

Przemysław MAZUREK

WEST-POMERANIAN UNIVERSITY OF TECHNOLOGY IN SZCZECIN, DEPARTMENT OF SIGNAL PROCESSING AND MULTIMEDIA ENGINEERING,
26. Kwietnia Str., 71-126 Szczecin

Track-Before-Detect Algorithm for Noise Objects

Ph.D. Przemysław MAZUREK

Assistant professor in the Department of Signal Processing and Multimedia Engineering at the Faculty of Electrical Engineering, West-Pomeranian University of Technology in Szczecin. Author of more than 80 papers related to the digital signal processing, estimation of object kinematics, biosignals acquisition and processing.



e-mail: przemyslaw.mazurek@zut.edu.pl

Abstract

Track-Before-Detect (TBD) systems are used for tracking of the object signal under a high noise conditions. Noise objects are special class of objects with a zero mean value so they can not be processed directly. Possibilities of object detection and tracking for modified tracking system by numerical examples (Monte Carlo approach) are proposed and tested in this paper. The moving window is used for selection of samples for the standard deviation calculation.

Keywords: tracking, estimation, signal processing, image processing, Track-Before-Detect.

Algorytmy śledzenia przed detekcją dla obiektów szumowych

Streszczenie

Systemy śledzenia przed detekcją wykorzystują podejście akumulacyjne do estymacji trajektorii obiektów w warunkach małego SNR, także dla $\text{SNR} < 1$. W artykule zaproponowano system śledzenia przed detekcją z wykorzystaniem algorytmu rekurencyjnego Spatio-Temporal TBD dla obiektów szumowych zakłóconych dodatkowym szumem. W przypadku gdy poziom szumów obiektu jest zbliżony a nawet mniejszy niż szum tła detekcja obiektu i wyznaczenie trajektorii nie jest możliwa za pomocą innych metod niż śledzenie przed detekcją. System bazuje na analizie zmian odchylenia standardowego dla szumów gaussowskich poprzez wykorzystanie ruchomego okna analizy dla sygnału wejściowego. Bez zastosowania przekształcenia sygnału do przestrzeni odchylen standardowych detekcja nie jest możliwa, ponieważ konwencjonalne rozwiązywanie śledzenia przed detekcją uśrednia sygnał, który dla obiektu szumowego ma wartość średnią równą zero. W analizie numerycznej wykorzystano podejście Monte Carlo do oszacowania własności algorytmu dla różnych wartości współczynnika wygładzania, rozmiaru okna oraz stosunku szumów obiektu do szumu tła. Jako miarę jakości wykorzystano odległość między znanym położeniem środka obiektu z generatora a położeniem największej wartości estymowanej przez algorytm śledzenia a położeniem największej wartości estymowanej przez algorytm śledzenia przed detekcją. Jakość estymacji rośnie ze wzrostem rozmiaru obiektu oraz wartością współczynnika wygładzania. Algorytm charakteryzuje się dużym stopniem możliwości zrównoleglenia przetwarzania.

Słowa kluczowe: śledzenie, estymacja, przetwarzanie sygnałów, przetwarzanie obrazów, śledzenie przed detekcją.

1. Introduction

Tracking systems are used for numerous applications. Typical tracking system separates the signal target from the background and processes positions of the target for the track creation. Background could be of any type and background estimation techniques are used for maximization of distance between the target and surrounding and overlapped background in a measurement space. Subtraction techniques for static or slowly evolving background could be used typically. Typical measurements are also disturbed by a noise, and the Gaussian noise is typical one. There are two main noise sources:

measurement noise (related to the acquisition system) and background/object noise. Object signal usually has a higher value than the background, and accumulative approach could be used for detection and tracking.

Track-Before-Detect (TBD) systems could be used for such case [1-3] and the detection is not direct but based on the accumulation of the signal values over possible trajectories. Calculations of TBD algorithm are very demanding but today available devices like the FPGA chips (Field Programmable Gate Arrays), VLSI custom chips, GPGPU chips (General Purpose Graphics Processing Units), SIMD multicore processors (Single Instruction Multiple Data), and computer clusters give abilities of real-time processing. Detection of the object is possible after testing of all trajectories even if none object is in the sensor range. Data fusion from multiple sensors of different types is supported by the TBD system what is very important for real applications [1].

Accumulative approach is based on calculation of the sum or mean from multiple measurements, so noises are reduced in the relation to the signal of the object. TBD techniques extend possibilities of this well known denoising technique by e.g. incorporation of the motion models and sensor characteristics [1, 3].

Incorporation of the motion model to the tracking system based on a priori knowledge gives abilities of accumulation over a set of possible trajectories [1]. Trajectories could be defined using transitions between previous state and a new one, so storage of a few previous measurements is not necessary. Alternatively a single trajectory could be defined as a set of a few positions (a small track). The first solution is used in the recurrent implementations (similar to IIR filters) [3-5] and the second is used in non-recurrent implementations (similar to FIR filters). Both techniques have denoising abilities.



Fig. 1. Model of Track-Before-Detect system
Rys. 1. Model systemu śledzenia przed detekcją

Positive signal values over the background signal level (a typically zero valued by previous background suppression) are supported by the accumulative approach. Such technique could be applied directly to the e.g. Spatio-Temporal (or Spatial-Temporal) TBD algorithm.

2. Spatio-Temporal TBD algorithm

This algorithm has very efficient software and hardware implementations what is very important for real applications and the recurrent form is the most well known. A following pseudocode shows structure and processing:

Start

// initialization:

$$P(k=0, s) = 0 \quad (1a)$$

For $k \geq 1$

//motion update:

$$P^-(k, s) = \int_s q_k(s | s_{k-1}) P(k-1, s_{k-1}) ds_{k-1} \quad (1b)$$

//information update:

$$P(k, s) = \alpha P^-(k, s) + (1 - \alpha) X(k, s) \quad (1c)$$

EndFor
Stop

where:

- k – iteration number,
- s – particular space,
- X – input data,
- P^- – predicted TBD output,
- P – TBD output,
- α – weight (smoothing coefficient),
- $q_k(s | s_{k-1})$ – Markov's matrix.

This algorithm could be processed in a real-time [4, 5] and there are two possible outputs: the first is from the motion update (prediction) and the second is from the information update formulas. Dynamic of the output signal depends on the smoothing coefficient and is high for low values and is low for high values. The last variant is especially important for TBD systems because response is smoothed and denoised. Typical smoothing coefficients are little less than 1.0 for best results.

Markov's matrix is responsible for switching between trajectories because it is very rare case of object motion ideally fitted to the assumed one. Knowledge about object possible motion could be incorporated into the measurement space and this matrix.

Measurements could be processed directly by information update formula or converted into more adequate space for better results. Selection of the measurement space is very important and is necessary for the considered case in this paper.

3. Measurement space for noise object

Assumed case is related to the object signal that is a zero mean Gaussian noise with some constant but unknown variance. This signal is disturbed by another a zero mean Gaussian noise with another constant and unknown variance. In Fig. 2 are shown example signals and in Fig. 3 is shown schematic of TBD system.

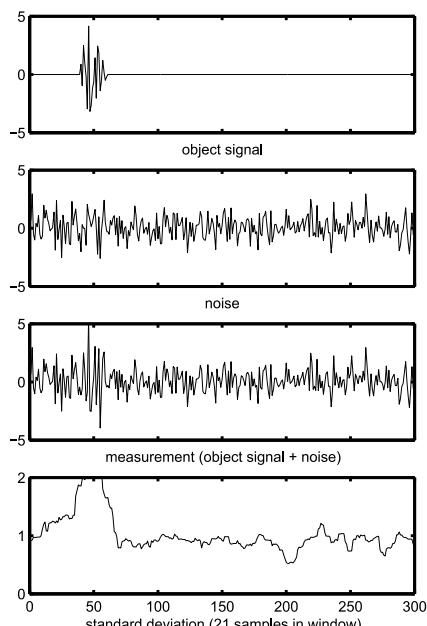


Fig. 2. Example signal and standard deviation detection results
Rys. 2. Przykładowy sygnał i wyniki detekcji za pomocą odchylenia standardowego

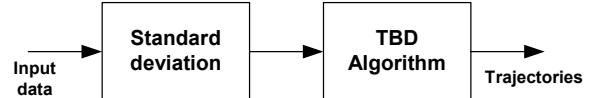


Fig. 3. Diagram of TBD system for noise object tracking
Rys. 3. Schemat systemu śledzenia przed detekcją dla obiektu szumowego

Both signal are additive and resulting standard deviation is higher in the place where the object is located. Depending on the moving window size a fluctuations of standard deviation could be large (if window size is small) or small (for large window size).

Calculating of standard deviation using moving window is a kind of signal filtering. Obtained results could be processed by TBD algorithm. Spatio-Temporal TBD process data independently on the input signal range. Target signal give higher values in comparison to the background noise so maximal value of the TBD output could be used as an estimated state (the position and the object velocity). There are no special requirements about the input signal range.

Accumulative approach (exactly the exponential filtering part of TBD) is assumed and the output value after some iteration steps will be about 1.0. Fluctuations will be smoothed due to this filter and multiple measurements (this is temporal smoothing). Additional smoothing (spatial) occurs if the Markov's matrix has transitions between neighborhood trajectories. This last effect is well known. Recurrent TBD algorithm process measurements by two separate processes: the first is sharpening (information update formula – 1c) and the second is blurring (motion update formula - 1b). Balance between them is defined by the smoothing coefficient that for TBD system should be high, and the blurring effect is the most significant part of the output signal.

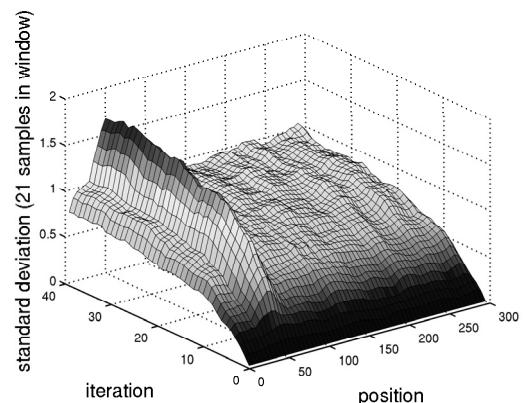


Fig. 4. Evolution of standard deviation for non-moving object (TBD output)
Rys. 4. Ewolucja odchylenia standardowego dla obiektu nieruchomego (wyjście TBD)

In Fig. 4 evolution of standard deviation is shown as an example for the non-moving object (located at the position 50). The size of the object is equal to the 21 samples with the standard deviation equal to the 1.5 for the Gaussian noise. Measurement noise is also Gaussian with standard deviation 1.0. Window size is equal to the 21 so it is assumed knowledge about object size.

TBD algorithm processes measurements from the start (a beginning value of the state space is 0) so it is observed non-steady state, with exponential profile. After some iterations the standard deviation values achieves expected 1.0 level.

4. Tracking performance

Estimation of TBD algorithms performance is possible by Monte Carlo tests. There are 1000 test with random standard deviation of noise for comparison of performance for different values of smoothing coefficients and object lengths. There are 100 iterations steps for every test and object is not initialized so final

value is obtained only by the TBD calculation. Maximal value is used for estimation of position and velocity after step no.100. This is very simple detection algorithm but it shows a quite good performance. The detected and the known from model positions are compared and distance error is calculated.

In Fig. 5-8 are shown results for four object sizes. The detection possibility is better for largest objects as it is expected. The position of curve slopes moves toward to zero value if larger object size is assumed. Low mean position errors are obtained for larger smoothing coefficients. Two smoothing coefficients are used (0.95 and 0.98) and difference between both is about 0.5 of standard deviation ratio (standard deviation of object compared to the standard deviation of measurement noise).

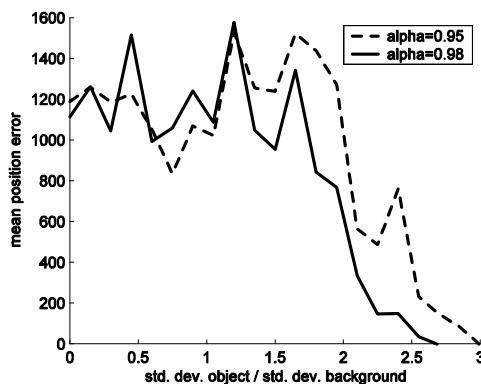


Fig. 5. Detection performance of TBD for windows and object size 5
Rys. 5. Możliwość detekcji przez TBD dla rozmiaru okna i obiektu równego 5

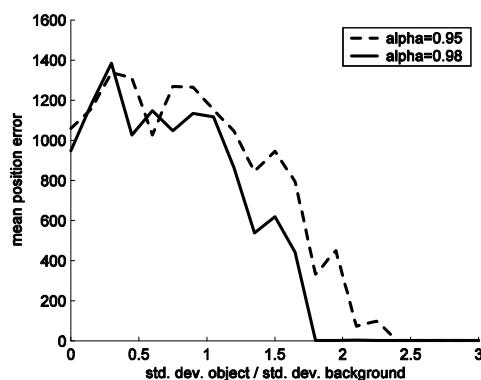


Fig. 6. Detection performance of TBD for windows and object size 10
Rys. 6. Możliwość detekcji przez TBD dla rozmiaru okna i obiektu równego 10

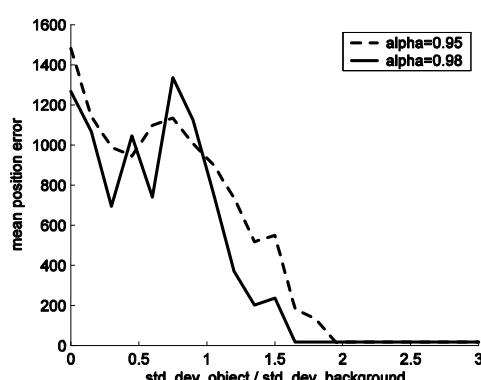


Fig. 7. Detection performance of TBD for windows and object size 20
Rys. 7. Możliwość detekcji przez TBD dla rozmiaru okna i obiektu równego 20

Significant mean position errors depend on detection algorithm and length of the measurement space. Extending the measurement space is responsible for increasing of the mean error level, but the most important is slope position that is visible in figures. Improved detection algorithm that is based on multiple measurements (e.g. using an additional tracking filter) could be used for performance improvement. Such technique will reduce area of testing and error will be lower.

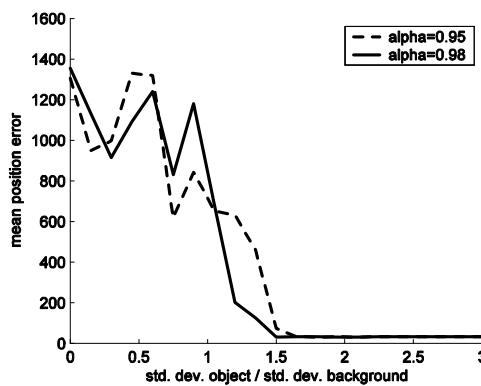


Fig. 8. Detection performance of TBD for windows and object size 30
Rys. 8. Możliwość detekcji przez TBD dla rozmiaru okna i obiektu równego 30

5. Conclusions

Direct processing of the noise objects is not possible by TBD algorithms but modification of measurement space using preprocessing data by moving window of standard deviations support them. Signal processing without proposed solution is not possible [1].

Proposed techniques are compared by Monte Carlo test for different parameters. Large window sizes and large smoothing coefficients improve the tracking and the detection. Standard deviations of the object and background noise could be comparable (Fig. 8) and algorithm supports the detection.

Knowledge about possible motion could be incorporated into the Markov's matrix. The FIR based variant of Spatio-Temporal TBD algorithm could be used for more complex trajectories.

The work was supported by finances of West Pomeranian Provincial Administration.

This work is supported by the MNiSW grant N514 004 32/0434 (Poland).

This work is supported by the UE EFRR ZPORR project Z.2.32/I/1.3.1/267/05 "Szczecin University of Technology - Research and Education Center of Modern Multimedia Technologies" (Poland).

6. References

- [1] Blackman S., Poupoli R.: Modern Tracking Systems. Artech House, 1999.
- [2] Bar-Shalom Y.: Multitarget-Multisensor Tracking: Applications and Advances. Vol II, 1998.
- [3] Stone L. D., Barlow C. A., Corwin T. L.: Bayesian Multiple Target Tracking. Artech House, 1999.
- [4] Mazurek P.: Implementation of Spatio-Temporal Track-Before-Detect Algorithm using GPU. Pomiary Automatyka Kontrola, vol. 55 nr 8, 657-659, 2009.
- [5] Mazurek P.: Optimization of Bayesian Track-Before-Detect Algorithms for GPGPUs Implementations. Electrical Review R.86 7/2010, 187-189, 2010.