Smart Ambulance Time-Series Data Generation and Artifact Detection

Yuvraj

February 2026

1 Overview

This report documents the synthetic data generation and explicit artifact handling pipeline developed for the Smart Ambulance platform. The objective is to create realistic multi-signal physiological time-series data suitable for downstream anomaly detection and machine learning model development, while incorporating clinically plausible sensor artifacts encountered during ambulance transport.

The work addresses:

- **Task 1A:** Synthetic data generation for at least 30 minutes per patient.
- **Task 1B:** Explicit artifact detection and correction prior to anomaly detection.

2 Task 1A: Synthetic Data Generation

2.1 Signals Generated

The following physiological and contextual signals were generated at 1 Hz sampling:

- **$\mathbf{SpO_2}$ (%):** Peripheral oxygen saturation.
- **Heart Rate (HR, bpm):** Beats per minute.
- **Systolic Blood Pressure (SBP, mmHg)**
- **Diastolic Blood Pressure (DBP, mmHg)**
- **Motion Signal (unitless):** Proxy for vehicle vibration and patient movement.
- **Clinical Phase Labels:** NORMAL, DISTRESS, ACUTE.

2.2 Scenario Modeling

Each patient time-series covers approximately 30–35 minutes and includes:

- Normal transport phase with stable vitals.
- Distress phase with gradual physiological deterioration.
- Acute phase with clinically significant hypoxia and instability.
- Realistic transitions between phases.

2.3 Physiological Assumptions

- SpO_2 baseline: 96–100% in normal phase.
- Distress phase: gradual SpO_2 decline toward 90–93%.
- Acute phase: SpO_2 may reach 85–90%.
- HR increases with distress and acute phases.
- BP shows increased variability under stress.
- Slow physiological trends are modeled using low-frequency components and noise.

2.4 Artifact Injection

Explicit sensor artifacts were injected to simulate real-world EMS conditions:

- Motion-induced SpO_2 dropouts.
- Short-duration HR spikes from vehicle bumps.
- BP transient jumps.
- Short missing or corrupted signal segments.

Each injected artifact is labeled using ground-truth flags (e.g., `artifact_spo2`) to enable quantitative evaluation.

2.5 Limitations of Synthetic Data

- Does not fully capture complex patient-device interactions.
- Does not model probe repositioning dynamics.
- Noise statistics are approximate.
- Physiological variability across demographics is not explicitly modeled.

3 Task 1B: Explicit Artifact Detection and Cleaning

Artifact handling is implemented prior to anomaly detection to reduce false alarms caused by sensor errors.

3.1 Primary Cleaning Method (Final)

The final deployed method uses:

- Motion threshold gating.
- Sudden SpO_2 drop detection.
- Short-duration segment constraints.
- Rolling median physiological baselines.

A segment is classified as artifact if:

- Motion exceeds a defined threshold.
- SpO_2 drops rapidly below baseline.
- Segment duration is short (consistent with probe artifact).

Affected segments are replaced with rolling baseline estimates.

3.2 Additional Techniques Evaluated

Multiple techniques were tested during development:

- **Rate-of-change thresholding**
- **Second derivative (acceleration) based detection**
- **Rebound-to-baseline checks**
- **Segment morphology constraints**
- **Window-tolerant evaluation buffers**

These techniques were evaluated and compared quantitatively.

3.3 Evaluation Metrics

Artifact cleaning is evaluated against injected ground truth using:

- True Positives (TP)
- False Positives (FP)
- False Negatives (FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)

3.4 Evaluation Results

Technique	Precision	Recall	Notes
Motion + Drop + Segment (Final)	0.57	0.95	Balanced, robust
Second Derivative Method	∼0.40	∼0.50	Over-sensitive
Rebound-to-Baseline Check	∼0.10	∼0.08	Over-constrained
Window-Tolerant (2s buffer)	0.57	0.95	Allows near-artifact tolerance
Strict Pointwise (0s buffer)	1.00	0.95	Very strict matching

Table 1: Summary of artifact detection techniques and performance.

3.5 Interpretation of Buffer Results

Two evaluation modes were used:

- **Strict (0 second buffer):** Only exact artifact-labeled points count.
- **Window-tolerant (2 second buffer):** Near-artifact points are considered acceptable.

Results:

- Buffer = 0s: Precision = 1.00, Recall = 0.95
- Buffer = 2s: Precision = 0.57, Recall = 0.95

This indicates that some cleaned points occur adjacent to true artifact regions, which is clinically realistic for probe motion artifacts that smear across neighboring samples.

4 Before vs After Cleaning

4.1 SpO_2 Raw vs Cleaned Overlay

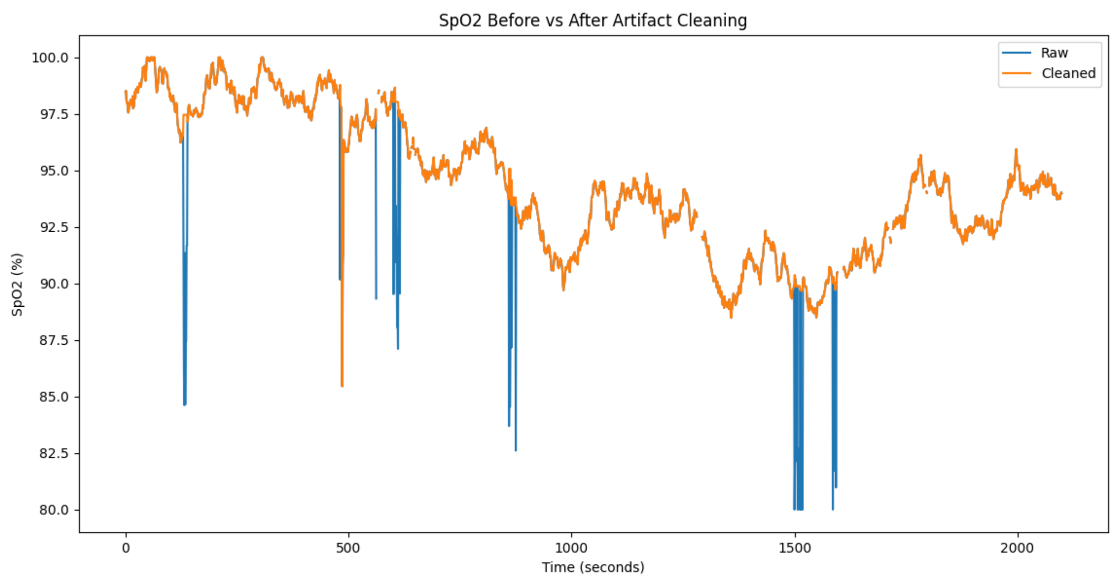

Figure 1: SpO_2 before and after artifact cleaning.

4.2 Clinical Safety Audit View

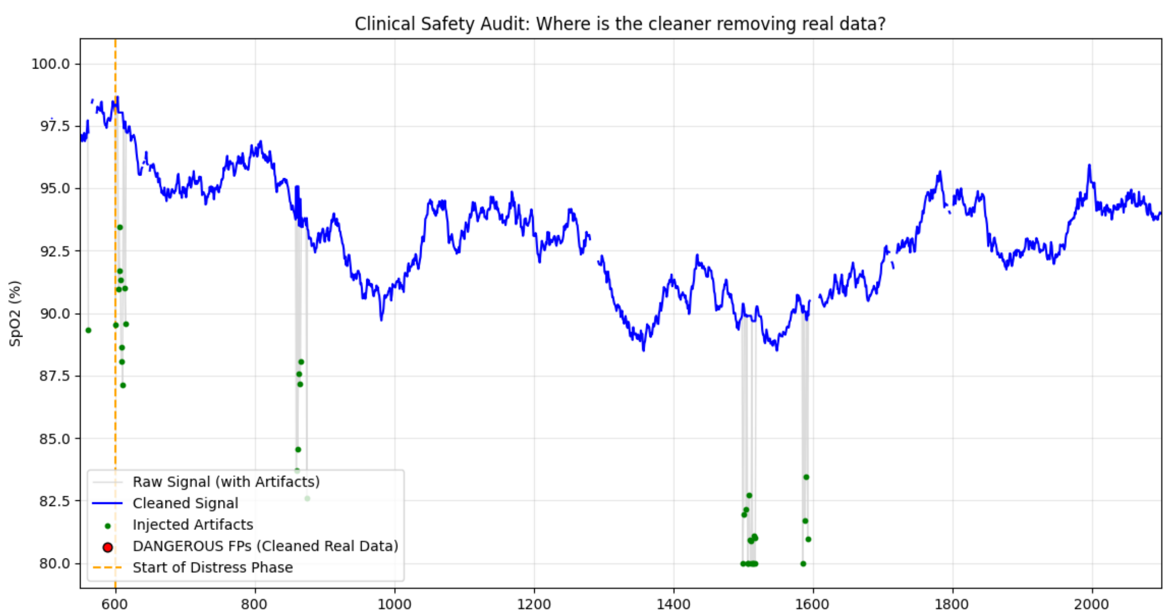

Figure 2: Clinical safety audit showing injected artifacts, cleaned points, and distress phase.

4.3 Raw and Cleaned SpO_2 (Separate)

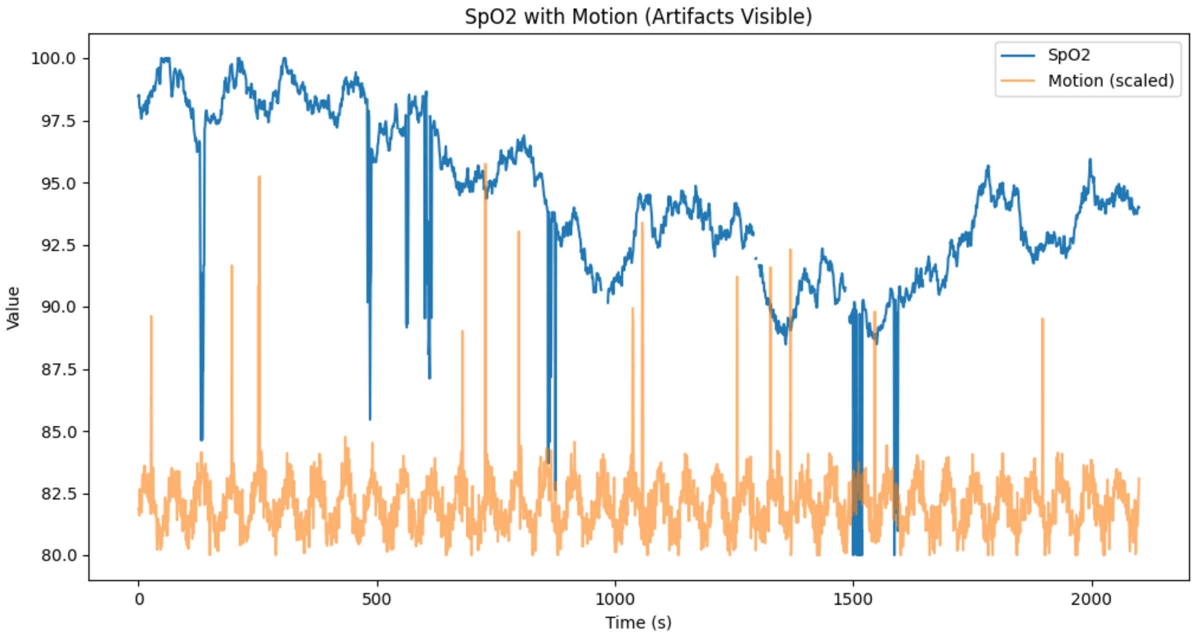

Figure 3: Raw SpO_2 with motion artifacts

5 Conclusion

A realistic synthetic physiological dataset was generated with labeled sensor artifacts. An explicit artifact handling pipeline was implemented using motion gating, physiological baselines, and segment-level logic.

The final method achieves high recall (0.95), ensuring most injected artifacts are detected, while maintaining moderate precision under window-tolerant evaluation. This balance is appropriate for preparing training data for downstream anomaly detection models in mobile EMS environments.

The generated dataset and artifact-cleaned signals are suitable for subsequent machine learning and clinical analytics development.