

INTELLIGENT QUALITY-AWARE MULTI-ELECTRODE POSITIONING WITH NEURAL SIGNAL PREDICTION AND DRIFT-AWARE ADAPTIVE OPTIMIZATION

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ABSTRACT

In addition to signal noise and variability in their temporal characteristics, long-term extracellular recordings of neural activity are also influenced by the relative position of recording electrodes to the source of the neurons. Historically, quality-aware repositioning of electrodes has been accomplished after the fact (post-hoc) when the quality of the recorded signal fell below a predetermined threshold. This leads to periods of non-optimal recording quality and delays in accurately repositioning the electrodes. To address these issues, we propose an Intelligent Quality-Aware Multi-Electrode Positioning (IQ-MEP) predictive methodology that integrates techniques for predicting the quality of a neural signal, estimating drift of electrodes, and adaptively optimizing electrode position. IQ-MEP employs historical features of the neural recordings (i. e., quality, signal-to-noise ratio, spike-related features. And electrode position) to predict future recording quality as well as identify potential quality degradations before quality reaches a critical threshold. Using both the predicted quality and the estimated drift direction and magnitude, an adaptive optimization module determines the future optimal position of the electrode(s) and proactively repositions them. A browser-based simulation environment has been developed to establish a reproducible experimental platform for simulating virtual neurons, electrode/tetrode configurations, controllable noise, spatial drift, variability in recording quality, and multi-electrode positioning. The framework supports a comparison between static, reactive threshold-based, and predictive electrode repositioning strategies under controlled drift and noise conditions. Performance metrics employed to evaluate the effectiveness of the proposed predictive methodology include prediction error of future quality prediction, accuracy of estimating drift direction, positional error of electrodes, early warning time, quality retention, recovery time, and movement efficiency of electrodes. This proposed predictive methodology provides a software-based approach to assess whether predictive analysis of neural signals may be employed to support proactive repositioning of electrodes to improve stability of long-term recordings of extracellular neural activity under simulated drift conditions.

KEYWORDS: Extracellular Neural Recording; Multi-Electrode Positioning; Neural Signal Quality Prediction; Electrode Drift; Machine Learning; Time-Series Prediction; Adaptive Optimization; Proactive Electrode Positioning.

INTRODUCTION

Extracellular neural recording is a vital means through which we can measure the activity of individual neurons and study the functional dynamics of neural systems. The quality of an extracellular neural recording is influenced by the spatial relationship between the recording electrode and the neuronal sources that give rise to the recorded signal. As a result, different electrode positions, variations in neuronal activity, different noise levels and recording conditions will all contribute to temporal fluctuations in signal amplitude, in the signal-to-noise ratio (SNR) of the recorded signal, and in the quality of spike detection from the recorded signal. These fluctuations are mainly important in long-term experiments since it is difficult to maintain stable recording conditions over time. Adaptive electrode positioning has been shown to be important for maintaining recording quality, and automated methods for online multi-electrode positioning and simulating electrode position have also been developed [1]. More recently, Large scale electrophysiology and spike sorting have proved the impact of both the variability of the signals recorded and the displacement of electrodes on the reliability of long-term neural recordings.[2–5].

A major challenge in long-term extracellular recording is electrode drift. Small changes in the relative position of an electrode and neuronal sources can modify the recorded extracellular waveform and consequently change the amplitude, SNR, spike rate, and overall recording quality. Such changes can also affect downstream processing methods, including spike detection and spike sorting. Existing approaches for handling this problem include signal-processing techniques, adaptive spike-sorting algorithms, and electrode-positioning strategies. For example, drift-resilient spike-sorting methods have been developed to compensate computationally for changes in neural signals without physically repositioning the

recording electrode [3]. Although these approaches can improve the robustness of neural-data analysis, they do not directly address the spatial cause of recording-quality degradation. In contrast, automated electrode-positioning systems provide a mechanism for physically adapting electrode locations in response to changes in recording quality [1]. These approaches establish an important basis for closed-loop electrode control, but a predominantly reactive strategy can still allow signal quality to deteriorate before corrective movement is initiated. Conventional quality-aware positioning can generally be formulated as a threshold-based control problem. The recording quality is continuously monitored, and when a quality metric falls below a predefined threshold, the system searches for a new electrode position that provides improved recording conditions. Although this strategy can restore signal quality, the corrective movement occurs after degradation has already taken place. For example, if the recording quality gradually decreases because of electrode drift, a threshold-based controller may remain stationary while the quality approaches the critical threshold and only initiate repositioning after the threshold is crossed. This may introduce a period of reduced-quality recording and potentially cause loss or distortion of neural information. The problem therefore motivates a transition from reactive electrode positioning toward predictive electrode positioning, in which future signal degradation is estimated before the recording reaches an unacceptable quality level.

Machine-learning-based time-series prediction provides a potential mechanism for such predictive control. Neural recordings contain temporal information that can be used to characterize changes in signal quality, spike-related features, noise conditions, and electrode position. Recent neural-signal analysis research has increasingly incorporated adaptive and machine-learning-based methods to address temporal variability, drift, and large-scale electrophysiological data [3–8]. However, prediction of future recording quality and estimation of the spatial direction of electrode drift can be considered separately from conventional spike-sorting or signal-classification problems. A predictive positioning system therefore requires an integrated framework in which historical signal characteristics are first used to estimate future recording quality, followed by estimation of drift direction and magnitude and optimization of a future electrode position. In this work, we propose Intelligent Quality-Aware Multi-Electrode Positioning (IQ-MEP), a predictive framework designed to investigate proactive electrode repositioning under simulated extracellular recording conditions. The central concept of IQ-MEP is to predict when and in which direction recording quality is expected to deteriorate, rather than waiting for the quality to fall below a predefined threshold. The framework combines three principal computational components: neural signal-quality prediction, electrode-drift estimation, and adaptive position optimization. Historical signal-quality measurements, SNR, spike-related characteristics, noise conditions, and electrode-position information are used as inputs to a predictive model to estimate future recording quality. When a potential degradation is detected, the system estimates the expected drift direction and magnitude and evaluates candidate electrode positions to identify a position that is expected to provide improved future recording quality while limiting unnecessary electrode movement.

The proposed approach also considers the multi-electrode nature of extracellular recording systems. Instead of treating electrode movement as an isolated single-channel operation, IQ-MEP is designed to support multiple electrodes whose recording conditions may change independently or simultaneously. This enables the investigation of coordinated quality monitoring, prediction, and positioning across multiple recording sites. Such an architecture is particularly relevant to modern high-density electrophysiological systems, where increasing electrode counts create both opportunities for large-scale neural recording and challenges associated with signal variability and long-term stability [2,6,9,10]. To enable controlled and reproducible experimentation, a browser-based neural recording simulator is developed as part of the proposed framework. The simulator represents virtual neurons, electrode or tetrode configurations, extracellular neural signals, controllable noise, spatial electrode drift, signal-quality variation, and electrode movement. It enables different positioning strategies to be evaluated under controlled experimental conditions without requiring immediate hardware implementation. In particular, the simulator provides a common environment for comparing three strategies: a static electrode that remains at a fixed position, a reactive threshold-based electrode that moves after quality degradation, and the proposed predictive electrode that estimates future degradation and moves proactively. The simulator is therefore intended as an experimental platform for evaluating the computational framework rather than as a replacement for biological or hardware validation.

The primary research question addressed in this study is: Can machine learning predict neural recording quality degradation and electrode drift early enough to enable proactive multi-electrode repositioning and maintain high-quality extracellular recordings? To investigate this question, the proposed framework evaluates future signal-quality prediction accuracy, drift-direction and magnitude estimation, electrode-position error, early-warning time, quality retention, recovery time, and movement efficiency. The comparison between static, reactive, and predictive positioning strategies is intended to determine whether incorporating temporal prediction and drift-aware optimization can provide a computational advantage over conventional threshold-based positioning under controlled simulated conditions.

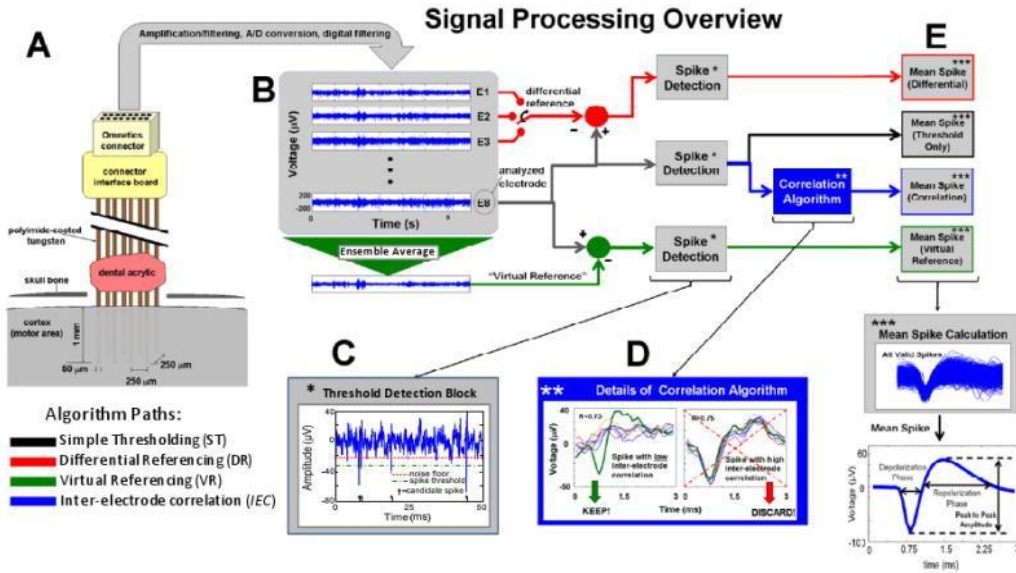


Fig. 1. Block diagram of the proposed Intelligent Quality-Aware Multi-Electrode Positioning (IQ-MEP) system.

The main contribution of this study is therefore the integration of future neural signal-quality prediction, drift-aware spatial estimation, and proactive multi-electrode position optimization within a single computational framework. Rather than considering electrode drift only as a post-processing problem or reacting after signal quality has degraded, IQ-MEP investigates whether predicted signal-quality changes can be incorporated into an adaptive positioning controller. The resulting framework provides a reproducible software-based methodology for studying predictive electrode positioning and establishes a foundation for subsequent validation using experimental neural-recording data and physical electrode-positioning hardware.

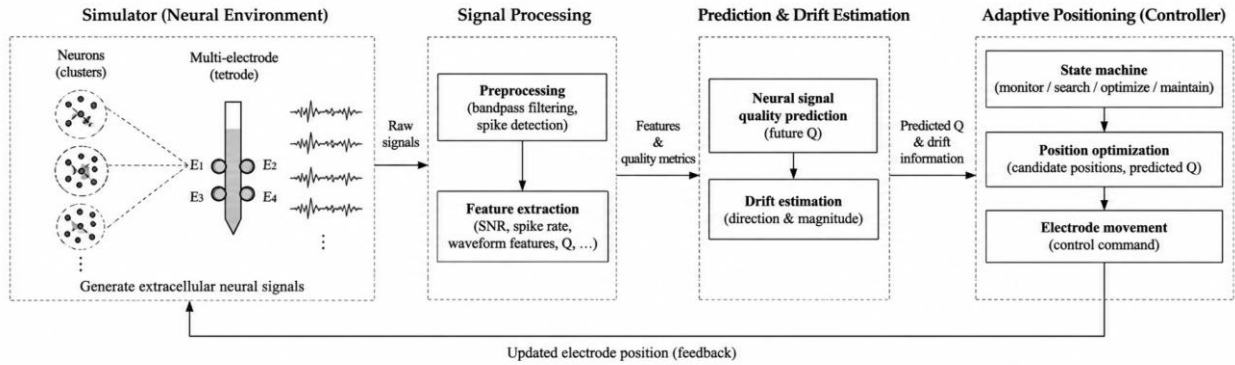


Fig. 1. Block diagram of the proposed Intelligent Quality-Aware Multi-Electrode Positioning (IQ-MEP) system.

II. QUALITY METRIC

The quality of an extracellular neural recording depends on the strength and detectability of neuronal activity relative to background noise. In the proposed IQ-MEP framework, the recording quality is continuously monitored for each electrode and is represented by a composite quality metric derived from signal-to-noise ratio (SNR), detected spike activity, spike amplitude, and other signal characteristics. SNR is commonly used to characterize the detectability of extracellular neural activity, while spike amplitude and firing-related features provide additional information about the quality and stability of the recorded neural signal [1]–[4]. These measures are particularly useful for electrode-positioning systems because changes in the relative distance between a neuron and an electrode can alter the amplitude and detectability of extracellular spikes [1,5].

A. Channel-Wise Signal-to-Noise Ratio

Let s_k^i denote the waveform of the i -th detected spike recorded on the k -th channel, and let N denote the total number of detected spikes within a recording segment X of duration T . The background noise associated with channel k is represented by its standard deviation σ_k . The detectability of an individual extracellular spike can be quantified using its peak-to-trough signal-to-noise ratio (SNR), defined as

$$SNR_k(s_i) = \frac{\max(s_k^i) - \min(s_k^i)}{\sigma_k} \quad (1)$$

where $\max(s_k^i)$ and $\min(s_k^i)$ represent the maximum and minimum amplitudes of the i -th spike waveform on channel k , respectively. A higher SNR indicates that the neural spike is more distinguishable from the background noise and therefore

represents a more favorable recording condition. This channel-wise formulation is particularly suitable for multi-electrode recordings because each channel may exhibit different noise characteristics and spike amplitudes. An_automated_online_positioning...

B. Aggregate Spike Detectability

For a recording interval containing multiple detected spikes, the overall signal detectability can be represented by the mean SNR across the detected spikes and recording channels:

$$Q^{SNR}(X) = \frac{1}{N} \sum_{i,k} P(s_k^i) \quad (2)$$

where $P(s_k^i)$ denotes the channel-wise peak-to-trough SNR of the i -th detected spike. This measure provides an aggregate representation of the strength and detectability of extracellular neural activity within the observation window. A higher value of $Q^{SNR}(X)$ indicates stronger and more reliably detectable neural activity.

C. Multi-Channel Spike Discriminability

In a multi-electrode recording system, signal quality is not determined exclusively by spike amplitude. The distribution of a spike across different electrode channels also provides useful information regarding its spatial characteristics and discriminability. To represent this property, the deviation between the SNR of an individual spike on a channel and the corresponding mean channel SNR can be calculated as

$$Q^{stereo}(X) = \frac{1}{N} \sum_{i,k} |\langle P_k \rangle - P(s_k^i)| \quad (3)$$

where $\langle P_k \rangle$ denotes the mean SNR associated with channel k , given by

$$\langle P_k \rangle = \frac{1}{N} \sum_i P(s_k^i). \quad (4)$$

The resulting discriminability measure captures variations in spike representation across the channels of the multi-electrode configuration. Such channel-wise differences can provide additional information about the spatial distribution of neural activity and can assist in distinguishing signals originating from different neuronal sources. The use of multiple channels therefore provides a richer characterization of the recording condition than SNR alone. An_automated_online_positioning...

D. Combined Signal Quality

The signal-detectability and multi-channel discriminability components can be combined to obtain a unified quality measure. For the proposed framework, the combined SNR-discriminability component is expressed as

$$Q^{SD}(X) = \frac{1}{N} \sum_{i,k} [P(s_k^i) + c |\langle P_k \rangle - P(s_k^i)|] \quad (5)$$

where c is a weighting coefficient that determines the contribution of the multi-channel discriminability component. The first term represents spike detectability, whereas the second term accounts for channel-wise variation in spike representation. This formulation allows the quality measure to reflect both the strength of the recorded neural activity and its distribution across the available recording channels. An_automated_online_positioning...

E. Composite Quality Metric for IQ-MEP

Although SNR and multi-channel spike characteristics provide important information about recording quality, the proposed IQ-MEP framework additionally considers spike amplitude, spike rate, and background noise. Therefore, the final electrode-specific quality metric is defined as

$$Q_i(t) = w_1 \widetilde{SNR}_i(t) + w_2 \widetilde{A}_i(t) + w_3 \widetilde{R}_i(t) - w_4 \widetilde{N}_i(t) \quad (6)$$

where:

- $\widetilde{SNR}_i(t)$ is the normalized signal-to-noise ratio of electrode i ,
- $\widetilde{A}_i(t)$ is the normalized spike amplitude,
- $\widetilde{R}_i(t)$ is the normalized spike rate,
- $\widetilde{N}_i(t)$ is the normalized background-noise level, and
- w_1, w_2, w_3, w_4 are weighting coefficients.

The weights can be selected experimentally or estimated using training data. The negative sign associated with the noise term ensures that increasing background noise reduces the overall quality score. The resulting quality value is normalized to the interval

$$0 \leq Q_i(t) \leq 1.$$

(7)

A larger $Q_i(t)$ represents a more reliable recording condition, whereas a lower value indicates reduced signal detectability, increased noise, or deterioration in the quality of the recorded neural activity.

F. Multi-Electrode Quality Representation

Since IQ-MEP is designed for multi-electrode recording systems, the quality of all recording electrodes is represented collectively as

$$\mathbf{Q}(t) = [Q_1(t), Q_2(t), \dots, Q_K(t)] \quad (8)$$

where K denotes the total number of recording electrodes. This representation enables the system to monitor each electrode independently and identify channels undergoing different levels of signal degradation. Electrode position is retained as an additional contextual feature rather than being directly interpreted as a positive or negative quality component, because the effect of a position depends on the spatial relationship between the electrode and the underlying neuronal sources.

G. Quality Threshold and Future-Quality Prediction

A minimum acceptable quality level Q_{min} is introduced to distinguish between acceptable and degraded recording conditions:

$$Q_i(t) \geq Q_{min} \quad (9)$$

indicates an acceptable recording condition, whereas

$$Q_i(t) < Q_{min} \quad (10)$$

indicates a degraded condition.

However, IQ-MEP does not use Q_{min} solely as a reactive trigger for immediate electrode movement. Instead, the temporal history of the recording is provided to a prediction model to estimate the future quality of each electrode:

$$\hat{Q}_i(t + \Delta t) = f_\theta(X_i(t)) \quad (11)$$

where $X_i(t)$ represents the recent temporal feature vector containing quality measurements, SNR, spike-related characteristics, noise information, and electrode-position history, while f_θ denotes the trained neural prediction model.

The predictive nature of the proposed framework becomes important when the current quality remains acceptable but is expected to deteriorate in the near future. If

$$Q_i(t) \geq Q_{min} \quad \text{and} \quad \hat{Q}_i(t + \Delta t) < Q_{min}, \quad (12)$$

the system identifies a potential future degradation event and initiates drift estimation and adaptive position optimization before substantial signal-quality loss occurs.

Thus, the quality metric serves three complementary purposes in IQ-MEP:

1. it provides a real-time measure of the current recording condition;
2. it provides the target variable for future neural-signal-quality prediction; and
3. it supplies the decision-making module with the information required for proactive electrode repositioning.

This formulation enables IQ-MEP to move beyond conventional threshold-based positioning by incorporating temporal prediction, multi-channel signal characteristics, and drift-aware adaptive control into a unified quality-aware positioning framework.

III. PROPOSED INTELLIGENT POSITIONING SYSTEM

The proposed Intelligent Quality-Aware Multi-Electrode Positioning (IQ-MEP) system is designed as a closed-loop framework that integrates extracellular signal preprocessing, recording-quality assessment, future-quality prediction, electrode-drift estimation, and adaptive position optimization. Unlike conventional positioning approaches that initiate electrode movement only after the measured recording quality falls below a predefined threshold, IQ-MEP uses temporal information from previous recordings to anticipate potential quality degradation and determine an appropriate electrode position proactively. The overall positioning architecture consists of four major computational stages: (i) neural signal preprocessing and feature extraction, (ii) neural signal-quality prediction, (iii) electrode-drift estimation, and (iv) adaptive position optimization and movement control. The updated electrode position is subsequently fed back into the recording environment, forming a closed-loop positioning process. The architecture is designed to support multiple electrodes, allowing the quality and movement requirements of individual recording sites to be evaluated independently. The reference positioning system similarly uses incoming extracellular recordings, preprocessing, quality estimation, and a feedback-based positioning controller. An automated online positioning.

A. Neural Signal Preprocessing and Feature Extraction

To support online positioning, the incoming extracellular recording is processed over short observation windows rather than requiring analysis of the complete recording sequence. The preprocessing stage converts the raw neural recording into a set of features required for quality assessment and prediction. Depending on the simulated recording condition, the input signal can undergo noise handling, signal filtering, and spike detection before the relevant neural characteristics are extracted.

For each electrode, the preprocessing stage estimates parameters such as spike amplitude, spike rate, signal-to-noise ratio, background noise, and the current electrode position. These measurements are subsequently used to calculate the electrode-specific quality score defined in Section II. In the reference positioning framework, the incoming recording is processed over short periods, individual spikes are detected, and their SNR values are calculated across the available channels before the resulting quality information is supplied to the positioning controller. An automated online positioning...

The feature vector associated with electrode i at time t can therefore be represented as

$$X_i(t) = [Q_i(t), SNR_i(t), A_i(t), R_i(t), N_i(t), P_i(t)] \quad (13)$$

where $Q_i(t)$ denotes the current recording-quality score, $SNR_i(t)$ represents signal-to-noise ratio, $A_i(t)$ denotes spike amplitude, $R_i(t)$ represents spike rate, $N_i(t)$ denotes the noise level, and $P_i(t)$ represents the current electrode position.

B. Neural Signal-Quality Prediction

The extracted temporal features are supplied to the prediction module to estimate the future recording quality of each electrode. Instead of waiting until the current quality falls below Q_{min} , IQ-MEP analyzes the temporal evolution of the quality-related features and predicts whether degradation is likely to occur within a future time interval Δt .

The predicted quality is expressed as

$$\hat{Q}_i(t + \Delta t) = f_\theta(X_i(t)) \quad (14)$$

where f_θ represents the trained prediction model and $\hat{Q}_i(t + \Delta t)$ denotes the estimated future quality of electrode i .

A predictive intervention condition can consequently be defined as

$$Q_i(t) \geq Q_{min}, \quad \hat{Q}_i(t + \Delta t) < Q_{min} \quad (15)$$

This condition indicates that the current recording remains acceptable, but the predicted future quality is expected to become unacceptable. In such a situation, IQ-MEP initiates drift estimation and position optimization before substantial recording degradation occurs.

C. Electrode Drift Estimation

Once potential future degradation has been identified, the framework estimates the direction and magnitude of electrode displacement associated with the observed temporal changes in recording quality. The drift-estimation module uses the temporal relationship between neural signal characteristics and electrode position to determine the likely movement of the recording environment.

The estimated drift state for electrode i can be represented as

$$\hat{\mathbf{D}}_i(t) = [\hat{d}_{i,x}, \hat{d}_{i,y}, \hat{d}_{i,z}] \quad (16)$$

where $\hat{d}_{i,x}$, $\hat{d}_{i,y}$, and $\hat{d}_{i,z}$ represent the estimated displacement components along the corresponding spatial directions. For a one-dimensional positioning configuration, the drift representation can be simplified to

$$\hat{D}_i(t) = \hat{d}_i(t) \quad (17)$$

The purpose of this stage is not merely to detect that signal quality has deteriorated, but to estimate the spatial tendency associated with the degradation so that the subsequent controller can select a compensatory electrode movement.

This predictive drift concept is consistent with the future direction identified in the reference study, where the authors suggested that multi-channel information could potentially be used to estimate the direction and speed of tissue/electrode drift and compensate for it before recording quality decreases substantially. An automated online positioning...

D. Adaptive Position Optimization

Following drift estimation, the adaptive optimization module evaluates candidate electrode positions and determines the position expected to provide improved future recording quality. Let P_i denote the set of feasible candidate positions for electrode i . The selected position can be formulated as

$$P_i^*(t + \Delta t) = \arg \max_{P \in P_i} \hat{Q}_i(P, t + \Delta t) \quad (18)$$

where P_i^* represents the optimized future electrode position and $\hat{Q}_i(P, t + \Delta t)$ denotes the predicted recording quality associated with candidate position P .

To prevent unnecessary electrode movement, the optimization can additionally consider the movement distance or control cost:

$$J(P) = \alpha [1 - \hat{Q}_i(P, t + \Delta t)] + \beta d(P, P_i(t)) \quad (19)$$

where $d(P, P_i(t))$ represents the movement distance between the candidate position and the current electrode position, while α and β control the relative importance of recording quality and movement efficiency.

The optimized position is therefore selected by minimizing the objective function:

$$P_i^* = \arg \min_{P \in P_i} J(P) \quad (20)$$

This formulation allows the proposed system to balance two competing objectives: maintaining high recording quality while avoiding unnecessary electrode displacement.

E. Electrode Movement and Closed-Loop Feedback

After determining the optimized position, the movement controller generates the corresponding positioning command. The electrode is then repositioned toward P_i^* , after which a new recording segment is acquired. The updated neural signal is processed again, and the quality, prediction, and drift estimates are recalculated. The complete closed-loop operation can therefore be summarized as

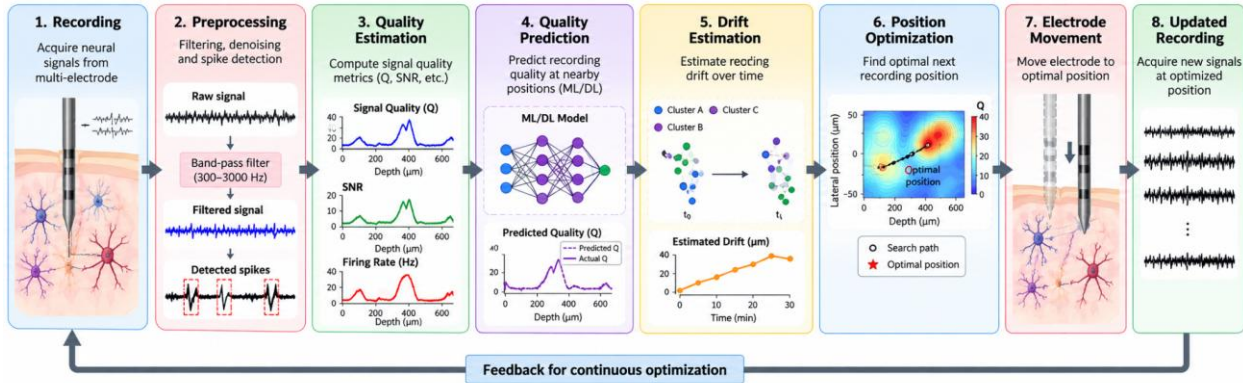


Fig 3

This feedback mechanism enables IQ-MEP to continuously adapt electrode positions according to the predicted evolution of recording quality. In contrast to a purely reactive controller, the proposed system does not require the current quality to become unacceptable before initiating corrective movement.

F. Multi-Electrode Positioning Strategy

For a system containing K electrodes, the above procedure is performed independently for each recording site while maintaining a common control framework. The quality state can be represented as

$$\mathbf{Q}(t) = [Q_1(t), Q_2(t), \dots, Q_K(t)] \quad (21)$$

and the optimized position vector as

$$\mathbf{P}^* = [P_1^*, P_2^*, \dots, P_K^*] \quad (22)$$

This formulation allows electrodes experiencing different levels of signal degradation or drift to receive electrode-specific positioning decisions. It also supports simultaneous monitoring of multiple recording sites, which is important for high-density extracellular recording systems.

G. Positioning Decision Logic

The positioning decision can be summarized using three principal operating conditions:

Condition 1 — Stable recording

$$Q_i(t) \geq Q_{min} \text{ and } \hat{Q}_i(t + \Delta t) \geq Q_{min} \quad (23)$$

The electrode remains at its current position because both the present and predicted recording conditions are acceptable.

Condition 2 — Predicted degradation

$$Q_i(t) \geq Q_{min} \text{ and } \hat{Q}_i(t + \Delta t) < Q_{min} \quad (24)$$

The system predicts future quality degradation and activates drift estimation followed by adaptive position optimization.

Condition 3 — Current degradation

$$Q_i(t) < Q_{min} \quad (25)$$

The recording has already entered a degraded state. The controller therefore performs corrective position optimization to recover the recording quality.

IV. SIMULATION ENVIRONMENT

An online simulation environment is developed to model extracellular neural recordings and provide feedback to the proposed electrode-positioning system. The simulation consists of three primary components: virtual neurons, recording electrodes, and noise sources. Each virtual neuron is characterized by its spatial location, orientation, and firing activity, while the recording electrodes are defined by their positions and sampling characteristics. Multiple recording channels can be combined to represent multi-electrode configurations such as tetrodes. The recorded signal depends on the spatial relationship between the electrodes and nearby neuronal sources; consequently, changes in electrode position can produce variations in the recorded neural waveform and signal quality. Background noise is additionally incorporated into the simulated recordings to reproduce realistic variations in recording conditions. This configuration enables the proposed IQ-MEP framework to evaluate neural signal quality and electrode positioning under controlled spatial and noise conditions.

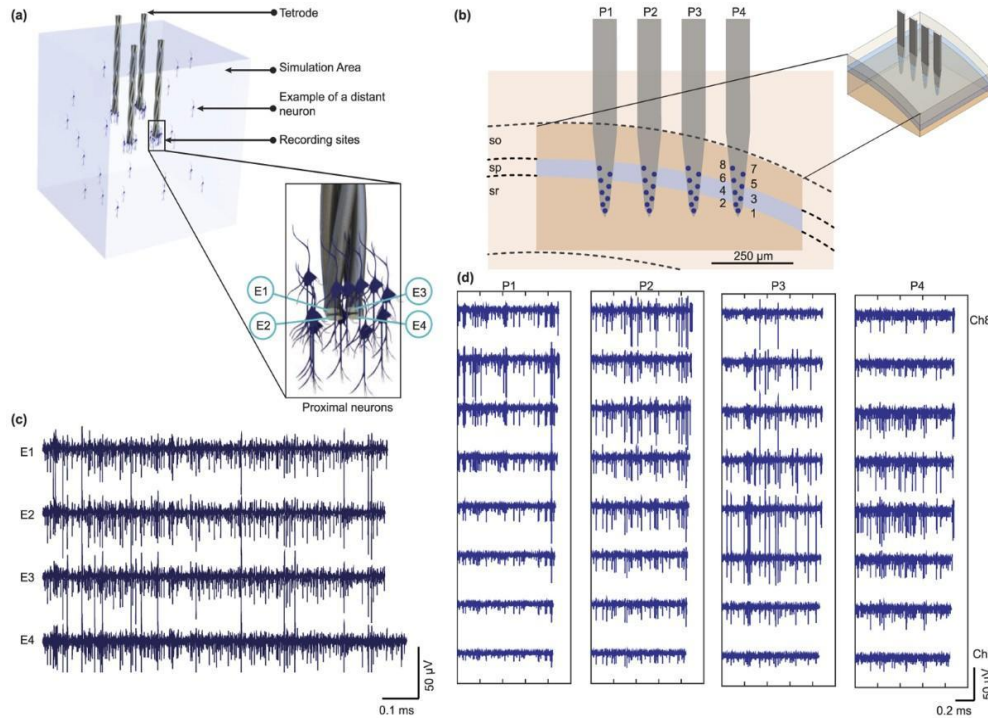


Fig. 3. Simulated neural recording environment and signal characteristics along a virtual one-dimensional electrode track. (a) Signal quality, (b) estimated firing rate, (c) spatial distribution of detected neurons, and (d) representative extracellular waveforms.

A. Estimation of Extracellular Field Potential

The extracellular field potential (EFP) in the proposed simulation environment is modeled as a spatially dependent neural signal generated by virtual neuronal sources. The recorded potential at an electrode depends on the relative distance between the electrode and the active neuronal source. Under a simplified quasi-static approximation, the contribution of a neuronal source to the extracellular potential can be represented as

$$\Phi(\mathbf{r}, t) = \frac{I(t)}{4\pi\sigma_e \|\mathbf{r} - \mathbf{r}_s\|} \quad (26)$$

where $I(t)$ denotes the time-varying source current, r represents the electrode location, r_s denotes the position of the neuronal source, and σ_e represents the effective extracellular conductivity.

For multiple neuronal sources, the resulting extracellular potential is obtained by superposition:

$$\Phi(\mathbf{r}, t) = \sum_{j=1}^{N_n} \frac{I_j(t)}{4\pi\sigma_e \|\mathbf{r} - \mathbf{r}_j\|} \quad (27)$$

where N_n is the number of active neuronal sources and $I_j(t)$ and r_j denote the source current and spatial position of the j -th neuron, respectively. The generated potentials are sampled at the simulated electrode locations to produce multi-channel extracellular recordings. Changes in electrode position consequently modify the measured potential and provide the basis for simulating signal-quality variation and electrode drift.

B. Line-Source Based Extracellular Potential Estimation

To model the spatial variation of extracellular potentials, the proposed simulation estimates the contribution of neuronal segments using a line-source representation. The extracellular potential at electrode position r and time t is expressed as

$$\Phi(\mathbf{r}, t) = \sum_{k=1}^{N_s} \frac{I_k(t)}{4\pi\sigma_e} \Delta s_k \ln \left(\frac{l_k + \sqrt{l_k^2 + \rho_k^2}}{h_k + \sqrt{h_k^2 + \rho_k^2}} \right) \quad (28)$$

where N_s denotes the number of neuronal segments, $I_k(t)$ is the transmembrane current associated with the k -th segment, Δs_k is its length, ρ_k represents the perpendicular distance from the electrode to the segment axis, h_k is the longitudinal distance to the corresponding segment endpoint, and l_k denotes the longitudinal distance measured from the segment origin. The parameter σ_e represents the effective extracellular conductivity.

To maintain numerical stability, a minimum distance constraint is applied between the electrode and each neuronal segment, preventing singular potential values when the electrode approaches a segment. The calculated extracellular potentials are sampled at predefined three-dimensional electrode locations to generate multi-channel neural recordings. Changes in electrode position consequently alter the observed potential, enabling the simulation of spatial drift and its resulting effect on signal quality. This spatially dependent potential model provides the neural signal input required by the proposed IQ-MEP quality estimation and adaptive positioning framework.

C. Noise Modeling

Background noise is incorporated into the simulation to represent realistic variability in extracellular neural recordings. A multivariate autoregressive (AR) model of order 12 is used to generate temporally correlated noise across multiple recording channels. The noise covariance structure can be estimated from spike-free recording segments, capturing the inter-channel dependencies present in multi-electrode recordings. The fitted AR model is then used to generate synthetic noise sequences that are added to the simulated extracellular potentials.

The resulting recorded signal for electrode i is represented as

$$x_i(t) = s_i(t) + n_i(t) \quad (29)$$

where $s_i(t)$ denotes the simulated extracellular neural signal and $n_i(t)$ represents the generated background noise. This noise model enables the IQ-MEP framework to evaluate signal-quality prediction and adaptive electrode positioning under controlled noisy recording conditions.

C. Simulation Parameters

The simulation environment is configured with 16 randomly oriented virtual neurons and a four-channel tetrode arranged in a tetrahedral geometry. The tetrode can move along a one-dimensional recording track containing three favorable recording regions, denoted as clusters A, B, and C. Cluster B provides the highest expected SNR because its neurons are positioned closest to the recording trajectory. The mean firing rates of neurons in clusters A, B, and C are set to 15 Hz, 7 Hz, and 5 Hz, respectively. The electrode is systematically moved along the recording track at 15 μm intervals, with 2.5 s of recording performed at each position. A quality coefficient of $c = 0.95$ is used for the quality metric. Different electrode positions therefore produce different extracellular signal qualities, allowing the positioning strategies to be evaluated under controlled spatial conditions. For comparative evaluation, the positioning system identifies favorable recording locations according to the selected minimum quality threshold. Depending on this threshold, the optimization process is activated at different recording regions and searches for the corresponding local quality maximum. These settings provide a controlled environment for evaluating electrode positioning and quality-maintenance performance.

V. DISCUSSION, CONCLUSIONS AND FUTURE WORK

A. DISCUSSION

Defining a single quality measure for a particular electrode position is challenging because the selected position directly influences all subsequent analyses performed on the recorded neural signals. A quality metric that emphasizes specific characteristics, such as high firing rates or particular neuronal activity patterns, may unintentionally introduce a systematic bias into the recording process. Therefore, a completely unbiased quality metric may be difficult to establish, particularly when the underlying properties of the surrounding neural network are not fully known. However, this limitation does not diminish the value of automated electrode-positioning approaches. Manual positioning also implicitly relies on the operator's experience and subjective interpretation of recording quality. For the proposed IQ-MEP framework, the quality criteria and optimization objectives should therefore be explicitly defined and documented as part of the experimental methodology. Such transparency makes potential sources of bias identifiable and allows the resulting recordings to be reinterpreted when additional knowledge about neural activity and network characteristics becomes available.

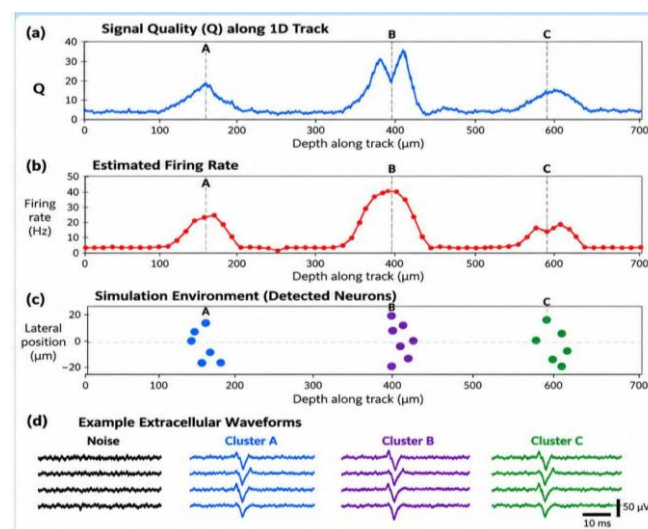


Fig. 1. Simulated neural recording environment along a virtual 1D electrode track. (a) Signal quality Q versus electrode depth. (b) Estimated firing rate versus electrode depth. (c) Spatial distribution of 16 simulated neurons forming three clusters (A–C). (d) Representative extracellular waveforms for background noise and clusters A–C.

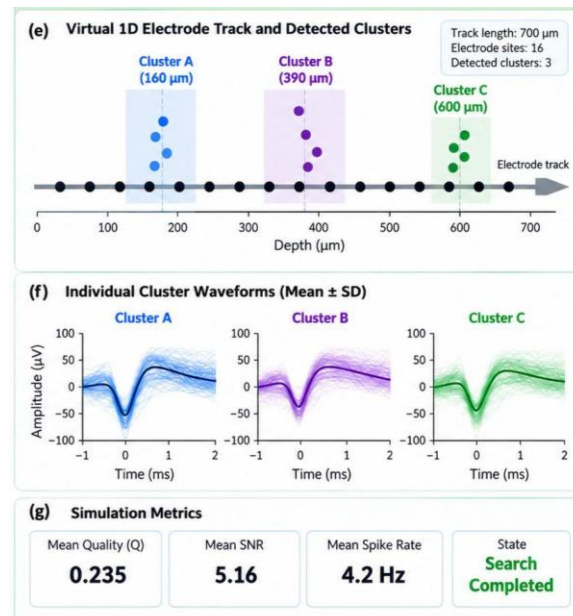


Fig. 2. Virtual electrode positioning and cluster-level signal characterization. (e) 1D electrode track with detected neuronal clusters and electrode sampling positions. (f) Cluster-specific extracellular spike waveforms with mean $\pm$ SD. (g) Summary simulation metrics including mean quality Q , SNR, spike rate, and search status.

B. CONCLUSIONS

The proposed IQ-MEP framework integrates neural signal-quality estimation, future quality prediction, drift estimation, and adaptive electrode-position optimization to support automated maintenance of favorable recording conditions in multi-electrode extracellular recordings. Unlike purely reactive positioning, the proposed approach aims to identify potential quality degradation in advance and initiate corrective positioning before substantial signal deterioration occurs. The framework is evaluated using a controlled simulation environment containing virtual neurons, multi-electrode configurations, spatial drift, and background noise. The simulation enables systematic evaluation of different positioning strategies using measures such as prediction accuracy, drift estimation, position error, quality retention, recovery time, and movement efficiency. The resulting framework provides a foundation for developing more robust and intelligent electrode-positioning systems for long-duration extracellular neural recordings. Intelligent Quality-Aware Multi... Furthermore, the simulation environment provides a computationally efficient platform for testing electrode-positioning and neural-signal analysis methods without requiring immediate hardware-based experimentation. The proposed approach can therefore support future research on automated neural recording optimization, spike detection, spike sorting, and adaptive electrode control.

C. Future Work

Future development of the IQ-MEP framework can explore more sophisticated measures for evaluating recording quality, particularly metrics based on spike-cluster separability, waveform consistency, and multi-channel discriminability. The selection of an appropriate quality measure can be adapted according to the specific requirements of the experimental application. Another important direction is the explicit modeling of electrode and tissue drift. Instead of responding only after the current recording quality falls below a predefined threshold, future versions can estimate the direction and magnitude of drift from multi-electrode observations and proactively compensate for the expected displacement. This can enable the positioning system to maintain favorable recording conditions while reducing unnecessary electrode movements. Future work will also include the integration of more realistic drift dynamics into the simulation environment, followed by systematic evaluation of the predictive positioning strategy under different drift conditions. Ultimately, validation using real extracellular recording experiments will be required to assess the practical effectiveness and robustness of the proposed IQ-MEP framework.

REFERENCES

1. E. Biffi, D. Ghezzi, A. Pedrocchi, and G. Ferrigno, "Development and validation of a spike detection and classification algorithm aimed at implementation on hardware devices," *Computational Intelligence and Neuroscience*, vol. 2010, 2010.
2. F. Franke, M. Natora, C. Boucsein, M. Munk, and K. Obermayer, "An online spike detection and spike classification algorithm capable of instantaneous resolution of overlapping spikes," *Journal of Computational Neuroscience*, 2009.
3. E. Branchaud, J. Burdick, and R. Andersen, "An algorithm for autonomous isolation of neurons in extracellular recordings," in *Proc. IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechanics (BioRob)*, 2006, pp. 939–945.
4. Z. Nenadic and J. W. Burdick, "A control algorithm for autonomous optimization of extracellular recordings," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 5, pp. 941–955, 2006.
5. M. T. Wolf, J. G. Cham, E. A. Branchaud, and J. W. Burdick, "A miniature robot for isolating and tracking neurons in extracellular cortical recordings," in *Proc. IEEE International Conference on Robotics and Automation (ICRA)*, 2008, pp. 1594–1601.

6. C. M. Gray, P. E. Maldonado, M. Wilson, and B. McNaughton, "Tetrodes markedly improve the reliability and yield of multiple single-unit isolation from multi-unit recordings in cat striate cortex," *Journal of Neuroscience Methods*, vol. 63, no. 1–2, pp. 43–54, 1995.
7. Z. F. Mainen and T. J. Sejnowski, "Influence of dendritic structure on firing pattern in model neocortical neurons," *Nature*, vol. 382, pp. 363–366, 1996.
8. NEURON, "The NEURON simulation environment." [Online]. Available: <https://www.neuron.yale.edu/>
9. M. L. Hines, A. P. Davison, and E. Muller, "NEURON and Python," *Frontiers in Neuroinformatics*, vol. 3, pp. 1–12, 2009.
10. G. R. Holt and C. Koch, "Electrical interactions via the extracellular potential near cell bodies," *Journal of Computational Neuroscience*, vol. 6, pp. 169–184, 1999.
11. J. Gentle and W. Härdle, *Handbook of Computational Statistics: Concepts and Methods*. Springer, 2004.
12. K. H. Pettersen and G. T. Einevoll, "Amplitude variability and extracellular low-pass filtering of neuronal spikes," *Biophysical Journal*, vol. 94, pp. 784–802, 2008.
13. G. R. Holt, "A critical reexamination of some assumptions and implications of cable theory in neurobiology," Ph.D. dissertation, California Institute of Technology, Pasadena, CA, 1998.
14. T. Schneider and A. Neumaier, "Algorithm 808: ARfit—A MATLAB package for the estimation of parameters and eigenmodes of multivariate autoregressive models," *ACM Transactions on Mathematical Software*, vol. 27, pp. 58–65, 2001.
15. J. G. Cham, E. A. Branchaud, Z. Nenadic, B. Greger, R. A. Andersen, and J. W. Burdick, "Semi-chronic motorized microdrive and control algorithm for autonomously isolating and maintaining optimal extracellular action potentials," *Journal of Neurophysiology*, vol. 93, no. 1, pp. 523–537, 2005.
16. G. T. Einevoll, A. E. Kayser, N. K. Logothetis, and S. Panzeri, "Modelling and analysis of local field potentials for studying the function of cortical circuits," *Nature Reviews Neuroscience*, vol. 14, pp. 770–785, 2013.
17. K. H. Pettersen, A. Devor, I. Ulbert, A. M. Dale, and G. T. Einevoll, "Current-source density estimation based on inversion of electrostatic forward solution: Effects of finite extent of neuronal activity and conductivity discontinuities," *Journal of Neuroscience Methods*, vol. 154, pp. 116–133, 2006.
18. J. Boussard, E. Varol, H. D. Lee, N. Dethe, and L. Paninski, "Three-dimensional spike localization and improved motion correction for Neuropixels recordings," in *Advances in Neural Information Processing Systems*, vol. 34, 2021.
19. P. Buccino, M. Hurwitz, H. Magland, et al., "SpikeInterface, a unified framework for spike sorting," *eLife*, vol. 9, e61834, 2020.
20. M. Pachitariu, M. Steinmetz, S. Kadir, M. Carandini, and K. D. Harris, "Kilosort: Realtime spike-sorting for extracellular electrophysiology with hundreds of channels," *bioRxiv*, 2016.
21. J. Jun, N. A. Steinmetz, J. Siegle, et al., "Fully integrated silicon probes for high-density recording of neural activity," *Nature*, vol. 551, pp. 232–236, 2017.
22. N. A. Steinmetz, C. Koch, K. D. Harris, and M. Carandini, "Challenges and opportunities for large-scale electrophysiology with Neuropixels probes," *Current Opinion in Neurobiology*, vol. 50, pp. 92–100, 2018.
23. J. Steinmetz, J. A. Koch, K. D. Harris, and M. Carandini, "Neuropixels 2.0: A miniaturized high-density probe for stable, long-term brain recordings," *Science*, vol. 372, no. 6539, eabf4588, 2021.
24. P. J. Magland, J. Jun, J. D. D. et al., "SpikeForest, reproducible validation of spike sorters," *eLife*, vol. 9, e55167, 2020.
25. J. Boussard, E. Varol, and L. Paninski, "Motion correction for high-density extracellular recordings," in *Advances in Neural Information Processing Systems*, 2021.
26. S. Garcia, A. Buccino, M. Magland, et al., "A modular implementation to handle and benchmark drift correction for high-density extracellular recordings," *eNeuro*, vol. 11, no. 2, 2024.
27. A. J. D. et al., "DREDge: robust motion correction for high-density extracellular recordings across species," *Nature Methods*, 2023.
28. S. K. Tuddu, U. Dubey, and W. G. H. Mohd, "Machine Learning-Based Load Balancing Mechanisms in Cloud Computing: Taxonomy, Challenges, and Future Directions," *ShodhKosh: Journal of Visual and Performing Arts*, vol. 7, no. 10s, pp. 240–264, 2026, doi: 10.29121/shodhkosh.v7.i10s.2026.8169.
29. S. Jain, V. Kumar, and S. K. Tuddu, "Multimodal Deep Learning Framework for Real-Time Fish Health Monitoring and Behavioral Analysis in Smart Aquaculture Systems," *International Journal of Drug Delivery Technology*, 2026.