Bayesian microsaccade detection

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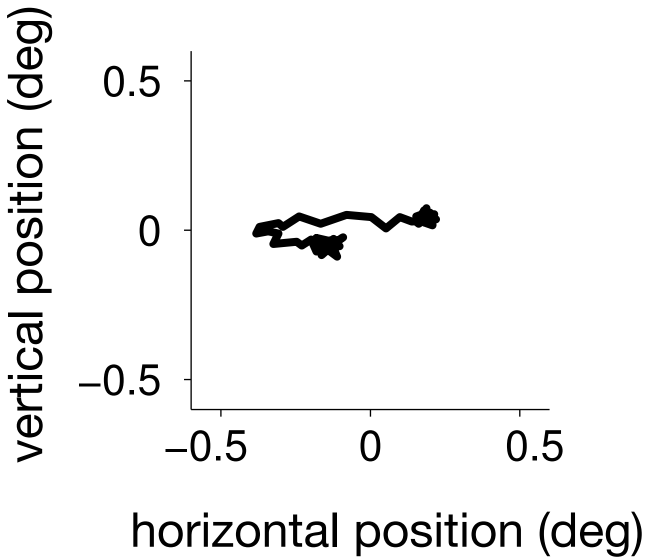
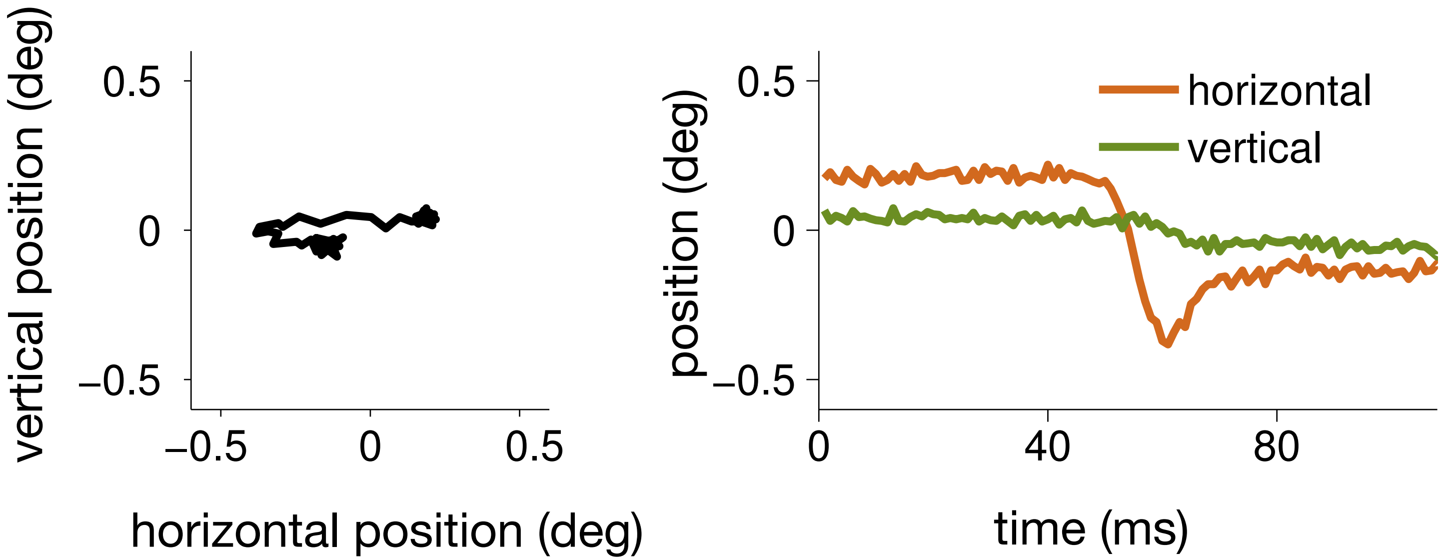
Microsaccades

- High velocity fixational eye movements
- Several proposed cognitive roles, such as indexing covert attention → but controversial
  - Engbert and Kliegl, 2003, Martinez-Conde et al., 2004, Horowitz et al., 2007, Rolfs, 2009, Yuval-Greenberg, Merriam et al., 2014
- Detection is complicated partly due to the eye tracker noise → important to have a good detection algorithm

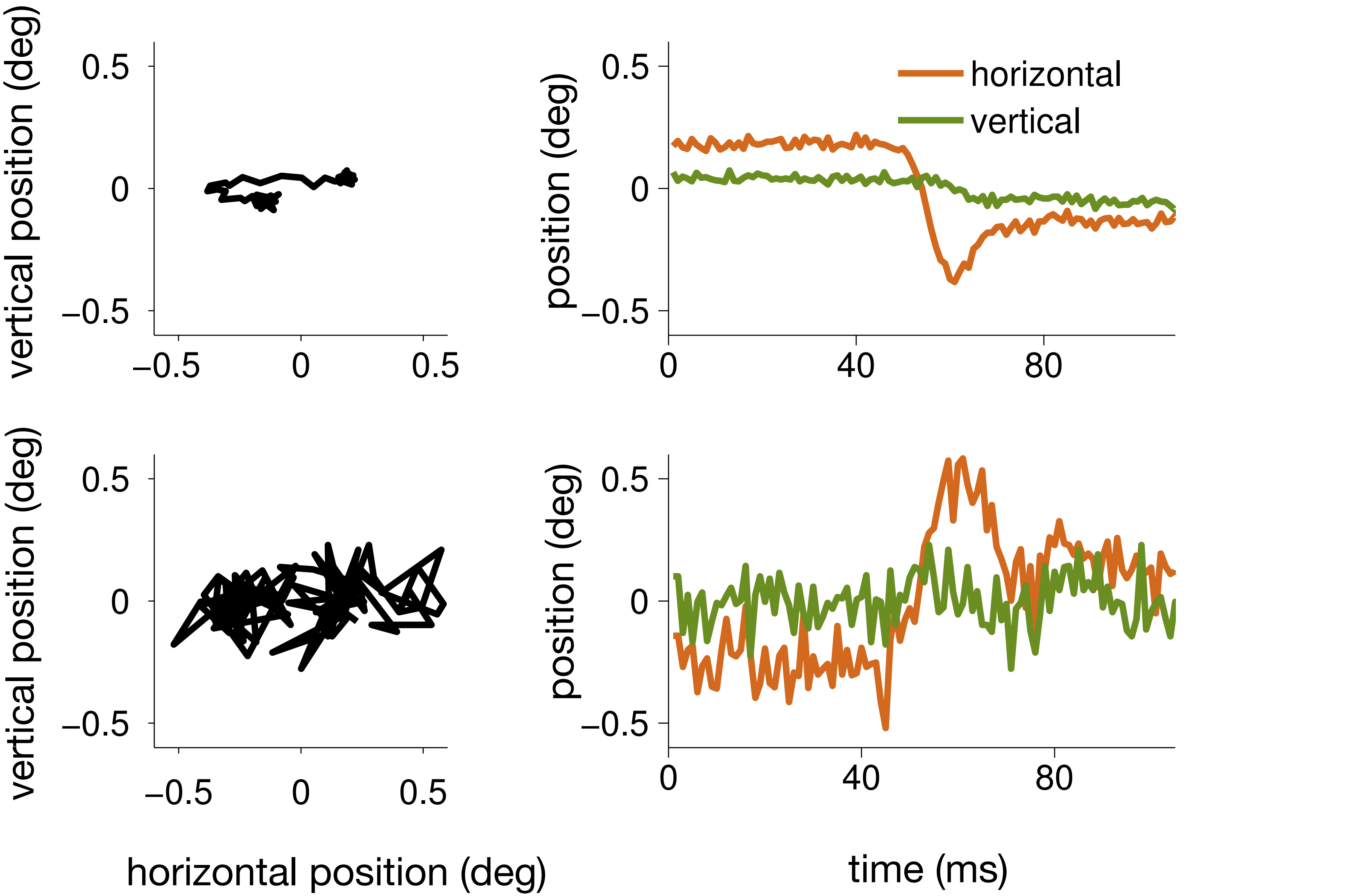


vertical position (deg)
0.5
0
−0.5
−0.5
0
0.5
horizontal position (deg)



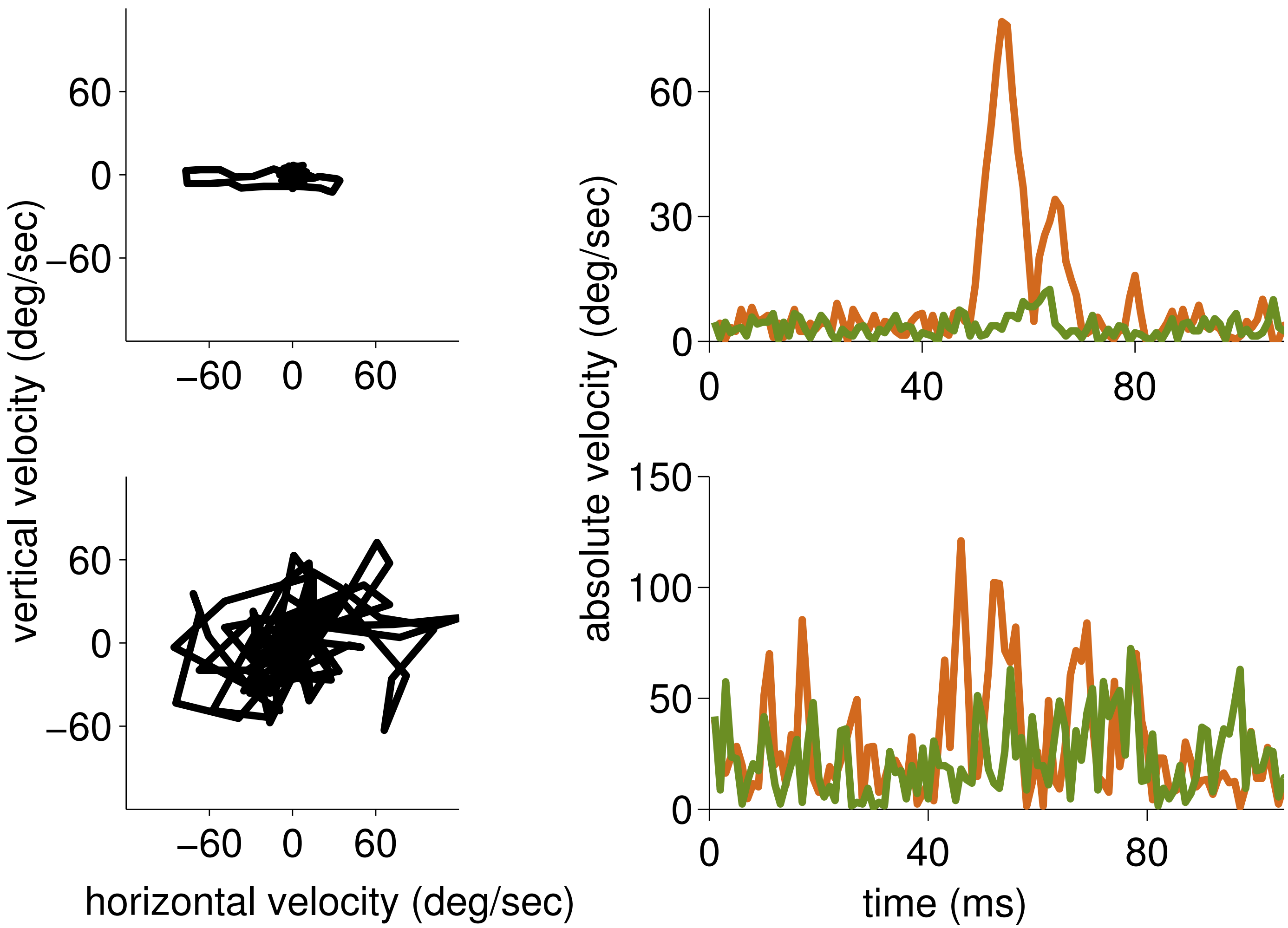
vertical position (deg)
0.5
0
−0.5
−0.5
0
0.5
horizontal position (deg)
position (deg)
0.5
0
−0.5
0
40
80
time (ms)
horizontal
vertical

Microsaccades can be hard to detect under high noise



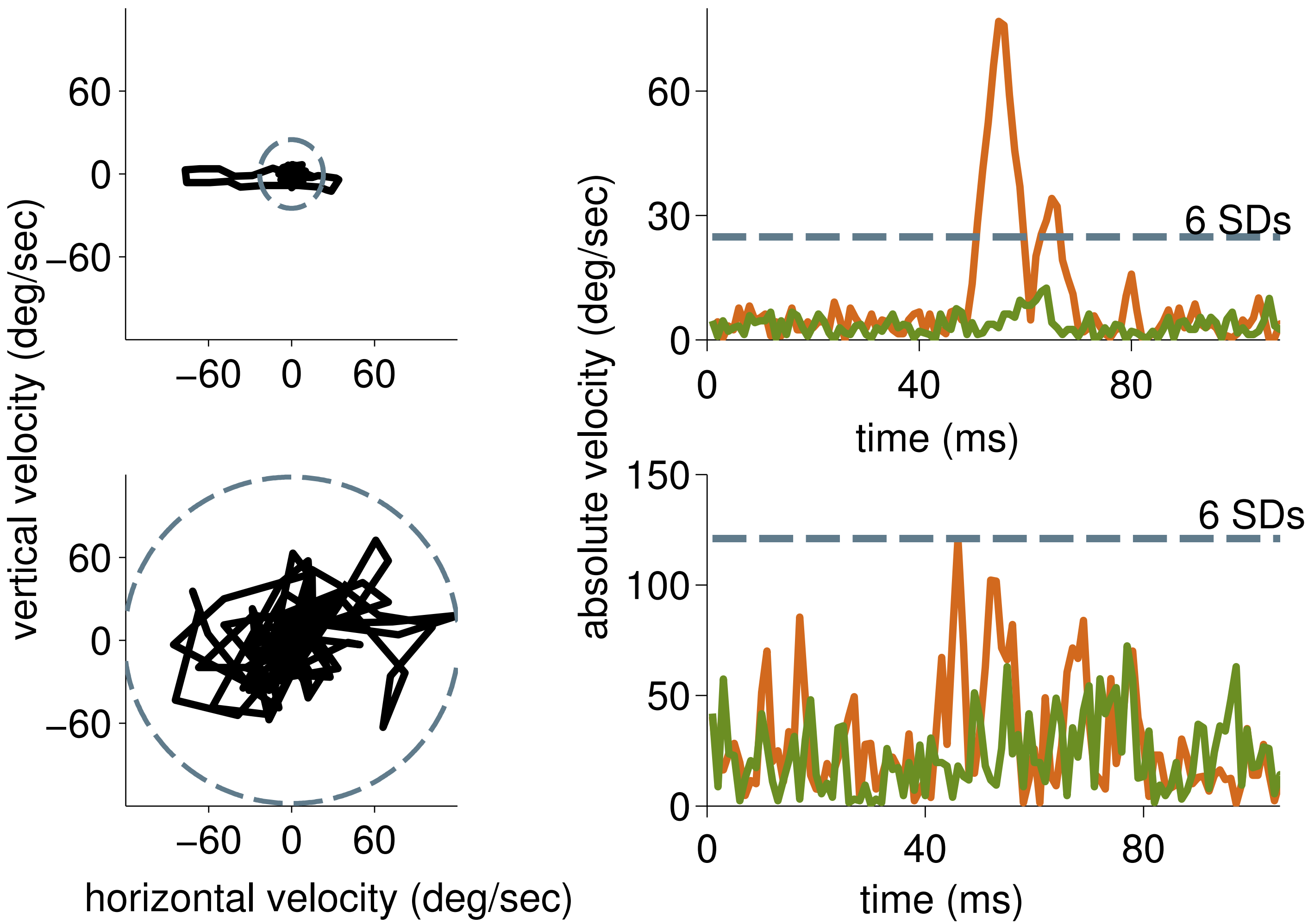
Engbert & Kliegl (EK) velocity threshold algorithm

Engbert and Kliegl, 2003



Engbert & Kliegl (EK) velocity threshold algorithm

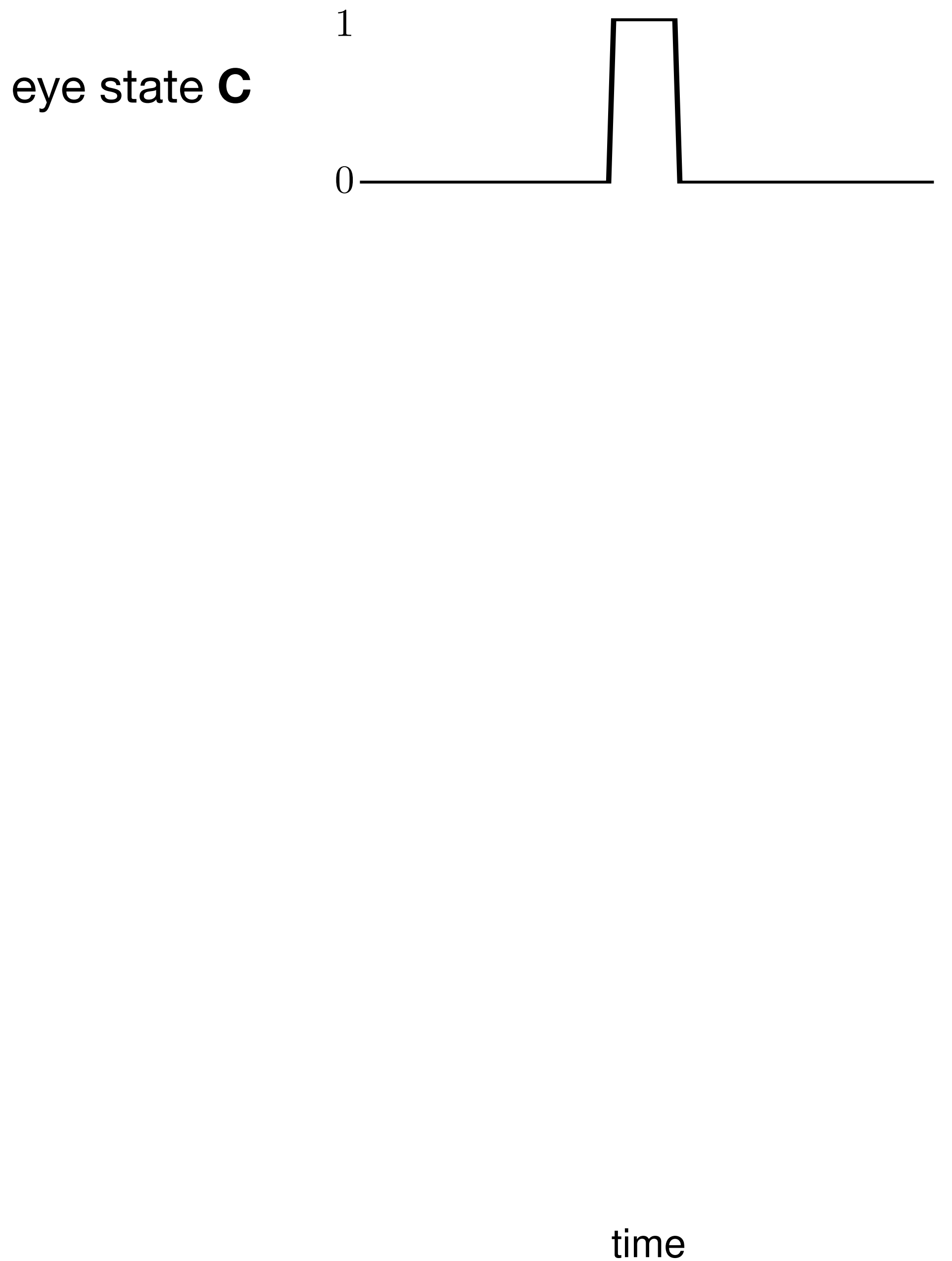
Engbert and Kliegl, 2003



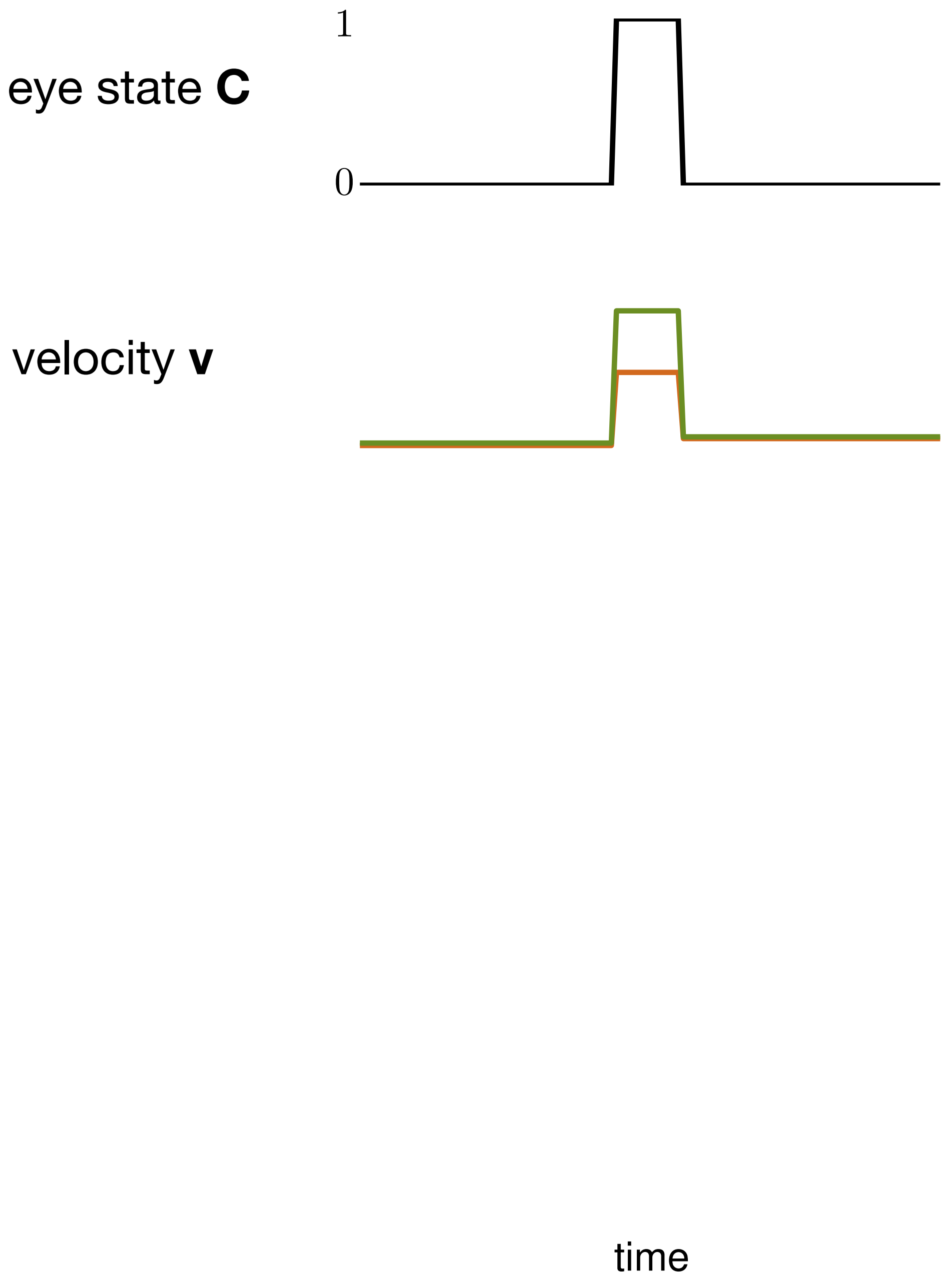
Bayesian microsaccade detection (BMD)

- Explicit assumptions about the process by which measured eye positions are generated
  - Probabilistic, not mechanistic
- Returns at each time point a probability instead of a binary answer

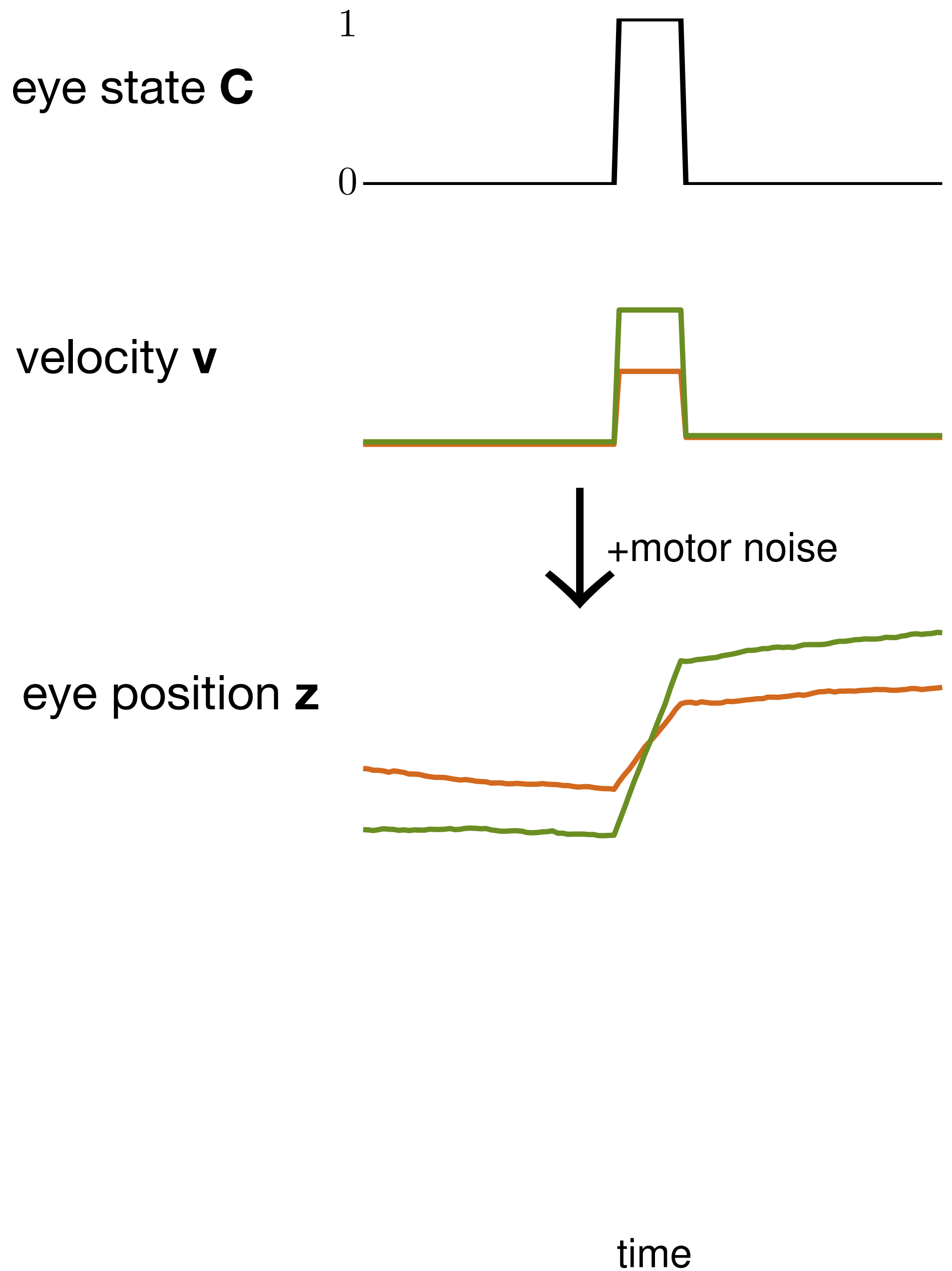
Generative model of fixational eye movements



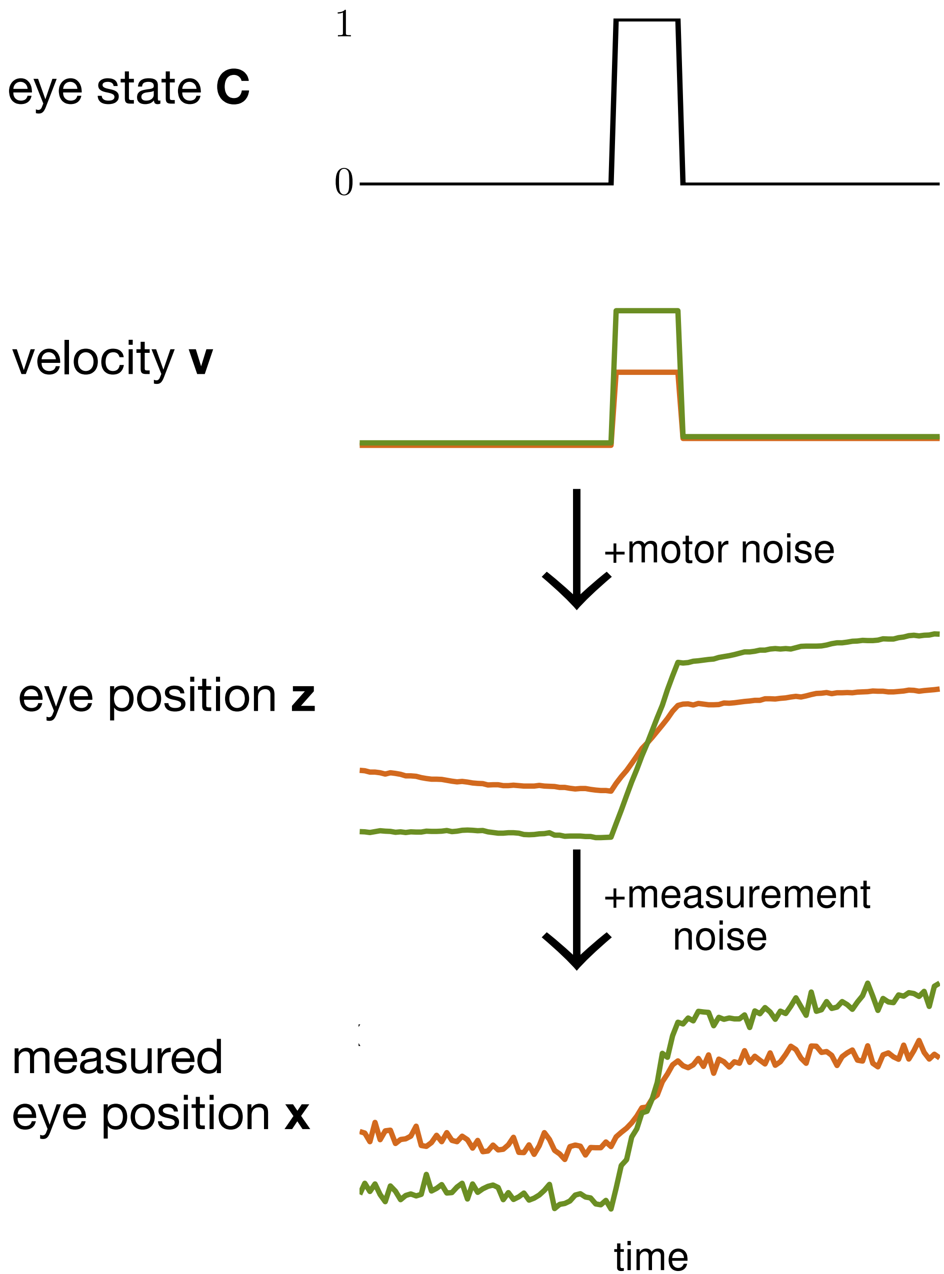
Generative model of fixational eye movements



Generative model of fixational eye movements



Generative model of fixational eye movements



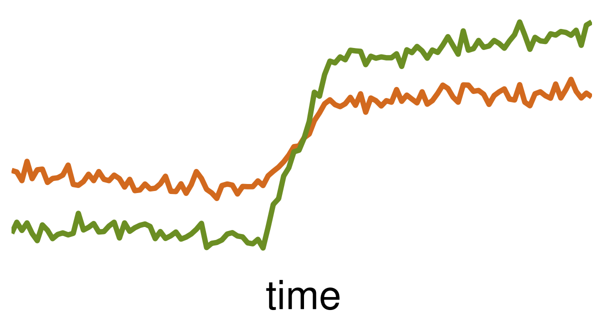
eye state **C**

?

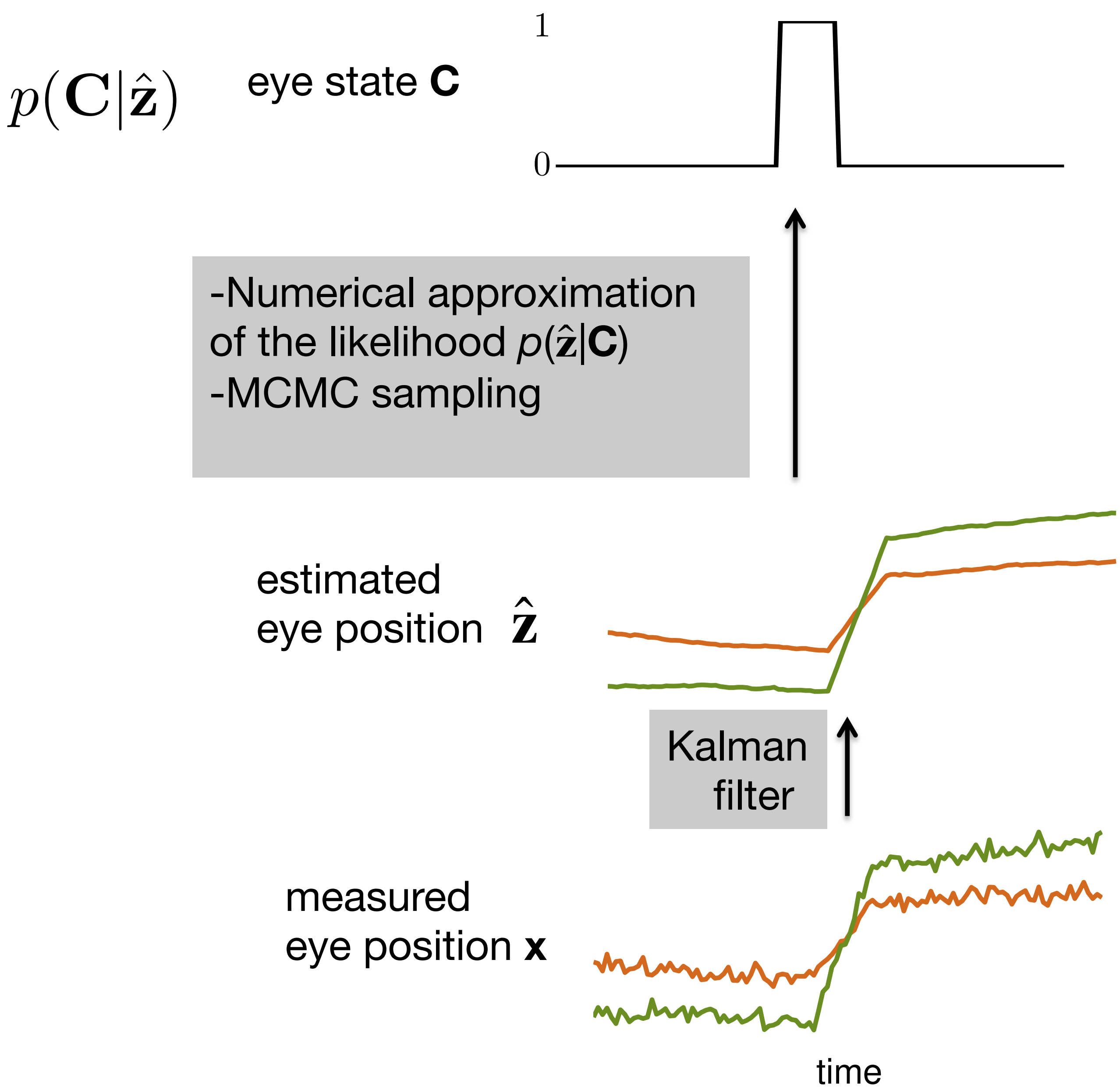
Bayesian inference

$$p(\mathbf{C}|\mathbf{x})$$

measured
eye position **x**

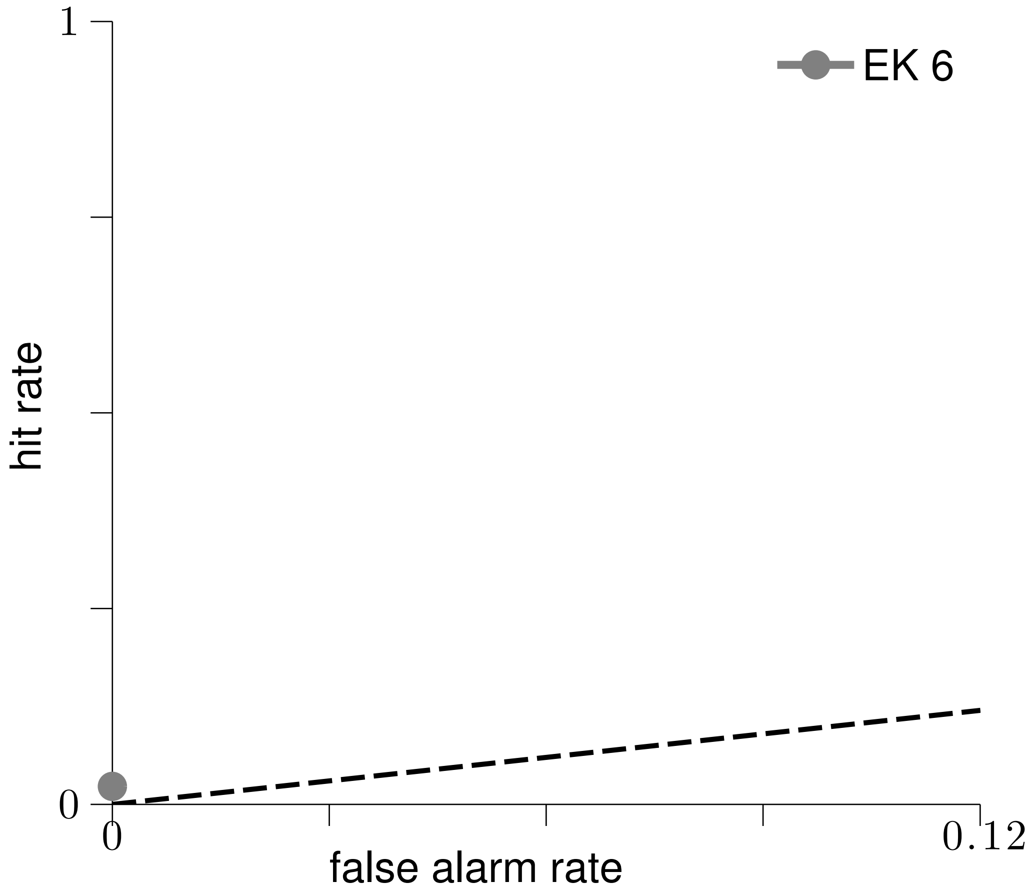


Approximate inference: BMD algorithm

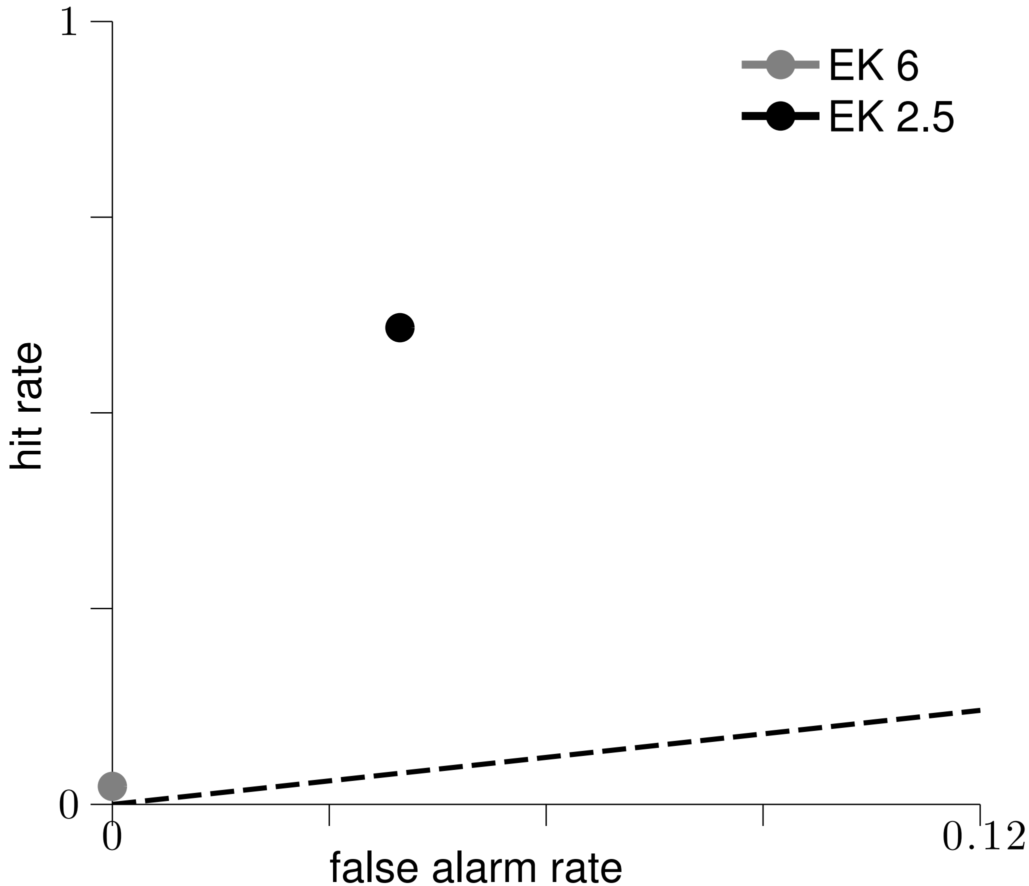


Test BMD algorithm: simulated data

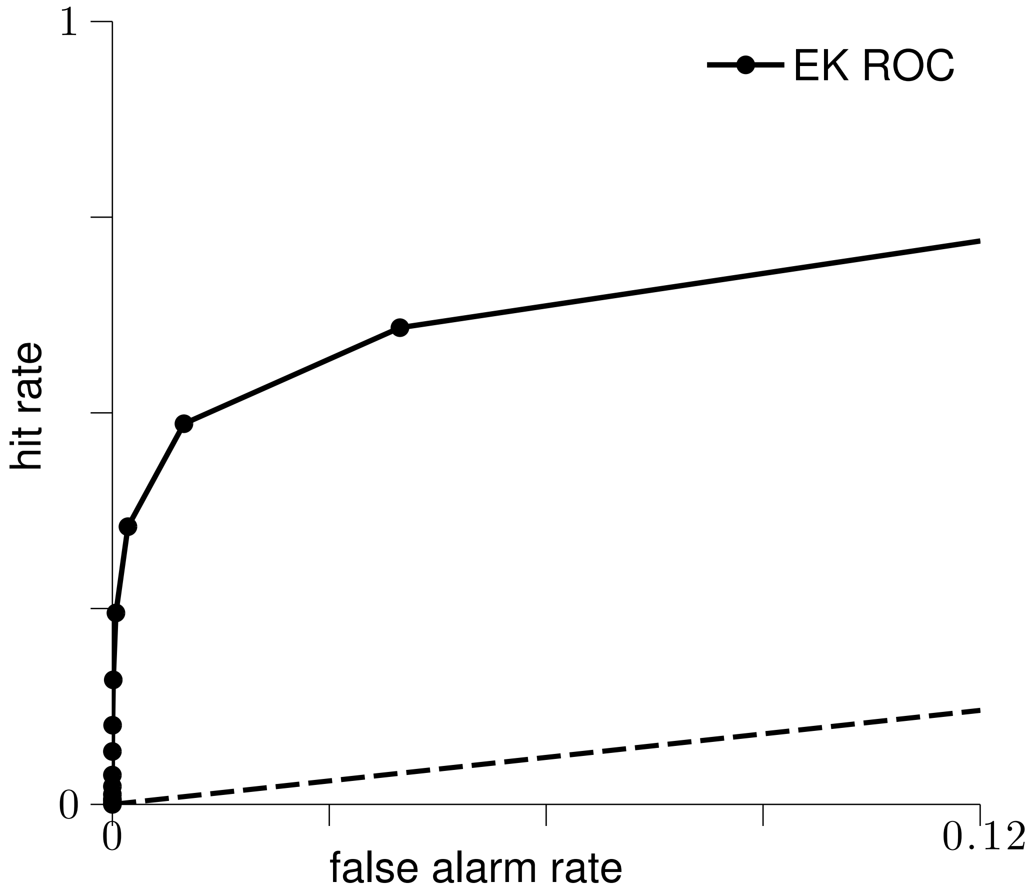
1. Simulate data from generative model with increasing levels of motor and measurement noise
2. Test BMD against alternative algorithms: variants of EK velocity threshold, unsupervised clustering (Otero-Milan et al, 2014)
3. Use hit rate and false alarm rate as metric for performance



1
0
EK 6
hit rate
0
0.12
false alarm rate

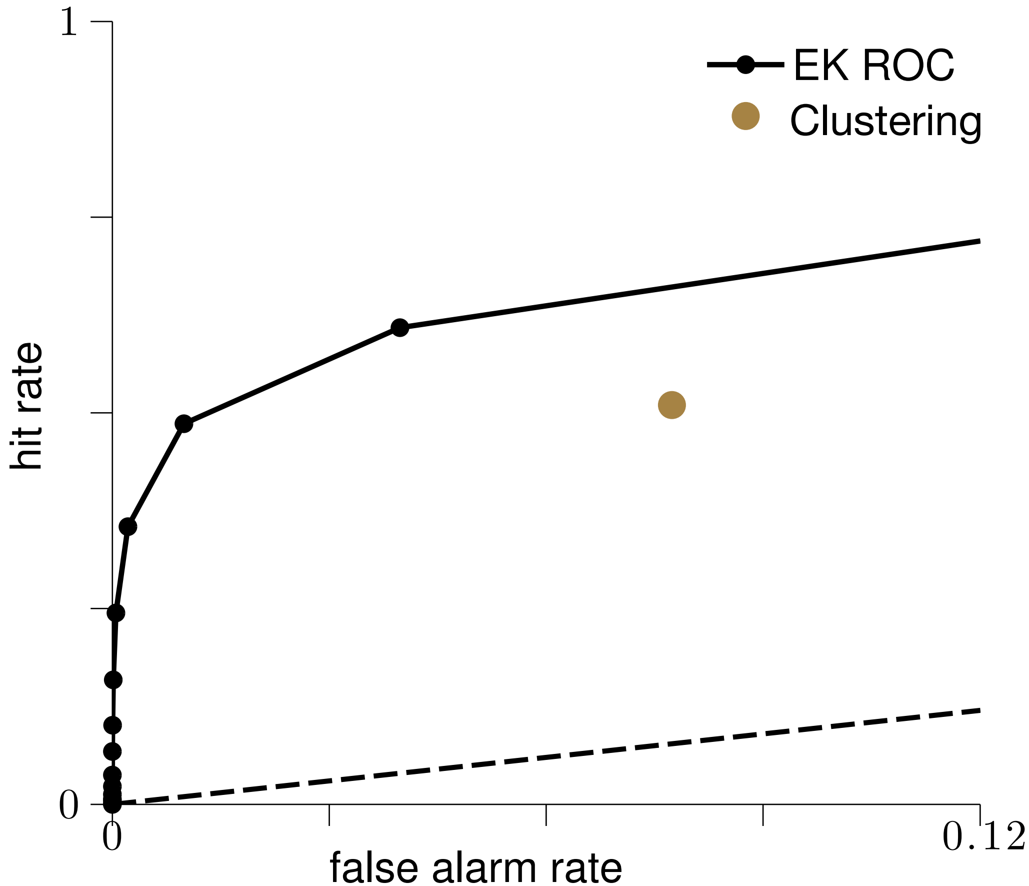


1
0
EK 6
EK 2.5
hit rate
0
0.12
false alarm rate

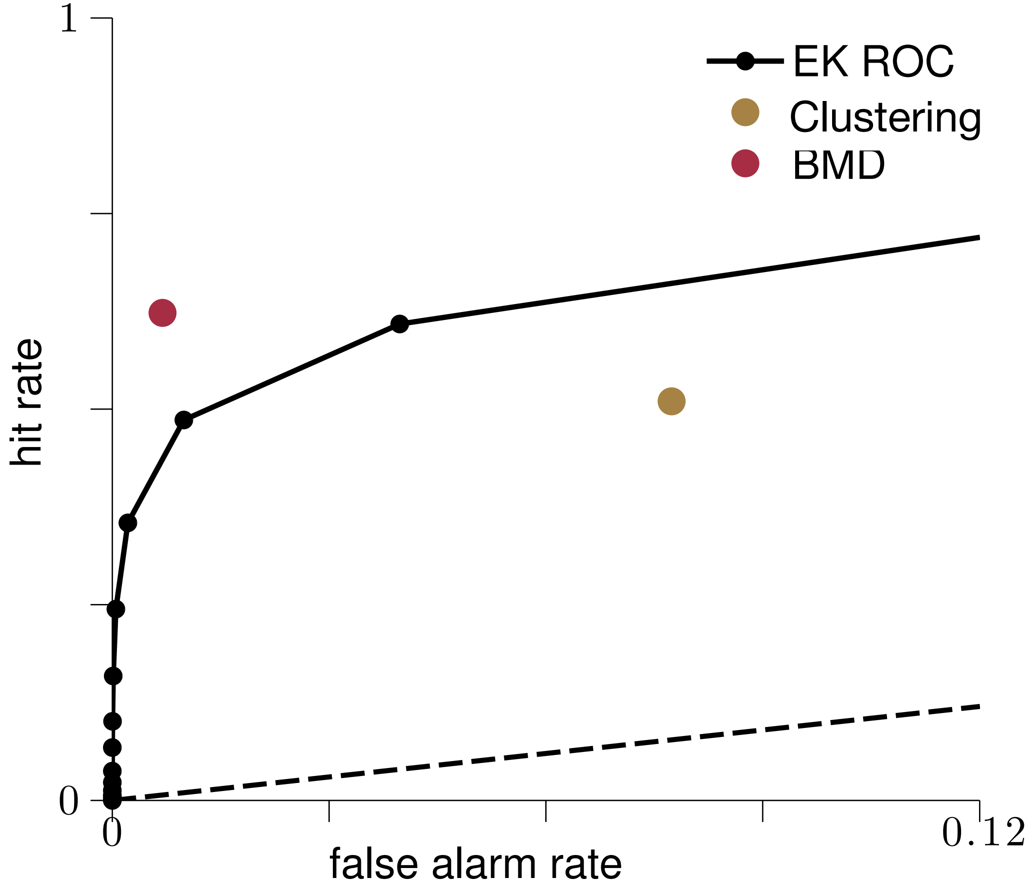


1
0
EK ROC
hit rate
0
0.12
false alarm rate

Unsupervised clustering is less robust to noise than EK on simulated data



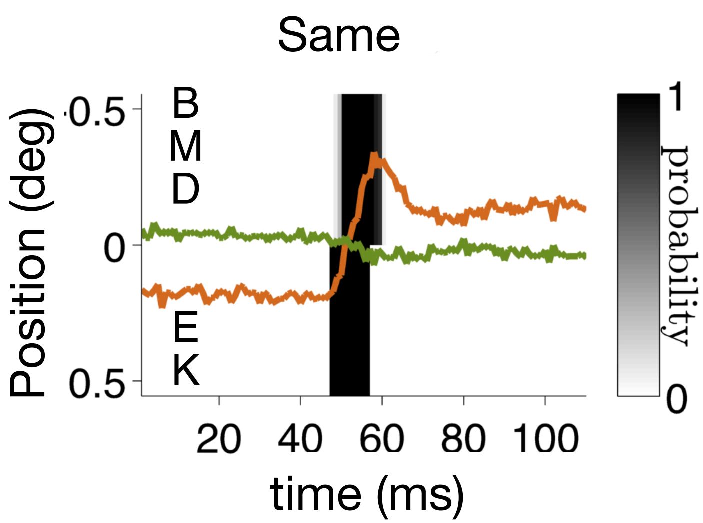
BMD is more robust to noise than EK on simulated data



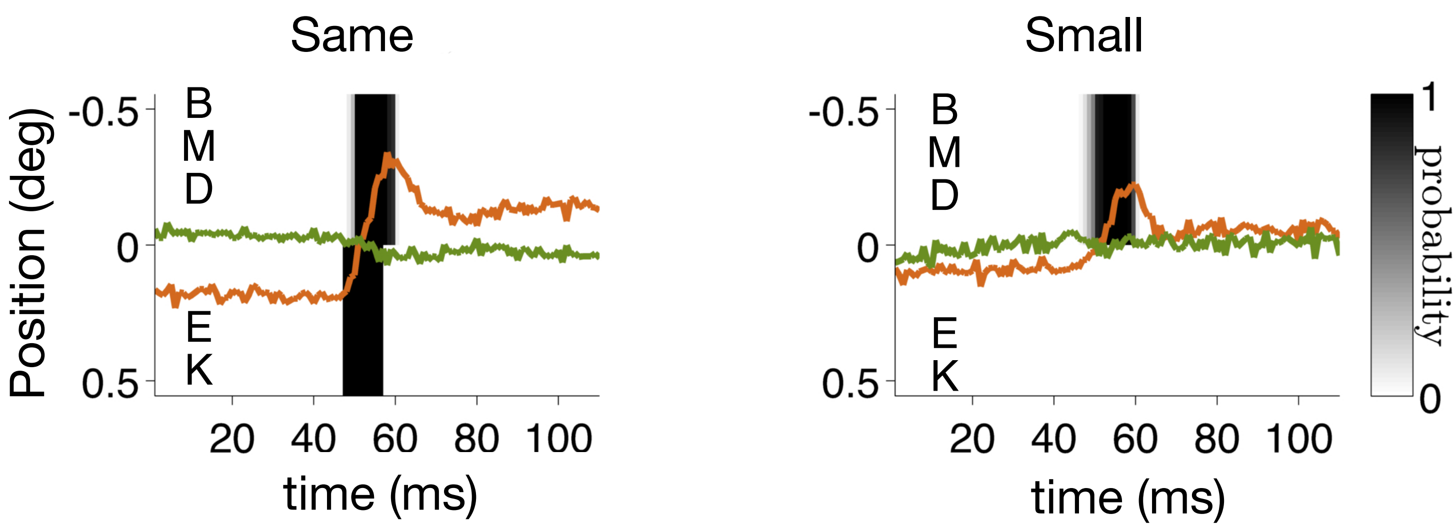
Tests on real data

1. EyeLink data
    - High measurement noise

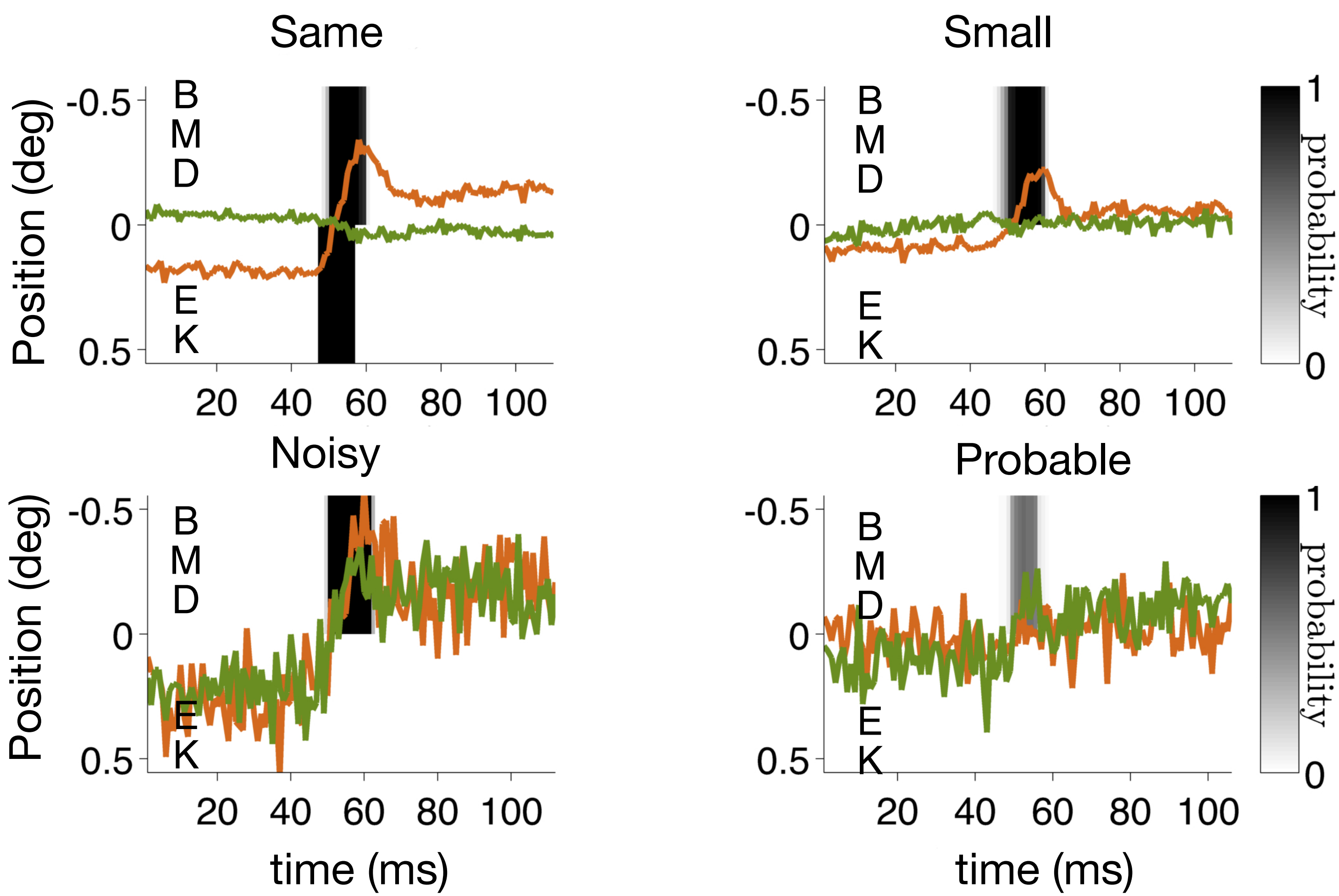
In most cases, BMD infers almost the same microsaccade as EK



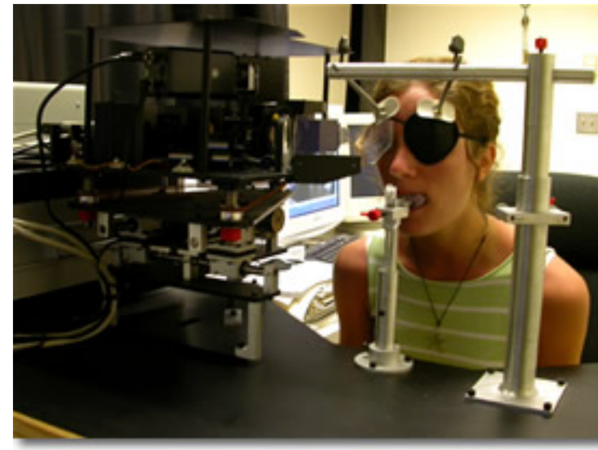
BMD infers a **small** microsaccade missed by EK



BMD infers probable microsaccades embedded in noise, undetected by EK



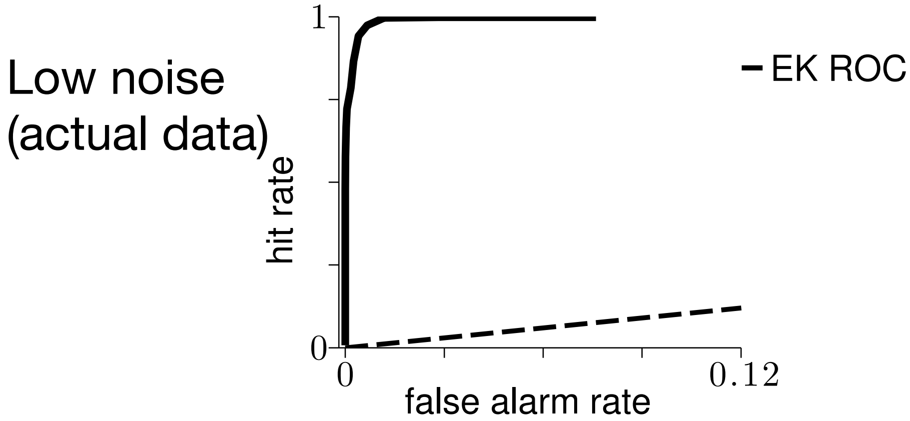
Tests on real data

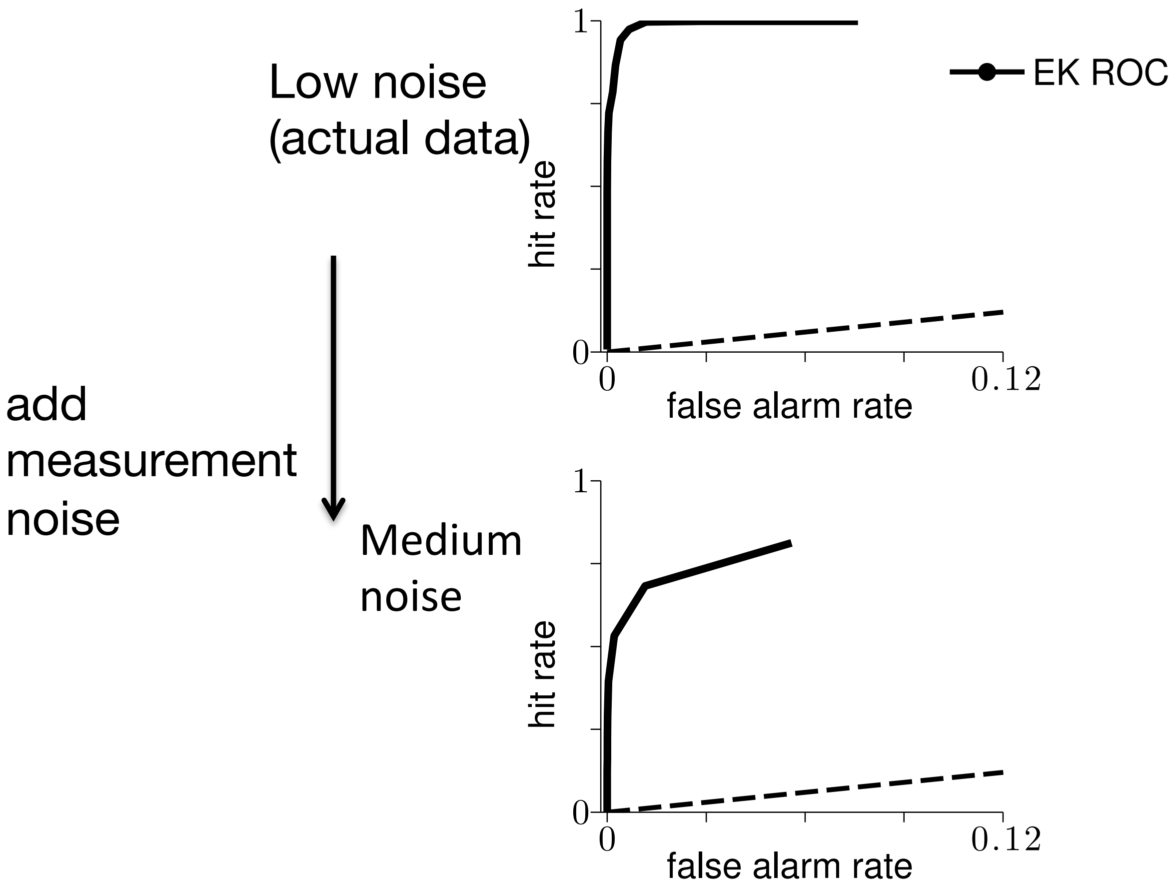


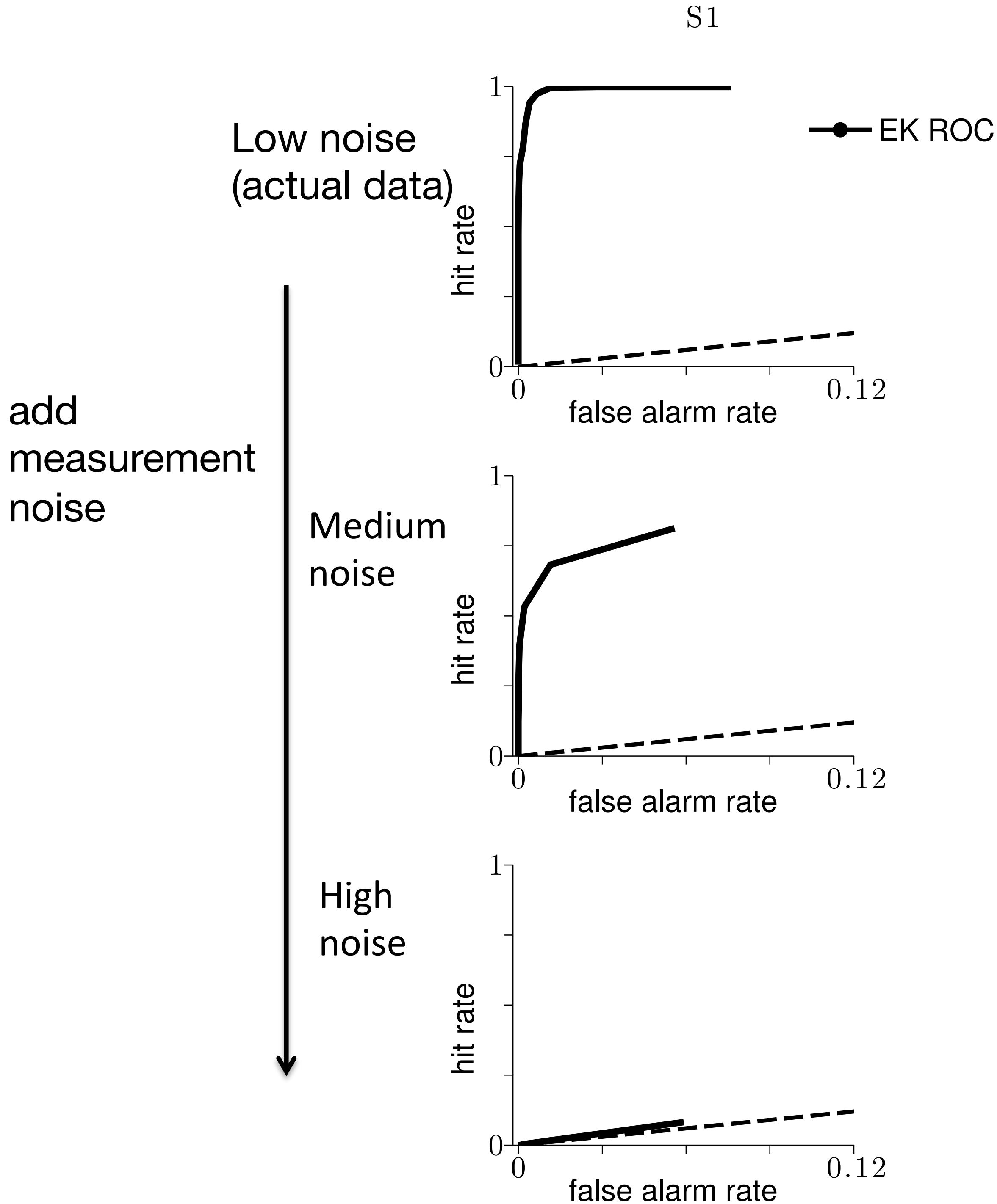
1. EyeLink data
   - High measurement noise
2. Dual Purkinje Image data
   - Low measurement noise
   - Ko, Poletti and Rucci, 2010 and Poletti and Rucci, 2015

Strategy

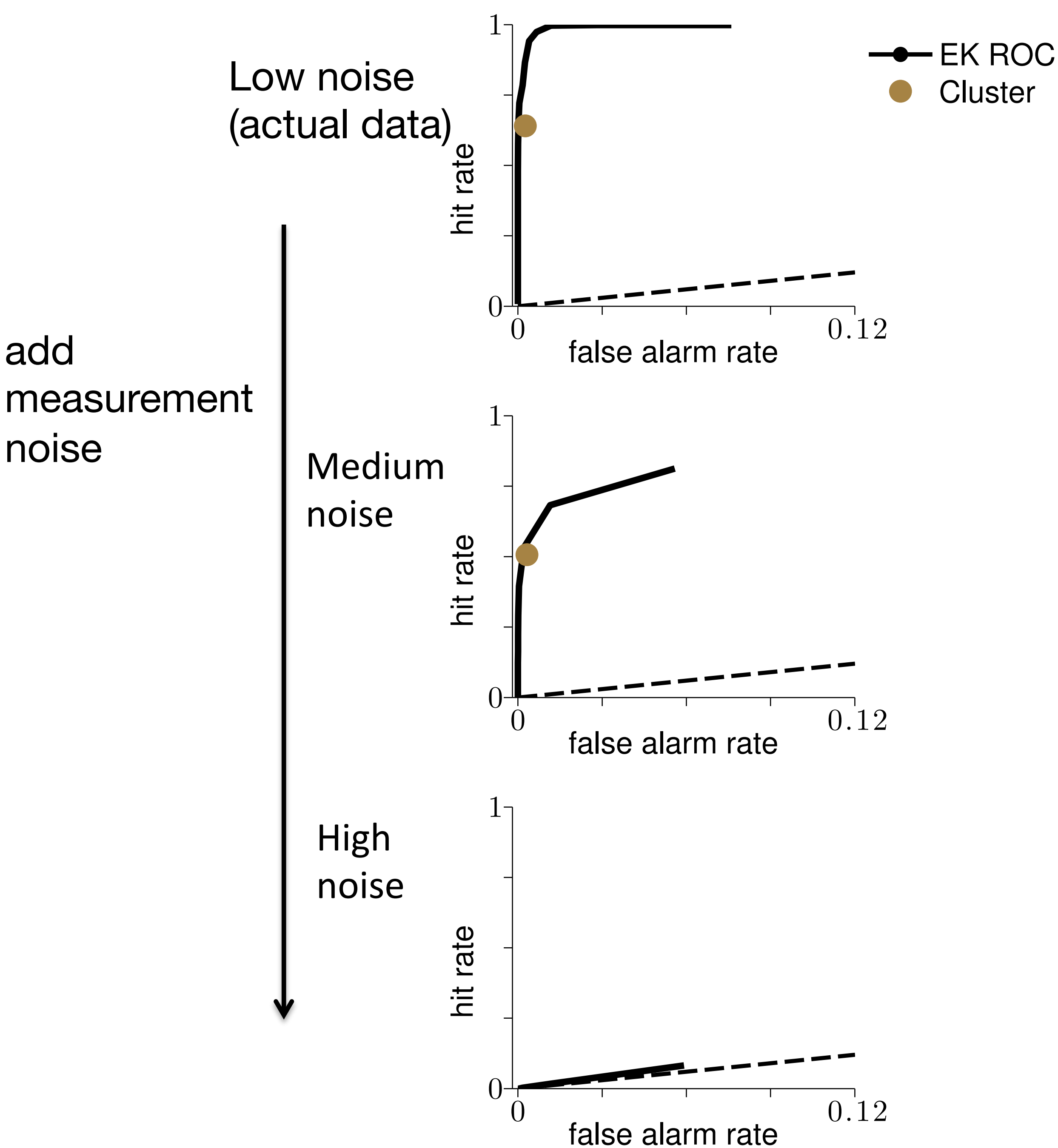
- Set ground truth as the inferred microsaccades on low-measurement noise DPI data
- Artificially add measurement noise
- Compare robustness of EK, clustering and BMD


Low noise
(actual data)
1
0
hit rate
0
0.12
false alarm rate
EK ROC

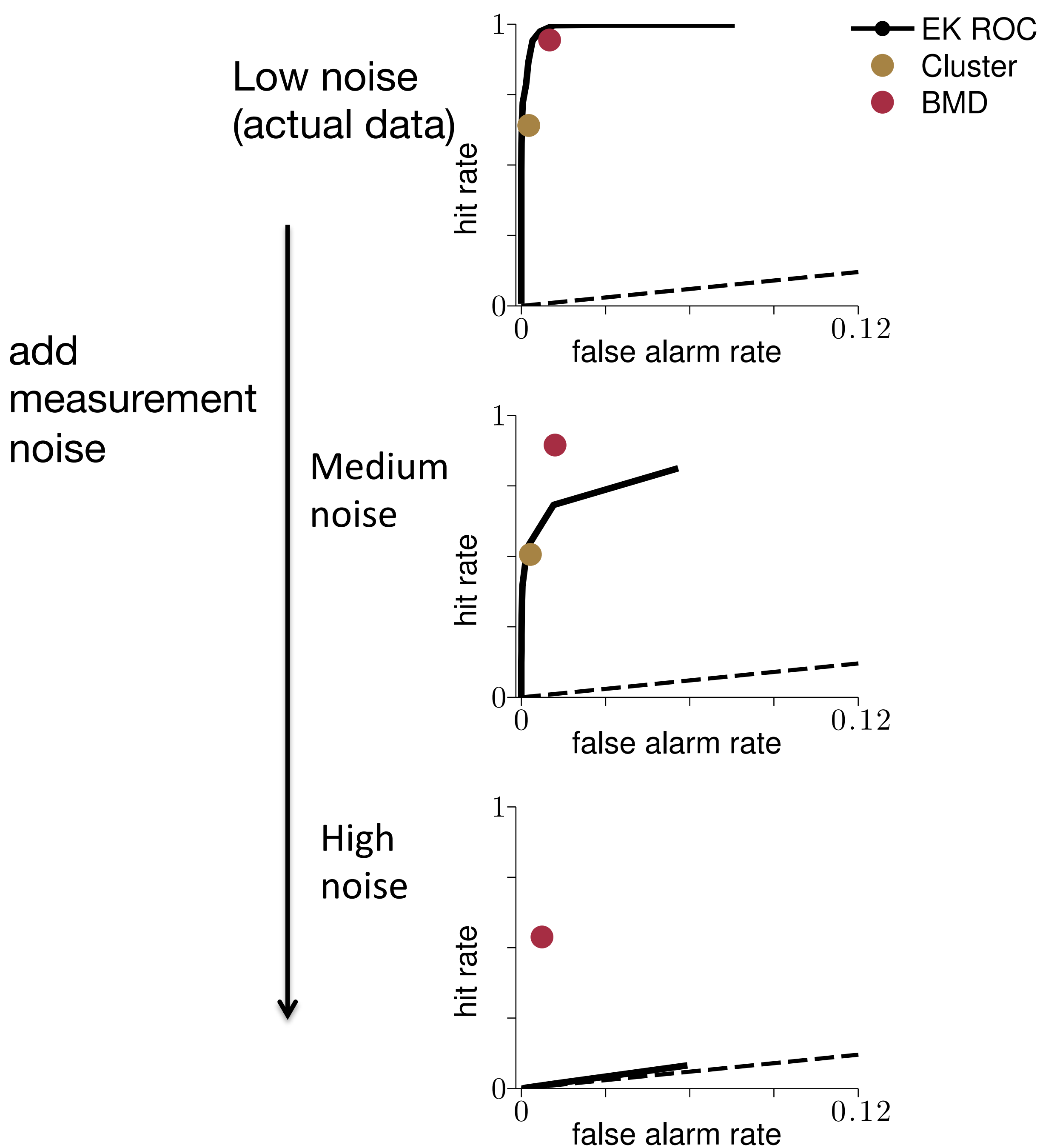

Low noise
(actual data)
add
measurement
noise
Medium
noise
EK ROC
hit rate
1
0
0
0.12
false alarm rate
hit rate
1
0
0
0.12
false alarm rate


S1
Low noise
(actual data)
EK ROC
hit rate
false alarm rate
1
0
0
0.12
add
measurement
noise
Medium
noise
High
noise

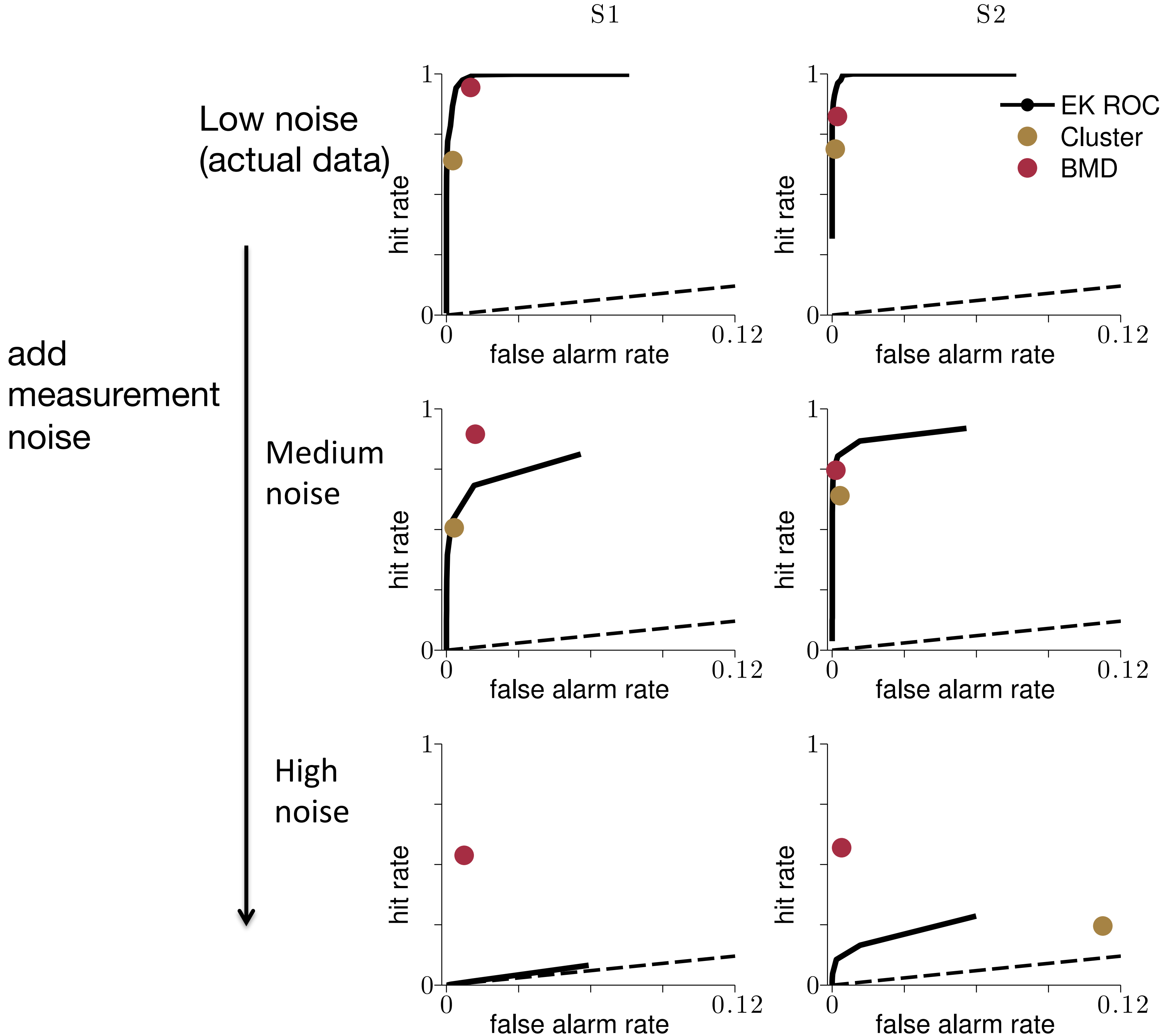
S1



Low noise
(actual data)
add
measurement
noise
Medium
noise
High
noise
EK ROC
Cluster
hit rate
false alarm rate
1
0
0
0.12



Low noise
(actual data)
add
measurement
noise
Medium
noise
High
noise
EK ROC
Cluster
BMD
hit rate
false alarm rate
1
0
0
0.12



S1
S2
Low noise
(actual data)
add
measurement
noise
Medium
noise
High
noise
EK ROC
Cluster
BMD
hit rate
false alarm rate
0
1
0.12

Conclusions and future directions

- BMD recovers previously undetected microsaccades as it is more robust to eye tracker noise
- BMD algorithm brings a principled, Bayesian framework to microsaccade detection
- BMD has limitations:
  - Speed
  - Assumptions: but improvements can be flexibly included

Acknowledgements

- **Ma Lab**
- **Wei Ji Ma**
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- Roozbeh Kiani
- 4th years

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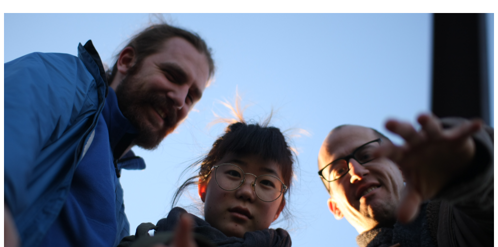
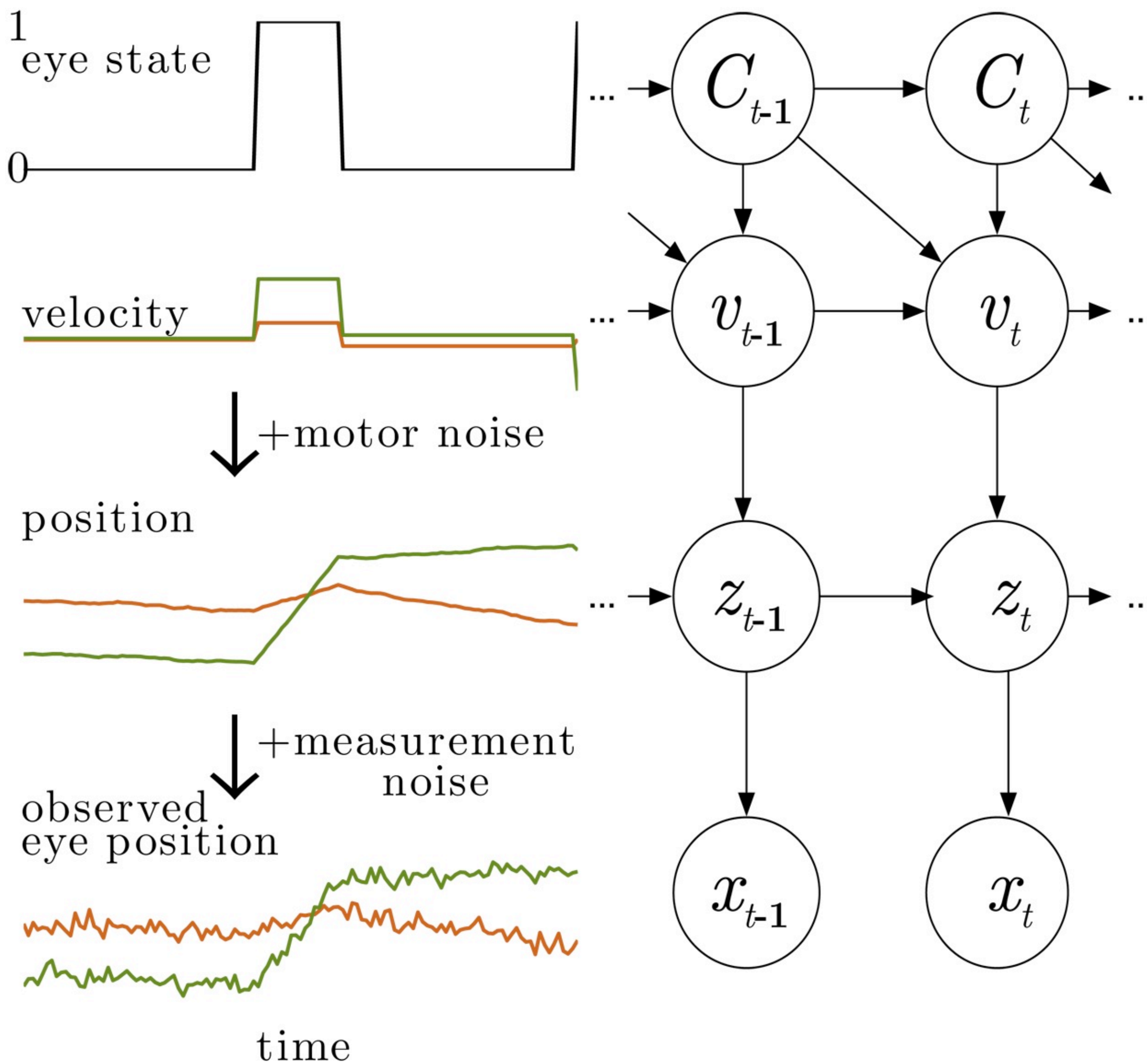
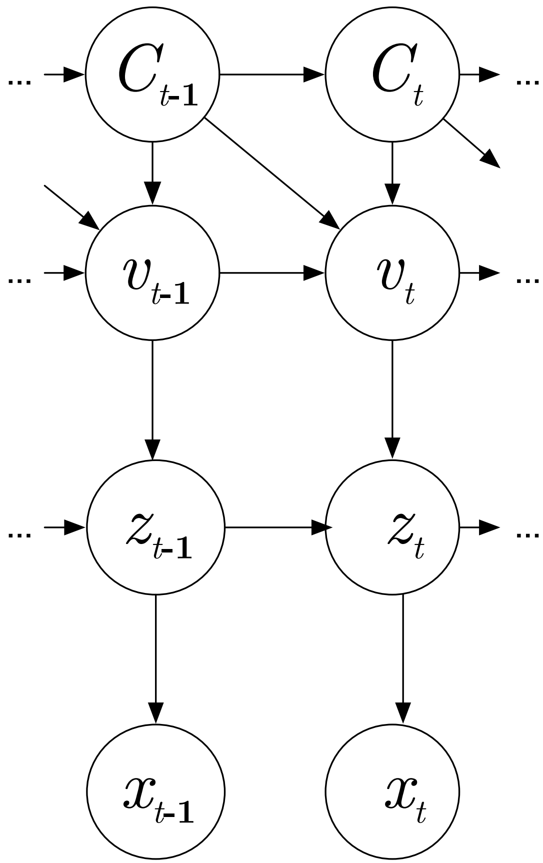
- Martina Poletti and Michele Rucci at BU



Generative model of fixational eye movements



Generative model of fixational eye movements



$$p(\mathbf{C}) \quad \propto \quad \prod_{k=1}^{2n-1} Gamma\left(\Delta\tau_k; 2, \frac{1}{\lambda_{k \pmod 2}}\right)$$

$$p(v_t | C_t = C_{t-1}) = \delta(v_t - v_{t-1})$$

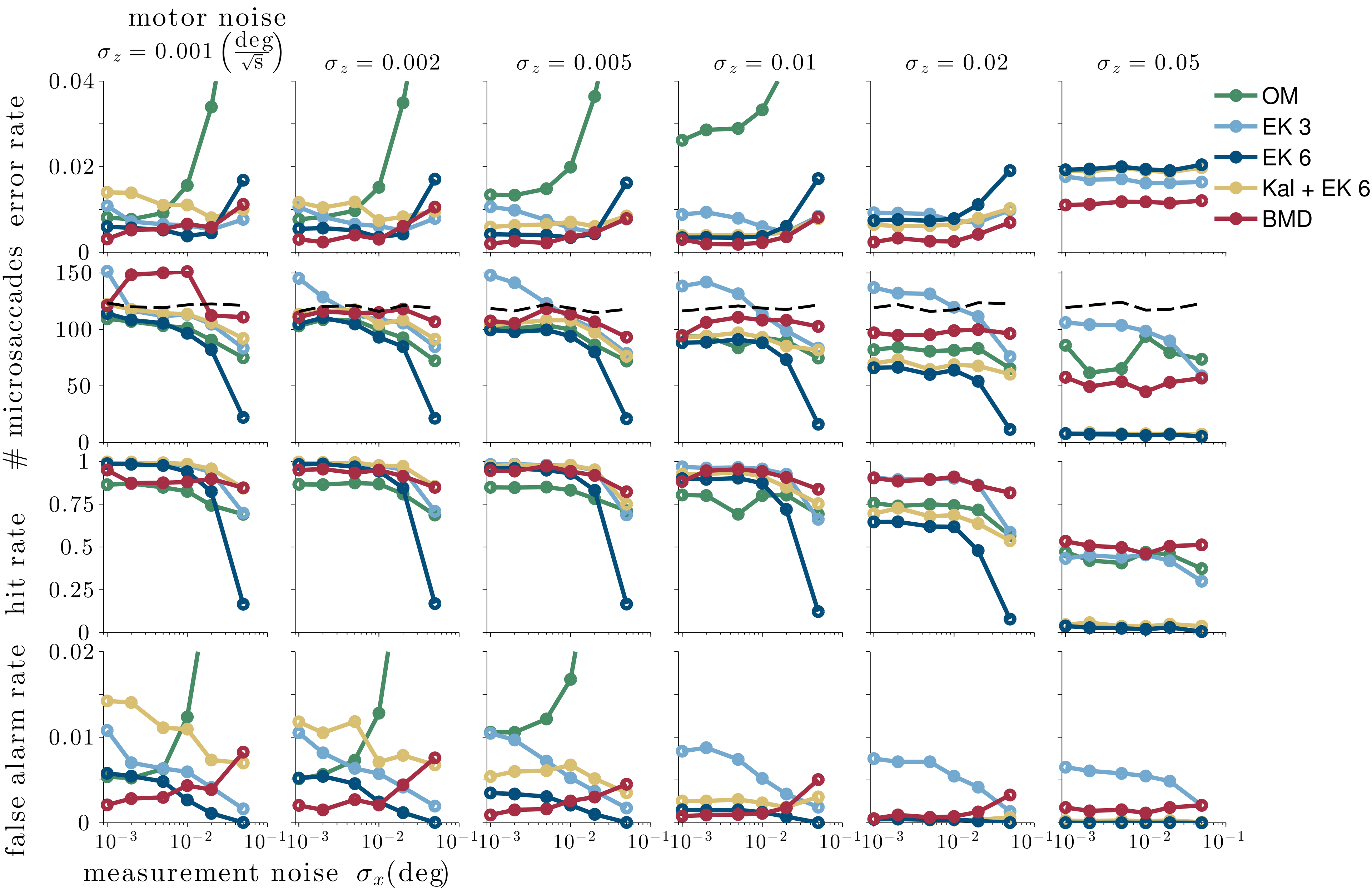
$$p(v_t | C_t = 1, C_{t-1} = 0) \quad \propto \quad Gen\ Gamma\,(||v_t||; \sigma_1, d_1, 2)$$

$$p(v_t | C_t = 0, C_{t-1} = 1) \quad \propto \quad Gen\ Gamma\,(||v_t||; \sigma_0, d_0, 2)$$

$$p(z_t | z_{t-1}, v_t) \quad = \quad \mathcal{N}(z_t; z_{t-1} + v_t, \Sigma_z)$$

$$p(x_t | z_t) \quad = \quad \mathcal{N}(x_t; z_t, \Sigma_x)$$

BMD is more robust to noise on simulated data



BMD is more robust to noise on real DPI data: DPI data + measurement noise