

LIKELIHOOD RATIO TRACK-BEFORE-DETECT ALGORITHM FOR MACHINE STATE ESTIMATION USING CLASSIFICATION METHODS BASED ON LOW SNR VIBROACOUSTIC ANALYSIS

АЛГОРИТМ LIKELIHOOD RATIO TRACK-BEFORE-DETECT ДЛЯ ОЦЕНКИ СОСТОЯНИЯ МАШИН С ИСПОЛЬЗОВАНИЕМ МЕТОДОВ КЛАССИФИКАЦИИ ОСНОВАННОЙ НА ВИБРОАКУСТИЧЕСКОМ АНАЛИЗЕ С НИЗКИМ SNR

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Abstract: In this paper some applications of using Track-Before-Detect (TBD) estimation method for impulse position and period estimation for low signal-to-noise ratio (SNR) signals are presented. Processing low SNR data is important in vibroacoustics but classical signal processing methods fail in the case of low signal-to-noise ratio measurements. However, such signal parameters can be determined using multiple signal frames. As the TBD algorithm used for that purpose the Likelihood-Ratio Tracker is utilised in this paper. Estimated parameters of the signal can be further used for machine state estimation using classification techniques.

KEYWORDS: TRACK-BEFORE-DETECT, VIBROACOUSTICS, FAULT DETECTION,

1. Introduction

Vibroacoustics is a very important method for estimation of parameters of mechanical devices. Its most powerful advantages are: non-intrusive measurement and the fact that estimation can be performed on machines during their normal work without stopping them [4]. Additionally, multiple parameters can be obtained if proper estimation technique and state knowledge is available. Besides, due to progress in vibroacoustic analysis, existing systems can be updated using better algorithms without replacement of the measurement part without additional costs.

Vibroacoustics based systems are typically machine diagnostic ones. It is possible also to control machines using estimated parameters obtained by such systems but these applications are not considered in this paper. Typical vibroacoustic system is divided into a few parts:

- machine
- sensors (measurement subsystem)
- signal processing subsystem
- estimation subsystem
- classification subsystem

Depending on the choice of algorithms some subsystems can be also combined into single subsystem. For example signal processing, responsible usually for early data processing, can be used as an estimation algorithm depending on the type of measurement data. Typically signal processing subsystem is used for data preparation and changing the measurement domain to another. Two domains are typically used in such applications: time and frequency. Some advances of signal processing extended these classical domains – a very popular trend is for example using wavelets (combined time-frequency analysis). As the estimation and classification algorithms various methods can be used. For example if process and measurement models are known at some level it is possible to use e.g. Kalman filter for parameter estimation regardless of the fact that they might not be available directly from measurements even after applying signal processing algorithms.

There are also some significant advances in classification methods. A lot of them are available for such purposes: heuristic, statistical, neural networks, fuzzy logic based. Contemporarily available systems use digital processing in signal processing as well as in estimation and classification subsystems. Only in the measurement subsystem analogue processing is still required due to analog-to-digital conversion. In some very specific cases (e.g. optical rotation sensors) analogue processing is seriously reduced.

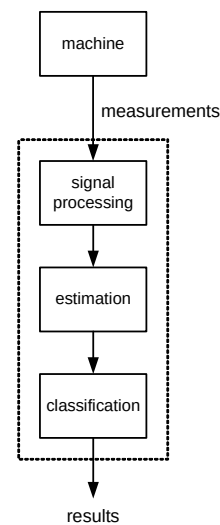


Fig. 1. Example model of vibroacoustic system

2. Impulse parameters

The simplest approach in conceptual sense is time domain estimation. Considering longer time measurements and assuming that object generates impulses periodically it also consists some frequency domain parameters. Some machines can generate acoustic periodic impulses due to they mechanical behaviour. Estimation of the distance (in time domain) between them can give information about machine state (e.g. rotation of some parts). It is also possible to use frequency domain after data processing by DFT (Discrete Fourier Transform) or computationally more efficient FFT (Fast Fourier Transform). However, in further part of this paper only the time domain will be considered.

There are a lot of parameters which can be measured separately for single impulse e.g.:

- height of the impulse,
- width of the impulse,
- impulse shape (more general then height and width),
- area under impulse (integral),

If the occurrences of impulses are expected in some regular positions it is possible to achieve frequency domain parameters directly.

Typically signal is observed in a long period of time and the distance between impulses can be quite easily measured.

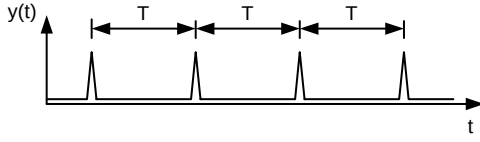


Fig. 2. Period/frequency measurement

If the expected frequency is known, using various windowing techniques that divide the time of observation into regular parts (frames) each consisting N signal samples, it is possible to describe the signal in more convenient space.

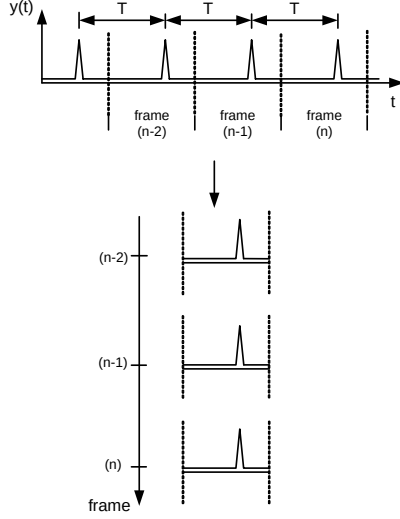


Fig. 3. Idea of using windowing for division the signal into frames with the period equal to the signal's period

In the ideal case frame period can be equal to impulse period (T). Observing the position of the impulses in the following frames it can be noticed that positions of impulses are exactly the same (Fig.3). It means that the signal's frequency is exactly equal to the inverse of the frame's period.

If some changes of the frequency occur, the impulse moves in the following frames (Fig.4). This situation occurs also if signal (impulse) phase changes because it is directly related to changes of frequency. Measuring velocity of the impulse it is possible to determine frequency/phase changes and achieved impulse's 1-D (one-dimensional) trajectory can be used in estimation and classification subsystems as valuable data.

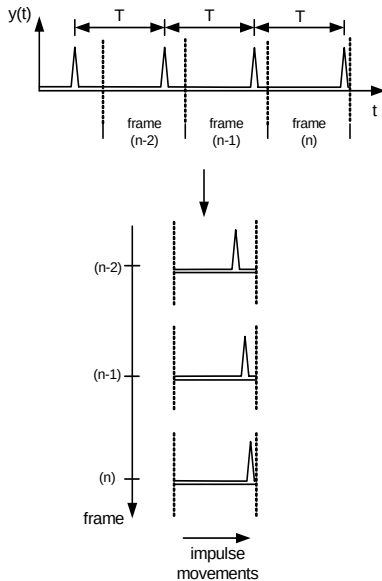


Fig. 4. Illustration of changes of the frequency for signal divided into frames

3. Classical impulse detection algorithms

If such impulse movements occur long enough, the impulse moving from left to right achieves the right frame boundary and then is available on the opposite left boundary. It means that timeline for each frame is not really bounded and can be treated as circular one.

There are many algorithms for impulse detection, usually based on fixed or adaptive thresholding techniques. Choosing the appropriate threshold value signal can be binarized:

$$b(t) = \begin{cases} 1 & \text{if } y(t) > T_v \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where: T_v – threshold value, $y(t)$ – measurements, $b(t)$ – binary output

Binary output value '1' is obtained for the impulse, and '0' value for the samples not related to the impulse.

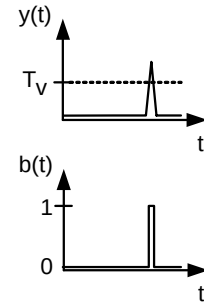


Fig. 5. Thresholding technique

The most important problem in thresholding is the noise level because if height of the impulse is not enough in comparison to the noise values it is hard to find it. In some cases impulses are comparable to noise level and choosing the appropriate threshold value for separating noise and impulse samples can be impossible.

If the SNR is high, impulses can be easily detected and there is quite wide range of acceptable threshold values (Fig.6).

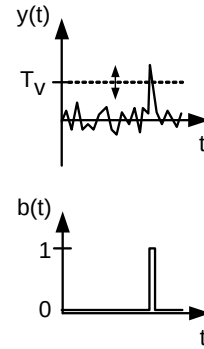


Fig. 6. Thresholding technique in the presence of noise (high SNR)

Sometimes signal-to-noise ratio is very low or negative (signal level is below the noise floor). Detection of such impulses using classical algorithms is impossible (Fig.7).

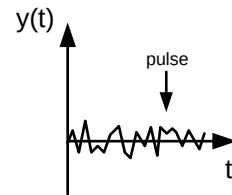


Fig. 7. Signal missing in noise

4. Track-Before-Detect (TBD) approach

The example presented in previous section shows the signal which is lost for classical algorithms but can be detected using modern Track-Before-Detect approach. Using the measurement model of impulse shape model considering also its movements (due to phase/frequency changes) it is possible to estimate the impulse parameters (such as position and velocity considered in this paper). There is only one requirement – more than one frame should be available or multiple sensors ought to be used. Further the single sensor and multiple frames case will be considered using one of the most powerful recurrent algorithms – Likelihood Ratio Tracker [1].

Presented algorithm belongs to the class of Bayesian algorithms which are successfully used for tracking 'stealth' signals (such as radar impulses from stealth airplanes). There are also some other TBD algorithms worth noticing, much faster and currently very popular particle filters (suboptimal) [2, 3]. Analysed algorithm can be used in vibroacoustic applications also for detection and tracking impulses.

It is assumed that the signal's impulse exists in each frame. For the case of possible switching process (sometimes impulse is available and in some frames not), formula should be extended [1].

Original Likelihood Ratio Tracker described in the book [1] is very flexible and can be used for any state space. For the case analysed in this paper the state space is two-dimensional (first dimension is the position corresponding to time and the second one is the velocity) and the time domain for tracking impulses movements is circular. If there are N samples then the following relation occurs:

$$y[t(N)] = y[t(0)] \quad (2)$$

or in more simpler form

$$y(N) = y(0) \quad (3)$$

and there are possible movement (state transition) using Markov matrix.

The algorithm considered in the paper can be presented as the following pseudo-code:

Begin

// Initial Likelihood Ratio:

$$\Lambda(t_0, s) = \frac{p(t_0, s)}{p(t_0, \phi)} \quad \text{for } s \in S \quad (4)$$

For $k \geq 1$ and $s \in S$

// Motion Update

$$\Lambda^-(t_k, s) = q_k(s | \phi) + \int_S q_k(s | s_{k-1}) \Lambda(t_{k-1}, s_{k-1}) ds_{k-1} \quad (5)$$

// Information Update

$$\Lambda(t_k, s) = \mathcal{L}_k(y_k | s) \Lambda^-(t_k, s) \quad (6)$$

EndFor

End

where: Λ - log likelihood ratio (log-LLR)

Λ^- - motion update matrix

$p(t_0, s)$ - initial distribution on target state if tracked target is present

$p(t_0, \phi)$ - initial distribution on target state if tracked target doesn't exist

S - discrete state space (positions and velocities)

t_k - discrete moments of time

y - input data (observation)

$\mathcal{L}_k$ - measurement likelihood ratio for the observation

q_k - Markov matrix (motion model)

Due to computation and analytic simplicity the direct Likelihood Ratio is less useful than Log-Likelihood Ratio (LLR).

4.1. Example 1

It is assumed that signal $u=2$ with additive zero-mean Gaussian noise with the identity standard deviation are measured. There are five possible impulse velocities considered: -2, -1, 0, +1 and +2. Analysed signal is always in the same position (velocity is equal to zero). It can be calculated that Log Measurement Likelihood function has the following form:

$$\mathcal{L}_k(y_k | s) = \frac{u}{2} \cdot y(i-1) + u \cdot y(i) + \frac{u}{2} \cdot y(i+1) - \frac{3}{4} \cdot u^2 \quad (7)$$

If impulse splits over adjacent samples:

$$\begin{cases} \frac{u}{2} & \text{for } (i-1) \\ u & \text{for } (i) \\ \frac{u}{2} & \text{for } (i+1) \end{cases} \quad (8)$$

where u - signal's strength

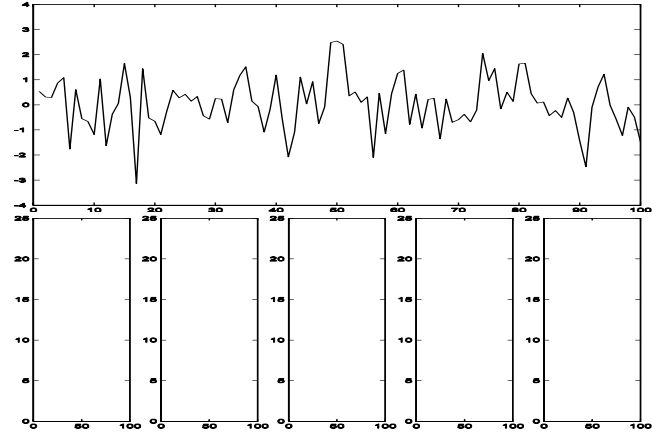


Fig. 8. Measured signal and LLR at time 1

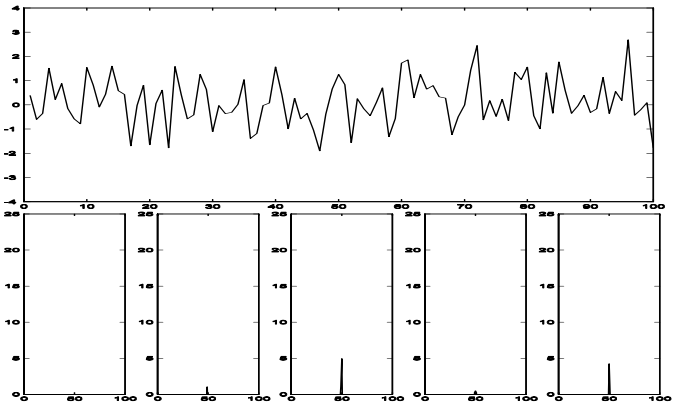


Fig. 9. Measured signal and LLR at time 4

Because of the assumption that single impulse signal is tracked and just the position and velocity are estimated, only the time moments for maximum value of LLR are important for all state spaces. For better visualisation all five velocity subspaces are drawn in Figures 8–13 instead of typically used 3D visualizations (top images show the signal while the bottom ones – LLR values in positions 0 – 100 for the velocities equal to -2 , -1 , 0 , $+1$ and $+2$ in five subplots).

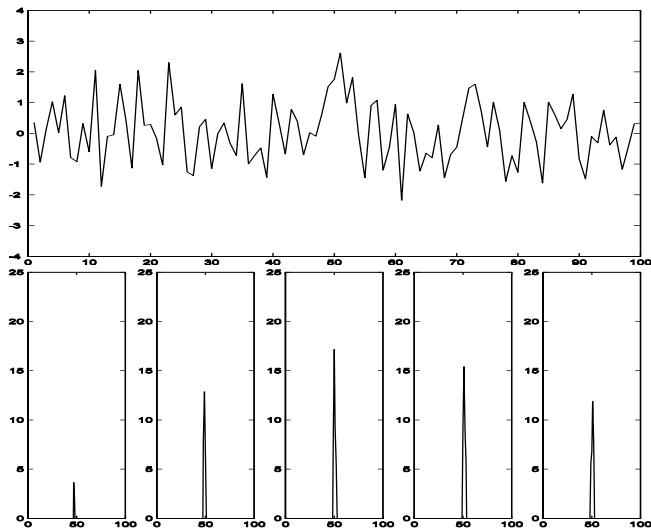


Fig. 10. Measured signal and LLR at time 7

Presented example shows that signal missing in noise can be detected using TBD methods as shown in figures. The highest peak which can be observed in the bottom image (Fig.10) corresponds to the most likely position and the state of the signal missing in noise which does not move (velocity equal to 0 and position equal to 50).

4.2. Example 2

This example is similar to the previous one with one modification – signal moves with velocity equal to $+2$ that reaches boundary and then appears on the other side because of the cylindrical state space.

As shown in Figures illustrating this example the highest likelihood values can be observed for the velocities equal to $+2$ with changing the most likely position.

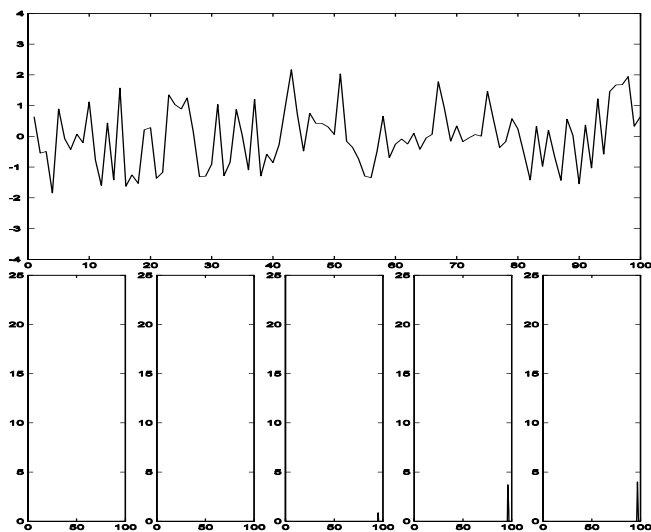


Fig. 11. Measured signal and LLR at time 4

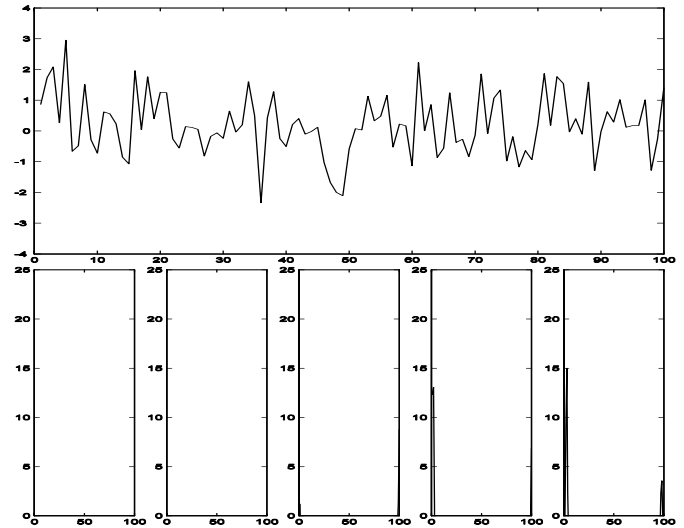


Fig.12. Measured signal and LLR at time 7

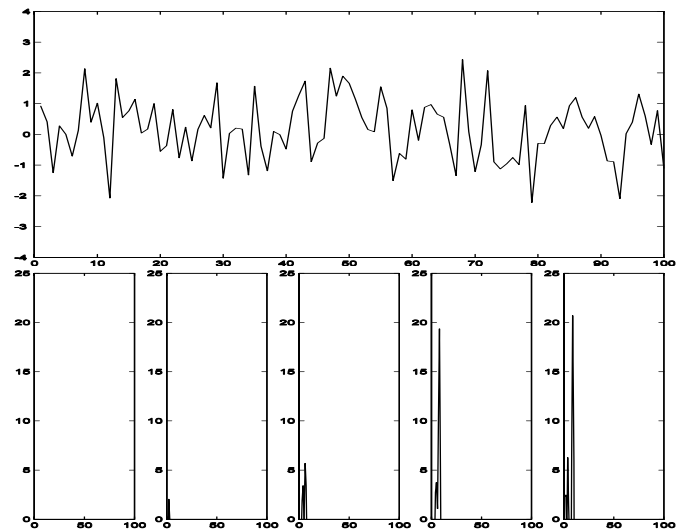


Fig.13. Measured signal and LLR at time 10

5. Conclusions

In the paper a tracking system for machine state estimation is presented. Presented method is rather slow – many computations are required in comparison to thresholding techniques but its main advantage is the ability to handle signals with low SNR.

Described approach is very useful because in some situations significant information related to the state of machine cannot be obtained from low SNR data using classical approach. Algorithms similar to the presented one can be also implemented in real-time applications due to constant progress in Digital Signal Processors performance.

6. Bibliography

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