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Heterogeneous multi-sensor fusion with GMPHD for Obstacle Detection in mobility systems

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Abstract: Obstacle detection is an essential process in Autonomous mobility systems such as driverless car and drone for delivery, and it has become a popular topic in this decade with the blooming of various object detection algorithms and the enhancement of sensor quality. On top of that, the problem of improvement ability of sensor fusion with regard to clutter and miss detection based on the incoming measurements from several type of sensors on autonomous mobility system are critical for those systems to track the final position of the obstacle accurately. To solve the problem in computationally efficient way, this paper presents the integration techniques and the performance of heterogeneous sensor fusion with Gaussian mixture probability hypothesis density (GMPHD) in the application of mobility systems or driverless system. We introduce the concept of integrating GMPHD to heterogeneous sensor fusion with three architectures, Track-to-Track-Fusion (T2TF), Measurement-to-Track-Fusion (M2TF) and Track-to-Association-Fusion (T2AF) and further evaluate their performance respectively in terms of fusion improvement ability with the simulation dataset that reproduces normal condition and poor condition with the degradation of sensors' performance.

Keywords: Obstacle detection, Mobility systems, GMPHD, Heterogeneous sensor fusion, T2TF, M2TF, T2AF

1. Introduction

In autonomous driving, the full and precise comprehension of obstacle position is of paramount importance for autonomous mobility systems to make a proper driving decision to maneuver the car safely to a destination. To strengthen the obstacle detection dedicated for autonomous vehicle under adverse circumstances that worsen some sensors' detection ability, the standard sensor system with several type of sensors including camera, Lidar and millimeter wave Radar has been proposed in the past to compensate for the deficiencies of each sensor and fulfil the detection requirement accordingly [1], [2] Even though such system with heterogeneous sensors could well assist itself to acquire necessary measurements for detecting the surrounding obstacle, the perfect comprehension of the obstacle with such deployment has been more challenging when the performance of sensors are subject to the environmental influence and it becomes unreliable due to the existence of clutter, scattering miss detection and other restraints of sensors' abilities such as the measurement error and narrow Field of View (FOV). In other words, the reliability of those collected datasets for the system is lower and there are still several arduous issues to deal with and enhance the reliability such as adapting moving environment in mobility system, reducing the false alarm, estimating the accurate positions of the objects as well as interpolating the missed detection. Therefore, sensor fusion with heterogenous sensors has become a prominent subject to resolve the association between incoming measurements from diverse types of sensor for tolerance of sudden change of sensor properties due to environmental influence.

In this decade, several researches regarding sensor fusion with Gaussian mixture probability hypothesis density (GMPHD) are ongoing to solve the above detection reliability problem. [3], [12] GMPHD is attributed to a new emerging paradigm of Random Finite Set (RFS) based on the rigorous mathematical foundation for stochastic multi-object problems—point process theory [4]. Among all prevalent RFS-based algorithms, GMPHD demands relatively low computational load and does not require data association techniques to obtain a closed-form PHD recursion.[5] Thus, it was chosen as our primary approach to developing multi-object tracking based sensor fusion. Our contribution in this paper is to propose architectures with integrating GMPHD to address those heterogenous senor fusion problems in application of mobility system with a significant improvement to perceive the correct position of obstacle and counteract the fault of each sensor under adverse environments which lower detection rates of some sensors for autonomous mobility systems. And we further study its applicability to heterogeneous sensor fusion in mobility system at different moving speed to find out if they could enhance the detection performance with our approaches in terms of improvement rate in three architectures with GMPHD.

The aim of this paper is to present the integration architecture of heterogeneous sensor fusion with GMPHD in the application of mobility systems. In section 2, the selection of tracking algorithm for sensor fusion and theory of GMPHD are presented. In section 3, the detailed problems to the heterogeneous sensor fusion are illustrated to emphasize the challenges which our sensor fusion in mobility system might suffer. In section 4, three proposed architectures with GMPHD integration for heterogeneous sensor fusion are explained in terms of their implementations to unravel the fusion problem. In section 5, the simulations of different environments for mobility systems are described and the improvement effectiveness of three architectures for sensor fusion under suggested environmental influence are examined respectively. In section 6, related work to the problem of sensor fusion and GMPHD are presented.

2. Gaussian Mixture Probability Hypothesis Density for sensor fusion

2.1 The selection of tracking Algorithms for sensor fusion

There are several popular data association approaches for

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tracking algorithms available in the past. The general ways include Global nearest neighbor (GNN), joint probability data association (JPDA) and Multiple hypothesis tracking (MHT). Despite the availability of the existing association approaches, the computational cost and the tracking performance are the concerned issues that we are facing, and many researchers tried to solve the problem by balancing these two aspects. For instances, classical MHT demands enormous computational resource due to accumulation of hypothesis from pedigree even though it has more superior performance than JPDA and GNN and comparable to state-of-the-art methods in recent years [16]. As a result, considerable techniques to handle its computational problem in MHT had been proposed. For examples, Fast MHT algorithm [17] endeavored to resolve the computational intractability issue in MHT, the rollout algorithm [18] tried to overpass the time efficiency of MHT, Tabu search and Gibbs sampling [19] enhanced the tracking performance and improved the computational efficiency in MHT. The similar problem also happens in JPDA even though JPDA is considered as the approach which has worse tracking performance but better computational efficiency due to its fewer combinatorial complexity than MHT. One of the papers proposed a JPDA embedment with simple tracking framework to reduce its processing time [20]. For GNN, it requires the least computational cost, but it could only perform well in less clutter environment. Therefore, GNN data association are only adopted for simple case with few clutters from the data measurements and some researchers proposed Suboptimal Nearest Neighbor (SNN) to improve the tracking performance of GNN-based method [21].

As data association involves the tradeoff between computational cost and implementation complexity, the tracking algorithm with good balance are therefore the critical criteria for our selection of sensor fusion algorithm to support large amount of incoming measurements. On the other hand, the approaches of those associations require the presumed number of targets to estimate the object position accurately. Because of that, we only focus on RFS-based GMPHD algorithm prominent in this decade without the need of providing unknown object numbers in this paper.

2.2 The theory of Gaussian Mixture Probability Hypothesis Density for sensor fusion

GMPHD is an analytic solution to the PHD recursion under Gaussian assumption and PHD is an approximation to multitarget Bayes filter with the first order statistical moment of the multi-target posterior density [22]. The derivation of PHD filter is at first provided to understand its fundamental concept before moving on to its approximation in the view of computational tractability.

Suppose the random finite set for multi-target (estimation target) set X_k and multi-target observation (measurement) set Z_k at time k are as follows [6],

$$X_k = \{ x_{k,1}, x_{k,2}, \dots, x_{k,M(k)} \} \epsilon \mathcal{F}(\chi) \quad (1)$$

$$Z_k = \{ z_{k,1}, z_{k,2}, \dots, z_{k,N(k)} \} \epsilon \mathcal{F}(Z) \quad (2)$$

where $\mathcal{F}(\chi)$ is the collections of all finite subsets of target states χ with M(k) states and $\mathcal{F}(Z)$ is the collections of all finite subsets of observation states Z with N(k) states. Each target $x_{k-1,\cdot}$ in multi-target set X_{k-1} generates a Bernoulli RFS $S_{k|k-1}(x_{k-1})$ at time k with survival probability $p_{S,k}(x_{k-1})$ and new targets at time k are modeled by an RFS of spontaneous births Γ_k. Hence, the multi-target state X_k at time k according to the previous state X_{k-1} [5], [6],

$$X_k = \bigcup_{x_{k-1} \in X_{k-1}} S_{k|k-1}(x_{k-1}) \cup \Gamma_k \quad (3)$$

Similarly, each measurement $z_{k,\cdot}$ in observation set Z_k is generated by Bernoulli RFS $D_k(x_k)$ with detection probability $p_{D,k}(x_k)$ based on each target x_k in the set X_k at time k and spurious measurement set F_k [5], [6],

$$Z_k = \bigcup_{x_k \in X_k} D_k(x_k) \cup F_k \quad (4)$$

Based on the theory of Bayes recursion with multi-target set X_k and multi-target observation set Z_k at time k, the optimal multitarget Bayes filter is derived given by the recursion as follows,

$$\begin{aligned} &p_{k|k-1}(X_k|Z_{1:k-1}) \\ &= \int f_{k|k-1}(X_k|X) p_{k-1}(X|Z_{1:k-1}) \mu_s(dX) \end{aligned} \quad (5)$$

$$p_k(X_k|Z_{1:k}) = \frac{g_k(Z_k|X_k) p_{k|k-1}(X|Z_{1:k-1})}{\int g_k(Z_k|X) p_{k|k-1}(X|Z_{1:k-1}) \mu_s(dX)} \quad (6)$$

where $p_k(\cdot|Z_{1:k})$ is the multi-target posterior density, $p_{k|k-1}(\cdot|\cdot)$ is the multi-target prior density $f_{k|k-1}(\cdot|\cdot)$ is the multi-target transition density, $g_{k|k-1}(\cdot|\cdot)$ is the multi-target likelihood and μ_s is an appropriate reference measure on the subset F_k [6], [23].

However, multi-target Bayes filter is computationally intractable and it only works when the number of target is small [6], [24], various approximations such as Sequential Monte Carlo (SMC), Cardinalized probability hypothesis density (CPHD), multi-Bernoulli, PHD and Dynamic factorization have been proposed in the past [23], [25], [26]. As PHD is more mature, swifter and more computationally efficient compared to the rest of other existing approximation tactics [5], [23], [25], [27], we only remark this filter and further elaborate it under the linear Gaussian multi-target model.

The PHD filter propagates a first order of statistical moment of the multi-target posterior [22] with the theory of finite-set statistics (FISST) to approximate the optimal multitarget Bayes filtering in the recursion (5) and (6). FISST is a systematic, unified and intuitive approach to multi-sensor-multi-target detection, tracking and information fusion based on the mathematical foundation for stochastic multi-object problems, point process theory [4], [28]. Thus, the following approximated intensities v_k and $\mathrm{v}_{k|k-1}$ are approximated with the first moment of multi-target posterior density p_k from equation (6) and multi-target predicted density $\mathrm{p}_{k|k-1}$ from equation (5) respectively through PHD recursion,

$$\begin{aligned} v_{k|k-1}(x) = &\int p_{S,k}(x_{k-1}) f_{k|k-1}(x_k|x_{k-1}) v_{k-1} dx_{k-1} \\ &+ \gamma_k(x_k) \end{aligned} \quad (7)$$

$$\begin{aligned} &v_k(x) \\ &= [1 - p_{D,k}(x_k)] v_{k|k-1}(x_k) \\ &+ \sum_{z \in Z_k} \frac{p_{D,k}(x_k) g_k(z|x_k) v_{k|k-1}(x_k)}{\kappa_k(z) + \int p_{D,k}(x_{k-1}) g_k(z|x_{k-1}) v_{k|k-1}(x_{k-1}) dx_{k-1}} \end{aligned} \quad (8)$$

where $f_{k|k-1}(\cdot|\cdot)$ is the multi-target transition density, $g_{k|k-1}(\cdot|\cdot)$ is the multi-target likelihood, $p_{S,k}(x_{k-1})$ is a survival probability at time k given state x at previous time k-1,

$p_{D,k}(x)$ is a detection probability given state x at time k, $\kappa_k(z)$ is an intensity of clutter RFS F_k and $\gamma_k(x)$ is an intensity of the birth RFS Γ_k [5], [6]. From equations (7) and (8), its approximation based on FISST demonstrates the computationally cheaper approach without combinatorial computations from unknown association of the Bernoulli RFS [6]. However, PHD filter does not offer any closed-form solution and suffers curse of dimensionality due to complexity of numerical integration [6], [29].

To obtain the closed form solution, particle PHD filters such as Auxiliary particle PHD filter [30] and SMC-PHD filter are developed in the past. They suffer from demanding computational cost even though they support highly nonlinear problems. For this reason, we rule out the approach of particle PHD filters and adopt GMPHD which is closed form solution to PHD recursion under the linear Gaussian multitarget model. Equations (9) and (10) shows the Gaussian approximation of equations (7) and (8).

$$v_{k-1}(x) = \sum_{i=1}^{J_{k-1}} w_{k-1}^{(i)} N(x; m_{k-1}^{i}, P_{k-1}^{(i)}) \tag{9}$$

$$v_k(x) = \sum_{i=1}^{J_{k-1}} w_{k-1}^{(i)} N(x; m_{k|k-1}^{i}, P_{k|k-1}^{(i)}) \tag{10}$$

Where, w is the weight of Gaussian distribution and $N(\cdot;$ m, P) represents a Gaussian density with mean m and covariance P and J is the number of components of the intensity. For simplicity, standard Kalman filter with both linear prediction model and linear update model for each sensor is exploited in this paper to acquire the closed form solution of Bayes filtering recursion under the assumption of linear Gaussian model for equations (9) and (10).

3. Problem formulation

This section presents the existing issues for the development of multi-target tracking-based heterogeneous sensor fusion. In section 3.1, we define the system requirements of heterogenous senor fusion to explain the goal of desirable sensor fusion. In section 3.2, the problems in heterogeneous Sensor fusion architectures with GMPHD are explained.

3.1 The requirements of heterogeneous sensor fusion

3.1.1 Improvement ability of sensor fusion in mobility system

The tracking-based algorithm in the local tracking and sensor fusion layer function as a role of jointly estimating the number of targets and recovering their trajectories from sensor data [5] so as to enhance detection rate and distinguish true object targets from a set of spurious measurements. Focusing on GMPHD strategy with heterogeneous sensor fusion on mobility systems, the requirement for the sensor fusion is that it could still maintain the fair improvement ability of any erroneous detection in the higher speed environment of mobility system.

3.1.2 Adaptivity to adverse scenario

In mobility systems, the illumination of environment fluctuates due to bad weather and operation area. This issue leads to the degradation of some optical sensor performance. As the sensor properties cannot be stably controlled and change unpredictably in reality due to the adverse influence from surrounding environment, this become our concerned problem for the improvement ability of heterogenous sensor fusion with default GMPHD and pre-defined model for the sudden sensor properties change. For example, the camera on mobility systems often cannot work well in dark tunnel but radioactive sensors such as radar and lidar usually function well instead. We would like our sensor fusion is still able to improve the detection error effectively under adverse condition.

3.2 Problems in heterogeneous Sensor fusion architectures

For multi-sensor fusion, the fusion architectures do not only influence the communication efficiency owing to the bandwidth requirement but also error certainty estimation and information correlation between measurements. There are two mainstream architecture of sensor fusion in the past, Centralized fusion architectures and Hierarchical fusion architectures. Centralized fusion architectures transmit the raw measurements from each deployed sensor directly to a global fusion node. (shown in figure 1) They provide local stovepiped processing centers that limit network-centric development [15].

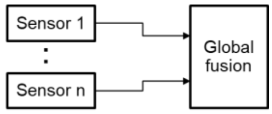

Figure 1. the structure of centralized fusion architecture

Hierarchical architectures combine all the track estimates from each local centralized fusion processing nodes, forming a subordinate–superior relationship [15]. (shown in Figure 2) This relationship forms the robust technique which further abates the estimation error and enhance the tracking performance.

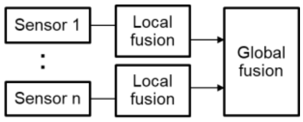

Figure 2. the structure of hierarchical fusion architecture

Despite the availability of these architectures' foundation, the first challenging problem is to handle the problem of adaptive architecture for heterogeneous sensors fusion with GMPHD in mobility systems due to operation speed and adverse scenario mentioned in 3.1. As the velocity of the first appearance object is far from zero for the problem of mobility speed, GMPHD models from the majority of existing methods such as [13] for stationary environment is no longer sensitive and with default setups from the current literature.

For the proposed methods with GMPHD in the past with only homogenous sensor required, only same prediction models and update models are needed usually without any change. Therefore, no special arrangement in such architecture is indispensable for better fusion performance as same models could cater well for only single sensor with the good consistency in local and global track estimation. However, the problem become tremendously challenging when it comes to heterogenous sensors and no current works address the architecture problem for heterogenous sensor with GMPHD. For the case of heterogenous sensors, the composition of architecture to satisfy different properties of sensors becomes complicated because of same global fusion track with incoming raw measurements or local track from the different types of sensors with variant FOV, clutter rate, error covariance and detection rate. Furthermore, the synchronization fusion order for those different prediction and update models based on sensor properties in the architecture is also the issue that influentially worsen the detection performance.

Therefore, opting the most proper architecture and the techniques of the fusion management are significant issues to enhance the fusion performance of the tracking estimation and address the adaptability of operation speed and adverse scenario.

4. Proposed architectures for the integration of GMPHD to heterogeneous sensor fusion

In this section, the details and the implementation concerns of three proposed architectures M2TF, T2TF and T2AF based on the fundamental fusion architectures with the integration of GMPHD in Kalman filter to heterogeneous sensors are presented. In each GMPHD with Kalman filter, the dedication of designing Gaussian components in two models based on equations (9) and (10), prediction and update models, are especially focused in this section.

4.1 Measurement-to-track heterogeneous sensor fusion (M2TF) with GMPHD integration

The structure of measurement-to-track fusion (M2TF) is illustrated in Figure 4 based on Centralized fusion architectures with GMPHD algorithm. In this architecture, the raw measurements from each type of sensor at each time step are sequentially fed into GMPHD algorithm.

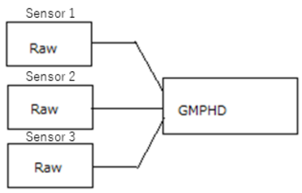

Figure 4. the structure of measurement-to-track fusion with GMPHD integration

Since this architecture with GMPHD does not require data association to group the corresponding measurements for each of the same target object, the asynchronistic models are exploited and the raw measurements from each type of sensor at each time step update the global fusion track sequentially as shown in Figure 5.

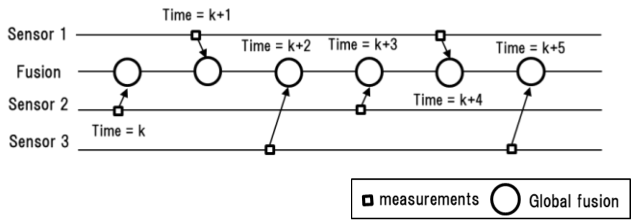

Figure 5. the measurement management of measurement-to-track fusion with GMPHD integration

In M2TF architecture, only single GMPHD for global fusion is required. The challenging part of this architecture is to build up two essential models for accurate global fusion with the implementation of GMPHD for heterogeneous sensors on non-stationary mobility system, global prediction model based on equation (9) and global update model based on equation (10).

For global prediction modeling, birth gaussian components based on the corresponding sensors' FOV of incoming measurement are appended into global track. The velocity of each birth component should be same as the speed of mobility systems when the first appearance point is most likely to vary based on current velocity of mobility system. The survival rate and prediction error covariance remain the same throughout the whole estimation. However, survival rate should not be too low, and the target states are supposed to survive for certain period even though other types of sensors might not successfully capture the object due to small area of FOV. In other words, only birth model change is conducted based on the sensor type of incoming measurements for each prediction step in recursion.

For global update model, the global track is retrieved for the fusion with incoming measurements. Based on the sensor type of incoming measurements, the corresponding detection rate, density of Poisson false alarm and error covariance are applied to each measurement point and update the target state correspondingly.

In this architecture, the computational requirement is lower as only single GMPHD is required to estimate all the incoming measurement from disparate sensors and no extra data association and clustering are needed.

4.2 Track-to-Track heterogeneous sensor fusion (T2TF) with GMPHD integration

The structure of track-to-track fusion (T2TF) is illustrated in Figure 6 based on Hierarchical fusion architectures with GMPHD algorithm. In this architecture, the raw measurements from each sensor at each time step are pre-filtered with local tracking in advance given that the raw measurements are the point object.

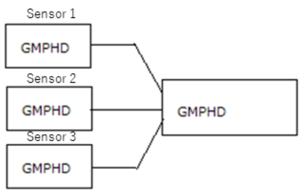

Figure 6. the structure of track-to-track fusion with GMPHD integration

Since this architecture with GMPHD does not require data association to group the corresponding measurement for the same object as M2TF structure does, the asynchronistic models are exploited and the filtered measurements from each type of sensor at each time step sequentially update the global fusion track as shown in Figure 7.

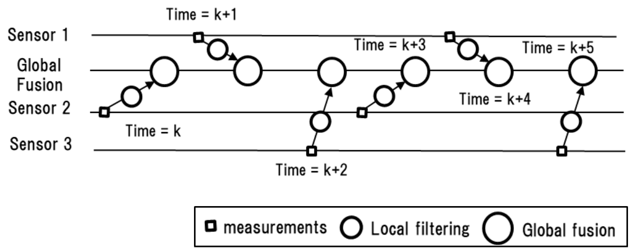

Figure 7. the measurement management of track-to-track fusion with GMPHD integration

In T2TF architecture for heterogeneous sensors on mobility system, GMPHD for local tracking and global fusion are required. In other words, the challenging part of this architecture is not only to build up prediction and update models for accurate global fusion as M2TF illustrates but also the prediction and update models in local tracking for each sensor before fusion.

For each local prediction model, birth gaussian components based on the corresponding sensors' FOV of incoming measurement are appended into local track for each sensor and the velocity of each component in first appearance tend to be the same as the speed of mobility systems. This technique further distinguishes the clutters which potentially have unalike velocity. The survival rate and prediction error covariance remain the same.

For each local update model, the local track from each sensor is retrieved for the fusion with incoming measurements. Based on the sensor type of incoming measurement, the corresponding density of Poisson false alarm and error covariance are applied to each measurement point and update the target state correspondingly.

For global prediction model, all the parameters are the same as the local prediction model based on the sensor type of incoming dataset and the speed of the mobility systems. However, more different configurations are required in the global update model. As we noticed that the local tracking dedicated for each sensor has already enhanced the local estimate track by reducing clutter and improved detection rate, the corresponding detection rate would be therefore higher and the density of Poisson false alarm relatively decreases in the global update model to update the global track with incoming filtered local track from respective heterogenous sensors for fusion.

This architecture could further swiftly weed out the random clutter because of the involvement of two-step filtering and therefore we assume this architecture perform well in high Signal Noise Ratio environment.

4.3 Track-to-Association heterogeneous sensor fusion (T2AF) with GMPHD integration

The structure of track-to-association fusion (T2AF) is illustrated in Figure 8 based on Hierarchical fusion architectures with GMPHD and global fusion with data association. In this architecture, the raw measurements from each sensor at each time step are first filtered with local tracking given that the raw measurements are the point object which indicates single point per object and then sequentially fed into data association algorithm for the fusion step.

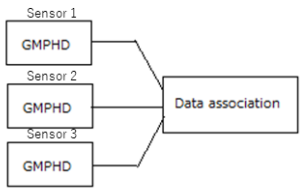

Figure 8. the structure of track-to-association fusion with GMPHD integration

Since this architecture with GMPHD requires data association in the final fusion step to group the corresponding measurement for the same target object, the synchronistic data association models are exploited and the filtered measurements from each type of sensor at each time step collectively update the global fusion track with data association as shown in Figure 9.

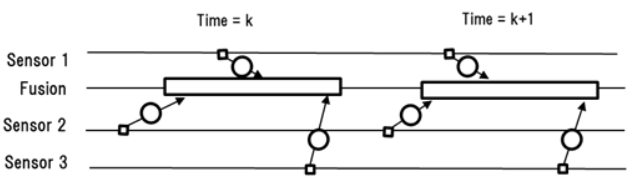

Figure 9. the measurement management of track-to-association fusion with GMPHD integration

The challenging part is to develop two models, local prediction model and local update model, for local tracking in respective heterogeneous sensors with the implementation of GMPHD.

The local prediction models are specifically built for each type of sensor. For each prediction model in local tracking in each sensor, the birth models based on FOV of respective sensors and velocity of mobility system are added to the existing local track. For each update model in local tracking of each sensor, the detection rate, the clutter rate based on density of Poisson false alarm and error covariance for local tracking are set up to update the local track as per the sensor properties. As for the global fusion, GNN is the suggested data association approach to associate the points in high Signal noise ratio environment and we assume GMPHD algorithm has already efficiently tackled almost all clutters and miss-detection issues beforehand.

The architecture requires low computational resource provided that the cheaper data association is utilized. Nevertheless, GMPHD in local tracking from each sensor plays a key role for dealing with the problem of miss detection and clutter in this architecture.

5. Simulation and Performance evaluation

5.1 Simulation environment

To determine the suitability whether our three sensor fusion architectures with GMPHD are applicable to the mobility systems, various scenarios for sensor measurements are simulated through our scripted simulation based on the consideration of these three aspects, 1. speeds of mobility system from 0km/h to 90 km/h based on the standard braking distance and the existing laws for train speed [31], [32], [33], [34] 2. natures of target obstacles with initial origins from respective sensor FOV and velocities with different directions and 3. sensor properties with camera and 2 non-optical sensors based on the prototype system in our setup.

5.2 Performance evaluation for sensor fusion

In our evaluation, generalized optimal sub-pattern assignment (GOSPA) was utilized as an indicator to evaluate the performance of tracking algorithm. The metric enables the researchers to express the penalty as an optimization over assignments instead of permutations between estimation set and ground truth compared to traditional optimal sub-pattern assignment (OSPA) [35]. As missed target and false target are the most concerned attributes for the performance of our algorithms, we decide to use GOSPA to determine how our sensor fusion architecture improves the detection performance.

Let X be ground truth set, $\hat{X}$ be the estimated set from sensor fusion and τ be the possible assignment set between X and $\hat{X}$ with combinatorial optimization algorithm such as Hungarian algorithm or auction algorithm, the GOSPA metric for $\alpha = 2$ which determines the error due to cardinality mismatch is formulated as follows,

$$d_p^{(c,2)}(X,\hat{X}) = [\min_{\gamma\in\tau}(\sum_{(i,j)\in\gamma} d(X,\hat{X})^p + \frac{c^p}{2}(|X| + |\hat{X}| - 2|\gamma|))]^{\frac{1}{p}} \qquad (12)$$

Where p represents the dimension of the L-norm and c is the maximum allowable localization error [35]. In our performance evaluation of our sensor fusion algorithms, we assigned value p as 2 and value c as 10.

To illustrate the improvement rate after sensor fusion, minimum GOSPA with less error among all the tracking results from each sensor before fusion is obtained. The improvement rate is the reduction of GOSPA in tracking result after sensor fusion over the minimum GOPSA among all sensors before fusion.

5.3 Simulation Dataset and Results

For our simulation dataset, the environment is in fulfillment of three criteria, 1. speed of mobility system, 2. moving nature of target objects and 3. sensor properties as mentioned in section 5.1. In this section, three cases with only camera detection properties change for four different speeds of mobility systems are evaluated to examine the improvement ability of the proposed architectures for sensor fusion with GMPHD. We selected the cases with camera detection properties change because the detection property of optical sensor is always subject to illumination and the mobility systems frequently encounter dark environments. Moreover, three objects are set up to move with constant velocity model and the assumption of those objects' properties for all the simulation scenes are shown as follows,

Table 1. The assumption of Objects' properties

	Initial position (m)	Velocity (m/s)
Object 1	(250, 1)	(-0.9, 0.5)
Object 2	(100, 4)	(-0.5, -1)
Object 3	(150, -6)	(-3, 0.7)

5.3.1 Evaluation of Normal case

For normal case, we consider that all the sensors perform normally and excel its general functions without any substantial influence from the surrounding environment, the parameter configurations with detection rate, FOV distance and clutter rate for each single sensor are detailed in the table 2 shown below.

Table 2. Configuration of sensor properties in normal case

	Detection rate	FOV distance	Clutter rate (clutter/frame)	Error covariance (x, y, v_x, v_y)
Camera	95%	300m	1	(10, 1, 3, 1)
Sensor 1	85%	100m	1	(3, 1, 2, 1)
Sensor 2	90%	150m	3	(3, 1, 2, 1)

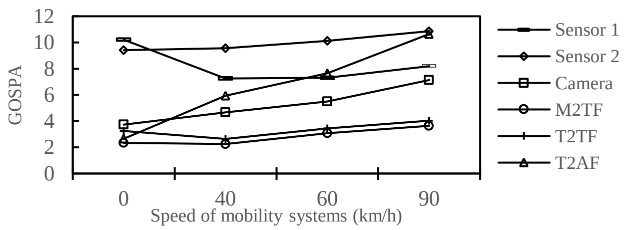

Figure 10. GOSPA performance evaluation for tracking and fusion at different speeds in normal case

In the results shown in figure 10, we found that the architecture M2TF performs superiorly compared to the rest of two architectures and has a significant improvement in GOSPA. To focus on its improvement rate to the tracking result from the smallest GOSPA before fusion, the architecture GOPSA values in M2TF for the mobility systems speed at 0 km/h, 20km/h, 60 km/h and 90 km/h decreases by around 37.27%, 51.82%, 44% and 48.95% respectively. In other words, the sensor fusion architecture M2TF remarkably reduces the localization error, the number of false detection as well as the number of miss detection compared to the ground truth data.

Overall, the architecture M2TF which perform better among all architectures has 45.5% GOSPA improvement in average from 5.00 to 2.83 to the relatively good tracking performance when T2AF and T2AF have 34.38% improvement from 5.00 to 3.34 and 0% improvement in average respectively. It is worth noting that even though the architecture T2AF does not have any excellent improvement overall especially when the mobility system is moving, it has 28.95% improvement from 3.73 to 2.65 for the stationary mobility system environment.

5.3.2 Evaluation of Abnormal case with camera detection rate 75%

For the abnormal case with camera detection 75%, we assume that all the sensors perform normally except camera and the detection rate of camera is lowered from original 95% to 75%, the parameter configurations for each sensor are detailed in the following table.

Table 4. Configuration of sensor properties in abnormal case with camera detection rate 75%

	Detection rate	FOV distance	Clutter rate (clutter/frame)	Error covariance (x, y, v_x, v_y)
Camera	**75%**	300m	1	(10, 1, 3, 1)
Sensor 1	85%	100m	1	(3, 1, 2, 1)
Sensor 2	90%	150m	3	(3, 1, 2, 1)

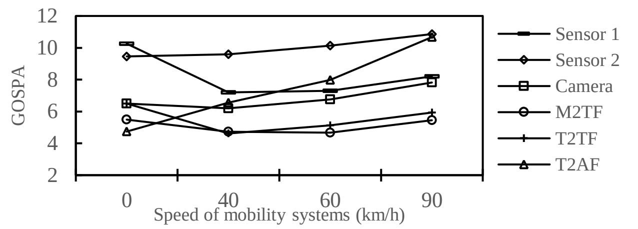

Figure 11. GOSPA performance evaluation for tracking and fusion at different speeds in abnormal case with camera detection rate 75%

In the result shown in figure 11, we found that the architecture T2AF performs superiorly with average 27.08% GOSPA improvement from 6.5 to 4.74 compared to the rest of two architectures when the mobility system is stationary. However, it performs the worst with higher GOSPA when the mobility systems operate at higher speed even though it has the excellent fusion performance when the mobility system is stationary. This insinuates that the achievement of satisfactory fusion performance in T2AF architecture is contingent on the speed of the mobility systems. The rest of the architectures M2TF and T2TF demonstrate their improvement abilities and perform stably regardless of the mobility system speed. Both architectures M2TF and T2TF have similar performance overall with smaller GOSPA in average for all cases when the mobility systems are moving at different speeds.

On the whole, the architecture M2TF which perform better among all architectures has 25.08% improvement in average from 6.87 to 5.09 to the relatively good tracking performance in Sensor 2 before fusion when T2TF has 18.41% in average from 6.87 to 5.55, It is worth noting that even though the architecture T2AF does not have any excellent improvement overall especially for the case when the mobility system is moving, it performs well in the stationary mobility system environment.

5.3.3 Evaluation of abnormal case with camera detection rate 50%

For the abnormal case with camera detection 50%, we assume that all the sensors perform normally except camera and the detection rate of camera drops from original 95% to 50%, the parameter configurations for each sensor are detailed in the table 6 shown below.

Table 6. Configuration of sensor properties in Abnormal case with camera detection rate 50%

	Detection rate	FOV distance	Clutter rate (clutter/frame)	Error covariance (x, y, v_x, v_y)
Camera	**0.5**	300m	1	(10, 1, 3, 1)
Sensor 1	0.85	100m	1	(3, 1, 2, 1)
Sensor 2	0.9	150m	3	(3, 1, 2, 1)

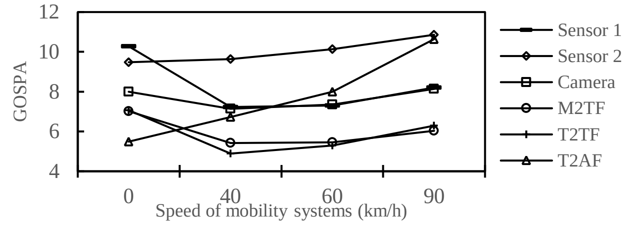

Figure 12. GOSPA performance evaluation for tracking and fusion at different speeds in abnormal case with camera detection rate 50%

From figure 12, the GOSPA improvement tendency is similar to the normal case and the abnormal case with camera detection 75% although all the GOSPA values are relatively higher overall compared to normal case and the case with 75% camera detection rate change. On the other hand, both architectures M2TF and T2TF have similar performance regardless of the mobility system speed overall with smaller GOSPA with 21.84% improvement rate from 7.39 to 5.98 and 23.29% improvement from 7.39 to 5.88 in average respectively. We further found that the GOSPA of the architecture T2AF performs superiorly with 31.29% improvement from 7.99 to 5.49 compared to the rest of two architectures and has a significant improvement in GOSPA when the mobility system is stationary. However, the architecture T2AF performs worst with higher GOSPA when the mobility systems operate at higher speed.

On the whole, the architecture T2TF which performs better among all architectures in average when M2TF has similar improvement in average. Similar to the normal cases and another abnormal cases, it is worth noting that even though the architecture T2AF does not have any excellent improvement overall, it performs well in the stationary mobility system environment.

6. Related work

From the current literatures, most of the proposed approaches that tackle the heterogenous sensor fusion problem are based on track-to-track fusion which was originally proposed in [7]. Its variants include the refined data association with clustering [8] and integrating the non-kinematic information [9]. Their proposed techniques for the improvement to heterogeneous sensor fusion provided more accurate estimation of the target position and data management during the fusion stage. However, the requirement of our goal in this paper also focus on missed detection and clutter with provenly efficient method in the fusion layer but not only the estimation of the positions of the target objects.

Furthermore, there are deep neural network based fusion approaches such as Deep Multimodal Encoding [10] and Deep Fusion [11]. Nevertheless, this machine learning based strategy requires enormous training data for creating the functional weighted model and it is still complicated at this point to ensure its faultlessness, safety and high reliability due to its ambiguous inductive properties driven by restrictedly available training data. This ambiguity leads to impracticality and difficulty of creating error-free model through debugging and re-training. Therefore, deep neural network-based approach for sensor fusion is not our study target in this paper.

Whilst most of the existing literatures focus on tracking problem of homogeneous sensor with GMPHD such as [12], [13] and they showed the feasibility of exploiting GMPHD for sensor application, focusing on the fusion of homogeneous sensor is not applicable to practical tracking-based sensor fusion system due to incomprehensiveness of the environment in some abnormal circumstances with the constraint of single type of sensor.

Even though there is a similar approach in literature [14] with one of our proposed architectures with GMPHD for heterogeneous sensors. They simply focus on extended object tracking which is a contrast to point object tracking that we focus here. Point object tracking only require cheaper hardware because of lower resolution of the sensor and this further saves the product cost. This paper further evaluates the performance of the proposed architecture with GMPHD for heterogenous sensor fusion in details.

7. Conclusion

This paper presents three architectures including T2TF, M2TF and T2AF of heterogenous sensor fusion with the integration of GMPHD in a bid to improve the detection ability in terms of the issues of clutter and miss-detection. We have gone through these three architectures and their improvement evaluation. Our results have demonstrated that they all have significant improvement ability but performed differently during the speed change in mobility system and the sudden change of one sensor properties.

In our empirical results with GOSPA, it has been showed that our all proposed sensor fusion architecture T2TF, M2TF and T2AF with GMPHD can effectively improve the detection performance when the mobility system is stationary. However, the performance of T2AF starts to deteriorate when the mobility system speeds up from 0km/h even though it has excellent 29.10% GOSPA improvement in average for all stationary situations compared to the rests. Among all architectures, M2TF architecture with GMPHD performs remarkably in general with average 45.50% GOSPA improvement for normal case, 25.09% improvement for the abnormal case with 75% camera detection rate and 21.83% GOSPA improvement for the abnormal case with 50% camera detection rate. This draw us the conclusion that we might have to set up the minimum requirement for our satisfactory sensor fusion performance and switch to the most appropriate architecture under circumstances of system moving with variant speed or stationary in order to get better detection enhancement through our sensor fusion algorithm. This evaluation is significantly critical for the adoption of sensor fusion architectures since it reflects their abilities to improve and keep the detection performance especially when there is sudden change in properties of sensors due to environmental influence and the speed of mobility system.

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