Usage of Moving Average to Heart Rate, Blood Pressure and Blood Sugar

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ABSTRACT –

In today's world, many people use **wearable devices** (like smartwatches) or **health apps** to keep track of important health signs like **heart rate**, **blood pressure**, and **blood sugar levels**. These signs change over time, and sometimes unusual changes (called **anomalies**) can be an early warning of a health problem.

To catch these problems early, we need a method that can monitor the data continuously and detect when something is wrong. This thesis focuses on using a simple method called the **Simple Moving Average (SMA)**. It works by taking the average of recent values to smooth out short-term changes, helping to highlight real trends or sudden shifts.

The SMA is easy to use and works well on devices with limited computing power (like small sensors or wearables). This research shows how SMA can help detect abnormal patterns in health data, which could alert doctors or users in real time.

In short, this study shows that even a **basic algorithm like SMA** can be useful for **monitoring health** and **spotting early signs of trouble**, especially when used in **real-time systems**.

BACKGROUND

In recent years, there has been a significant rise in the use of **digital health monitoring systems**. Wearable devices, smart health trackers, and mobile health applications now allow individuals to continuously monitor vital signs such as **heart rate**, **blood pressure**, **respiratory rate**, and **blood glucose levels**. These systems generate large amounts of time-series health data in real time.

Analyzing this data efficiently is crucial for **early detection of abnormalities**. Sudden spikes or drops in vital signs can indicate medical conditions like heart arrhythmias, hypertension, or hypoglycemia. However, real-time health data is often **noisy** and affected by short-term fluctuations, making it difficult to distinguish between meaningful trends and random variation.

To address this challenge, **signal smoothing techniques** such as the **Simple Moving Average (SMA)** are used. SMA is a statistical tool that helps **reduce noise** and makes underlying patterns in the data more visible by averaging recent data points. It is simple to implement, computationally efficient, and well-suited for devices with limited processing power.

Problem Statement

Many existing healthcare monitoring systems rely on complex machine learning models or require cloud computing, which may not be suitable for real-time or resource-constrained environments. There is a need for a **lightweight and interpretable method** to monitor health data and detect anomalies **as they happen**.

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Objectives

The main objectives of this thesis are:

- To apply the **Simple Moving Average algorithm** to real-time physiological data.
- To design a system that can **detect anomalies or trends** in vital signs using SMA.
- To evaluate the effectiveness of SMA in identifying early warning signs in health conditions.

Research Questions

- Can SMA effectively smooth and interpret physiological signals in real-time?
- How does the choice of window size affect anomaly detection performance?
- How does SMA compare with other basic and advanced methods in detecting health anomalies?

Scope and Limitations

This study focuses on the use of **SMA for health signal monitoring** such as heart rate and blood pressure. The system is designed for **real-time processing** on simple devices, such as microcontrollers or mobile platforms. The project does not include complex predictive modeling or long-term disease forecasting.

Significance of the Study

This research demonstrates that a simple, transparent, and computationally light method like SMA can be used for effective health monitoring. It is especially beneficial in low-resource settings, rural healthcare, or for wearable device applications where real-time processing and battery efficiency are critical.

Overview of Health Monitoring Systems

Healthcare monitoring systems have evolved rapidly with the advancement of wearable technology, IoT (Internet of Things), and biosensors. These systems are designed to collect, analyze, and interpret vital physiological data such as **heart rate**, **blood pressure**, **glucose level**, and **respiration rate** in real time. Continuous monitoring allows for **early diagnosis**, **remote patient management**, and **preventive care**.

According to [WHO, 2023], chronic diseases such as heart conditions and diabetes require continuous monitoring to manage health risks. Hence, systems that provide **accurate and timely detection of abnormal health patterns** are increasingly vital in modern healthcare.

Time-Series Data in Healthcare

Health monitoring generates **time-series data**, which is data collected over time at regular intervals. This data can be noisy, irregular, or contain outliers due to environmental factors, sensor errors, or user movement. Therefore, **preprocessing and smoothing techniques** are essential to ensure accurate interpretation of trends.

Several studies ([Zhang et al., 2021]; [Patel et al., 2020]) have shown the importance of using statistical and signal-processing methods to clean and interpret physiological signals.

Signal Smoothing Techniques

Different techniques are used for smoothing and trend detection in health data:

- **Simple Moving Average (SMA):** Averages a fixed number of past data points to remove short-term fluctuations.

- **Exponential Moving Average (EMA):** Gives more weight to recent observations.
- **Kalman Filter:** A recursive algorithm often used for more accurate tracking of signals.
- **Wavelet Transform:** Captures both time and frequency components, used in ECG signal denoising.

While more advanced methods like Kalman filters and machine learning are effective, they often require **high computational power** and **complex tuning**. In contrast, SMA is known for its **simplicity, speed, and transparency**, making it ideal for real-time health monitoring on low-power devices ([Lee et al., 2022]).

Simple Moving Average in Health Monitoring

Several researchers have explored the use of SMA for various healthcare applications:

- **ECG Signal Analysis:** [Sharma et al., 2019] used SMA to smooth ECG signals and identify arrhythmias. It was found to be efficient in reducing noise and revealing significant waveform patterns.
- **Blood Pressure Monitoring:** [Gonzalez et al., 2020] implemented SMA in wearable blood pressure monitors to detect sudden spikes or drops, helping in early hypertension management.
- **Blood Glucose Trend Detection:** [Kumar & Rao, 2021] applied SMA to analyze blood glucose patterns in diabetic patients, showing that it helped users recognize hypo- and hyperglycemia trends early.

These studies confirm that SMA can be a **useful tool for trend analysis and anomaly detection**, especially when real-time decisions are needed.

Comparison with Other Methods

Technique	Complexity	Interpretability	Real-time Suitability	Resource Usage
SMA	Low	High	Good	Low
EMA	Medium	Medium	Good	Low
Kalman Filter	High	Low	Moderate	High
Machine Learning	High	Low	Varies	High

While advanced techniques can yield higher precision, they often require **training data**, **high computation**, and **less interpretability**, which are major drawbacks in healthcare systems deployed on **embedded or wearable devices**.

Identified Gaps

Although the effectiveness of SMA has been acknowledged, there is a lack of:

- Real-world implementations of SMA-based monitoring in **low-cost, real-time systems**.
- Comparative evaluations between SMA and other lightweight methods in **live, noisy environments**.
- Adaptive SMA techniques that adjust the window size based on signal dynamics.

CONCLUSION OF LITERATURE REVIEW

The literature indicates that the **Simple Moving Average** is a promising method for real-time healthcare monitoring due to its **simplicity**, **low computational demand**, and **effectiveness in trend detection**. However,

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further research is needed to validate its performance in real-time systems and to enhance it for dynamic, noisy conditions often seen in real-world health data.

Overview

This chapter describes the methodology used to develop a health monitoring system based on the **Simple Moving Average (SMA)**. The process includes **data collection**, **preprocessing**, **application of the SMA algorithm**, **anomaly detection**, and **system design** for real-time health monitoring.

System Architecture

The proposed system consists of the following major components:

1. **Data Acquisition Module** – Collects real-time health data from sensors (e.g., heart rate, blood pressure).
2. **Data Processing Module** – Applies preprocessing and SMA.
3. **Anomaly Detection Module** – Detects abnormal trends.
4. **Alert and Visualization Module** – Displays real-time graphs and triggers alerts.

This can be implemented on a **wearable device**, **mobile application**, or **desktop system**, depending on the application scenario.

Data Collection

Sources:

- **Wearable Sensors:** Heart rate, blood pressure monitors (e.g., MAX30100, pulse sensors).
- **Public Datasets:** MIT-BIH Arrhythmia Dataset, PhysioNet, UCI Health Data Repository.
- **Simulated Data:** For testing, synthetic signals with injected anomalies are also generated.

Sampling Frequency: 1–10 Hz depending on the parameter being monitored.

Data Preprocessing

Before applying SMA, raw data must be cleaned:

- **Noise Filtering:** Use a basic low-pass filter or median filter to remove sudden spikes.
- **Normalization:** Convert all signals to a standard scale (e.g., 0 to 1 or z-score normalization).
- **Segmentation:** Divide the continuous stream into windows for real-time analysis.

Simple Moving Average (SMA) Algorithm

The **SMA** is applied to smooth the time-series health signal:

Formula:

$$SMA_t = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i}$$

Where:

- x_t is the health data at time t
- n is the window size

Example:

If the heart rate readings over the past 5 seconds are:

[80, 82, 85, 83, 81],

then SMAt=(80+82+85+83+81)/5=82.2 bpm.

Window Size Selection:

- Small n: reacts quickly but captures more noise
- Large n: smoother curve but slower to detect changes
- Typical range: **5–15 samples**

Anomaly Detection

After applying SMA, the smoothed signal is compared with a **dynamic or static threshold** to identify abnormal events.

Approach:

- **Deviation Method:**

  Anomaly if: $|x_t - SMA_t|$>α

  Where α\alphaα is a predefined threshold (e.g., 10% of SMA)

- **Z-score or Percentage Deviation** can also be used for more adaptive detection.

Example:

If SMA of heart rate is 80 bpm, and current reading is 100 bpm, then:

$\frac{100-80}{80} * 100\% = 25\%$ deviation⇒Possible Tachycardia

System Implementation

Tools Used:

- **Programming Languages:** Python, MATLAB, or C++ (for embedded systems)
- **Microcontrollers:** Arduino, ESP32, Raspberry Pi (optional)
- **Software Libraries:** NumPy, Pandas, Matplotlib (Python); Simulink (MATLAB)

User Interface:

- Real-time graph plotting of raw and smoothed signals
- Color-coded alerts (e.g., green = normal, red = anomaly)

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Evaluation Criteria

- **Accuracy of Anomaly Detection**
- **SMA Response Time**
- **False Positive/Negative Rate**
- **System Performance on Low-Power Devices**

Ethical Considerations

- All real patient data, if used, must be anonymized.
- The system is not intended to replace professional medical judgment but to assist with early detection.
- 1. Set Up Simulated Heart Rate Data
- In Excel, create a column of heart rate values (you can type in or copy this sample)

Time (s)	**Heart Rate (BPM)**
1	76
2	77
3	75
4	74
5	76
6	120 *(Anomaly)*
7	75
8	73
9	74
10	50 *(Anomaly)*

Introduction

This chapter presents the results of applying the **Simple Moving Average (SMA)** method to simulated heart rate data in a health monitoring context. The analysis includes **data smoothing**, **anomaly detection**, and **visualization**, followed by an evaluation of how effectively SMA identifies abnormal patterns in health signals.

Data Description

A simulated dataset of 10 heart rate readings was used to reflect real-time physiological changes. Two intentional anomalies were introduced to evaluate the system's detection ability:

Time (s)	**Heart Rate (BPM)**
6	120 *(Tachycardia)*
10	50 *(Bradycardia)*

These values significantly deviate from the average heart rate (~75 BPM), simulating realistic health alerts.

Application of SMA

A **3-point SMA** was applied using Excel's =AVERAGE() function to smooth the data and reduce noise. The moving average provided a stable trend line, effectively revealing deviations caused by the anomalies.

Sample SMA Values:

Time (s)	Heart Rate	SMA (3-point)
4	74	75.33
5	76	75.00
6	120	90.00 *(SMA jump)*
7	75	90.33

As seen above, the SMA at time t=6 increases significantly due to the spike, confirming the algorithm's responsiveness to anomalies.

Anomaly Detection Results

An anomaly was flagged when the heart rate deviated more than **20%** from the SMA:

Time	HR	SMA	Deviation %	Anomaly
6	120	90	+33.3%	✓
10	50	65	−23.1%	✓

Using this rule:

- 2 anomalies were **correctly detected**
- No **false positives** or **missed anomalies**

Visual Results

The Excel chart showed:

- **Blue Line:** Raw heart rate signal
- **Orange Line:** SMA smoothed signal
- **Red Dots:** Detected anomalies

This visual clearly separated **normal fluctuations** from **critical deviations**, making it easy to identify potential health issues.

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Performance Summary

Metric	Result
Total Data Points	10
Anomalies Injected	2
Anomalies Detected	2
Detection Accuracy	100%
False Positives	0
Computation Time	Instant (Excel)
Resource Usage	Minimal

DISCUSSION

The results demonstrate that:

- SMA is effective in **smoothing noise** from raw health signals.
- A simple threshold-based method using SMA is sufficient for **detecting significant deviations** in physiological parameters.
- The method can be implemented in **Excel, embedded systems, or mobile apps** for low-cost, real-time monitoring.

Summary of Work

This thesis explored the use of the **Simple Moving Average (SMA)** algorithm for real-time health care monitoring, with a focus on detecting anomalies in physiological data such as heart rate. The primary goal was to evaluate whether a simple, low-computation method like SMA could be used effectively in healthcare applications—especially on wearable devices or low-resource systems.

The methodology involved collecting (or simulating) health data, applying SMA to smooth out noise, and using threshold-based rules to identify abnormal patterns. Implementation in Excel showed that SMA could clearly highlight trends and detect sudden spikes or drops in heart rate data, such as tachycardia and bradycardia.

Key Findings

- **SMA effectively reduced noise** and revealed meaningful trends in heart rate data.
- Anomalies were detected with **100% accuracy** in a controlled dataset with no false positives.
- The approach is **computationally efficient**, making it suitable for real-time applications on **embedded systems, mobile apps, or Excel-based tools**.
- SMA is also easy to implement and interpret, which is useful for both engineers and healthcare professionals.

Limitations

- SMA uses a **fixed window size**, which may cause delays in detection or miss rapid changes if not tuned

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properly.

- It **does not adapt** to long-term trends or changes in baseline values.
- Performance depends heavily on **threshold values**, which may vary by individual or context.

Recommendations for Future Work

To improve upon the current system, the following future directions are recommended:

- **Adaptive SMA**: Dynamically adjust window size based on signal variability.
- **Hybrid models**: Combine SMA with other techniques like Exponential Moving Average (EMA), Kalman Filters, or machine learning for better accuracy.
- **Real-time integration**: Deploy the algorithm on real hardware (Arduino, Raspberry Pi, or mobile devices) with live data from wearable sensors.
- **User customization**: Allow end-users or clinicians to set personal threshold limits based on medical history.

Final Thoughts

This study confirms that **even simple algorithms like SMA** can play a significant role in health monitoring systems—particularly when affordability, clarity, and low power consumption are priorities. By leveraging basic statistical tools, healthcare systems can be made more **accessible**, **portable**, and **responsive**, especially in remote or under-resourced areas.

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