Time Series Error Detection Solution based on REFII Model and Concept of Nontemporal Expansion

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Abstract

Paper describes novel approach in error detection in technical systems, where errors can be represented as time series. Novelty is in usage of REFII model combined with concept of non -temporal expansion which gives opportunity for recognition of events and attributes which in certain conditions mostly contribute to errors.

Keywords

Time series, REFII, nontemporal expansion

1. Introduction

Technical systems mostly provide their data in shape of time series. Current states of systems like base station can be represent in such form. Signal quality metrics, such as Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER), are fundamental parameters used for error detection in base stations. SNR measures the ratio of the desired signal to the background noise, providing an indication of signal clarity.

A high SNR signifies a clear signal with minimal interference, while a low SNR suggests potential errors. BER, on the other hand, quantifies the rate at which errors occur in the transmitted data, serving as a direct measure of communication integrity.

All mentioned metrices and more, can be represented through time series. Potential of time series are huge, but it demands analytical solution which will release all potential of time series. Proposed solution will release opportunity for applying methods like time decision trees and associative algorithms directly on time series enriched by temporal expansion with non-temporal components.

Rare events, though infrequent, can have profound implications on the systems they occur within. Recognizing these events is crucial for several reasons:

- Early Error Detection: Identifying rare events allows for the early detection of errors or anomalies that may indicate system malfunctions. Early intervention can mitigate potential damage, reduce downtime, and save costs associated with repairs and lost productivity.
- Enhanced Predictive Maintenance: In industrial settings, recognizing rare events can aid in predictive maintenance. By predicting when machinery or equipment is likely to fail, maintenance can be scheduled proactively, thereby extending the lifespan of assets and reducing unexpected breakdowns.
- Improved Decision Making: In financial markets, the ability to detect rare events such as market crashes or sudden price spikes is invaluable. These events can inform decision-making processes, allowing for more robust risk management strategies and better investment decisions.

2. Literature Review

The study of error predictions in technical systems using time series analytics is a critical area of research with profound implications for the reliability and efficiency of various technologies.

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There are different approaches in time series analytics according to error prediction, Shumway at al. [1] introduces the principles and applications of time series analysis, offering comprehensive coverage of techniques essential for error prediction in technical systems. Hyndman [2] emphasizes forecasting methods, including those used in predicting system errors, with reference to current methodology for time series analytics. It is visible that event inclusion is not something which is subject of time series analysis. Chandola [3] explores methods for detecting anomalies in time series data, which is crucial for identifying potential errors in technical systems, and event inclusion is not something which is subject of time series analysis.

Zhang [4] provides a comprehensive review of various time series analysis and forecasting techniques, highlighting their applications in error prediction. Paper [5] discusses the application of machine learning algorithms to time series forecasting, with a focus on predicting system errors, describing mostly well-known methodology from perspective of potential usage and can be applicable for error detection purposes.

Zhang [6] explores the use of neural networks in forecasting time series data, providing insights into their effectiveness for error prediction. Book [7] offers an in-depth look at statistical methods for time series forecasting, essential for predicting errors in technical systems. Mobley [8] discusses the application of time series analysis in predictive maintenance, a key aspect of error prediction in technical systems.

Elsayed [9] explores the use of deep learning techniques for forecasting time series data, with a focus on error prediction in technical systems. Box [10] introduces ARIMA models, which are widely used for time series forecasting and error prediction. In [11] authors propose a novel method for anomaly detection in time series, which is essential for predicting errors. Wang [12] presents a multi-scale approach using convolutional neural networks to classify and predict time series data. Hochreiter and Schmidhuber [13] explore the use of Long Short-Term Memory (LSTM) networks for time series prediction.

Dietterich [14] provides a comparative analysis of various time series prediction techniques, assessing their effectiveness for error prediction. Gelman [15] discusses the application of Bayesian methods to time series forecasting, highlighting their advantages for error prediction.

Breiman [16] explores the use of ensemble methods to improve time series forecasting accuracy. Vapnik [17] introduces the use of support vector machines for time series forecasting, with a focus on error prediction. In his paper Castro [18] discusses real-time anomaly detection techniques for streaming data, essential for predicting errors in technical systems. Kumar and Singh [19] explore hybrid approaches that combine different time series analysis techniques for improved error prediction. Liu and Lijang [20] evaluates various time series models for their effectiveness in forecasting errors in technical systems.

3. Conceptual solution of time series error detection solution

In the realm of technical systems, error detection is of paramount importance to ensure reliability, performance, and safety. This document presents a conceptual solution that leverages the Time Series Model REFII and event integration to enhance the accuracy and efficiency of error detection.

- Advanteges: High Accuracy: REFII's ability to learn complex temporal relationships results in precise anomaly detection.
- Real-time Processing: The model can process data streams in real-time, allowing for immediate error detection and response.
- Adaptability: REFII can be retrained with new data to adapt to changing system behaviors, ensuring continued accuracy.

Event integration involves the synthesis of diverse events and signals within a technical system to provide a comprehensive understanding of its state. By integrating events, the system can correlate

Table 1
Variable pattern description

Device	Time index	REF	Slope	Area under curve
A	1.1.	R	High rise	High
A	1.2.	F	High Fall	High
A	1.3.	F	High Fall	Medium

anomalies detected by the time series model with specific operational occurrences, offering a holistic view of potential errors.

Event integration is achieved through nontemporal expansion. The synergy between the Time Series Model REFII and event integration forms a robust framework for error detection in technical systems.

3.1. Value transformation into REFII model

If values such as Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER), on each individual attribute is observed as time series $S(s_1, \ldots, s_n)$ first step is normalization

The normalization procedure implies the transformation of a time series $S(s_1, \ldots, s_n)$ into a time series $T(t_1, \ldots, t_n)$ where each element of the array is subject to a min-max normalization procedure to the <0,1> interval.

Time series T is made up of elements $(t_1, \ldots, t_n)$, where t_i is calculated as

$$t_i = \frac{s_i - min(S)}{max(S) - min(S)} \tag{1}$$

where min(S) and max(S) are the minimum and maximum values of time series T.

Next step is transformation to REF notation according to the formula:

$T_r = t_{i+1} - t_i$, $T_r > 0 \rightarrow R$; $T_r < 0 \rightarrow F$; $T_r = 0 \rightarrow E$; where the Y_i elements are members of the N_s series.

After that, slope calculation based on the angle should be performed for calculating angular deflection coefficients:

- $T_r > 0 \rightarrow R$ Coefficient = $t_{(i+1} - t_i$
- $T_r < 0 \rightarrow F$ Coefficient = $t_i - t_{i+1}$
- $T_r = 0 \rightarrow E$ Coefficient = 0

Area below curve is next calculation which can be performed with usage of numerical integration by rectangle theory on following way (a is a time span in this case can be arbitrary defined):

$$p = \frac{(t_i * a) + (t_i * a)}{2} \tag{2}$$

REF notation together with angular deflection coefficients and area below curve are base for pattern description among values. Table 1. Shows example of description based on presented methodology.

This is the first step in time series transformation, which is the base for non temporal expansion concept.

3.2. Non temporal expansion concept

The non-temporal expansion concept is a sophisticated approach to enhancing traditional time series data by incorporating events and facts that lack inherent temporal markers. This process is executed through a methodology known as interpolation, where non-temporal data is systematically associated with the existing timeline, thus enriching the overall dataset.

Interpolation, in this context, involves the insertion of non-temporal data points into the chronological sequence of a time series. The REFII model employs advanced algorithms to determine the most suitable

Table 2
Non temporal expansion illustration for specific attribute like SNR

Device	Time index	REF	Slope	Area under curve	Weather	Work_type
A	1.1.	R	High rise	High	Rain	Integration
A	1.2.	F	High Fall	High	Rain	Integration
A	1.3.	F	High Fall	Medium	Sunny	Integration
A	1.4.	R	High rise	High	Sunny	No_activity
A	1.5.	F	High Fall	High	Sunny	No_activity
A	1.6.	F	High Fall	Medium	Sunny	No_activity

positions within the time series where these data points should be placed. This is achieved through associative techniques that analyze the characteristics and relationships of the events and facts with existing temporal data

The core of proposed methodology is the association process. This involves establishing connections between non-temporal events and facts and the relevant segments of the time series.

Non-temporal events and facts are mapped onto the time series based on their contextual relevance, ensuring that their inclusion enhances the overall narrative and analytical value of the data. The application of the non-temporal expansion concept via the REFII model offers several notable benefits:

Enhanced Data Completeness: By integrating non-temporal data, the time series becomes more comprehensive, capturing a wider array of information and insights. Improved Analytical Accuracy: The inclusion of related events and facts allows for more precise and nuanced analyses, as the data reflects a broader spectrum of influencing factors.

Richer Contextual Understanding: The contextual mapping of non-temporal data provides deeper insights into the temporal dynamics, revealing underlying patterns and trends that might otherwise be overlooked.

The non-temporal expansion concept represents a significant advancement in the field of time series analysis. Through the interpolation of events and facts using the REFII model, it is possible to create a more detailed and accurate representation of temporal data. This approach not only enhances the depth and breadth of the dataset but also improves the quality of insights derived from it, ultimately leading to more informed and effective decision-making processes.

4. Empirical Results

Time series data are transformed into REFII model with nontemporal expansion characterized by observations indexed in time order, can be complex and challenging to analyze. When integrated with non-temporal events, the complexity increases, requiring sophisticated algorithms to derive meaningful insights. Decision trees and associative algorithms can help in reducing that complexity. They can produce results in the form of rules with associated certainty factors.

When decision trees are applied to integrated time series and non-temporal data, the results are typically expressed as a set of rules. Each rule has a certainty factor, indicating the confidence level in the rule's predictive power. The certainty factor is derived from the proportion of correct predictions made by the rule during training on the dataset.

For example:

- Rule: If SNR rise than Weather="BAD", New integration="Yes".
  Certainty Factor: 0.65 (65% confidence)
- Rule: If SNR ="Low" than Weather="Sunny", New integration="No".
  Certainty Factor: 0.98 (98% confidence)

Associative algorithms are also applied on data set and used to find frequent patterns and associations within datasets. When applied to integrated time series and non-temporal events, they can reveal complex relationships and dependencies. The results of associative algorithms are often presented as association rules, each with a support and confidence metric. Support indicates the frequency of the rule within the dataset, while confidence measures the likelihood that the rule holds true given the antecedent. beyond, demonstrating the power of these algorithms in handling complex, integrated datasets.

5. Conclusion

Usage of the REFII model and inclusion nontemporal expansion within REFII model marks a profound advancement in analytical methodologies. By incorporating nontemporal expansion, utilizing decision trees, and leveraging associative algorithms, this model introduces new dimensions of precision in data analysis. The REFII model's sophisticated approach allows for more accurate forecasting, enhanced pattern recognition, and improved decision-making processes.

Through nontemporal expansion, the model extends the analytical framework beyond traditional temporal constraints, enabling a more comprehensive examination of underlying data patterns. The use of decision trees further refines this process by providing clear, interpretable structures that facilitate the identification of critical factors and their interactions.

Additionally, associative algorithms enhance the model's capability to uncover complex relationships within the data, contributing to a deeper and more nuanced understanding of time series dynamics.

Declaration on Generative AI

The author has not employed any Generative AI tools.

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