New environmental dependent modelling with Gaussian particle filtering based implementation for ground vehicle tracking

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***Abstract*—This paper proposes a new domain knowledge aided Gaussian particle filtering based approach for the ground vehicle tracking application. Firstly, a new form of modelling is proposed to reflect the influences of different types of environmental domain knowledge on the vehicle dynamic: i) a non-Markov jump model is applied with multiple models while transition probabilities between models are environmental dependent ii) for a particular model, both the constraints and potential forces obtained from the surrounding environment have been applied to refine the vehicle state distribution. Based on the proposed modelling approach, a Gaussian particle filtering based method is developed to implement the related Bayesian inference for the target state estimation. Simulation studies from multiple Monte Carlo simulations confirm the advantages of the proposed method over traditional ones, from both the modelling and implementation aspects.**

I. Introduction

Ground vehicle tracking is an important preliminary step in many applications such as surveillance, advanced driver assistance systems (ADAS) and autonomous vehicles. Many model based state estimation methods (i.e. Kalman or particle filtering based methods [1]), have been proposed for vehicle tracking. However, the majority of methods in [1] assume an open field environment in which the tracked vehicle(s) could move freely. This contradicts with the realistic scenario where the motion of the ground vehicle(s) is often affected by its operational environment. Information from the environment could be taken as domain knowledge and exploited in the development of tracking algorithms in order to enhance tracking quality.

Different approaches have been proposed to exploit domain knowledge for ground vehicle tracking. The most apparent domain knowledge is the road constraint information such as the constrained region imposed by a road map. Studies on road network-aided ground vehicle tracking have been reported in different works such as [2], [3] and [4]. In these works, different state estimation algorithms (such as the Gaussian (s) approximation filtering method in [2] and [4], and particle filtering method [3]) have been applied together with the road constraint information for the state estimation. Besides, the manoeuvre of a vehicle will also be affected by its surrounding environment. For example, a vehicle is likely to accelerate to overtake. To incorporate domain knowledge related to manoeuvre determination, [5] and [6] consider a non-Markov jump modelling system originally proposed in [7] for vehicle tracking. Multiple state models are applied to represent different possible vehicle movements. State-dependent model transition probabilities are then adopted to model vehicle manoeuvre type changes with respect to environmental conditions.

In our work, a new domain knowledge aided method is proposed for ground vehicle tracking. Compared with the aforementioned works, domain knowledge is exploited in a more comprehensive way; besides, a more efficient filtering algorithm is applied for the state estimation. Firstly, the non-Markov hybrid model framework in [7] is proposed to model multiple vehicle behaviours. For a particular dynamic model, both constraints and forces [8] are incorporated to refine the target state distribution. Based on the proposed model approach, a Gaussian particle filtering [9] based state dependent interactive multiple model Gaussian particle filtering (SD-IMMGPF) method is proposed. Compared with the traditional generic particle based filtering approach for the hybrid non-Markov jump model implementation as in [7], the measurement information is exploited for constructing an importance function to generate more effective particles.

The structure of this paper is listed as follows: The developed domain knowledge aided model is proposed in Section II. Bayesian inference and the proposed SD-IMMGPF approach are presented in Section III. Simulations in Section IV present the comparison results between the proposed method and others. Final conclusions and future works are presented in Section V.

II. Proposed environmental dependent model

In this section, we propose a new environmental dependent model approach for ground vehicle tracking, which exploits different environmental information in a comprehensive way for both the manoeuvre type determination and state dynamic/distribution refinement.

In a realistic scenario, a vehicle will move with different manoeuvre types, which can not be reflected by a single state model. In this way, multiple state models have been exploited for target tracking as in [10] and [11]. However, these approaches assume a Markov jump model, with transition probabilities between different state models being constant without considering any environmental information. However, the manoeuvre type of a certain target is actually environmentally related. For example, a vehicle will commonly overtake when it approaches another vehicle with a high speed and turn when it comes to a bend road segment. To this end, the non-Markov jump modelling framework as in [7] is adopted, for which the transition probabilities between different models are not constant but modeled in a state dependent way related to the target's surrounding environmental conditions.

A general dynamic model in the non-Markov jump modelling framework can be represented as:

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}) + \mathbf{w}_t \tag{1}$$

where $\mathbf{x}_t$ represents the state vector, which usually includes the position and velocity for the vehicle tracking problem; $\mathbf{w}_t$ is generally known as the process noise term, which represents the model uncertainty; $f(\cdot)$ represents a dynamic function reflecting the desired target dynamics.

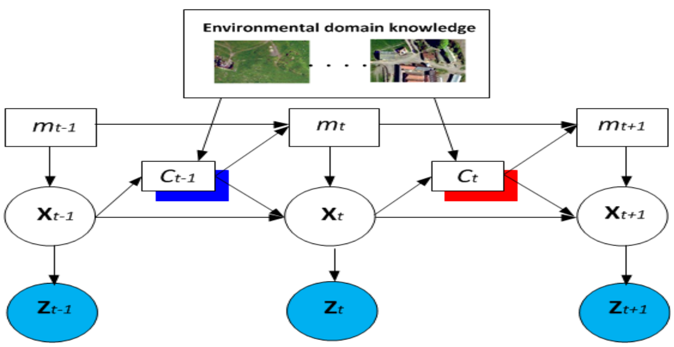

Fig. 1. The proposed modelling framework. Related parameters are defined as: $\mathbf{X}_t$: state vector, $\mathbf{Z}_t$: measurement vector, m_t: model index and C_t: surrounding environmental conditions of a target, which is dependent on the target state (i.e., position and velocity) and environmental domain knowledge (i.e., road map information, geographic data, moving obstacles information, etc.).

Currently most models (as in [12]) for target tracking do not consider any environmental information. So the predicted state distribution by (1) may contradict with the realistic environmental conditions (for example, the predicted position of a vehicle may be outside the road boundary). In this work, a new modelling framework is proposed as shown in Fig. 1. The non-Markov jump modelling framework is adopted. Furthermore, the target's surrounding environmental condition does not only determine the manoeuvre type but also refines a particular dynamic model and corresponding state distribution. The refinement of the state distribution is achieved by introducing *forces* and *constraints*.

A. Force based environmental effects modelling

In realistic scenarios, targets' movements are affected by the surrounding environment. For example, a vehicle keeps away from the road border to avoid collisions or it may be attracted by certain objects (such as the lane centreline).

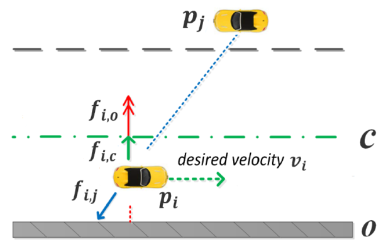

Fig. 2. The illustration of different forces for modelling environmental effects. $\mathbf{f}_{i,j}$ models the repulsive effect between vehicles i and j, $\mathbf{f}_{i,o}$ models the repulsive effect between the vehicle i and road boundary o and $\mathbf{f}_{i,c}$ models the effect that a vehicle tends to move along with the lane centreline c.

In [8], a force based method has been proposed to model such repulsive/attractive effects on pedestrians posed by their surrounding environment. This idea is exploited in this work for modelling the environmental influences on the vehicle dynamics. As in Fig. 2, different types of 'virtual forces' have been applied, which model the repulsive/attractive effects on a vehicle determined by its surrounding environmental conditions.

Same exponential force definition forms are applied to formulate the repulsive/attractive forces as in [8], with:

$$\begin{aligned} \mathbf{f}_{i,j}^{repulsive} &= a \cdot \exp(-b \cdot d)\mathbf{n}_{i,j} \\ \mathbf{f}_{i,j}^{attractive} &= a' \cdot (1 - \exp(-b' \cdot d))\mathbf{n}_{i,j}, \end{aligned} \tag{2}$$

where $\mathbf{f}_{i,j}^{repulsive}$ and $\mathbf{f}_{i,j}^{attractive}$ represent repulsive and attractive forces between objects i and j; a, b, a' and b' are constant parameter values; $\mathbf{n}_{i,j}$ ($\mathbf{n}_{j,i}$) represents the unit vector pointing from object i to j (j to i).

Forces from different objects are summed to a total one (denoted as $\mathbf{f}^e$) which represents the effect of the surrounding environmental conditions on the vehicle. In this way, an additional acceleration term $\mathbf{a}^e = \frac{\mathbf{f}^e}{m}$ is introduced and the original model of (1) is thus modified to reflect the influence of the environment on dynamic modelling. In general, the modified dynamic model can be represented as:

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}) + I(\mathbf{a}^e) + \mathbf{w}_t \tag{3}$$

where the term $I(\mathbf{a}^e)$ is a function of $\mathbf{a}^e$, which is dependent on the particular dynamic model definition as in [12].

B. Constraint information

In reality, there are constraints existing in the realistic environment, which can be further applied to refine the state distribution. We denote the distribution determined by the force based model (3) as $p(\mathbf{x}_t)$, by incorporating the constraint information the distribution is truncated as:

$$p_C(\mathbf{x}_t) = \begin{cases} \frac{p(\mathbf{x}_t)}{\xi_t}, & \mathbf{x}_t \in C \\ 0, & otherwise \end{cases} \tag{4}$$

where $p_C(\mathbf{x}_t)$ represents the truncated distribution, C represents the constrained region and ξ_t is calculated as $\xi_t = \int_C p(\mathbf{x}_t) d\mathbf{x}_t$. The probability value which is out of the constraint region becomes zero. In this way, the uncertainty of the state distribution is further reduced.

III. State dependent interactive multiple model Gaussian particle filtering

Based on the new modelling approach as defined in the previous section and a proper measurement model, a state dependent interacting multiple model Gaussian particle filtering (SD-IMMGPF) algorithm is developed for the state estimation. Different from the generic SD-IMMPF method [7], the proposed algorithm applies Gaussian particle filtering for every mode-matched filter with an importance function constructed with both the state dynamics and measurement information, which generates more effective particles.

The proposed SD-IMMGPF algorithm is based on the exact Bayesian inference framework for a multiple model system, whose overall process is divided into four steps: mode mixing, state interaction, evolution and correction.

Mode mixing: The mode mixing is related to the evolution of the model probability between consecutive discrete time instances $t-1$ and t. Using the law of total probability, we have:

$$\begin{aligned} p(m_t = s|\mathbf{Z}_{t-1}) &= \sum_{r\in\mathcal{M}} p(m_t = s, m_{t-1} = r|\mathbf{Z}_{t-1}) \\ &= \sum_{r\in\mathcal{M}} p(m_t = s|m_{t-1} = r, \mathbf{Z}_{t-1}) p(m_{t-1} = r|\mathbf{Z}_{t-1}), \end{aligned} \tag{5}$$

where m_t represents the dynamic model index variable whose value m or r could be any one element in the set $\mathcal{M}$, which represents the model index ensemble. $\mathbf{Z}_{t-1}$ represents the measurements collection $\{\mathbf{z}_1, ..., \mathbf{z}_{t-1}\}$ during previous time instances. And $p(m_t = s|m_{t-1} = r, \mathbf{Z}_{t-1})$ can further be decomposed as:

$$\begin{aligned} &p(m_t = s|m_{t-1} = r, \mathbf{Z}_{t-1}) \\ &= \int \pi^E_{rs}(\mathbf{x}_{t-1}) \cdot p(\mathbf{x}_{t-1}|m_{t-1} = r, \mathbf{Z}_{t-1}) \,\mathrm{d}\mathbf{x}_{t-1}. \end{aligned} \tag{6}$$

where $\pi^E_{rs}(\mathbf{x}_{t-1})$ represents the environmental information related state-dependent model transition probability between models r and s, which is problem-specific.

State interaction: State interaction generates the initial mode-conditioned density $p(\mathbf{x}_{t-1}|m_t = s, \mathbf{Z}_{t-1})$. According to the conditional probability relation and the law of total probability, one has:

$$p(\mathbf{x}_{t-1}|m_t = s, \mathbf{Z}_{t-1}) = \frac{\sum_{r\in\mathcal{M}} \pi^E_{rs}(\mathbf{x}_{t-1}) \cdot p(\mathbf{x}_{t-1}, m_{t-1} = r|\mathbf{Z}_{t-1})}{p(m_t = s|\mathbf{Z}_{t-1})}. \tag{7}$$

Domain knowledge aided state evolution: The state evolution step is to propagate the mode-conditioned state density from $t-1$ to t by the dynamic model. Given the initial density is provided in (7) and the s-th environmental information aided dynamic model, the mode-conditioned prior distribution $p(\mathbf{x}_t|m_t = s, \mathbf{Z}_{t-1})$ at t can be calculated as:

$$\begin{aligned} &p(\mathbf{x}_t|m_t = s, \mathbf{Z}_{t-1}) \\ &= \int p(\mathbf{x}_t|\mathbf{x}_{t-1}, m_t = s, \mathbf{Z}_{t-1}) p(\mathbf{x}_{t-1}|m_t = s, \mathbf{Z}_{t-1}) \,\mathrm{d}\mathbf{x}_{t-1}. \end{aligned} \tag{8}$$

where $p(\mathbf{x}_t|\mathbf{x}_{t-1}, m_t = s, \mathbf{Z}_{t-1})$ is determined by the force aided dynamic model (3) and constraints (4).

Correction: Finally, the updated measurement is incorporated to correct the prior by following Bayes' rule:

$$\begin{aligned} p(\mathbf{x}_t, m_t = s|\mathbf{Z}_t) \propto\ & p(\mathbf{z}_t|\mathbf{x}_t, m_t = s) p(\mathbf{x}_t|m_t = s, \mathbf{Z}_{t-1}) \\ & \cdot p(m_t = s|\mathbf{Z}_{t-1}). \end{aligned} \tag{9}$$

The state estimation at time t can then be derived from the updated posterior distribution $p(\mathbf{x}_t, m_t = s|\mathbf{Z}_t)$.

A. SD-IMMGPF implementation

The SD-IMMGPF algorithm is then proposed to implement the above Bayesian inference. Initially, it starts at time $t-1$ with the set of weighted particles $\{\mathbf{x}^{r,k}_{t-1}, w^{r,k}_{t-1}; r \in \mathcal{M}, k \in \{1, \dots, N\}\}$ to approximate the probability $p(\mathbf{x}_{t-1}, m_{t-1} = r|\mathbf{Z}_{t-1})$. Based on this, the Bayesian inference procedure is implemented as follows:

Mode mixing implementation: Prior mode probability in (5) is approximated with generated particles as:

$$p(m_t = s|\mathbf{Z}_{t-1}) \approx \sum_{r\in\mathcal{M}} \sum_{k=1}^{N} \pi^E_{rs}(\mathbf{x}^{r,k}_{k-1}) \cdot w^{r,k}_{t-1} \triangleq \Lambda^s_{t-1}, \tag{10}$$

where Λ^s_{t-1} is defined to facilitate the rest of the derivation.

State interaction implementation: The state interaction process can be implemented by inserting particles at $t-1$ with the different mode index r, into (7) such that

$$\begin{aligned} &p(\mathbf{x}_{t-1}|m_t = s, \mathbf{Z}_{t-1}) \approx \\ &\sum_{r\in\mathcal{M}} \sum_{k=1}^{N} \pi^E_{rs}(\mathbf{x}^{r,k}_{t-1}) w^{r,k}_{t-1} \delta(\mathbf{x}_{t-1} - \mathbf{x}^{r,k}_{t-1}) / \Lambda^s_{t-1}. \end{aligned} \tag{11}$$

Evolution and correction implementation:

For every mode a Gaussian particle filtering (GPF) [9] based approach is exploited. An importance function which is a Gaussian approximation of the mode-conditioned posterior distribution $p(\mathbf{x}_t|m_t = s, \mathbf{Z}_t)$ is constructed, from which effective particles are generated. Firstly, the mean μ^s_{t-1} and covariance Σ^s_{t-1} of a Gaussian distribution to approximate $p(\mathbf{x}_{t-1}|m_t = s, \mathbf{Z}_{t-1})$ are obtained as:

$$\begin{aligned} \mu^s_{t-1} &= \sum_{r\in\mathcal{M}} \sum_{k=1}^{N} \pi^E_{rs}(\mathbf{x}^{r,k}_{t-1}) w^{r,k}_{t-1} \mathbf{x}^{r,k}_{t-1} / \Lambda^s_{t-1} \\ \Sigma^s_{t-1} &= \sum_{r\in\mathcal{M}} \sum_{k=1}^{N} \pi^E_{rs}(\mathbf{x}^{r,k}_{t-1}) w^{r,k}_{t-1} (\mathbf{x}^{r,k}_{t-1} - \mu^s_{t-1}) \cdot (\mathbf{x}^{r,k}_{t-1} - \mu^s_{t-1})^T / \Lambda^s_{t-1} \end{aligned} \tag{12}$$

Based on the domain knowledge aided dynamic model and measurement model, the mean and covariance are then updated to obtain μ^s_t and Σ^s_t at time instance t, which determine a Gaussian distribution $N(\mathbf{x}_t|\mu^s_t, \Sigma^s_t)$ as an approximation of the distribution $p(\mathbf{x}_t|m_t = s, \mathbf{Z}_t)$. Different algorithms can be applied for the updating, in our work, the truncated unscented Kalman filtering (t-UKF) scheme as in [13] is adopted, which exploits both the constraint information and unscented transformation to better deal with the non-linearities in both dynamic and measurement models.

A new set of particles $\{\mathbf{x}_t^{i,s}\}_{i=1,\dots,N}$ is sampled from $N(\mathbf{x}_t|\mu_t^s, \Sigma_t^s)$. According to the concept of importance sampling in [1] and (9), the posterior distribution $p(\mathbf{x}_t, m_t = s|\mathbf{Z}_t)$ is approximated as:

$$p(\mathbf{x}_t, m_t = s|\mathbf{Z}_t) \approx \sum_i w_t^{i,s} \delta(\mathbf{x}_t - \mathbf{x}_t^{i,s}) \quad (13)$$

with particle weights $\{w_t^{i,s}\}_{i=1,\dots,N}$ being estimated as:

$$w_t^{i,s} \propto \frac{p(\mathbf{z}_t|\mathbf{x}_t^{i,s}, m_t = s) N(\mathbf{x}_t^{i,s}|\mu_{t|t-1}^s, \Sigma_{t|t-1}^s) p(m_t = s|\mathbf{Z}_{t-1})}{N(\mathbf{x}_t^{i,s}|\mu_t^s, \Sigma_t^s)} \quad (14)$$

where $N(\mathbf{x}_t^s|\mu_{t|t-1}^s, \Sigma_{t|t-1}^s)$ is a Gaussian approximation of $p(\mathbf{x}_t|m_t = s, \mathbf{Z}_{t-1})$ and $p(\mathbf{z}_t|\mathbf{x}_t^s, m_t = s)$ is a measurement likelihood function determined by a particular measurement model. From the obtained particles and corresponding weights, both the state estimation and the s-th model probability can be estimated as:

$$\begin{aligned} \hat{\mathbf{x}}_t &= \sum_{s\in\mathcal{M}} \sum_{i=1}^{N} w_t^{i,s} \mathbf{x}_t^{i,s} \\ p(m_t = s) &= \sum_{i=1}^{N} w_t^{i,s} \end{aligned} \quad (15)$$

IV. Simulation studies

The proposed method is tested in a simulated scenario as shown in Fig. 3, with two vehicles being simulated to move along two road segments in a total of 30s. The first vehicle is simulated to move with a constant velocity of 10 (m/s) along the straight road segment for 27.5 (s) after which a turning manoeuvre is performed with angular velocity 0.2 (rad/s) for 2.5 (s). The second vehicle firstly moves with a constant velocity of 12.5 (m/s) on the straight road segment for 8s before it begins to overtake the first vehicle. After 7 seconds, vehicle 2 overtakes vehicle 1 and moves again with 12.5 (m/s) for 7s along the straight segment. Then it begins to move along the bend road segment with an angular velocity of 0.2 (rad/s).

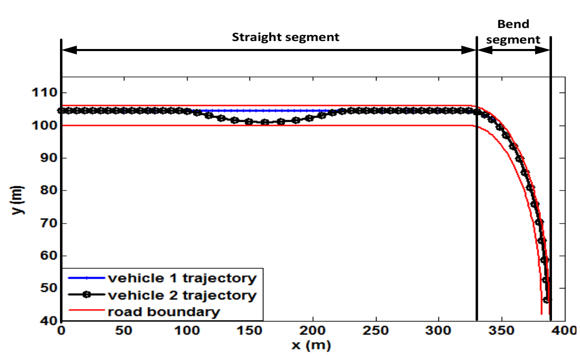

Fig. 3. Simulated vehicles trajectories.

Multiple dynamic models as in [12] are applied to model different manoeuvre types of vehicles, which include: a constant velocity (CV) model with a low process noise intensity level for modelling the CV manoeuvre, a CV model with a high process noise intensity level for modelling the overtaking manoeuvre and a constant turning (CT) model for modelling the turning manoeuvre. A sensor positioned at [200,30] (m) is applied to measure the range r_t and bearing angle θ_t of a particular vehicle with:

$$\mathbf{y}_t = \begin{bmatrix} r_t \\ \theta_t \end{bmatrix} = \begin{bmatrix} \sqrt{(x_s - x_t)^2 + (y_s - y_t)^2} \\ \arctan(\frac{y_s - y_t}{x_s - x_y}) \end{bmatrix} + \mathbf{n}_k \quad (16)$$

where $[x_t, y_t]$ represents a target's position at time instance t, $[x_s, y_s]$ represents the sensor position and $\mathbf{n}_t$ represents the measurement noise. In our work, we assume it as a Gaussian distribution with zero means and covariance $\begin{bmatrix} 5^2(m^2), & 0 \\ 0, & 0.02^2(rad)^2 \end{bmatrix}$. Currently, we assume that the sensor always receives the two vehicles' measurements without any measurement association ambiguities.

Based on the simulated scenario, dynamic and measurement models, the proposed method is applied for the vehicle tracking. The tracking results are compared with other methods from both *model* and *filtering algorithm*.

Model comparison: For the proposed modelling approach, the transition probabilities between different models are defined with respect to distances between a target and its surrounding objects (such as another vehicle and the bend road entry). The road region is applied as the constraints and forces are used to represented the repulsive effects of vehicle-to-vehicle and vehicle-to-boundary. These forces are defined in the form of (2) with the related parameters being selected empirically for the simulation study.

Comparisons are made between different modelling frameworks, including Markov jump (MJ) model, non-Markov jump (NMJ) model, non-Markov model with constraint information (CNMJ) and the proposed non-Markov modelling framework with both constraints and forces (FCNMJ). For a fair comparison, the same Gaussian particle filtering based approach is applied for every modelling method and the number of particles for every dynamic mode is chosen as $N = 300$. 100 Monte-Carlo simulations are performed. For every vehicle, the averaged position root-mean-square-errors (RMSEs) for every time instance is plotted in Fig. 4 corresponding to every modelling method. While the averaged RMSEs of the tracked trajectories compared with ground truth one are shown in Table I. From the results, we can see that the proposed modelling method exploiting the domain knowledge in the most comprehensive way, achieves the most accurate result for the trajectory tracking (as in Table I with the smallest averaged RMSEs for both vehicles) and lowest RMSEs during the majority of the time as shown in Fig. 4.

Filtering algorithms comparison: We compare different Bayesian inference implementation algorithms. The proposed modelling framework as in Section II is adopted, with the generic particle filtering based SD-IMMPF (N=3000 for one

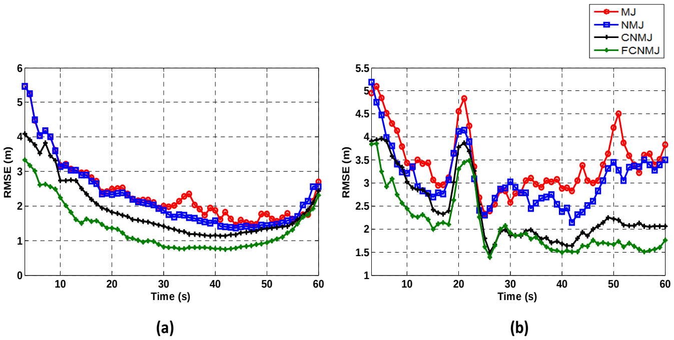

Fig. 4. Position RMSEs comparisons for vehicle 1 (a) and vehicle 2 (b) by different modelling approaches.

TABLE I
AVERAGED POSITION RMSES (M) COMPARISONS FOR DIFFERENT MODELLING APPROACHES

	MJ	NMJ	CNMJ	FCNMJ
Vehicle 1 RMSE (m)	2.52	2.43	2.17	1.51
Vehicle 2 RMSE (m)	3.45	3.25	2.42	2.10

dynamic model) and SD-IMMGPF approaches (N=300 for one dynamic model) implementation approaches being compared. The same state model is applied for these two approaches and the same 100 Monte-Carlo simulations have been performed for RMSEs analysis. From the comparison results as shown in Fig. 5 and Table II, we can see that the SD-IMMGPF approach achieves better performance, with smaller RMSEs being obtained (especially for vehicle 1 with around 45% of the RMSE reduction as implied in Table II) with a smaller number of particles and a low computational cost. The reason behind it is that the SD-IMMGPF approach exploits both the constraint and measurement information for more effective sampling.

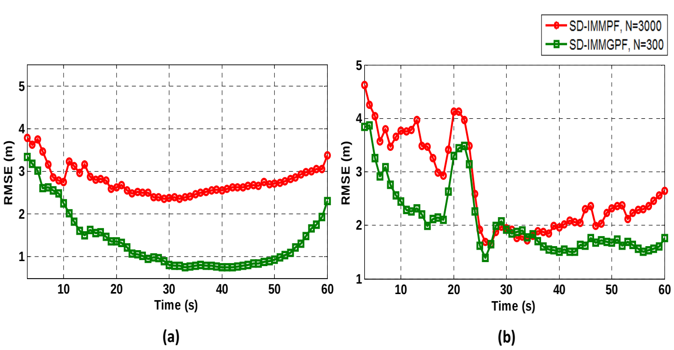

Fig. 5. Position RMSEs comparisons for vehicle 1 (a) and vehicle 2 (b) for different filtering algorithms

V. CONCLUSION

In this work, a new domain knowledge aided tracking method is proposed. A new environmental dependent model is developed. Multiple models are applied with the state dependent probabilities being used to model the realistic vehicle manoeuvre transitions. Both the constraint and force information are applied to refine the dynamic model and state distribution. Based on the modelling framework, a SD-IMMGPF approach is applied to implement the related Bayesian inference for the state estimation. Simulation studies show the advantages of the proposed method from both the modelling and implementation algorithm aspects. In the future, the proposed algorithm will be extended to a more complicated scenario with miss detections/false alarms and measurements association ambiguities.

TABLE II
AVERAGED POSITION RMSES (M) COMPARISONS FOR DIFFERENT FILTERING ALGORITHMS

	SD-IMMPF, N=3000	SD-IMMGPF, N=300
Vehicle 1 RMSE (m)	2.77	1.51
Vehicle 2 RMSE (m)	2.65	2.10
Computational time (s)	3.6	0.8

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