

Realistic Seismic Signal Detection Simulation for GMS Testing

CONTENTS

1. Abstract
2. 1. Introduction
3. 1.1 Motivation
4. 1.2 Scope
5. 2. Seismic Waveform Generation
6. 2.1 Continuous Waveform Model
7. 2.2 Station-Specific Parameters
8. 2.3 Waveform Generation Algorithm
9. 3. Signal Detection Algorithms
10. 3.1 STA/LTA (Short-Term Average / Long-Term Average)
11. 3.2 Phase Identification
12. 3.3 Signal-to-Noise Ratio (SNR)
13. 4. Signal Detection Data Structure
14. 4.1 Detection Object
15. 4.2 Waveform Data Structure
16. 5. Event Association
17. 5.1 Association Algorithm
18. 5.2 Event Object
19. 5.3 Location Estimation
20. 6. Processing Configuration
21. 6.1 Filter Definitions
22. 6.2 Detection Parameters
23. 6.3 Channel Configuration
24. 7. Implementation Specification
25. 7.1 Go Implementation
26. 7.2 Data Stream Specification
27. 8. Testing Scenarios
28. 8.1 Test Dataset 1: Regional Earthquake
29. 8.2 Test Dataset 2: Teleseismic Event

- 30. 8.3 Test Dataset 3: Explosion
- 31. 9. Performance Requirements
- 32. 9.1 Latency Requirements
- 33. 9.2 Throughput Requirements
- 34. 9.3 Data Volume
- 35. 10. Conclusion
- 36. References

Realistic Seismic Signal Detection Simulation for GMS Testing

Abstract

This paper presents a comprehensive framework for generating realistic seismic signal detection data for testing Geophysical Monitoring System (GMS) software. We define mathematical models for waveform generation, signal detection algorithms, and data structures that match the actual SNL-GMS implementation. The simulator provides continuous waveform data at configurable sample rates, realistic signal detections with phase identification, and event associations following seismic analysis standards.

Keywords: seismic simulation, signal detection, GMS, waveform generation, testing framework

1. Introduction

1.1 Motivation

Testing seismic monitoring systems requires realistic data that exercises all components of the signal processing pipeline. Current mock implementations provide only basic metadata without actual waveforms, limiting the effectiveness of integration testing. This work defines a realistic simulation framework that generates:

1. Continuous seismic waveforms at configurable sample rates
2. Signal detection objects with phase identification
3. Event associations and location estimates
4. Processing configuration parameters

1.2 Scope

This paper covers: - Seismic waveform generation - Signal detection algorithms (STA/LTA) - Phase identification - Event association methodology - Data structure specifications - Implementation guidelines

2. Seismic Waveform Generation

2.1 Continuous Waveform Model

2.1.1 Mathematical Model

The seismic waveform ($w(t)$) is modeled as:

$$[w(t) = s(t) + n(t)]$$

where: - ($s(t)$) = seismic signal (P-wave, S-wave, surface waves) - ($n(t)$) = background noise

2.1.2 Seismic Signal Components

The seismic signal is composed of:

$$[s(t) = s_P(t) + s_S(t) + s_{\text{surface}}(t)]$$

P-wave (Primary wave):

$$[s_P(t) = A_P e^{-\alpha_P (t - t_P)} (2f_P (t - t_P)) H(t - t_P)]$$

where: - (A_P) = P-wave amplitude - (α_P) = P-wave attenuation coefficient (0.5-2.0 s^{-1}) - (f_P) = P-wave dominant frequency (0.5-5 Hz) - (t_P) = P-wave arrival time - ($H(t)$) = Heaviside step function

S-wave (Secondary wave):

$$[s_S(t) = A_S e^{-\alpha_S (t - t_S)} (2f_S (t - t_S)) H(t - t_S)]$$

where: - (A_S) = S-wave amplitude (typically 1.5-3× P-wave amplitude) - (α_S) = S-wave attenuation coefficient (0.3-1.5 s^{-1}) - (f_S) = S-wave dominant frequency (0.2-2 Hz) - ($t_S = t_P + \dots$) (S-wave arrival time)

Surface waves (Love and Rayleigh):

$$[s_{\text{surface}}(t) = A_L e^{-\alpha_L (t - t_L)} (2f_L (t - t_L)) H(t - t_L) + A_R e^{-\alpha_R (t - t_R)} (2f_R (t - t_R)) H(t - t_R)]$$

2.1.3 Background Noise Model

Background noise follows a colored Gaussian process:

$$[n(t) = \sum_{i=1}^N a_i (2f_i t + \dots)]$$

with: - (f_i) = frequencies from 0.01 to 20 Hz - (a_i) = amplitudes from noise spectrum - (ϕ_i) = random phase in $[0, 2\pi)$

The noise power spectral density follows:

$$[P(f) = P_0 (f/f_0)^{-\alpha}]$$

where: - (P_0) = reference power level - (f_0) = reference frequency (1 Hz) - (α) = spectral slope (typically 2-4)

2.2 Station-Specific Parameters

Each station has unique characteristics:

```
{
  "stationId": "STA001",
  "networkType": "IU",
  "location": {
    "latitude": 35.9275,
    "longitude": -106.4572,
    "elevation": 1845.0
  },
  "channels": [
    {
      "name": "BHZ",
      "type": "BROADBAND",
      "orientation": "VERTICAL",
      "sampleRate": 40.0,
      "response": {
        "poles": [-0.03661, -7.549, -7.549],
        "zeros": [0.0, 0.0, 0.0],
        "gain": 2946.6
      },
      "sensitivity": 1.589e9
    },
    {
      "name": "BHN",
      "type": "BROADBAND",
      "orientation": "NORTH",
      "sampleRate": 40.0
    },
    {
      "name": "BHE",
```

```

        "type": "BROADBAND",
        "orientation": "EAST",
        "sampleRate": 40.0
    }
],
"noiseModel": {
    "type": "PetersonNLNM",
    "level": "LOW_NOISE"
}
}

```

2.3 Waveform Generation Algorithm

```

func GenerateWaveform(station Station, event Event, duration time.Duration, sampleRate float64) []float64 {
    // Calculate travel times
    distance := haversine(station.Location, event.Location)
    tP := distance / vP // P-wave velocity
    tS := distance / vS // S wave velocity

    // Calculate amplitudes
    AP := event.Magnitude * stationGain(station, event)
    AS := AP * sWaveRatio(station, event)

    // Generate samples
    nSamples := int(duration.Seconds() * sampleRate)
    samples := make([]float64, nSamples)

    for i := 0; i < nSamples; i++ {
        t := float64(i) / sampleRate

        // P-wave
        if t >= tP {
            samples[i] += AP * math.Exp(-alphaP*(t-tP)) *
                math.Sin(2*math.Pi*fP*(t-tP))
        }

        // S-wave
        if t >= tS {

```

```

        samples[i] += AS * math.Exp(-alphaS*(t-tS))
                    math.Sin(2*math.Pi*fS*(t-tS))
    }

    // Surface waves
    tL := tS + distance/vL
    tR := tS + distance/vR
    if t >= tL {
        samples[i] += AL * math.Exp(-alphaL*(t-tL))
                    math.Sin(2*math.Pi*fL*(t-tL))
    }
    if t >= tR {
        samples[i] += AR * math.Exp(-alphaR*(t-tR))
                    math.Sin(2*math.Pi*fR*(t-tR))
    }

    // Add noise
    samples[i] += generateNoise(frequency, t)
}

return samples
}

```

3. Signal Detection Algorithms

3.1 STA/LTA (Short-Term Average / Long-Term Average)

3.1.1 Algorithm Description

The STA/LTA algorithm detects signal onsets by comparing short-term and long-term averages of the waveform.

3.1.2 Mathematical Formulation

Short-Term Average (STA):

$$[\text{STA}(t) = \sum_{i=0}^{N_{\text{STA}}-1} |x(t - i \tau)|]$$

where: - (N_{STA}) = number of samples in STA window (typically 0.5-2 seconds) - (τ) = sample interval - ($x(t)$) = waveform sample at time (t)

Long-Term Average (LTA):

$$[\text{LTA}(t) = \sum_{i=0}^{N_{\text{LTA}}-1} |x(t - N_{\text{STA}} \tau - i \tau)|]$$

where: - ($N_{\{LTA\}}$) = number of samples in LTA window (typically 10-60 seconds)

Characteristic Function:

[CF(t) =]

Detection Trigger:

[Detection(t) =

]

where: - ($\{on\}$) = trigger threshold (typically 3-5) - ($\{off\}$) = detriger threshold (typically 2-3)

3.1.3 Implementation

```
func STALTA(waveform []float64, sampleRate float64,
staWindow, ltaWindow time.Duration, thresholdOn,
thresholdOff float64) []Detection {
    nSTA := int(float64(staWindow.Seconds()) * sampleRate)
    nLTA := int(float64(ltaWindow.Seconds()) * sampleRate)

    detections := make([]Detection, 0)
    inDetection := false

    for i := nLTA + nSTA; i < len(waveform); i++ {
        // Calculate STA
        sta := 0.0
        for j := 0; j < nSTA; j++ {
            sta += math.Abs(waveform[i-j])
        }
        sta /= float64(nSTA)

        // Calculate LTA
        lta := 0.0
        for j := 0; j < nLTA; j++ {
            lta += math.Abs(waveform[i-nSTA-j])
        }
        lta /= float64(nLTA)

        // Calculate characteristic function
        cf := sta / lta
    }
}
```

```

        // Detect onset
        if cf > thresholdOn && !inDetection {
            inDetection = true
            detections = append(detections, Detection{
                Time:      time.Unix(0,
int64(i)*int64(time.Second)/int64(sampleRate)),
                Type:      "ONSET",
                STA:      sta,
                LTA:      lta,
                Ratio:     cf,
                Confidence: math.Min(cf/thresholdOn, 1
            })
        }

        // Detect end
        if cf < thresholdOff && inDetection {
            inDetection = false
        }
    }

    return detections
}

```

3.2 Phase Identification

3.2.1 P-Wave Identification

P-waves are identified by:

1. **First arrival** at each station
2. **Higher frequency content** (0.5-5 Hz)
3. **Shorter duration** than S-waves
4. **Particle motion** primarily vertical

P-wave polarity determination:

[Polarity = sign($w_P(t_{\text{onset}})$) u_z]

where: - ($w_P(t_{\text{onset}})$) = first P-wave sample - (u_z) = vertical unit vector

3.2.2 S-Wave Identification

S-waves are identified by:

1. **Arrival after P-wave** with time delay: [$t = d (-)$] where:
 - (d) = source-station distance
 - (v_P) = P-wave velocity (5.5-8.5 km/s)
 - (v_S) = S-wave velocity (3.0-4.5 km/s)
2. **Lower frequency content** (0.2-2 Hz)
3. **Larger amplitude** than P-wave (1.5-3×)
4. **Particle motion** perpendicular to propagation

3.2.3 Phase Picking Algorithm

```
func IdentifyPhase(waveform []float64, sampleRate float64,
onsetTime time.Time) Phase {
    // Extract window around onset
    windowStart := onsetTime.Add(-0.5 * time.Second)
    windowEnd := onsetTime.Add(5.0 * time.Second)

    // Calculate frequency content
    spectrum := fft.FFT(waveform)

    // Find dominant frequency
    dominantFreq := findDominantFrequency(spectrum,
sampleRate)

    // Calculate polarization
    polarization := calculatePolarization(waveform)

    // Classify phase
    if dominantFreq > 0.5 && polarization.Vertical > 0.7 {
        return PhaseP
    } else if dominantFreq < 2.0 && polarization.Horizontal
> 0.6 {
        return PhaseS
    }

    return PhaseUnknown
}
```

3.3 Signal-to-Noise Ratio (SNR)

3.3.1 Definition

[SNR(t) =]

3.3.2 SNR Calculation

```
func CalculateSNR(waveform []float64, detectionTime
time.Time, sampleRate float64) float64 {
    // Pre-signal window (noise)
    noiseStart := detectionTime.Add(-10 * time.Second)
    noiseEnd := detectionTime.Add(-1 * time.Second)

    // Signal window
    signalStart := detectionTime
    signalEnd := detectionTime.Add(5 * time.Second)

    // Calculate RMS noise
    noiseRMS := calculateRMS(waveform, noiseStart, noiseEnd,
sampleRate)

    // Calculate RMS signal
    signalRMS := calculateRMS(waveform, signalStart,
signalEnd, sampleRate)

    // SNR in dB
    return 20 * math.Log10(signalRMS / noiseRMS)
}
```

4. Signal Detection Data Structure

4.1 Detection Object

```
{
  "id": "SD-2024031400001",
  "stationId": "STA001",
  "channel": "BHZ",
  "phase": "P",
```

```
"detectionTime": "2024-03-14T00:00:15.500Z",
"detectionTimeUncertainty": 0.05,

"amplitude": {
  "value": 5.2e-7,
  "units": "meters",
  "type": "PEAK",
  "confidence": 0.95
},

"signalToNoiseRatio": {
  "value": 12.5,
  "units": "dB",
  "staWindow": 1.0,
  "ltaWindow": 30.0
},

"period": {
  "value": 1.5,
  "units": "seconds",
  "measurement": "DOMINANT"
},

"classification": {
  "type": "EARTHQUAKE",
  "confidence": 0.87,
  "subtype": "TELESEISMIC"
},

"polarities": {
  "firstMotion": "COMPRESSIONAL",
  "uncertainty": 0.05
},

"featureMeasures": {
  "frequencyBand": {
    "low": 0.5,
    "high": 5.0,
    "units": "Hz"
  },
}
```

```

    "emergenceAngle": {
      "value": 45.0,
      "units": "degrees"
    },
    "slowness": {
      "value": 0.08,
      "units": "s/km"
    }
  },

  "processingInfo": {
    "algorithm": "STA/LTA",
    "version": "1.0",
    "parameters": {
      "staWindow": 1.0,
      "ltaWindow": 30.0,
      "triggerThreshold": 3.5,
      "detriggerThreshold": 2.0
    },
    "channelsUsed": ["BHZ", "BHN", "BHE"],
    "filterApplied": {
      "type": "BANDPASS",
      "lowFrequency": 0.5,
      "highFrequency": 5.0
    }
  },

  "associatedEventId": "EVENT-2024031400001",
  "locationContribution": {
    "residualTime": 0.15,
    "weight": 1.0
  }
}

```

4.2 Waveform Data Structure

```

{
  "id": "WF-2024031400001",
  "stationId": "STA001",

```

```
"channel": "BHZ",

"timeRange": {
  "startTime": "2024-03-14T00:00:00.000Z",
  "endTime": "2024-03-14T00:01:00.000Z",
  "duration": 60.0
},

"sampleRate": 40.0,
"sampleCount": 2400,

"samples": [0.123, -0.045, 0.089, ...],

"units": "counts",

"quality": {
  "completeness": 1.0,
  "minAmplitude": -0.5,
  "maxAmplitude": 0.8,
  "rmsAmplitude": 0.12,
  "meanAmplitude": 0.001,
  "gaps": [],
  "qualityFlags": ["GOOD"]
},

"processing": {
  "responseCorrected": true,
  "unitsConverted": true,
  "filters": [
    {
      "type": "BANDPASS",
      "lowFrequency": 0.5,
      "highFrequency": 5.0,
      "order": 4
    }
  ]
}
}
```

5. Event Association

5.1 Association Algorithm

Events are formed by associating detections across stations:

```
func AssociateDetections(detections []Detection, maxTimeGap float64, minStations int) []Event {
    events := make([]Event, 0)

    // Sort by time
    sort.Slice(detections, func(i, j int) bool {
        return
detections[i].DetectionTime.Before(detections[j].DetectionTime)
    })

    // Group detections by time proximity
    groups := make([][]Detection, 0)
    currentGroup := []Detection{detections[0]}

    for i := 1; i < len(detections); i++ {
        timeDiff :=
detections[i].DetectionTime.Sub(detections[i-1].DetectionTime).Seconds
        if timeDiff < maxTimeGap {
            currentGroup = append(currentGroup,
detections[i])
        } else {
            groups = append(groups, currentGroup)
            currentGroup = []Detection{detections[i]}
        }
    }
    groups = append(groups, currentGroup)

    // Create events from groups
    for _, group := range groups {
        if len(group) >= minStations {
            event := createEvent(group)
            events = append(events, event)
        }
    }
}
```

```
    return events  
}
```

5.2 Event Object

```
{  
  "id": "EVENT-2024031400001",  
  "originTime": "2024-03-14T00:00:10.000Z",  
  "originTimeUncertainty": 0.5,  
  
  "location": {  
    "latitude": 35.9275,  
    "longitude": -106.4572,  
    "depth": 10.5,  
    "uncertainty": {  
      "horizontal": 2.5,  
      "vertical": 5.0,  
      "units": "kilometers"  
    }  
  },  
  
  "magnitude": {  
    "value": 5.2,  
    "type": "ML",  
    "uncertainty": 0.3,  
    "numStations": 15  
  },  
  
  "type": "EARTHQUAKE",  
  "status": "AUTOMATIC",  
  
  "associatedDetections": [  
    "SD-2024031400001",  
    "SD-2024031400002",  
    "SD-2024031400003"  
  ],  
  
  "locationMethod": {
```

```

    "algorithm": "LEAST_SQUARES",
    "iterations": 5,
    "residualRMS": 0.15
  }
}

```

5.3 Location Estimation

Geiger's Method:

The event location is found by minimizing:

$$\sum_{i=1}^N (\Delta t_i)^2$$

where: - t_i^{obs} = observed arrival time at station (i) - t_i^{calc})
 = calculated travel time - Δt_i = arrival time uncertainty - (x, y, z) =
 event location - t_0 = origin time

Travel Time Calculation:

$$t^{\text{calc}} = t_{\text{station_correction}}$$

where: - d = source-station distance - $v(x,y,z)$ = velocity model -
 $t_{\text{station_correction}}$ = station-specific correction

6. Processing Configuration

6.1 Filter Definitions

```

{
  "filterDefinitions": [
    {
      "name": "bandpass-1-5hz",
      "type": "BUTTERWORTH",
      "order": 4,
      "lowFrequencyHz": 1.0,
      "highFrequencyHz": 5.0,
      "passbandRipple": 0.1,
      "stopbandAttenuation": 40.0
    },
    {
      "name": "highpass-0.1hz",
      "type": "BUTTERWORTH",
      "order": 2,

```

```
        "cutoffFrequencyHz": 0.1,  
        "passbandRipple": 0.1  
    }  
]  
}
```

6.2 Detection Parameters

```
{  
  "detectionParameters": {  
    "staWindow": {  
      "value": 1.0,  
      "units": "seconds",  
      "range": [0.5, 2.0]  
    },  
    "ltaWindow": {  
      "value": 30.0,  
      "units": "seconds",  
      "range": [10.0, 60.0]  
    },  
    "triggerThreshold": {  
      "value": 3.5,  
      "range": [2.5, 5.0]  
    },  
    "detriggerThreshold": {  
      "value": 2.0,  
      "range": [1.5, 3.0]  
    },  
    "minimumSNR": {  
      "value": 5.0,  
      "units": "dB"  
    }  
  }  
}
```

6.3 Channel Configuration

```
{
  "channels": [
    {
      "name": "BHZ",
      "type": "BROADBAND",
      "orientation": "VERTICAL",
      "response": {
        "transferFunction": "POLES_ZEROS",
        "poles": [-0.03661+0.03661j, -7.549+0.0j],
        "zeros": [0.0j, 0.0j],
        "normalizationFactor": 1.0,
        "gain": 2946.6
      },
      "sampleRate": 40.0,
      "sensitivity": 1.589e9,
      "bandwidth": {
        "lowFrequency": 0.01,
        "highFrequency": 20.0
      }
    }
  ]
}
```

7. Implementation Specification

7.1 Go Implementation

```
package main

import (
    "math"
    "time"
)

// SignalDetection represents a detected signal
type SignalDetection struct {
    ID string `json:"id"`
}
```

```

        StationID          string    `json:"stationId"`
        Channel            string    `json:"channel"`
        Phase              string    `json:"phase"`
        DetectionTime      time.Time `json:"detectionTime"`
        DetectionTimeUncertainty float64
    `json:"detectionTimeUncertainty"`
        Amplitude          float64   `json:"amplitude"`
        AmplitudeUnits     string    `json:"amplitudeUnits"`
        SignalToNoiseRatio float64
    `json:"signalToNoiseRatio"`
        Period             float64   `json:"period"`
        Classification     string    `json:"classification"`
        Confidence         float64   `json:"confidence"`
    }

    // WaveformGenerator generates realistic seismic waveform
    type WaveformGenerator struct {
        sampleRate float64
        noiseModel  NoiseModel
        stationParams StationParams
    }

    func (g *WaveformGenerator) GeneratePWave(amplitude,
duration float64) []float64 {
        nSamples := int(duration * g.sampleRate)
        samples := make([]float64, nSamples)

        // P-wave parameters
        fP := 2.0 // Hz
        alphaP := 1.0 // attenuation

        for i := 0; i < nSamples; i++ {
            t := float64(i) / g.sampleRate
            samples[i] = amplitude * math.Exp(-alphaP*t) *
                math.Sin(2*math.Pi*fP*t)
        }

        return samples
    }

```

```

    func (g *WaveformGenerator) GenerateSWave(amplitude,
duration float64) []float64 {
    nSamples := int(duration * g.sampleRate)
    samples := make([]float64, nSamples)

    // S-wave parameters
    fS := 1.0 // Hz
    alphaS := 0.5 // attenuation

    for i := 0; i < nSamples; i++ {
        t := float64(i) / g.sampleRate
        samples[i] = amplitude * math.Exp(-alphaS*t) *
            math.Sin(2*math.Pi*fS*t)
    }

    return samples
}

func (g *WaveformGenerator) GenerateNoise(duration float64) []float64 {
    nSamples := int(duration * g.sampleRate)
    samples := make([]float64, nSamples)

    // Colored noise model
    for i := 0; i < nSamples; i++ {
        samples[i] = g.noiseModel.Generate()
    }

    return samples
}

func (g *WaveformGenerator) GenerateWaveform(event Event,
station Station) []float64 {
    // Calculate travel times
    distance := haversine(station.Location, event.Location)
    tP := distance / 5.5 // P-wave velocity km/s
    tS := distance / 3.5 // S-wave velocity km/s

    // Generate components
    pWave := g.GeneratePWave(event.Magnitude * station.Distance,

```

```

10.0)
    sWave := g.GenerateSWave(event.Magnitude * station.C
* 2.5, 15.0)
    noise := g.GenerateNoise(60.0)

    // Combine with timing
    samples := make([]float64, len(noise))
    for i := 0; i < len(samples); i++ {
        t := float64(i) / g.sampleRate

        // P-wave arrival
        pIndex := int(tP * g.sampleRate)
        if i >= pIndex && i < pIndex + len(pWave) {
            samples[i] += pWave[i - pIndex]
        }

        // S-wave arrival
        sIndex := int(tS * g.sampleRate)
        if i >= sIndex && i < sIndex + len(sWave) {
            samples[i] += sWave[i - sIndex]
        }

        // Add noise
        samples[i] += noise[i]
    }

    return samples
}

```

7.2 Data Stream Specification

```

// DataStream represents a continuous data stream
type DataStream struct {
    StationID    string    `json:"stationId"`
    Channel      string    `json:"channel"`
    SampleRate   float64   `json:"sampleRate"`
    StartTime    time.Time `json:"startTime"`
    EndTime      time.Time `json:"endTime"`
    Samples      []float64 `json:"samples"`
}

```

```

    Quality      QualityInfo  `json:"quality"`
}

// QualityInfo contains data quality information
type QualityInfo struct {
    Completeness      float64  `json:"completeness"`
    MinAmplitude      float64  `json:"minAmplitude"`
    MaxAmplitude      float64  `json:"maxAmplitude"`
    RMSAmplitude      float64  `json:"rmsAmplitude"`
    MeanAmplitude     float64  `json:"meanAmplitude"`
    Gaps              []Gap    `json:"gaps"`
    QualityFlags      []string `json:"qualityFlags"`
}

```

8. Testing Scenarios

8.1 Test Dataset 1: Regional Earthquake

```

{
  "event": {
    "magnitude": 5.2,
    "location": {"latitude": 35.0, "longitude": -106.0,
"depth": 10.0},
    "time": "2024-03-14T00:00:10Z"
  },
  "stations": ["STA001", "STA002", "STA003"],
  "expectedDetections": [
    {
      "station": "STA001",
      "channel": "BHZ",
      "phase": "P",
      "arrivalTime": "2024-03-14T00:00:15.5Z",
      "snr": 15.2
    }
  ]
}

```

8.2 Test Dataset 2: Teleseismic Event

```
{
  "event": {
    "magnitude": 6.5,
    "distance": 5000, // km
    "location": {"latitude": 40.0, "longitude": -120.0,
"depth": 50.0},
    "time": "2024-03-14T01:00:00Z"
  },
  "stations": ["STA001", "STA002"],
  "expectedDetections": [
    {
      "station": "STA001",
      "channel": "BHZ",
      "phase": "P",
      "arrivalTime": "2024-03-14T01:08:20Z",
      "snr": 8.5
    }
  ]
}
```

8.3 Test Dataset 3: Explosion

```
{
  "event": {
    "magnitude": 4.0,
    "type": "EXPLOSION",
    "location": {"latitude": 37.0, "longitude": -105.0,
"depth": 0.5},
    "time": "2024-03-14T02:00:00Z"
  },
  "stations": ["STA001", "STA002"],
  "expectedDetections": [
    {
      "station": "STA001",
      "channel": "BHZ",
      "phase": "P",
      "arrivalTime": "2024-03-14T02:01:30Z",

```

```
        "snr": 25.0,  
        "classification": "EXPLOSION"  
    }  
]  
}
```

9. Performance Requirements

9.1 Latency Requirements

Operation	Maximum Latency
Waveform generation (1 minute)	< 100 ms
Signal detection	< 500 ms
Event association	< 1 second
WebSocket broadcast	< 50 ms

9.2 Throughput Requirements

Metric	Minimum
Stations	100+
Channels per station	3
Sample rate	40 Hz
Detection rate	100/second

9.3 Data Volume

Metric	Value
Waveform data	14.4 KB/station/channel/second
Detection data	1 KB/detection
Event data	0.5 KB/event

10. Conclusion

This specification defines a realistic seismic simulation framework that:

1. Generates physically realistic waveforms using seismic wave propagation models
2. Implements standard STA/LTA signal detection
3. Produces signal detection objects matching SNL-GMS data structures
4. Associates detections into events with location estimates
5. Provides continuous data streams via WebSocket

The implementation enables comprehensive testing of GMS signal processing pipelines without requiring access to classified DoD data.

References

- [1] Peterson, J. (1993). "Observation and Modeling of Seismic Background Noise." USGS Open-File Report 93-322.
- [2] Havskov, J., & Alguacil, G. (2006). "Tools in Seismology: SO-2." Instituto Andaluz de Geofísica.
- [3] Trnkoczy, A. (2002). "Understanding and Setting STA/LTA Trigger Algorithm Parameters for Broadband Seismometers." IASPEI New Manual of Seismological Observatory Practice.
- [4] Havskov, J., & Ottemöller, L. (2010). "Routine Data Processing in Seismology." Springer.
- [5] Bormann, P. (2002). "New Manual of Seismological Observatory Practice." GeoForschungsZentrum Potsdam.