Multi-objective Tracking Algorithm for Intelligent Networked Vehicles in Hybrid Traffic

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Abstract. The increase in the number of automobiles has expanded the scope of public travel, bringing great convenience to people's lives and bringing many social problems such as traffic accidents, urban road congestion and the gradual increase of foggy weather. As an important part of the intelligent transportation system, intelligent networked vehicles are of great value and significance in solving the negative problems that exist in current hybrid transportation. The objective of this paper is to study the multi-objective tracking algorithm for intelligent networked vehicles based on hybrid traffic. A robust VB-RMTCT multi-target tracking algorithm is proposed. Considering the unknown localization noise statistics and random wild values of the relative positions of Hv and Cv, the mean-field theory is used to model the student t-distribution and non-Gaussian properties for numerical simulation of the localization noise, and the results show that the VB-RMTCT tracking algorithm can effectively and consistently improve the target state estimation performance compared with other traditional research methods.

Keywords: Hybrid Traffic, Intelligent Networked Vehicles, Multi-Target Tracking, Tracking Algorithm

1 Introduction

In recent years, with the rapid development of the national economy, China's transport business has achieved unprecedented rapid development. In particular, China's surface transportation has formed a national network of radial roads, starting with different levels of roads such as national highways and local motorways. At the same time, great progress has been made in the construction of urban roads [1-2]. The construction of urban roads and the upgrading and addition of traffic management equipment have improved urban traffic conditions [3]. However, with the rapid socio-economic development and the rapid increase in traffic mobility levels, urban traffic problems have become more and more serious, with traffic congestion and traffic accidents occurring so frequently that road expansion alone is not sufficient to fully solve the traffic problems [4-5].

In order to assess the risk of non-collision decisions of intelligent vehicles in

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complex road traffic environments, the state of various vehicle targets should be continuously tracked and evaluated. Arnob Ghosh therefore proposes a multi-objective tracking method that conforms to priority data association rules. Firstly, a standard coordinate rotation process model for two-dimensional ground vehicle translational rotation is derived. Secondly, a traceless Kalman filtering algorithm is proposed with a non-linear radar measurement model as the target. Finally, since vehicle targets (e.g. inertial systems) do not immediately show or disappear, a priority data association rule is created to place targets in a priority queue based on the number of target associations for filtered noise [6]. keya Roy investigates tracking control of external and network-induced disturbances in intelligent vehicle network control systems. A new high-order adaptive discrete-time sliding mode control algorithm (H-ADSMC) is proposed. First, a high-order adaptive sliding mode function is constructed to track the error and reduce the influence of external disturbances by using the estimated external input disturbances as the adaptive factor. The adaptive sliding mode controller is then obtained and the convergence of the sliding mode motion is checked. In addition, the effect of network disturbances on the sensor output is considered. A new observer is designed to compensate for the disturbances caused by the network. Finally, the tracking error is analysed and the effectiveness of the proposed H-ADSMC algorithm and the designed observer is verified by simulation [7]. Today, accurate and real-time vehicle tracking is crucial to ensure the safety of intelligent vehicles. However, tracking in complex traffic environments remains a challenge.Mehrdad Tajalli introduced a Gaussian mixed probability hypothesis density filter (RA-GMPHD) for tracking several automotive radar vehicles. Since road maps are usually available in traffic scenarios, we focus on using road map information to improve tracking performance. They first model the vehicle dynamics in a two-dimensional road coordinate system, then consider map errors and assign them roughly to the earth coordinate system. In addition, several variable structure interaction models are integrated into the ra - GMP HD filter due to the dynamic uncertainty of the targets and the geographical constraints of the roads. In addition, they perform extensive simulations and physical tests to demonstrate the superiority of their method over state-of-the-art methods. Experimental results show that their approach improves the quality and continuity of follow-up operations [8].

In a typical mixed traffic system such as ours, non-motorised vehicles and pedestrians are among the main participants in urban traffic and cannot be ignored by motorised vehicles. Mixed traffic flows of motor vehicles, non-motor vehicles and pedestrians will continue to be a prominent feature of urban traffic in China in the future. In the current research on urban transport systems, vehicles are the focus and traffic of unmanned vehicles and pedestrians, therefore, this paper's research on the detection of traffic data for mixed traffic is crucial to achieving safe and efficient urban transport.

2 Research on Multi-objective Tracking Algorithms for Intelligent Networked Vehicles in Hybrid Traffic

2.1 Smart Connected Cars

The smart connected car consists of six main components: car/road communication, high precision positioning and navigation, environmental awareness, intelligent decision making, route planning and vehicle control. Among them, car-vehicle-road communication is responsible for intelligent information interaction between the car and surrounding vehicles or road facilities, such as obtaining area maps, obtaining signal lights and obtaining the location of surrounding vehicles, thus helping to locate and sense the smart car. High-precision positioning navigation provides mainly high-precision positioning information and topological maps of the environment. The environment recognition component relies on various heterogeneous sensor fusion data sources to identify and understand the environment in which the vehicle is located [9-10]. Based on these three components of comprehensive communication, localisation and sensing, smart Internet vehicles can make informed decisions and plan routes. The planned route includes location and speed information that will be submitted to the Vehicle Control Section. Highly accurate trajectory tracking algorithms are combined with route control technology to achieve precise motion control of the Internet-connected vehicle. The efficient collaboration of these six components allows online intelligent vehicles to work together safely, efficiently and easily [11-12].

2.2 Bayesian Tracking Framework

Target tracking is an estimate of the state of one or more moving targets, based on time-series observations obtained by sensors. The main goal of target tracking is to align the estimated target with the actual target. The second is the accurate estimation of moving target motion, such as position, velocity, acceleration, target characteristics, etc. [13-14]. A typical target tracking system includes data alignment, data linking, filtering and tracking management, and requires iterations when updating the target path. Data alignment is primarily based on data format requirements for data pre-processing, including differencing, and removal of noise external to the tracking port. Some observations on the tracking port are compared below with target tracking and observations, and tracking results are compared with specific data partner strategies. Data correlation is a challenge when the target is high density and incorrectly detected due to noise and noise interference observed by the sensor. When information is associated with a target, a screening algorithm is used to predict and update the target status. Finally, a trajectory management target tracking process is initiated and maintained to enable the entire target tracking process [15]. The basic block diagram of target tracking is shown in Fig.ure 1.

An important step in the Bayesian target state estimation algorithm is to consider the observation assumptions of all sensors, where sensor observations are often incomplete, inaccurate and ambiguous. If the sensor is characterised by detection Pd<1 probability and pf>0 pseudo-space alarm density, the $g(Z^k|x_k)$ likelihood function in equation (1) typically contains all possible interpretations of the sensor observations. The target may or may not be detected due to Pd<1. Because pf>0, the current set of sensor observations also contains a certain number of false detection observations.

$$p(x_k|Z^k) = \frac{g(Z^k|x_k)p(x_k|Z^{k-1})}{\int g(Z^k|x)p(x|Z^{k-1})dx} \tag{1}$$

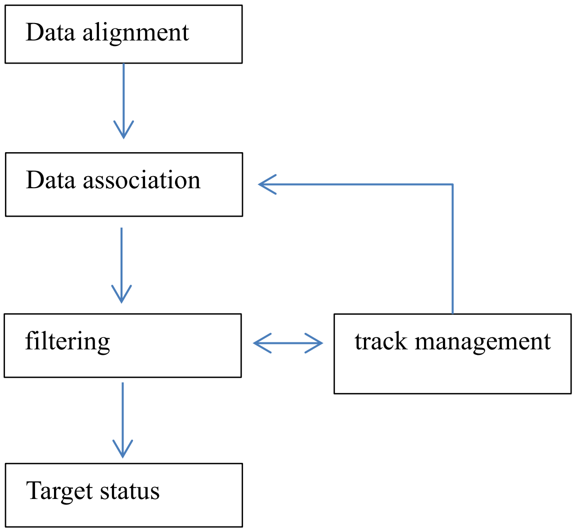

Fig. 1. Basic principle block diagram of target tracking

2.3 Variational Bayesian Inference Principles

Inference methods for probabilistic graphical models are usually grouped into two types:exact and approximate inference. The first method includes deletion of variables, propagation of beliefs, and other exact values designed to resolve restricted distributions or conditional distributions of systematic variables, but the computation of this method doubles as the maximum group size increases. The latter includes methods such as MCMC sampling, variable inference, and others designed to provide approximate solutions to the original problem at a lower time cost, thus better meeting real-time requirements.

The xk target state variables, accuracy Λ_k , uk bootstrap variables and degrees of freedom λ_k are chosen as the system parameters to be estimated. The posterior distribution $p(\Xi_k|z_{1:k},\Delta_k)$ is derived from Bayesian theory:

$$p(\Xi_k|z_{1:k},\Delta_k) = \frac{p(z_{1:k},\Xi_k,\Delta_k)}{p(z_{1:k},\Delta_k)} = \frac{p(z_{1:k}|\Xi_k)p(\Xi_k|z_{1:k-1},\Delta_k)}{p(z_k|z_{1:k-1},\Delta_k)} \tag{2}$$

where: $\Xi_k = \{x_k, \Lambda_k, u_k, \lambda_k\}$ system parameter, $\Delta_k = \{a_k, b_k, c_k, d_k\}$ is the hyperparameter of the localisation noise prior distribution.

In the case of large data, closed solutions or numerical calculations of the normalised coefficients are not available. To solve this problem, the variational distribution $q(\Xi_k)$ is introduced to approximate the true posterior distribution $p(\Xi_k | z_{1:k}, \Delta_k)$. Starting from mean field theory, the variational distribution is assumed to satisfy the following set of coefficients for the estimated parameters:

$$q(\Xi_k) = q(x_k)q(\Lambda_k)q(u_k)q(\lambda_k) \quad (3)$$

In turn, the variational posterior distribution is obtained by maximising the free energy $Fq(\Xi_k)$. By the nature of the variable-parameter coupling, the optimal $q(\Xi_k^i)$ can be alternated and the general solution is as follows:

$$Inq(\Xi_k^i) \infty E_{\Xi_k^{-i}}[In(p(z_k | \Xi_k | z_{1:k-1}, \Delta_k))] \quad (4)$$

where $E_{\Xi_k^{-i}}[.]$ is the expectation of the logarithmic joint probability distribution with respect to the remaining parameters excluding Ξ_k^i.

3 Numerical Simulation Experiments

3.1 Scenario Description

The multi-objective collaborative tracking scenario considered in this paper includes the primary vehicle Hv, Cv collaborative vehicle, and Tvs target vehicles (motor vehicles, non-motor vehicles, pedestrians). Where Hv and Cv are equipped with target detection radar, positioning navigation system and V2V communication devices. hv and Cv collect Tvs information within sensing range based on their respective vehicle sensors, and Cv sends its Tvs measurement and positioning data to Hv using V2V communication devices. finally, Hv is a fusion centre that combines the sensing data with the data sent by Cv to provide accurate TV state estimation.

Assume that Hv and Cv are moving in a two-dimensional plane at a constant velocity. The initial states of Tvs and Cv are set to [12, 0, 1, 0]T, [6, 3.5, 1.1, 0]T, [10, -3.5, 1.1, 0]T and [15, 0, 1.2, 0, 0, 0]T. wk process noise is constrained by the q covariance of Gaussian mean white noise 0. The model parameters: $\Delta t = 0.1s$, K=400, are established as 40s. The convergence condition for the variable fractional Bayesian iteration was set as follows: $\varepsilon = 5 \times 10^{-6}$, B=10. The number of simulations of MC in the performance evaluation metric was T=100.

Wild values in the location data can seriously affect the performance of collaborative tracking. Due to the thick-tailed nature of the student t-distribution, wild-value data processing is more powerful in parameter estimation than Gaussian or mixed finite Gaussian models. Therefore, using this distribution to model the thick-tailed, non-Gaussian localisation noise $v_k^2 \in R^{m_2}$, the probability density function of the m2 -dimensional student t -distribution is defined as follows:

$$st(v_k^2;\mu_k,\Lambda_k,\lambda_k)=\frac{r(\frac{d+\lambda_k}{2})}{r(\frac{\lambda_k}{2})(\lambda_k\pi)^{\frac{m_2}{2}}}|\Lambda_k|^{\frac{1}{2}}[1+\frac{1}{\lambda_k}(v_k^2-\mu_k)^T\Lambda_k(v_k^2-\mu_k)]^{-\frac{m_2+\lambda_k}{2}} \tag{5}$$

where $\Gamma(\cdot)$ is the gamma function with the thickness of the tail end determined by the degree of freedom λ_k. As λ decreases, the tail end decays more slowly.

3.2 Robust Multi-target Collaborative Tracking Process

In this paper, a robust multi-target cooperative tracking algorithm based on variable Bayesian inference is introduced to solve the problem of low accuracy of traditional tracking algorithms, and the process is shown in Fig.ure 2:

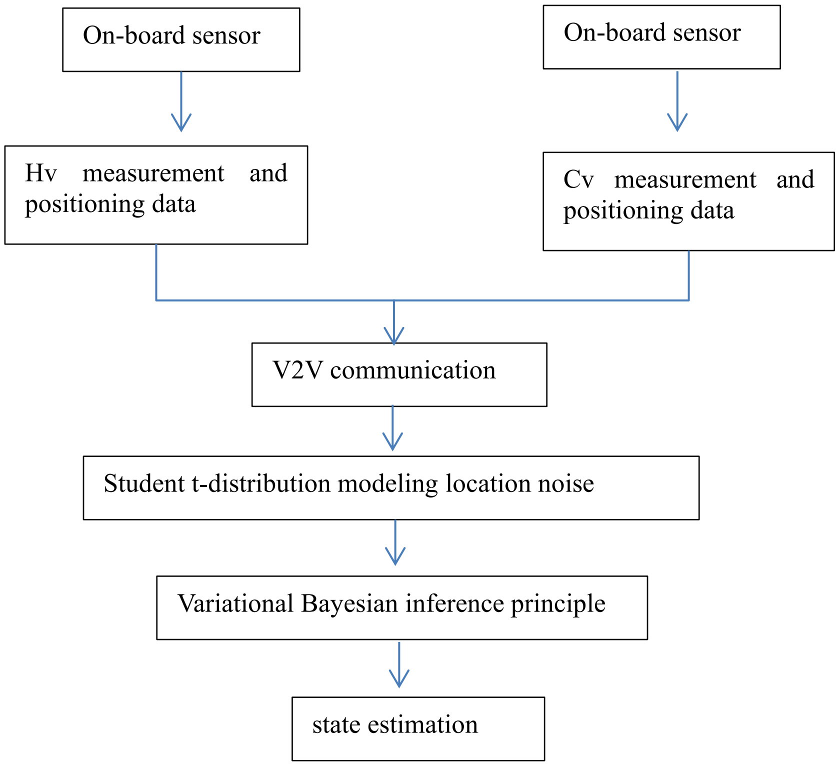

Fig. 2. Multi-target collaborative tracking model flow chart

3.3 Comparing Algorithms

In order to verify the effectiveness and robustness of the VB-RCMTT algorithm in dealing with wild-value localization noise, this paper conducts performance comparison simulation experiments on the following methods:

(1) a non-collaborative tracking algorithm (KF-SMTT) that relies only on Hv to estimate Tvs states.

(2) An EKF-based collaborative tracking algorithm (EKF-MTCT) using a fixed value of potential localisation noise variation.

(3) A variational collaborative tracking algorithm (VB-MTCT) modelled as the position acoustic covariance of the inverse gamma distribution.

(4) The VB-RMTCT algorithm proposed in this paper.

4 Analysis of Experimental Results

4.1 Tracking Error Analysis

In this paper, we visually describe the variation in tracking performance for uncommon target states in localization noise based on parameter settings and forgetting factor p = 0.95. The estimated position and velocity RMSEs of the four filtering algorithms in the simulation results are shown in Fig.ure 3 and Fig.ure 1, respectively. Analysing the experimental results, we can see that the EKF-MTCT, VB-MTCT and VB-RMTCT tracking errors are significantly better than KF-SMT, indicating that target measurement data can be fused to effectively improve target tracking accuracy through co-vehicle fusion. Due to the wild values of the localisation measurement noise, the localisation data exhibit coarse, non-Gaussian wake characteristics.EKF-MTCT sets the covariance of the localisation noise to a fixed value, based on the assumption of Gaussian measurement noise, and failure to adapt to wild values leads to covariance variations, resulting in lower performance than the VB-MTCT and VB-RMTCT algorithms.Although the VB-MTCT algorithm is also suitable for adjusting the covariance, it is more sensitive to atypical values. At high atypical rates, the target tracking performance is significantly reduced. The algorithm in this paper uses a student t-distribution than a Gaussian coarse-tailed distribution to model the localisation noise. The tracking results are significantly better than other algorithms. It is shown that the algorithm can effectively handle coarse, non-Gaussian tail noise measurements, with position and velocity estimation errors 37.4% and 25.3% lower than the conventional KF-SMT bicycle tracking algorithm.

Table 1. Improvement of Tracking Error Performance

algorithm	seat	Performance improvement	Velocity ARMSE/(m)	Performance improvement
KF-SMTT	0.567	/	0.211	/
EKF-MTCT	0.521	11.2%	0.208	10.5%
VB-MTCT	0.503	21.5%	0.195	18.8%
VB-RMTCT	0.488	37.4%	0.184	25.3%

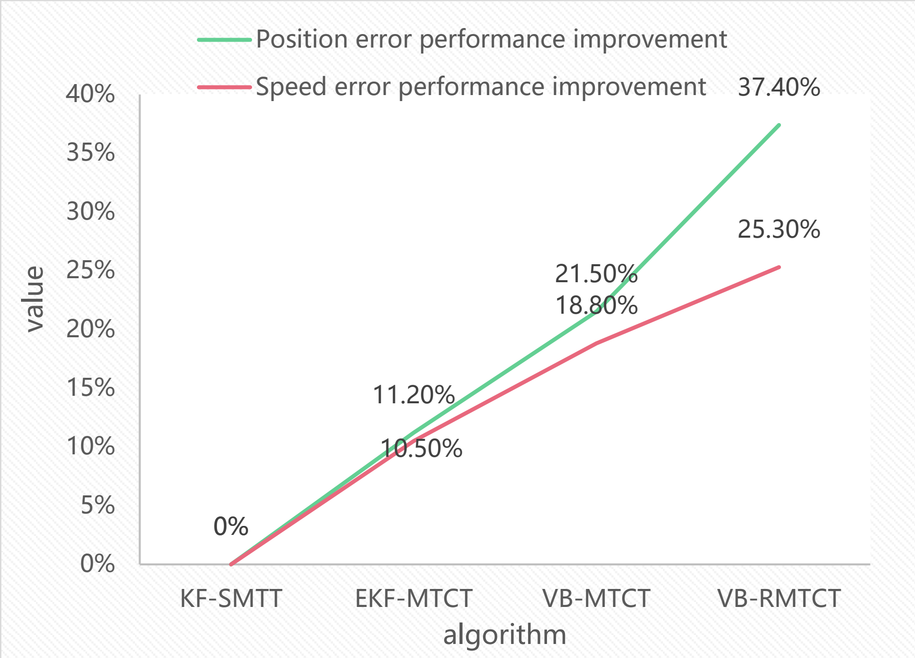

Fig. 3. Performance of tracking error under different algorithms when p=0.95

4.2 Algorithm Time Degree Analysis

Fig. 4. Running time of various algorithms based on different missed detection rates

Fig.ure 4 shows the running times required for the four algorithms based on different leak detection rates. In terms of time complexity, KF-SMT does not need to combine the target state with the perceived measurements, which takes less time. the VB-CMTT and VB-RCMTT algorithms take a long time because they have to switch to estimate the subsequent distribution parameters and noise of the target state in the state update step. The algorithm proposed in this paper runs in about 0.29 seconds, without affecting the real-time performance of the algorithm.

5 Conclusions

Smart Internet-connected vehicles are an important direction for the development of the automotive industry. Smart Internet-connected vehicles with advanced assisted driving functions are an important transitional stage of autonomous vehicle driving. By continuously enhancing the main safety functions and passive safety functions of vehicles, it can not only improve vehicle safety, but also reduce road traffic safety accidents, improve traffic efficiency, relieve traffic congestion and save energy. The study of multi-objective cooperative tracking technology for intelligent networked vehicles is still an immature research area, and so far there is no systematic and comprehensive solution in academia and industry. In this paper, a robust multi-target cooperative tracking algorithm based on variable Bayesian inference is proposed for mixed traffic scenarios, and good tracking results are achieved. However, due to time constraints, many complications that exist in real driving scenarios, such as non-linear target motion and communication lag, are not considered.

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