# Collaborative Positioning - Concepts And Approaches for More Robust Positioning

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**Key words**: cooperative positioning, sensor fusion, Kalman filter

## SUMMARY

Collaborative or cooperative positioning techniques (CP) have been adopted from the field of wireless sensor networks as an approach to improving the navigation and positioning performance for a range of human and land vehicle navigation applications. This is particularly relevant for those applications operating in GNSS challenged environments where requirements for positioning availability cannot be met and/or which are safety critical, requiring higher levels of reliability and integrity. CP techniques typically leverage an available communications infrastructure to share information between users operating within a defined neighbourhood or so-called ad hoc network. This shared information can be integrated to deliver more robust positioning performance. Under certain conditions, the communications infrastructure itself can be used as a measurement source for positioning. For example, Dedicated Short Range Communications (DSRC) infrastructure which is being deployed in many countries to facilitate a range of Intelligent Transportation systems (ITS), has the potential to provide a ranging measurement between vehicles in a vehicular ad hoc network (VANET). What is emerging as a significant consideration for CP are the benefits for positioning in terms of availability, integrity, reliability and accuracy versus cost in terms of infrastructure, computational overheads and the overall quantity and quality of information that needs to be shared to meet the positioning requirements of a specific application.

In this paper, the broad applicability of CP algorithms and techniques for land mobile applications is discussed. A range of qualitative and quantitative measurement information that can support CP is presented such as low cost MEMS based inertial sensors, map matching and DSRC. An initial cost benefit assessment of these 'measurements' is undertaken, in addition to considerations for determining the point of diminishing marginal utility for positioning i.e. at what point does the integration of additional information provide a negligible return to the positioning performance. This is an important step forward in redefining the concept of ubiquitous positioning from the traditional idea ofintegrating all available signals of opportunity, towards identifying the optimal set of measurements for the requirements of the application i.e. fitness for use.In this paper, measurements collected during field experiments conducted under a joint FIG working group (5.5) and IAG sub commission (4.2.1) entitled Ubiquitous Positioning and their use across a range of CP research efforts is summarised and presented.

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## 1. INTRODUCTION

Robust positioning is typically described in terms of performance metrics including accuracy, availability, continuity and accuracy. These metrics have been fully defined in the aviation community where safety critical needs have mandated requirements for standards of positioning performance. Similar trend are evidenced in the maritime sector with the international martitime orgnaisation (IMO) developing standards for positioning based on current and future capabilities of Global Navigation Satellite Systems (GNSS). The land mobile sector however, has lagged significantly behind these performance based standards and there are currently no formal specifications for land based applications. The emerging capabilities of Cooperative Intelligent Transport Systems (C-ITS) have significantly changed the landscape for positioning information and in particular, positioning quality. C-ITS are driving the development of an increasing range of safety and liability critical applications that expect certain levels of positioning peformance in order to realise the maximum benefits for improving road safety and efficiency of the road network.

In aviation(Ochieng et al, 2013), the metrics used to describe positioning quality are: accuracy is defined as the degree of conformance of an estimated or measured position ata given time to a defined reference value; integrity relates to the level of trust that can be placed in theinformation provided by the navigation system. It includes the ability of the navigation system to providetimely and valid warnings to users when the system must not be used for the intended operation or phaseof flight. Specifically, a navigation system is required to deliver a warning (an alert) of any malfunction (asa result of a set alert limit being exceeded) to users within a given period of time (time-to-alert); continuityof a navigation system is its capability to perform its function without non-scheduled interruptions duringthe intended period of operation; availability is defined as the percentage of time during which the serviceis available (i.e. reliable information is presented) for use taking into account all the outages whatevertheir origins. The service is available if accuracy, integrity and continuity requirements are satisfied.

What is evident across these definitions is that their computation is based on the availability of sufficient measurements that not only facilitate computation of the position solution but typically will enablethe identification and potential adaptation of incorrect or spurious measurements. To ensure that sufficient measurements are available, the majority of positioning solutions rely on the integration of multiple sensors and signals. These hybrid solutions typically integrate GNSS with measurements from inertial navigation sensors or similar in-vehicle sensor systems. The error characteristics of these inertial sensors are such that, over periods of prolonged GNSS outages as experienced in dense urban environments,the overall positioning outcome deteriorates significantly.Over recent years, another emerging technique is being proposedto overcome the shortcomings of GNSS, often termedas Cooperative Positioning (CP). It is a technique which allowsvehicles within a vehicular ad hoc network (VANET) toshare positioning related information with other vehicles orinfrastructures in trying to improve their positioning solutions.

In this paper, the broad applicability of CP algorithms and techniques for land mobile applications is discussed. A range of qualitative and quantitative measurement information that can support CP is presented such as low cost MEMS based inertial sensors, map matching and DSRC. An initial cost benefit assessment of these "measurements" is undertaken, in addition to considerations for determining the point of diminishing marginal utility for positioning i.e. at what point does the integration of additional information provide a negligible return to the positioning performance. This is an important step forward in redefining the concept of ubiquitous positioning from the traditional idea ofintegrating all available signals of opportunity, towards identifying the optimal set of measurements for the requirements of the application i.e. fitness for use.In this paper measurements collected during field experiments conducted under a joint FIG working group (5.5) and IAG sub commission (4.2.1) entitled Ubiquitous Positioning and their use across a range of CP research efforts is summarised and presented.

## 2. COOPERATIVE NAVIGATION CONCEPT

Cooperative positioning (CP) is a technique which can potentially overcome the shortcomings ofGNSS for a range of ITSapplications. CP originated in Wireless Sensor Networks research where individual nodes are able toshare information with other nodes in its "neighbourhood"in order to localize the network of nodes as a whole. One advantage of CP is that the localization accuracy, integrity, availability and continuity is expected to improve with the node density (number of neighbour vehicles used in collective localization).

In the context of C-ITS, the nodes are vehicles within a road network neighbourhood called a Vehicular Ad-hoc Network (VANET), see Figure 1. The CP approach relies on information being shared between vehicles within a VANET, to overcome the limitations for positioning in difficult environments such as high-rise, dense urban areas, where multipath effects and the complete or partial obscuration of satellites limit GNSS positioning capabilities.The sharing of information between vehicles can only be achieved through the availability of a communications infrastructure that supports information exchanges between vehicles in the VANET and/orbetween vehicles and roadside infrastructure. Dedicated short-range communications (DSRC) is a wireless communication channel designed specifically to support vehicle to vehicle (V2V) and vehicle to infrastructure (V2I)communications. In the U.S., the Federal Communication Commission (FCC) has allocated DSRC with a dedicatedbandwidth of 75 MHz in the 5.850-5.925 GHz band, whereas the European Telecommunications Standards Institute(ETSI) has allocated a dedicated bandwidth of 30 MHz in the 5.9 GHz band. Some of the planned applications ofDSRC includes intelligent transportation system (ITS), traffic management, safety and efficiency as it is able toprovide low latency, high speed communication, and strong and relative close proximity signals (Parker and Valaee,2007), hence making it a suitable candidate for the enablement of CP techniques within a VANET. In fact, DSRC underpins plans in the US to develop telematics regulations that will require new cars and light trucks sold in the US to be equipped with systems for vehicle to vehicle communications. Raising concerns about privacy, the intention is for "vehicles equipped with DRSC chips to receive and process signals from nearby DRSC-enabled cars to learn their location, direction and speed. If a driver does not react to an impending collision, the car could then sound a warning or apply the brakes automatically to prevent an accident". Fundamentally, DSRC communications combined with a robust positioning capability and the core technologies are required to realise the significant benefits of C-ITS for road safety (TTAC, 2014).

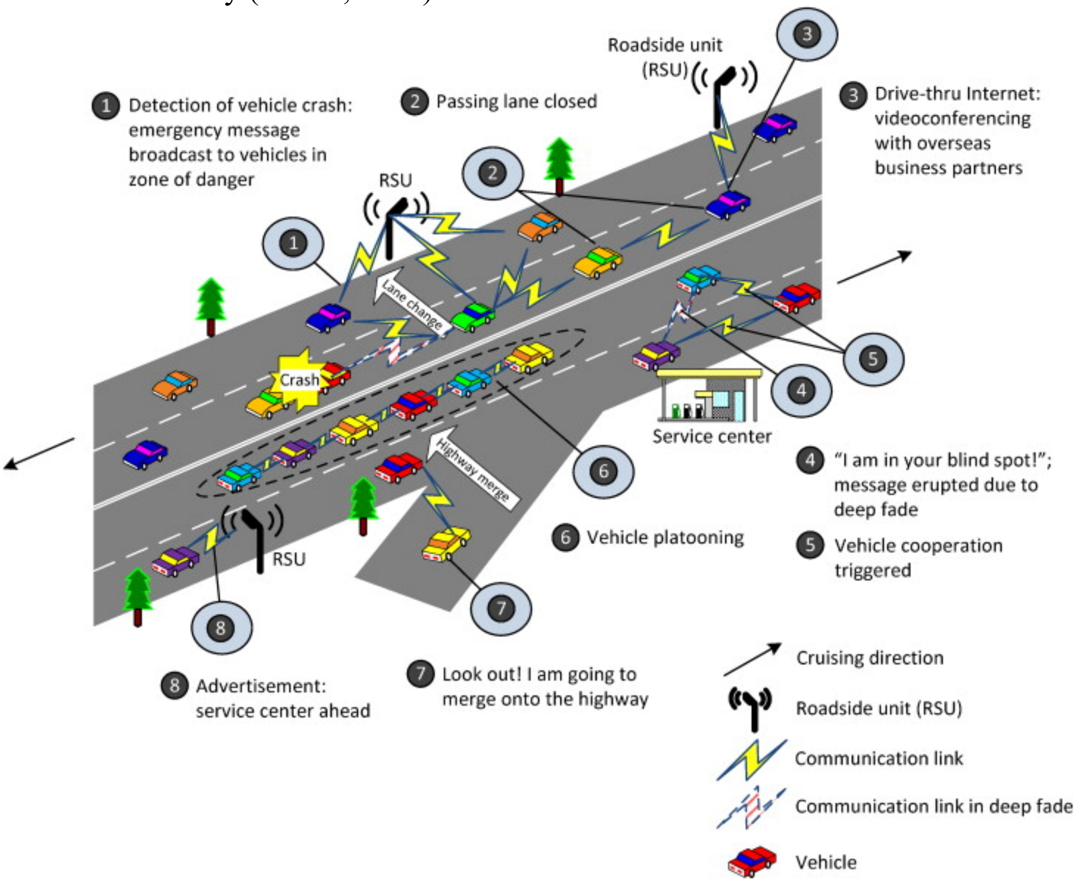


Figure 1: CP positioning concept(from Intelligentdots, 2012).

In a VANET, the information shared between vehicles can be in the form ofinter-vehicle ranges, relative speed, orientation, and satellite related data. This is the case when all or some of the nodes (vehicles) – so called anchor nodes –are equipped with GPS. The network collective positioning is done once the ranges and the position information are exchanged between the nodes. Sharing information could help the vehicleswithin the network to obtain positioning solutions even when the requirement of GNSS positioning cannot be met.The key considerations in developing a CP system are therefore(1) the sensor systems for positioning of individual nodes;(2) the communication subsystem; (3) an inter-node ranging sub system and (4) data fusion algorithms, see Figure 2.
In the next section, a summary of some of the approaches to address these considerations is presented along with an assessment of the improvements in positioning quality. The underlying motivation for this work is that the practical use of CP algorithms for C-ITS

applications requires a cost effective solution, both in terms of the in-vehicle positioning sub-system, the roadside infrastructure and the computational overhead. The focus is therefore on the use of low cost (such as MEMS based inertial navigation units) or "no cost signals of opportunity" (such as DSRC) to develop robust hybrid positioning solutions for individual vehicles. Our thesis is that through this approach, anoptimal balance between infrastructure costs and performance can be achieved.

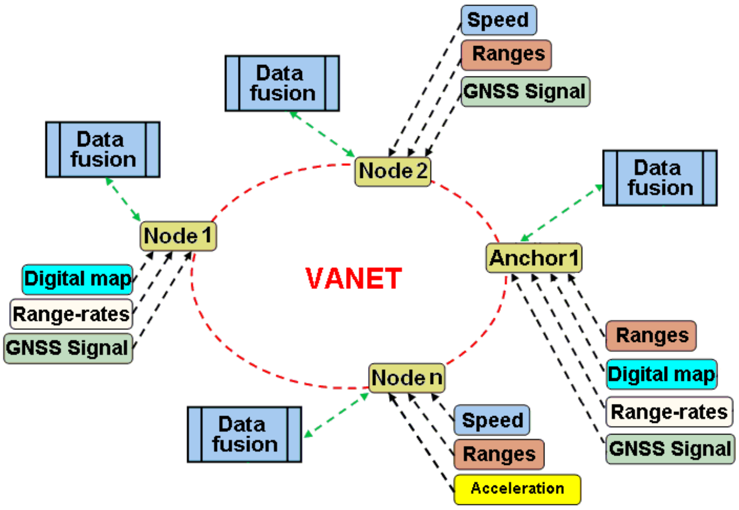


Figure 2: CP positioning architecture.

## 3. LOW COST MICRO-ELECTROMECHANICALSYSTEM(MEMS) INERTIALNAVIGATION SENSORS (INS)

Low cost MEMS inertial sensors (accelerometers and gyroscopes) are routinely considered for applications requiring positioning in difficult GNSS environments without a significant addition in terms of cost and form factor. It is therefore a likely candidate for use in the development of CP algorithms in which each node in the VANET computes its own hybrid solution based on GNSS and INS. What is emerging as significant in the use of low cost INS, is their applicability to the increasing range of safety and liability applications. Lane level positioning and collision avoidance require high performance positioning capabilities specifying higher levels of accuracy, integrity, continuity and availability than that required for vehicle route guidance. The increasing stability and improved performance of MEMS sensors combined with the potential for even further enhancements has driven the investigations of this research task - to evaluate the capabilities of MEMS technologies with the aim of delivering high performance positioning for C-ITS applications.

Field experiments to evaluate the quality of low cost MEMS sensors have been performedin an international cooperation of the joint International Associations of Geodesy (IAG) Working Group WG 4.1.1 and International Federation of Surveyor (FIG)WG 5.5 on "Ubiquitous Positioning Systems" with participating members of the University of Melbourne, Australia, the Ohio State University, Columbus, USA, the University of Nottingham, UK, the University of New South Wales, Sydney, Australia, the National Technical University of Athens, Greece, and the Vienna University of Technology, Austria at the University of Nottingham in May 2012. These tests were conducted as part of a broader research agenda in CP, with multiple vehicles and personnel navigating simultaneously in different operating environments. Figure 3, shows the experimental setup for evaluating the performance of a range of commercially available MEMS sensors. A train was equipped with a Novatel GPS, a tactical gradeNovatel SPAN IMU, and two MEMS-based IMUs, i.e., theXsens MTi-G and the Systron Donner Inertial MMQG. The two MEMS sensors represent state-of-the-art in low cost MEMS sensors, and their performance was evaluated against that of the higher grade unit.Figures4 and 5 show a comparison of accelerations and turning rates respectively between the MEMS MMQG sensor and the SPAN. Figure 6 shows the solutions obtained from the onboard GPS receiver (Single Point Position), the SPAN integrated solution and the computed MEMS INS/GPS integrated solution.

Although the MEMS sensors have higher noise levels than the SPAN IMU, the two data sets correlate well in terms of the rotations and accelerations made by the platform.It is often argued that the errors of inertial navigation, especially with commercial MEMS INS modules, rapidly increase over time due to integrations over the measured accelerations and angular velocities through the positioning process. This make them difficult to integrate into a robust navigation solution as these errors tend to degrade significantly during significant periods of satellite outage, and regular updates from a GNSS are essential in order to contain the MEMS noise levels – which is not always possible in dense urban environments for example. There are many methods to combine INS and GNSS data to improve the performance of GNSS positioning. Some examples are presented in Carvalho et al , 1997; Hide et al, 2003 andHuang and Tan, 2006.These INS/GPS implementations cannot be classified as CP, as defined here, because the position-related data are not shared between separate nodes for data fusion.

Figure 3: Train trajectory for MEMS INS testing

A variety of analyses and compensation methods for inertial navigation errors are available in the literature. Some examples are presented in Lee,et al, 2008; Fong, et al, 2008; Akeila, et al, 2008. Without entering into the details of these methods, we emphasize these techniques have a common attribute, the standalone approach. This means that error compensation solutions are conducted for a single user/node.

In the following section we show the benefits to GPS/INS of further improving the hybrid GPS/INS capability through the integration of range information between vehicles in the VANET.In addition, we contend that an assessment of the MEMS sensor from a qualitative perspective (see Figure 7) is informative from the perspective of identifying activity patterns in the data. This information offers other benefits for positioning – i.e. the ability to detect movement versus stopping can be useful in tuning the algorithms for sensor fusion.

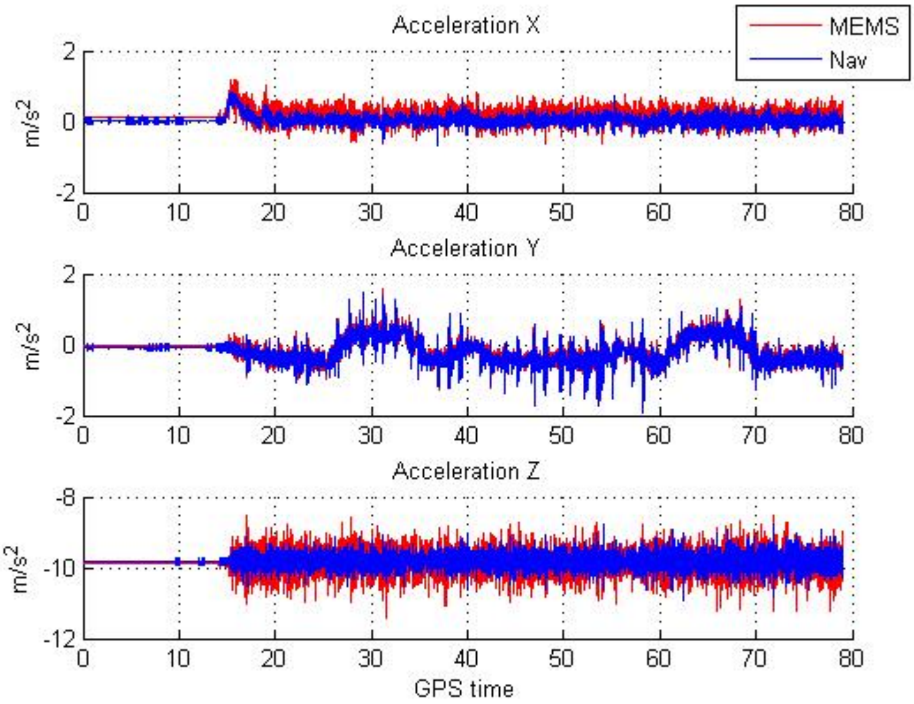


Figure 4: MEMS INS performance tests - accelerations.

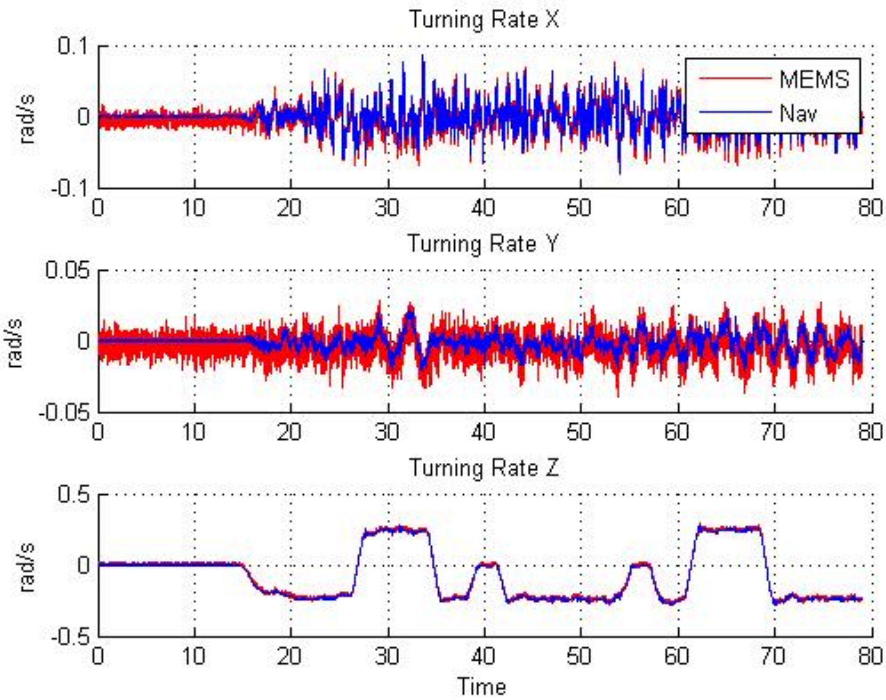


Figure 5: MEMS INS performance tests - turning rates.

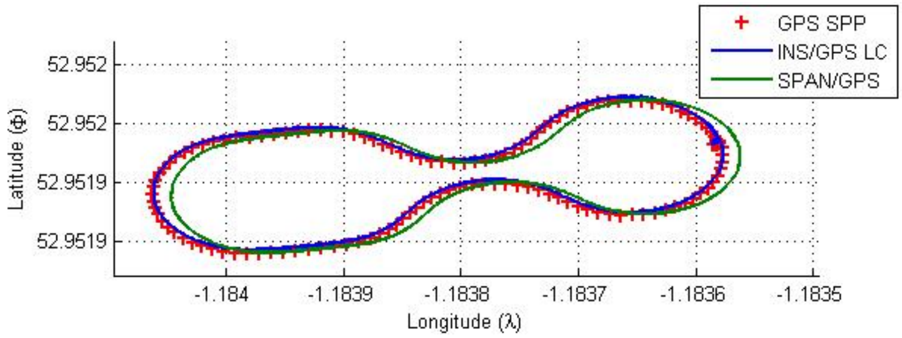


Figure 6: Train trajectory for MEMS INS testing

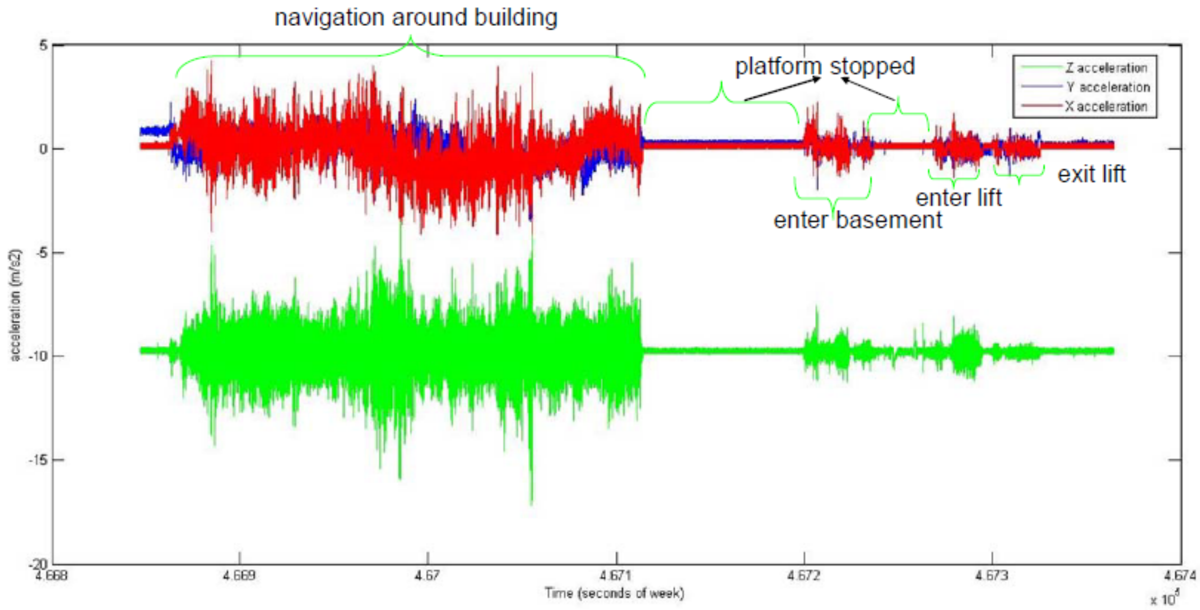


Figure 7: Qualitative information extracted from noisy MEMS data

## 4. INTER-NODE RANGING BASED ON DSRC

Radio basedranging determines the distance between vehicles in the VANET using time of arrival (TOA), time difference of arrival (TDOA) orReceived Strength Signal (RSS) techniques. Parker and Vallee, 2008;Huang, et al, 2006 and Mao, et al, 2007,have shown that these techniquescan be used in support of CP but that they also present major practical challenges for use in VANETs. For example, rangingusing TDOA technique suffers severely in the presence ofmultipath. RSS on the other hand is difficult to model accurately as the signalsare easily affected by reflection, scattering and diffractionwhich changes from one place to another.Non-radio based ranging techniques on the other hand, usesconnectivity information(Mao, et al, 2007). Although less complex thanradio based ranging techniques, most of these techniquesare not suitable for VANETs due to their low positionalaccuracy (Doherty, et al, 2001 and Fayed, et al, 2007). However, the low level GNSS datasharing technique has produced some promising resultsas presented in Alam, et al, 2012. The study has shown that relativepositioning using code based double difference betweentwo moving vehicles can achieve better accuracy of relativepositioning than differential GPS (DGPS).

However, thetechnique can only work when four common satellites areobserved simultaneously.

Experiments were conducted as part of the Nottingham trials, in which two mobile mapping vans were equipped with a pair of DSRC transceivers.The important parametersfor evaluating the functionality and performance of theseequipment include the Received Signal Strength (RSS)observation noise, precision of the received packets time tags,Carrier Frequency Offset (CFO) observation noise, and thepacket delivery rate.RSS is widely considered for radio ranging purposes in theliterature for CP due to itssimplicity. Here, the level of RSS observation noise ofour DSRC equipment will be explained.CFO can also be used for range-rating and positioningenhancement in vehicular networks. The accuracy of rangeratingdepends on the CFO observation noise. Packet delivery rate depends on the number of competingnodes which use a common channel of DSRC for a specificapplication, for example CP. Only two transceivers wereavailable for this experimental campaign and, therefore, theevaluation of packet delivery rate constraints was not possibletechnically.Here, we summarize the different parameters evaluated forthe DSRC transceivers employed in this experimentalcampaign. For RSS and CFO observation noise, transmitpower was set at two different levels, 10dBm and 20dBm.Table 1 shows the Standard Deviation (STD) of theobservations for different conditions. As can be seen, theRSS observation noise is the same for both transmit powersbut the performance of CFO estimation improves when thetransmit power is higher. This is consistent with the resultsfor CFO estimation performance presented in Garello, et al, 2013 and Alam, et al, 2012 andsimilar articles.

For evaluating the precision of the received packets timetags, two different packet transmit rates wereconsidered. Foreach case, the STD of the receive time tags with regard to theset rate was calculated. Table 2 shows the results. As canbe seen, the time tags of the received packets have someuncertainty which is less for a higher transmit rate. Here, wedo not have enough insight and motive to investigate thisbehaviour of timing in terms of transmission rate butconsidering the very accurate and high resolution of receivetime tagging, in the order of ns, it can be concluded that suchuncertainty is due to the transmit schedule at Physical Layer(PHY) of the DSRC transmitter. A more important issue isthe order of the timing uncertainty. Although DSRC clockswere synchronised with GPS time, millisecond order isachieved which is absolutely useless for ranging purposes.Further investigations regarding the utility of DSRC for ranging between vehicles is currently underway.

| Parameter | Transmit Power: 10dBm | Transmit Power: 20dBm |
|---|---|---|
| STD of RSS observation noise | 1.4dBm | 1.4dBm |
| STD of CFO observation noise | 135Hz | 115Hz |

Table1: Standard deviation (STD) of the DSRC observations.

| Parameter | Transmit Rate: 10 packet/sec | Transmit Rate: 20 packet/sec |
|---|---|---|
| STD of time tags around the anticipated receive times | 2.3ms | 1.6ms |

Table2: Standard deviation (STD) of two different packet transmit rates.

## 5. CP LOCALISATION ALGORITHMS

A localization algorithm is a computational algorithm that addresses the problem formulation, robustness, estimation accuracy, coordination and computational complexity, given some measurement information. The common theme in VANET localization is the employment of distributed localization algorithms (due to their ad hoc nature); however, a centralized, or hierarchical (i.e. combination of centralized and distributed) algorithm that advocates vehicle to infrastructure communication or even a hybrid/modal algorithm has its own appeal for higher accuracy and greater availability (i.e. reliability) (Costa, et al, 2006). According to Blum, et al, 2004, VANETs show frequent fragmentation, rapid topological evolution over time and short link life (e.g. less than a second for vehicles travelling in opposite directions). As such any localization algorithm must take these factors into account since communication overhead can overwhelm the network and exhaust its channel capacity. A CP algorithm for VANETs, must have the following characteristics: first it must be real time and very fast; second it must be adaptive with respect to the traffic conditions and/or the node density; third it must be robust to inter-node connection failure.

Monte Carlo Localization (Dellaert, et al, 2007), Convex Optimization (Doherty, et al, 2001), Iterative Multilateration (Tay, et al, 2006), and Multidimensional Scaling (MDS) (Blum, et al, 2004) are the most popular network localization techniques. Parker and Valaee, 2007 presented CP estimation for VANETs as a distributed positioning algorithm. They introduced an iterative algorithm based on LMSE. The algorithm had two steps: an initialization and a refinement. The initialization of an estimate of all vehicle positions was made through exchanging GPS information, trilateration by using three vehicles that were GPS-equipped (known as Adhoc trilateration). Each vehicle then uses all the other nodes' information to make a more accurate position estimate: this was the refinement stage. In Parker and Valaee, 2007they introduced an Extended KF to incorporate kinematic information of the vehicles into the position estimation.

Two approaches investigated in this research addresses the use of the KF in (1) developing a hybrid CP algorithm that integrates map information and (2) a hybrid CP algorithm that integrates MEMS INS data. Many in-car navigation systems already provide map databases from which directional information is provided to the driver. These databases possess intelligent information that can be incorporated either as constraints to the KF solution or integrated directly as measurements within the filter. In this paper two map matching (MM) rules have been implemented. The first rule makes the assumption that the vehicle is travelling on a road (which is typically the case).This simple topological constraint can be included in the location solution, immediately improving the accuracy of the computed position of the vehicle. In the next sub-section we apply this rule to the KF solution. The simple algorithm is effective when the nearest road/lane to the estimated position (from GPS or other sources) is in fact the road being travelled. However, when approaching intersections or when two roads are close to each other, the nearest road may not be the road being travelled.In these situations, searching for the nearest road can downgrade the position solution.To overcome this problem, a second geometric MM rule applied in parallel takes into account the direction of the road the vehicle is travelling on. This second rule requires that the nearest road to which the vehicle's position is corrected (using the first MM rule) must have a similar bearing to the direction of travel.This corrects the problems previously described. Figure 8 describes the algorithm architecture and Figure 9 presents the results based on simulated data which shows the positioning improvements achievable from using the MM information.

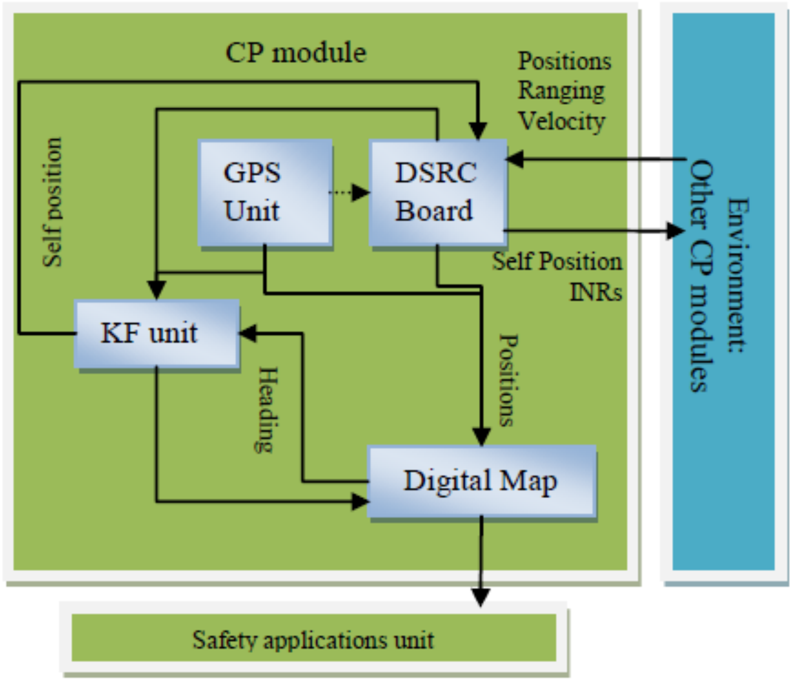


Figure 8:A CP module, consisting of positioning device (GPS unit), communication and ranging device (DSRC), computational processor (KF processing unit) and digital map.

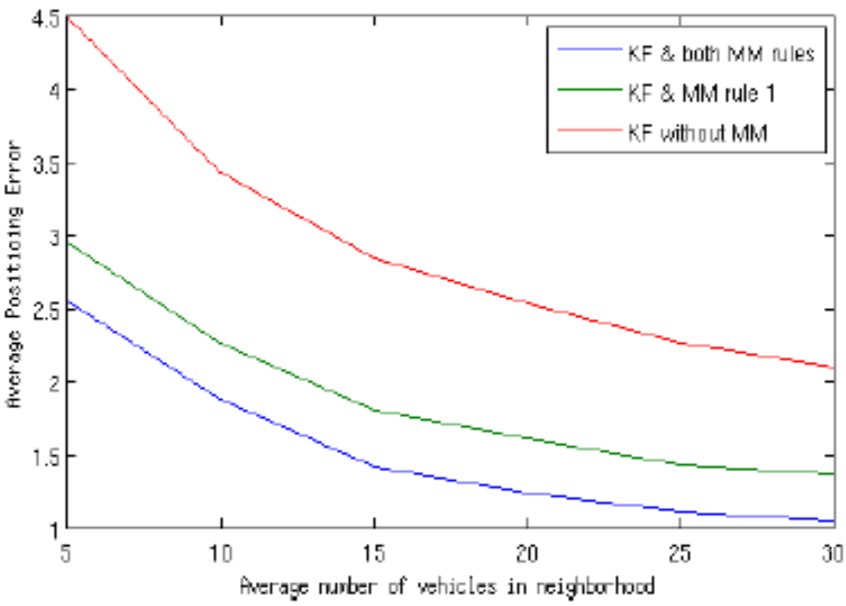


Figure 9:Simulation result shows that KF with both MM rules have better performance than KF with second MM rule only and KF without MM.

In the second technique, vehicles communicate their ID, position estimate computed from dead reckoning, the Euler angles (determined from the INS measurements), and odometer-based speed estimates with the other vehicles travelling in the opposite direction. The technique has been termed Cooperative Inertial Navigation (CIN). The key idea for CIN is todetermine the passage time and distance between vehicles travelling in opposite directions using the Doppler shift of the communication signal, in the case of a VANET the DSRC signal.At each vehicle, the INS navigation estimates are fused with those of the passing vehicle as well as the Carrier Frequency Offset (CFO) of the received packets from DSRC. Considering constraints on the geometry of the vehicles as they pass each other as well as their geometry with respect to the road network, better estimates of the dead reckoned vehicle position can be computed. Figure 10 shows the results obtained from tests conducted as part of the Nottingham trials. As can be seen, the proposed CIN method decreased the dead reckoning error at the time of passage of a vehicle travelling in the opposite direction and the consequent epochs as a result. This is due to the improved Euler angles and position estimates at the passage time using CIN.

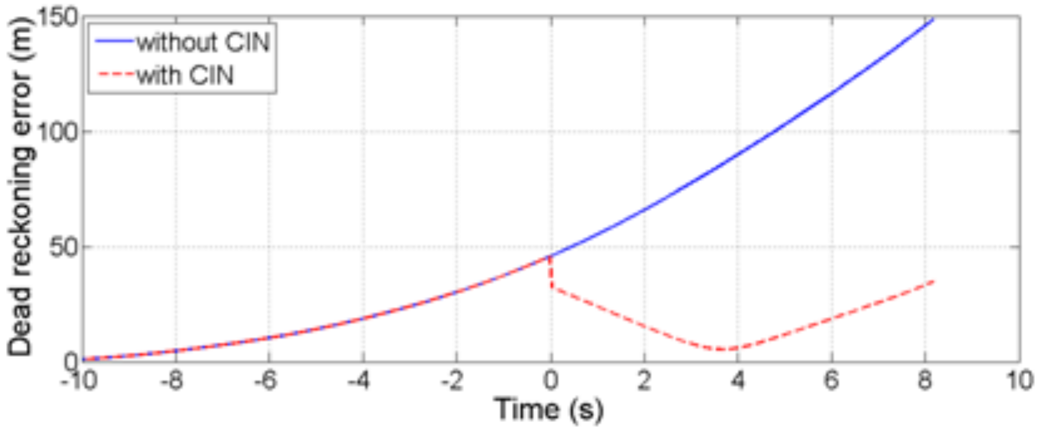


Figure 10: The performance of dead reckoning with and without CIN.

## 6. CONCLUSIONS

Cooperative positioning (CP) techniques are a potential solution for meeting the accuracy, availability, integrity and continuity requirements of C-ITS. CP relies on the availability of a communications infrastructure through which vehicles can share information that can improve the overall positioning quality. In this paper,research activities under the IAG working group 4.2.1 and FIG working group 5.5 on ubiquitous positioning have been summarised. In particular, we have demonstrated the performance and role of low cost MEMS based sensors in CP algorithms. Results that demonstrate improved performance from hybrid positioning solutions with additional constraints from map matching and DSRC based inter node ranging have been presented. These preliminary results are encouraging and will motivate future algorithm developments that further improve the capabilities of GNSS/INS based CP.

## 7. ACKNOWLEDGMENT

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## BIOGRAPHICAL NOTES

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