REMoDNaV is free, open source software for **robust** event classification in **eye tracking** data from **natural viewing** paradigms.

A Python-based Algorithm for Robust Event Detection for Eye Movements During Natural Viewing

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Introduction

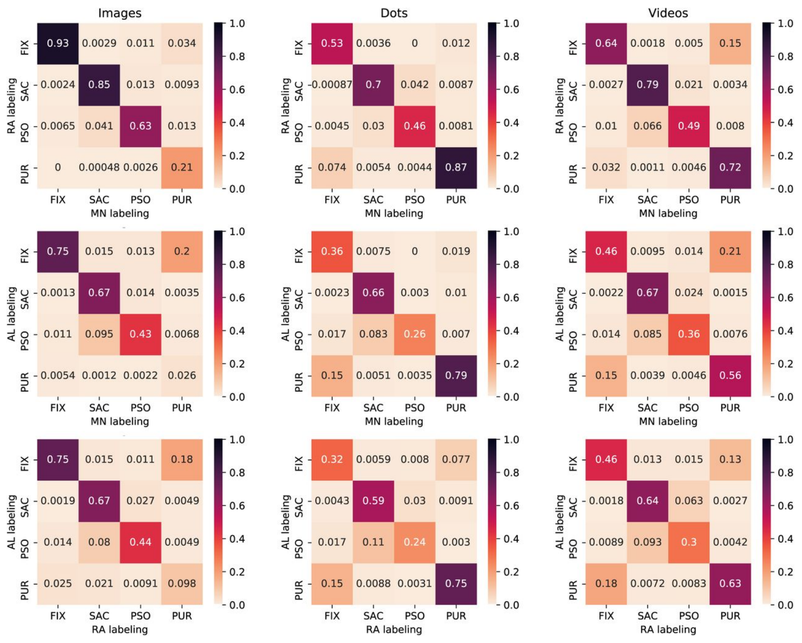
- State-of-the-art tools for event detection in gaze data do not perform satisfactory on data from dynamic stimulation with naturalistic paradigms (e.g. movies) (Anderson et al., 2017).
- For simultaneous fMRI and eye gaze acquisition (e.g. Hanke et al., 2016), we need event detection algorithms that perform robust on lower quality (high noise, high spatial uncertainty) data.
- Contemporary algorithms are often written in closed source software and not easily available.

Methods

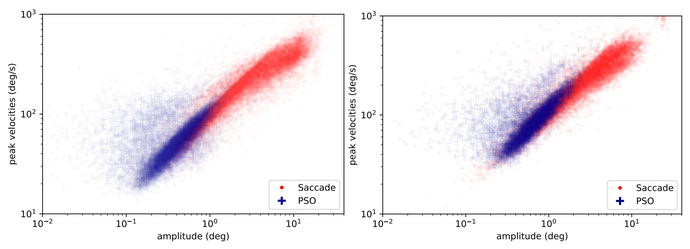
- Development of REMoDNaV (robust eye movement detection for natural viewing) as a pip-installable, OS-independent Python package based on an existing algorithm (Nyström & Holmqvist, 2010).
- Validation on

1) annotated data from watching images, moving dots, or videos (Andersson et al., 2017)
2) high and low quality data from movie watching (acquired in lab or MRI scanner) (studyforrest.org)

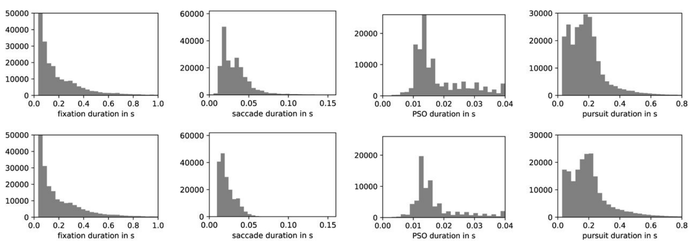
Results



Confusion patterns for pairwise classification comparison of human raters (MN, RA) and REMoDNaV (AL) for data from stimulation with images (left), moving dots (middle) & videos (right). Matrices present Jaccard indices (JI; Jaccard, 1901): The diagonals depict the fraction of time points labeled congruently by any rater.



Main sequence of eye movement events during 15 minutes of the movie for lab (left), and MRI participants (right), each N = 15.



Eye movement event duration distributions for high- (lab, top row) & lower-quality (MRI, bottom row) data for N = 15 subjects from the ~2h movie. Histograms depict absolute number of events. Differences are a lower number of events & fewer long saccades in the MRI sample. These are attributable to higher noise level & more signal loss (see Hanke et al., 2016, Fig. 4b) in the MRI sample, and stimulus size differences (23.75° MRI vs. 34° lab).

Conclusions

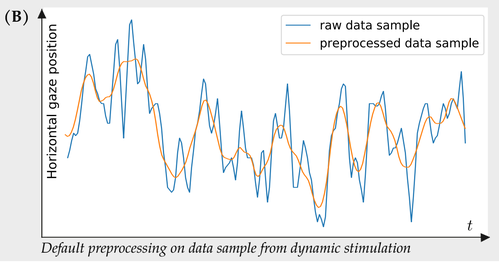
- REMoDNaV performs on par or better than state-of-the-art algorithms when comparing its classification to coding of human experts, and it yields plausible and robust (similar) results both on high and lower quality data.
- In its present form, REMoDNaV is suitable for world-centered eye gaze data from static and dynamic stimulation, and it can classify fixations, saccades, smooth pursuits, and post-saccadic oscillations.
- Importantly, it is FOSS and easily available.

Algorithm overview

(A) Preprocessing

1) Apply heuristic spike filter (Stampe, 1993)
2) Mask signal loss (opt): **dilate_nan, min_blink_dir**
3) Noise reduction (opt):
   - Median-filter (**median_filter_length**)
   - Savitzky-Golay filter (**savgol_length, savgol_polyord**)
4) Calculate velocity
   - if velocity > **max_vel**; trim sample to **max_vel**
5) Calculate acceleration

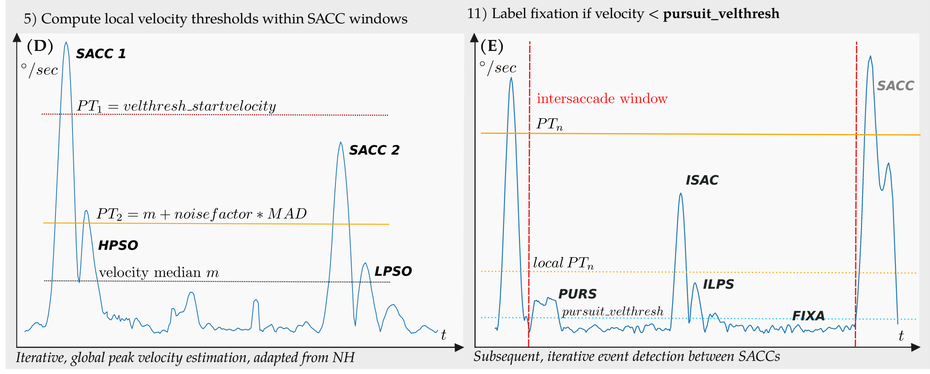
(B)



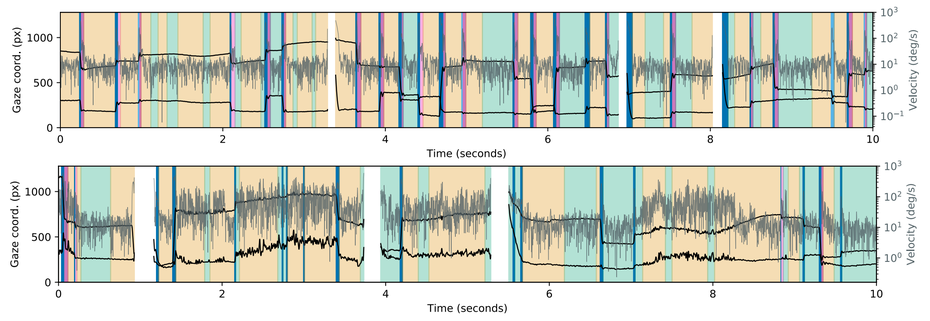
Default preprocessing on data sample from dynamic stimulation

(C) Event detection

1) Calculate peak velocity threshold from entire data iteratively (adapted from NH, using robust statistics). Initial threshold: **velthresh_startvelocity**
2) Determine major saccades (SACC) from sorted velocity samples exceeding the final threshold
   - if ms frequency > **max_initial_saccade_freq**; stop
3) Detect saccade onset/offset and LPSOs/HPSOs for all SACC (adapted from NH, with local velocity thresholds within **saccade_context_window_length**). PSOs are classified as HPSO or LPSO following the definition of NH.
4) Segment data into saccade windows between ms.
5) Compute local velocity thresholds within SACC windows
6) Label saccade if
   - peak velocity > **local velocity threshold**, and
   - duration > **min_saccade_duration**, and
   - distance to ms > **min_intersaccade_duration**
7) Detect saccade onset/offset and PSOs as before
8) If unlabeled window > **min_pursuit_duration** Butterworth low-pass filter (**lowpass_cutoff_freq**)
9) Detect smooth pursuit peaks similarly to SACC detection, using a **pursuit_velthresh**
10) Compute pursuit onset/offset as saccade onset/offset procedure, using **pursuit_velthresh**
11) Label fixation if velocity < **pursuit_velthresh**



Iterative, global peak velocity estimation, adapted from NH | *Subsequent, iterative event detection between SACCs*



Classification performance in lab (top) and MRI (bottom) setting. Filtered gaze coordinates (black) & computed velocity time series (gray) overlayed on the eye movement event segmentation with periods of fixation (green), pursuit (beige), saccades (blue), and high/low-velocity post-saccadic oscillations (dark/light purple)

Fixations

Algorithm	Images Mean	SD	#	rank	Dots Mean	SD	#	rank	Videos Mean	SD	#	rank
MN	248	271	380	1	161	30	2	1	318	289	67	0
RA	242	273	369	0	131	99	13	0	240	189	67	1
CDT	397	559	251	10	60	127	165	9	213	297	211	7
EM	-	-	-	-	-	-	-	-	-	-	-	-
IDT	399	328	242	7	323	146	8	5	554	454	48	8
IKF	174	239	513	5	217	184	72	6	228	296	169	4
IMST	304	293	333	3	268	140	12	3	526	825	71	10
IHMM	133	216	701	8	214	286	67	8	234	319	194	6
IVT	114	204	827	9	203	282	71	7	202	306	227	9
NH	258	299	292	2	380	333	30	10	429	336	83	2
BIT	209	136	423	4	189	113	67	4	248	215	170	3
LNS	-	-	-	-	-	-	-	-	-	-	-	-
REMoDNaV	187	132	426	6	116	65	43	2	147	107	144	5

Saccades

Algorithm	Images Mean	SD	#	rank	Dots Mean	SD	#	rank	Videos Mean	SD	#	rank
MN	30	17	376	0	23	10	47	0	26	13	116	0
RA	31	15	372	1	22	11	47	1	25	12	126	1
CDT	-	-	-	-	-	-	-	-	-	-	-	-
EM	25	22	787	9	17	14	93	8	20	16	252	6
IDT	35	15	258	3	32	14	10	7	24	53	41	9
IKF	62	37	353	10	60	26	29	10	55	20	107	8
IMST	17	10	335	6	13	5	18	6	18	10	76	4
IHMM	48	26	368	8	41	17	27	9	42	18	109	7
IVT	41	22	373	5	36	14	28	4	36	16	112	5
NH	50	20	344	7	43	16	42	5	44	18	1104	10
BIT	-	-	-	-	-	-	-	-	-	-	-	-
LNS	29	12	390	2	26	11	53	2	28	12	122	2
REMoDNaV	39	20	388	4	30	13	40	3	33	15	118	3

Post-saccadic oscillations

Algorithm	Images Mean	SD	#	rank	Dots Mean	SD	#	rank	Videos Mean	SD	#	rank
MN	21	11	312	1	15	5	33	0	20	11	97	1
RA	21	9	309	0	15	8	28	1	17	8	89	2
NH	28	13	237	4	24	12	17	4	28	13	78	4
LNS	25	9	319	2	20	9	31	2	24	10	87	3
REMoDNaV	19	8	277	3	18	8	14	3	18	8	86	0

Pursuit

Algorithm	Images Mean	SD	#	rank	Dots Mean	SD	#	rank	Videos Mean	SD	#	rank
MN	363	187	3	1	375	256	37	1	521	347	50	1
RA	305	184	16	0	378	364	33	0	472	319	68	0
REMoDNaV	197	73	118	2	440	385	34	2	314	229	97	2

Event characteristics (no., mean duration, standard deviation of duration) for classified eye movement events (subheaders: fixations, saccades, post saccadic oscillations, smooth pursuits) for all stimulation types (images, dots, videos) for two human coders (MN, RA), ten contemporary event detection algorithms (identified by abbreviations), and REMoDNaV. The algorithm REMoDNaV is based on is abbreviated as "NH".

Root mean squared deviations (RMSD) of event properties from each algorithm to human classification are transformed into ranks (lower ranks indicate more human-like performance) for a comparison between algorithms.

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Want to learn more?
Get all data and code from Github (powered by Datalad) and compile our manuscript from scratch!

Want to use REMoDNaV?
Pip install remodnav or find the source code here!
Contribute?
PRs and issues are always welcome!

References

Andersson R, et al. (2017) One algorithm to rule them all? BRM, 49(2)
Hanke M,, et al. (2016). A studyforrest extension, simultaneous fMRI and eye gaze recordings during prolonged natural stimulation. SciData 3
Jaccard P (1901) Étude comparative de la distribution florale dans une portion des alpes et des jura. Bull Soc Vaudoise Sci Nat 37:547–579
Nyström M, & Holmqvist K (2010). An adaptive algorithm for fixation, saccade, and glissade detection in eyetracking data. BRM 42(1)