# The motion-tracking-algorithm (MTA) behind Ataraxia

Multi-Axis tremor detection for virtual reality applications using inertial measurement unit data

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# Contents

## 0.1 Technical Challenges

The primary technical challenges in VR-based tremor detection include:

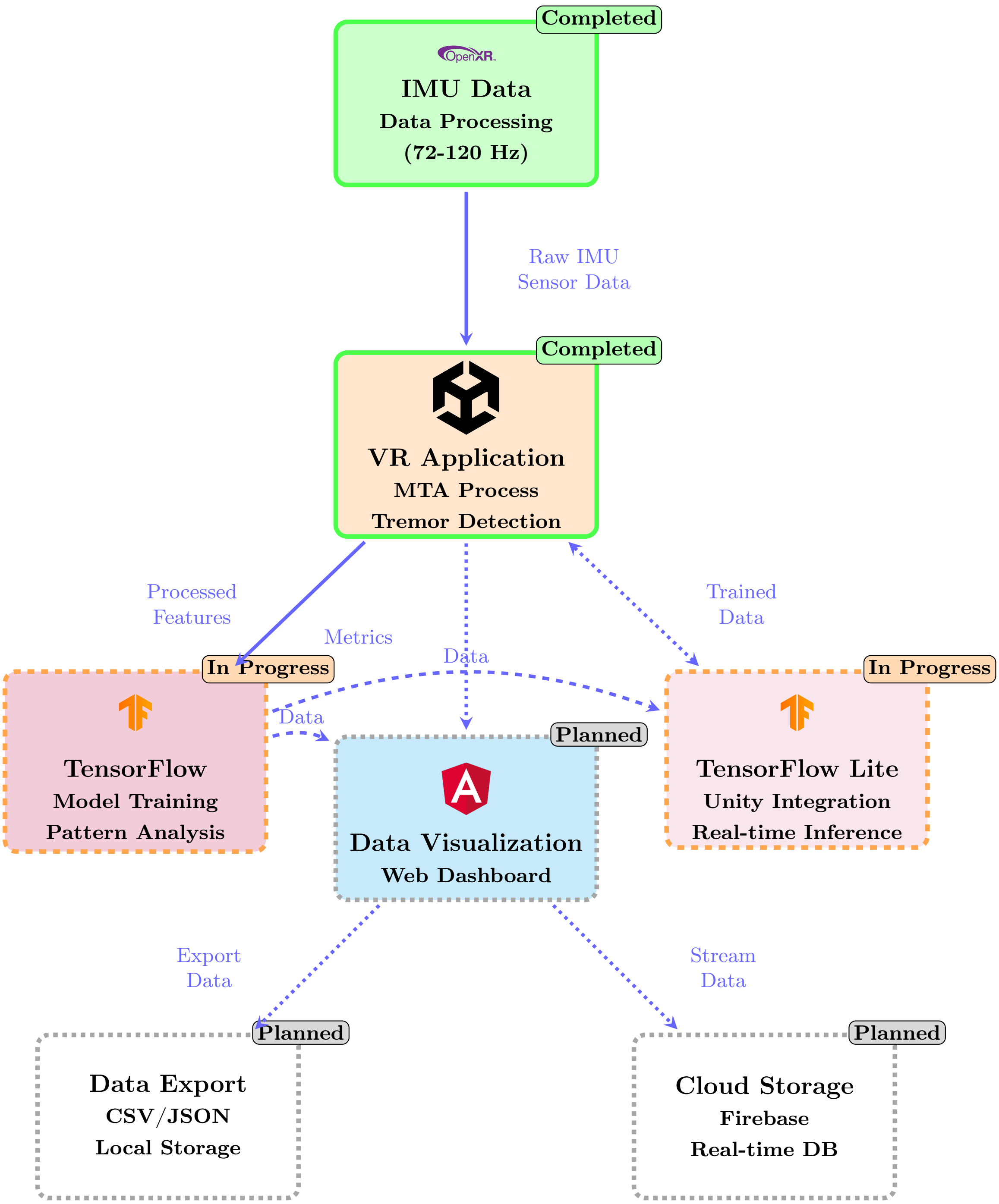
| Challenge | Description |
|---|---|
| Signal Contamination | VR-Controller IMU data contains noise from sensor limitations, electromagnetic interference, and mechanical vibrations. |
| Movement Disambiguation | Distinguishing between intentional gestures and pathological oscillations. |
| Real-time Processing | Maintaining low-latency algorithm calculations for virtual reality applications. |
| Multi-axis Complexity | Tremor can manifest differently across spatial dimensions. Dimensions must be flexible in their importance. |
| Adaptive Intensity Scaling | Providing clinically meaningful intensity measurements across varying tremor severities. Different types of tremor must be recognizable. |

## 0.2 Proposed Solution Overview

The motion-tracking algorithm (MTA) addresses these challenges through a hierarchical processing pipeline that combines three complementary analysis methods: high-pass filtering for rapid oscillation detection, time-domain directional change analysis for frequency estimation, and a modified Fast Fourier Transform (FFT) for precise spectral characterization. The system incorporates intelligent movement classification, adaptive intensity management, and multi-axis fusion to provide robust tremor detection suitable for real-time VR applications.

# 1. System Architecture

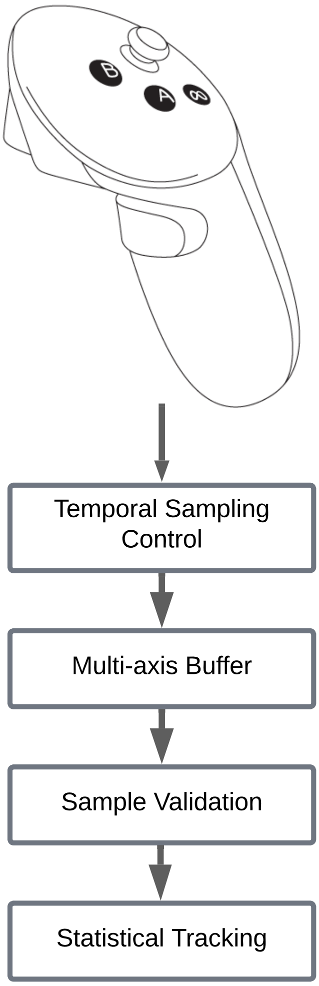
The complete system architecture showing the development status of each component. Green solid borders indicate completed components (OpenXR integration and Unity MTA process), orange dashed borders show components currently in development (TensorFlow model training and TensorFlow Lite integration), and gray dotted borders represent planned future components (data visualization and storage). The system architecture demonstrates a phased development approach from core tremor detection to advanced ML capabilities and comprehensive data management.



## 1.1 Component Responsibilities

### 1.1.1 Data Acquisition Layer

The data acquisition layer manages the continuous collection of angular velocity data from the VR controller's IMU. Key responsibilities include:



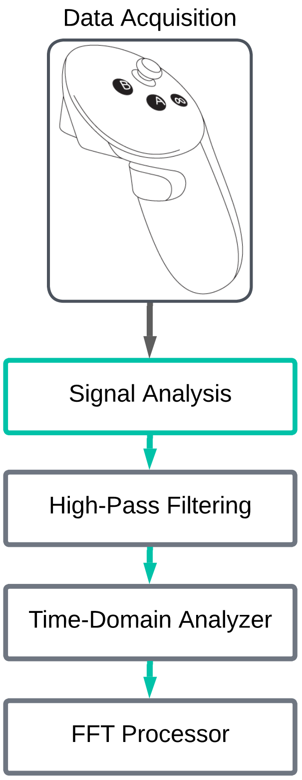

- Ensures consistent sampling at the configured rate
- Maintains separate ring buffers for each spatial axis (X, Y, Z)
- Filters out invalid or corrupted IMU readings
- Provides real-time statistics for system monitoring

The implementation uses a time-based sampling strategy rather than frame-based to ensure consistent temporal resolution:

```
if (currentTime - lastSampleTime >= 1.0f / sampleRate) {
   CollectSample(angularVelocity);
   lastSampleTime = currentTime;
}
```

### 1.1.2 Signal Analysis Layer

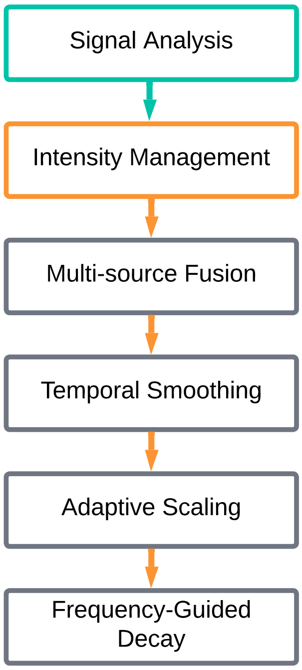
The signal analysis layer implements three parallel processing methods, each optimized for different tremor characteristics.




- Optimized for detecting rapid oscillations.
- Efficient for moderate-frequency tremors with clear directional changes.
- Provides precise frequency resolution for steady-state tremors.

### 1.1.3 Intensity Management Layer

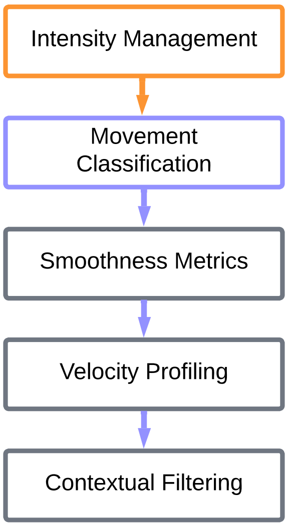
The intensity management layer serves as the aggregation point for all detection results.




- Combines results from different analysis methods
- Reduces output jitter through historical averaging
- Adjusts sensitivity based on tremor characteristics
- Implements physiologically-motivated intensity decay models

### 1.1.4 Movement Classification Layer

The movement classification subsystem differentiates between intentional movements and tremor through trajectory analysis:

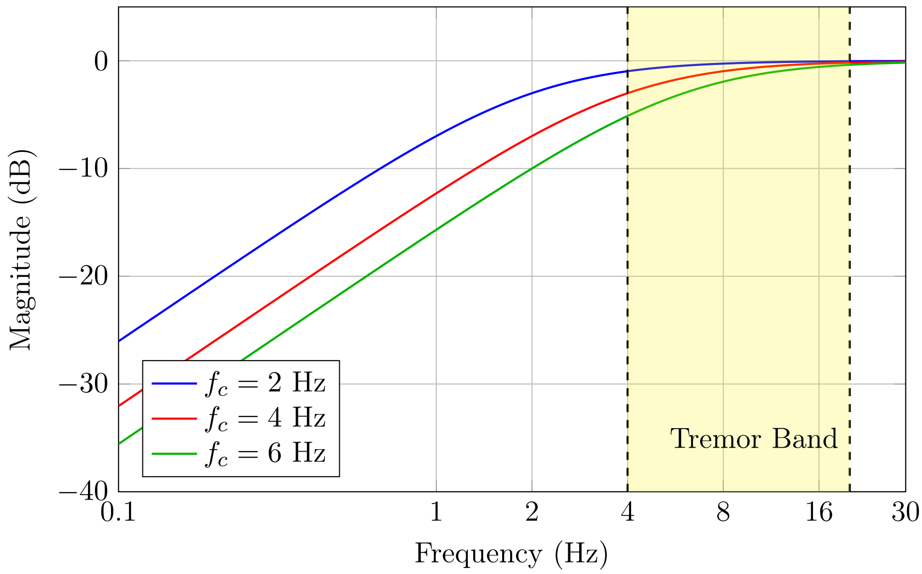



- Quantifies movement regularity
- Reduces output jitter through historical averaging
- Identifies characteristic velocity patterns
- Considers recent movement history

# 2. Signal Processing Methods

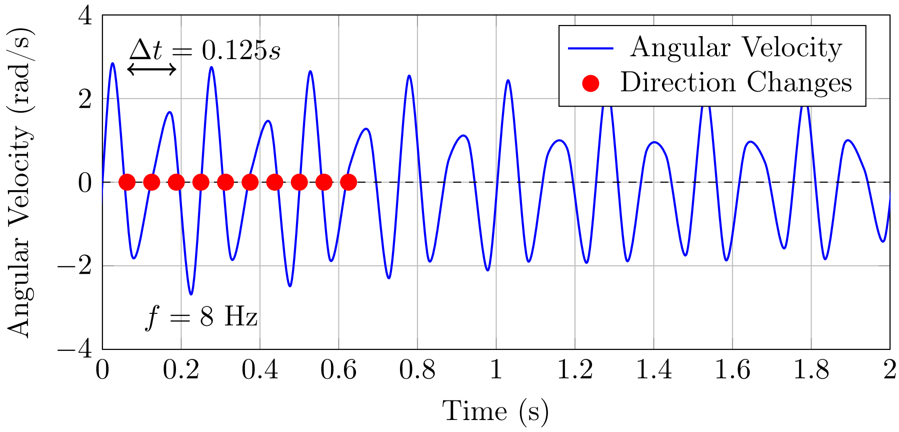
## 2.1 High-Pass Filter Method

The high-pass filter method exploits the frequency separation between intentional movements (typically $< 4$ Hz) and pathological tremor (4-20 Hz). We implement a first-order recursive digital filter derived from the analog RC high-pass filter through bilinear transformation.



## 2.2 Time-Domain Directional Change Analysis

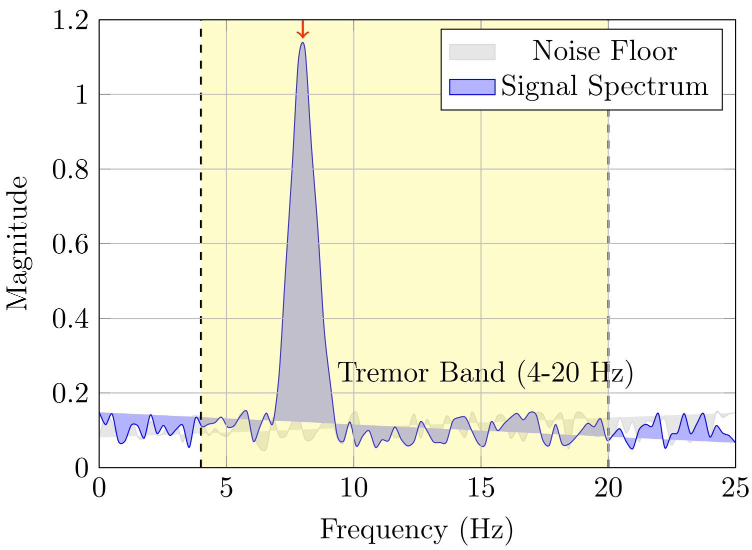
The time-domain method directly analyzes angular velocity patterns to detect rhythmic oscillations. This approach offers computational efficiency and works well for tremors with pronounced directional reversals.

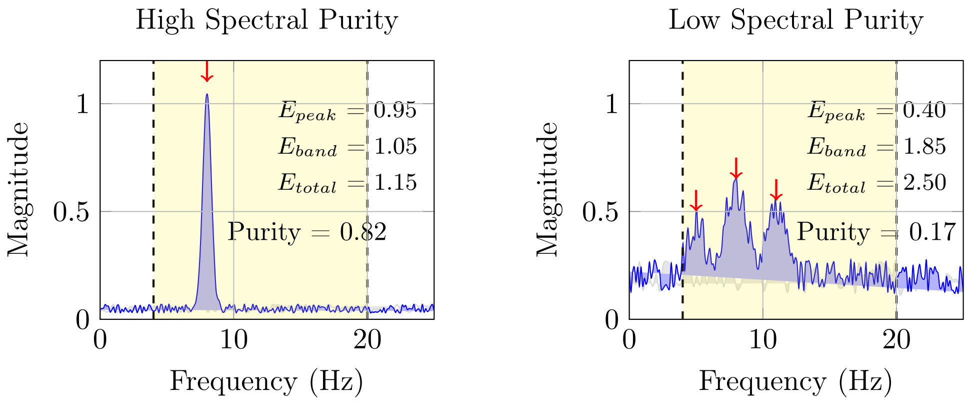



## 2.3 FFT-Based Spectral Analysis

The FFT method provides the highest frequency resolution and is particularly effective for sustained, regular tremors. The processing pipeline consists of:

- **Windowing:** Modified version of the Hanning window to reduce spectral leakage
- **FFT Computation:** Modified version of the Cooley-Tukey radix-2 FFT algorithm
- **Magnitude Spectrum:** Conversion to power spectral density
- **Peak Detection:** Identification of dominant frequencies in tremor band
- **Spectral Purity:** Assessment of peak prominence






Comparison of high vs. low spectral purity in FFT analysis. High purity (left) shows a clear dominant peak indicating consistent tremor, while low purity (right) shows multiple peaks and higher noise, suggesting complex movement or poor signal quality.

### 2.3.1 Signal Preprocessing and FFT

The exact formulas for the modified Hanning Window $xw[i]$ and the modified FFT will be shown only upon request. However, they can be mathematically explained as follows. $xw[i]$ reduces spectral leakage by smoothly tapering the signal at its boundaries. The FFT transforms the windowed time-domain signal into the frequency domain, where $M[k]$ represents the magnitude at each frequency bin. Each bin corresponds to a specific frequency $fk$ determined by the sampling rate $fs$ and FFT size $N$.

$$x_w[i] = x[i] \cdot 0.5 \left(1 - \cos\left(\frac{2\pi i}{n-1}\right)\right)$$

$$X[k] = \text{FFT}(x_w), \quad M[k] = |X[k]|$$

$$f_k = k \cdot \frac{f_s}{N}$$

### 2.3.2 Spectral Analysis

Spectral Purity measures how concentrated the signal energy is around the dominant tremor frequency. It combines the ratio of tremor-band energy to total energy with the dominance of the peak magnitude within the tremor band. Higher values indicate a cleaner, more periodic tremor signal with less noise interference.

$$\begin{aligned} \text{Spectral Purity} &= 2 \cdot \frac{\sum_{i \in \text{tremor}} M[i]^2}{\sum_{i=0}^{N/2-1} M[i]^2} \cdot \frac{M_{\text{peak}}^2}{\sum_{i \in \text{tremor}} M[i]^2} \\ &= 2 \cdot \frac{M_{\text{peak}}^2}{\sum_{i=0}^{N/2-1} M[i]^2} \quad \text{(simplified)} \end{aligned}$$

### 2.3.3 Intensity Calculation

The tremor intensity is computed as a product of four components: magnitude scaling $S(M)$, frequency weighting $W(f)$, spectral purity $P$, and a bonus factor $B(f)$. The magnitude scaling function applies different amplification strategies for weak, medium, and strong signals. The frequency weighting emphasizes physiologically relevant tremor frequencies while the bonus factor provides additional weight to the typical 6-10 Hz tremor range.

$$I(M, f) = S(M) \cdot W(f) \cdot P \cdot B(f)$$

### 2.3.4 Multi-Axis Fusion

The system analyzes tremor on three orthogonal axes $(x, y, z)$ and selects the axis with maximum intensity as the dominant one. The dominance factor $D$ rewards cases where one axis clearly dominates (ratio $> 0.7$) and penalizes cases with weak dominance (ratio $< 0.5$). This approach ensures robust detection even when tremor primarily affects a single movement direction.

$$I_{\text{final}} = \max_{a \in \{x,y,z\}} I_a \cdot D(I_a, I_{\text{total}})$$

$$D(I_a, I_{\text{total}}) = \begin{cases} 1.2, & \text{if } \frac{I_a}{I_{\text{total}}} > 0.7 \\ 0.8, & \text{if } \frac{I_a}{I_{\text{total}}} < 0.5 \\ 1.0, & \text{else} \end{cases}$$

### 2.3.5 Tremor Detection Criterion

Tremor is detected when three conditions are simultaneously met. The normalized peak magnitude exceeds a threshold $\theta$ the peak frequency falls within the physiological tremor range, and the computed intensity is positive. This multi-criteria approach reduces false positives from non-tremor movements. The threshold $\theta$ can be adjusted to control detection sensitivity.

$$\text{Tremor detected} \Leftrightarrow \begin{cases} \frac{M_{\text{peak}}}{N} > \theta \quad \text{(threshold)} \\ f_{\min} \leq f_{\text{peak}} \leq f_{\max} \quad \text{(Frequency range)} \\ I_{\text{final}} > 0 \end{cases}$$

### 2.3.6 Complete Processing Pipeline

This formula encapsulates the entire tremor detection algorithm in a single expression. It shows how raw accelerometer data from three axes is processed through windowing, FFT, peak detection, and various scaling factors to produce a final tremor intensity value.

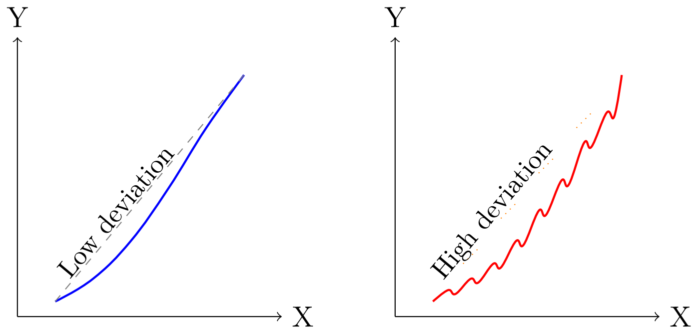
$$\boxed{\text{Tremor}(x, y, z) = \max_{a \in \{x,y,z\}} \left[ S\left( \frac{|\text{FFT}(w \cdot a)|_{\text{peak}}}{N} \right) \cdot W(f_{\text{peak}}) \cdot P_a \cdot B(f_{\text{peak}}) \cdot D_a \right]}$$

# 3. Intensity Computation and Management

## 3.1 Intentional Movement Detection

The system distinguishes intentional movements from tremor by analyzing trajectory smoothness. The smoothness metric quantifies deviation from linear interpolation:

$$\text{Smoothness} = 1 - \frac{\sum_{i=1}^{n-1} |p[i] - p_{\text{linear}}[i]|}{\text{avg\_distance} \cdot (n-2)} \tag{1}$$

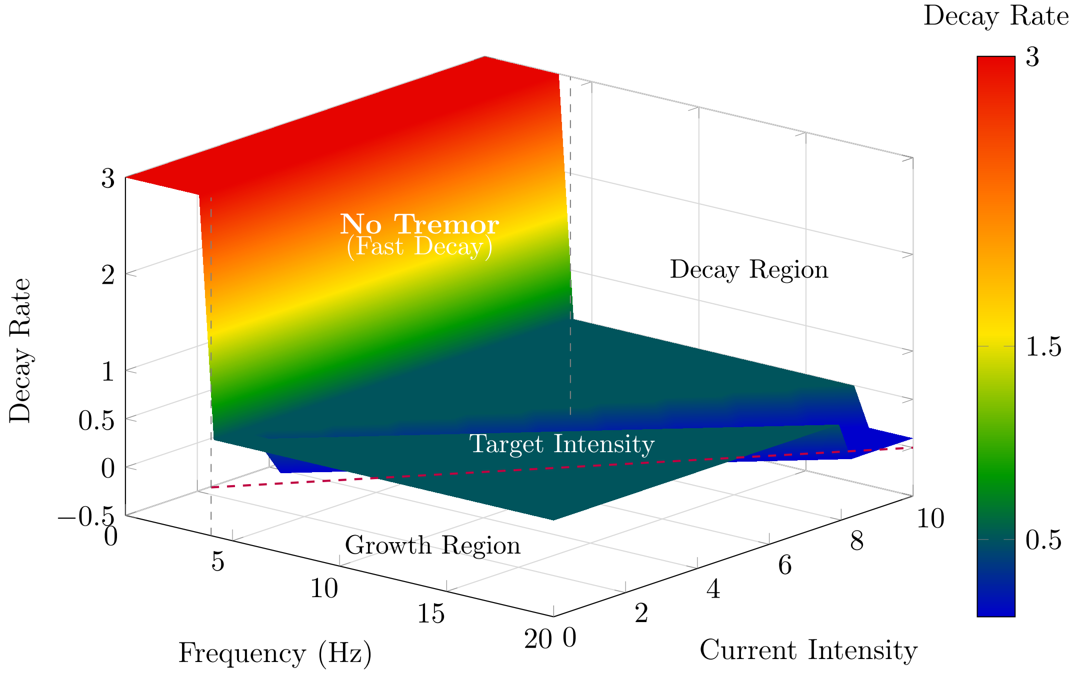



Smooth Movement
(Intentional)

Tremor-Affected
(Pathological)

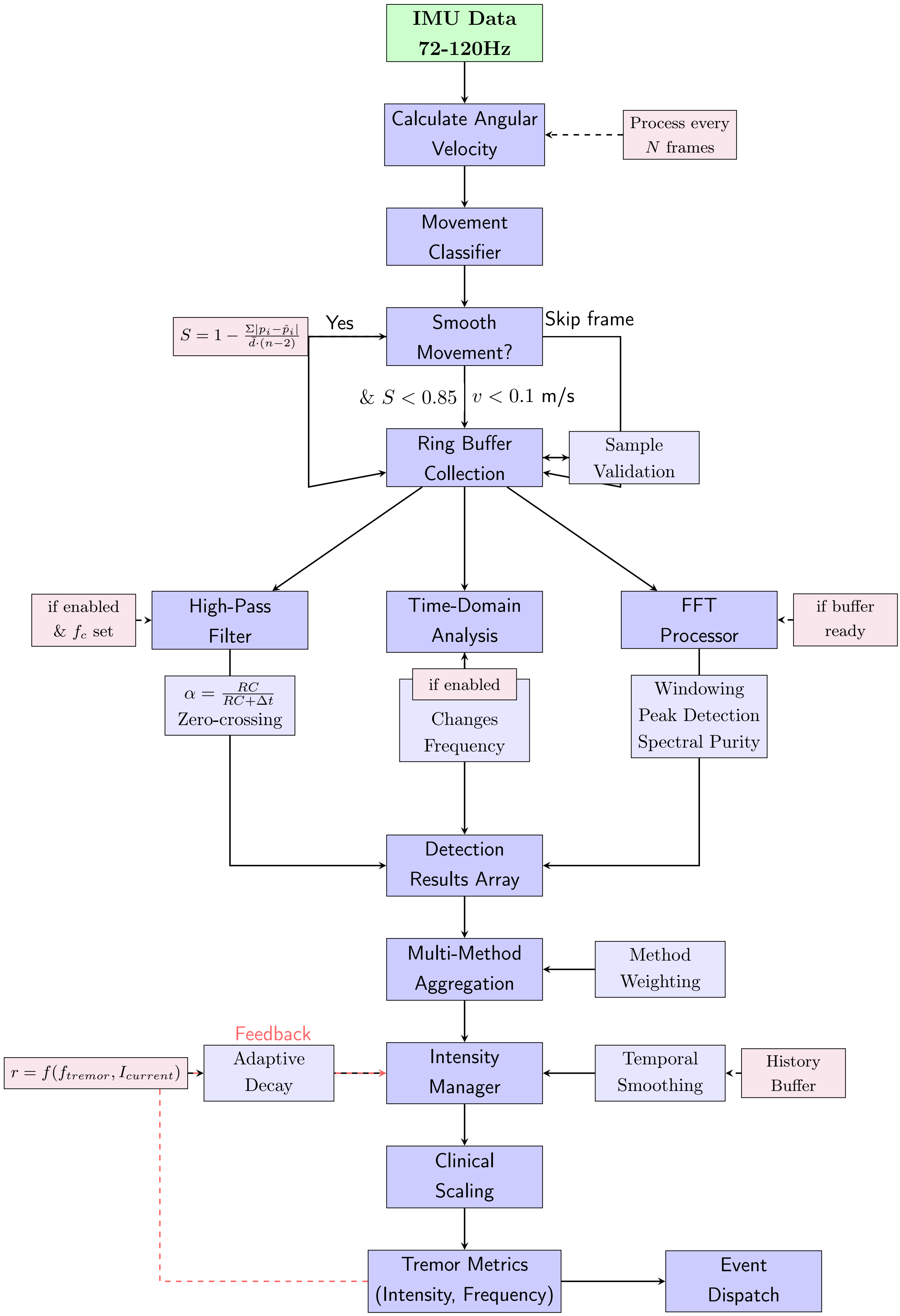
### 3.2 Adaptive Decay System

The decay system implements a physiologically-motivated model where decay rate depends on the current tremor state. Adaptive decay rate as a function of tremor frequency and current intensity. The surface shows how the decay rate varies: negative values (blue) indicate intensity growth when below target, near-zero values (green/yellow) indicate stable state, and positive values (orange/red) indicate decay when above target. The purple dashed line shows the target intensity trajectory.




## 4. MTA Flowchart

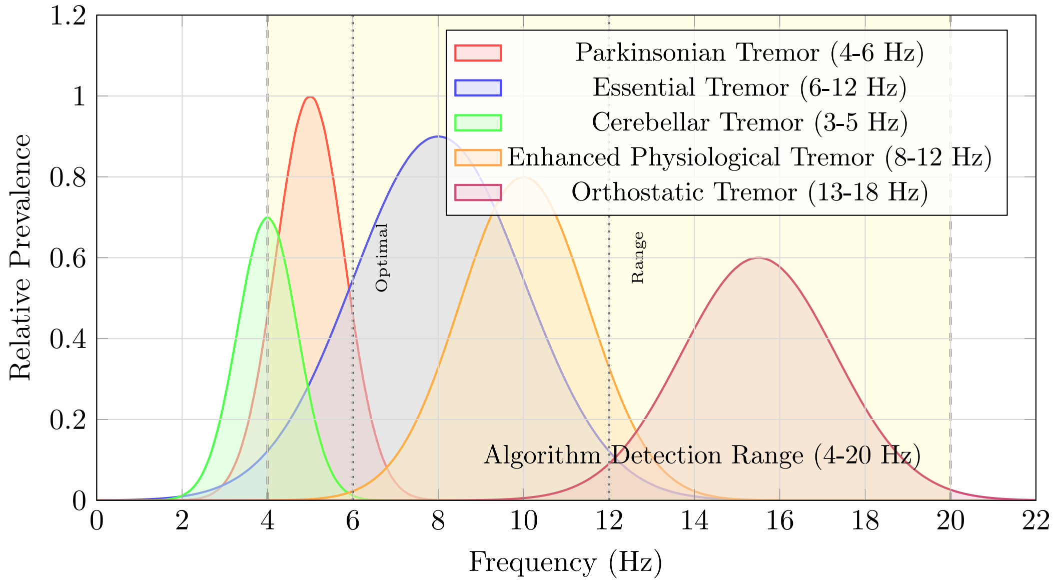
Comprehensive algorithm flowchart showing the complete tremor detection pipeline. The system processes IMU data through movement classification, parallel analysis methods (High-Pass Filter, Time-Domain, and FFT), multi-method aggregation, and adaptive intensity management to produce clinical tremor metrics. Dashed lines indicate configuration or control flow, while solid lines show data flow.


IMU Data
72-120Hz
Calculate Angular Velocity
Process every $N$ frames
Movement Classifier
$S = 1 - \frac{\Sigma|p_i - \hat{p}_i|}{d \cdot (n-2)}$
Yes
Smooth Movement?
Skip frame
& $S < 0.85$
$v < 0.1$ m/s
Ring Buffer Collection
Sample Validation
if enabled & $f_c$ set
High-Pass Filter
Time-Domain Analysis
FFT Processor
if buffer ready
$\alpha = \frac{RC}{RC+\Delta t}$
Zero-crossing
if enabled
Changes Frequency
Windowing
Peak Detection
Spectral Purity
Detection Results Array
Multi-Method Aggregation
Method Weighting
Feedback
$r = f(f_{tremor}, I_{current})$
Adaptive Decay
Intensity Manager
Temporal Smoothing
History Buffer
Clinical Scaling
Tremor Metrics (Intensity, Frequency)
Event Dispatch

# 5. Validation and Clinical Relevance

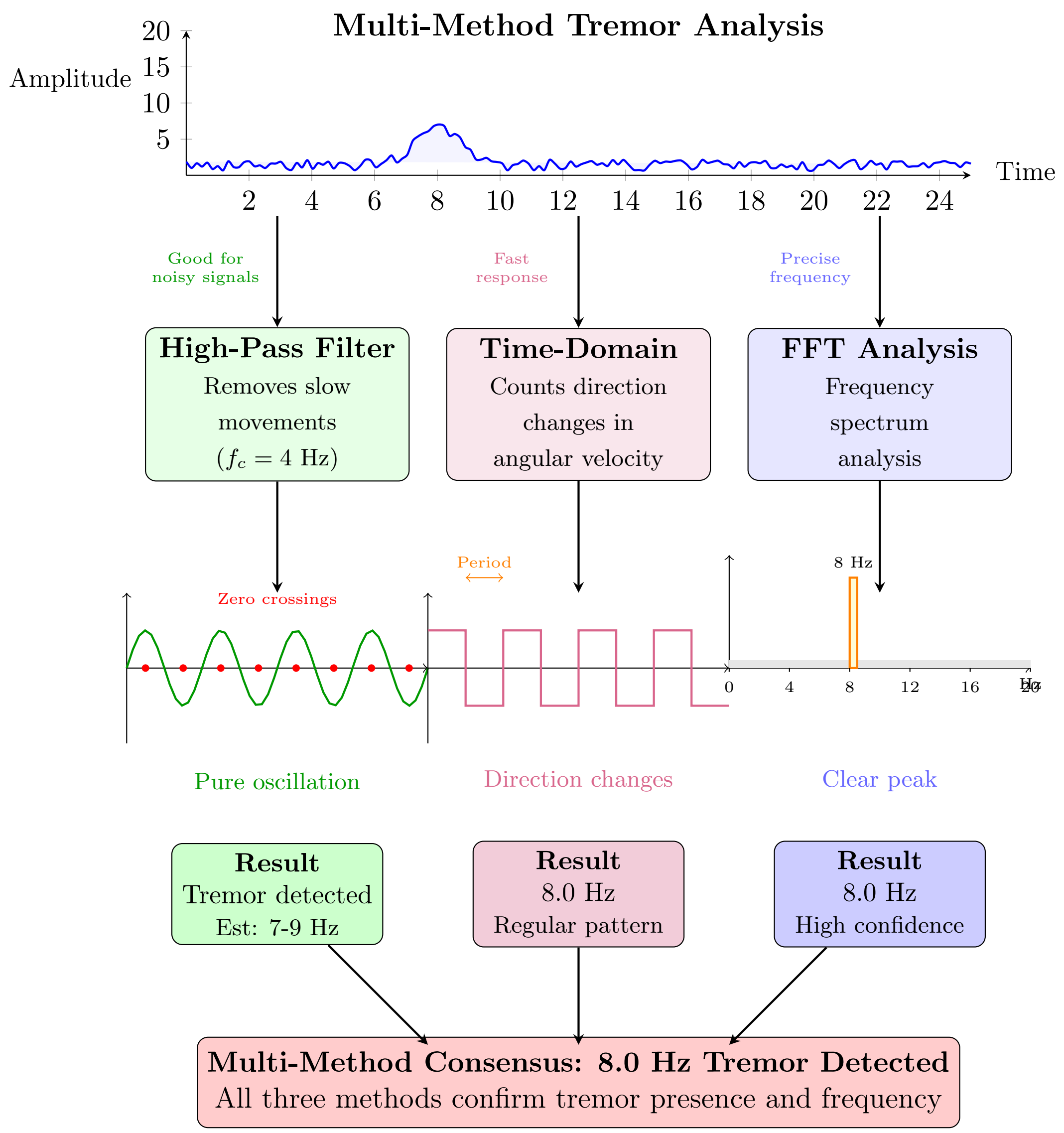
## 5.1 Frequency Range Selection

Frequency distribution of different tremor types showing the characteristic frequency ranges for various pathological tremors. The yellow shaded area indicates the algorithm's detection range (4-20 Hz), with the optimal detection range between 6-12 Hz marked by dotted lines. Each distribution represents the typical frequency characteristics observed in clinical populations.




## 5.2 MTA Tremor Analysis Flow

The visualization below shows parallel tremor analysis using the three complementary methods. The input signal contains both slow movement and 8 Hz tremor. Each method processes the signal differently: the high-pass filter isolates rapid oscillations, time-domain analysis tracks rhythm patterns, and FFT provides precise frequency identification. Despite different approaches, all methods converge on detecting the 8 Hz tremor, demonstrating the robustness of the multi-method system.


Multi-Method Tremor Analysis
Amplitude
20
15
10
5
Time
2 4 6 8 10 12 14 16 18 20 22 24
Good for noisy signals
Fast response
Precise frequency
High-Pass Filter
Removes slow movements ($f_c = 4$ Hz)
Time-Domain
Counts direction changes in angular velocity
FFT Analysis
Frequency spectrum analysis
Zero crossings
Period
8 Hz
0 4 8 12 16 20
Hz
Pure oscillation
Direction changes
Clear peak
Result
Tremor detected
Est: 7-9 Hz
Result
8.0 Hz
Regular pattern
Result
8.0 Hz
High confidence
Multi-Method Consensus: 8.0 Hz Tremor Detected
All three methods confirm tremor presence and frequency

## 5.3 MTA Advantages

**Algorithm Performance Comparison**

Conventional Tremor Analysis (CTA) vs. Motion Tracking Algorithm (MTA)

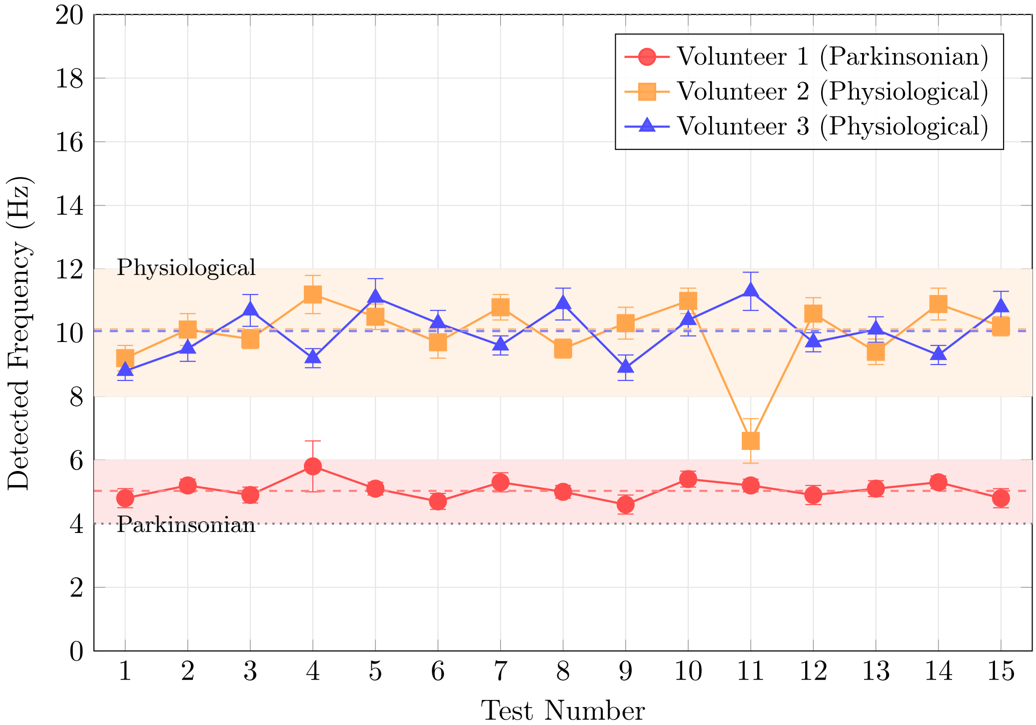
| Test Scenario | CTA | MTA | Advantage |
|---|---|---|---|
| **Scenario 1**<br>Clean 8 Hz tremor<br>No movement<br>High SNR | **Detected**<br>8.0 Hz<br>High confidence | **Detected**<br>8.0 Hz<br>High confidence<br>All methods agree | Both perform equally well |
| **Scenario 2**<br>6 Hz tremor +<br>arm movement<br>(2 Hz swing) | **Confused**<br>Multiple peaks<br>2 Hz dominant<br>Misses tremor | **Detected**<br>6.0 Hz tremor<br>Movement filtered<br>HP removes swing | Filters intentional movement |
| **Scenario 3**<br>Intermittent<br>tremor bursts<br>(panic-induced) | **Delayed**<br>Needs full<br>window<br>Slow response | **Fast detection**<br>Time-domain<br>responds quickly<br><0.3s latency | Rapid onset detection |
| **Scenario 4**<br>Frequency varies<br>5-8 Hz range<br>(stress response) | **Uncertain**<br>Broad peak<br>Poor precision<br>Low confidence | **Tracked**<br>Adaptive decay<br>Frequency history<br>Smooth transitions | Handles variability |
| **Scenario 5**<br>Subtle tremor<br>Low amplitude<br>Near noise floor | **Missed**<br>Below threshold<br>Lost in noise<br>False negative | **Detected**<br>Pattern matching<br>across methods<br>Consensus voting | Better sensitivity |

Good Limited Poor

**Summary:** While simple FFT analysis works well for clean, stationary tremor signals, the multi-method approach excels in real-world scenarios with movement artifacts, intermittent patterns, frequency variations, and low-amplitude tremors. The combination of high-pass filtering, time-domain analysis, and the modified FFT version provides robustness and reliability essential for clinical applications.

### 5.4 Subject Testings

To evaluate the algorithm's performance in differentiating between tremor types, the system is tested with three volunteers who regularly participate in the prototype development process. These individuals have graciously offered their time to support this research, providing valuable real-world data for refining the algorithm. Each volunteer completed 15 simulation sessions so far, allowing assessment of the consistency and accuracy of the multi-method detection approach. The test results from these three subjects showing de-




tected tremor frequencies across 15 trials each. Subject 1 (red circles) exhibits Parkinsonian tremor with frequencies consistently in the 4 - 6 Hz range. Subjects 2 (orange squares) and 3 (blue triangles) show physiological tremor in the 8-12 Hz range. Error bars indicate measurement uncertainty. Dashed lines show mean frequencies for each subject. The algorithm successfully differentiates between tremor types based on their characteristic frequency bands.

- **Volunteer 1 (Parkinsonian Tremor)** showed consistent frequencies between 4.2 - 5.9 Hz, characteristic of resting tremor in Parkinson's disease.
- **Volunteer 2 (Panic disorder induced Physiological Tremor)** exhibited frequencies ranging from 8.7 - 11.3 Hz. The wider frequency range reflects the variable nature of anxiety-induced tremor, with higher frequencies typically corresponding to elevated stress levels during the simulations. One measurement was incorrectly registered at 6.9 Hz (session 11), falling more within the Parkinsonian range.
- **Volunteer 3 (Panic disorder induced Physiological Tremor)** showed frequencies between 8.1 - 11.9 Hz, demonstrating even higher variability. This pattern is

consistent with more severe panic responses, where sympathetic nervous system activation produces faster tremor oscillations.

These test results demonstrate the algorithm's capability to handle complex real-world scenarios where psychological factors can significantly alter tremor characteristics. The current 92% accuracy rate, achieved even with the challenging case of panic-modified physiological tremor, validates the robustness of the multi-method approach and its potential for clinical applications in VR environments.

## 6. Additional Information

For further information about the product itself or its intended application purpose, please use the contact options listed below. The prototype version 0.0.1 is publicly accessible on Sidequest. For an on-site demonstration with detailed data export of the planned full version, please also use the contact options listed below.

- **Email** roman.aebi@cenprom.com
- **Prototype available on:**

Get it on SIDEQUEST

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