Proceedings of the
2007 IEEE Intelligent Vehicles Symposium
Istanbul, Turkey, June 13-15, 2007

An Information Theoretic Vehicle Following System

Teck Chew Ng†, Martin Adams♮ and Javier Ibañez-Guzmán♭
†*Singapore Institute of Manufacturing Technology, 71 Nanyang Drive, Singapore.*
♮*School of Electrical & Electronics Engineering, Nanyang Technological University, Singapore.*
♭*Renault - Research Division - Electronics Systems Department, France*
†*tcng@SIMTech.a-star.edu.sg*, ♮*eadams@ntu.edu.sg*, ♭*javier.ibanez-guzman@renault.com*

***Abstract*— Vehicle following can be achieved by minimizing the relative information (Kullback-Leibler or K-L distance), between the estimated poses of leader and follower vehicles. To achieve successful vehicle following, a Bayesian formulation for the system has been derived, and two probabilistic distributions, one for each vehicle's pose, can be obtained. Based on the assumption that the two pose distributions are Gaussian functions, the K-L distance of the vehicle following system can be computed with these two computed distributions. With a series of achievable actions, such as steering and velocity commands, for the follower vehicle at each pose prediction step, and by minimizing the K-L distance, an optimized action for the follower vehicle can be obtained. The information theoretic vehicle following algorithm has been tested under a simulated environment by analyzing the performance of the follower vehicle when the leader vehicle undergoes various kinds of maneuvers. The simulated experimental results validate that the follower is able to trail the trajectories of the leader vehicle satisfactorily and at the same time maintain a safe following distance.**

I. Introduction

Information theoretic frameworks have been used extensively in mobile robotics applications. Typical applications are the surveillance system in Unmanned Aerial Vehicle (UAV) [1] and active exploration of an area for Unmanned Ground Vehicle (UGV) [2]. These systems aim to maximize the knowledge, or information, gained by the robot, through the optimized control actions [4][5][6]. The strategy also aims at minimizing the uncertainties of the system state through the selection of a sequence of control actions. Moreover, information theoretic frameworks have been used in the machine vision community as a tool in image association. For example, the K-L distance was used as a measure for feature selection such that the feature was classified by maximizing the K-L distance between target classes [3].

To achieve autonomous vehicle following function, data regarding the states of both the follower and leader vehicles are necessary. Data such as the dynamics and poses of the leader vehicles are commonly transmitted to the follower via the inter-vehicle communication system [7][8]. Beside using the inter-vehicle communication system, other vehicle following systems use on board sensors, such as laser scanner and cameras, as the main source of perception tools [9][10]. However, handling of the uncertainty or noises inherent in the sensors is a challenge in vehicle following system. The sensor data uncertainty may affect the reliability of the vehicle following system if it is not addressed properly. In anticipation of the above challenge, this paper focuses on the control of a follower vehicle in pursing a leader vehicle, taking into consideration the uncertainty in the measurement data obtained by the follower vehicle. The control commands to the follower vehicle are computed based on the minimization of the relative information (K-L distance) between the two vehicles. By formulating the vehicle following system in a Bayesian representation, we obtain two probabilistic distributions describing the uncertainties of the states of the leader and the follower vehicles. Before issuing an action to the follower vehicle, a series of reachable actions is identified. With this series of reachable actions as the input to a pose estimation filter of the follower vehicle, a set of expected predictions of uncertainty for the follower vehicle can be obtained. By computing the relative information based on this series of expected uncertainties with respect to the uncertainty of the state of the leader vehicle, a desired action for the follower vehicle can be obtained by selecting the action that yield a minimum relative information for the system.

Relative Information

As the relative information formulation will be used in this paper, a summary of the concept is included here.

Relative information (K-L distance) [11] is a matrix that quantifies the closeness of two probability density functions. The K-L distance is defined as:

$$R_{p,q} = \int Q(x) \cdot log \frac{Q(x)}{P(x)} dx \tag{1}$$

and in discrete form:

$$H(Q \| P) = \sum_{x_i} Q_{x_i} \cdot log(\frac{Q_{x_i}}{P_{x_i}}) \tag{2}$$

where Q and P are the two distributions to be compared. If the two distributions are similar, then their K-L distance will be close to zero. $[H(Q\|P) \geq 0$ with equality if and only if $Q = P]$.

K-L distance is a measure for the goodness of fit or closeness of two distributions. As compared to information gain measure, whereby the change in entropy only quantifies how much of the probability distributions changes, the K-L distance represents a measure of how much the distribution

1-4244-1068-1/07/$25.00 ©2007 IEEE.

has moved. For example, if P and Q are the same distributions, translated by different mean values, the change in entropy (ie., information gained), is zero whereas the relative entropy is not.

For the case of two Gaussian distributions [12][13],

$$\begin{aligned} H(Q\|P) &= \sum_{x_i} Q_{x_i} \cdot log(\frac{Q_{x_i}}{P_{x_i}}) \\ &= \frac{1}{2}\log\frac{|\Sigma_P|}{|\Sigma_Q|} \\ &+\frac{1}{2}Tr\{\Sigma_P^{-1}(\Sigma_Q-\Sigma_P)\} \\ &+\frac{1}{2}(\mu_Q-\mu_P)^T\Sigma_P^{-1}(\mu_Q-\mu_P) \end{aligned} \quad (3)$$

where (μ_P, Σ_P) and (μ_Q, Σ_Q) are the mean and covariance matrices pair for distributions P and Q respectively. The first term on the right hand side, of the second line, of equation 3 represents the information gained, the second term represents mutual information and the last term is actually the Mahalanobis distance of the two pdfs. From equation 3, if the uncertainties of the two distributions to be compared are of the same magnitude, the K-L distance is exactly the same as the measure of the Manalanobis distance. Whereas, in the case of the two distributions having the same mean values, the K-L distance measures the information gained and the mutual information. Hence, the K-L distance formulation compares both the mean and covariance of the two distributions under consideration.

II. Problem Formulation

A. Bayesian Formulation for Vehicle Following System

For vehicle following systems, the poses, of the follower and leader vehicles with respect to a known reference frame, or the relative poses of the vehicles, are needed. Mathematically, the complete vehicle following system can be formulated as a probability density function (pdf)[1]:

$$P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_k) \quad (4)$$

where $\mathbf{x}_{F,k}$ and $\mathbf{x}_{L,k}$ are the poses of the follower and leader vehicles respectively at time k, $\mathbf{U}_k = (u_0, u_1, ..., u_k)$ is the history of the control inputs (for example, the speed and steering angle commands) of the follower vehicle, and $\mathbf{Z}_k = (\mathbf{z}_0, \mathbf{z}_1, ..., \mathbf{z}_k)$ is the history of sensor measurement data collected up to, and including, time instant k. For a tractable solution to the vehicle following problem, the following usual assumptions are made:

- The vehicle following function is a Markov process and the current measurement $\mathbf{z}_k$ is independent of $\mathbf{Z}_{k-1}$ and $\mathbf{U}_k$, when conditioned on the pose of the follower vehicle. Hence,

$$\begin{aligned} &P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_k) \\ &\propto P(\mathbf{z}_k|\mathbf{x}_{F,k}, \mathbf{x}_{L,k})P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}) \end{aligned} \quad (5)$$

[1]The lowercase notation, eg $\mathbf{x}_k$ denotes the current state and the uppercase notation, eg $\mathbf{X}_k$ denotes the entire history of the state up to and including time k.

- Two separate sensors may be used in the pose estimation process. For example, odometry may be used for the localization of the follower vehicle whilst a range sensor may be used to acquire the pose of the leader vehicle. Hence, the measurement vector $\mathbf{Z}_k$ may be expressed as two independent measurement vectors, when conditioned on the pose of the follower:

$$\mathbf{Z}_k = (\mathbf{z}_0^p, \mathbf{z}_0^r, \mathbf{z}_1^p, \mathbf{z}_1^r, ..., \mathbf{z}_k^p, \mathbf{z}_k^r) = (\mathbf{Z}_k^p, \mathbf{Z}_k^r) \quad (6)$$

where $\mathbf{Z_k^P} = (\mathbf{z}_0^p, \mathbf{z}_1^p, ..., \mathbf{z}_k^p)$ and $\mathbf{Z_k^r} = (\mathbf{z}_0^r, \mathbf{z}_1^r, ..., \mathbf{z}_k^r)$ are the proprioceptive sensor measurement vector and range sensor measurement vector respectively, obtained up to, and including, time k. Hence,

$$\begin{aligned} &P(\mathbf{z}_k|\mathbf{x}_{F,k}, \mathbf{x}_{L,k})P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}) \\ &= P(\mathbf{z}_k^p, \mathbf{z}_k^r|\mathbf{x}_{F,k}, \mathbf{x}_{L,k}) \\ &\times P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}^p, \mathbf{Z}_{k-1}^r) \\ &= P(\mathbf{z}_k^p|\mathbf{x}_{F,k}, \mathbf{x}_{L,k})P(\mathbf{z}_k^r|\mathbf{x}_{F,k}, \mathbf{x}_{L,k}) \\ &\times P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}^p, \mathbf{Z}_{k-1}^r) \end{aligned} \quad (7)$$

- As the sensor measurement, $\mathbf{z}_k^p$ will be used for the estimation of the pose of the follower vehicle, it will not be affected by the pose of the leader vehicle. Then $\mathbf{z}_k^p$ can be assumed to be independent of $\mathbf{x}_{L,k}$, when conditioned on the current state of the follower vehicle. Hence,

$$P(\mathbf{z}_k^p|\mathbf{x}_{F,k}, \mathbf{x}_{L,k}) = P(\mathbf{z}_k^p|\mathbf{x}_{F,k}) \quad (8)$$

- In the vehicle following function, a control command (e.g steering angle and velocity), to be issued to the follower vehicle, has to be computed based on the pose of the leader vehicle. This, will affect the future pose of the follower vehicle. Thus, the state of the follower vehicle is statistically independent of the state of the leader, when conditioned on the history of the inputs to, and observations made from, the follower vehicle. Hence,

$$\begin{aligned} &P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}^p, \mathbf{Z}_{k-1}^r) \\ &= P(\mathbf{x}_{F,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}^p, \mathbf{Z}_{k-1}^r) \\ &\times P(\mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}^r) \end{aligned} \quad (9)$$

By consolidating equations 4 to 9, the formulation for the vehicle following model can be factored as:

$$\begin{aligned} &P(\mathbf{x}_{F,k}, \mathbf{x}_{L,k}|\mathbf{U}_k, \mathbf{Z}_k) \\ &\propto \underbrace{P(\mathbf{z}_k^p|\mathbf{x}_{F,k})P(\mathbf{x}_{F,k}|\mathbf{U}_k, \mathbf{Z}_{k-1}^p)}_{localization\ of\ follower} \\ &\times \underbrace{P(\mathbf{z}_k^r|\mathbf{x}_{F,k}, \mathbf{x}_{L,k})P(\mathbf{x}_{L,k}|\mathbf{Z}_{k-1}^r)}_{Tracking\ of\ leader\ vehicle\ w.r.t\ follower} \end{aligned} \quad (10)$$

Thus, we can conclude that the joint posterior for the vehicle following system can be factored into two separate estimation processes, one for the localization of the follower whilst the other is used to track the leader vehicle.

B. Information Theoretic Vehicle Following

The formulation proposed in equation (10) relies on the accuracy of the localization of the leader and follower vehicles. If this is to be implemented, two main issues need to be considered:

- **Sensor uncertainty**, which affects the performance of the vehicle following system. The uncertainty in the pose estimates of the leader vehicle must be considered by the follower when determining its next control action. Furthermore, possible consequences due to sensor uncertainty that might cause vehicle following operation failure has to be considered during implementation.
- **Vehicle Constraints**: Typically, a command is sent to the follower vehicle so it can maneuver towards the pose of the leader vehicle at time t. This is based on the estimations of the leader pose from the follower vehicle (c.f. figure 1). In practice, the alignment of the follower vehicle at time $t+1$ may not allow it to attain the pose of the leader vehicle at time t, mainly due to the kinematic constraints.

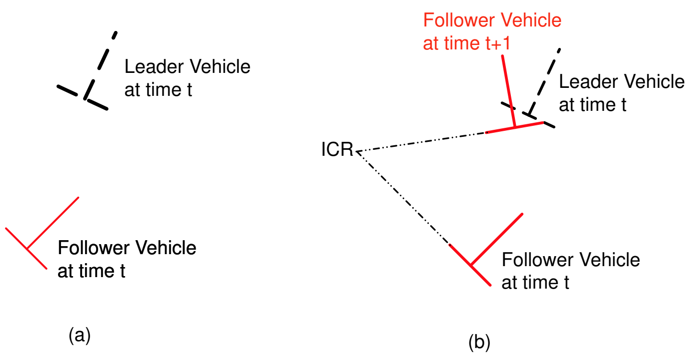

Fig. 1. Demonstration of vehicle kinematic constraints. a) At time t, the follower vehicle observes the leader vehicle and estimates its pose. A control command is generated based on the relative poses of both vehicles and the follower vehicle kinematics. b) At t + 1 the vehicle follower reaches the expected position. This may not match that of the leader vehicle at time t due to the kinematic constraint of the vehicle.

To minimize the effects of sensor uncertainty and vehicle kinematic constraints, the concept of relative information is used to determine the control actions for the follower vehicle to follow the leader vehicle closely. This has been made possible by equation 10. Two probabilistic distributions, representing the uncertainty of the poses of the vehicles, can be obtained in the recursive estimation process and be used in the computation of relative information.

III. Generalized Information Theoretic Vehicle Following in a Finite Time Window

In general, the vehicle following algorithm can be formulated in a finite time horizon $[k, k+N-1]$, where k is the current time step and N is the finite time window size in the time horizon. Suppose that the follower vehicle is controlled by a set of actions at each time step denoted by

$$\mathbf{a_t} = \{a_k, a_{k+1}, ..., a_{k+N-1}\} \quad (11)$$

where $\mathbf{a_t}$ for $t = k, k+1, ..., k+N-1$ is the vector of actions specifying the control command issued to the follower vehicle at time t. At every time step, the follower vehicle makes observations about the leader vehicle. The observation is denoted as

$$\mathbf{b_t} = \{b_k, b_{k+1}, ..., b_{k+N-1}\} \quad (12)$$

Let $\mathbf{U}_t^f$ and $\mathbf{U}_t^l$ denote the sets of uncertainty terms and mean control values, for all time steps t defined earlier, for the follower and leader vehicle, affected by the set of follower actions and observations of the follower vehicle, in the referred time horizon as follows:

$$\mathbf{U}_t^l = \{u_{it}^l(a_k, a_{k+1}, ..., a_{k+N-1}) | i = 1, 2, ..., n_t\} \quad (13)$$

$$\mathbf{U}_t^f = \{u_{it}^f(a_k, b_k, a_{k+1}, b_{k+1}, ..., a_{k+N-1}, b_{k+N-1}) | i = 1, 2, ..., n_t\} \quad (14)$$

where n_t denotes the number of uncertainty terms at time step t. The terms u_{it}^f and u_{it}^l denote the i^{th} uncertainty term at time step t. The information theoretic vehicle following problem can now be formulated as follows:

$$a = arg\min_a C(H(\mathbf{U}_{j+1}^f \| \mathbf{U}_j^l) | j = k, k+1, ..., k+N-1) \quad (15)$$

subject to the constraints

$$\mathbf{g}(\mathbf{X}(k), \mathbf{X}(k+1), ..., \mathbf{X}(k+N-1), a_k, a_{k+1}, ..., a_{k+N-1}) \leq g_{th} \quad (16)$$

where $C(.)$ is the composite scalar function representing the K-L distance, $H(.)$ is the K-L distance computed at time j, X is the augmented state vector of both the leader and follower vehicles, $\mathbf{g}(.)$ is the nonlinear constraint vector function and g_{th} is a constrainted threshold vector. The constraints include the maximum allowable steering angle of the vehicle, safe following distance and the allowable following speed.

Equation 15 provides an unique decision-theoretic solution to the vehicle following problem. In general, a control command, such as velocity or steering angle, for the follower vehicle can be generated by analyzing the relative information between the two vehicles over a certain time horizon. However, optimization of equation 15 involves complex computation, which involves multiple iterations of optimization, which in turn consumes large computation power, thus hindering the real-time control of the follower vehicle. Hence, for implementation, the look-ahead time horizon for optimization is limited to one time step, which is also known as the greedy method.

A. Greedy Algorithm for Information Theoretic Vehicle Following

From equation 10, under the Gaussian distribution assumptions, it is possible to obtain the estimated poses of the follower and leader vehicles by using recursive filters such as the Extended Kalman Filter. At time t, let $N(X_t^f, Q_t)$

and $N(X_t^l, P_t)$ denote the normal distribution functions of the estimated poses of the follower and leader vehicles respectively. Q_t and P_t are the covariances for the follower and leader vehicles respectively. It is possible to predict the pdf, at time $t+1$, of the follower vehicle based on the control command to be issued to the follower vehicle at time t. Let $N_{c(t)}(X^f_{t+1|t}, Q^f_{t+1|t})$ denotes the predicted pdf of the follower vehicle at $t+1$ based on a certain vehicle command $c(t)$. The aim of the greedy algorithm is to determine a control command,a_k, to be sent to the follower so it yields a minimum K-L distance between the two distributions, $N(X_t^l, P_t^l)$ and $N_{c(t)}(X^f_{t+1|t}, Q^f_{t+1|t})$. Assuming that both distributions are Gaussian, the K-L distance between them can be computed as:

$$
\begin{aligned}
H(p\|q) &= \frac{1}{2}\log\frac{|P|}{|Q|} \\
&+\frac{1}{2}Tr\{P^{-1}(Q-P)\} \\
+\frac{1}{2}(X^f_{t+1|t} - X^l_t)^T P^{-1}(X^f_{t+1|t} - X^l_t) &
\end{aligned}
\tag{17}
$$

The optimization step for computing the control actions for the follower vehicle is:

$$c = arg\min_c H(N(X^l_t)\|N_{c(t)}(X^f_{t+1|t}, Q^f_{t+1|t})) \tag{18}$$

under the vehicle constraint of

$$\alpha_{min} \leq c(t) \leq \alpha_{max} \tag{19}$$

where α_{min} and α_{max} denote the minimum and minimum steering angle of the follower vehicle.

IV. Implementation and Experimental Results

The simplified block diagram in figure 2 shows the two feedback loops in the vehicle following system. The inner loop comprises a motion controller that maintains the stable traction of the vehicle. The outer loop guides the vehicle to follow the estimated trajectory of the leader vehicle.

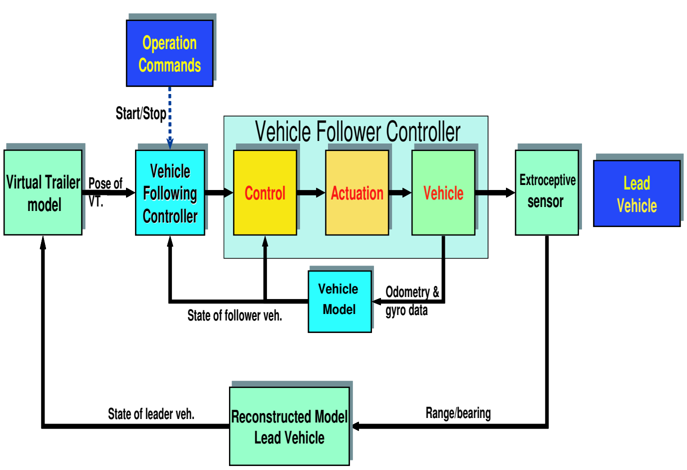

Fig. 2. Control block diagram for the proposed vehicle following system.

The follower vehicle is assumed to have on board sensors that enable it to estimate the pose of the leader vehicle with respect to the follower vehicle reference frame. The process of implementing the vehicle following system can be subdivided as follows:

- *Localization of the follower vehicle.* For vehicle following system, a common reference is needed. In our implementation, the odometry data and the information from gyroscope were use to localize the follower vehicle.
- *Detection and tracking of the target vehicle.* The pose of the leader vehicle can be detected using a laser scanner. To ensure a reliable and safe following distance, the use of a virtual trailer (VT) link model has been proposed by the authors [14]. In this model, the vehicle following system is formulated as if the leader vehicle is pulling a trailer. It was shown that, a VT containing at least 2 links of equal length is necessary for a follower vehicle to be able to exactly execute the identical path of the leader vehicle. It was also shown that a two link trailer is a sensible choice, since increasing the number of links would reduce the string stability of the platoon [15]. It is thus possible to command the follower vehicle to safely follow the path of the virtual trailer link. The purpose of this formulation is to improve the accuracy and safety of vehicle following.
- *Following the leader vehicle.* The greedy method presented in III-A was implemented to determine the control actions for the vehicle following function. First the pose of the virtual trailer link model is estimated based on the results of the localization and observation acquired by the follower model. Next a series of possible steering commands are used as input to the compute the predicted poses of the follower vehicle at the next time step. The K-L distances are then computed and the control action with the minimum K-L distance is then selected.

A. Experimental Setup

The proposed method was validated using simulation techniques. For this purpose, a well known simulator, the USARSim (Urban Search and Rescue Simulator), developed at Carnegie Mellon University [16], was used. This is based on the industrial game engine Unreal Engine 2004 (www.unrealtournament.com). The Unreal Engine has been deployed for the development of networked multi-player 3D games, and, has solved many of the issues related to modelling, animation and rendering of the virtual environment. Furthermore, to some extend, the dynamics of the various entities (e.g. our vehicles) can be handled by the in-built Karma physical engine [17].

For experimentation purposes, two similar mass market vehicles are simulated. An open test area on which the vehicles can be run a different speed was built as shown in Fig.3.

The leader vehicle was controlled by a standalone program during the simulation. Its position was recorded as ground

Fig. 3. Scenario built using the Unreal Game Engine. Both vehicles are equipped with a 2D laser scanner attached to their front bumper.

truth. The follower vehicle was controlled by the K-L algorithm embedded in the program.

To test the feasibility of the new vehicle following theory, a S-Curve trajectory for the leader vehicle is generated. This trajectory involved moving the leader vehicle in a straight path, right turn, left turn followed by another left turn. The trajectory represents constraint found in typical road conditions whilst trying to challenge the controller response.

1) Performance Analysis: The purpose of this experiment is to test the feasibility of the proposed vehicle following algorithm. The leader vehicle is commanded to manoeuvre in a straight path for about 150 time steps, make a right turn for another 150 time steps and finally left turn for about 300 time steps. Figures 4 to 7 show the results of the run.

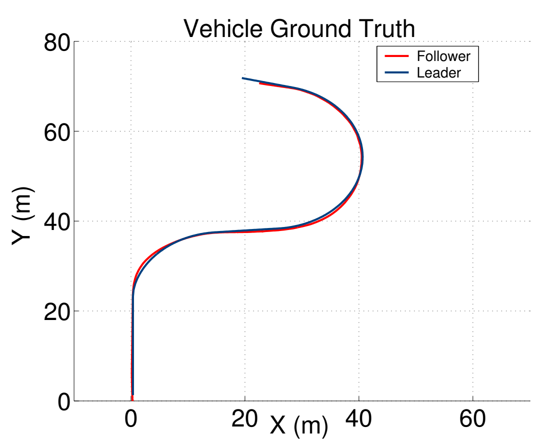

Fig. 4. S-Path Trajectory. The ground truth of vehicle trajectories.

In Figure 4, the error between the two trajectories are rather small despite the trajectory following error as estimated by the filter as shown in figure 4. As our algorithm uses 1-step look ahead for vehicle following, this is effectively a relative pose vehicle following. The small following

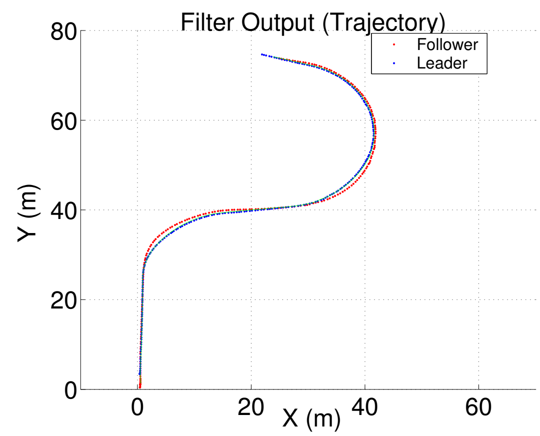

Fig. 5. S-Path Trajectory. Trajectories estimated by the filter.

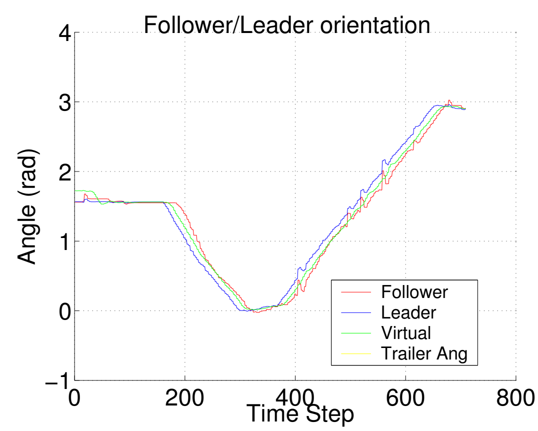

Fig. 6. Orientations of the leader vehicle, the virtual trailer and the follower vehicle as estimated by the filter.

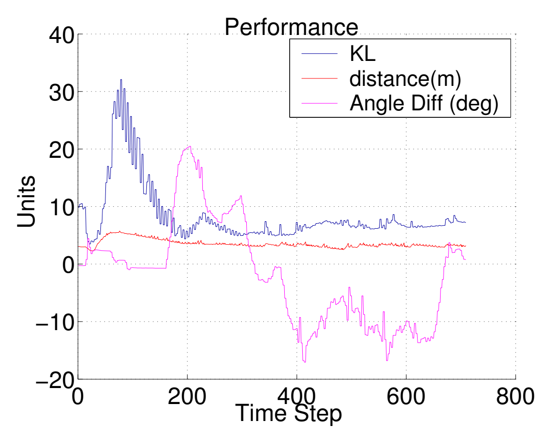

Fig. 7. Comparison of the KL distances with respect to the inter-vehicle distance and the orientation difference.

error as shown in figure 5 has suggested that the information theoretic based vehicle is robust to cope with various kind of maneuver.

In Figure 6, the orientation error, for time steps up to 150, when following the leader trajectory, is almost close to zero as expected for any vehicle following system moving in a straight path. At time step 180, the leader vehicle started to make a curve maneuver. From figure 6, we observed that the orientation of the follower vehicle still maintained in the straight moving angle for a period of time despite the curve maneuver of the leader. This is the effect of the virtual trailer link model as described in section IV. This is an important observation as we do not want the follower vehicle to start making turns when the leader vehicle has started the curve maneuver, as there will always be latency between the systems due to the vehicle inter distance and kinematics. The result of the virtual trailer link model yield a better following performance and hence prevent the follower vehicle from hitting obstacles such as road curbs. There are, however, orientation differences when the vehicles are maneuvering on the curve path. This error is also expected as the two vehicles should not be aligned in the same orientation when they are travelling along a curve, the priority in this case is to maintain a constant inter vehicle distance.

Figure 7 shows the performance of the information theoretic vehicle following algorithm. The inter-vehicle distance is relatively constant throughout the run. Initially, from time steps 0 to 50, the inter-vehicle distance increases in time. This is mainly caused by the initial relative position of the two vehicles. After the initialization of the vehicle following algorithm, the inter-vehicle separation increases with time until it reaches a separation equivalent to the total length of the virtual links (4m for our case). As the separation increases, the K-L distance increases. However, there exist an acceleration period for the follower vehicle from the start of the algorithm, hence, K-L distance increases with respect to the inter-vehicle separation. This is due to the vehicle dynamics, inertia needs to be overcome as the follower vehicle moved and hence the increase in latency. Note that the orientation difference between the leader and follower vehicle increases from approximately 0^o to 20^o from time step 150 to 200. This is the effect of virtual trailer link effect. As the leader vehicle is starting to make the curve maneuver, the follower vehicle is still in the straight moving path, hence, the angle difference increases.

Overall, the K-L algorithm is able optimized the control actions for the follower vehicle in achieving a close following of the leader vehicle and at the same time maintaining a safe following distance between the two vehicles.

V. CONCLUSIONS

An autonomous vehicle following system, that aim to achieve close pursuing of a leader vehicle, has been formulated by using an information theoretic framework. The aim of this framework is to select an optimized control input for the follower vehicle so as to minimize the pose error between the follower and the leader vehicles. Under this framework, the relative information (or K-L distance)has been used as a matrix to evaluate a sequence of control actions, to be input to the follower vehicle. Simlation results have shown that the information theoretic vehicle following system is robust and safe to implement. The system is robust as the uncertainties of the poses of both of the vehicles are considered during the execution of the vehicle following. A safe following distance has been maintained throughout the vehicle following process. However, in our experiment, only the steering control of the follower vehicle is considered. In order to optimize the system performance, multiple control actions need to be considered as shown in figure 2. If there is a priori information in the form of a digital road map, this can be used as an additional observation and hence enhance the information contend for the follower.

ACKNOWLEDGEMENT

The authors would like to acknowledge Mr. Chong Wee Kiat from Nanyang Technological University, for setting up the Unreal environment and Mr. Aylwyn Lai and Mr. Suliman from Nanyang Polytechnic, for building and modelling the experimental vehicle.

REFERENCES

[1] Ben Grocholsky, *Information Theoretic Control of Multiple Sensor Platforms*, PhD Thesis, ACFR, University of Syndy, 2002
[2] S. Thrun, Wolfram Burgard, Dieter Fox, *Probabilistic Robotics*, The MIT Press, Sept. 2005
[3] Frans M Coetzee, *Correcting The Kullback-leibler Distance for Feature Selection*, Pattern Recognition Letters 26(11): 1675-1683, 2005
[4] Brendan Burns, Oliver Brock *Information Theoretic Construction of Probabilistic Roadmaps*,Int. Conf. on Intelligent Robots and Systems, pp 650-655, 2003
[5] P.Wang and K. Gupta, *View Planning via Maximal Entropy Reduction*, Proc. of Workshop on the Algorithmic Foundations of Robotics, 2002
[6] Francesco Amigoni and Alessandro Gallo, *A Multi-Objective Exploration Strategy for Mobile Robots*, Proce. Int. Conf. on Robotics and Automation, pp 3861-3866, 2005
[7] P. Borodani, "Full Automatic Control for Trucks in a Tow-Bar System", *Proc. Of AVEC*, 2000.
[8] D. Swaroop, S.M Yoon, "The design of a Controller for a Following Vehicle in an Emergency Lane Change Maneuver", *Report for MOU 319*, ISSN 1055-1417, 1999.
[9] G.Lu and M.Tomizuka, "Vehicle following as backup control schemes for magnet-magnetometer-based automated highways", *IEEE transaction on Control System and Technology*, Vol.3, No. 2., March 2005.
[10] Teck Chew Ng, Ibanez-Guzman, J., Jian Shen, Zhiming Gong, Han Wang and Chen Cheng; "Vehicle following with obstacle avoidance capabilities in natural environments" Proceedings. ICRA '04. 2004 Volume 5, 26 April-1 May 2004 Page(s):4283 - 4288 Vol.5
[11] S. Kullback, *On information and Sufficiency*, Annals of mathematical Statistics, Vol. 22, pp 79-86, 1951
[12] Kleeman, *Measuring dynamical prediction utility using relative entropy*, Journal of Atmos. Sci, 59, pp 2057-2072, 2002
[13] S. Kullback, *Information Theory and Statistics*, Wiley & Sons, 1968
[14] T.C. Ng, M.D. Adams, J.I.Guzmàn, "Autonomous Vehicle-Following Systems: A Virtual Trailer Link Model", *IROS 2005*, pp 2968-2973, 2005.
[15] D. Swaroop, J.K. Hedrick, "String Stability of Interconnected Systems", *IEEE Trans. Automation and Control*, vol 41, no 3, pp 349-356, March 1996.
[16] Wang, J., Lewis, M. and Gennari, J. "USAR: A Game-Based Simulation for Teleoperation." *Proceedings of the 47th Annual Meeting of the Human Factors and Ergonomics Society*, pp 13-17, 2003
[17] Mathengine, *MathEngine Karma User Guide*, March (2002).