

# Digital Thermometer (IR based) Simulation

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## Abstract

This report shows the simulation of a Digital thermometer (Infrared Thermometer) to measure the body temperature. The main objective of this simulation is the capture the temperature values during a specific period of time with real world disturbances. Here 60 seconds of time was considered. The simulation helps to see how the temperature readings can change slightly each and every time because of environmental errors and noises. Finally, an implementation was done to make the simulation more realistic by taking into account temperature drift, outliers, and spikes.

**Keywords:** Digital Thermometer, Infrared radiation, Temperature measurement

## 1. Simulation Aspect

The main goal of this simulation is to measure the temperature readings with a digital (IR) thermometer over a 60 seconds of period of time, by considering how real world errors effect the raw readings and demonstrate how signal processing techniques (used signal processing techniques are moving average filter and outlier rejection) [1] to get more accurate and reliable temperature readings.

## 2. Formula as the Basis of the Simulation

The fundamental physical principle relating the temperature of an object to the thermal radiation it emits is the Stefan-Boltzmann Law. For a perfect blackbody, the power (P) radiated per unit area (A) is given by: [2] [3]

$$\frac{P}{A} = \sigma T^4$$

where:

- $\frac{P}{A}$  is the radiant power emitted per unit area (W/m<sup>2</sup>)
- $\sigma$  is the Stefan-Boltzmann constant ( $\approx 5.67 \times 10^{-8}$  W/m<sup>2</sup>K<sup>4</sup>)
- $T$  is the absolute temperature of the object in kelvins (K)

$$S \propto \epsilon T^4$$

Real objects do not emit their all heat. Emissivity (0-1) shows how they emit compared to a blackbody (which means 100%). In real world device the detected signal is affected by the object's true emissivity and temperature as well as the sensor noise,

$$S_{\text{detected}} = K \times \epsilon_{\text{true}} \times (T_{\text{true}})^4 + \text{Noise}$$

Where K is a constant related to the sensor characteristics. But the thermometer has fixed emissivity,  $\epsilon_{\text{calib}}$  during the calibration and calculates the measured temperature using,

$$T_{\text{measured}} = \left( \frac{S_{\text{detected}}}{K \times \epsilon_{\text{calib}}} \right)^{1/4}$$

The core formula for first step of this simulation is much simpler.

Measured Temperature = Ideal Temperature + Noise Value

## 3. Simulation Code Environment

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import pandas as pd
4
5 print("Libraries imported: numpy, matplotlib.
6     pyplot, pandas.")
7
8 # Simulation parameters
9 simulation_duration_seconds = 60
10 measurement_interval_seconds = 0.5
```

```
10 ideal_body_temperature_celsius = 37.0
11 noise_celsius = 0.15
12
13 # Total number of simulated readings
14 num_readings = int(simulation_duration_seconds /
15     measurement_interval_seconds) + 1
```

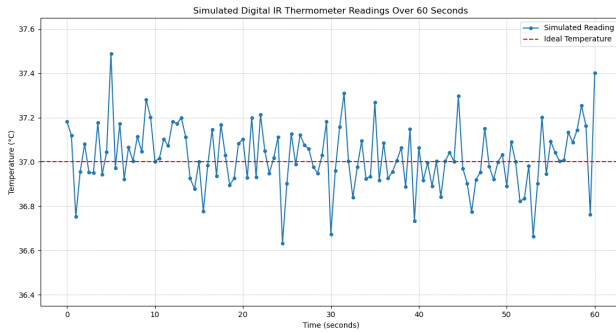
Code 1. Setting up of Initial Simulation Parameters

```
1 # Generate evenly spaced time points.
2 time_points = np.linspace(0,
3     simulation_duration_seconds, num_readings)
4
5 # Add normally distributed noise to each reading
6 measurement_noise = np.random.normal(
7     loc=0,
8     scale=noise_celsius,
9     size=num_readings)
10
11 simulated_temperatures =
12     ideal_body_temperature_celsius +
13     measurement_noise
14
15 print("Simulated data generation complete.")
16 print(f"Generated {len(time_points)} time points
17     and {len(simulated_temperatures)}
18     temperature readings.")
19
20 # Plot the simulated temperature readings over
21 time
22 plt.figure(figsize=(14, 7))
23
24 plt.plot(time_points, simulated_temperatures,
25     marker='o',
26     linestyle='--',
27     markersize=4,
28     label='Simulated Reading')
29
30 plt.axhline(y=ideal_body_temperature_celsius,
31     color='r',
32     linestyle='--',
33     label='Ideal Temperature')
34
35 plt.title('Simulated Digital IR Thermometer
36     Readings Over 60 Seconds')
37 plt.xlabel('Time (seconds)')
38 plt.ylabel('Temperature (C)')
39 plt.grid(True, which='both', linestyle='--',
40     linewidth=0.5)
41
42 # Set y-axis limits around the ideal temperature
43 3 times noise std dev, with a small
44 buffer
45 y_lower_limit = ideal_body_temperature_celsius -
46     3 * noise_celsius - 0.2
47 y_upper_limit = ideal_body_temperature_celsius +
48     3 * noise_celsius + 0.2
49 plt.ylim(y_lower_limit, y_upper_limit)
50
51 plt.legend()
```

```
plt.show()
```

**Code 2.** Simulating and plotting temperature readings

This code visualizes the Digital IR thermometer readings over 60 seconds. It generates noisy readings by adding random noise to a constant ideal temperature. This plot shows that noisy readings relative to the ideal temperature baseline over time.



**Figure 1.** Simulated Digital IR Thermometer Readings Over 60 Seconds

Over a 60-second time period simulation was completed for 121 number of readings. Each blue dot here represents the temperature reading taken at a certain time. Those readings were not constant because of the random noise was added to make it more like real life measurements. At the final step we can observe the average of all readings (Mean Temp. value), typical spread of the readings around the mean (Standard Deviation) and Min, Max temperature values. Also overall variation can be found from max and min temperature difference.

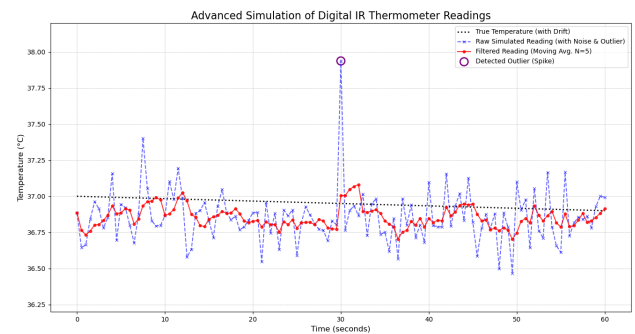
#### 4. Advanced Simulation with Signal Processing

But in a real scenario, the objects will cool down over time (drift temp.), emissivity mismatch can happen because surface properties can affect the readings (bias) and sudden spikes (outliers) can happen during these temperature readings also. Based on these reasons we can make a close simulation about this IR thermometers.

```
1 # Modeling Errors
2 noise_celsius = 0.15
3 drift_celsius_per_minute = -0.1
4 emissivity_offset_celsius = -0.1
5 outlier_time_seconds = 30
6 outlier_magnitude_celsius = 1.0
7
8 # Signal Processing Parameters
9 moving_average_window_size = 5
10 outlier_rejection_threshold_std = 3.0
11
12 # Derived Values
13 num_readings = int(simulation_duration_seconds /
14                     measurement_interval_seconds) + 1
15 time_points = np.linspace(0,
16                           simulation_duration_seconds, num_readings)
17 total_drift = np.linspace(0,
18                           drift_celsius_per_minute, num_readings)
19 measurement_noise = np.random.normal(loc=0,
20                                     scale=noise_celsius, size=num_readings)
21
22 # Raw Signal Generation
23 base_temperature =
24     ideal_body_temperature_celsius + total_drift
25     + emissivity_offset_celsius
26 raw_simulated_temperatures = base_temperature +
27     measurement_noise
28
29 # Insert Outlier
```

```
23 outlier_index = np.argmin(np.abs(time_points -
24     outlier_time_seconds))
25 raw_simulated_temperatures[outlier_index] +=
26     outlier_magnitude_celsius
27
28 # Applying signal processing
29 raw_series = pd.Series(
30     raw_simulated_temperatures)
31 # Apply a moving filter
32 filtered_temperatures = raw_series.rolling(
33     window=moving_average_window_size,
34     min_periods=1).mean()
35
36 # Outlier Rejection
37 mean_raw = raw_series.mean()
38 std_raw = raw_series.std()
39 threshold = outlier_rejection_threshold_std *
40     std_raw
41 is_not_outlier = (raw_series - mean_raw).abs() <
42     threshold
43 cleaned_temperatures = raw_series.where(
44     is_not_outlier)
```

**Code 3.** Advanced simulation setup with noise, drift, bias, and outlier



**Figure 2.** Advanced Simulation Readings in IR thermometer

#### 5. Simulation Results and Conclusion

The core idea behind this simulation was how these thermometer readings are affected by measurement noise, sensor errors, temp. drift, and occasional outliers which lead to inaccurate raw data. Also normally sensors introduce random variations due to environmental factors and internal noises. To overcome these challenges signal processing techniques like moving average filter is very important. These methods help to minimize the noises and impact of outliers and allow measured temperature to better true temperature values. This graph shows that without filtering, raw measurements can mislead, but with proper processing, we can generate more accurate and reliable temperature readings.

#### References

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- [2] J. Prosper, "Fundamentals of non-contact temperature measurement", *ResearchGate*, 2023, Accessed on June 2025. [Online]. Available: <https://www.researchgate.net/publication/389776500>.
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