

A novel seizure detection algorithm informed by hidden Markov model event states

Supplemental Information

Methods:

Surgical Protocol:

Dogs were anesthetized using a standardized protocol for intracranial surgery^{11,12}. Bilateral craniectomies were performed using standard aseptic procedures and two silicone strip electrodes each containing 4 contacts were placed bilaterally in the subdural space (Figure S1A). Lead tails were tunneled subcutaneously to the telemetry unit implanted in a dorsal tissue pocket on the dog. The dogs were intermittently maintained on anti-epileptic medications during this study with very rare seizure occurrence during these periods.

Device:

A custom implantable iEEG acquisition system was used to acquire long-term continuous iEEG in two dogs. The system has three major components: (1) Implantable Lead Assembly (ILA) consisting of four silicone strips each containing four platinum-iridium contacts (4 mm² surface area) separated by 20 mm; (2) Implantable Telemetry Unit (ITU); and (3) external Personal Advisory Device (PAD). The iEEG signals are recorded from the ILA contacts, filtered, amplified, and digitized (sampling rate 400 Hz) within the ITU and then wirelessly transmitted to the external PAD device. The ITU is charged daily for approximately 1 hour via an external battery powered device. The PAD was kept on the dog's back within a harness, and collected continuous iEEG data wirelessly from the ITU. The PAD has embedded seizure detection algorithms, and includes a user interface with functional lights for seizure warning, audible alarms, text messaging, and email algorithm outputs.

Data curation: For each dog 16-channel iEEG recordings (Figure S1B) were wirelessly transmitted to the PAD and stored on a flash memory card. Continuous video and iEEG data were archived to a central storage each week. A high sensitivity automated seizure detection algorithm was used to detect candidate seizures. All candidate detections were visually reviewed and correlated with the continuous video to verify clinical seizure activity. The entire iEEG record was annotated by expert readers and all subclinical and clinical seizures verified. Canine data from this study are freely available on the iEEG portal (<https://www.ieeg.org/>).

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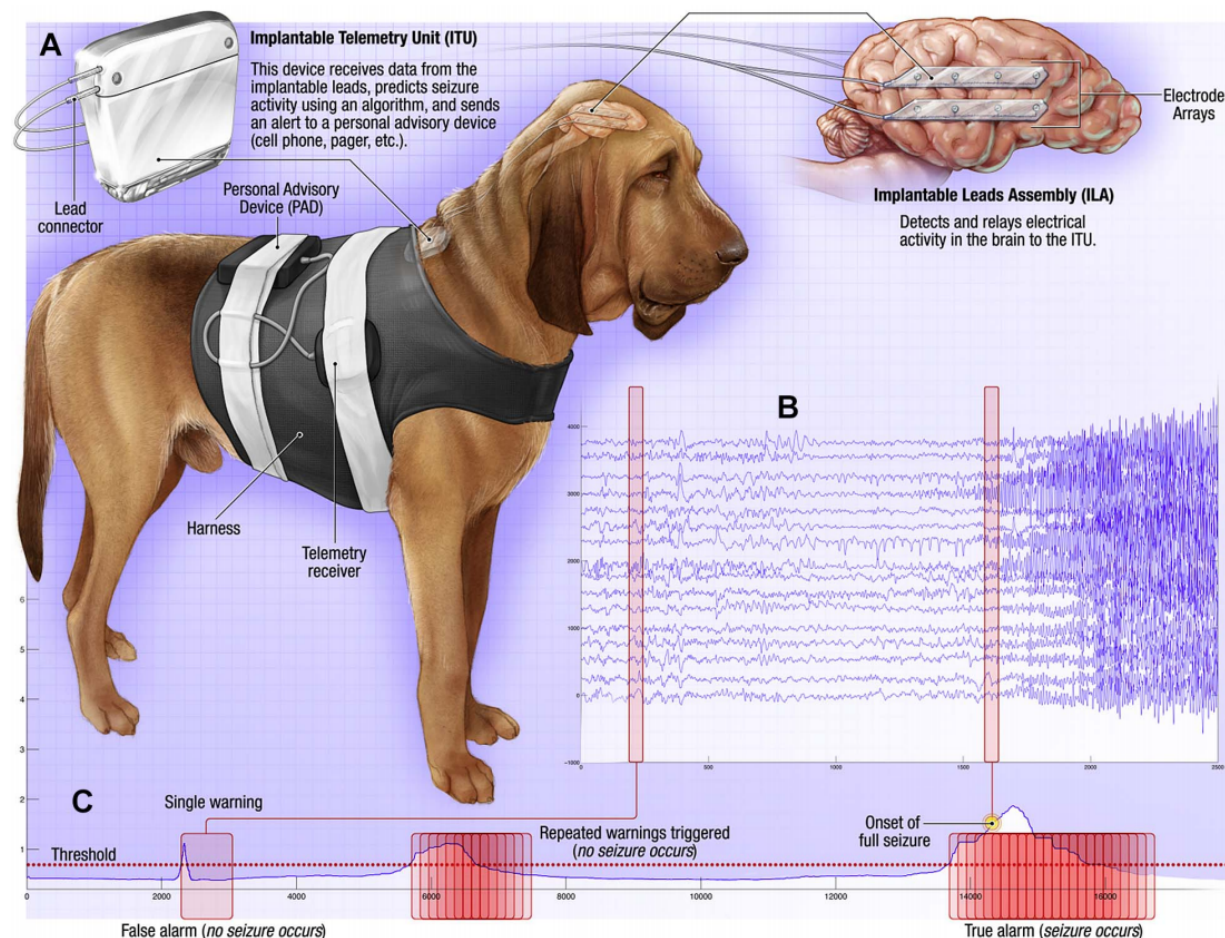


Figure S1. Seizure Advisory System (SAS) in Canines with Epilepsy. (A) The implantable device for recording and storing continuous iEEG includes: Implantable Lead Assembly (ILA) placed in the subdural space (right), Implantable Telemetry Unit (ITU), and Personal Advisory Device (PAD). The system acquires 16 channels of iEEG and wirelessly transmits the data to the PAD. Data is stored on a flash drive and uploaded weekly via internet to a central data storage site. (B) Sixteen channels of intracranial EEG recorded with SAS. A focal onset, secondarily generalized seizure is shown. The top 1–8 channels are from the left hemisphere and 9–16 from the right hemisphere, as shown on the brain schematic above. The onset of the seizure is from left hemisphere electrodes 3 & 4. Figure reprinted with permission from Howbert, J. J. *et al.* Forecasting seizures in dogs with naturally occurring epilepsy. *PLoS One* **9**, e81920 (2014).

Results:

Predictive accuracy of Gaussian method

We sought to assess the accuracy of our predictive model in sorting incoming data to event states. While the Gaussian distributions used in our analysis have predicting capabilities in their own right, this analysis is useful to support our claim that the predicted states are truly representations of the same states that would be generated by the HMM. We determined the “predicted” event state of each time point in the training dataset using the Gaussian distributions, and compared these states to the true event states generated from the HMM. We limited our comparison to time points during burst or seizure events to

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eliminate long epochs of baseline activity during which event states are relatively unchanging and easy to predict. On a point-by-point basis during these events, the Gaussian prediction matched the HMM event state with an accuracy of 0.62 ± 0.15 . However, when analyzed using a sliding window and threshold to determine seizure onset zones the windows with a number of SOIs exceeding the threshold overlapped with an accuracy of 0.89 ± 0.06 . Therefore, our method of predicting event states using Gaussian distributions is very accurate in determining areas enriched in SOIs despite less consistent point-by-point assignments.