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Are there discrete gamma sub-bands in hippocampus during spatial learning?

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**Introduction**

- Theta (\(\theta\)) and gamma (\(\gamma\)) oscillations are believed to organise hippocampal activity, via their cross-frequency coupling.
- Classic view: \(\gamma\) (\(\sim 30-60\) Hz) are related to memory retrieval; and \(\theta\) (\(\sim 1-60\) Hz) are related to sensory information and memory encoding.
- However, recent evidence suggests a wider repertoire of coupling patterns when considering individual \(\theta\) cycles.

**AIM OF THE STUDY**

Explore theta-gamma oscillatory dynamics in CA1 and DG across learning in an ecologic spatial navigation task and without a priori on frequencies and phases that should be observed.

**The Arm-to-Arm task**

- **Subjects**: water-restricted mice (\(n=4\)).
- **Maze**: 8 arm radial arm maze; distal visual cues available.
- **Task**: finding the rewarded arm starting from another (semi-random) arm; fixed reward arm across the 10-day training, 4 daily trials.
- **Reward**: 0.05 ml of water at last arm end.

**Unsupervised EEMD decomposition**

- Unsupervised empirical ensemble mode decomposition (EEMD for cycle-by-cycle analysis; see \(\sim\) xiang, 2005; EEMD for power spectrum; see \(\sim\) xiao et al., 2010).
- Power spectra of EEMD-derived IMFs is stable along training.
- Need to correct for theta harmonics.

**Power across learning**

**\(\theta\) cycle-by-cycle analyses**

- Identification of \(\theta\) cycles: preservation of \(\theta\) asymmetry (2-5 Hz filtering); phase estimation with piece-wise linear interpolation.
- \(\gamma\) spectral content of each \(\theta\) cycle: coincident segment of the spectrogram of \(\gamma\)-composite signal (complex Morlet wavelets, 1-200 Hz; 1 Hz steps).

**\(\theta\)-\(\gamma\) coupling: means vs counts**

- Mean \(\theta\)-\(\gamma\) motifs from representative channels and trials do correspond to the “classical model”.
- However, the possibility of multiple \(\theta\) motifs per \(\gamma\) cycle is not “classical”, as well as the presence of both medium and slow \(\gamma\) episodes in both dendritic layers.
- The large variability of individual cycles and the broad count distributions suggest that the landscape of possible \(\theta\)-\(\gamma\) couplings is better described as a structured continuum.

**A structured continuum of cycles...**

- At all stages of learning and all anatomical layers, \(\gamma\) are highly variable, but phase, freq and power are not uniformly distributed.
- The “swarms” of cycles morph along learning (e.g., migration of high power SLM cycles toward higher frequencies).
- Yet, despite complexity, non-trivial coding of navigation speed or location?

... which conveys decodable information

- We trained classifiers (Random forests, via RUSBoost method) to predict speed and maze location as a function of individual cycle properties.
- Decoding is possible, revealing that different inputs convey different information at different times (but not simply “recall” or “encoding”).