Predicting Micro-Tremor Propagation in Human Muscles Using High-Resolution Accelerometry and Diffusion Models

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Abstract

Physiological micro-tremor in human skeletal muscle emerges from the interaction of motor unit firing variability, spinal reflexes, and mechanical resonance in the muscle–tendon–bone system. Although its amplitude is typically below conscious perception, micro-tremor carries rich information about neuromuscular control, fatigue, and early pathology. Traditional tremor characterization relies on single-point measurements or simple frequency-domain metrics, which fail to capture the spatiotemporal propagation of micro-tremor across the muscle belly.

In this work, we propose a framework for modeling and predicting micro-tremor propagation using high-resolution accelerometry and conditional denoising diffusion probabilistic models (DDPMs). A 4×4 grid of tri-axial accelerometers (16 nodes, 48 channels) was positioned over the wrist extensor muscles of 24 healthy participants. Data were collected at 2 kHz during rest, isometric wrist extension at multiple force levels, slow and fast dynamic wrist cycles, and a sustained submaximal contraction to fatigue. Signals were band-pass filtered (8–40 Hz) to isolate tremor-related components, segmented into overlapping windows, and normalized. Each window was represented as a spatiotemporal tensor encoding micro-tremor fields across time and space.

We trained a conditional DDPM to learn the distribution of micro-tremor fields, conditioned on task type, contraction level, and fatigue state. For prediction, the model used a short history (128 ms) to generate probabilistic forecasts of future micro-tremor propagation (next 128 ms). We compared the diffusion model against LSTM and temporal CNN (TCN) baselines using amplitude root-mean-square error (RMSE), spatial correlation of tremor energy, a custom propagation velocity error (PVE), and spectral divergence in the 8–40 Hz band.

The diffusion model reduced amplitude RMSE by ~30% relative to LSTM and ~25–30% relative to TCN and improved spatial correlation from ~0.61–0.66 to ~0.78 on average. PVE decreased from ~1.0 m/s for LSTM to 0.54 m/s for the diffusion model, indicating more accurate tracking of wave-like propagation along the muscle. Qualitative inspection showed that the diffusion model preserved oblique wavefronts and focal tremor “hotspots” more faithfully than baselines.

These results suggest that diffusion models are well-suited for capturing the stochastic, high-dimensional dynamics of micro-tremor propagation and can generate physiologically plausible tremor fields. The proposed framework may support early detection of neuromuscular dysfunction, fatigue monitoring, and data augmentation for tremor-related machine learning tasks.

Keywords: physiological tremor, micro-tremor, accelerometry, mechanomyography, diffusion models, time-series forecasting, neuromuscular control

1. Introduction

Physiological tremor is a ubiquitous feature of human motor control. Even in healthy individuals, muscles exhibit low-amplitude, high-frequency oscillations driven by motor unit firing variability, stretch reflex loops, and mechanical resonance of the limb segments [1], [2]. These oscillations, often in the 8–12 Hz range, are typically sub-perceptual in daily life but can become clinically relevant as they increase in amplitude or change in pattern, as in essential tremor or Parkinson's disease [2], [9].

Historically, tremor has been characterized primarily through single-point measurements

for example, using surface electromyography (EMG) or single accelerometer recordings placed on the limb or instrumented objects [3], [4], [9]. While these approaches are valuable for estimating amplitude, dominant frequency, and basic temporal dynamics, they do not capture how tremor propagates across the muscle belly and surrounding tissues. In reality, tremor is not a scalar signal but rather a spatiotemporal field, where small oscillations appear, interact, and propagate through the muscle–tendon complex in space and time.

The spatial structure of micro-tremor may encode subtle neuromuscular information:

- Early changes in motor unit synchronization before overt symptoms appear.
- Localized regions of increased mechanical stiffness or altered muscle recruitment.
- Fatigue-related changes in propagation velocity or coherence across the muscle.

Capturing these effects requires high-resolution sensing across multiple locations rather than a single measurement point. Advances in wearable sensors now make it feasible to deploy dense arrays of accelerometers or mechanomyography (MMG) sensors on the skin surface [11]–[14]. These arrays can capture micro-vibrations at kilohertz sampling rates while remaining sufficiently small and lightweight for human subjects.

However, these rich datasets are high-dimensional, noisy, and stochastic. Classical analytical methods struggle to model the joint spatiotemporal distribution of micro-tremor, especially under varying tasks and fatigue states.

Recent advances in generative modeling, particularly denoising diffusion probabilistic models (DDPMs) [15] provide a powerful alternative. Diffusion models have achieved state-of-the-art performance in image, audio, and time-series generation by learning to reverse a gradually applied noise process [15]–[19]. They can represent complex, multi-modal distributions in high-dimensional spaces, making them attractive for modeling micro-tremor fields.

1.1 Objective

The primary objective of this work is to model and predict the propagation of micro-tremor in human skeletal muscle using high-resolution accelerometry and diffusion models. Specifically, we aim to:

1. Represent micro-tremor as a spatiotemporal field captured by a grid of accelerometers.
2. Use a conditional diffusion model to learn the probability distribution of these fields given task context and fatigue state.
3. Evaluate the ability of the diffusion model to predict future tremor propagation compared to strong deep learning baselines.

1.2 Contributions

The main contributions of this work are:

- A data collection protocol using a 4×4 tri-axial accelerometer grid over the forearm extensor muscles under multiple controlled tasks and fatigue conditions.
- A spatiotemporal representation of micro-tremor suitable for generative modeling, including task-conditioned windows of accelerometry data.
- A conditional DDPM architecture adapted for multichannel time series, enabling probabilistic prediction of future micro-tremor fields.
- A comparative evaluation against LSTM and temporal CNN (TCN) baselines using metrics sensitive to amplitude, spatial structure, propagation velocity, and spectral content.

2. Background

2.1 Physiological and Pathological Tremor

Physiological tremor is present in all individuals and is typically low in amplitude [1]. It arises from multiple sources:

- Fluctuations in motor unit discharge.
- Mechanical properties of muscles and joints (e.g., inertia, stiffness).
- Stretch reflex and sensorimotor feedback loops.

- Possible central oscillatory activity.

Pathological tremors, such as Parkinsonian, essential, or functional tremor, involve exaggerated or abnormal tremor behavior and often require careful electrophysiological assessment [2], [8], [9]. Accelerometry and EMG are widely used to quantify tremor amplitude, frequency spectra, and coherence [4], [9], [10].

However, many studies treat tremor as a 1D signal measured at a single site (e.g., the fingertip) [3], [5], [6]. This simplifies data collection and analysis but loses detail about how tremor patterns vary over muscle and limb segments.

2.2 High-Resolution Accelerometry and Mechanomyography

Wearable inertial sensors and mechanomyography (MMG) can record subtle mechanical oscillations associated with muscle activation [11]–[14]. MMG signals reflect lateral oscillations of muscle fibers during contraction and have been shown to correlate with muscle force, fatigue, and motor unit behavior [11], [12].

Recent work demonstrates placing multiple accelerometers or MMG sensors over a muscle belly to obtain spatial maps of muscle activity and tremor [7], [14]. These multi-point recordings can be leveraged for:

- Mapping regional activation patterns during specific tasks.
- Tracking the evolution of fatigue across muscle segments.
- Distinguishing voluntary movement from involuntary tremor [7], [13].

Our work builds on this concept by using a 4×4 tri-axial accelerometer grid to obtain a 16-node snapshot of micro-tremor across the wrist extensor region. Each sensor provides a local measurement of 3D accelerations, collectively forming a dense field.

2.3 Diffusion Models for Time-Series

Denoising diffusion probabilistic models (DDPMs) define a generative process where data are gradually corrupted by Gaussian noise over many time steps, and a neural network is trained to reverse this process [15]. During inference, samples from the learned distribution are generated by starting from pure noise and iteratively denoising.

While originally developed for images [15], diffusion models have been successfully extended to time-series forecasting [16]–[19]. In this context, they can model complex temporal trajectories and generate probabilistic forecasts that capture uncertainty and multi-modal future outcomes.

Compared to auto-regressive or deterministic models, diffusion models excel at:

- Capturing nonlinear, multi-modal dynamics.
- Providing diverse, plausible future trajectories rather than a single point estimate.
- Handling high-dimensional signals with complex correlations, such as multichannel sensor arrays.

These properties make diffusion models promising for modeling micro-tremor, which is stochastic, high-dimensional, and influenced by both neural and mechanical processes.

3. Methods

3.1 Participants

Twenty-four healthy adults (12 female, 12 male; age 21–35 years) were recruited. Inclusion criteria:

- No history of neuromuscular or musculoskeletal disorders affecting the upper extremities.
- No known movement disorders or implanted electronic devices.

All participants provided written informed consent in accordance with institutional review board guidelines.

3.2 Instrumentation

A 4×4 grid of tri-axial MEMS accelerometers (16 nodes total) was used:

- Range: ±16 g
- Sensitivity: manufacturer-specified low noise density suitable for micro-vibration detection
- Sampling frequency: 2 kHz
- Resolution: at least 16 bits

Sensors were mounted on a flexible backing to conform to the curvature of the forearm extensor compartment. Inter-sensor spacing was 15 mm (center-to-center), providing a compact yet spatially informative grid.

3.2.2 Placement

The array was positioned over the dorsal aspect of the forearm, centered approximately over the extensor carpi radialis longus and brevis, with orientation aligned to the muscle fiber direction (proximal–distal axis). Exact placement was adjusted based on anatomical landmarks but kept consistent across participants as much as possible. Sensors were attached with medical-grade double-sided tape and secured with an elastic wrap to minimize skin–sensor motion.

3.3 Experimental Protocol

Participants were seated with the forearm supported and the wrist in neutral alignment. A handle or dynamometer measures wrist extension force for isometric tasks.

Four primary task conditions were evaluated:

1. Rest (R):
    - Forearm supported, hand relaxed.
    - 3 trials × 60 s.
2. Isometric Extension (ISO):
    - Wrist extension at 20%, 40%, and 60% of maximal voluntary contraction (MVC).
    - Target force displayed on a screen with real-time feedback.
    - 3 trials per level × 30 s each.
3. Dynamic Extension–Flexion (DYN):
    - Repeated wrist flexion–extension cycles at 0.5 Hz and 1 Hz with light resistance.
    - Metronome-guided cadence.
    - 3 trials per frequency × 60 s.
4. Fatigue Protocol (FAT):

    - Sustained isometric wrist extension at 40% MVC until self-reported fatigue ≥ 15 on Borg RPE scale or failure to maintain target.
    - Single trial, duration typically 60–180 s.

Rest breaks of at least 90 s were provided between trials, and longer rest (3–5 min) between conditions, to avoid carry-over fatigue.

3.4 Data Acquisition and Preprocessing

All 48 channels (16 nodes × 3 axes) were recorded simultaneously. Preprocessing steps:

- Offset and Drift Removal:
    - Per-channel means subtraction over each trial.
    - Linear detrending to remove slow drift.
- Band-Pass Filtering:
    - 4th-order zero-phase Butterworth filter, 8–40 Hz, targeting physiological tremor and related micro-oscillations [1], [3], [5].
- Segmentation:
    - Signals segmented into windows of 512 samples (256 ms) with 50% overlap (step size 256 samples).
    - Each window contained 512 × 48 data points.
- Normalization:
    - Within each window, z-score normalization per channel:

$$x't_{,c} = \frac{xt\,c - \mu_c}{\sigma_c + \epsilon}$$

Where μ_c and σ_c are the mean and standard deviation of channel ccc within the window, and ϵ is a small constant.

3.4.2 Spatiotemporal Representation

Each window was reshaped as a tensor

$X \in R^{TxC}$

where T=512T = 512T=512 (time samples) and C=48C = 48C=48 (16 sensors × 3 axes). To emphasize prediction, we defined:

- History segment: first 256 samples $L_{in} = 256,\ 128\,ms)$
- Future segment: last 256 samples $L_{out} = 256,\ 128\,ms)$

The model input thus consisted of a history $X_{hist} \in R^{L_{in} x\ C}$ and task context; the target was X future $\in R^{L_{out} x\ C}$.

3.5 Conditioning Variables

Each window was associated with task-level metadata:

- Task type: {R, ISO, DYN, FAT}, encoded as a one-hot vector.
- Force level: {0, 0.2, 0.4, 0.6}, representing rest and percentage MVC.
- Fatigue state: binary (pre-fatigue vs. during fatigue protocol).
- Dynamic frequency: {none, 0.5, 1.0} Hz for DYN tasks.

These variables were embedded in a low-dimensional vector c $\in R^{d}$ via a learned embedding layer and concatenated with the time-encoding for the diffusion model.

3.6 Diffusion Model Architecture

We adopted a conditional denoising diffusion probabilistic model (DDPM) [15] tailored for multichannel time series [16]–[19].

3.6.1 Forward Diffusion Process

Given a clean future segment $x_0 = vec(X_{future})$, the forward process defined a sequence:

$q(x_t|x_t - 1) = N(x_t; \sqrt{\alpha_t} x_{t-1},\ (1 - \alpha_t)I),$

With α_t following a cosine variance schedule over diffusion steps t=1,…,T_d. We used T_d. We used $T_d = 1000$ steps in training. Closed-form sampling from q(x_t| x_0) allowed efficient training [15].

4. Results

4.1 Overall Prediction Accuracy

Across all tasks and participants, the conditional diffusion model outperformed both the LSTM and TCN baselines.

- Amplitude RMSE (normalized units):
    - LSTM: 0.98 ± 0.12
    - TCN: 0.91 ± 0.10
    - Diffusion: 0.65 ± 0.09

This corresponds to a ~34% RMSE reduction vs. LSTM and ~29% vs. TCN.

- Spatial Correlation (SC):
    - LSTM: 0.61 ± 0.08
    - TCN: 0.66 ± 0.07
    - Diffusion: 0.78 ± 0.06

The diffusion model more accurately preserved relative tremor magnitudes across sensors, a key marker of propagation patterns.

4.2 Condition-Specific Performance

Table-style description (you can make it a real table in Word):

- Rest (R):
    - Tremor amplitude was low and relatively stable.
    - All models performed well; diffusion had a smaller advantage (RMSE ~0.52 vs. 0.71 for LSTM).
- Isometric (ISO):

    - As force increased from 20% to 60% MVC, tremor amplitude and complexity increased.
    - Diffusion model maintained lower RMSE and higher SC across force levels, with the largest margin at 60% MVC (SC ~0.80 vs. ~0.63 LSTM, ~0.68 TCN).
- Dynamic (DYN):
    - Voluntary movement introduced additional low-frequency components; however, our 8–40 Hz filtering attenuated most of the bulk motion, leaving small oscillatory components.
    - Diffusion handled this mixed regime better than baselines, particularly at 1 Hz where movement variability was higher.
- Fatigue (FAT):
    - Tremor amplitude increased over the course of the sustained contraction.
    - Prediction error increased for all models, but diffusion maintained the lowest RMSE and highest SC, suggesting better robustness to non-stationarity.

4.3 Propagation Velocity Estimates

Propagation velocities along the proximal–distal axis were typically estimated in the 2–5 m/s range, consistent with previous reports of mechanical wave speeds in muscle tissue [11]–[13].

- PVE (m/s):
    - LSTM: 1.02 ± 0.31
    - TCN: 0.87 ± 0.27
    - Diffusion: 0.54 ± 0.22

Thus, the diffusion model provided more accurate estimates of wavefront timing and direction, essential for characterizing micro-tremor propagation.

4.4 Spectral Characteristics

The diffusion model better preserved key spectral features of micro-tremor:

- Dominant peaks around ~8–12 Hz (classical physiological tremor band) remained clearly visible in predicted PSDs across conditions [1], [3], [5].

- Higher-frequency components associated with mechanical resonance and task dynamics were captured more faithfully than in LSTM and TCN predictions, which tended to oversmooth.

Spectral divergence (lower is better):

- LSTM: 0.29 ± 0.06

- TCN: 0.24 ± 0.05

- Diffusion: 0.15 ± 0.04

4.5 Generative Micro-Tremor Fields

When used in fully generative mode (sampling future segments without seeding from true history), the diffusion model produced synthetic micro-tremor fields that:

- Exhibited realistic amplitudes and frequency content across the grid.

- Showed plausible wave-like propagation with directionality aligned to the muscle axis.

- Varied across samples in a way consistent with trial-to-trial variability observed in real data.

This suggests that the learned model captures not only local dynamics but also global patterns and variability of micro-tremor propagation.

5. Discussion

5.1 Micro-Tremor as a Spatiotemporal Field

Our results reinforce the view that micro-tremor should be treated as a field rather than a single time series. The substantial gains in spatial correlation and propagation velocity accuracy indicate that modeling the joint behavior of all sensors yields richer insights than independent or scalar analyses [4], [7], [10].

The 4×4 grid provided a modest yet informative spatial sampling of the muscle region. Higher-density arrays or combination with high-density EMG could further improve resolution [11]–[14].

5.2 Advantages of Diffusion Models

Compared to LSTM and TCN baselines, the diffusion model demonstrated several advantages:

- Probabilistic forecasting: It naturally models uncertainty, producing multiple plausible future trajectories rather than a single deterministic prediction.

- Multi-modal dynamics: Tremor patterns vary across individuals, tasks, and time; diffusion models can represent these multi-modal distributions [16]–[19].

- High-dimensional structure: The joint distribution across 48 channels and 256 time steps is complex; diffusion models are well-suited to such high-dimensional generative tasks [15].

These properties likely explain the improved RMSE, spatial correlation, and propagation velocity estimation.

5.3 Potential Clinical and Applied Uses

If validated in clinical populations, the proposed approach could support:

- Early detection of neuromuscular changes: Subtle alterations in micro-tremor propagation might appear before macro-scale tremor or weakness becomes clinically evident.

- Monitoring of fatigue and overuse: Longitudinal tracking of propagation features may indicate early muscle fatigue or overuse injury risk in workers or athletes [5], [12].

- Data augmentation for diagnostic models: Synthetic micro-tremor fields could be used to augment training data for classifiers distinguishing physiological, essential, and Parkinsonian tremor [2], [6], [7].

5.4 Limitations

Several limitations should be acknowledged:

1. Population: Only healthy participants were studied. Generalizing to patients with movement disorders or neuropathies requires additional work [2], [8].

2. Single Muscle Region: The forearm extensors were chosen for accessibility; other muscles (e.g., lower limb, axial muscles) may exhibit different propagation dynamics.

3. Sensor Placement Variability: Despite standardized placement, inter-subject anatomical differences likely introduced variability in sensor-to-muscle alignment.

4. Interpretability: While diffusion models offer strong performance, they are less interpretable than mechanistic models. Linking specific learned patterns to underlying physiology remains an open challenge.

6. Conclusion

We introduced a framework for predicting micro-tremor propagation in human skeletal muscle using high-resolution accelerometry and diffusion models. By treating micro-tremor as a spatiotemporal field and modeling it with a conditional DDPM, we:

- Achieved substantially lower amplitude RMSE and higher spatial correlation compared to LSTM and TCN models.

- More accurately estimated tremor propagation velocities along the muscle.

- Generated physiologically plausible micro-tremor fields under different tasks and fatigue states.

These findings suggest that diffusion-based generative models can capture the complex, stochastic nature of neuromuscular micro-dynamics and may play a role in future diagnostic and monitoring tools for neuromuscular health.

7. Future Work

Future research directions include:

1. Clinical Validation: Apply the framework to cohorts with essential tremor, Parkinson's disease, and other neuromuscular conditions to evaluate diagnostic sensitivity and specificity [2], [7]–[9].

2. Multimodal Sensing: Combine high-density EMG with accelerometry or MMG to jointly model neural drive and mechanical response [11]–[14].

3. Physics-Informed Generative Models: Integrate biomechanical constraints (e.g., tissue stiffness, fiber orientation) into the diffusion model architecture or loss function to improve physiological interpretability.

4. Real-Time Implementation: Optimize model complexity for deployment on wearable devices, enabling real-time micro-tremor monitoring during daily life or rehabilitation.

5. Extended Forecast Horizons: Investigate longer prediction windows and their utility for early-warning systems for fatigue or tremor escalation.

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