Abstract—In this paper we describe a method for detection, localization and tracking of multiple non-cooperative moving targets by multiple static ultra-wideband (UWB) radar sensors. The targets are detected using electromagnetic waves backscattered by the target towards the receivers. The sensors consist of two receiving and one transmitting antenna connected to a single UWB module, making the sensors capable of autonomous target localization. Gaussian mixture implementation of the probability hypothesis density (PHD) filter is used for estimating the ranges of the detected targets and fusion of the location estimates provided by each sensor, resulting in refined target tracks. The proposed method is verified in a realistic scenario with three moving persons. The results show that UWB sensors can be used as complimentary technology for multiple moving target tracking.

Index Terms—UWB, tracking, PHD filter, multi-target tracking.

I. INTRODUCTION

In the past decades there was a growing need for non-intrusive monitoring systems for civilian and military applications. Localization and tracking of non-cooperative targets (targets that do not carry an active tag or device to help their detection) is needed for both security and rescue applications. Optical or visual sensors have limited performance in poor visibility conditions, infrared sensors are temperature dependent and LADAR performance decreases in dusty and foggy environments. The ultra-wideband (UWB) radar technology has advantages for detection and localization of moving objects in poor visibility, through-wall or in multipath conditions. This makes it suitable as a complimentary technology for human or other moving object detection. Due to the multipath immunity [1], it is well suited for indoor applications. It is also useful for detection of small movements such as heartbeat or respiration of a stationary person due to the high spatial precision [2]. It is suitable in search and rescue applications for detection and localization of humans trapped under rubble, snow and other non-metallic objects.

UWB sensors suffer interference from coexisting systems, shadowing in the presence of multiple targets and limited area coverage. By using multiple distributed UWB sensors the targets invisible to one sensor can be detected by another sensor of the network. The positions of the detected targets can be refined by fusing target location information from the multiple sensors [3], [4]. In this paper, when referring to UWB sensor we consider an independent UWB module with two receiving and one transmitting antenna connected to a local processing unit.

Target tracking has raised a lot of interest as a method for improving target location estimates. Single target tracking methods such as Kalman filter are widely used since the 1960s. Multiple target tracking (MTT) methods are traditionally based on observation-target data association followed by a single target tracking approach [5]–[7]. A method most commonly used for multiple target tracking is the multiple hypothesis tracking (MHT) [8], [9]. Based on threshold heuristics, each observation is either associated to an existing target, or it is considered to be a detection of a new target or false alarm. It is a solid approach with computational and combinatorial load increasing exponentially with the number of targets due to the observation-target data association step and the propagation of multiple hypothesis.

Following the work of Mahler [10], there has been increasing interest in applying finite set statistics (FISST) to Bayesian MTT. It allows for tracking unknown, time-variant number of targets in the presence of false alarms, miss-detections and clutter. Approximation of the Bayesian MTT represented as a random finite set (RFS) by its first order moment leads to the probability hypothesis density (PHD) filter [10]. Two possible implementations of the PHD filter are found in literature, the Gaussian mixture approach (GM-PHD) [11] and the Sequential Monte-Carlo approach (SMC-PHD) [12]. The first implementation is a closed-form solution for linear Gaussian target dynamics, and is easier for implementation in MTT context since the target states are simply represented by the Gaussian mixture components. The second approach requires extraction of the target states from the posterior target density represented by a number of particles. Typically clustering techniques are applied [13], [14].

Target localization and tracking based on UWB radar technology has been investigated before for single targets and by using a single UWB radar [15]–[18]. In [19] multiple target localization and tracking by using measurement-target data association and a Kalman filter bank is presented. Similarly, multiple sensor multiple target localization based on a simplification assumption of single target detection per sensor and sensor data fusion based on imaging is presented in [20].
We use a sensor network as in [20] without the limitation of a single target detection per sensor. Targets are localized by each sensor using a time-of-flight (ToF) information i.e. the time needed for a transmitted electromagnetic signal to reflect of a target and its backscattered echo to be received by the sensors’ receivers. Since persons are used as targets, we have the case of extended target detection which means that each target is detected by multiple ToF values. Noise, clutter, miss-detections and false alarms influence the ToF values. By applying GM-PHD filter before sensor information fusion most clutter and false alarms are removed, however this also results in loss of some target information. The information loss is insignificant compared to the benefits of false information reduction for further processing. The estimated ToF target information from both receivers of each sensor is used to estimate target locations with respect to that sensor. These locations are then fused together to result in a two dimensional target location estimation. The ToF information of all sensors can also be fused together directly by using a likelihood function. Although this method is more prone to target information loss, it can lead to “ghost” tracks due to the multiple possible combinations. In this paper we concentrate on the first method, which is more immune to the “ghost” tracks.

The rest of the paper is structured as follows. Section II gives a description of the sensor network and scenario considered. A short overview of the GM-PHD filter implementation is given in Section III. The proposed MTT method is explained in Section IV. In Section V the verification measurement scenario and results are presented and finally conclusions are derived in Section VI.

II. DISTRIBUTED UWB SENSOR NETWORK

Since UWB needs to share its spectrum with other existing communication systems which transmit at higher power levels, it may suffer from some interference. In addition, for the application of multiple target localization, an UWB radar sensor capabilities may be hindered by the presence of a target very close to the sensor which causes shadowing over the other targets in the scenario. This target attenuates the propagated electromagnetic wave, preventing the sensor from detecting target echoes by any other target. By using a network of distributed UWB sensors, the multiple target detection and localization is improved by fusing the target information available by all sensors. Targets are observed from different angles, resulting in more target information available for localization.

Depending on the application, a distributed UWB sensor network can be defined in different ways. A multi-static structure uses multiple widely distributed and synchronized cooperating sensor nodes. Each node’s position can be estimated (and tracked in case of moving nodes) with regard to anchor nodes placed in strategic positions around the area of interest. Another sensor structure is defined by using stand-alone bistatic bat-type UWB radar sensors [4]. This means that each sensor consists of two receivers placed in a linear array with a transmitting antenna placed in the middle of them. The antennas are connected to an UWB radar module which in turn is connected to a local processing unit. The sensor nodes are stationary and able to autonomously localize the detected targets. There is no direct synchronization between the sensors since each module is controlled by an independent RF clock. For the scope of this paper we assume that the sensor locations are known. The fusion node is responsible for sensor node discovery and control, as well as for the final fusion of the target locations.

Since the targets of interest are non-cooperative, the ToF information by each sensor receiver is used for localization. Having two receivers, and directional antennas directed toward the area of interest, the target locations can be calculated analytically. Once targets are detected by a sensor, the detections are locally processed to result in target range estimates, which are then fused together by the fusion node to result in final target locations. A similar sensor arrangement is used in [20].

III. TARGET TRACKING VIA GM-PHD

The target tracking problem can be summarized as an estimation of the number of targets and their states (locations) at each point in time using a set of noisy measurements and the information of the previous target states. In FISST terminology, at a given time $t$, the RFS of targets states is $X_t = \{x^{(i)}_t\}_{i=1}^{N_x,t}$ and the RFS of measurements is $Z_t = \{z^{(i)}_t\}_{i=1}^{N_z,t}$, where $N_{x,t}$ is the estimated number of targets at time $t$ and $N_{z,t}$ is the number of available measurements at time $t$. Each $z^{(i)}_t$ is either a noisy measurement of one of the targets or a false alarm. There can be multiple measurements belonging to a single target. Each target state is represented by $x^{(i)}_t$.

A. The PHD filter

The probability hypothesis density is the first moment of the multi-target posterior distribution. It is a multi-modal distribution over the target space, where each mode, or peak, means there is a high probability of a target being present there. Since at a given time the target states are considered to be a set-valued state, it operates on single target state space and avoids the complexities arising from data association. It is not a density function and does not integrate to unity. Its integration over a finite subset of the space gives an estimated number of the targets in this subset.

In this work we use the Gaussian mixture implementation of the PHD filter similar to the one in [11]. Linear Gaussian target state dynamics is assumed for modeling the targets and the measurements

$$f_{t|t-1}(x|\xi) = N(x; F_{t|t-1} \xi, Q_{t|t-1})$$
$$g_t(z|x) = N(z; H_t x, R_t)$$

where $N(\cdot; \mathbf{m}, \mathbf{P})$ denotes a Gaussian density function with mean $\mathbf{m}$ and covariance $\mathbf{P}$, $O_{t|t-1}$ is the process noise covariance, $R_t$ is the measurement noise covariance, $F_{t|t-1}$ is the state evolution matrix, and $H_t$ is the observation matrix.

The PHD is approximated by weighted Gaussian mixtures which are projected to the next time step by prediction.
as Gaussian components describing the detected targets are given

\[ v_{t-1}(x) = \sum_{i=1}^{N_{s,t}} w_{t-1}^{(i)} N(x; m_{t-1}^{(i)}, P_{t-1}^{(i)}) \]  

(2)

where \( m_{t-1} \) and \( P_{t-1} \) are the mean and covariance of the Gaussian components representing the RFS of target states at time \( t-1 \).

The predicted intensity at time \( t \) is then

\[ v_{t|t-1}(x) = v_{S,t|t-1}(x) + \gamma_t(x) \]  

(3)

where

\[ v_{S,t|t-1}(x) = p_s \sum_{i=1}^{N_{s,t}} w_{t-1}^{(i)} N(x; m_{S,t|t-1}^{(i)}, P_{S,t|t-1}^{(i)}) \]  

(4)

\[ m_{S,t|t-1}^{(i)} = F_{t|t-1} m_{t-1}^{(i)} \]  

(5)

\[ P_{S,t|t-1}^{(i)} = F_{t|t-1} P_{t-1}^{(i)} F_{t|t-1}^T + Q_{t|t-1} \]  

(6)

is the intensity of the targets that survive from time \( t-1 \) with state independent survival probability \( p_s \) and

\[ \gamma_t(x) = \sum_{i=1}^{N_{\gamma,t}} w_{\gamma,t}^{(i)} N(x; m_{\gamma,t}^{(i)}, P_{\gamma,t}^{(i)}) \]  

(8)

is the target birth RFS intensity defined as a weighted Gaussian mixture with \( N_{\gamma,t} \) components with weight \( w_{\gamma,t}^{(i)} \), mean \( m_{\gamma,t}^{(i)} \) and covariance \( P_{\gamma,t}^{(i)} \). Target spawning is not considered, however random target birth at each time step is considered. When measurements or observations of the targets are obtained, the weights of the Gaussian mixture components are updated based on the likelihood function \( q_t(z|x) \).

Let the predicted intensity \( v_{t|t-1}(x) \) be a Gaussian mixture of the form

\[ v_{t|t-1}(x) = \sum_{i=1}^{N_{x,t|-1}} w_{t|t-1}^{(i)} N(x; m_{t|t-1}^{(i)}, P_{t|t-1}^{(i)}) \]  

(9)

with \( N_{x,t|-1} = N_{x,t} + N_{\gamma,t} \). The posterior intensity at time \( t \) is

\[ v_t(x) = (1 - p_D) v_{t|t-1}(x) + \sum_{z \in Z_t} v_{D,t}(x; z) \]  

(10)

where \( p_D \) is the state independent target detection probability and

\[ v_{D,t}(x; z) = \sum_{i=1}^{N_{x,t|-1}} w_{t}^{(i)}(z) N(x; m_{t|t-1}^{(i)}(z), P_{t|t-1}^{(i)}) \]  

(11)

is the intensity of the detected targets. The parameter of the Gaussian components describing the detected targets are given as

\[ w_t^{(i)}(z) = \frac{p_D w_{t|t-1}^{(i)} q_t^{(i)}(z)}{\lambda_c(z) + p_D \sum_{i=1}^{N_{x,t|-1}} w_{t|t-1}^{(i)} q_t^{(i)}(z)} \]  

(12)

\[ m_t^{(i)}(z) = m_{t|t-1}^{(i)} + K_t^{(i)} (z - H_t m_{t|t-1}^{(i)}) \]  

(13)

\[ P_t^{(i)} = [I - K_t^{(i)} H_t] P_{t|t-1}^{(i)} \]  

(14)

with \( \lambda_c(z) \) is the clutter intensity.

The components with a weight below a predefined truncation threshold \( \tau_{\text{trunc}} \) are eliminated and the components within a small distance of each other are merged together. The Gaussian mixture components with weight above a confirmation threshold \( \tau_c \) (typically 0.5) are considered for target state estimation, and their mean component is considered as the target state estimate. The number of targets is estimated by the sum of the weights of the Gaussian mixture components used for target state estimation.

\[ S_t^{(i)} = H_t P_{t|t-1}^{(i)} H_t^T + R_t \]  

(15)

\[ K_t^{(i)} = P_{t|t-1}^{(i)} H_t^T \frac{S_t^{(i)}}{S_t^{(i)}} \]  

(16)

\[ q_t^{(i)}(z) = N(z; H_t m_{t|t-1}, S_t^{(i)}) \]  

(17)

B. State and measurement models

In our application we apply the PHD filter twice: first for pre-filtering range estimates and then for fusing the location estimates together. In the first case the target state consists of a target range and velocity with respect to the sensor i.e.

\[ x = [r \dot{r}]^T \]  

(18)

The classical constant velocity model is used

\[ F_{t|t-1} = \begin{pmatrix} 1 & dt \\ 0 & 1 \end{pmatrix} \]  

with \( dt \) being the time interval between two measurements and is different for each sensor depending on the measurement rate used. The observations consist of the ToF values represented as target range measurements

\[ H_t = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \]  

In the second case the target state consists of the Cartesian position and velocity vector of the target:

\[ x = [x \dot{x} y \dot{y}]^T \]  

(19)

and the observations are the target Cartesian coordinates calculated analytically by each sensor node as described in Section IV-C

\[ H_t = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & dt \end{pmatrix} \]  

with \( dt \) being the time interval between two measurements for the slowest sensor node.
IV. THE UWB MULTI-SENSOR MULTI-TARGET TRACKING METHOD

The method described in this section consists of multiple algorithms. The data received by each receiver of each sensor goes through the target detection and range estimation stage. The estimated ranges with the information of the identity of the respective receiver are then sent to the fusion node, where target locations are calculated and fused together to result in final target locations and tracks. In Fig. 1, we show the processing done on a measured impulse response starting from raw measurement until the target ranges are estimated. The impulse response in the figure is from a measurement taken by one of the receivers of an UWB sensor in the presence of two moving targets. The ToF of the two targets is approximately 21 ns and 60 ns, respectively.

![Normalized measured impulse response](image)

**Fig. 1.** Target echo detection - measured impulse response (blue), normalized signal magnitude after background subtraction (green), CFAR test statistic (red), CFAR adaptive threshold (cyan), indexes of detected targets by CFAR (magenta) and Gaussian mixtures representing the estimated target ranges (black) are shown.

The received impulse response is shown in dark blue. As can be seen, the targets’ echoes are not detectable. After we apply a background subtraction algorithm as described in Section IV-A, the resulting signal emphasizes the target echoes (shown in green in Fig. 1). For estimating the ranges of the targets we first use a constant false alarm rate (CFAR) algorithm as explained in Section IV-B. In Fig. 1 the adaptive threshold is shown in cyan and the multiple range estimates per target are shown in magenta. As can be seen in the figure, there is one false target detection around 77 ns. After applying the GM-PHD algorithm and the subsequent Gaussian component merging and pruning as explained in Section III, only two Gaussian components remain to represent the states of the detected targets, as shown in Fig. 1 in black.

A. Detection of targets

Each sensor of the network performs a target detection stage using the backscattered electromagnetic wave. The target echoes are very weak compared to the strong multipath signals such as the direct Tx-Rx feed and the reflections of dominant or metallic objects. However, these signals are usually time-invariant, and since the sensors are static they can be estimated using a sequence of impulse responses. The estimated background can then be subtracted from the received impulse response to result in a signal where the weak target echoes can be more easily detected. Different approaches for background subtraction have been suggested in the literature [21], [22]. We use a method based on exponential averaging as in [15]. The background estimate as seen by receiver $i$ of sensor $s$ at time $t$, $b_{i}^{s,i}$, is computed using the previous background estimate $b_{i-1}^{s,i}$ and the newly received impulse response $m_{i}^{s,i}$

$$b_{i}^{s,i} = \kappa b_{i-1}^{s,i} + (1 - \kappa) m_{i}^{s,i}$$  \hspace{1cm} (20)

with $\kappa$ being a constant scalar weighting (or forgetting) factor between 0 and 1. This factor determines whether recent or long-term events are emphasized. The signal of interest is then

$$s_{i}^{s,i} = m_{i}^{s,i} - b_{i}^{s,i}$$  \hspace{1cm} (21)

B. Range estimation of targets

Once the background has been subtracted from the received impulse response, the range information of the detected targets should be extracted. For this purpose we use a Gaussian adaptive threshold CFAR method as in [23]. A Neyman-Pearson detector is used to discriminate between noise and target echo, and the adaptive threshold is determined using exponential weighted moving average (EWMA) filter. First a test statistic $X$ is defined using an EWMA over the unbiased, normalized signal magnitude. The background $Y$ is estimated using a slower moving EWMA over the signal magnitude and the signal variance $\sigma^{2}$ is defined by using the same slow-moving EWMA filter over the signal energy. The adaptive threshold is then computed using

$$\theta = \alpha \sigma + Y$$  \hspace{1cm} (22)

where $\alpha$ satisfies

$$P_{FA} = 1 - \int_{-\infty}^{\alpha} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^{2}} dx$$  \hspace{1cm} (23)

for a given false alarm rate $P_{FA}$. The calculated threshold $\theta$ is then used to define the output of the CFAR detector as

$$H(X) = \begin{cases} 1 & \text{if } X > \theta \\ 0 & \text{if } X \leq \theta \end{cases}$$

The resulting binary sequence is used to define the time indexes of the signal when a target has been detected (the indexes of the 1’s). This in turn gives us the time of flight (ToF) information. The range of target $k$ at time $t$ detected by sensor $s$ using receiver $i$ is defined as the distance from the transmitter to the target, $d_{Tx,k,t}$ plus the distance from the target to receiver $i$, $d_{Rx,k,t}$. It is calculated using the ToF, $\tau_{x,k,t}^{s,i}$

$$\tau_{x,k,t}^{s,i} = d_{Tx,k,t} + d_{Rx,k,t} = \tau_{x,k,t}^{s,i} c$$  \hspace{1cm} (24)

where $c$ is the speed of light.
The performance of the detector depends on the false alarm rate and the choice of parameters for the EWMA filters. Although these parameters can be adjusted, depending on the position, quality and direction of the sensors, some clutter points will still be classified as targets. These false positives hinder the target localization and should be removed to improve it. In addition to the false-positives, due to the extended nature of the targets, there are multiple detections available for each target. One possibility to deal with the multiple detections is to model or define the extent of the targets of interest. In our case this raises some difficulties since targets further from the sensors (especially the third or further detected target at a given time) are represented by much less observations compared to the targets closer (or detected first) by the sensor.

To improve the target range estimates and remove clutter, a GM-PHD filter as explained in Section III is applied on the CFAR range detections. The target states are defined by the target’s range and velocity with respect to the sensor, $\mathbf{x} = [r \ \dot{r}]^T$, whereas the observations used for state update are the CFAR range detections.

C. Target localization

Typically, a target is detected by both receivers of a respective sensor. This means that for each target detected by the sensor, range information with respect to both receivers is available. By choosing the right range estimates available from both receivers corresponding to the same target, it’s location can be calculated analytically. A target range estimate defines an ellipse whose focal points are determined by the location of the transmitting and the respective receiving antenna. This ellipse represents all possible locations a target can have around the sensor for the given range. Having the range estimate of the same target with respect to the other receiver of the sensor, another similar ellipse is defined. This reduces the possible target location to the ellipse intersection points. Since the ellipses share one foci and all foci lie on the same line, the number of possible ellipse intersections is maximum two. In addition, the sensor direction is also known, which helps in choosing the ellipse intersection that lies in the correct half-plane as the target location.

When there is only one target, in theory there is only one range estimate per receiver, leading to only one possible ellipse intersection for the target location. However, when multiple targets are detected, there are multiple possible combinations of range estimates. Ellipse intersection calculation is computationally expensive and time consuming, thus we associate the range estimates from both receivers that correspond to the same target before calculating all possible ellipse intersections.

For each sensor we define an intersection threshold. It is defined as the maximum possible difference between range estimates of the same target but with respect to the different receivers, such that the target lies in the inspected area $A$ (see (25)). The size of the inspected area is known (at least approximately due to the sensor locations) leading to calculation of the intersection threshold $T_s$ once before the start of the procedure

$$T_s = \max_{k \in A} |r_{k,1}^{s,1} - r_{k,2}^{s,2}|$$

(25)

For each range estimate available from the first receiver, $r_{k,1}^{s,1}$, we choose the range estimate from the second receiver, $r_{k,2}^{s,2}$, which satisfies

$$|r_{k,1}^{s,1} - r_{k,2}^{s,2}| \leq T_s$$

(26)

as a range estimate that belongs to the same target. When multiple range estimates that satisfy (26) are available, the estimate, with which the absolute difference is the smallest, is chosen. The target location is then estimated by calculating the intersection of the ellipses defined by the range estimates found to correspond to the same target.

The above association does not only reduce the computational load, but it also helps in reducing ghost location estimates. Ghost location estimates may result due to intersection of ellipses defined by ranges belonging to different targets, or by choosing multiple intersections of one ellipse with the other ellipses.

D. Sensor data fusion

The estimated target locations by each sensor are finally fused together resulting in a single target location per target. The estimated target locations using the analytical method contain significant amount of noise due to the small errors in the range estimation procedure. These location estimates are used as noisy observations of the targets in the scenario, and a simplified GM-PHD filter is applied for fusing these noisy observations from all sensors and result in final target location estimates for all targets in the scenario. The target state is defined by the two dimensional Cartesian target coordinates and velocity vector, $\mathbf{x} = [x \ \dot{x} \ y \ \dot{y}]^T$.

V. MEASUREMENT RESULTS

A. Measurement setup

A sensor network constellation as shown in Fig. 2 is used for verification of the proposed method. Six similar UWB sensors are used, five of which are placed inside the room with the targets and one is placed behind one of the walls. Each module has one transmitter and two receivers perfectly synchronized on the platform driven by a digital resonance oscillator. The sensors are driven by different clocks and have a different measurement rate. Four sensors (1,3,5 and 6 in Fig. 2) have a 7 GHz clock and measurement rate of about 25 impulse responses per second, one (Sensor 2) has a 9 GHz clock and measurement rate of about 6.25 impulse responses per second, and the last one (Sensor 4) has a 4.5 GHz clock and measurement rate of about 12.5 impulse responses per second. The antennas used on the sensors are directional horn antennas with different size and quality resulting in varying sensor performance with respect to data quality. The UWB module of the sensors is connected to a local PC where the measured impulse responses are stored. There is no synchronization or cooperation between the sensors. The processing is later done.
off-line using MATLAB. The measurements were taken in our university foyer with most of its furniture removed. The sensor locations are measured in advance. A scenario with three targets moving in a straight line towards a wall and back is used. One target moves from the vicinity of sensor 5 toward the opposite wall and back to its original position. The other two targets move parallel with respect to each other, one from vicinity of Sensor 3 and the other from the vicinity of Sensor 4, toward the opposite wall and back. The starting position of the targets and the direction of the initial movement is shown in Fig. 2 by the gray circles and arrows for initial movement direction. The same scenario was used in [20].

B. Method verification

In this section we present the results obtained from processing the measured data using the proposed method. The normalized impulse responses after background subtraction are shown in Fig. 3. The horizontal axis of the figure represents the measurement time and the vertical axis is the sensor range. The color is related to the normalized magnitude of the impulse response. It can be seen that when a target is very close to a sensor, it completely shadows the other targets from the scenario. This is explained by the fact that a target in close vicinity of the transmitting antenna attenuates the electromagnetic signal. When the target closest to a given sensor is further from it, the electromagnetic wave is propagated around in the inspected area, and part of it reaches the other moving targets. However, a target positioned behind another target with respect to the sensor is shadowed since only a very small attenuated signal reaches it. For reducing the shadowing influence of targets close to a sensor, the sensor antennas can be placed on an elevated surface with a skewed viewing angle toward the scenario.

Next the CFAR range detection algorithm is applied on the impulse responses processed by the background subtraction. Fig. 4 shows the ranges estimated for Sensor 1 and 6. Due to the nature of the data, the range of the closest target is best detected, whereas the other two targets are mostly invisible.

This is due to the fact that the sensors were positioned with around 1 meter elevation from the ground, and when a target was close to the sensor, the other targets were mainly invisible.

![Fig. 2. The verification scenario](image1)

![Fig. 3. Moving target signal echoes as seen by Sensor 1](image2)

![Fig. 4. Ranges detected by GM-PHD for a) Sensor 1 and b) Sensor 6](image3)
By applying the PHD filter, we remove most of the clutter points and the multiple detections per target are reduced to one (Fig 5).

The estimated ranges related to the two receivers of each sensor are used to calculate the location estimates. Each location estimate is a probable location of one of the targets the sensor could detect. Fig. 6a shows the location estimates for each sensor for half of the measurement time. The different colors represent the locations estimated by the different sensors. It can be noticed that for each sensor, the closest target has the least noisy location estimate. This is due to the geometrical dilution of precision. The estimated locations by each of the sensors are fused together to compliment each other and arrive at a more precise location estimates for the target in the room. As can be seen in Fig. 6b, the target tracks are much more clear after the location information fusion.

VI. CONCLUSION AND FUTURE WORK

Target localization for surveillance, security and rescue applications can be complimented by UWB technology due to it’s immunity to visual, temperature, humidity and other interferences. In this paper we described a method for localization and tracking of multiple moving targets by using multiple UWB radar sensors. Each sensor has a transmitter and two receivers and is thus capable of autonomous target localization in 2D. The method is applicable for intruder detection and localization since it does not require cooperation of the targets with the sensor network. It is implemented and optimized for on-line real-time application. For verification, data measured by six independent M-sequence UWB radar sensors in the presence of three moving persons is used. The data analysis show that the detected targets can be accurately localized.

The proposed method can be improved by using the sensor information of the target location which has been discarded in the target localization stage. Direct fusion of the target range estimates using belief functions is considered. However, since this method suffers from ghost track detections, solutions for ghost track elimination should be first investigated. The method performance can be improved by using Cardinalized PHD filter and iterative multiple movement models.
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