Classifying neurons using virtual reality recordings

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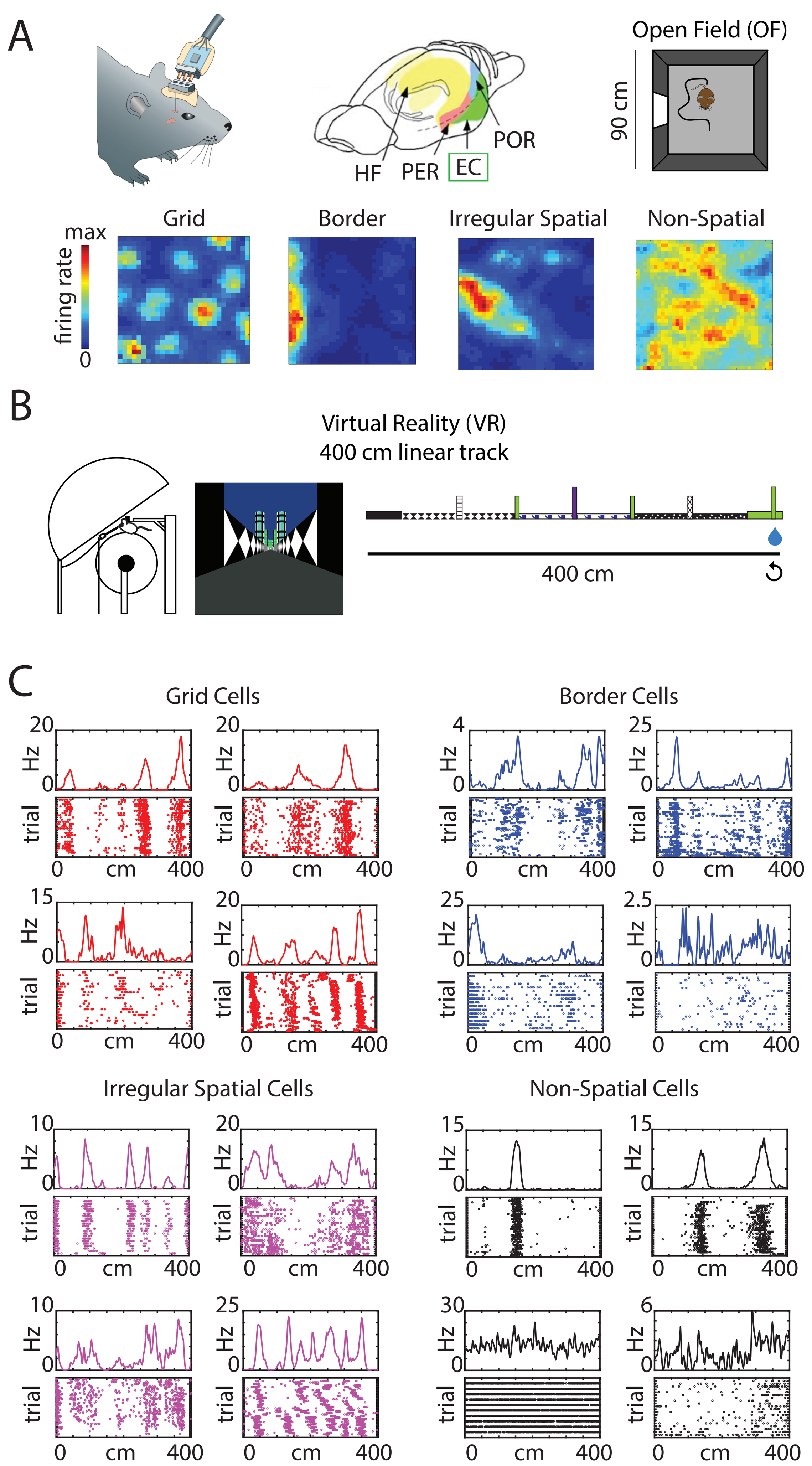
1. Introduction and data

- Neurons in the mammalian medial entorhinal cortex (MEC) respond to the current location of the animal, forming a cognitive map of its environment [1].
- These neurons can be classified based on their pattern of activity relative to the environment as "grid," "border," and other cell types (A).
- To leverage new recording technologies, we wish to record these neurons while the animal's head is fixed in place. To achieve this, we trained mice to run along a virtual hallway (VR, B).
- We would like to know whether classical MEC cell types are separable based on VR recordings alone (C).



2. Grid vs. {border, non-grid}

Dataset: 781 cells (96 grid, 97 border, 590 other)

1. Baseline features (n = 323)

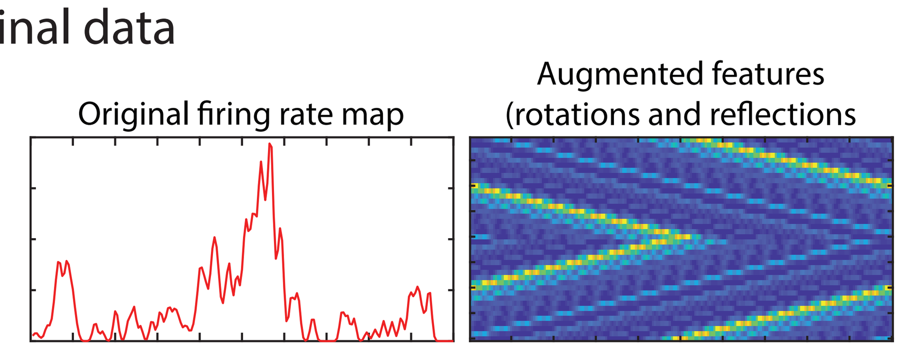
- Mean firing rate (1x1)
- Firing rate map (200 x 1)
- Magnitude of FFT of firing rate map (100 x 1)
- Average cross-correlation between single trial rate maps (21 x 1)
- Location of peak average trial cross correlation (1x1)

Classifier performance (accuracy, LOOCV)

	L2-Logistic	Linear SVM	RBF-SVM	GDA
Grid vs. non-grid (downsampled)				
Train	54.4	60.4	84.4	100
Test	49.0	53.7	54.2	54.7
Grid vs. border				
Train	52.2	61.0	90.7	99.0
Test	52.3	58.0	58.0	54.4

2. Data-augmentation

- Idea: Get classifier to generalize features over location by feeding it rotated and reflected copies of the original data

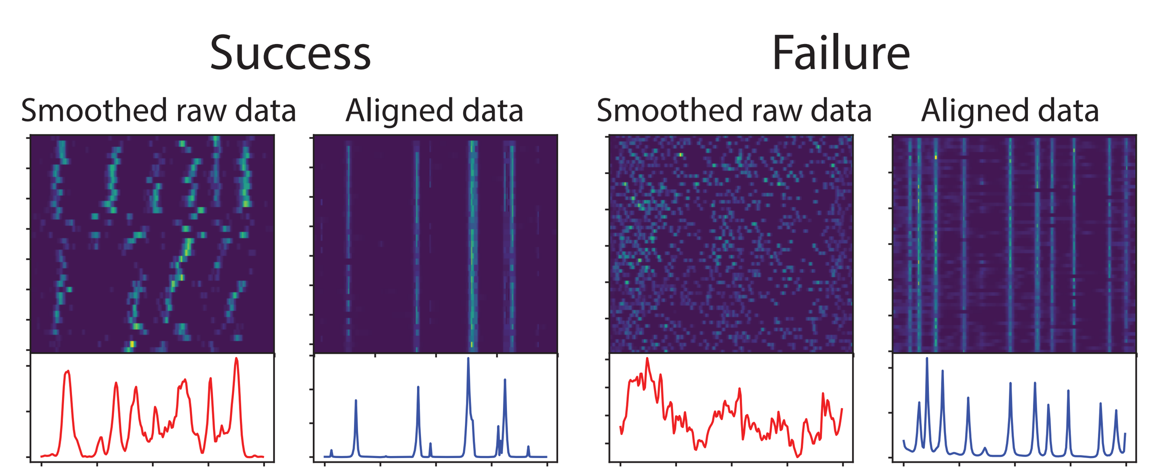


Classifier performance (accuracy, LOOCV): Grid vs. non-grid

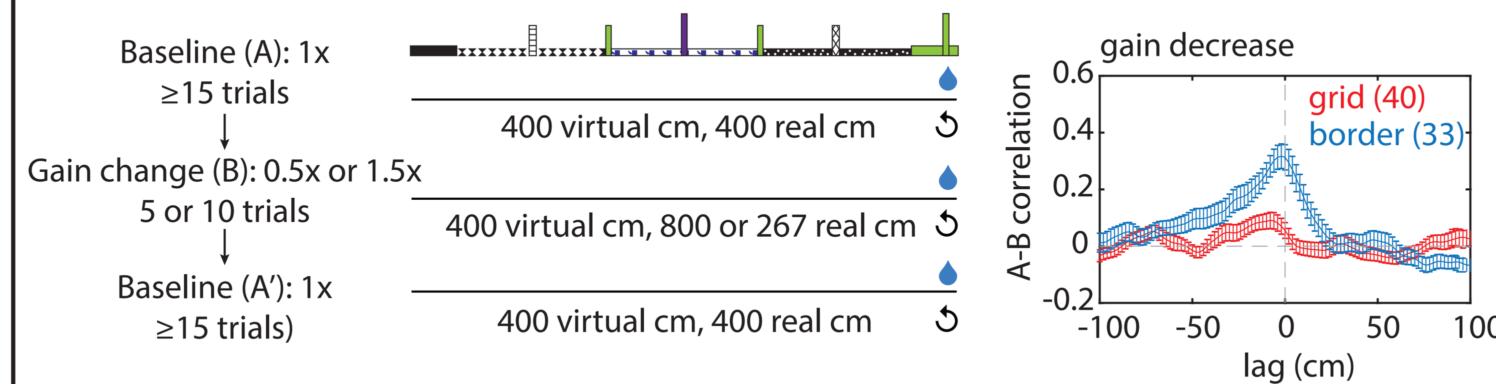
	L2-Logistic	Linear SVM	RBF-SVM	GDA
Train	97.5	97.5	97.5	97.5
Test	50.3	50	50	50

3. Dynamic time-warping

- Idea: Re-align cells that drift over time to extract underlying structure [2]



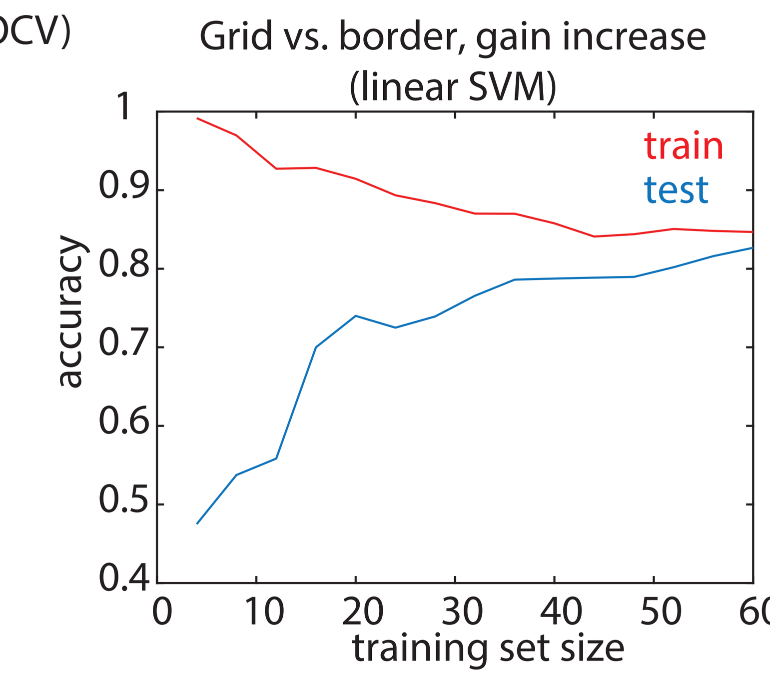
3. Gain manipulations



Features: Cross-correlation of A and B period firing rate maps (101 x 1)

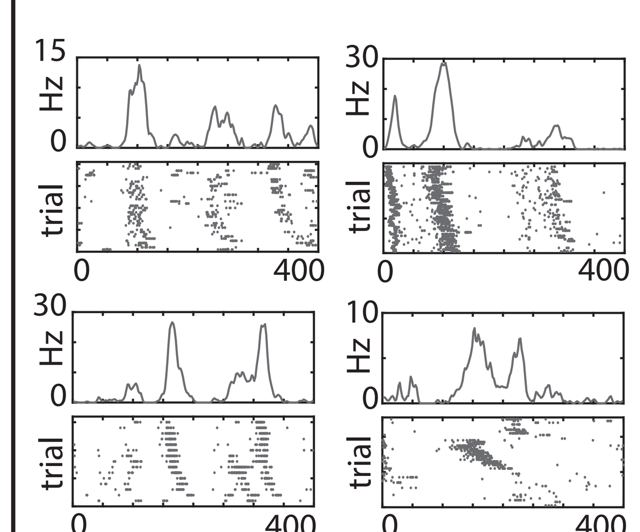
Classifier performance (accuracy, LOOCV)

	L2-Logistic	Linear SVM	RBF-SVM	GDA
Grid vs. border, gain decrease				
Train	77.6	78.1	90.0	1
Test	73.9	72.5	71.0	53.6
Grid vs. border, gain increase				
Train	80.7	84.4	92.7	1
Test	77.1	81.4	81.4	52.9



4. Drifty bursting cells

A new cell class: "Drifty bursting cells"



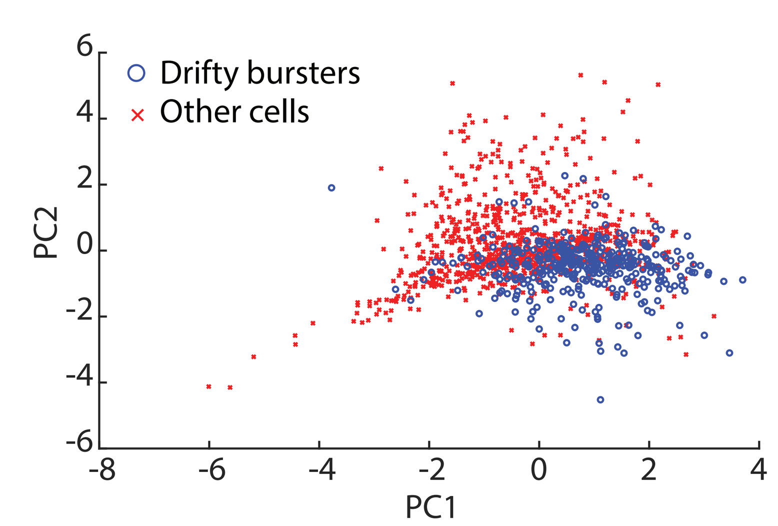
Features (n = 7)

1) Mean firing rate (r)
2) Median inter-spike interval (i)
3) Burstiness (1/(r·i))
4) Stability (s): *Correlation between firing rate map computed in first and second half of recording*
5) Trial-to-trial stability (t): *Mean correlation between firing rate maps computed from adjacent trials*
6) Stability ratio (t/s)
7) Field size (f): *Width of autocorrelation*

- Hand labeled 1,244 recordings (375 drifty bursters)

Classifier performance (accuracy, LOOCV)

	L2-Logistic	Linear SVM	RBF-SVM	GDA
Drifty bursters vs. other cells				
Train	74.0	74.0	87.5	78.7
Test	73.7	73.8	74.7	78.4



5. Summary and discussion

- So far, it was not possible to separate MEC cell types based on features of the firing rate map alone, even with data augmentation
- Adding features derived from cells' responses to gain manipulations improved performance
- This could reflect the fact that different cell types derive their spatial responses from different inputs
- 80-85% accuracy appears to be the limit of performance using this feature
- We identified by eye and hand-labeled a new cell class which we call "drifty bursting cells"
- Using 7 hand-crafted features, we could separate drifty bursting cells (~30% of the population) from other cells with ~75% accuracy
- Dynamic time-warping could in theory identify cells whose firing patterns drift over time, but on first pass this technique tended to over-fit our data

6. Future directions

- Unbalanced classes (grid, border, other): How much of a problem?
- Penalize false-positives more highly in cost function
- Refine definition of "drifty bursting cells"
- How well can we predict response to gain manipulations?
- Convolutional approaches to identify spatially-invariant features of firing rate maps
- Identify and eliminate failure modes of dynamic time-warping
- Use dynamic time-warping to identify neurons that drift, warp, or bifurcate over time in particular ways

References

1) Rowland, D.C., Roudi, Y., Moser, M.B. & Moser, E.I. Ten years of grid cells. Annu Rev Neurosci 39, 19-40 (2016).

2) Cuturi, M., and Blondel, M. Soft-DTW: a Differentiable Loss Function for Time-Series. arXiv:1703.01541v1, 5 Mar 2017.