УДК 004.67
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SIMPLE EXPONENTIAL SMOOTHING FOR BODY TEMPERATURE SENSOR DATA-SEQUENCE DENOISING

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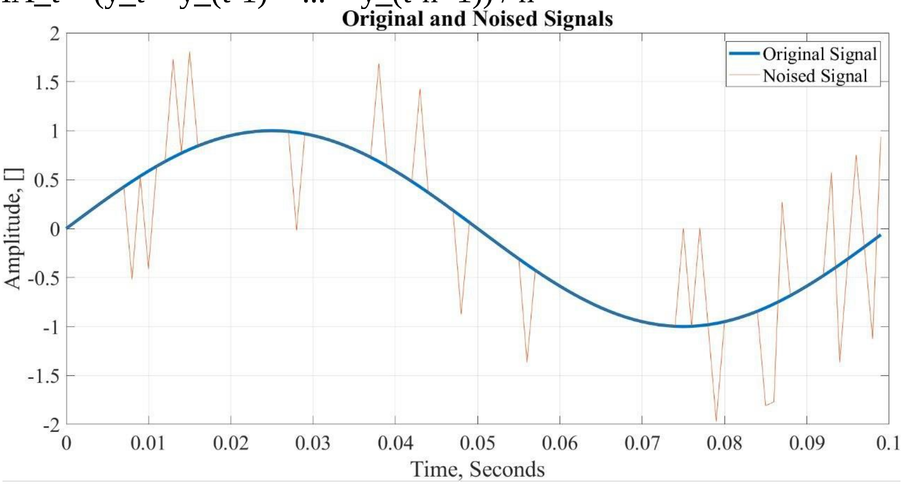
Keywords: temperature, noise, filter, Simple Exponential Smoothing.

Monitoring human body temperature is critical for detecting potential health issues. However, temperature sensor data often get contaminated with noise, which can conceal true trends and lead to erroneous conclusions. Accurate body temperature analysis is crucial for disease detection. However, sensor data is frequently polluted by noise. This noise can result in incorrect assessments and harmful medical decisions. Various filtering methods are employed to tackle this. One such method is the Simple Exponential Smoothing (SES) filter, which reliably smooths time series without clear trends or seasonal patterns. Simple Exponential Smoothing (SES) is a widely used technique for forecasting and filtering noise in time series. It is based on the assumption that data can be modeled as a constant level (average) with random fluctuations around this level. The smoothed estimate at time t, denoted as S_t, is obtained as a weighted combination of the current observation, y_t, and the previous smoothed estimate, $S_{(t-1)}$, according to the following equation: $S_t = \alpha * y_t + (1 - \alpha) * S_{(t-1)}$ where α is the smoothing parameter, which lies between 0 and 1. The initial smoothed estimate, S_1, is usually set equal to the first observation, y_1. To better understand the behavior of SES, it is instructive to examine its mathematical properties. By recursively substituting the SES equation, we can express the smoothed estimate at time t as an exponentially weighted moving average (EWMA) of all past observations: $S_t = \alpha * y_t + \alpha * (1 - \alpha) * y_{(t-1)} + \alpha * (1 - \alpha)^2 * y_{(t-2)} + ... + \alpha * (1 - \alpha)^{(t-1)} * y_1$.

This representation highlights the fact that SES assigns exponentially decaying weights to past observations, with more recent observations receiving higher weights than older ones. The rate of decay is controlled by the smoothing parameter, α, with smaller values leading to a slower decay and higher weights on older observations, unlike a widely used denoising technique is the Simple Moving Average (SMA), which computes the average of a fixed number of recent observations. For a window size of n, the SMA at time t is given by:

$$SMA_t = (y_t + y_{(t-1)} + ... + y_{(t-n+1)}) / n$$



a)

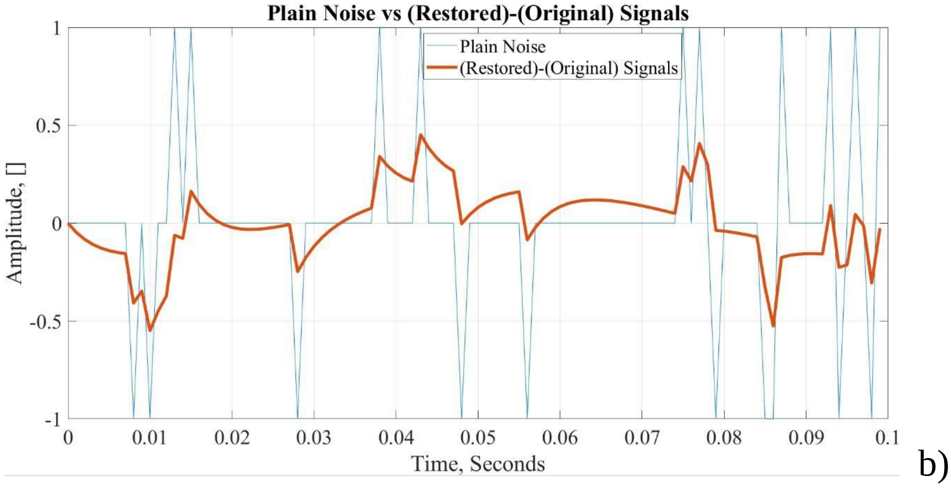


Figure 1 - Original and SaP Noised Signals (a) and Plain Noise vs (Restored)-(Original) Signals (b)

	Alpha Value of Exponential Moving Average filter		
	Alpha = 0.1	Alpha = 0.25	Alpha = 0.33
Root mean square error between Original and Noised Signals	0.447	0.447	0.447
Root mean square error between Original and Restored Signals	0.311	0.190	0.197
Quality Metric: 1-(Root mean square error Ratio)	0.304	0.576	0.560

Table 1 – Alpha Value of Exponential Moving Average filter

Simple Exponential Smoothing (SES) is a powerful and effective technique for denoising human body temperature data collected from sensors. By recursively updating a smoothed estimate based on the current observation and previous smoothed values, SES can effectively reduce the impact of various noise sources while preserving the underlying temperature trends and patterns. Compared to the widely used Simple Moving Average (SMA) method, SES offers several advantages, including adaptive weighting of observations, smoother transitions between smoothed estimates, and reduced sensitivity to parameter choice. These properties make SES an attractive choice for applications in healthcare monitoring, where accurate and reliable temperature data is crucial for early detection and diagnosis of potential health issues. While this article focused on the application of SES to body temperature denoising, the technique can be readily applied to other time series data in various domains, such as finance, engineering, and environmental monitoring. Future work could explore extensions of SES to handle more complex scenarios, such as data with trends or seasonal patterns, or investigate the integration of SES with other denoising or signal processing techniques for improved performance.