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Accounting for localization errors in a mixed-vehicle centralized control system

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Abstract

Future autonomous vehicles are expected to coordinate controls to improve traffic efficiency, fuel consumption and most importantly safety. A centralized vehicle control system is a system where a centralized entity computes control inputs considering variables like vehicles' localization, velocity, etc. and transmits it to the vehicles to implement them. Due to the presence of localization errors, perceived localization of a vehicle is different from its true localization. Control inputs calculated using erroneous localization, when implemented on vehicles result into collisions.

In this paper we propose a centralized control approach which takes into consideration localization errors for collision free braking in a mixed traffic scenario. The performance of the proposed approach is evaluated under three different traffic scenarios with vehicles having erroneous localization. Results show significant increase in the number of collisions avoided, while using proposed approach, as compared to scenarios where localization errors were not accounted for. Moreover, despite localization errors, the proposed approach can ensure upto the same number of collision avoidance as in a scenario where true localization was known.

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Keywords: Autonomous vehicles, Manually driven vehicles, Collision avoidance, Localization inaccuracies, GPS, Mixed traffic scenario

1. Introduction

Future autonomous vehicles will rely on traffic perceptions from sensors, radars, LIDARS integrated in a control mechanism called Adaptive Cruise Control (ACC) to autonomously take driving actions. When equipped with Vehicle-to-Vehicle (V2V) Communication technologies, these autonomous vehicles may also cooperatively exchange their traffic perception for enhanced cooperatively driving control through Cooperative ACC (CACC). These different types of automated vehicles will need to coexist in future roads along with manually driven vehicles. Accordingly, we

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differentiate active participants (APs) from passive participants (PPs), where the former allows coordinated perceptions, decisions and traffic control (e.g.: CACC enabled vehicles), the latter only influences APs and are not capable of coordinating with other vehicles (e.g. ACC enabled vehicles or manually driving vehicles).

Most work on autonomous vehicles is based on coordinated control decision making between APs for maneuvering intersection clearances, lane merging, etc, considering perfect detection of any danger. Assuming less ideal circumstances, where APs are alerted to potential danger with delay or when the position of danger is not clearly known, APs can not coordinate a maneuver thus face emergency situations making it imperative to brake and to come to a halt. Thus, the objective changes from coordinated control for maneuvering to cooperative braking between APs with potential PPs. The presence of PPs particularly introduces challenges in terms of localizing them, modeling their behaviour and predicting their reactions (Monteil et al., 2015) which complicates cooperative braking strategies. Flawless sensing and perception, control and communications, are required for APs to take optimal driving decision (Wymeersch et al., 2015). Imperfections in either of these will lead to safety issues.

In this paper, we consider the impact of imperfect localization on cooperative braking strategies involving APs and PPs. We first model cooperative braking strategy to avoid front and rear end collisions assuming perfect localization information. We then assume inaccurate localization information and study the increase in collisions. The main contribution of the paper is an enhanced control methodology to avoid collisions caused due to inaccurate localization. We formulate a methodology consisting of (i) initial and final state parameters for different vehicles like velocity, position and distance between vehicles (ii) constraints like maximum braking strength, maximum distance within which vehicles must come to a halt, limitations on jerks, collision avoidance conditions, etc. and (iii) localization errors for both APs and PPs. Kinematic equations are modeled in a control theory based input-output format with system limitations to generate control inputs for APs.

Section 2 introduces some of the important related work, section 3 introduces a generic centralized control methodology for mixed vehicle braking scenario. The decrease in the number of collisions avoided due to localization inaccuracies is discussed in Section 4 and our proposal to counter localization inaccuracies is introduced in section 5. The proposed methodology is implemented on three scenarios with different kinds of traffic and is evaluated in section 6. Conclusions are drawn and summarized in section 7.

2. Related Work

Related work on automated control may be categorized into two: first category considers scenarios with homogeneous autonomous vehicles and second category considers mixed traffic scenario with autonomous and manually driven vehicles. In the first category, centralized and decentralized algorithms have been developed for collision avoidance at intersections in (Hult et al., 2015) and (Qian et al., 2015) respectively. (de Campos et al., 2017) proposes and compares centralized and decentralized approaches for traffic coordination at intersections. Rios-Torres surveys different coordination algorithms for intersection clearances and highway on-ramps merging (Rios-Torres and Malikopoulos, 2016). Model Predictive Control (MPC) based coordinated braking control for longitudinal collision avoidance is considered by Wang et al. (Wang et al., 2015). Optimal trajectory planning for obstacle avoidance, overtaking, speed bump and lane changing scenarios has been recently proposed Qian et al. (2016).

Relatively lesser work has been accomplished in the second category which considers work on mixed traffic scenario with manually driven vehicles and CACC vehicles: (Monteil et al., 2016) focuses on evaluating PID feedback controller for implementing CACC controls, whereas (Fountoulakis et al., 2016) tries to estimate highway traffic state using data from connected vehicles. Authors in (Liu et al., 2015) (Guo et al., 2012) work on algorithms for safe, collision free coexistence of vehicles in mixed vehicle scenario. Authors (Roncoli et al., 2015) try to optimize traffic capacity by assigning longitudinal and lane change controls to CACC vehicles considering other manually driven vehicles on a highway. The limitation of the Intelligent Driver Model (IDM) as ACC mechanism in avoiding rear-end collisions of autonomous vehicle with following manually driven vehicles was proven in (Patel et al., 2017a), and Patel et al. extend it to a multi vehicle braking scenario and propose a centralized control model (Patel et al., 2017b).

If we analyze how manually driven vehicles are modeled we observe: they are assumed to implement IDM (Monteil et al., 2016) or are assigned a predefined path to follow (Guo et al., 2012) or are assumed to brake at maximum capacity after driver's perception response time (Patel et al., 2017b) to avoid collisions. Manually driven vehicles are assumed to have same statistical behavior (of acceleration, braking, etc.) as that of CACC vehicles in (Fountoulakis et al., 2016). (Liu et al., 2015) allows harder braking and a different headway distance on manually driven vehicle compared to CACC vehicles. In the limited literature on mixed traffic scenarios we observe that manually driven vehicles are mostly assigned predefined controls according to the requirements of the simulations.

Most of the vehicles sold today have GPS which can achieve an accuracy between 3 to 5 m depending on the environment (DoD, 2008). This accuracy is not considered sufficient for autonomous vehicles. Other GNSS based systems like RTK (Aponte et al., 2009) or DGPS Kuter and Kuter (2010) claim to provide cm and meter level accuracy respectively, but are relatively expensive and their use in CACC vehicles seems less likely. An accuracy of a couple of meters was achieved for an autonomous-off road vehicle (Schönberg et al., 1996) by fusing DGPS and inertial navigation systems. HIGHTS is an example of an European project with a goal to achieve high precision positioning system with the accuracy of 25cm for ITS (HIG). Wolcott and Eustice came close to this accuracy using single monocular camera by obtaining a ranging estimation error between 20 to 50 cm (Wolcott and Eustice, 2014). Cooperative localization techniques in VANETs by fusing GNSS and Infrared range measurements managed to achieve an accuracy between 20 to 40 cms (Hoang et al., 2016). Map matching techniques have been implemented on autonomous vehicles which have covered hundreds of miles with std of accuracy better than 10-cm (Levinson et al., 2011). Thus std of localization accuracy of vehicles used in this paper is between 4 m (from GPS) to 30 cms (from advanced techniques).

Even CACC vehicles can neither achieve perfect localization nor determine their true localization. According to literature review and to the best of authors' knowledge, none of the previously accomplished work evaluates the impact of localization inaccuracies in a centralized coordination methodology. Only a few actually consider the influence of localization inaccuracies e.g.: (Yang et al., 2016),(Mazzola et al., 2016) but this their motive was to achieve traffic signal optimization and to determine latency requirements for centralized controller using LTE based communications respectively. Therefore the goal of the paper is precisely to bridge this gap and investigate the impact of localization inaccuracies in centralized coordinated braking scenarios.

3. Centralized vehicular coordination control system in mixed traffic

Without loss of generality, we consider single dimensional scenario (1D) with multiple vehicles braking on a single lane containing APs (*CACC enabled*) and PPs (*manually driven vehicles*) as illustrated in Fig. 1. We assume PPs to be vehicles (without any control capabilities with human drivers) which can communicate information using DSRC/ cellular data connection. Thus it can be assumed that the centralized controller has a full knowledge (at instant n=0) about the state parameters of all PPs and APs and their vehicular constraints.

We model PP's reaction time as the perception reaction time of driver (t_{prt}) (McLaughlin et al., 2009), and we assume visibility of the driver limited to the vehicle in front. Moreover, we define $t_{prt,i}$:=$[t_{i,i-1}, t_{i,1}]$ as the pair of perception response time of a PP i compared to the vehicle in front and the first vehicle respectively. It means that a PP i would react $t_{i,i-1}$ seconds after vehicle $i-1$ and $t_{i,1}$ seconds after vehicle 1. And $t_{i,1}= t_{i,i-1}+t_{i-1,i-2}+...+ t_{2,1}$ if all $2, 3..i$ front vehicles are PPs (refer Fig. 1). Thus the reaction time of a PP is proportional to the number of other PPs immediately ahead. Assuming all PPs brake at maximum capability after their corresponding perception response time until they fully stop (vehicle i stops at th_i second of braking at maximum strength), the braking profile of PPs is given by:

$$u_i(n) = \begin{cases} 0 & \text{if } 0 \le n \le nt_{i,1} \\ u_i^{min} & nt_{i,1} < n \le nth_i \\ 0 & n > nth_i \end{cases} \quad \forall \quad i \in Z^c \tag{1}$$

Where n is any instant in the prediction horizon N ($n \in 1...N$). Values corresponding to th_i, $t_{i,i-1}$, etc. in seconds are represented in instances as nth_i and $nt_{i,i-1}$, etc. for discrete time domain calculations (1 second = 10 instances). Z is the set of all APs amongst n_v vehicles, $0 \le size\{Z\} \le n_v$. Note: Z^c is complement set of Z which signifies $i \notin Z$. Z^c is a null set ($Z^c = \varnothing$) if there are no PPs.

Consider APs: we assume all APs are warned at the same instant about a potential collision and immediately react based on received control inputs from the centralized entity. APs implicitly warn PPs of their braking through braking lights. Accordingly, the reaction time of a PP(i) behind an AP will be much shorter than a PP(k) behind another PP i.e.: $t_{i,1} < t_{k,1}$, as indicated in Fig. 1.

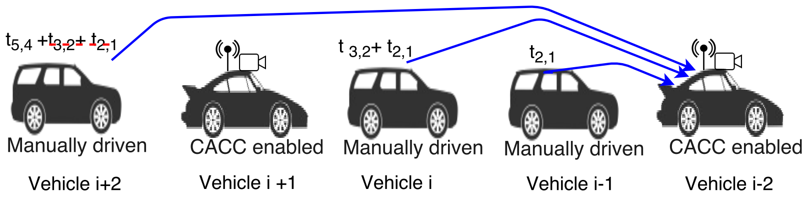


Fig. 1: Delays in commencing reaction of manually driven vehicles with respect to the first vehicle

An optimal control strategy for each of the AP to come to a halt while avoiding collisions within a finite prediction horizon N, subject to various parameters (e.g. speed, inter-distance, braking capability, etc..) of all n_v vehicles is described below. It is important to set the correct value of horizon as it influences the calculation time. Considering the *state* variable x_i of a vehicle i ($i \in 1...n_v$) as:

$$x_i = [p_i \; v_i]^T \tag{2}$$

where p_i and v_i corresponds to the location and velocity of the vehicle, the control system assumed to be linear (de Campos et al., 2017) can be expressed in continuous time domain as:

$$\begin{aligned} \dot{x}_i(t) &= f_i(x_i(t), u_i(t)) \\ \dot{x}_i(t) &= Ax_i(t) + Bu_i(t) \end{aligned} \tag{3}$$

where $u(t)$ is control input ($u_i(t) \in \mathbb{R}$). In discrete form, the previous equation can be expressed as:

$$x_i(n+1) = Ax_i(n) + Bu_i(n) \tag{4}$$

where n is any sampling instant ($n \in 1...N$), Assuming basic kinematic relationships (e.g. $\dot{p}_i = v_i$, $\dot{v}_i = u_i$, $\dot{u}_i = j_i$), *exact* discretization of equation 3 leads to equation 5 (Qian et al., 2015):

$$A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} (\Delta t)^2/2 \\ \Delta t \end{bmatrix} \tag{5}$$

Δt is the time between two consecutive samples n and $n+1$; j denotes jerks. Equation 3 needs to be solved obeying the following constraints:-

- Initial and Final state constraints
  Starting and terminal position and velocity can be represented as constants $x_i(0)$ and $x_i(N)$. $p_i(0)$ and $p_i(N)$ indirectly defines the range of the vehicle and the path it needs to follow in a 1D scenario. When all vehicles attain zero final velocity, starting from a non-zero (initial) velocity, it represents a braking scenario. This is can be defined as:

$$v_i(N) = 0 \tag{6}$$

- Vehicle and Passenger Constraints
  In real life scenarios, there would be various limitations related to admissible values of jerks, acceleration, velocities etc. which can be modeled as follows:

$$\begin{bmatrix} p_i^{min} \\ v_i^{min} \end{bmatrix} \leq x_i(n) \leq \begin{bmatrix} p_i^{max} \\ v_i^{max} \end{bmatrix} \tag{7a}$$

$$u_i^{min} \leq u_i(n) \leq u_i^{max} \tag{7b}$$

$$j_i^{min} \leq j_i(n) \leq j_i^{max} \tag{7c}$$

Where $(\cdot)_i^{min}$, $(\cdot)_i^{max}$ corresponds to minimum and maximum value of that parameter for vehicle i. Note: u_i^{min} and u_i^{max} stand for maximum braking and maximum acceleration capabilities.

- Safety constraints
  Distance between vehicles can not reduce to zero, at any given moment. These conditions can be expressed as:

$$d_{ik}(n) = p_i(n) - p_k(n) - l_i > 0 \qquad \forall i \in 2...n_v, \;\; k = i - 1 \tag{8}$$

  where $d_{ik}(n)$ denotes the distance between vehicles i and k at instant n and l_i is the true length of any vehicle, vehicle i is ahead of vehicle k.
- Cost Function
  Change in acceleration causes discomfort and the goal is to minimize discomfort. 1-norm usually gives equal importance to errors where as ∞-norm just considers the largest error. Thus, we chose the 2-norm on change in acceleration as one cost function J (equation 9a). Note: Acceleration is the control input in this system. Alternately, we also propose another cost function (equation 9b) which penalizes the deviation of actual distance between vehicles d_{ik} from desired distance between vehicles $\hat{d_{ik}}$.

$$J = \sum_{i=1}^{n_v} \sum_{n=1}^{N} ||u_i(n) - u_i(n-1)||_2 \tag{9a}$$

$$J = \sum_{i=2}^{n_v} \sum_{n=1}^{N} \hat{d_{ik}}(n) - d_{ik} \quad ; \;\; k = i - 1 \tag{9b}$$

Our proposal is thus to calculate control inputs for APs taking into account APs and PPs. APs will implement control inputs derived from Eq 10, where as PPs will implement braking model described in equation 1. This braking scenario has 2 primary objectives: collision avoidance (equation 8) and coming to a halt (equation 6), which are put as constraints. Restricting jerks within certain bounds (equation 7c) ensures smooth braking for APs. [1] The cost function can be anything, but in our case, is set to maximize comfort (equation 9a). By integrating all of these equations, a centralized mixed vehicle braking coordination model can be represented as:

$$\text{minimize} \quad J = \sum_{i=1}^{n_v} \sum_{n=1}^{N} ||u_i(n) - u_i(n-1)||_2 \qquad subject \quad to \quad equation\ 1, 2, 4, 5, 6, 7, 8 \tag{10}$$

The centralized controller is expected to be able to solve the convex optimization problem represented by Eq 10[2] . We solve it using CVX (CVX Research, 2012) on MATLAB. [3]

4. Collisions due to erroneous localization information: Heterogeneous AP scenario

To study the impact of erroneous localization on a centralized control system, we simulate a 6 vehicle scenario consisting of a string of heterogeneous APs of different builds (different software and have different hardware). As vehicles are heterogeneous, the localization error profiles of all of these vehicles would be different. We draw localization error e_i for each vehicle i from a Gaussian distribution with zero mean and std value randomly chosen from $\Phi = [4; 2; 1; 0.5; 0.3]$ based on range derived from the related work in section 2. The perceived localization p_i^* is generated by adding the error e_i to the true localization value p_i. We assume the error to be constant for a particular vehicle over N instants.

Simulation parameters:
The starting (true) location of the first vehicle ($p_1(0)$) is fixed at 95.9m, considering that this is a distance at which at

[1] PPs have a braking profile defined by equation 1 and thus jerks are not considered for PPs.
[2] If collisions are inevitable, this methodology will not return any control inputs. Solving such a scenario is out of scope of this paper
[3] Strict inequalities have been avoided wherever possible by adding a small offset and converting it into a non-strict one

Table 1: General values

Symbol	Parameter description	Value
g	gravitational constant	$9.88 m/s^2$
l_i	true length of any vehicle	$4m$
Δt	sampling time	$0.1s$
N	sampling horizon	160 instants (16 s)

Table 2: Heterogeneous autonomous vehicles simulation results

α	$\beta1$ [6]	$\beta2$	γ
70	1	38	56

least one DSRC/ITS-G5 safety message would be received with 99.5% probability (An et al., 2011) [4]. The location of the potential collision is assumed to be the origin (0 in 1D space), and vehicles are moving towards the origin. $p_i^{min} > 0$ ensures vehicles stop before intersection. If $i+1$ represents the vehicle following the vehicle i, then $p_{i+1} > p_i$. For all vehicles , v^{min} is set to zero, thus implying that vehicles can not go in reverse. $u^{max} = 0$, guarantees a pure deceleration scenario, and j^{min} and j^{max} values are capped to -0.25 and 0.25 m/s^3 respectively. Simulations performed in this paper don't require the use of p^{max} and v^{max}.

The maximum braking strength u^{min} of each vehicle is chosen from a normal distribution: $\mathcal{N}(-0.6g, (0.1g)^2)$ (Brunson et al., 2002), and is capped between – 0.4g and – 0.8g (Fig. 4); the perception response time of a manually driven vehicle t_{prt} is drawn from a normal distribution $\mathcal{N}(1.33, (0.27)^2)$ (McLaughlin et al., 2009) and is capped between 0.8 s and 1.8 s; vehicles are randomly allocated an initial velocity $v_i(0) = 96 \pm 2.5\%$ kmph to replicate a high-velocity scenario.

The initial distance between vehicles i and k denoted by $d_{i,k}(0)$, represented as time headway, is chosen between 0.2s (≈5m) and suggested time headway 1.8s motivated from (Dar et al., 2010). We deliberately cap the inter vehicular distance to the suggested value of 1.8s to reflect aggressive driving where collisions would be more probable.The time horizon N of simulations were set to 16s (160 instants), where a second is divided into 10 instants. This is motivated by the fact that GPS update frequency and Cooperative Awareness Message (CAM)/ Basic Safety Message (BSM) transmission frequency is supposed to be 10 Hz (ETSI, 2011).

Evaluation Parameters:

We define three evaluation criteria and three key parameters to understand and evaluate the simulations.

1. Criteria 1:

The centralized coordination system is assumed to be aware of the 'true localization information p' and it calculates control inputs η_α using equation 10 for APs such that it avoids all collisions, satisfying all constraints. Let α represent the total number of feasible collision avoidance scenarios. The rest of the scenarios (100 - α) are those, where no matter what, atleast one collision is unavoidable.

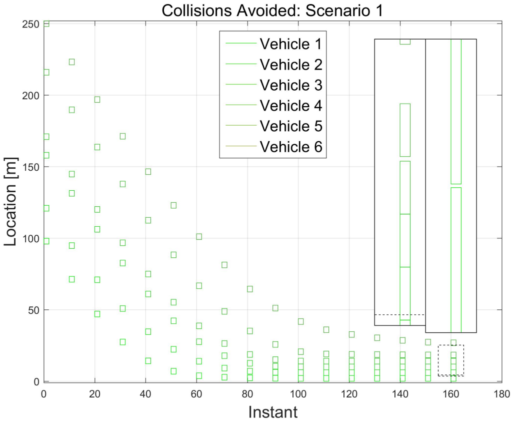
2. Criteria 2:

The centralized coordination system is assumed to be aware of the 'perceived localization information p^*' and it calculates control inputs η_β for APs using equation 10 (with p^* in place of p) such that it avoids all collisions had the vehicles been in their perceived locations (which they are not, they are in their true locations p).[5] When control inputs η_β are implemented on vehicles in their true locations p, the number of collisions actually avoided is represented by β. The third criteria and key parameter will be introduced in section 6.

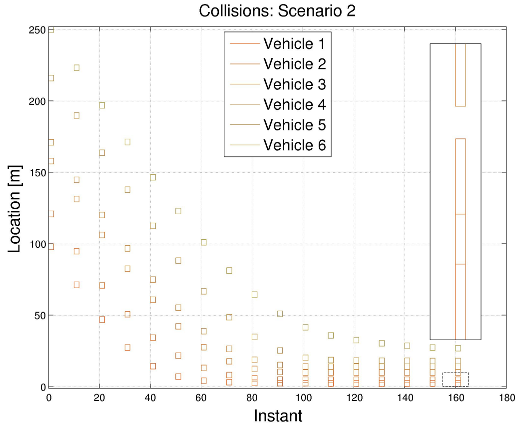
[4] We leave a more detailed investigation of such detection range to future work

[5] Note: The control unit is actually unaware of the true localizations. If perceived distance between vehicles which is the distance between perceived locations of two consecutive vehicles is less than or equal to zero, the situation is unfeasible and it is judged to be a collision avoidance failure.

[6] $\beta1$ and $\beta2$ corresponds to the number of collisions avoided with cost function 1 and 2 respectively.



(a) Collisions avoided using true location information



(b) Collisions occur when controls η_β are used on true vehicle locations

Fig. 2: Results for 6 heterogeneous CACC vehicle braking simulation

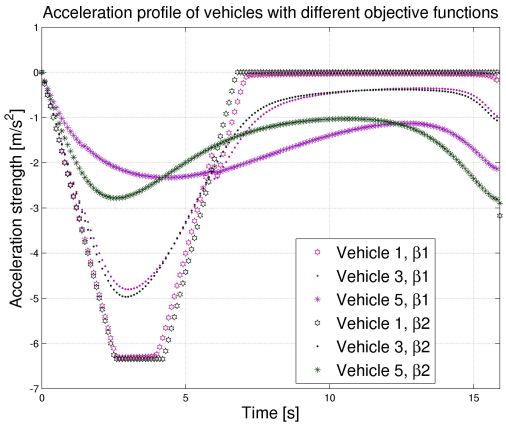


Fig. 3: Different control inputs for different objective functions

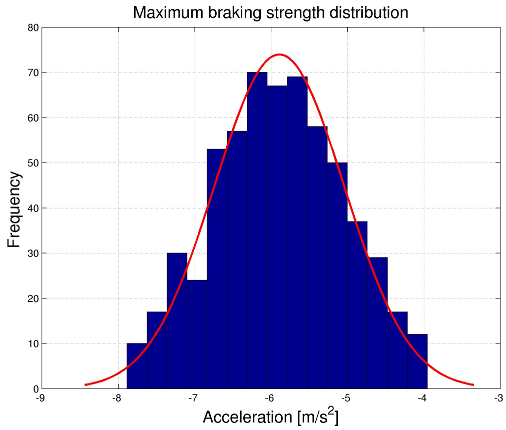


Fig. 4: Histogram of braking strength distribution

Analysis and observations:
From 100 runs we observe that 70 times, collisions were avoided using the true localization information. These 70 (represented by α) are considered reference scenarios (rest 30 are considered invalid as no matter what, in those cases, collisions can not be avoided). When there are multiple possible control inputs that achieve a desired final state from an initial state, the cost function helps choose one set of control inputs which would optimize the cost function. Thus, different cost functions return different control inputs $\eta_{\beta,1}$ and $\eta_{\beta,2}$ using perceived location (refer to Fig. 3). The number of collisions avoided when control inputs $\eta_{\beta,1}$ and $\eta_{\beta,2}$ are implemented on vehicles(true localization) are different β values 1 and 38 respectively. Refer to Table 2. The reason for this vast difference is: cost function 1 (equation 9a) focuses on optimizing comfort whereas cost function 2 (equation 9b) focuses on maintaining a desired distance ($\hat{d_{ik}} = 3$ m) between vehicles.

Location of vehicles corresponding to a particular run which demonstrates successful collision avoidances when true localization is known and failure when only perceived localization is known is plotted in Fig. 2a and 2b respectively. These figures show the location of vehicles over N instances. Length of rectangles represent the length of the vehicles. Thus overlapping rectangles would imply a collision. A magnified version of the location of vehicles at the end of time horizon is shown to help better comprehend these images. Note that in some images, despite best efforts,

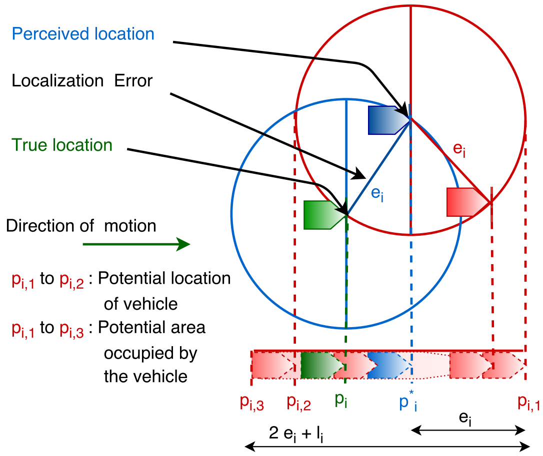


Fig. 5: Error explanation

it is not possible to zoom to a level to show the non-zero distance between vehicles, where as actually it is (atleast 0.1 m); In Fig. 2b first three vehicles are located within 7 meters, which implies collisions.

We observe 69 and 22 collisions take place (using cost functions 1 and 2), because we have not considered localization errors in the modeling of centralized control system. In the next section, we propose a methodology to counter this by accounting for localization errors.

5. Proposal: Accounting for localization inaccuracies

We differentiate true position p_i and the perceived position (erroneous localization) p_i^* of a vehicle i, where the former is the actual position of the vehicle where as the latter is the calculated position of the vehicle. Neither the transmitting vehicle nor the receiver would know the true positions. Perceived position is different from the true position when there is an error in localization e_i. As localization error is generally available in 2D, perceived position can be represented as:

$$p^*_{i,x} = p_{i,x} + e_{i,x} \qquad p^*_{i,y} = p_{i,y} + e_{i,y} \qquad p_i = [p_{i,x}, p_{i,y}] \qquad p^*_i = [p^*_{i,x}, p^*_{i,y}] \tag{11}$$

error e_i has been split into longitudinal error $e_{i,x}$ and lateral error $e_{i,y}$, which are related as:

$$e_i = \sqrt{e^2_{i,x} + e^2_{i,y}} \tag{12}$$

Consider figure 5, where the object in green is ego vehicle's true location. The perceived location of the vehicle is shown in blue, which is at a distance equal to the localization error magnitude. With the knowledge only about the perceived localization and the error in the localization, the 'potential location' of the vehicle which is anywhere on the circumference in red is going to be used in our methodology.

We adapt this 2D scenario to a 1D scenario (as shown in the bottom part of the figure 5), accounting for errors in longitudinal direction only. Note that ego-vehicle can be assumed to be located anywhere between $p_{i,1}$ and $p_{i,2}$ and thus the potential area which could be occupied by the ego vehicle would be between $p_{i,1}$ to $p_{i,3}$. This is the maximum area which needs to be 'reserved' for this vehicle in order to guarantee collision avoidance with this vehicle. Distance between bounds $p_{i,1}$ and $p_{i,2}$ is 2*e_i. The new length of the vehicle $l_{i,e}$, and the location of the vehicle is assumed to be at $p_{i,1}$ is given by equations 13, 14.

$$l_{i,e} = l_i + 2 * e_i \tag{13}$$

$$p_{i,1} = p^*_i + e_i \tag{14}$$

Table 3: 3 Types of simulations- different traffic scenarios

	Heterogeneous APs	Homogeneous APs	Mixed traffic consisting of APs and PPs
APs present	Yes	Yes	Yes
PPs present	No	No	Yes
Vehicles with same build	No	Yes	No

where l_i is the actual length of the vehicle. As $e_i > 0$, $l_{i,e} > l_i$.

Our goal is to incorporate the above explained concept (equations 13, 14) into the mixed vehicle control technique introduced in subsection 3 which is done as follows:

$$\text{minimize} J = \sum_{i=1}^{n_v} \sum_{n=1}^{N} \|u_i(n) - u_i(n-1)\|_2 \tag{15}$$

subject to

$$\begin{aligned}
&l_{i,e} = l_i + 2 * e_i \\
&p_{i,1} = p_i^* + e_i \\
&x_i = [p_{i,1} \ v_i]^T \\
&x_i(n+1) = Ax_i(n) + Bu_i(n) \\
&\dot{p_{i,1}} = v_i; \qquad \dot{v_i} = u_i; \qquad \dot{u_i} = j_i \\
&A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} (\Delta t)^2/2 \\ \Delta t \end{bmatrix} \\
&\begin{bmatrix} p_{i,1}^{min} \\ v_i^{min} \end{bmatrix} \leq x_i(n) \leq \begin{bmatrix} p_{i,1}^{max} \\ v_i^{max} \end{bmatrix} \\
&u_i^{min} \leq u_i(n) \leq u_i^{max} \\
&j_i^{min} \leq j_i(n) \leq j_i^{max} \\
&d_{ik}^*(n) = p_{i,1}(n) - p_{k,1}(n) - l_{i,e} > 0 \qquad \forall i \in 2...n_v, \ \ k = i-1 \\
&u_i(n) = \begin{cases} 0 & \text{if } 0 \leq n \leq nt_{i,1} \\ u_i^{min} & nt_{i,1} < n \leq nth_i \\ 0 & n > nth_i \end{cases} \qquad \forall i \in Z^c \\
&v_i(N) = 0
\end{aligned}$$

Note: If $d_{ik}^*(0) \leq 0$, the situation is unfeasible and it is judged to be a collision avoidance failure. Any cost function used, will not change the number of collisions avoided.

6. Performance Analysis of proposed approach

To evaluate the proposed methodology under different road-traffic situations (refer Table 3), we introduce criteria 3: the centralized controller implements the proposed approach (equation 15) in cases where the true location is not known to calculate control inputs η_γ and the key parameter γ represents the number of collisions avoided. Note that equations 10, 15 are flexible and if there are no manually driven vehicles ($Z^c = \emptyset$), equations corresponding to manually driven vehicles will be ignored. Parameters' values are derived from the distributions, introduced in Section 4 unless specified otherwise.

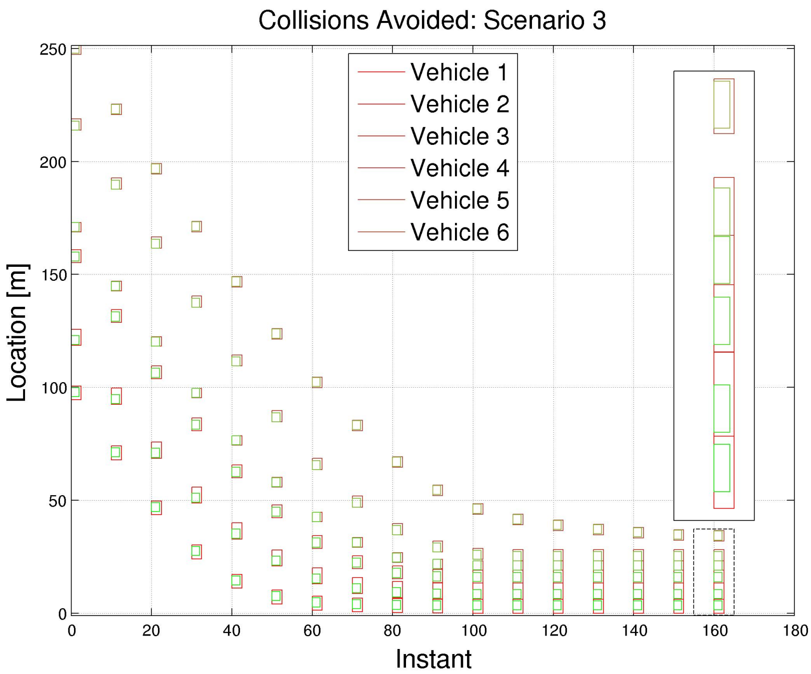


Fig. 6: Collision avoidance using the proposed approach with Heterogeneous APs

6.1. Simulation Scenarios

Scenario 1: Heterogeneous APs
Heterogeneous APs scenario was introduced in section 4.

Scenario 2: Homogeneous APs
Consider a scenario where the road contains six homogeneous APs. They can be assumed to have same localization error profile i.e.: localization errors for such vehicles are drawn from a specific std of error ϕ chosen from a range $\Phi = [4; 2; 1; 0.5; 0.3]$. For each $\phi \in \Phi$, we run 100 simulations with each simulation having different values of parameters and evaluate α, β, and γ.

Scenario 3: Mixed traffic consisting of APs and PPs
Consider a six vehicle mixed traffic conditions consisting of APs and PPs. The number of APs and PPs, and the arrangement of vehicles change in each run. We assume all PPs use GPS for localization and APs use map matching using cameras and other sensors on the car enabling them to achieve better precision. Thus, for PPs and APs, positioning errors are derived from a distribution with std of 4 m and 30 cm respectively.

6.2. Evaluation:

We evaluate the performance of the proposed approach based on the number of collisions avoided using erroneous localization data against the number of collisions avoided using true localization data.

In scenario 1, we observe that the proposed methodology can assure collision avoidances in 56 of 70 possible times, represented by γ in Table 2. Fig. 6 shows an example where all collisions are avoided despite having erroneous localization using the proposed approach as opposed to the case where errorneous localization caused collisions (refer to Fig. 2b). Rectangles in red represent potential area occupied of vehicles based on the proposed approach (plotted with a slightly bigger width for better visualization) and they contain rectangles in green representing the true location of vehicles. Neither of the red nor green rectangles touch signifying total collision avoidance. The increase in the

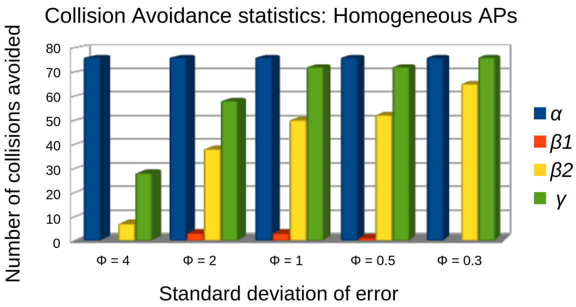


Fig. 7: Homogeneous APs scenario: simulation results

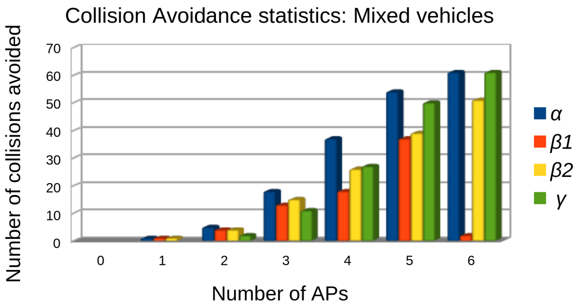


Fig. 8: Mixed APs and PPs scenario: simulation results

number of collisions avoided from 1 or 38 (corresponding to cost functions 1 or 2) to 56, highlights the effectivity of the proposed algorithm.

In scenario 2, the true localization dataset is kept constant, and then based on the value of ϕ localization errors are allocated to vehicles and simulations are carried out. This results in constant α and varying values of $\beta1$,$\beta2$ and γ (refer to Fig. 7). For any value of ϕ, the value of γ is greater than $\beta1$,$\beta2$ which proves the superiority of proposed algorithm in terms of collisions avoided compared when there are localization errors compared to those algorithms which don't consider localization errors. If α represents the maximum number of collision avoidance scenarios when true localization is known, for lower values of ϕ, we observe, proposed approach avoids the maximum number of collisions possible (γ=α).

Similar analysis can be done on the results obtained from 100 simulation runs for each value of number of APs (0,1,2...n_v) in Scenario 3. The number of collisions avoided increases with an increase in the percentage of APs in mixed traffic (refer Fig. 8). This is because APs are assumed to have smaller (distribution of) error and control inputs of only APs can be controlled. This helps us conclude that a higher market penetration of APs can help reduce accidents. In a scenario where a traffic consisting of manually driven vehicles can not avoid any accidents (in 100 simulations), 50% penetration of APs would ensure atleast 10% collision avoidance where as 83% of penetration would ensure atleast 50 % of collision avoidance despite localization errors and other vehicular constraints.

In summary, the proposed approach counters localization errors and achieves the best possible performance by providing 100% collision avoidance (compared to the reference scenario α) when errors are small, the performance degrades depending on the magnitude of localization errors, but is almost always better than the scenario where localization errors are not considered.

7. Conclusions

Vehicle coordination in a mixed vehicle scenario has challenges of its own. Online modeling of the driving behavior of the neighboring manually driven vehicles might be required to predict the response of the manually driven vehicle to a certain maneuver. Such profiling of manually driven vehicles when taken into consideration while computing control inputs for CACC vehicles will characterize a true mixed vehicle coordinated control methodology better capable of avoiding collisions. When there are issues with either of positioning, control or communication techniques, CACC enabled vehicles might face issues. This paper showed the decrease in the number of collisions avoided when CACC vehicles implement control inputs from centralized coordination systems calculated using imperfect localization.

Motivated by the this, a new methodology has been proposed in this paper that counters localization errors in a mixed vehicle scenario. The number of collisions avoided when true localization is known and the number of collisions avoided using proposed approach when erroneous localization is known, is shown to be similar. When the localization errors are small, the proposed approach manages to achieve 100% collision avoidance (compared to the reference scenario with true localization information which highlights the performance of the proposed methodology.

Despite the performance, there are two key drawbacks: 1. The proposed methodology assumes vehicles occupy a large area to counter localization errors, but indeed there may be cases where collisions could be avoided (where vehicles do not require such large area), such scenarios are not accounted for and thus it doesn't provide the exact number of collisions avoided. 2. The proposed methodology ensures collision avoidance at the cost of reduced the road traffic throughput. Although reduced road traffic throughput is not desirable, this work is one of the first steps to counter localization errors and to ensure safety and needs further improvements on these two aspects.

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