_left	fix_rate
sacc_left	fix_count
sacc_up_left	long_fixation
sacc_up	brief_fixation
sacc_up_right	
sacc_variance	
sacc_std	
sacc_mean	

Table 1: The most important features.

Person-Dependent Evaluation

- The top performing classifier is Random Forest, 0.94, Figure 2.
- The second best ML model is SVM, 0.86.
- The k-NN classifier scores the lowest, 0.77.

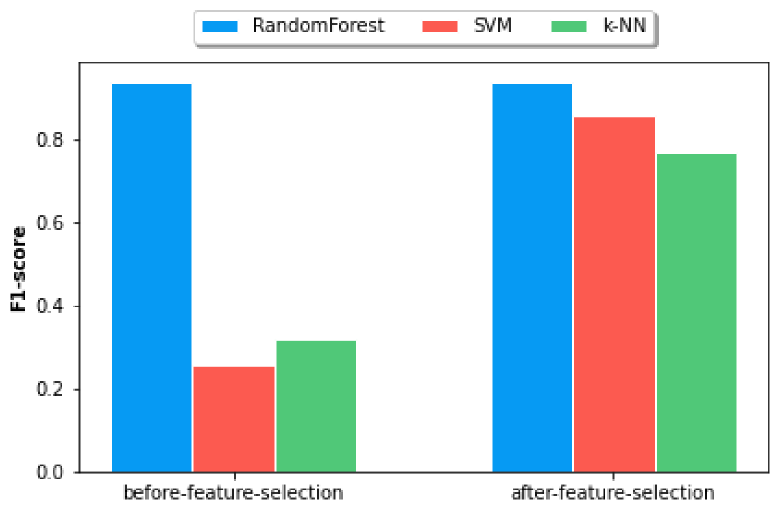

Figure 2: The impact of feature selection on the classification accuracy.

Person-Independent Evaluation

- Apply leave-one-subject-out cross validation.
- Test on an unseen subject: resembles a real-world application of the system.
- The classification accuracy drops, Table 2, in comparison with the person-dependent evaluation, but the order of classifiers performance does not change.

Participant	Random Forest	SVM	k-NN
1	0,703	0,680	0,672
2	0,380	0,380	0,347
3	0,582	0,362	0,383
...			
10	0,921	0,750	0,750
...			
22	0,712	0,337	0,448
23	0,515	0,404	0,346
24	0,569	0,492	0,392
Mean Accuracy	**0,654**	**0,524**	**0,480**

Table 2: A summary of the recognition accuracy of the person-independent evaluation.

DISCUSSION

- The gaze signals of some subjects in the dataset are missing data points due to large gaps in the timestamp. This influences the accuracy in the person-independent evaluation, subject 10, Table 2.
- In a future research, person-independent evaluation can be performed on a subset of the training subjects to further explore the impact of different subjects on the recognition accuracy.

CONCLUSION

- The Random Forest classifier performs best and most reliably, f1-score of 0.94, followed by the SVM model, f1-score of 0.86 using 18 features.
- The low accuracy of the k-NN classifier proves it unsuitable for the task of sedentary activity recognition due to its nature of storing the training data.
- All saccade-based features together with a subset of fixation-based features, Table 1, contribute to achieving good classification accuracy.

References

[1] Wikipedia, Eye tracking, 2022.
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[5] Namrata Srivastava, Joshua New, and Eduardo Velloso. Combining low and mid-level gaze features for desktop activity recognition. 2018.