Analysis of noise suppression techniques for Track-Before-Detect algorithms using spatial noise estimators

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In the paper the noise suppression algorithms for Track-Before-Detect (TBD) systems are evaluated. Three estimators are considered: the global, local, and single local. The estimator based on the impulse counting for large number of pixels is proposed. Estimation of the noise parameters gives abilities of suppression of the salt-and-paper or high-valued impulse noise.

1. Introduction

Tracking of dim objects needs specially designed systems. Conventional tracking systems are based on the detection and tracking scheme. The detection algorithm is based on the threshold algorithm. Detection is not possible if the signal is below noise floor because multiple false detections are possible. Another problem is that threshold level should be set at appropriate level. The adaptive threshold techniques do not supports low SNR objects also.

Alternative approach, based on Track-Before-Detect (TBD) scheme, is the only-one solution for tracking of such objects. TBD algorithms test all possible trajectories and accumulate signal values over every trajectory (it is the tracking phase). Accumulated values are tested using the threshold value and the detection occur if the accumulated signal strength is higher then the threshold level (it is the detection phase). TBD systems are computationally demanding because all trajectories are tested even if no-one object is in the range. Multiple objects tracking ability is the advantage of the TBD algorithms.

Fig. 1 Track-Before-Detect processing scheme

Tracking abilities of TBD algorithm are obtained by the application of the accumulative approach [1]. The multiple measurements technique is simplest choice for the noise suppression. TBD algorithms support the time-based and the spatial-based signal accumulations (integration). The time-based accumulation technique is important for single measurement sensor. The spatial-based accumulation technique is used for multiple sensor systems. Both of them are combined together for the best results if it is possible.

Typical TBD algorithm [1,2] uses advanced integration of signal instead the simple accumulation. Some systems accumulate only over assumed trajectories and the computation cost is very high. Reduction of the computation cost is possible by the support of the trajectories switching using the Markov matrix. The motion model supported by this matrix allows reusability of the obtained values from previous basis trajectory.

2. Recurrent spatio-temporal Track-Before-Detect algorithm

There are two variants of this algorithm. Non-recurrent version is based on the implementation of the multiple FIR filters. The more important is the recurrent version based on spatio-temporal IIR filters. Following pseudocode shows this algorithm.

Start

$$P(k=0,s)=0 \quad \text{// initialization} \tag{1a}$$

For $k \geq 1$

$$P^{-}(k,s)=\int_{S} q_k(s \mid s_{k-1}) P(k-1,s_{k-1}) ds_{k-1} \quad \text{// motion update} \tag{1b}$$

$$P(k,s)=\alpha P^{-}(k,s)+(1-\alpha)X(k,s) \quad \text{// information update} \tag{1c}$$

EndFor

Stop

k – iteration number,
s – particular space,
X – input data,
P^{-} – predicted TBD output,
P – TBD output,
α – weight (smoothing coefficient), range: 0-1.

Detection abilities of this algorithm depend on many parameters, especially on the smoothing coefficient and the Markov matrix (q). High value of the smoothing coefficient reduces noise influence, but it can be applied for the object with a slow transition between trajectories only. Low value of the smoothing coefficient improves system response for without fast transition between trajectories or higher SNR scenarios.

3. Noise in TBD systems

Noise in TBD systems could be different types and the Gaussian noise is considered mostly. Impulse noise is very important for real systems also. There are a few sources of impulse noise: electromagnetic interferences, high energy particles, and other. Such noise peaks should be suppressed. Noise related to the objects is another possibility, especially if the objects make maneuvers (change trajectory), the signal value may change rapidly. The good example is the signal reflected or emitted by the airplane. Radar and vision sensors may measure large peaks due to physical orientation of the plane surfaces in relation to the e.g. radar source (for radar wavelengths) or Sun (for vision wavelength sensors). Satellites also create complex light signal sources.

Such high peak related to the object should be carefully considered. The large peak improves SNR for TBD systems, but disturbs a possibility of the trajectory change. A previous trajectory is preserved over a next scans due to value, and the current position is not observable and is hidden in impulse response of TBD related to this peak.

Suppression of impulses of both types is important and the robust filtering techniques are necessary. The background signal is useful for adaptive estimation of the noise floor and selection of the threshold level of saturation filters.

4. Robust filtering techniques

Robust filtering techniques give abilities of the impulse noise suppression. Simplest filtering technique is based on the saturation or removal such pulses. Threshold based algorithm is the simplest one algorithm.

Another method is the median filtering of the signal, but temporal filtering is very costly. Computation of the median value needs an implementation of the sorting algorithm. A specific case, based on the recursive computation of the median value by the removal of oldest and by insertion of the new value is possible, but the computation cost due to reorganization of stored data in the table is significant. Temporal median filtering is well fitted to the FIR type TBD algorithms.

Spatial median filters are also important for signal preprocessing and detection of impulses. They have similar computation problems like temporal filters. The implementation of the sliding window median filter is possible but still there are additional sorting costs. Spatial median filters are well fitted into recursive (IIR type) and non-recursive (FIR type) TBD systems. The median filtering is independent on the TBD processing. A new incoming data are filtered before computation using (1c) formula, only. Median filter are robust filter, well fitted into different cases, but the computation cost reduction is also important factor for real-time systems.

Another possibility is the tracking of the values and removal impulses using the predictor (1b) response. The predicted value corresponding to the expected level (reduced little due to smoothing coefficient). The new incoming data for particular trajectory should be inside the expected range.

The gatting algorithm with a fixed gate (clipping values) is very simple and robust. The predictor gives abilities of the adaptive changes of the predicted signal level and especially the upper gate level. More advanced techniques, based on adaptive gatting, are possible using the Kalman filter, but the computation cost of the Kalman filter is much higher in comparison to the fixed gate. Computation of the large number of trajectories is typical for TBD systems. Assuming 1000x1000 measurement grid and 100 motion vectors, there are 100M trajectories. Computation of huge number of Kalman filters is very demanding, using conventional electronics devices. Even a processing of TBD algorithms in real-time is very challenging task and special design is necessary for specific computation platforms.

Detection of the peaks and clipping them using the saturation function is simple and effective. Removal of the peaks from computations is similar, alternative technique. They are discussed in [4-8].

5. Saturation based techniques for impulse noise suppression

Saturation techniques for impulse noise are simple and they have efficient software and hardware implementations [4-8]. The saturation level should be estimated using noise observations. Proposed solutions [7] are specific for TBD systems - available signal has value similar to the background level.

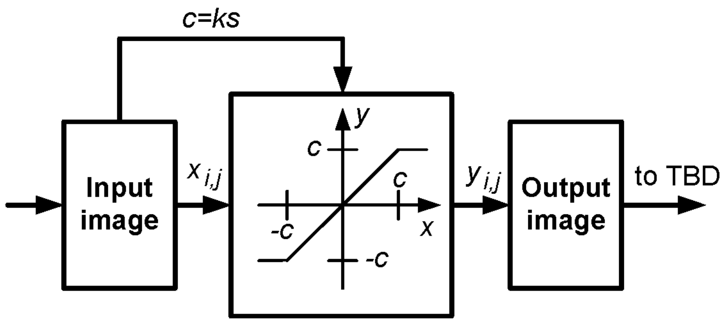

Fig. 2. Saturation function controlled by the scaled standard deviation

The saturation should be value estimated for the case when there are no impulses. This is simple if the single target is observed and the impulses are related to the target. Standard deviation is much higher is there are many impulses not correlated to the target. There are a many possible control strategies of the clipping level c.

The standard deviation should be computed for the case when there are not available disturbing pulses and fixed. The application of the 3σ level saturation allows preserving 99.7% signal values without clipping. The right tail of the distribution and higher then 3σ positive pulses are suppressed to this level. The left tail and negative pulses are clipped to the -3σ level. This clipping level should be extended if the signal values are not weak for improving of tracking. The additional clipping of the values reduce detection ratio due to lower SNR introduced by the clipping to the signal part.

5.1. Global spatial noise estimator for TBD

Global spatial noise estimator is based on the standard deviation calculation. The noise parameters are similar statistically independent on target availability and location. Single measurement is sufficient for estimation of the standard deviation s so all pixels (N) are processed in all image.

$$s_B = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - m_B)^2} \tag{2}$$

The background (DC level) is equal to the zero for most applications so $m_B \approx 0$. This is very often a result of the background suppression algorithms or acquisition technique (pass-band filtering). Simplified formula is obtained due to a zero valued mean:

$$s_B = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i)^2} \tag{3}$$

Saturations are based on the estimated variance. Not all values of the Gaussian noise are inside range, defined by the variance, so additional constant k should be considered for range extension if it is necessary (Fig. 2).

This simple estimator has very important and practical feature. The changes of variance of the Gaussian noise are immediately calculated and applied for the current measurements, because there is no delay that is typical for more advanced algorithms, predictors especially.

The much better is the calculation of histogram, because measured probability distribution has long tails, but is not considered here.

5.2. Local spatial noise estimator for TBD

Calculation of the global variance for all measurements is not necessary. There are two interesting techniques from implementation point-of-view. The first is the local estimation of standard deviation, depending on currently processed pixel (x,y), that limit spatial range to neighborhood area only A. Overall measurements space S is substituted by the region A.

$$s_B(x,y)=\sqrt{\frac{1}{N_A-1}\sum_{x,y\subset A} x_{x,y}{}^2} \tag{4}$$

This technique should be carefully implemented, because multiple calculations of the standard deviation using direct implementations repeat most temporal results. Implementation techniques, similar to decomposition of the 2D FIR filter to the vertical and horizontal filters, should be applied. Such local method is well suited if the standard deviation depends on the position.

5.3. Single local spatial noise estimator for TBD

Simpler technique that assumes fixed standard deviation for overall image (measurement space) is possible. Instead of global or local (position dependent) computations a selected and small area should be used for estimation. There is a small number of targets and the expected targets' signal level is low. Estimation is possible using small a fixed piece of measurement space so this technique is low demanding.

6. Impulse noise statistics

Impulse noise influences the global or local standard deviation. The background estimation algorithms suppress DC signal from the background and preserve impulse level relative to background level. The result of the background suppression algorithm is the zero mean Gaussian noise ($m_B=0$), with preserved standard deviation (s_B) in the ideal case. Nonlinear effects, related to the pixel value representation and non-ideal background suppression, are not considered. Assuming stable strength of the signal, the fixed mean value ($m_O=const$) is observed and the standard deviation of the object's signal is zero ($s_O=0$). Such situation is related to the point size object, where a single pixel or measurement cell is excited. In real situation the excitation may be different and the Gaussian profile of the signal is typical. The signal of the object is additive to the suppressed background also.

The impulse noise, related to the object or false measurements, is a high value peak. This high value is located on the trajectory, if it source is the object. False measurement may exist in any pixel, including trajectory also. The impulse signal is additive also, or may replace low-level value, related to the measurement Gaussian noise.

The estimation of the background related parameters like mean or standard deviation (or variance) of the specific area of the image is disturbed by the object's signal and impulse noise. There is only one signal's related a weak peak for 2D measurements if the object is in measurement area. The mean value of the signal for TBD systems is at noise level values, and signal is hidden in ±3σ range very often, and such weak signal is omitted from the analysis.

The impulse noise needs a special consideration, because this signal influent on the mean and standard deviation value of the selected image area. Variance for specific area is shown by the following formula:

$$s_A^2 = s_B^2 + s_O^2 + s_I^2 = s_B^2 + s_I^2 \, , \tag{5}$$

and the mean by the following formula:

$$m_A = \frac{m_O}{N} + \frac{M}{N} c \, , \tag{6}$$

where N is the number of pixels in the specific area A, and M is the number of pixels excited by the impulse noise. The level of the impulse noise is the c value and need additional description.

Assuming that object's signal is smaller in comparison to the peaks an approximated formula for the mean is obtained:

$$m_A = \frac{M}{N} c \, . \tag{7}$$

The high value peaks are especially important as source of disturbances of TBD algorithms. The high values are simple to clip using saturation function, but the clipping level is not known. The raw settings of the clipping level reduce higher pulses to the c level. Some pulses that are below c level are preserved. It is assumed, that all peaks are higher then c level, and are clipped.

The variance of impulse noise is derived using the following formulas:

$$s_I^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - m_I)^2 \, , \tag{8a}$$

$$m_I = \frac{1}{N} \sum_{i=1}^{N} x_i = \frac{M}{N} c \, . \tag{8b}$$

Values of complete impulse signal x_i are c and zero. After derivation the following formula is obtained:

$$s_I^2 = \frac{M(N-M)}{N(N-1)} c^2 \, . \tag{9}$$

The following formula is related to the variance of the area signal including background and impulse noises:

$$s_A^2 = s_B^2 + \frac{M(N-M)}{N(N-1)} c^2 \, . \tag{10}$$

The following example shows influence for the real case, tested using Monte Carlo approach. The 1000 samples are used for two areas (3x3 and 7x7 pixels) and medium value of the single peak limited to the $c=10$ level (Fig 3 and 4). The empirical values are very close the theoretical values. The most valuable estimator of the mean value without impulse is the median what is well known fact, but the cost of estimation is high due to necessary values sorting algorithm. The variance is higher for smaller area and it is very important for estimation of the current standard deviation for clipping control.

The local estimation of the standard deviation is necessary, especially if the standard deviation is different depending on the area. The global estimation of the standard deviation is not adequate, estimation of the standard deviation using only one arbitrary selected area is not recommended also.

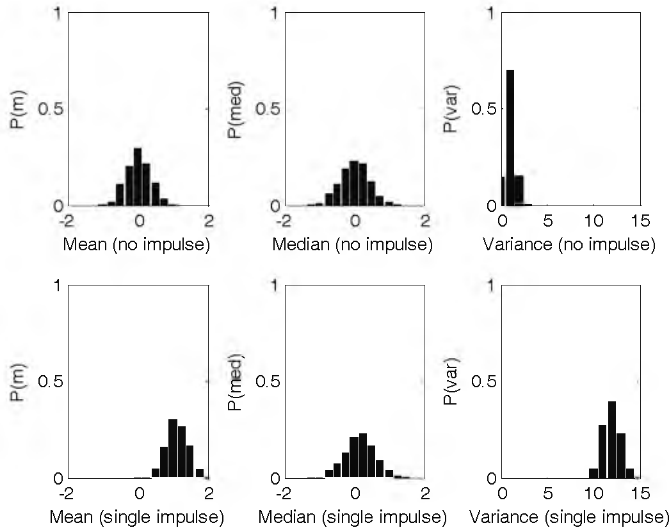

Fig. 3. Histogram for 1000 tests of empirical parameters estimation (3x3 pixels area, impulse noise level 10)

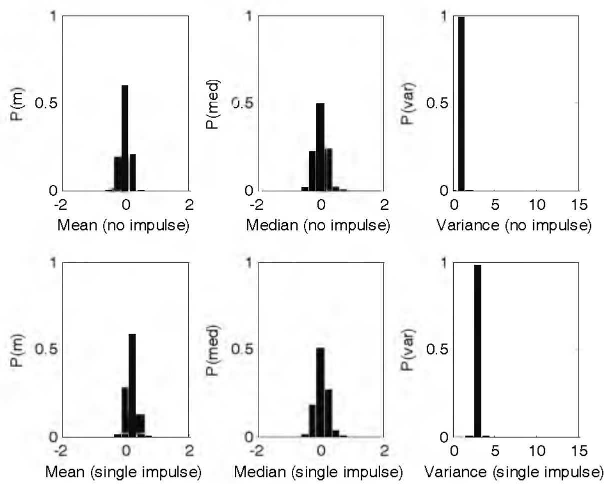

Fig. 4. Histogram for 1000 tests of empirical parameters estimation (7x7 pixels area, impulse noise level 10)

The additional variance for single impulse is depicted in Fig.5. for standard deviation equal to unity of the background Gaussian noise.

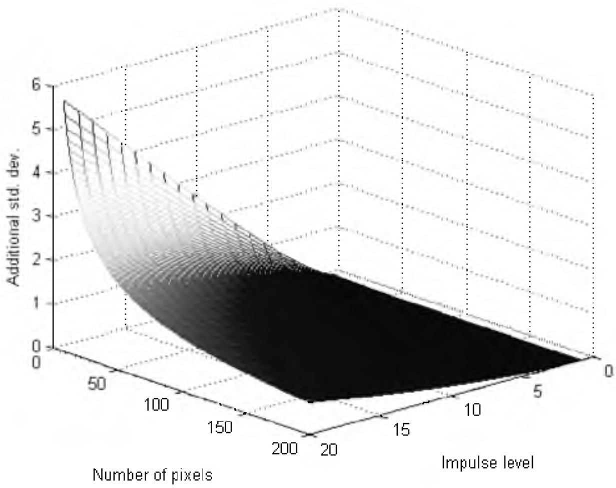

Fig. 5. Additional standard deviation due to single pulse availability, dependent on the area (number of pixels), and the impulse level c

7. Impulse suppression using impulse counting

Obtained formula (10) is very useful for another interesting impulse suppression algorithm. This algorithm uses two saturation blocks (Fig.6).

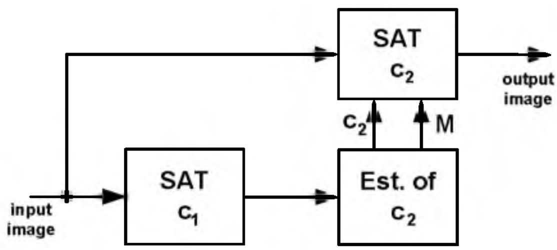

Fig. 6. Impulse suppression using impulse counting

First saturation block uses saturation c_1 value set at high level for counting of pulses (M). Application of derived formula (14) gives a possibility of estimation of c_2 for pulse suppression. It allows suppression of impulses to the $3s_B$ range.

$$s_B^2 = s_A^2 - \frac{M(N-M)}{N(N-1)} c_1^2 \tag{11}$$

The saturation level is defined as:

$$3s_B = c_2 \tag{12}$$

so

$$\frac{c_2^2}{3^2} = s_A^2 - \frac{M(N-M)}{N(N-1)} c_1^2 \tag{13}$$

and finally:

$$c_2 = 3\sqrt{s_A^2 - \frac{M(N-M)}{N(N-1)} c_1^2} \tag{14}$$

The following Monte Carlo example shows results for the proposed algorithm.

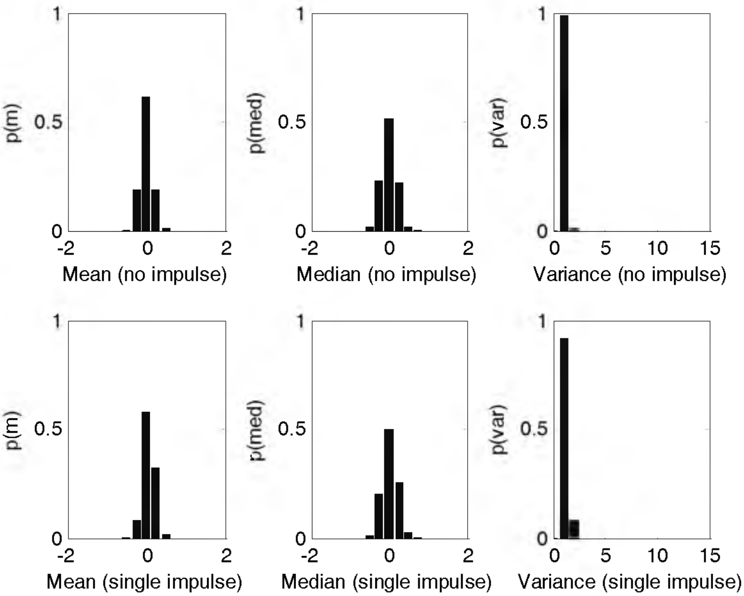

Fig. 7. Histogram for 1000 tests of empirical parameters estimation (7x7 pixels area, impulse noise level 100, first saturation level 10, suppression to $3s_B$ range)

Impulses that are between $3s_B$ range and first saturation values are not counted and degrade suppression. The cost of median filtering is much larger especially for large input set, so proposed algorithm is interesting. Proposed algorithm restores quite well statistic of the original image (Fig.7) for large number of pixels. Small number of pixels (e.g. $N=9$) is not well suppressed due to significant dependence (number of pixel dependent) between impulse and data. The formula (10) is true for independent data, only. Large and saturated value from impulse should be additive to particular signal value, but it is not true, and particular signal value is lost. Larger sets reduce dependence, but the check of square root of the formula (14) is necessary, because a negative argument forbids calculation. Very small values may also disturb signal.

6. Conclusions

Proposed techniques for salt and paper noise or even for any high valued impulse noise are recommended due to low cost if the proper variant is selected. Computation of giant amount of Kalman filters or median filters is not possible using today available devices. Simpler techniques based on the standard deviation and known characteristic of noise should be used. Saturation technique is very fast and has direct implementations in hardware. In this chapter selected techniques are presented. The statistical parameters for additive impulse and Gaussian noise are derived and alternative impulse suppression algorithm is proposed, based on the counting of the impulses.

The most promising techniques are based on the applications of the TBD predictors for gatting, due to adaptive processing for local image areas. It will be considered in the further works.

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References

[1] Blackman S., Popoli R.: Design and Analysis of Modern Tracking Systems. Artech House 1999.

[2] Stone L.D., Barlow C.A., Corwin T.L.: Bayesian Multiple Target Tracking. Artech House 1999.

[3] Boers, Y., Ehlers, F., Koch, W., Luginbuhl, T., Stone, L.D., Streit, R.L. (eds.): Track Before Detect Algorithm, EURASIP Journal on Advances in Signal Processing, Hindawi 2008.

[4] Mazurek P.: Improving response of recurrent Track-Before-Detect algorithms for small and point targets. 14. Konferencja Naukowo-Techniczna "Zastosowania Komputerów w Elektrotechnice" ZKwE'2009 Poznań, pp. 351-354, 2009.

[5] Mazurek P.: Impulse noise of small and point targets in recurrent Track-Before-Detect algorithms, "Academic Journals: Electrical Engineering". Poznań University of Technology no.61, pp. 53-62, 2010.

[6] Mazurek, P.: Suppresion of impulse noise in Track-Before-Detect algorithms using saturation and pulse removal, 15. Konferencja Naukowo-Techniczna "Zastosowania Komputerów w Elektrotechnice" ZKwE'2010 Poznań, 301-302, 2010.

[7] Mazurek, P.: Suppresion of impulse noise in Track-Before-Detect algorithms, "Computer Applications in Electrical Engineering", vol.8, 201-211, 2010.

[8] Mazurek P.: Noise suppression for Track-Before-Detect algorithms using spatial noise estimators, 16. Konferencja Naukowo-Techniczna "Zastosowania Komputerów w Elektrotechnice" ZKwE'2011 Poznań, pp. 281-282, 2011.