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Objective Measure of Working Memory Capacity Using Eye Movements

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ABSTRACT

Working memory capacity is an important measurement in the development of autonomous systems that require human supervision. Currently, there is no direct method of determining working memory capacity. This study utilizes a publicly available dataset, containing multiple response measurements to tasks requiring various levels of cognitive load, to generate machine learning models that infer a relationship between participant eye tracking measurement and their subjective responses to the cognitive workload of each task. The focus of the study is to analyze the relationship between eye-tracking measurements and working memory capacity.

BACKGROUND

- Working memory capacity is the measurement for how information is being stored for a short time and interacting with long term memory with a capacity limit that is dependent on attention and other executive functions.
- Working memory capacity is crucial for human autonomy teaming (humans and autonomous systems working together) because the human operator's working memory capacity must be kept at appropriate levels to monitor the system.
- The dataset contained data on each participant for two levels: single (without DRT, three trials) and dual (with DRT, four trials including a control).

METHODOLOGY

Participants

- 28 participants aged between 18-30 years (16 M, 12 F)

Task Measurements

- N-back task (recalling numbers read aloud from an audio file)
- DRT task (vibrotactile stimulus response time)

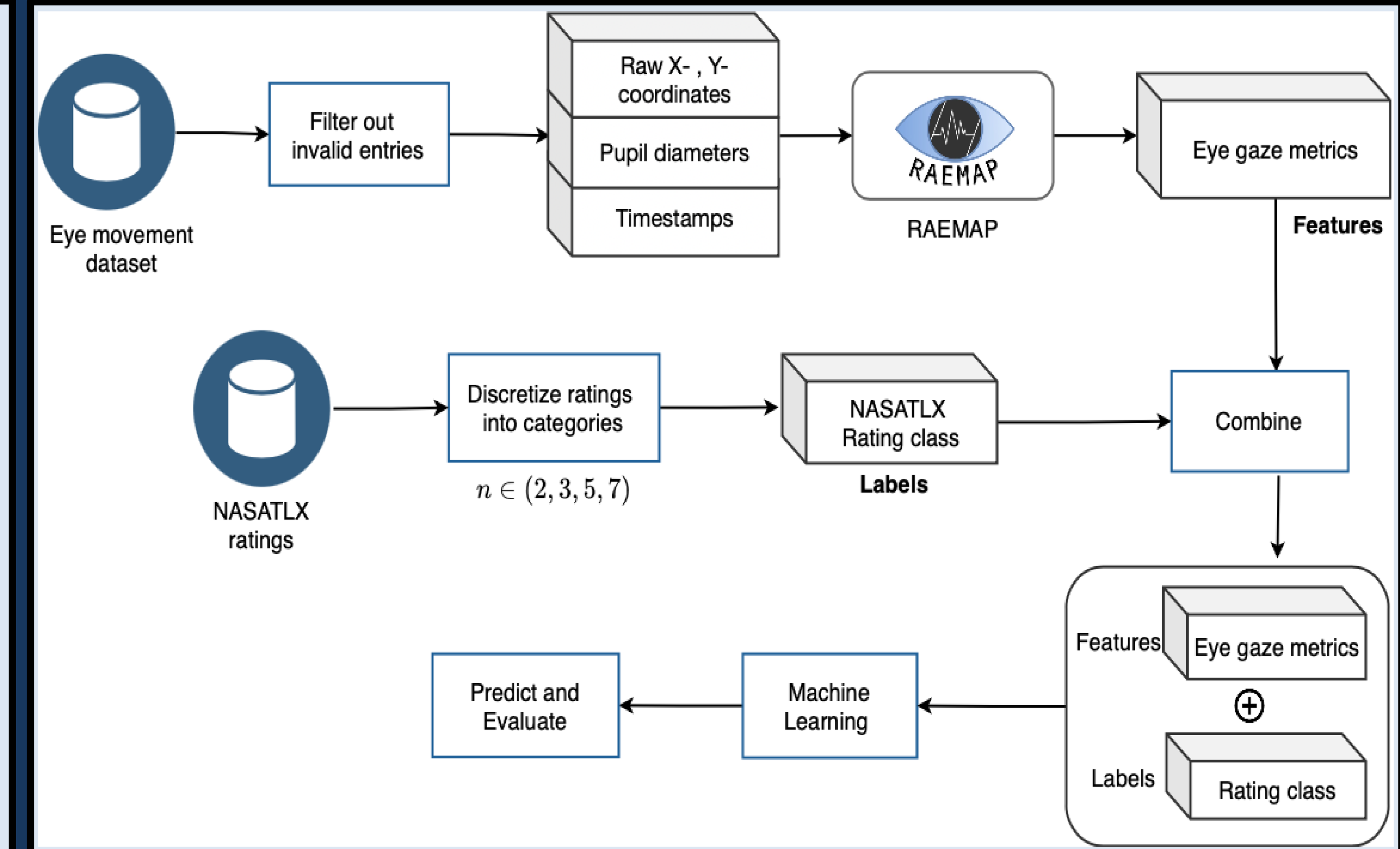

Fig. 1: Processing Pipeline including RAEMAP for Advance Eye Movement Analysis.

- Eye Tracking Measurements (participants were told to look at a "+" on a monitor while doing the other tasks and an eye tracker took gaze and pupil measurements)
- NASATLX (NASA Task Load Index, a retrospective questionnaire that measures subjective workload)

Data Processing

- The eye tracking files for each participant were concatenated and the invalid entries and irrelevant columns were deleted.
- RAEMAP was used to compute positional gaze metrics.
- The resulting metrics were concatenated with the respective machine learning classes that had been applied to the NASATLX scores.
- Finally, the dataset was run through selected machine learning classifiers.

RESULTS

- The Random Forest classifier yielded the highest accuracy at 97.37% for the physical demand measurement using the dual machine learning classification.
- The physical demand was the only measurement that could be predicted at an accuracy greater than 75% by any classifier.

Classification	ML Approach	Mental	Physical	Temporal	Performance	Effort	Frustration
Binary	Random Forest	68.53	**97.37**	67.22	70.94	53.87	69.6
Binary	K Neighbors	53.39	**96.83**	61.62	69.27	51.04	66.47
Binary	Logistic Regression	69.04	**96.46**	69.76	71.85	62.5	74.04
Binary	Linear SVC	55.42	**95.59**	59.87	59.57	51.96	62.75
Binary	Decision Tree	61.82	**95.55**	59.79	70.23	53.85	62.37
Three	Ridge Classifier	66.15	**95.16**	68.26	70.43	59.13	68.86
Three	Naïve Bayes	61.29	**94.64**	62.36	66.15	55.35	59.66
Three	Gaussian	60.74	**94.1**	59.13	63.43	50.54	56.43
Three	Linear Discriminant Analysis	64.54	**93.02**	65.57	69.88	58.04	63.99
Three	Logistic Regression	67.77	**90.31**	66.12	66.12	54.84	66.67
Five	Random Forest	29.05	**77.79**	30.48	47.51	34.99	40.57
Five	Extra Trees Classifier	29.29	**77.78**	33.8	47.01	31.11	39.93
Five	Neural Network	27.43	**65.56**	29.57	34.42	25.11	30.36
Five	Decision Tree	23.51	**63.27**	25.97	37.51	24.45	27.45
Five	Logistic Regression	26	**50.75**	32.11	38.58	27.07	28.71
Seven	Random Forest	26.67	**70.65**	30.96	35.14	26.34	31.94
Seven	Extra Trees Classifier	24.9	**69.23**	26.66	33.29	27.08	31.54
Seven	Ridge Classifier	25.95	**67.94**	26.75	34.93	25.64	33.74
Seven	Linear Discriminant Analysis	26.67	**62.36**	23.7	36.93	24.93	28.37
Seven	Gaussian Naïve Bayes	21	**55.98**	21.75	30.7	23.5	26.33

Fig. 2: Accuracy results for all the categorizations for different ML approaches.

CONCLUSION & FUTURE WORK

- The results suggest that it possible to use eye tracking metrics to predict working memory capacity, but more research must be done to improve accuracy.
- Future work in this area should include the DRT and N-back measurements in predicting the working memory capacity.
- NASATLX scores should be made less subjective by being placed on a scale that is normalized for each participant based on the mean and variance of their responses.

REFERENCES

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