

Eye Movement Classification with K-Means

Extended to Smooth Pursuit

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Introduction:

- Clustering is a machine learning approach to dividing data points into groups.
- K-Means is a clustering algorithm that allows which allows a user to specify the exact number of grouping which should exist in the data.
- Eye Movement Classification is fundamentally a problem of grouping data points by similarity, which suggest clustering is an effective approach.

Algorithm:

Remove Outliers:

1. Calculate velocity for every datapoint as the geometric mean of x and y velocities.
2. Calculate acceleration for every data point as the absolute difference of consecutive velocities.
3. Calculate a moving median across all data points.
4. Mark points which are 3 or more local median absolute deviations away from median as Noise.

Cluster Points with 3-Means:

1. Initialize 3 random cluster centers.
2. Assign each point to its closest cluster center.
3. Adjust the cluster centers as the mean of all points assigned to the cluster.
4. Repeat steps 2 and 3 until stability is reached.

Associate Clusters with Movements Based on Mean Cluster Velocity:

1. Calculate the mean velocity for each of the 3 clusters.
2. Assign movements for each point as:
 - a. Slowest -> Fixation
 - b. Middle -> Pursuit
 - c. Fastest -> Saccade

Pseudo Code:

Given set of data points $s = \{s_1, \dots, s_n\}$

Randomly initialize set $c = \{c_1, \dots, c_k\}$ of k centroids

Initialize a set of results $r = \{r_1, \dots, r_n\}$ to zeros

Loop until c does not change:

 for $i = 1$ to n :

$\text{min_cluster} = 0$

$\text{min_distance} = \text{MAX_FLOAT}$

 for $j = 1$ to k :

 calculate $\text{distance}(s_i, c_j)$

 if ($\text{distance} < \text{min_distance}$):

$\text{min_cluster} = j$

$\text{min_distance} = \text{distance}$

$r_i = \text{min_cluster}$

 for $i = 1$ to k :

 calculate the centroid of each cluster i

 set c_i = to centroid i

Return sets c and r . R is the cluster for each point in s , and c is the centroid of each cluster.

Differences:

IVVT:

- Relies only on velocity.
- Compares values to user-defined thresholds.
- Uses validity for noise detection.

K-Means:

- Uses velocity and acceleration.
 - Learns divisions from data.
 - Uses moving median for noise detection.
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Parameters:

- **K**: the number of clusters to detect in the data. 3 was used in this project and any other value would not be valid for 3 behavior classification.
- **Outlier Window**: the width of the window used to calculate the local median for outlier detection. 31 was used in this project. Much larger values (>100) and much smaller values (<10) do not work but behavior does not change much inside of that range.



A screenshot of a software window titled "User Model Settings". It contains two input fields. The first field is labeled "K" and has the value "3" entered. The second field is labeled "Outlier Window" and has the value "31" entered.

Parameter	Value
K	3
Outlier Window	31

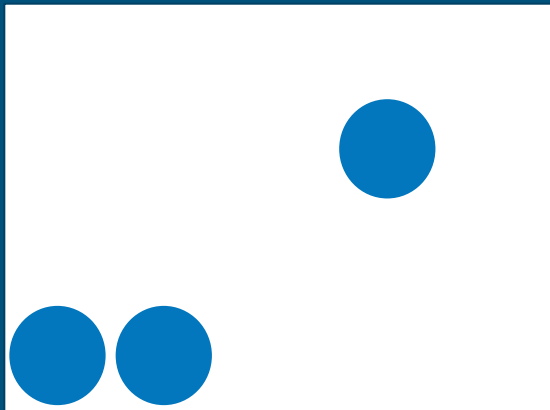
Challenges:

- K-means is very noise sensitive. Early implementations would often create single-point clusters for very high velocity and acceleration points.
- Very positive values and very negative velocity and acceleration values actually belong in the same cluster.
- The clusters are not as crisp as I'd hoped.
- K-Means is non-deterministic. Occasionally a run will produce unusual results.

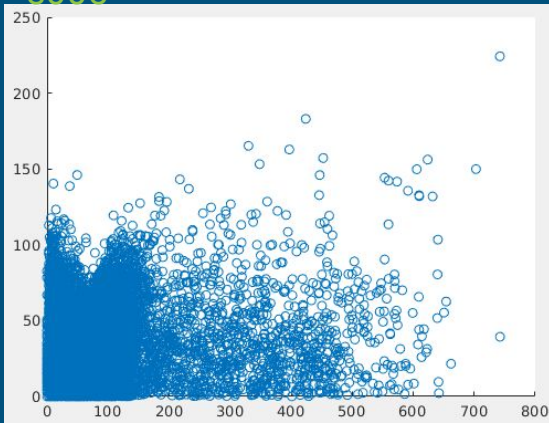
Visualizing Velocity and Acceleration:

Acceleration

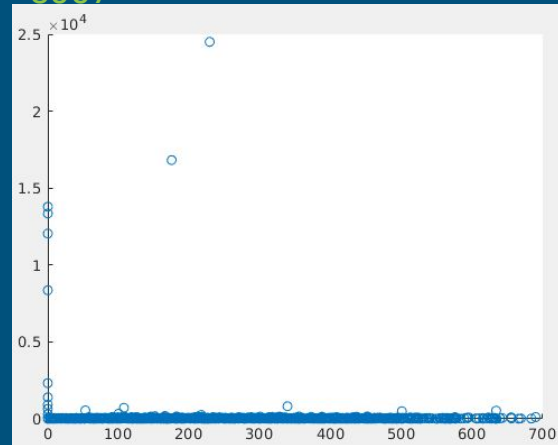
Ideal Values



s005



s007



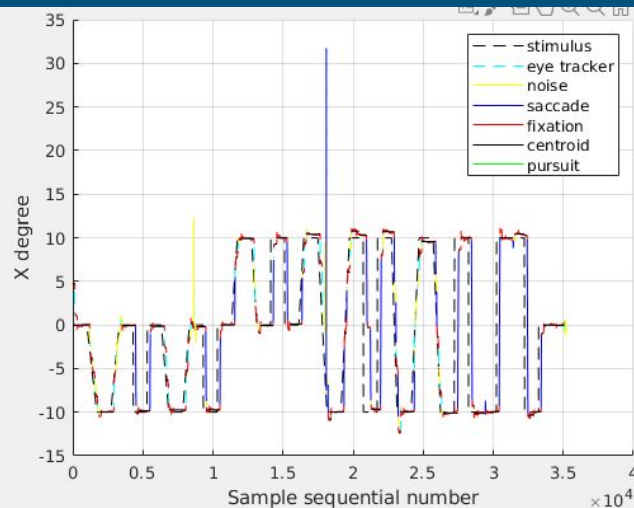
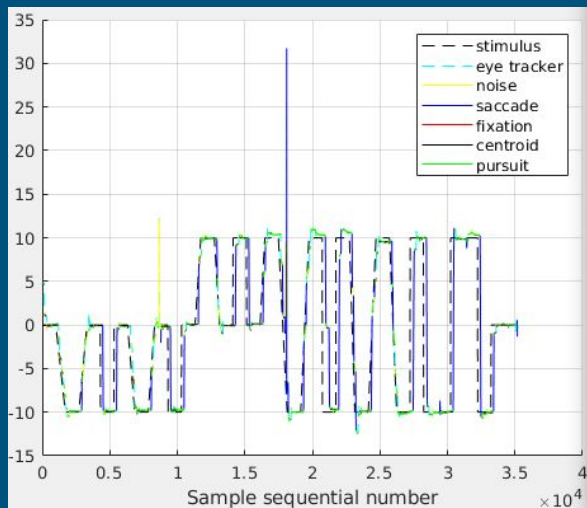
Velocity

Scores:

s007

	SQnS	FQnS	PQnS	MisFix	FQIS	PQIS_P	PQIS_V	AFD	AFN	ASA	ANS	
IVT	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I-VVT	96.2551	29.8609	38.8550	50.2261	0.4060	3.5792	15.9519	0.1925	54	12.1298	38	N/A
User	86.2991	80.8015	0.0641	0	0.4989	N/A	N/A	0.4802	65	12.7843	28	N/A

IVVT



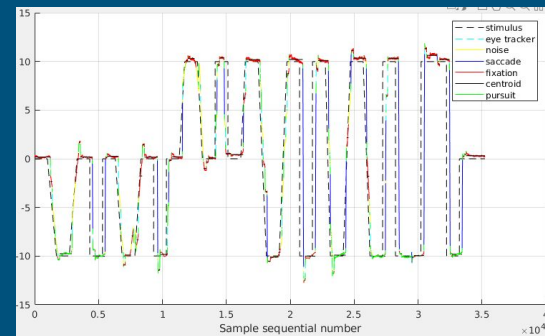
K-Means

Number of Fixation points :33225
 Number of Saccade points :1346
 Number of Pursuit points :5
 Number of Noise points :661

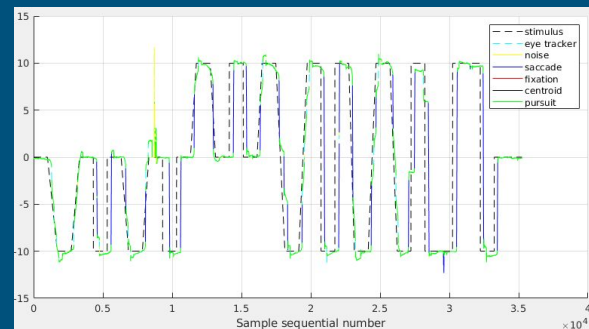
Performance:

- A few high acceleration points push the remaining points into all being fixations.
- Assigning too many points as Noise affects the clusters by introducing 0-values points.
- Fixation and Pursuit merge together more than is desirable.
- Non-determinism sometimes substantially degrades the performance of K-Means.

s005



s004



Future Improvements:

- Consider other clustering algorithms (K-Means++, C-Means, K-Medoids).
- Improve de-noising.
- Add features other than velocity and acceleration.



Questions or
Comments?