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doi:10.15199/48.2025.01.37

Building an analytical model for inference, detection and early warning in UST measurements

***Abstract**: This article will present the concept of creating an analytical model for inference, detection and early warning of detection of measurements, rapid measurement deviations, and the correctness of the process under study in ultrasonic tomography measurements. The research describes an algorithm's operation for inference, detection and early warning of the appearance of a stochastic trend in a time series.*

Streszczenie:** W tym artykule została przedstawiona koncepcja stworzenie modelu analitycznego pozwalającego na wnioskowanie, wykrywanie i wczesne ostrzeganie wykrywania błędnych pomiarów, odchyleń pomiarowych, jak również prawidłowości przebiegu badanego procesu, w pomiarach za pomocą tomografii ultradźwiękowej. Prace badawcze opisują działanie algorytmu wnioskowania, wykrywania i wczesnego ostrzegania o pojawieniu się trendu stochastycznego w szeregu czasowym **(Budowa modelu analitycznego do wnioskowania, wykrywania i wczesnego ostrzegania w pomiarach UST).

Keywords: time series, ultrasound tomography, early warning
Słowa kluczowe: szeregi czasowe,tomografia ultradźwiękowa, wczesne ostrzeganie

Introduction

In ultrasound tomography, we analyze the measurements (readings) from the $x_t \in \mathbf{R}^k$ sensors separately, where $x_t=(x_t^1, x_t^2, \ldots x_t^k)$ [1]. The occurrence of non-randomness in the series $\{x_j^i\}_{1\le j\le t}$. The occurrence of non-randomness in the series in the form of a trend, integration means the appearance of an inclusion in the field of view. The following will present an algorithm for dynamic analysis and detection of non-randomness at any time t based on the realization of the $\{x_j^i\}_{max(0,t-m)\le j\le t}$ for each channel $1 \le i \le k$.

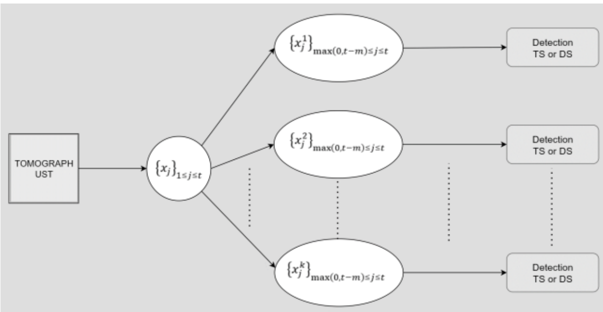

Fig.1. Signal analysis

Randomization study

In the case where the elements of the $\{x_j^i\}_{max(0,t-m)\le j\le t}$ series for each $1 \le i \le k$ channel are identical, or evaluate randomly around a certain level, there is no indication of concern regarding the occurrence of additional inclusion in the viewing area.

We use the var(xji)=const to check whether the measurements are constan*t*. condition To check whether the elements of the $\{x_j^i\}_{max(0,t-m)\le j\le t}$ series evolve randomly around the $\bar{x}^i = \sum_{j=max(0,t-m)}^{t} x_j^i$level we use the Wald-Wolfowitz test. We define the $\{\varepsilon_j\}_{max(0,t-m)\le j\le t}$, where $\varepsilon_j = x_j^i - \bar{x}^i$ series (we apply the test to each channel separately) [2].

At the α level of significance, the working hypothesis is

H_0:no non-random component in the series of residuals $\{\varepsilon_j\}$, the elements of the series evaluate randomly around the zero level, against the alternative hypothesis

H_1: in the analyzed series $\{\varepsilon_j\}_{1\le t\le N}$.

For the series $\{\varepsilon_j\}_{max(0,t-m)\le j\le t}$,, there is a non-random component or the elements of the series are correlated.

We first calculate the number of series *S*, where a series is called any subsequence consisting only of positive or negative elements, and then determine the number of positive residuals n_1 and the number of negative residuals n_2 (zero elements are omitted).

The random variable *S* tends asymptotically to the normal distribution $\mathbf{N}(m,\sigma^2)$, where we estimate the estimators of the mean and variance of the random variable *S* as follows

$$\hat{m} = \frac{2n_1n_2}{N} + 1 \tag{1}$$

$$\hat{\sigma} = \frac{2n_1n_2(2n_1n_2 - N)}{(N-1)N^2} \tag{2}$$

Statistic $U = \frac{S-\hat{m}}{\hat{\sigma}}$, has a normal distribution of $N(0,1)$. At the α significance level, we read the value of the critical statistic

$$u^* = F^{-1}\left(1 - \frac{\alpha}{2}\right), \tag{3}$$

where F denotes the distribution of the normal distribution $N(0,1)$. If $-u^* < U < u^*$,then at the significance level of α there are no grounds for rejecting the working hypothesis H_0 (in Ultrasound the algorithm does not report an alert, the channel readings fall randomly), otherwise we reject the working hypothesis H_0 against the alternative hypothesis H_1 (there is a suspicion of non-random components, so we test stationarity in the series $\{x_j^i\}_{max(0,t-m)\le j\le t}$.[3].

Stationary time series

Definition 1 A series $\{x_t\}_{t\ge 1}$ is called strictly stationary (stationary in the narrower sense) if for any $m, t_1, t_2, \ldots, t_m, \tau$ the joint probability distribution of m elements $x_{t1}, x_{t2}, \ldots, x_{tm}$ is identical to the distribution of m elements $x_{t1+\tau}, x_{t2+\tau}, \ldots, x_{tm+\tau}$.

The definition shows that any series containing non-random components (trend factor, seasonality factor, conjunctural factor) depending on time instant t are non-stationary. From definition 1, it follows that for a stationary series at any time shift τ, the dynamic properties of the series remain unchanged.

Definition 2 A series of $\{x_t\}_{t\ge 1}$, for which the second ordinary moment is finite ($Ex_t^2<\infty$ for t≥1), is called weakly stationary (stationary in the broader sense) if:

- the expected value of the elements of the series does not depend on the moment t

$$\bigwedge_{1\le t\le n} Ex_t = const, \tag{4}$$

- the covariance depends only on the shift of τ, while it does not depend on the moment t

(5) $$\bigwedge_{1\le t\le N} \quad \bigwedge_{0\le\tau\le N-1} cov(x_t, x_{t+\tau}) = cov(x_0, x_\tau),$$

A strictly stationary process with a finite second moment is a weakly stationary process. The inverse statement is not true. However, for Gaussian processes, a weakly stationary process is strictly stationary.

TS and DS ranks

Definition 3 A time series of the form $\{x_t\}_{t\ge 1}$ is stationary concerning the trend $f(t)$ if the series of the form $\{x_t\text{-}f(t)\}_{t\ge 1}$ is stationary, where $f(\cdot)$ is a deterministic function.

We call the time series a TS (Trend stationary) series relative to the trend. We define a differential operator Δ of the form

(6) $$\begin{aligned} \triangle\, \varepsilon_t &= \varepsilon_t - \varepsilon_{t-1}, \\ \triangle^k\, \varepsilon_t &= \triangle^{k-1}\, \varepsilon_t - \triangle^{k-1}\, \varepsilon_{t-1} \end{aligned}$$

For any k $\in$ **N.**

Definition 4 A time series of $\{x_t\}_{t\ge 1}$ is integrated into degree d (we denote it as $\{x_t\}_{t\ge 1}\sim I(d)$) if the series of $\{x_t\}_{t\ge 1}$ is nonstationary, while the differential series $\{\Delta^d x_t\}_{t\ge 1}$ is stationary, with d being the smallest integer for which the stationarity property of the series $\{\Delta^d x_t\}_{t\ge 1}$ is satisfied.

The time series $\{x_t\}_{t\ge 1}$ integrated in degree d ≥1 is called a DS (Difference Stationary) series. If the time series $\{x_t\}_{t\ge 1}$ is stationary, we say that the elements of the series are integrated in degree zero and denote $\{x_t\}_{t\ge 1}\sim I(0)$ [4].

Test stacjonarności

To test for stationarity, we use the Augmented Dickey-Fuller test. For the analyzed series $\{\varepsilon_j\}_{max(0,t-m)\le j\le t}$, where $\varepsilon_j = x_j^i - \bar{x}^i$ at the α level of significance, we create the working hypothesis

H_0: The time series $\{\varepsilon_t\}_{t\ge 1}$ is non-stationary - the degree of integration is greater than zero).

and the alternative hypothesis

H_1: the time series of $\{\varepsilon_t\}_{t\ge 1}$ is stationary, thus the elements of the series are integrated to a degree of zero.

To verify the hypothesis, we analyze the equation

(7) $$\triangle\, \varepsilon_t = \kappa\varepsilon_{t-1} + \sum_{i=1}^{p} \varkappa_i \triangle\, \varepsilon_{t-i} + \epsilon_t,$$

The row of autoregression p is selected to eliminate the correlation of external disturbances and

(8) $$p < \left[4\left(\frac{N}{100}\right)^{0.25}\right],$$

Thus, if \n0, then the time series $\{\varepsilon_t\}_{t\ge 1}$ is non-stationary and the degree of integration is greater than zero. If, on the other hand $\kappa\in(-2,0)$ then the time series of $\{\varepsilon_t\}_{t\ge 1}$ is stationary. Unlike the Dickey-Fuller test ($\varkappa_i=0$ *for* $i=1,2,...,p$) the extended Dickey-Fuller test takes into account the components of Δ_{t-i} , $i=1,2,...,p$ in order to eliminate the autocorrelation of the residuals of ϵ_t *for* $t\ge 1$.

Test statistics

(9) $$DF = \frac{\hat{\kappa}}{S(\kappa)},$$

has a Dickey-Fuller distribution, where $\hat{\kappa}$ the estimator and $S(\kappa)$ -standard deviation of the κ parameter.

From the arrays for the Dickey-Fuller test, we read the critical value of DF^*. If $DF^*\le DF$, then at the significance level of α, there is no basis for rejecting the working hypothesis H_0, the time series is integrated to a degree greater than one ($\varepsilon_t\sim I(l), l\ge 1$).

If $DF< DF^*$, we reject the working hypothesis H_0 in favor of the alternative hypothesis H_1 at the level of significance, so the time series $\{\varepsilon_t\}_{1\le t\le N}$ satisfies the stationarity condition (the elements of the series are integrated to degree zero, i.e. (($\varepsilon_t\sim I(0)$).

Note If the series is non-stationary (contains a stochastic trend), we determine the degree of integration by successive differentiation and stationarity checks using the ADF test. The degree of integration is the smallest integer $d\in\boldsymbol{N}$ for which the property of stationarity of the series $\{\Delta^d\varepsilon_t\}_{t\ge 1}$ is satisfied [2].

Algorithm

The figure below shows a graphic description of the operation of the algorithm for inference, detection and early warning of the appearance of a trend or stochastic trend in a time series. Detection of non-randomness in the form of a trend or integration in the series on any channel means the possibility of the appearance of an insertion in the field of view [5].

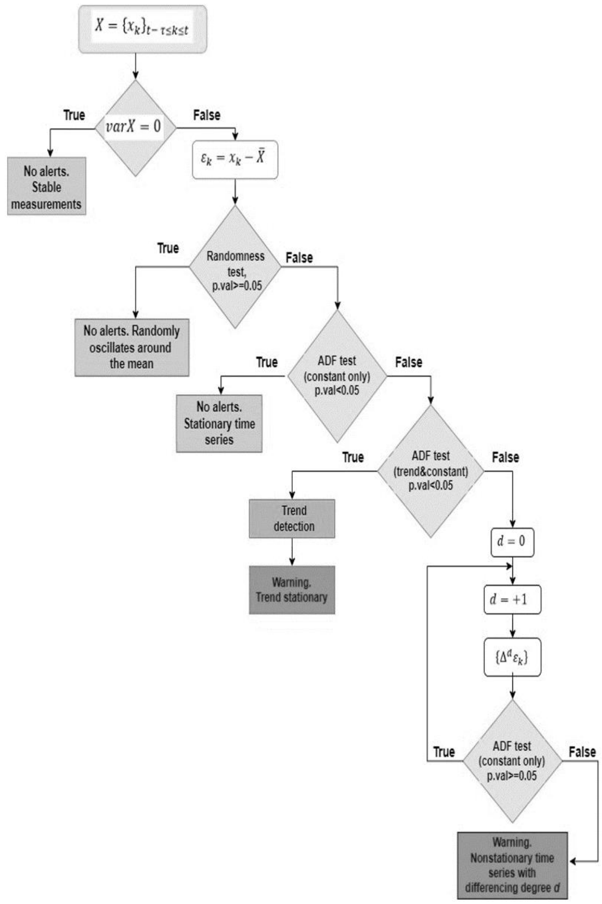

Fig.2. Inference and detection algorithm

Early warning and optimization

Many methods are used to solve optimization tasks and inverse problems [6-15]. Early warning and optimization are based on measurement data. The algorithms discussed above allow analysis of Ultrasound tomography signals in the context of signal trend changes [16]. The analysis is performed in the time domain for each measurement channel. Figures 3-7 show examples for which a change in trend was detected. Figure 3 shows a case for which the signal trend does not change abruptly. Figures 4-7 showcases for which the trend change is significant. However, the analytical system needs to provide zero-one information (alert or no alert). Early detection of trend changes will allow early warning and optimization in the form of:

- Detection of erroneous measurements - an erroneous measurement can occur if the probe is dirty or if it becomes detached from the test object.

- Detection of rapid measurement deviations - These can result due to rapid changes inside the object under test

- Correctness of the course of the studied process - If a change in the trend is expected, the magnitude of the trend change is analyzed. If the change is too large, a correction of the process parameters may occur and consequently, its optimization aimed at replicating the model process.

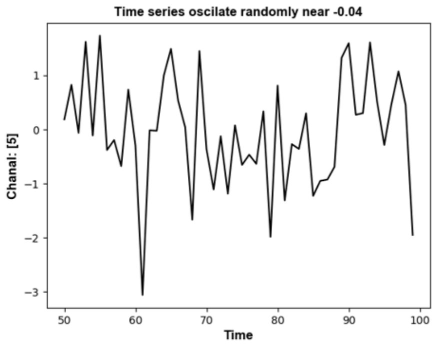

Fig.3. Signal analysis

The analyses above are performed directly on the measurement data, thus ensuring speed. If the analyses were performed on tomographic images or processed or averaged data, early warning and optimization would involve some delay due to the time required for adequate raw data processing.

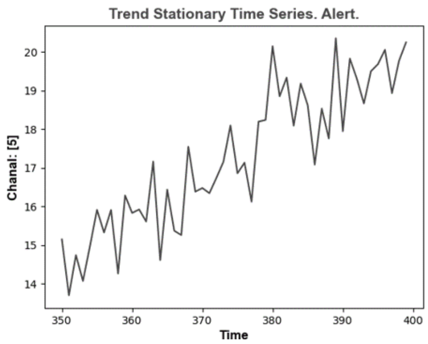

Fig.4. Signal analysis

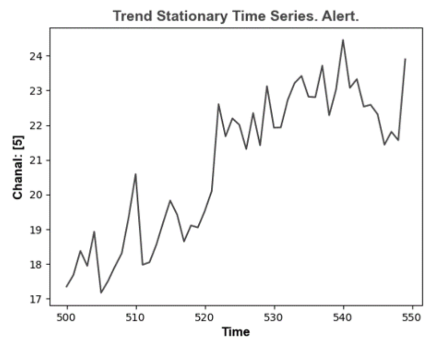

Fig.5. Signal analysis

The developed code, operation schemes, and model will become part of an analytical system, allowing for the overall analysis and optimization of industrial processes studied by ultrasonic tomography.

From the point of view of signal analysis, it is also important that the analyzed signal can be considered regardless of the excitation frequency of piezoelectric transducers. It is particularly important in the context of multimodality of the tomograph.

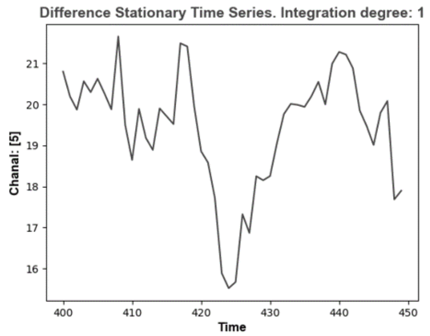

Fig.6. Signal analysis

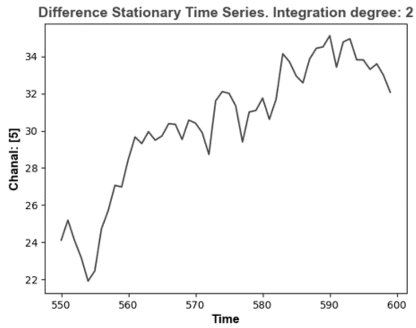

Fig.7. Signal analysis

Summary

This article presents the concept of creating an analytical model that allows early warning to detect erroneous measurements. An algorithm for dynamic analysis and detection of non-randomness at any time is presented. Early warning and optimization are based on measurement data. The algorithms discussed above allow for analysing ultrasound tomography signals in the context of signal trend changes.

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