Deghosting Methods for Track-Before-Detect Multitarget Multisensor Algorithms

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1. Introduction

Track-Before-Detect (TBD) algorithms are very powerful for tracking applications. In comparison to classical (Detect-Before-Track) algorithms they are computationally demanding but allow achieving incredible SNR (Signal-to-Noise Ratio) performance. For classical systems SNR should be greater then one. If this condition is fulfilled classical tracking algorithms does not need a lot of computations and they process acquired data by filtering, detection and estimation algorithms. Typical detection algorithms based on fixed or adaptive threshold fails for SNR<1 because if signal is below noise floor a lot of false measurements occurs or target can not be detected correctly. Improving performance for low SNR systems is very important from applications point of view and it is research very active area using alternative approaches and improved algorithms.

Track-Before-Detect algorithms are excellent alternative for low SNR signals because signal (target) detection is processed after intensive testing set of hypotheses related to possible signal states (e.g. object trajectories). Even if there are no any signal from target complete search is used for best performance. Huge discrete state-space needs a lot of computations mostly not related to real state of target. Today available computing devices like fast processors, specialized VLSI circuits and distributed computing methods allows gives a possibility of using real-time TBD algorithms for dim target tracking. It is worth to be noted that computation cost for TBD algorithms is serious disadvantage because it significantly influent on financial cost of system but it can be meaningful for military applications (air, naval or space surveillance) where plane, ship or political costs are much more significant.

There are two groups of TBD algorithms. The first one group contains deterministic TBD algorithms statistical computations oriented for results calculation. All hypotheses are tested and computation cost is usually constant. The second one group contains nondeterministic TBD algorithms. Such algorithms do not test all hypotheses only use statistical methods for finding most probable results but optimality of results is not guarantied. For example particle filters are statistical search based and they gives results sometimes faster in comparison to first group of algorithms (Gordon et al., 1993; Doucet et al., 2001; Arulampalam et al., 2002; Ristic et al., 2004), but deterministic group is much more reliable for many application and is only considered in this chapter. For real-time applications first group has advantages of results quality and constant processing time - very important for every system developer. It is worth to be noted that useful TBD algorithms for practically applications are not optimal. There is optimality in some sense for particular algorithms but only bath processing is optimal from detection quality point-of-view. Bath algorithm tests all hypotheses (all object trajectories) using all information from beginning up to actual time moment (Blackman & Popoli, 1999). Unfortunately bath processing is not feasible for real-time applications because memory and computation cost is growing. Much more popular are recurrent TBD algorithms and last results and actual measurements are used for computations (like 1'st order IIR filter). There are also popular algorithms based on FIR filters and they use N-time moments for computation results.

Independently on computation cost of TBD there are other limitations that are challenges for developers. Classical and TBD algorithms are quite simple for single object tracking but more complex approach is necessary if there are multiple targets or false target due to measurement errors. A false measurement occurs due to occasional high noise peaks that are detected as targets. Assignment, targets track live control, targets separation algorithms and multiple sensors are considered for multiple target tracking. Excellent books (Blackman, 1986; Bar-Shalom & Fortmann, 1988; Bar-Shalom ed. 1990; Bar-Shalom ed. 1992; Bar-Shalom & Li, 1993; Bar-Shalom & Li, 1995; Brookner, 1998; Blackman & Popoli, 1999; Bar-Shalom & Blair eds. 2000) includes thousand references to much more specific topic related papers are available but there is a lot of to discover, measure and investigate.

Most multiple target tracking algorithms are related to classical systems but there are also well fitted algorithms for improving TBD trackers. Simple method is using TBD algorithm results as input for high level data fusion algorithm that should be tolerant for redundant information from TBD algorithms. Very important part of TBD is state-space that should be adequate for application and decide about algorithm properties significantly. In this chapter is assumed strength correspondence of state-space to the measurement space. It allows simplify description of behaviours of TBD algorithms using kinematics properties. The measurement space depends on sensor type. From Bayesian point of view different sensors outputs can be mixed for calculation joint measurements. This data fusion approach is very important because there are sensors superior for angular (bearing) performance like optical based and sensors superior for distance measurements like radar based. Diversification of sensors for measurement for tracking systems improvements is contemporary active research area. Progress in optical sensors development for visible and infrared spectrum gives passive measurements ability that is especially important for military applications and linear and two-dimensional optical sensors (cameras) are used. Unfortunately distance measurement using single sensor without additional information about target state is not possible. Another disadvantages of optical sensors is an atmospheric condition so dust, clouds, atmospheric refraction can limits measurement and tracking abilities for particular applications. Because targets move between sensors and background (for example moving clouds) background estimation is a very important for improving SNR. Another problem is optical occlusion that limits tracking possibilities (for example aircraft tracking between or above clouds layer). Such limitations related to optical measurement sensors are related to single and multiple targets tracking also, but there is another non-trivial multiple target related problem known as a ghosting (Pattipati et al, 1992). For every bearing only system ghosting should be considered and suppression methods should be used or obtained tracking results are false.

2. Ghosting and basic methods of ghost suppression

2.1 Ghosting

In this chapter are considered sources of ghosts and methods for suppression them using illustrative examples for usually hard to visualize high dimensionality state spaces. For single or multiple targets positions estimation two or more sensors are necessary. Using LOS (Line-of-Sight) triangulation target position and distance estimation is possible.

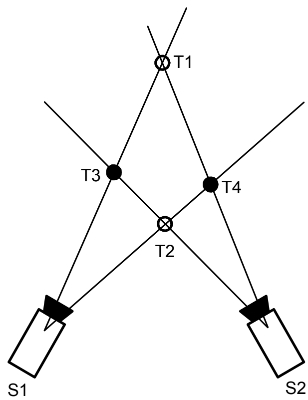


Fig. 1. Two targets and two ghosts

Assuming two targets and two sensors triangulation fails because there are two possible solutions:

T1 and T2 – true targets,
T3 and T4 – false targets (ghosts)

or

T1 and T2 – false targets (ghosts),
T3 and T4 – true targets.

If there is no available additional information there is no answer which solution is correct. This problem is not related to tracking method only to geometrical properties of bearing only sensors and common to classical and TBD tracking systems. Many methods can be used for finding solution or eliminate some false assignments.

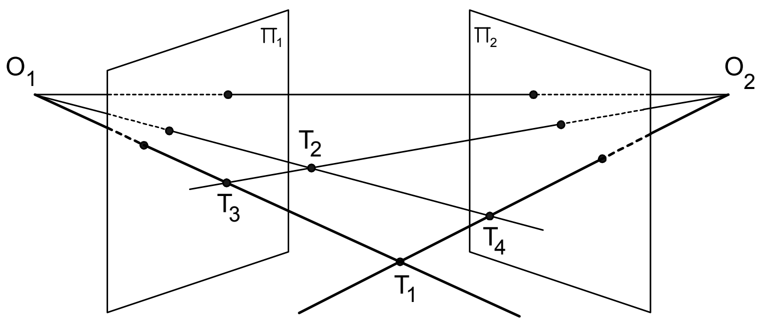


Fig. 2. Ghosting in 3D observation space

If two targets are on common plane (O_1, O_2, T_1 and O_1, O_2, T_2) ghost effect occurs (Fig.2). It can be little surprising that number of ghosts is smaller for 3D space in comparison to 2D space. If one of the targets is placed outside second plane ghost effect does not occur (Fig.3). For 2D space ghosts are always (Fig.1).

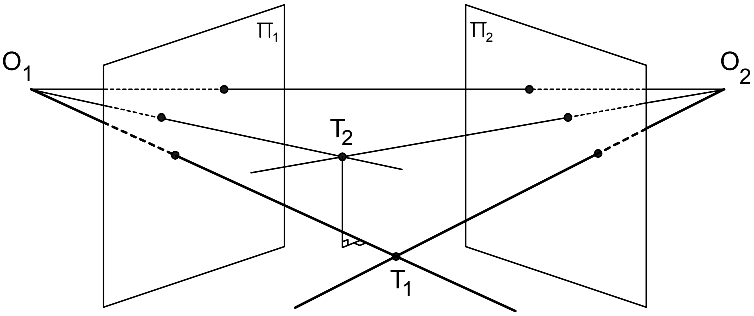


Fig. 3. Two targets and no ghosts in 3D space

2.2 Influence of measurement errors

Angle measurement errors can influent on results for trivial cases. Due to calibration errors and measurements noises all LOS for single target do not cross in single point (Fig.4). For 2D object plane all LOS are crossed but not in single point but for 3D space practically they almost never cross and approximation is required. If there are multiple closely located targets problem arises.

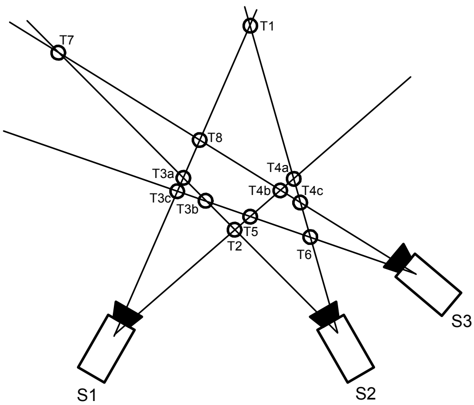


Fig. 4. True objects T3 and T4 are dispersed due to measurement errors

Increasing number of sensors is probably most popular solution, because for true targets number of LOS crosses increases also. Unfortunately number of ghosts increases also.
Using additional information about targets is promising because it allows eliminate some ghosts. Amount of eliminated ghosts depends on sensors and object position. Even if not all ghosts are eliminated it can helps for estimation proper positions of targets using other algorithms.

Constraints oriented deghosting methods uses typically knowledge about allowed position, maximal or minimal velocity, maximal acceleration, direction of movements and others (Mazurek, 2007). If it is possible all constraints can be used together for best performance.

2.3 Counting and accumulative strategies

For classical methods for every target position (true or ghost) constraints using is straightforward even if constraints tests are performed for every scan separately. Much more reliable is extensive tracking where ghosts are tracked and constraints are used for marking them as ghosts if they forbid constraints limit.

Because TBD algorithms are signal accumulation oriented algorithms they do not consider LOS crossing as sum of number of crosses but they accumulate signals for particular state space cell where crossing occurs. It following example is assumed availability of two targets and three sensors. Signal values registered by sensors for targets are P1=1 and P2=0.5 equal. True targets are located in T1 and T4 positions. It is worth to be noted that all noises are omitted so this is very comfortable for any algorithm case.

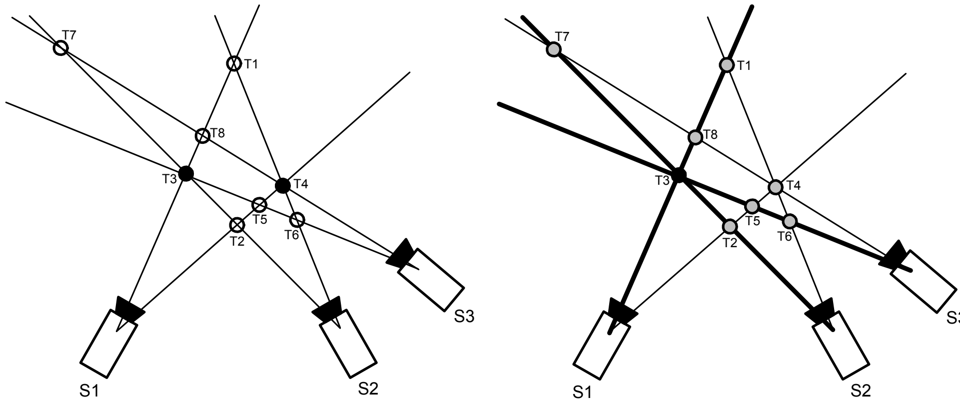


Fig. 5. Counting strategy (left) and accumulative strategy (right) for two targets and three sensors

LOS cross point	LOS value Counting strategy	LOS value Accumulative strategy
T1	2	1.5
T2	2	1.5
T3	3	3
T4	3	1.5
T5	2	1.5
T6	2	1.5
T7	2	1.5
T8	2	1.5

Table 1. LOS values for Fig.5

This example shows how counting and accumulative strategy algorithms differ. For counting strategy maximal values corresponding to most probable position of targets and three sensors help to solve ghosting problem if we know maximal number of targets.
Accumulative strategy fails because T4 value is equal to ghosts' values and only one target (T3) is detected as a true target. Even knowledge about number of targets can not help to solve this simple example.
Only one way for improving accumulative strategy is increasing number of sensors and in next example is assumed four sensors availability (Fig.6).

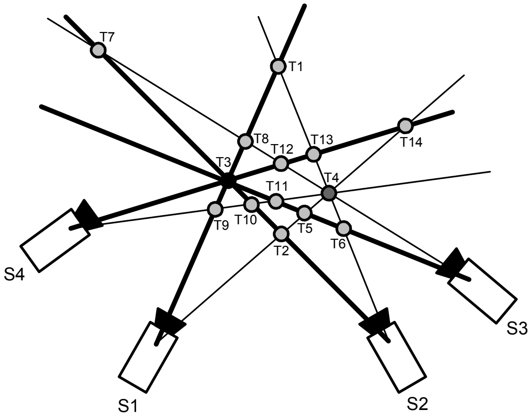


Fig. 6. Improving accumulative strategy using additional sensor

LOS cross point	LOS value Counting strategy	LOS value Accumulative strategy
T1	2	1.5
T2	2	1.5
T3	4	4
T4	4	2
T5	2	1.5
T6	2	1.5
T7	2	1.5
T8	2	1.5
T9	2	1.5
T10	2	1.5
T11	2	1.5
T12	2	1.5
T13	2	1.5
T14	2	1.5

Table 2. LOS values for Fig.6

Counting methods gives correct results and maximal values correspond to true targets. Accumulative methods give two largest values corresponding to true targets but T4 cross point has only 50% higher value over ghosts. Counting strategy work better but it needs detection of correct LOS so if SNR>1 it is recommended to use. Accumulative strategy inherently available in TBD algorithms can be used also and it will be discussed in next examples.

2.4 Accumulative strategy examples

Examples of results for noiseless and noised measurements space will be shown. For simplification instead of projective cameras are used orthographic cameras. First example shows how number of sensors improves results for accumulative strategy. Selected part of state space is shown and some ghosts are outside image.
For two target T1=1.0 and T2=0.5 the 3x3 matrix values filled by target value and filtered by 3x3 low pass filter (all values of filter are equal) so small size blurred targets are available.
Values for every case are normalized separately. Black value is zero level and white corresponds to maximal value.

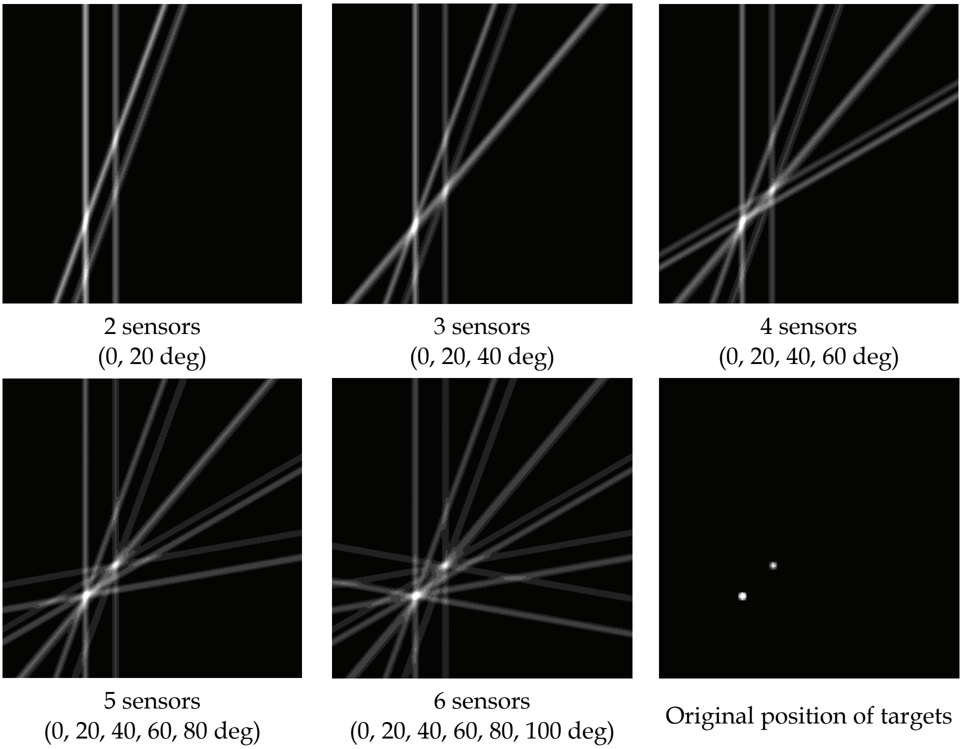
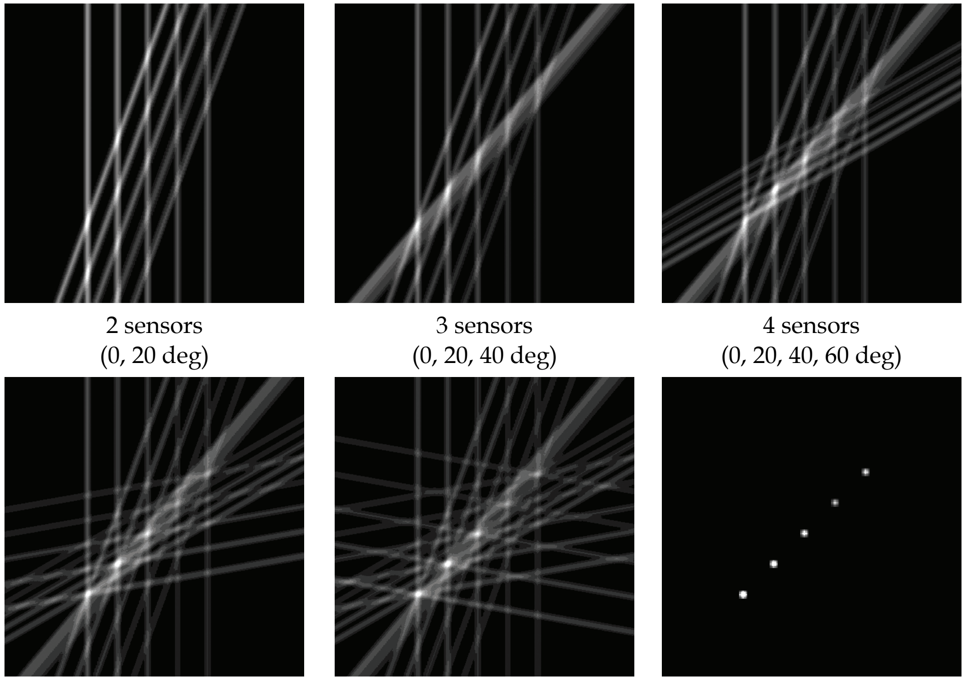


Fig. 7. Measurement spaces for two targets and variable number of sensors

For two sensors ghosting effect is well visible and there is one large value (true target), two medium values (ghosts) and one small (true target). Increasing number of sensors improves value for true targets and reduces values of ghosts. A lot of LOS is sources of many lines.

Shape of target blob and ghosts depends on sensors placement and number of them. If small number of sensors is used and they are close together targets blobs are elliptical. If sensors are much more dispersed blobs are more circular and better recognized.

In next example five true targets are placed in this space and they have following values: T1=1.0 (bottom); T2=0.8; T3=0.6; T4=0.2 and T5=0.4 (upper). The order of values T4 and T5 is intentional for reducing human related adaptive effects of results observation for image blobs series.



2 sensors (0, 20 deg) | 3 sensors (0, 20, 40 deg) | 4 sensors (0, 20, 40, 60 deg)

5 sensors (0, 20, 40, 60, 80 deg) | 6 sensors (0, 20, 40, 60, 80, 100 deg) | Original position of targets

Fig. 8. Measurement spaces for five targets and variable number of sensors

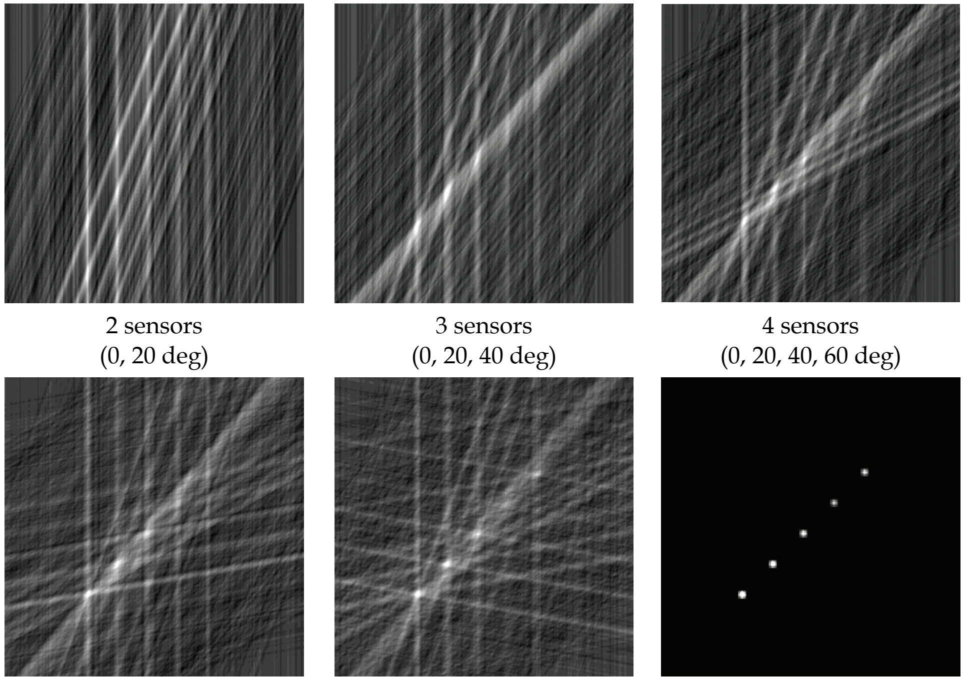
For two sensors a lot of ghosts are and some of them are outside image and it is not possible to find solution. Different values of targets are mixed and generate a lot of different ghosts' values.

Sensor 40 gives well visible thick line that occurs if targets are collinear (it is well visible in examples for 3 and more sensors). Increasing number of sensors positioned at other angles reduce this effect. In subfigures 4 and 5 is a visible strength blob below target number T2 that shows sensitivity of this strategy – a lot LOS can accumulate in bad conditioned case and ghost appear.

Dim target T4 is visually recognized when there are 5 sensors because humans expect position in proper place but from computation point of view there are also a lot similar value blobs (ghosts). Increasing number sensors improves results for dim targets but it is worth to be noted that problem of detection is also related to collinear placement of targets.

Accumulative strategy work well if there is similar values of targets but in real applications it can not be guaranteed especially if there is measurement noise.

In next example noises is added. There can be two sources of noise. The first one is measurement noise like Gaussian noise that is sources of giant amount of visible parallel lines in figures (Fig.9). The second one is related to observation space of additional objects that is projected onto all sensors and in this chapter is omitted.



2 sensors (0, 20 deg) | 3 sensors (0, 20, 40 deg) | 4 sensors (0, 20, 40, 60 deg)

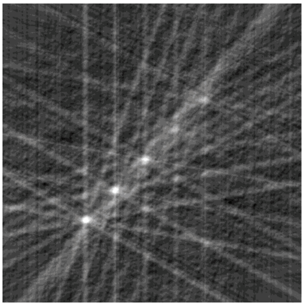
5 sensors (0, 20, 40, 60, 80 deg) | 6 sensors (0, 20, 40, 60, 80, 100 deg) | Original position of targets

Fig. 9. Measurement spaces for five targets and variable number of sensors. Noise is added to measurements

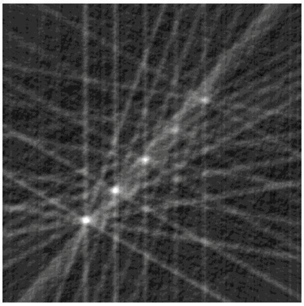
It is interesting to compare this and previous example. For 5 sensors only three targets are visible for human. Targets T4 and T5 are missing in noise and as is expected due to accumulation from different direction increasing number of sensors helps to find such targets. For 6 sensors target T5 is visible but dim target T4 is still missing.

Noise effects can be reduced by multiple measurements what is a kind of the simplest TBD algorithm. If targets are not moving measurements averaging reduce noise and increase SNR. This is well known noise reduction techniques that can be approved for tracking. This technique correspondence to FIR based TBD. Class of TBD algorithms can be derived from this technique if set of motion vectors is incorporated for averaging. Advantages of averaging for statically placed targets and sensors are shown in next example. This method reduces noise and suppresses values of ghosts also (Fig.10).

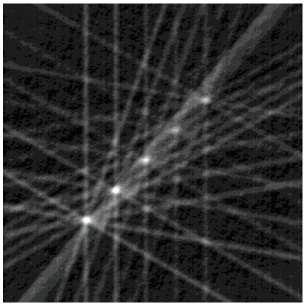
For single measurements noises gives a lot of noise in LOS and crossing them gives ghosts. Averaging stabilizes values for cross measurement cells and it is especially visible as lower values for every LOS line between two neighborhoods cross points (ghosts).



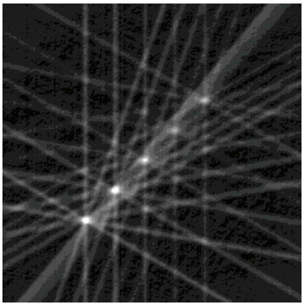
Single space



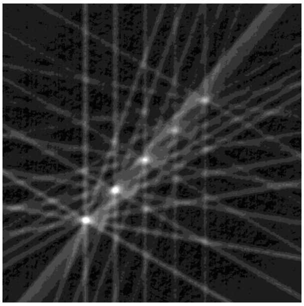
2 averages of spaces



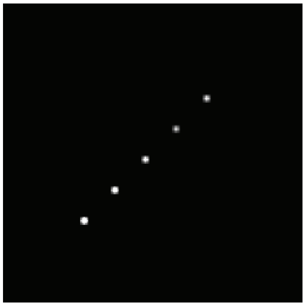
4 averages of spaces



8 averages of spaces



16 averages of spaces



Original position of targets

Fig. 10. Measurement spaces for five targets and variable number of averaging. Noise is added to measurements

Averaging of measurements can be used for improving signal quality and two methods should be considered in real applications. The first one is a sensor related averaging by registration time extending and the second one method is numerical averaging based. For real applications both should be considered because TBD algorithms are very good but work much better if signal strength as high as possible. Tracking effort and requirements for additional ghosts suppression algorithms can be reduced by proper designed system. Optical sensor noises can be greatly reduced by cooling and careful analog front-end design what is non trivial for dim targets signal acquisition.

It is worth to be noted that averaging technique can be implemented by parallel sensors. It is interesting method because extending registration time can not be used at any cost. If registration time is long time resolution is usually reduced also. For proper tracking of maneuvering targets and high frame rates linear approximation of movement can be used. Additionally long registration time is not correct for today available sensors because signal accumulated in one sensor cell (pixel) influent on values of neighborhoods pixels.

An additionally parallel sensor averaging is important for dim targets because sensors can be bombarded by high energy particles from space and register very high values for some frames. Using signal processing filters like median filters high values can be detected and removed before averaging and significantly improving overall acquisition process, because TBD algorithms are accumulation oriented.

3. Track-Before-Detect algorithms

Two recursive algorithms can be used as examples of TBD algorithms. Spatio-temporal TBD based on fading memory (exponential smoothing) and simplified version of LLR TBD (Stone et al., 1999). Main difference is that LLR TBD use strict Bayesian approach and spatio-temporal not, but both have similar algorithm structure and they have similar behaviors in a case of ghosting. Spatio-temporal TBD with exponential smoothing can be written as a following pseudoalgorithm:

Start

$P(k=0,s)=0$ //Initial value (1a)

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

$$P^{-}(k,s)=\int_S q_k(s \mid s_{k-1})P(k-1,s_{k-1})ds_{k-1} \quad \text{//Motion update} \quad (1b)$$

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

EndFor

End

S - state space (2D position and motion vectors Vx, Vy in this chapter),

s - state (spatial and velocity components in this chapter),

k - step number or time moment,

α - smoothing coefficient $\alpha \in (0,1)$,

X_k - measurements (input image),

$P(k,s)$ - estimated value of targets,

$q_k(s \mid s_{k-1})$ - state transitions (Markov matrix).

Simplified LLR TBD can be written as a following pseudoalgorithm:

Start

$$\Lambda(k=0,s)=\frac{p(k=0,s)}{p(k=0,\phi)} \text{ for } s \in S \quad \text{//Initial likelihood ratio} \quad (2a)$$

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

$$\Lambda^{-}(k,s)=\int_S q_k(s \mid s_{k-1})\Lambda(k-1,s_{k-1})ds_{k-1} \quad \text{//Motion update} \quad (2b)$$

$$\Lambda(k,s)=L_k(y_k \mid s)\Lambda^{-}(k,s) \quad \text{//Information update} \quad (2c)$$

EndFor

End

$\Lambda(k,s)$ - likelihood ratio (LLR),

$\Lambda^{-}(k,s)$ - motion update likelihood ratio,

$L_k(y_k \mid s)$ - measurement likelihood, usually calculated using target signal model,

y_k - measurement.

It is worth to be noted that LLR TBD is very attractive from computational point of view because logarithmic implementation allows reduce number of computation and is very useful in analytical analysis (Stone et al., 1999). Initial likelihood ratio value can be fixed value.
As was mentioned state space in this chapter correspond to measurement space. It allows simplifying analysis and testing TBD algorithms in convenient way. State space is divided on to set of subspaces. Every subspace correspond to measurement space in represents objects positions for specific motion vector and number of subspaces is dependent on number of different velocities and movement directions.
Unidirectional graph show in Fig.11 describes possible target movements – velocity and direction. This graph can be position dependent but in this chapter is assumed as a fixed.

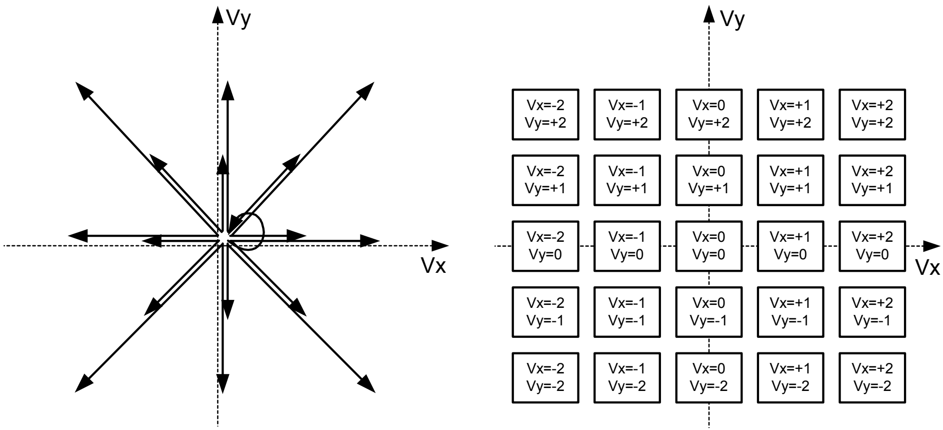


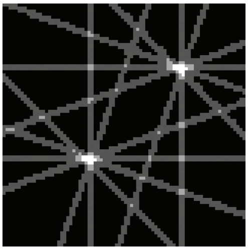
Fig. 11. Motion vectors (left) and corresponding subspaces of TBD algorithm (right)

For assumed motion graph Markov matrix can be prepared directly or implemented in another computational efficient way but there is other important application of motion vectors. Due to high dimensionality visualization of results is complicated especially if after TBD processing there is not available another data fusion algorithm. Joint space can be used but for multiple targets and different directions and velocities only position of targets is visible. The second one visualization method (Mazurek, 2007) is based on placement of multiple subspaces corresponding to motion vector like in Fig. 11 for selected time moment.
Central position (looped vector in Fig.11) is very similar to averaging of input measurement (Fig.10) but is not exact average, because there are Markov transitions from other motion vector states and from this state to others.

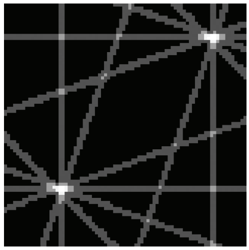
4. Ghost suppression and Track-Before-Detect Algorithms

4.1 Ghost suppression by accumulative strategy

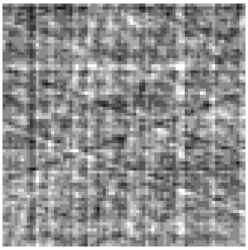
In following example results for spatio-temporal algorithm for two moving targets and $\alpha = 0.95$ are shown. There are 21 motion vectors and 6 sensors. The first one target starts from left-down area and has assigned Vx=+1, Vy=+1 motion vector. The second one target start from right-up area and has assigned Vx=-1, Vy=-1 motion vector. Target trajectories crosses own trajectories.



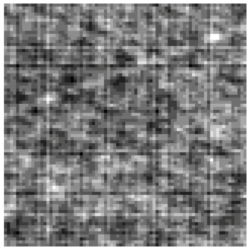
Measurement space for time moment k=20 without noises



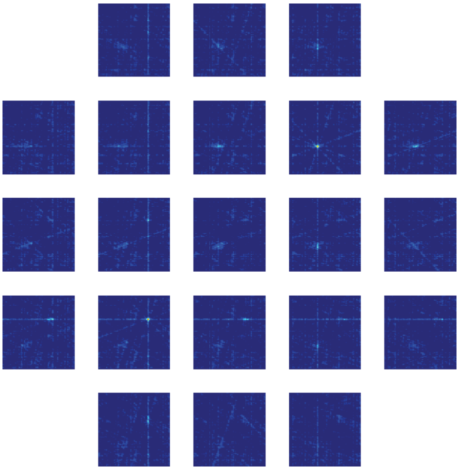
Measurement space for time moment k=60 without noises



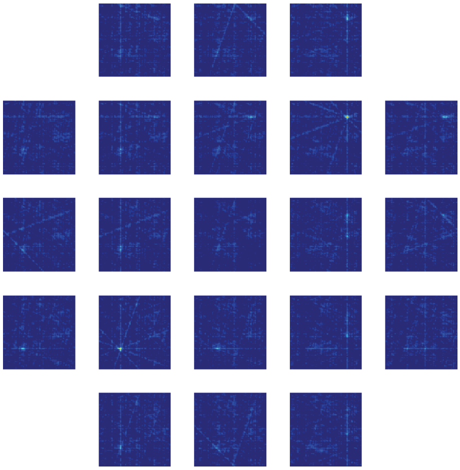
Measurement space for time moment k=20 with noises



Measurement space for time moment k=60 with noises



TBD state space for time moment k=20 with noises and motion analysis



TBD state space for time moment k=60 with noises and motion analysis

Fig. 12. State spaces for two time moments

Noiseless input measurements show well visible positions of targets but due to noise in input measurements such parameters like positions and number of targets or ghosts are not possible to estimate. Comparing measurement spaces with and without noise shows how it is hard to find targets and classical threshold based algorithms are useless for detection. Targets separated by TBD algorithms motion vectors are the largest values in state spaces for Vx=+1,Vy=+1 and Vx=-1,Vy=-1 subspaces (Fig.13). Due to averaging of multiple sensors measurements ghosts are almost at LOS levels.

Fig. 13. Enlarged selected subspaces for time moment k=60

The Markov matrix describe dispersion of values from particular subspace to neighborhoods subspaces that is necessary for tracking if target changes own motion vector or if target motion vectors is not well fitted to motion vectors defined by motion graph so additional blobs in neighborhoods subspaces surrounding largest one. Using average of all subspaces it is possible obtaining joint space without motion vectors but it is not recommended for good trackers because motion should use for better separating crossing targets.

4.2 Ghost suppression by additional dimension measurements

It was mentioned very interesting behavior of angular sensors that are very sensitive in 1D measurement (2D observation space) and always generate ghosts (Fig.4). In the case of 2D measurements (3D observation space) and proper position of sensors in relation to targets separation (Fig.3) can be obtained. Such forced separation reduces number of ghosts or even completely eliminate them if targets and sensors are not coplanar. In real applications should be considered such technique for example instead of two linear (1D) IR sensitive sensors in marine surveillance two 2D sensors properly placed can help if one of them is at some high over sea surface (e.g. aircraft). This example shows how cooperative measurements and data fusion from many and distance sensors can solve unsolvable problems. This technique can be used in TBD but direct implementation increases computation cost significantly. TBD algorithms for 3D space can be used in two ways:

- Full processing 3D space by TBD needs state space for position only as 3D so even for small state space cost is huge. For example if 2D measurement space has 100x100 cells and full 3D tracking is assumed state space for position has 100x100x100 cells for two orthogonal sensors. Number of computations increases additionally because not only spatial component is much larger but also movement direction (velocity component) increases and amount of computations is gigantic (Barniv, 1990). In near future using optical or electro-optical processing tracking in real-time for such spaces will be possible or it is already possible in today available secret military trackers because optical technology is well suited for TBD algorithms. Unfortunately research papers related to available military applications of TBD are not available.
- Partial TBD processing where only 2D image frames are processed by TBD algorithms for every sensor separately. After targets detection classical assignment or other ghost elimination algorithms are used. This method is very useful because number of computation is exactly proportional to number of sensors.

4.3 Ghost suppression by using positions constraints

This technique is very popular because possible spatial position of targets can be simple measured and used as constraint for reducing number of ghosts. For example as shown in Fig. 14 three targets (T1, T7, T14) should be a ghosts because they are outside of area where targets are.

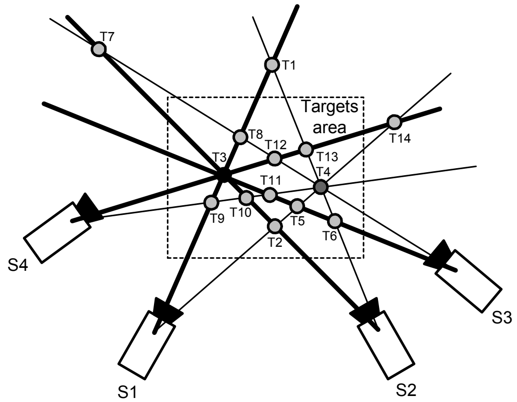


Fig. 14. Ghost suppression by using positions constraints

4.4 Ghost suppression by using proper placement of sensors

This technique is very useful but is not well emphasized in literature and usually it is assumed no target area constraints. Such assumption is important in some cases but if there is possibility of control measurement scenario by experiment planning knowledge about possible trajectories allows finding much better position of sensors and reduce or even eliminate ghosts (Fig.15).

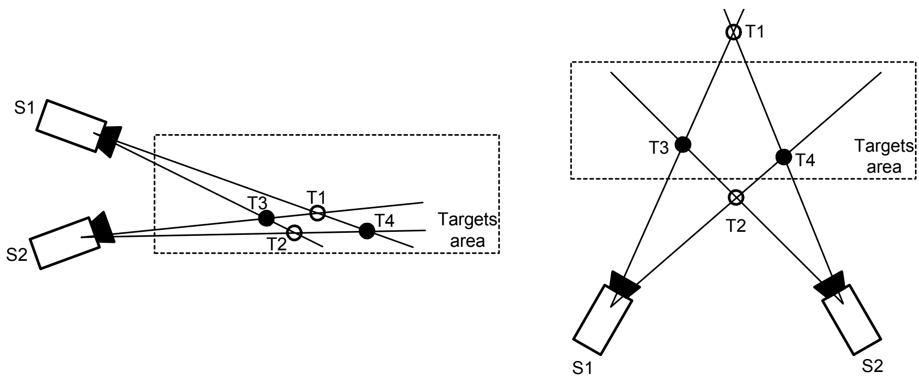


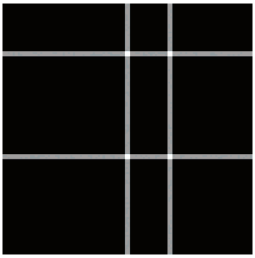
Fig. 15. Two examples same targets positions in area

In left figure bad sensor placement and in right figure solution are shown. For know target are there is possible place ghosts outside area of interest. Proper placement is very interesting from application and research point of view. Using optimization techniques before measurements ghost elimination can be obtained. For simple cases optimization is even not required and geometrical analysis can be used.

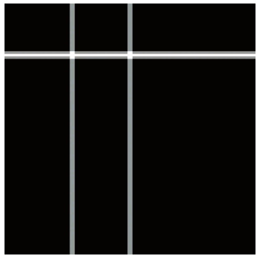
4.5 Ghost suppression by using velocity constraints

Very often mentioned in literature are velocity constraints for ghost detection. Usually is emphasized case where projective sensors are used and for two sensors and targets one of the ghosts has much higher velocity in measurement space.

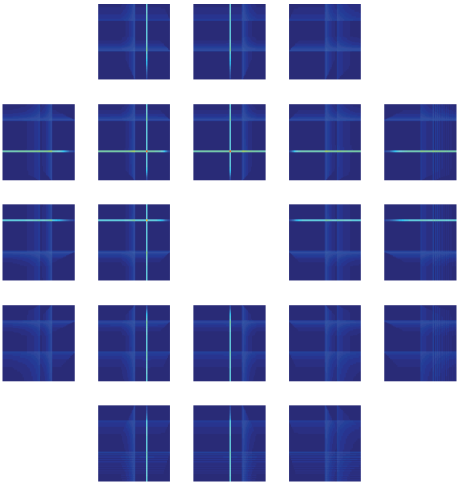
In following example will be show results for two targets and two sensors that can not be solved in general case. Assuming knowledge about targets velocities and movement direction motion graph gives reduced Markov matrix and reduced number of subspaces because some state transitions are forbidden. Due to orientation of sensors or direction of movements of targets the fist one ghost has highest velocity and second one has zero velocity.



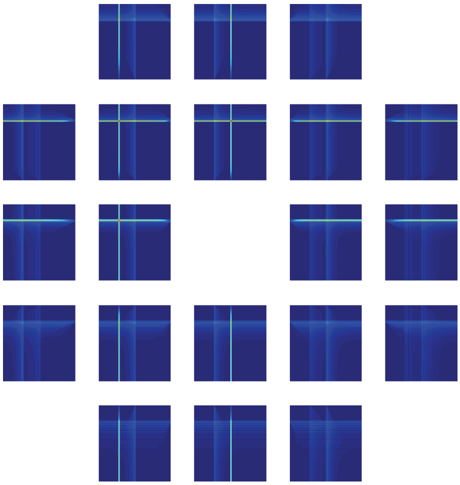
Measurement space for time moment k=20 without noises



Measurement space for time moment k=60 without noises



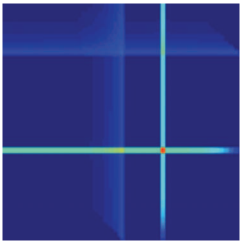
TBD state space for time moment k=20 without noises and with motion analysis



TBD state space for time moment k=60 without noises and with motion analysis

Fig. 16. Selected state spaces for two time moment

Usually velocity constraints are recognized in literature as a maximal velocity limitation, but as shown in this example (Fig.16) minimal velocity can be used for ghost suppression also. Without TBD motion analysis ghosts' elimination is not possible but only one ghost is eliminated (Fig.16). The first one ghost has similar values to target (Fig.17).



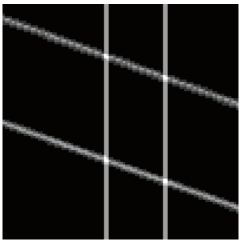
Vx=-1,Vy=+1 (ghost)

Vx=-1,Vy=0 (true target)

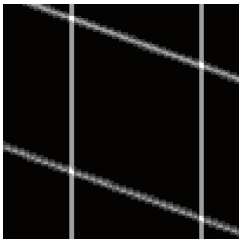
Fig. 17. Zoom of motion separated targets for time moment k=20

4.6 Ghost suppression by using motion direction constraints

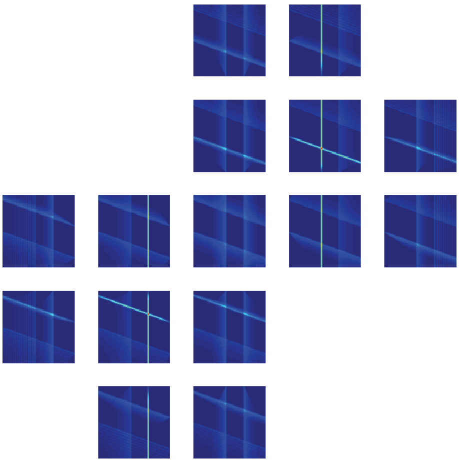
This technique allows reducing values for ghosts if they are not moving in proper direction. If there is knowledge available about object trajectory even for small number of sensors like two for two targets can be used. In following noiseless example there are motion vectors ($Vx \geq 0$ and $Vy \geq 0$) and ($Vx \leq 0$, $Vy \leq 0$) allowed for targets (the first one starts from left-up corner and move towards to right-down corner and the second one use opposite direction).



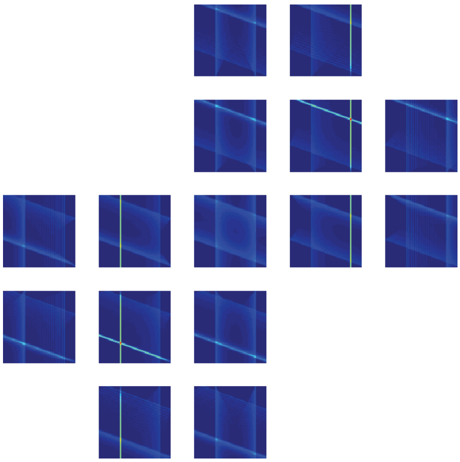
Measurement space for time moment k=20 without noises



Measurement space for time moment k=60 without noises



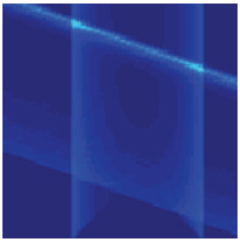
TBD state space for time moment k=20 with motion analysis



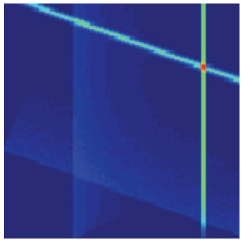
TBD state space for time moment k=60 with motion analysis

Fig. 18. Selected state spaces for two time moment

As show in Fig.18 there are two ghosts in measurement spaces and they have similar values in comparison to the true targets.



Vx=0,Vy=+1 (left blob is a weak ghost)



Vx=+1,Vy=+1 (true target)

Fig. 19. Zoom of motion separated targets for time moment k=60

Ghost values are suppressed (Fig.19) but results depend on number and configuration of sensors and targets trajectories.
There is additional advantages of this and previous method because TBD algorithms need a lot of computation and subspaces reduction decrease computation cost.

4.7 Ghost suppression by increasing angular resolution

Not only coplanar targets and sensors position is source of ghost effect. Angular measurements are sensitive for noises that influent on position measurements even for single target. There almost always errors and ideal triangulation is not possible so two LOS are not crossed in single point for 3D space. Triangulation algorithm estimate (Hartley & Sturm, 1997) target position by minimal distance search between two or more LOS, so approximated position of target P_E is obtained.

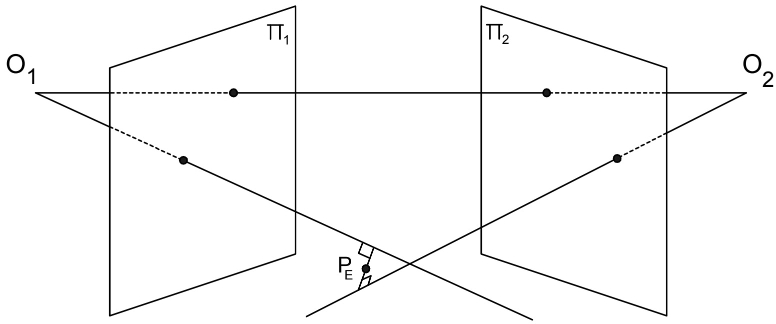


Fig. 20. Triangulation error in 3D observation space

If there are more targets and some of them are closely spaced measurement errors are source of ghosts depending on sensor resolution and measurement noise. Classical track maintenance algorithms can reduce such effect but improving sensor resolution can reduce noise and separate closely located targets also. Optical sensors have resolution dependent on number of optical elements (sensor pixels) and field of view (FOV). Using variable focal length controlled by tracking algorithm is very interesting for improving angular resolution performance.

Spatial errors that induce ghost effect can be reduced by proper placement of sensors. Uncertainly of target position can be modeled as a cone from focal point of sensors. If distance between sensor and target is small position errors are smaller also and ghosts occurrence is less probable. Tracking distant target using bearing only sensors is always challenging.

4.8 Ghost suppression by using additional attributes of targets

This idea uses diversification measurements and allows extend measurement space. For example instead simple IR measurements can be used: two wavelengths for IR measurements, IR and visible light wavelengths, or color light (RGB) measurements.

Good multispectral approach can improves separation between targets significantly and if targets are separated ghosts effect does not occur or is reduced.

The first one technique that use additional attributes uses them directly inside TBD processing.

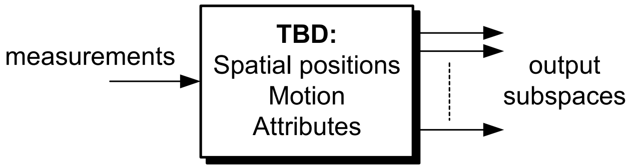


Fig. 21. Additional attributes TBD - combined processing

The second one technique where additional attributes can reduce ghost effect is implementation divide-and-conquer approach using set of filter fitted to attributes for extraction important signal from measurement.

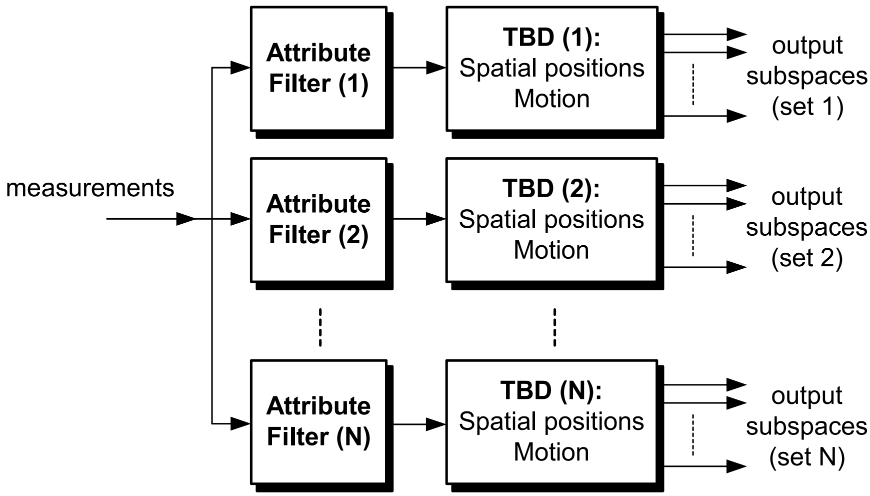


Fig. 22. Additional attributes TBD - separate processing

Attribute based TBD algorithms are very interesting research area because this approach greatly improves tracking and can be used for many practical systems.
In this chapter is considered example of separate processing TBD for tracking colored targets. In this case measurement space is greatly extended because for every measurement cells (pixels) is available more then one value representing spectral data like three R, G and B components. This method is general approach and has very efficient parallel implementation. Unfortunately separate processing does not have ability of using information between spectral components and if target color evolves in time obtained measurements in some channel can not be used by another directly by TBD algorithm. For such situation combined processing TBD approach can be used or additional data fusion algorithms for tracks maintenance are necessary.
Assuming constant color for every target and Gaussian noise filters can be designed using geometric properties of color space. It is assumed typical RGB color space where all color components are orthogonal so point target (pixel size) is a vector in such space and noise can be represented as 3σ radius sphere like in Fig.23 and noise is additive for target signal.

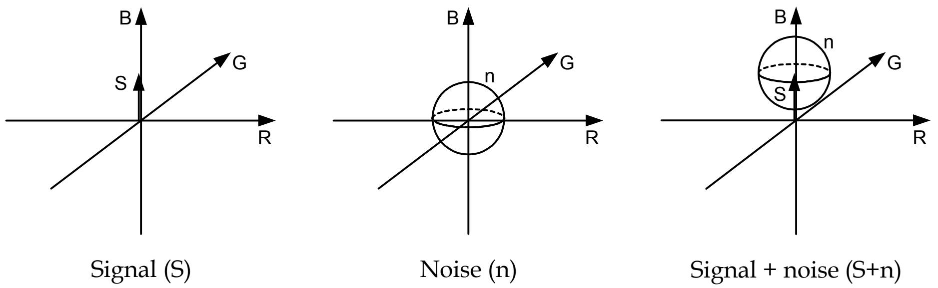


Fig. 23. Single pixel vector representation

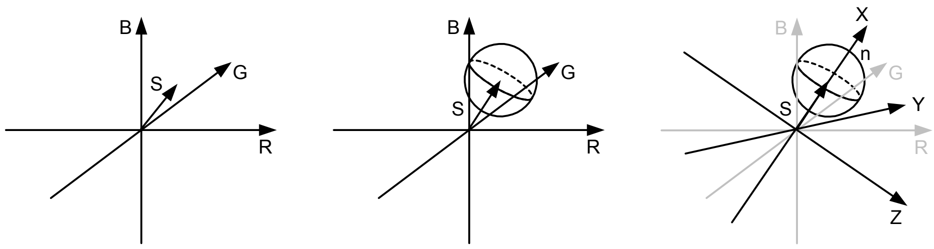
In Fig.23 is shown blue color only target and if target color is any but known, transformation using rotation matrix is necessary and signal vector should be parallel to the one of the space vectors (X,Y,Z) for example parallel to the X (Fig.24).

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} r \\ g \\ b \end{bmatrix} \tag{3}$$

Because only one space vector X is important previous formula can be rewritten to more compact and useful form:

$$[x] = [a_{11} \quad a_{12} \quad a_{13}] \begin{bmatrix} r \\ g \\ b \end{bmatrix} = \frac{1}{\|s\|} [s_r \quad s_g \quad s_b] \begin{bmatrix} sn_r \\ sn_g \\ sn_b \end{bmatrix} \tag{4}$$

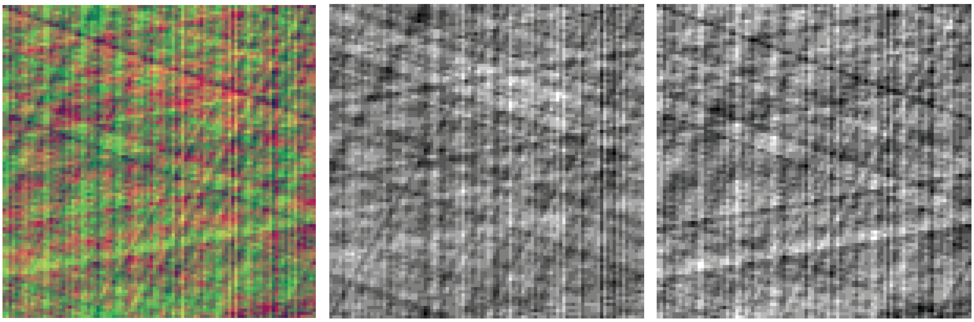
where *sn* is any signal plus noise and *s* is expected signal without noise. Such formula can be simple extended to any multispectral case if color space is orthogonal.



Signal (S) Signal + noise (S+n) Signal + noise (S+n) and new XYZ space

Fig. 24. Single pixel vector representation

Three noised targets are for following example: red (1,0,0), yellow (0.707, 0.707, 0) and green (0,1,0) and three *s* vectors are used for separation for three measurement spaces. Values for targets are intentionally selected because length of all target vectors is equal so all of them have equal strength.



RGB measurement (B is false noiseless color) Red measurement Green measurement

Fig. 25. Input signal for time moment k=60

Blue subspaces are omitted in TBD process because blue component is orthogonal to noiseless target signals. There is only noise in blue color component of RGB space and for separate processing strategy this component is not important.

Full or partial separation between color components is not only related to the targets but LOS also and cross points values are also reduced. Red target use Vx=0, Vy=+1; yellow target use Vx=+1, Vy=+1; green target use Vx=-1, Vy=-1 motion vector.

Without multispectral approach a lot of ghosts should be visible. Separation helps for eliminate ghosts or reduce them. Because yellow target consist component from red and green components there are some signals from this target in both components. Red and green components of target are visible in yellow component also. Crosstalk between nonorthogonal components is a result of simple method of separation but obtained results shows that ghost are weak.

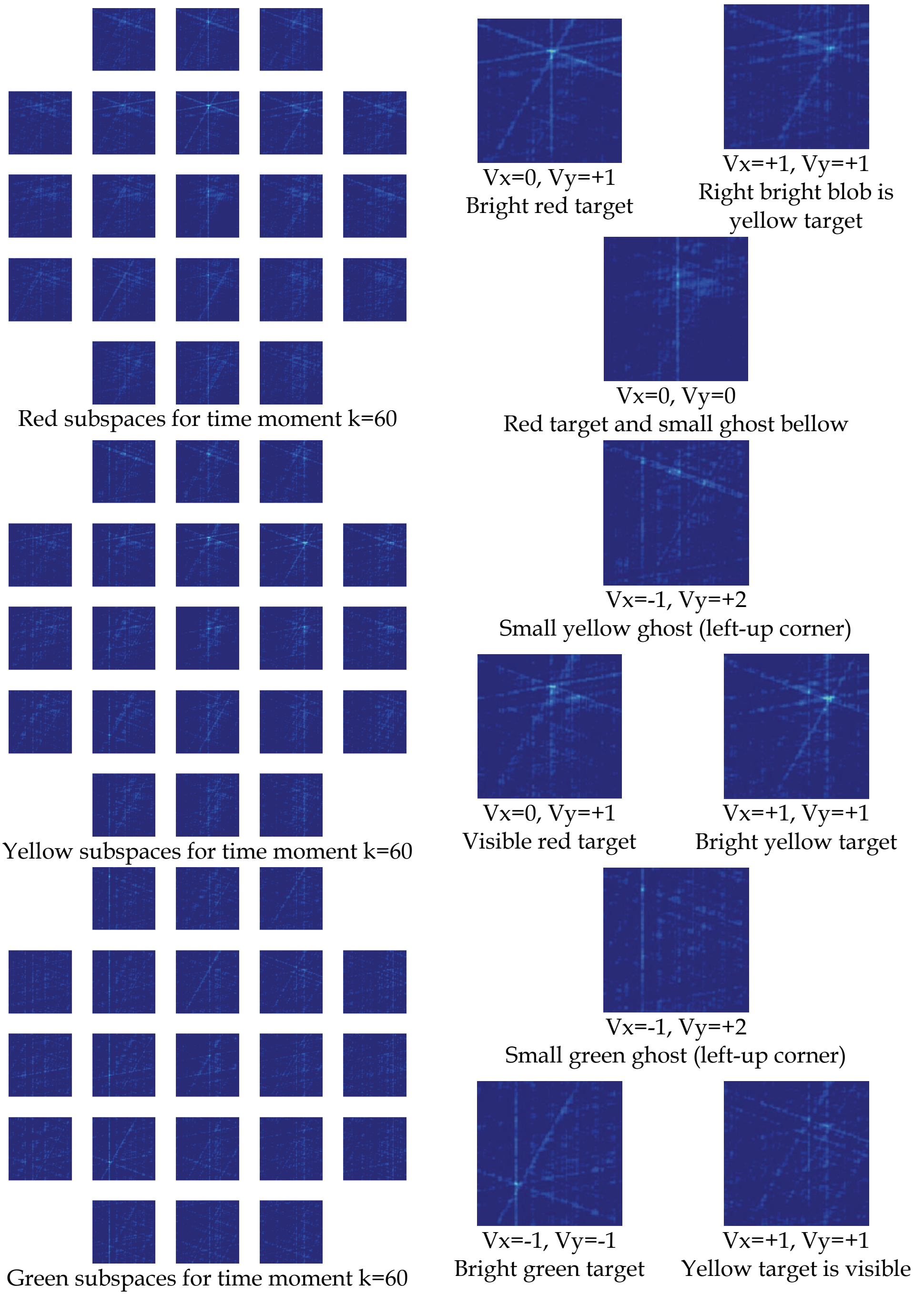


Fig. 26. Three subspaces and selected enlarged subspaces

5. Conclusions

Ghosts are phenomenon that occurs for bearing only sensors and many methods can be used for elimination or reduction them. For accumulative algorithms like considered group of TBD are presented and discussed possible solution.

Comparing discussed deghosting methods is not possible because every method uses another approach and different knowledge about targets. For specific case one method can be better in comparison to others but can fail in another case and all of them should be used carefully. In this chapter are proposed deghosting methods using TBD algorithms directly without additional postprocessing and some of them are used in classical deghosting algorithms.

This approach based on deghosting in TDB algorithms together with main tracking purpose is correct but serious developer should consider other methods also as an additional improvement of systems or even if necessary as replacement for considered in this chapter methods. Ghosting is very serious problem for serious applications. Using suggested method of state space implementation allows design and test systems. Decomposition of 4D state space allows visualize results of TBD for human also. Very popular Monte Carlo based tests for determine system quality is good idea also but it should be used carefully.

Extension of deghosting directly in TBD algorithms is possible but there a lot of interesting question for future researches, for example influence of projective measurements on ghosts because measurement space is not rectangular and approximation is necessary. Measurement likelihood has knowledge about sensor properties and also influent on ghost values and real sensors needs good description of this function additionally so there is question about this influence on ghosts.

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