Positioning Enhancement using Low Cost GNSS Receivers Data Exchange in Critical Intelligent Transport Systems

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***Abstract*—Next-generation Intelligent Transportation Systems (ITS) require collaboration between vehicular communication systems and transport networks to provide highly safety-critical services. For accurate land-vehicle positioning, they rely on high-end Global Navigation Satellite System (GNSS) receivers which are cost-wise inefficient while discontinuities are prevalent in multi-story urban centers. In this paper, a Cooperative Positioning (CP) solution is presented to improve the accuracy of low-cost GNSS receivers, mainly in obstructed propagation areas. Specifically, a multi-attribute decision-making (MADM) methodology is proposed for the dynamic neighboring vehicles' ranking. Afterward, the target's vehicle receiver can select the optimal neighboring vehicle to cooperate with and retrieve GNSS corrections from, improving its own Position-Velocity-Time (PVT) state. Experimental criteria data are employed to emulate a scenario of neighboring cars equipped with low-cost GNSS receivers to evaluate the feasibility and ranking performance of the proposed MADM algorithm. The positioning data time series and the numerical results are then presented, exhibiting interesting findings, and a good ranking and selection performance.**

***Index terms*—intelligent transportation systems, cooperative positioning, low-cost GNSS, multi-criteria decision making, ranking methods, NMEA.**

I. Introduction

Intelligent Transportation Systems (ITS) have evolved dramatically over the last decades and advanced ITS applications are on the verge of large-scale deployment [1-2]. Loop detectors, dynamic message signs, entrance ramp meters, electronic toll collection, traffic telematics were some traditional ITS technologies designed to prioritize safety, and improve traffic and commuters' convenience [1-2]. However, the increased motorization, urbanism, population density, and speed limits gradually surpassed the existent transport network's capacity. To overcome this barrier, the 5.8 GHz band was allocated to the Dedicated Short-Range Communications (DSRC) enabling, thus, the connected ITS (C-ITS) and Automated Vehicles (AVs) [3]. Therefore, next-generation ITS are expected to solve congestion-based problems and optimize road safety among others [1-2]. For a beneficial actualization, the collaboration between communication, information and location-based technologies is crucial to optimize route planning, reduce crashes and fatalities, and ensure the secure operation among road infrastructure and vehicles [1-3]. Specifically, the ITS applications can be categorized into three major fields: a) active road safety, b) traffic efficiency and management, and c) infotainment. The identified disadvantages are the high equipment and maintenance cost, the control system hacking security, the underserved road infrastructures, the traffic data collection and privacy regulations [3].

By means of DSRC, wireless e.g., Wi-Fi, cellular mobile network e.g., 5G, or any other standardized connectivity framework, a C-ITS vehicular network can be established. A Vehicle Ad Hoc Network (VANET) is a self-organized network with a highly variable topology and node density where vehicles comprise the network nodes or routers. They are able to broadcast PVT information to other vehicles (V2V), to infrastructure (V2I), to pedestrians (V2P), to internet cloud (V2C), to network (V2N), and in general, to everything (V2X) [1-3].

The exact location of each vehicle is derived from the Global Navigation Satellite System (GNSS), a multi-constellation satellite network that allows receivers on Earth to estimate their exact Position-Velocity-Time (PVT) state [4]. It is the keystone for a variety of safety-critical ITS services and many other navigation-related applications. Most high-end, survey-grade GNSS receivers are capable of achieving centimeter-level horizontal and vertical accuracy by acquiring differential corrections from base stations through a process called Differential GNSS (DGNSS) or Real Time Kinematic (RTK) [4]. The Precise Point Positioning (PPP) is another useful method that provides satellite-delivered corrections, eliminating the need for base station but achieves decimeter-level accuracy and has a high convergence time [4].

On the other hand, consumer-grade, low-cost and ultra-low-cost GNSS receivers are steadily manufactured and drawing attention [5]. Modern smartphones, wearables and

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drones are equipped with such receivers because they're very light, easy to install, they have a low energy consumption, and are able to connect to networks [5]. Typically, low-cost GNSS receivers carry patch antennas and operate on a single carrier (L1).

The discontinuity of GNSS satellite signal in obstructed propagation environments due to multipath, atmospheric delay and visibility errors indicates the fusing of low-cost receivers with other technologies to enhance their accuracy and reliability [4]. Inertial Navigation Systems (INS), Ultra-Wideband (UWB), cameras are some commonly employed technologies to compensate the errors [4]. Even so, a hybrid INS/GNSS or an RTK implementation are unsuitable for ordinary portable devices and are far from low-cost. Instead, Cooperative Positioning (CP) uses radio-communication to connect vehicles and create V2V links so that the low-cost GNSS receivers can exchange information and obtain differential corrections by estimating inter-vehicular ranges (IVRs), carrier phase, relative speed [6].

In this paper, a Cooperative Differential GNSS (C-DGNSS) scenario is investigated where an ego-vehicle and several neighbor vehicles are considered connected and equipped with low-cost GNSS receivers. The objective is the ego-vehicle to identify the optimal neighbor to cooperate and acquire GNSS corrections to improve its relative positioning accuracy. For this reason, a Multi-Attribute Decision-Making (MADM) module is employed to rank the alternative vehicles in the vicinity via a number of position-related criteria and assist the target vehicle. The proposed C-DGNSS concept aims to enhance the performance of low-cost GNSS receivers in safety-critical scenarios. The scenario is emulated using real data from experimental sessions in various operating conditions (i.e., suburbs, urban canyons, and countryside). The experimental data input (i.e., criteria values) to the MADM module are National Marine Electronics Association (NMEA) sentences. An evaluation of the MADM algorithm in terms of ranking performance and optimal selection is realized. Then, the derived emulations' ranking tables, time series diagrams, MADM algorithms' performance results are presented and discussed.

The rest of the paper is organized as follows: In Section II related work about the low-cost GNSS receivers and cooperative positioning is introduced. In Section III the MADM module and its functionality are described. In Section IV the emulation environment (trajectory, alternative vehicles, input parameters) is detailed and MADM emulations using experimental data are provided. The ranking and numerical results are exhibited and commented. Finally, Section V concludes the paper.

II. Preliminaries/Related Works

In [5] the authors perform experimental measurements in a closed trajectory with urban surroundings. By employing only low-cost GNSS receivers they evaluate several Single Positioning (SP) and CP algorithms. They demonstrate that the SP is more accurate than CP. The dropped CP accuracy signifies the presence of NLoS and multipath effects. However, the CP is realized through a fixed V2I link with a road-side unit, not through V2V.

In [6] the authors propose CooPS, a combined GNSS/V2X system, to cooperatively optimize absolute and relative accuracy. They carry out successful experiments with a low-cost, 5 Hz GNSS receiver and exhibit an accuracy order of 1.0 and 1.5 m for road and lane, accordingly.

In [7-8] the authors propose low-cost solutions for land vehicle navigation and positioning accuracy improvement. Specifically, they propose MEMS INS/GNSS integrations and provide field experiments' results to show the feasibility and efficiency of their work. In [9] a low-cost GNSS receiver aided with RTK is proposed and achieves reliable and precise positioning in forest canopies.

In [10] and [11] the authors propose a "moving base station" CP approach to enhance the accuracy and precision of low-cost GNSS receivers embedded into smartphones. The results exhibit a 40% increased accuracy when applying the moving base station method compared to an RTK GNSS solution generated by a virtual reference station.

III. Proposed MADM Methodology

Safety-critical and delay-critical ITS applications demand the acquirement of GNSS corrections from the mobile neighbor vehicles by the fewest data transactions. In order to pick the optimal neighbor car for cooperation, the ego-vehicle in C-DGNSS receives serially position-related information from the M alternatives and ranks them using N criteria/ attributes. The NMEA 0183 is a universal data protocol to connect communication apps and hardware devices. The NMEA simply provides ASCII strings where each data field contains location-based parameters. Some of the main message identifiers within the NMEA messages are as follows: Geographic 3D coordinates ($GNGNS), visible GNSS satellites ($GNGSV), dilution of precision ($GNGSA), accuracy standard deviation ($GNGST).

The NMEA messages are radio-transmitted. They are suitable because they connect incompatible GNSS receivers while the users don't have to develop receiver-specific implementations.

The proposed MADM unit constitutes a fast and computerized decision-making methodology that converges on the optimal alternative or yields a ranking of a given set of alternatives [12]. Initially, a decision matrix of size (M x N) is constructed with the normalized criteria values i.e., the performance of i_{th} alternative to j_{th} attribute/criterion. Then, criteria weights are assigned either objectively or subjectively/directly [12]. Finally, the MADM methodology manipulates the normalized data according to the weighted criteria and produces a ranking output [12]. There are numerous MADM methods and normalization approaches in the literature. Their decision-making processes and similar features typically classify them to scoring-based, outranking-based, hierarchy structure-based, distance-based and others for optimal ranking and selection [12]. In our work, the following two MADM methods will be considered for a proof-of-concept demonstration.

The Simple Additive Weighting (SAW) is a scoring-based MADM algorithm [12]. SAW is very simplistic and understandable as it works with the minimum complexity and latency. Specifically, normalized criteria values are drawn from the decision matrix, and a scoring function linearly aggregate them into a single value for each alternative. However, SAW makes plenty of unrealistic assumptions while exhibiting ranking instability when the input data are varying e.g., negative criteria values, large fluctuations in data.

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a distance-based MADM algorithm [12]. TOPSIS works with a moderate complexity and latency but it's proven stable even if the input values are greatly varying. It considers a pair of ideal geometric points and considers that the optimal alternative is the one that has the smallest distance from the ideally best and the largest distance from the ideally worst point. The potential drawback of this method is the use of Euclidean distance which may be inefficient if the criteria are highly correlated.

IV. Simulation Results

The emulated data used for testing and validation of the proposed methodology concern five passenger vehicles moving simultaneously for 40.88 min (about 2500 epochs) [13]. Each car moved at different trajectory consisting of variable observation conditions: (i) open area, (ii) urban canyon with narrow streets and multi-story buildings, and (iii) suburban environment with tall trees of dense foliage, causing significant losses and partial interruption of the satellite signal. Emulation framework implemented using: a) real GNSS PVT data, b) MATLAB script and c) MATLAB toolbox for testing MADM algorithms. GNSS PVT data occurred from low-cost ITS compatible GNSS receivers [13].

GNSS receivers are configured to compute PVT solution at 1Hz rate and report it through standardized GNS and GST messages of NMEA protocol. Table I exhibits the list of criteria used per NMEA sentence. The number of visible GNSS satellites (NS), (2) the root mean square of the double-difference L1 phase residuals (Range RMS), (3) the horizontal accuracy standard deviation (Hz std), (4) the position's solution ambiguity status (Amb Stat), and (5) the horizontal dilution of precision (HDOP). Furthermore, the Range RMS, Hz std, V std are all measured in meters, while the Amb Stat may output an autonomous, a differential GNSS, a float, and a high-resolution fixed solution. The HDOP takes values inversely proportional to the number of visible satellites low in the sky (ideally < 1).

TABLE I. Position-Related Criteria For The MADM Module

a/a	Criteria name	NMEA		Type
		Sentence	*Field no*	
1	Number of satellites	GNS	7	Benefit
2	Range RMS	GST	2	Benefit
3	Horizontal std	GST	6,7	Expense
4	Integer ambiguity status	GNS	6	Benefit
5	HDOP	GNS	8	Expense

Finally, the criteria are classified to "Expenses" and "Benefits". The first class means that the lower the criterion value, the better (minimum), while the second class denotes that the higher the criterion value, the better (maximum).

From five passenger vehicles that were used, the first vehicle (veh. #1) is the target vehicle and the remaining four (veh. #2, veh. #3, veh. #4, veh. #5) are the neighbor vehicles. Fig. 1 shows a plot of the number of visible satellites of the GNSS receiver for all engaged vehicles. From Fig. 1 it is clearly seen the various observation conditions for the participating vehicles. For instance, veh. #5 is moving in open area settings as the satellites in-view are constant during its trajectory exhibiting only minor fluctuations. On the contrast, the multipath effects in urban settings cause a high NS variability in Fig.1.

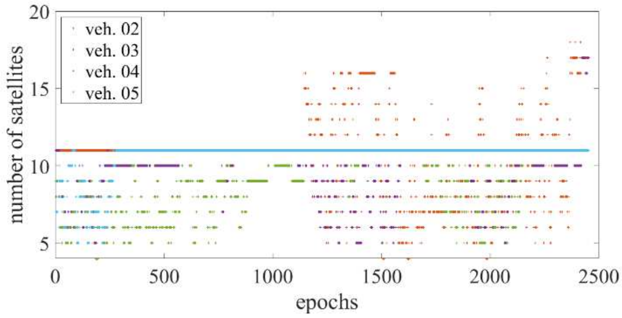

Fig. 1. Number of satellites in view per neighbor vehicle (veh. 02/03/04/05) for the entire trajectory.

Fig. 2 plots the horizontal accuracy standard deviation (Hz std) of each vehicle along the whole trajectory. As expected, as the number of satellites decreases the Hz std increases. Also, the greater the fluctuation of the visible satellites the larger the Hz std becomes.

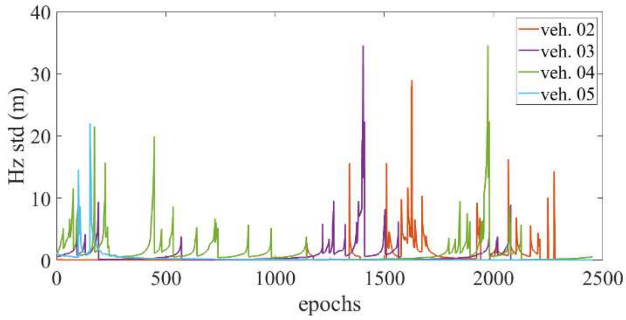

Fig. 2. Horizontal std per neighbour vehicle (veh. 02/03/04/05) for the whole trajectory.

A trajectory of 2453 timestamps (epochs) subject to $N = 5$ criteria is investigated using $M = 4$ alternative vehicles (veh. 02 – veh. 05) while the ranking results are determined using two MADM algorithms: TOPSIS and SAW. For every timestamp, the decision matrix is formulated using normalized criteria data of every neighbor vehicle via the MAX method – divide by the maximum value. The decision matrix is fed then in the MADM methods and the Ranking (R(i)) matrix of the alternative vehicles, with their corresponding Performance indicator (Q(i)) matrix are estimated.

Table II contains the decision matrix of 1221th timestamp. Tables III and IV include the Ranking and Performance indicator results of both TOPSIS and SAW MADM methods, for equal weighting w = [0.2 0.2 0.2 0.2 0.2].

TABLE II. MADM Decision Matrix

Veh.	Criteria				
	NS	*L1 rms*	*Hz std*	*Amb Stat*	*HDOP*
02	12	0.006	0.015	Fixed	0.87
03	8	0.004	1.123	Float	1.31
04	11	0.004	0.101	Float	0.92
05	11	0.006	0.093	Float	0.66

TABLE III. TOPSIS METHOD RESULTS

R(i)	Veh.	Q(i)
1	02	0.966
2	05	0.748
3	04	0.705
4	03	0.000

TABLE IV. SAW METHOD RESULTS

R(i)	Veh.	Q(i)
1	02	0.968
2	05	0.869
3	04	0.762
4	03	0.470

We observe that TOPSIS and SAW produce very similar rankings for this timestamp indicating veh. 02 as the optimal selection.

In Fig. 3, the selected rank I vehicle ID (optimal neighbor) along the trajectory is depicted by employing the TOPSIS method. The results are derived using the MAX normalization method and an assumption of equi-weighted criteria (w = 0.2).

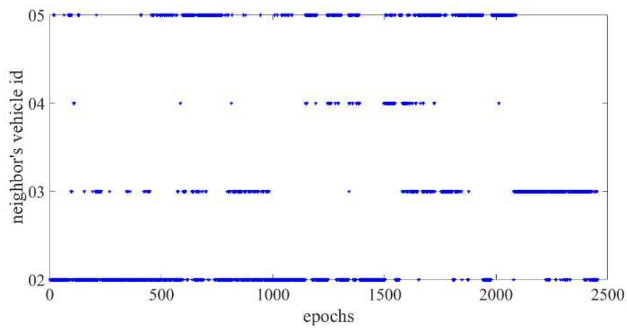

Fig. 3. Rank I vehicle ID vs epochs, using MAX normalization method, TOPSIS method and equi-weighted criteria.

In order to validate the proposed method using real data of simultaneously moving vehicles, a pilot experiment was organized and took place at the Zografou Campus of National Technical University of Athens. Six neighbor vehicles and one Target Vehicle were equipped with low-cost ITS-compatible GNSS receivers. The Target Vehicle was also equipped with a Tactical Grade GNSS/IMU to compute the reference trajectory of the vehicle and compare it with the C-DGNSS solution produced.

During the experiment, various moving scenarios of participating vehicles were scheduled and took place, under variable observation conditions. GNSS corrections data exchange between vehicles was achieved using the NTRIP caster/server. Data obtained from the experiment are investigated and preprocessed in order to have the appropriate form for the final C-DGNSS processing.

V. CONCLUSIONS

In this paper, a C-DGNSS solution is presented to enhance the positioning accuracy of low-cost GNSS receivers in critical ITS applications. The objective is the target-vehicle to identify the optimal neighbor to cooperate and acquire GNSS corrections. For this reason, a MADM module is employed to rank the alternative vehicles in the vicinity via a number of position-related criteria. The emulation framework employs real data from experimental sessions in various operating conditions (i.e., suburbs, urban canyons, and open sky). The emulated criteria values fed to the MADM module are in the form of NMEA data. Then, the derived emulations' ranking tables, criteria-epochs diagrams, MADM algorithms' performance results are presented and discussed. An evaluation of the TOPSIS and SAW methods in terms of ranking performance and optimal selection is realized.

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