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Accurate platoon control of urban vehicles, based solely on monocular vision

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***Abstract*— Automated electric vehicles for public use constitute a promising very efficient and environment-friendly "urban transportation system". An additional functionality that could enhance this transportation service is vehicle platooning. In order to avoid inter-distance oscillations within the platoon, a global control strategy, supported by inter-vehicle communications, is investigated. Vehicle localization in an absolute frame is needed and is derived here from monocular vision. The vision data is however expressed in a virtual world, slightly distorted with respect to the actual metric one. It is shown that such a distortion can accurately be corrected by designing a nonlinear observer that relies on odometric data. A global decentralized control strategy, relying on nonlinear control techniques, can then be designed to achieve accurate vehicle platooning. Simulations and full-scale experiments demonstrate the performance of the proposed approach.**

***Index Terms*— automatic guided vehicles, platooning, nonlinear control, observer, monocular vision, urban vehicles**

I. INTRODUCTION

Traffic congestion in urban areas is currently a serious concern, since it prevents efficient movement and increases air pollution. Automated electric vehicles available on a short term rental basis from distributed stations within some given zone, appear as an attractive alternative concept. The large flexibility that can be obtained (commuting at any time and along any route) is a desirable feature which should meet user expectations. An additional functionality of special interest is vehicle platooning, i.e. several automated vehicles moving in a single line. Such a functionality allows to easily match transportation supply to the need (via platoon length), and can also ease maintenance operations, since a single person can then move several vehicles at a time (e.g. to bring them back to some station). Moreover, enhanced safety and a more efficient traffic can be expected from such a cooperative navigation. Platooning is therefore considered in this paper.

Different approaches have been proposed. They can be classified into two categories, according to the information used for vehicle control. The most common approaches rely on ***local strategies***, i.e. each vehicle is controlled exclusively from the information it can acquire, relative only to the neighboring vehicles. The well-known *leader-follower approach* considers only the preceding vehicle. For instance, visual tracking has been proposed in [2] and generic control laws have been designed in [12] and [5]. Alternatively, *virtual structure approaches* rely on mechanical analogies and allow to take into account all neighboring vehicles. For instance, an analogy to a serial chain of spring-mass-damper models is considered in [13] and a control law is then derived from the combined front and rear virtual forces.

However, a drawback inherent to any local strategy is error accumulation: the servoing errors, introduced by sensor noises and/or actuator delays, grow from the lead vehicle to the final one in the chain, leading to unacceptable oscillations when the chain is long. Such problems can be overcome by considering ***global strategies***, i.e. each vehicle is now controlled from data shared between all the vehicles. In opposition to [13], most of the *virtual structure approaches* belong to this category: in [4], vehicles are regarded as unconstrained mass particles impacted by control forces, and this analogy is used to design feedback controllers to achieve straight line motion. In [6], a single virtual rigid structure is considered relying on graph theory. Nevertheless, these techniques aim at imposing some pre-specified geometric pattern, and not that each vehicle accurately reproduces the trajectory of the first one. Instead, in previous work [3], a trajectory-based strategy has been proposed, relying on nonlinear control techniques: lateral and longitudinal controls are decoupled, so that lateral guidance of each vehicle with respect to the same reference path can be achieved independently from longitudinal control, designed to maintain a pre-specified curvilinear vehicle inter-distance.

Fig. 1. Experimental vehicles: two Cycab leading a RobuCab

The previous control approach has been demonstrated with the experimental vehicles shown in Fig.1 relying, as a first step, on RTK-GPS receivers for vehicle localization [3]. However, these sensors are not reliable in urban applications, since satellite signals are often masked by tall buildings.

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Relying on cameras for sensing is arguably more appropriate, since the buildings offer a rich environment for image processing and it is a cheaper sensor. Localization in an absolute frame can be obtained from monocular vision, by processing successive images acquired when the vehicle is moving (structure from motion approach). Since a single camera is used, localization data are supplied up to a scale factor w.r.t. the real world. However, this scale factor is not perfectly constant: it changes when the vehicle moves through the environment. Consequently, the absolute localization derived from monocular vision is expressed in a ***virtual vision world***, distorted w.r.t. the real one, denoted ***metric world*** in the sequel. This affects the estimate of inter-vehicle distances, and therefore impairs longitudinal control performances. In previous work [1], the local distortions are estimated from the actual distance between two vehicles, measured with a laser rangefinder. This information is then shared with the whole platoon and longitudinal control performance is improved. However, synchronizing telemetry and visual data is intricate, and corrections are only approximated ones, since the scale factor at some point in the vision world is inferred from the comparison of several meters long inter-vehicle distances.

In this paper, a nonlinear observer, relying solely on standard odometric data, is designed to correct in an easier and more accurate way, the distortions of the virtual vision world. The paper is organized as follows: platooning control strategy is first sketched in Section II. Then, absolute localization from monocular vision is discussed in Section III. Next, the local correction to the visual world is presented in Section IV. Finally, experiments reported in Section V demonstrate the capabilities of the proposed approach.

II. Global decentralized control strategy

A. Modeling assumptions

Urban vehicles involved in platooning applications are supposed to move at quite low speed (less than $5m.s^{-1}$) on asphalted roads. Dynamic effects can therefore be neglected and a kinematic model can satisfactorily describe their behavior, as verified by extensive tests performed with our experimental vehicles shown in Fig. 1, see [11]. In this paper, the kinematic tricycle model is considered: the two actual front wheels are replaced by a single virtual wheel located at the mid-distance between the actual wheels. The notation is illustrated in Fig. 2.

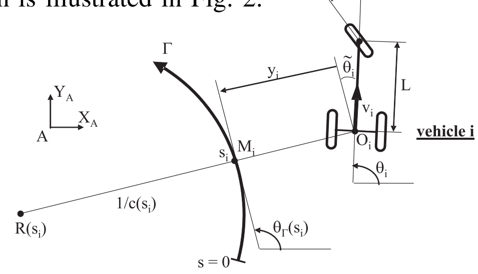

Fig. 2. Tricycle model description

- Γ is the common reference path for any vehicle, defined in an absolute frame $[A, X_A, Y_A]$.
- O_i is the center of the i^{th} vehicle rear axle.
- M_i is the closest point to O_i on Γ.
- s_i is the arc-length coordinate of M_i along Γ.
- $c(s_i)$ is the curvature of path Γ at M_i, and $\theta_\Gamma(s_i)$ is the orientation of the tangent to Γ at M_i w.r.t. $[A, X_A, Y_A]$.
- θ_i is the heading of i^{th} vehicle w.r.t. $[A, X_A, Y_A]$.
- $\tilde{\theta}_i = \theta_i - \theta_\Gamma(s_i)$ is the angular deviation of the i^{th} vehicle w.r.t. Γ.
- y_i is the lateral deviation of the i^{th} vehicle w.r.t. Γ.
- δ_i is the i^{th} vehicle front wheel steering angle.
- L is the vehicle wheelbase.
- v_i is the i^{th} vehicle linear velocity at point O_i.

B. Vehicle state space model

The configuration of the i^{th} vehicle can be described without ambiguity by the state vector $(s_i,\, y_i,\, \tilde{\theta}_i)$. The current values of these variables can be inferred on-line by comparing vehicle absolute localization to the reference path. It can then be shown (see [10]) that tricycle state space model is:

$$\begin{cases} \dot{s}_i = v_i \, \frac{\cos\tilde{\theta}_i}{1 - y_i\, c(s_i)} \\ \dot{y}_i = v_i \, \sin\tilde{\theta}_i \\ \dot{\tilde{\theta}}_i = v_i \left(\frac{\tan\delta_i}{L} - \frac{c(s_i)\, \cos\tilde{\theta}_i}{1 - y_i\, c(s_i)} \right) \end{cases} \tag{1}$$

Platooning objectives can then be described as ensuring the convergence of y_i and $\tilde{\theta}_i$ to zero, by means of δ_i, and maintaining the gap between two successive vehicles to a fixed value $d^\star$, by means of v_i. It is considered that $y_i \neq \frac{1}{c(s_i)}$ (i.e. vehicles are never on the reference path curvature center). In practical situations, if the vehicles are well initialized, this singularity is never encountered.

C. Control law design

In previous work [3], it has been shown that exact linearization techniques offer a relevant framework to address platoon control: equations (1), as most of kinematic models of mobile robots, can be converted in an exact way into a so-called chained form, see [10]. Such a conversion is attractive, since the structure of chained form equations allows to address independently lateral and longitudinal control.

Steering control laws δ_i can first be designed to achieve the lateral guidance of each vehicle within the platoon w.r.t. the common reference path Γ. In these control laws, v_i just appears as a free parameter. Since conversion of equations (1) into chained form is exact, all nonlinearities are explicitly taken into account. High tracking performances (accurate to within $\pm 5cm$ when relying on an RTK GPS sensor) can then be ensured, whatever initial errors or reference path curvature are. Details can be found in [11].

Control variables v_i can then be designed to achieve longitudinal control. In nominal situation, the objective for the i^{th} vehicle is to regulate $e_i^1 = s_1 - s_i - (i-1)\, d^\star$, i.e. the arc-length longitudinal error w.r.t. the leader. This control objective is attractive, since the location s_1 of the leader represents a common index for all the vehicles into the platoon, so that error accumulation and inherent oscillations can be avoided. In addition, since it is an arc-length error, this control objective remains consistent whatever the reference path curvature is (in contrast with euclidian inter-distances). Nevertheless, for obvious safety reasons, the location of the preceding vehicle cannot be ignored. Therefore, in previous work [3], the longitudinal control law has been designed to control a composite error, where the global error e_i^1 dominates in the nominal case and the local error $e_i^{i-1} = s_{i-1} - s_i - d^\star$ dominates if inter-vehicle distance is close to the stopping distance at maximum deceleration. Once more, exact linearization techniques have been used, so that nonlinearities in equations (1) are still explicitly accounted, ensuring high accurate regulation. More details, as well as experiment results carried out with Cycab and RobuCab vehicles (see Fig. 1), relying on RTK GPS sensors for vehicle localization and WiFi technology for inter-vehicle communications, can be found in [3].

III. Localization with monocular vision

The implementation of the platooning control laws presented in previous section requires that some sensors provide each vehicle with its absolute localization, in a common reference frame (so that the composite errors can be evaluated). RTK GPS receivers can supply such a localization, with a very high accuracy ($\pm 2cm$). They have successfully been used in [3]. However, they are expensive sensors and are not appropriate for urban environments, since satellite signals are likely to be frequently blocked by tall buildings. In previous work [8], absolute localization from monocular vision has been alternatively proposed, and satisfactory accurate lateral guidance of a sole vehicle along a given reference path has been demonstrated. An overview of the localization approach is given in Section III-A, and its limitations with respect to platooning applications are discussed in Section III-B.

A. Localization overview

The localization algorithm relies on two steps:

First, the vehicle is driven manually along the desired trajectory and a monocular video sequence is recorded with the on-board camera. From this sequence, a 3D reconstruction of the environment in the vicinity of the trajectory is computed (structure from motion techniques). The computation of the reconstruction is done off-line with a method relying on bundle adjustment. The trajectory is thus defined in a non-metric virtual vision world. However, the total covered distance supplied by on-board odometers, when compared to the same quantity evaluated from vision algorithms, allows to propose a global scale factor such that this virtual vision world is nevertheless close to the actual metric world.

The second step is the real time localization process. Points of interest are detected in the current image with Harris corner detector. These features are matched with the features stored during the 3D reconstruction step, and the complete pose (6 degrees of freedom) of the camera is inferred. Then, the pose of the vehicle on the ground plane is deduced, and finally the vehicle state vector $(s_i, y_i, \tilde{\theta}_i)$ and the curvature $c(s_i)$ required in control laws can be inferred. Details and localization performances can be found in [9].

B. Distortion in the virtual vision world

Platoon control in urban environment requires vehicle localization to be accurate to within some centimeters. The global scale factor computed from odometric data cannot guarantee such an accuracy: first, odometers cannot supply a covered distance accurate to within some centimeters when the reference trajectory length comes up to few hundred meters. Secondly, the distortion between the two worlds is alas varying along the trajectory. These limitations are illustrated in Fig.3: when the vehicle was moving, its trajectory has been recorded from an RTK-GPS sensor and from monocular vision with an accurately calibrated camera. The distortion between the virtual vision world and the actual metric one appears clearly in the inserted plot in Fig.3 since the two trajectories do not properly fit, despite the global scale factor correction. In order to investigate further the discrepancy between the two worlds, the error between the covered arc-length distances computed from monocular vision and from RTK-GPS data is reported as the main plot in Fig.3. It can be noticed that, on one hand the drift in odometric measurement does not allow a proper evaluation of the global scale factor, so that the total arc-length distance is erroneous in the vision world (the error is $1.72m$, although the trajectory is only $115m$-long), and on the other hand the distortion between the two worlds is largely varying, since the error comes up to $7.48m$ in the mid-part of the trajectory.

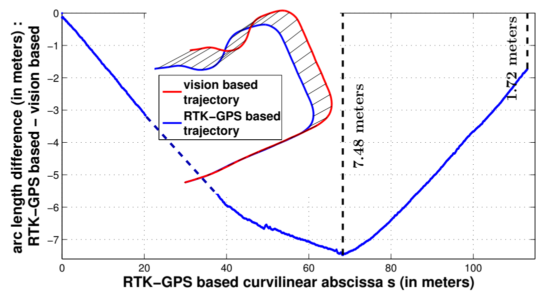

Fig. 3. Error in arc-length distance estimation with vision

These distorsions in the virtual vision world are not a concern as long as only lateral guidance is considered: since the sign of the lateral and angular deviations y_i and $\tilde{\theta}_i$ supplied by vision algorithms is always correct, these distorsions act only as control gain modifications. Asymptotic convergence of y_i and $\tilde{\theta}_i$ to 0 is therefore always guaranteed, and very satisfactory path following results can be obtained, as reported in [8].

The situation is different when longitudinal control is addressed: the distortions in the virtual vision world lead to inaccurate inter-vehicle distance evaluation, and therefore poor longitudinal control performances with respect to the metric world. However, the analysis of experimental results reveals that the distorsions are reasonably repeatable: lateral guidance along the $115m$-long trajectory shown in the upper-left part in Fig.4 has been carried out with several vehicles, different cameras and light conditions. For each trial, the set of local scale factors ensuring consistency, on successive $2m$-long segments, between the arc-length distance obtained by monocular vision and the actual one supplied by an RTK-GPS sensor, has been computed off-line. Two of these sets are reported in Fig.4. It can be observed that they present a very similar profile, and so do the other sets. More precisely, it can be noticed that the local scale factors are roughly constant in the straight line parts of the trajectory, and fast varying in the curved parts (at the beginning and at the end of the cyan segment). As a conclusion, since distortions between the virtual vision world and the actual metric one are reasonably repeatable, accurate longitudinal control relying solely on monocular vision appears attainable, provided that the set of local scale factor could be precisely estimated.

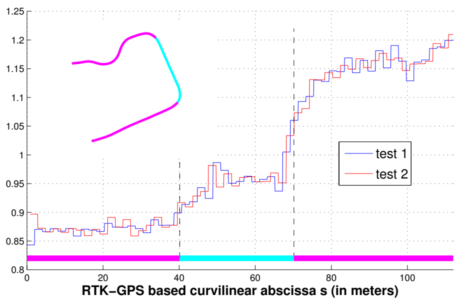

Fig. 4. Off-line local scale factor computation

IV. Curvilinear distance estimation

Local scale factor estimation requires that some distances in the virtual vision world could also be accurately evaluated in the actual metric world. Very precise measurements in the metric world can be obtained from RTK-GPS receivers. However, as mentioned in Section I, these sensors are not appropriate to urban environments. In previous work [1], it is proposed to rely on a laser rangefinder to obtain a reference measurement in the metric world: the distance between the leader and the first follower vehicles supplied by this sensor is compared with the same inter-distance derived from monocular vision. The major limitation is that distortion corrections thus obtained are necessarily averaged corrections, computed along segments whose lengths are the distance between the two first vehicles, that is to say several meters. The local distortions between the virtual vision world and the metric one might then not be accurately represented, especially in the curved parts of the trajectory, where the local scale factors are supposed to change abruptly, see Fig.4. To relax these limitations, an alternative approach, based on observer theory, and relying solely on standard odometric data, is proposed below.

A. Observer design

In the proposed approach, the reference measurement in the metric world to be used to infer local scale factors is the vehicle linear velocity v_i supplied by the odometers. In the sequel, let us denote $(s_i, y_i, \tilde{\theta}_i)$, $(\dot{s}_i, \dot{y}_i, \dot{\tilde{\theta}}_i)$ and $c(s_i)$ the i^{th} vehicle state vector, state vector derivative and reference path curvature at s_i expressed in the actual metric world, and $(s_i^v, y_i^v, \tilde{\theta}_i^v)$, $(\dot{s}_i^v, \dot{y}_i^v, \dot{\tilde{\theta}}_i^v)$ and $c^v(s_i^v)$ the same quantities expressed in the virtual vision world. Then, in view of the reference measurement to be used, a relevant way to describe the local scale factor at curvilinear abscissa s_i^v is the function:

$$\lambda(s_i^v) = \dot{s}_i \,/\, \dot{s}_i^v \tag{2}$$

The distortions in the virtual vision world can realistically be assumed to be locally homogeneous, i.e. the two dimensions in the plane of motion are similarly distorted. Therefore, the following relations can also be written:

$$\begin{aligned} \lambda(s_i^v) &= \dot{y}_i \,/\, \dot{y}_i^v && (3)\\ \tilde{\theta}_i^v &= \tilde{\theta}_i && (4)\\ y_i^v\, c^v(s_i^v) &= y_i\, c(s_i) && (5) \end{aligned}$$

Then, injecting relations (2) to (5) into model (1), the vehicle state space model expressed in the virtual vision world is:

$$\begin{cases} \dot{s}_i^v = \dfrac{v_i .\cos\tilde{\theta}_i^v}{\lambda(s_i^v).(1 - y_i^v\, c^v(s_i^v))} \\ \dot{y}_i^v = \dfrac{v_i .\sin\tilde{\theta}_i^v}{\lambda(s_i^v)} \\ \dot{\tilde{\theta}}_i^v = \dot{\tilde{\theta}}_i \end{cases} \tag{6}$$

Model (6) describes the vehicle motion from the variables actually available, i.e. the vehicle localization in the vision world and its linear velocity in the metric world. The objective now is to design an observer to estimate $\lambda(s_i^v)$ from model (6). Since distortions are the result of a complex and unpredictible optimization process, the time derivative of the variable $\lambda(s_i^v)$ to be observed is completely unknown. Consequently, $\lambda(s_i^v)$ cannot be incorporated into the state vector with the aim to design a standard Luenberger observer.

It is here proposed, just as in [7], to rely on the duality between control and observation to design the observer. More precisely, mimicking the first equation in (6), let us introduce the following observation model:

$$\dot{\hat{s}}_i^v = \frac{v_i .\cos\tilde{\theta}_i^v}{u_i .(1 \,-\, y_i^v\, c^v(s_i^v))} \tag{7}$$

with $\hat{s}_i^v$ the observed curvilinear abscissa in the virtual vision world, y_i^v, $\tilde{\theta}_i^v$ and $c^v(s_i^v)$ measured quantities in the vision world, v_i a measured quantity in the metric world, and u_i a control variable to be designed. Then, the observer principle can be described as follows: if the control variable u_i of the observation model (7) could be designed such that the observed state $\hat{s}_i^v$ converges with the measured one s_i^v, then the control variable u_i would be representative of the local scale factor $\lambda(s_i^v)$ (in view of equations (6) and (7)).

Such a convergence can easily be imposed, by designing u_i straightforwardly as:

$$u_i = \frac{v_i .\cos\tilde{\theta}_i^v}{(\dot{s}_i^v - K.\epsilon)(1 \,-\, y_i^v.c^v(s_i^v))} \tag{8}$$

with $\epsilon = (\hat{s}_i^v - s_i^v)$ and K a positive gain to be tuned, since injecting (8) into (7) leads to :

$$\dot{\epsilon} = -K \cdot \epsilon \tag{9}$$

Equation (8) can then be regarded as an accurate estimation of the local scale factor at the curvilinear abscissa s_i^v. If the observer state $\hat{s}_i^v$ is properly initialized, then $|K \cdot \epsilon|$ is largely inferior than $|\dot{s}_i^v|$ (directly related to the vehicle velocity), and observer equation (8) proposes no singularity.

Finally, if $\Gamma(\tau) = (\Gamma_x(\tau), \Gamma_y(\tau))$ denotes the 2D-parametric equations of the reference trajectory Γ in the virtual vision frame, then the corrected curvilinear abscissa at s_i^v can be computed according to:

$$\hat{s}_i = \int_0^{\tau(s_i^v)} \lambda(\tau) \left|\left| \frac{\partial \Gamma}{\partial \tau}(\tau) \right|\right| d\tau \qquad (10)$$

where $\tau(s_i^v)$ is the parameter value of the 2D-curve $\Gamma(\tau)$ (here, a B-Spline) associated with the curvilinear abscissa s_i^v. Longitudinal errors e_i^1 and e_i^{i-1} can finally be inferred, without any drift since they are inter-distances.

B. Simulations

Two simulations have been run with the following parameters, tuned in order to be representative of actual conditions:

- Local scale factors similar to those obtained in Fig. 4 have been generated via line segments, see Fig. 5.
- Visual data are provided with a $15Hz$ sampling frequency and two standard deviations $\sigma_v = 0m$ and $\sigma_v = 0.02m$ have been considered.
- Standard deviation of odometry is $\sigma_{odo} = 0.015m.s^{-1}$.
- Observer gain is $K = 2$, to achieve a compromise between a fast convergence and small oscillations. The observed local scale factor is logically initialized at 1.

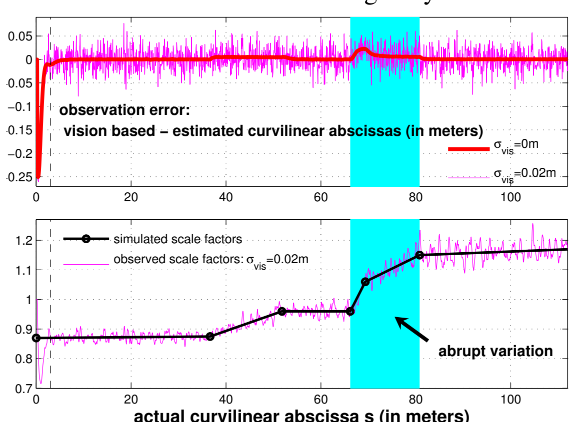

Fig. 5. Simulated scale factor estimation (on-line process)

First, to investigate the performances of observer (8), a single vehicle moving with a constant velocity $v = 1m.s^{-1}$ in the metric world has been simulated. The top graph in Fig. 5 shows that observer convergence is achieved within $3m$ (dotted black line). Without any noise on visual data (i.e. $\sigma_v = 0m$), the convergence is very smooth and the average value of the error ϵ is less than $2.4mm$, excepted when the local scale factor changes abruptly (cyan area): then, a very limited $3cm$ overshoot can be noticed. When visual data are corrupted by noise (i.e. $\sigma_v = 0.02m$), the observer error remains inferior than $7cm$, with an average value less than $17.6mm$. Finally, it can noticed in the bottom graph in Fig. 5 that the observed local scale factor accurately reproduces the simulated one, as desired.

Next, platooning with three vehicles has been simulated. The vehicle initial curvilinear abscissas are $s_1 = 10m$, $s_2 = 5m$ and $s_3 = 0m$. Since the desired inter-vehicle gap is $d^\star = 5m$, initial longitudinal errors are zero. Prior to $s = 30m$, platoon control relies on raw vision data. It can be observed in Fig. 6 that inter-vehicle distances in the virtual vision world converge with zero, as expected, but alas actual inter-distances are unsatisfactorily large: since the local scale factor is roughly 0.87 in this part of the trajectory, see Fig. 5, $0.65m$ and $1.3m$ steady errors (i.e. $0.13d^\star$ and $2{\times}0.13d^\star$) are recorded in the actual metric world. Beyond $s = 30m$, observer (8) is used within platoon control algorithms. Since $d^\star = 5m$, the distance between vehicles 1 and 2 *(resp. between vehicles 1 and 3)* is properly corrected when $s_1 = 35m$ *(resp. when* $s_1 = 40m$*)* (dashed lines in Fig. 6) and platooning is then accurately achieved with respect to the actual metric world, although raw vision inter-distances are largely erroneous ($e_2^1 = 0.75m$ and $e_3^1 = 1.5m$ when $s_1 = 110m$) and even when local scale factors are abruptly varying (when $s_1 \in [70, 80]m$).

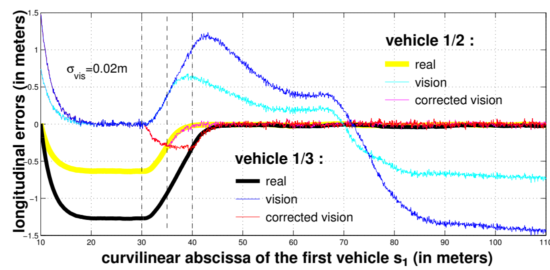

Fig. 6. Performances of simulated platoon control

V. Experimental results

In order to investigate the capabilities of the proposed approach, several experiments have been carried out in Clermont-Ferrand at the "PAVIN Site", an open platform devoted to urban transportation system evaluation.

1) Experimental set-up: The experimental vehicles are shown in Fig. 1. They are electric vehicles, powered by lead-acid batteries providing 2 hours autonomy. Two *(resp. four)* passengers can travel aboard the Cycab *(resp. the RobuCab)*. Their small dimensions (length 1.90m, width 1.20m) and their maximum speed (5m.s^{-1}) are appropriate for urban environments. Vehicle localization algorithms and platoon control laws are implemented in C++ language on Pentium based computers using RTAI-Linux OS. The cameras supply visual data at a sampling frequency between 8 and 15*Hz*, according to the luminosity. The inter-vehicle communication is ensured via WiFi technology. Since the data of each vehicle are transmitted as soon as the localization step is completed, the communication frequency is similar to the camera one. Finally, each vehicle is also equipped with an RTK-GPS receiver, devoted exclusively to performance analysis: its information are not used to control the vehicles.

2) Experimental results: The experiment reported below consists of platoon control with three vehicles. The reference supplied to any vehicle is the $115m$-long trajectory shown in Fig. 4. Alternatively, the reference could have been created on-line by a manually driven lead vehicle, provided that it moves in streets where preliminary 3D reconstruction had been achieved. The local scale factors computed on-line by the lead vehicle (whose speed is $1m.s^{-1}$) are shown in green in Fig. 7. In order to ease the comparison with the local scale factors computed off-line in Section III-B (and reported in blue in Fig. 7), the ones obtained on-line have also been averaged on $2m$-long segments and then shown in red in Fig. 7. It can be noticed that local scale factors computed on-line with observer (8) are as satisfactory as those computed off-line and very close to the actual ones evaluated from RTK-GPS measurements.

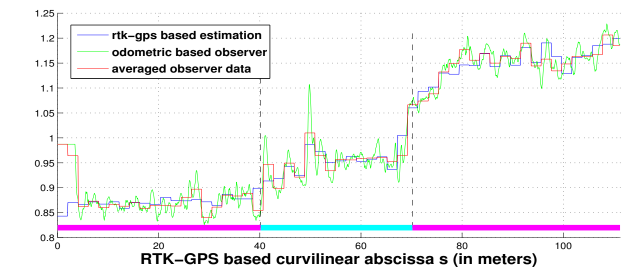

Fig. 7. On-line scale factor estimation

Finally, platoon control performances with corrected vision data are evaluated in Fig. 8. The vehicle inter-distance errors (obtained from RTK-GPS measurements) when longitudinal control relies solely on monocular vision data is as accurate as previously when RTK-GPS data were used (see [3]) to control the vehicles: the longitudinal errors satisfactorily remain within $\pm 10cm$. Performances are just slightly depreciated during the abrupt scale factor variation, when $s_1 \in [70, 80]m$. Nevertheless, the inter-distance errors do not exceed *resp.* $14cm$ and $17cm$. During this experiment, the inter-distance errors deduced from raw localization vision data, shown in Fig. 9, were largely erroneous and similar to those obtained in simulation, see Fig. 6. These large errors (*resp.* $1m$ and $1.7m$) show clearly the significance and the relevance of observer (8).

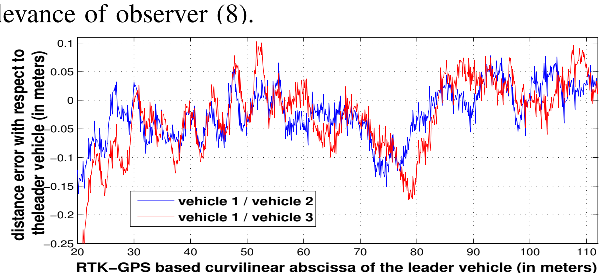

Fig. 8. Vehicle inter-distance errors with corrected vision data

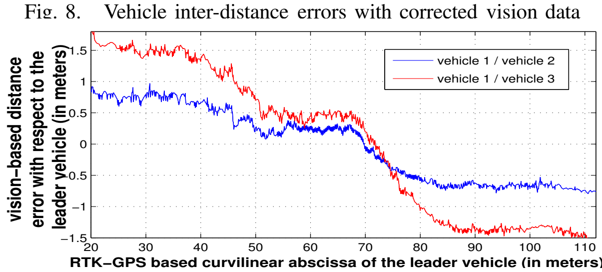

Fig. 9. Vehicle inter-distance errors with raw vision data

VI. CONCLUSION

In this paper, vehicle platooning in urban environments has been investigated. First, a global decentralized control strategy, taking advantage of inter-vehicle communications, has been proposed, in order to avoid error accumulation inherent to local control approaches. Moreover, nonlinear control techniques have been considered, in order to take explicitly into account the nonlinearities in vehicle models, so that the same high accuracy can be expected in any situation (for instance, whatever the reference trajectory curvature).

Vehicle absolute localization has been derived from an on-board camera, since it is a very appropriate sensor in urban environments. However, it has been pointed out that the localization thus obtained is expressed in a virtual vision world slightly distorted with respect to the actual metric one, and relying on raw vision data would impair platooning performances. A nonlinear observer, only supported by odometric data, has then been designed to estimate on-line local scale factors, and enable accurate platooning relying solely on monocular vision. Full scale experiments, carried out with three vehicles, have finally demonstrated the efficiency of the proposed approach. Further experiments, involving vehicles led by a manually guided vehicle have to be conducted to emphasize the benefits of on-line corrections when the reference trajectory is being created.

REFERENCES

[1] P. Avanzini, E. Royer, B. Thuilot, and P. Martinet. A global decentralized control strategy for urban vehicle platooning using monocular vision and a laser rangefinder. In *IEEE Intern. Conf. on Control, Automation, Robotics and Vision (ICARCV)*, Hanoi (Vietnam), 2008.

[2] S. Benhimane and E. Malis. Vision-based control for car platooning using homography decomposition. In *IEEE Intern. Conf. on Robotics and Automation (ICRA)*, pages 2173–2178, Barcelona (Spain), 2005.

[3] J. Bom, B. Thuilot, F. Marmoiton, and P. Martinet. A global strategy fo urban vehicles platooning relying on nonlinear decoupling laws. In *IEEE Intern. Conf. on Intelligent Robots and Systems (IROS)*, pages 1995–2000, Edmonton (Canada), 2005.

[4] R.E. Caicedo, J. Valasek, and J.L. Junkins. Preliminary results of one-dimensional vehicle formation control using structural analogy. In *American Control Conference (ACC)*, Denver (USA), 2003.

[5] L. Consolini, F. Morbidi, D. Prattichizzo, and M. Tosques. Leader-follower formation control of nonholonomic mobile robots with input constraints. *Automatica*, 44(5):1343–1349, 2008.

[6] W. Dong and Y. Guo. *Formation Control of Nonholonomic Mobile Robots Using Graph Theoretical Methods*, chapter in Cooperative Systems, Springer Verlag LNEMS series n°588, pages 369–386. 2007.

[7] R. Lenain, B. Thuilot, C. Cariou, and P. Martinet. Adaptive and predictive path tracking control for off-road mobile robots. *European Journal of Control*, 13(4):419–439, 2007.

[8] E. Royer, J. Bom, M. Dhome, B. Thuilot, M. Lhuillier, and F. Marmoiton. Outdoor autonomous navigation using monocular vision. In *IEEE Intern. Conf. on Intelligent Robots and Systems (IROS)*, pages 3395–3400, Edmonton (Canada), 2005.

[9] E. Royer, M. Lhuillier, M. Dhome, and T. Chateau. Localization in urban environments : monocular vision compared to a differential GPS sensor. In *Intern. Conf. on Computer Vision and Pattern Recognition (CVPR)*, pages 114–121, San Diego (USA), 2005.

[10] C. Samson. Control of chained systems: application to path following and time-varying point stabilization of mobile robots. *IEEE Trans. on Automatic Control*, 40(1):64–77, 1995.

[11] B. Thuilot, J. Bom, F. Marmoiton, and P. Martinet. Accurate automatic guidance of an urban electric vehicle relying on a kinematic GPS sensor. In *IFAC Symposium on Intelligent Autonomous Vehicles (IAV)*, Lisbon (Portugal), 2004.

[12] D. Wang and M. Pham. *Unified control design for autonomous car-like vehicle tracking maneuvers*, chapter 8 in "Autonomous Mobile Robots: sensing, control decision-making and applications", pages 295–329. CRC Press, 2006.

[13] S.Y. Yi and K.T. Chong. Impedance control for a vehicle platoon system. *Mechatronics*, 15(5):627–638, 2005.