The 2010 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 18-22, 2010, Taipei, Taiwan

Benchmark Tools for Evaluating AGVs at Industrial Environments

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Abstract— **The paper addresses the problem of evaluating AGVs with different degrees of autonomy by defining benchmark tools to grade the performance of each approach. Based on the proposed benchmark, different experiments have been performed from manual driving to autonomous navigation, at different velocities and a scenario containing wide and narrow corridors, small and large isles, rooms, slalom-like parts requiring zig-zag maneuvering and static objects. However, this benchmark is also applicable to dynamic environments, including moving objects and other vehicles. In particular, experiments have been used for evaluating the performance of AGVs, in terms of robustness, efficiency, safety and comfortability. The underlying objective is to evaluate the potential advantages of manual-assisted driving as well as autonomous navigation against standard manual driving. To obtain valid and significant results, more than 180 experiments have been carried out on each approach.**

I. Introduction

Commercial AGVs are typical based on magnets, wires or laser guidance, which require a specific infrastructure. Another type of guidance for AGVs is the inertial navigation, using accelerometers and gyroscopes aided with esteroceptive transponders embedded in the floor. As advantages, fully autonomous solution with capacity to react, obstacles avoidance and path computation are included in the vehicle by using the most advanced techniques. As drawbacks, high implantation cost and general lack of flexibility make unfordable comercial AGVs, especially for SME (Small-Medium Enterprises).

On the other hand, traditional manually maneuvering with forklifts has the advantage in providing human intelligence to adapt to unstructured and cluttered environments. However, human behavior is occasionally risky and dangerous because they may underestimate a particular situation.

Auto-Guided Vehicles (AGVs) involved in industrial applications constitute interesting Intelligent Transportation Systems (ITS) for researchers and engineers.

It seems appropriate to investigate on new ITS that combine both, human intelligence in traditional maneuvering and computational capabilities of AGVs, to improve security and reduce the risk of having accidents. This kind of ITS have become increasingly common in automobile, see section I-A for details, but rarely used in industrial environments.

This work was supported by PISALA Project funded by Vicerectorado de Investigacion Desarrollo e Innovacion, Universidad Politecnica de Valencia and PROMETEO Program funded by Conselleria Educacio, Generalitat Valenciana,

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Many industrial companies are very concerned in reducing accidents when using transpontation vehicles. Accidents have negative consequences such as: delays in scheduled tasks affecting to the manufacturing process, damages on the vehicles which require expensive reparations and maintenance, worker casualties and economical looses. Accidents can be caused by human driving errors, but also by unexpected obstacles, machine failures or incorrect signaling of restricted areas, among other causes.

It is possible to combine traditional driving with some kind of ITS technologies in order to provide a new approach for manual-assisted driving.

This paper proposes a benchmarking of different driving modes from traditional manual driving to AGVs, including a hybrid solution based on ITS technologies for assisted-driving, where human operator and intelligent system play cooperative roles. The benchmarking provides quantitative data about robustness, efficiency, safety and comfortability for each approach and allow us to compare one solution against the other.

A. Intelligent Transportation System Technologies

The Antilock Braking System (ABS) first brought to market by Bosch in 1978 prevents wheel lock during full braking. This ensures that the vehicle can still be steered and moved out of the way of unexpected obstacles. Adaptive Cruise Control (ACC) technology improves the function of standard cruise control by automatically adjusting the vehicle speed and distance to the vehicle ahead. Adaptive Headlights (AH) can direct the beams by moving each headlamp left, right, up or down in reaction to steering wheel angle, speed and movement of the vehicle. The Lane Change Assistant [1] or the Blind Spot Detection systems [2] continuously monitor the rear blind spots on both sides of the vehicle. Driver Drowsiness Monitoring and Warning systems [3] can detect the driver's drowsiness in several ways: by tracking the driver's facial features, movements of hands and feet, by analyzing eye-closures and head pose or even changes in heartbeat. The Electronic Brake assist System (EBS) is a very efficient aid in emergency braking situations when the driver wants the vehicle to stop as quickly as possible which can be found in Mercedes-Benz (S-Class, SL-Class). The Electronic Stability Control [4] detects the deviation between the vehicle's trajectory and the intended direction. Without any action on the part of the driver, small amounts of braking are applied separately to each wheel and this can bring the vehicle back to the intended course. Lane Departure Warning Systems (LDWS) are electronic systems, found initially in Nissan, Toyota and Citroen that monitor

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the position of the vehicle within its lane and warn the driver if the vehicle deviates or is about to deviate from the lane. Obstacle Collision Warning Systems help the driver to prevent or mitigate accidents by detecting vehicles or other obstacles on the road ahead and by warning the driver if a collision becomes imminent. Current solutions with limited performance are an additional function of Adaptive Cruise Control, using information obtained from radar sensors to give visual and acoustic warnings [5] and [6]. Intelligent Speed Adaptation (ISA), also known as Intelligent Speed Assistance, is any system that constantly monitors vehicle speed and the local speed limit on a road and implements an action when the vehicle is detected to be exceeding the speed limit, see [7] for a complete review. Other assistance systems are gear shift indicator, night vision, adaptive light control, automatic parking, traffic sign recognition and hill descent control, among others.

B. Motion planning and obstacle avoidance techniques

Literature on motion planning and reactive obstacle avoidance of mobile robots considers the problem of how to reach a goal pose without colliding with the environment. Potential Field (PF) methods [8] and [9] addressed the first sensor-based motions, where a large set of different potential functions have been proposed [10], [11], [12] among others. The Vector Field Histogram (VFH) [13], [14], [15] considers sensor uncertainty to avoid obstacles using occupancy grids. Generalized Perception Vector (GPV) [16] is comparable to the VFH but linked to sensors instead of occupancy grids. In [17], an extension of the GPV was developed by considering an orientable eccentric ellipsoid based on the movement direction for non-holonomic mobile robots. The Elastic Bands (EB) [18] was the first technique combining planning and reaction schema in a unified framework. The Dynamic Window Approach (DWA) was the first technique to address kinematics and dynamics to carry out motion at high speeds [19] and similarly [20]. More recently, the Nearness Diagram (ND) navigation [21] was the first technique to address motion in troublesome scenarios, where several variations of the algorithm can be found [22], [23], [24], [25].

II. AGV Description

Within the context of several research projects (Auto Trans, GATA and LITRONA), we have developed different approaches for automating industrial vehicles such as teleoperation of industrial vehicles [26] and vision-based line tracking [27], [28]. More recently, we have proposed an unified and general approach for automating vehicles in a range from manual driving [29] and manual-assisted driving in addition to teleoperation, vision-based line tracking [30], etc.

A. Vehicle Automation

The Nichiyu FBT15 industrial forklift has been automated to perform as an AGV. The forklift has three wheels in tricycle configuration (an orientable rear wheel and two fixed wheels at the front). It also has a power-assisted steering wheel that minimizes the torque through a mechanical link and a DC motor attached to the rear wheel. In addition, two DC motors are also attached to the front wheels, coordinated through an electronic differential.

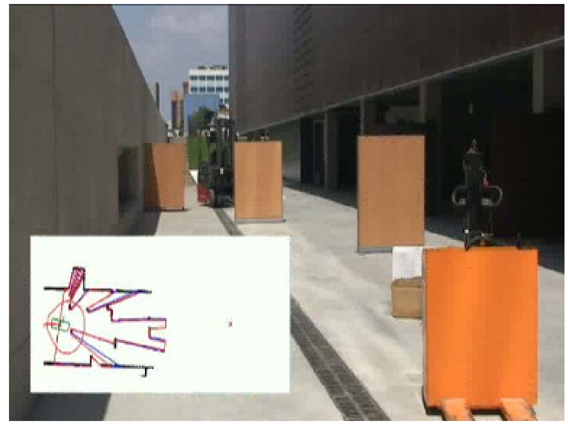


Fig. 1. Autonomous navigation forklift on a cluttered environment.

The original vehicle has been modified by including a PLC for low-level vehicle control and an industrial PC at high level, implementing the intelligence of the AGV. The PLC is connected to the most critical signals regarding with emergency stops and main sensor/actuator interface (analog and digital inputs and outputs), while range sensors are connected to the PC. Two lasers rangers from SICK provide 180^o range scans with 0.5^o angular precision at a maximum rate of 75Hz located at the rear and front of the vehicle. They also provide warning and protection zones that activate a digital signal directly connected to the PLC. Two incremental encoders that measure speed of fixed wheels are also connected to PLC counter boards, while an absolute encoder measures the angle of the rear steering wheel. Analog inputs are used for sensing the throttle pedal and the torque applied to the steering wheel; and analog outputs for controlling the vehicle drive velocity. That analog output replaces de original throttle pedal signal corrected by the control algorithm.

B. Autonomous Navigation

In orther to transform a comercial AGV into an ITS, we have defined a software architecture as shown in Figure 2(c) are using Adaptive Monte-Carlo Localization (AMCL) to estimate the vehicle pose [31] and wavefront planner [32] to globally provide way points. In addition, we can select between ND [23] and VFH+ [15] as real-time obstacle avoidance technique. In simulation implemented algorithms and drivers including SICK laser driver have been taken from Player [33].

Fig. 1 shows an example of the autonomous navigation application using ND, where the vehicle moved on a cluttered unstructured environment ([34]).

C. Manual-Assisted Driving

In manual-assisted driving, the driver normally operates the vehicle, receiving feedback from different kind of visual, audio and haptic devices. The main idea is to investigate on feasible ready-to-market solutions that improve driving security aspects with industrial forklifts, aimed to reduce the risk of collisions. Our particular approach focuses on haptic feedback devices, so the driver can feel the danger of selecting an inappropriate steering wheel direction by applying a torque on the steering wheel opposite to that direction. In addition to this, the vehicle speed is automatically regulated as in Adaptive Cruise Control (ACC) systems. Our implementation is based on the GPV technique [17], where the main ideas can be summarized as follows: Only obstacles inside an influence ellipsoid area surrounding the vehicle are taken into account to compute repulsive forces. These forces are used to cancel the throttle pedal commands introduced by the driver and even to generate a negative acceleration if required. These forces are also used to generate a proportional reactive torque on the rear motor that is feedback on the steering wheel so the driver feels higher stiffness while trying to move towards an inappropriate direction. See [35] for more details on the algorithm implementation and [36] for a video showing the manual-assisted driving preventing from collisions.

III. Benchmarking Methodology

The purpose of this section is to provide general tools for benchmarking the performance of vehicle driving modes in an industrial environment, although the methodology can be used to other vehicles and environments. Our goal is to grade the benefits of using manual-assisted driving performed by a skillful driver.

The benchmark methodology includes the following steps:

- Define different types of scenarios where vehicles may move. Possible scenarios include wide and narrow corridors, small and large isles, rooms, slalom-like parts requiring zig-zag maneuvering, moving objects (other vehicles or people), separately or combining several of them.
- For each scenario a set $\mathcal{G}$ of pairs start or goal positions are defined (in our case, we have defined 9 different positions, see Figure **??** for details).
- Define a set $\mathcal{V}$ of maximum speeds that the vehicle can move when the driver fully accelerates (in our case, we have defined 5 different velocities $1m/s, 2m/s, 3m/s, 4m/s, 5m/s$). Most of well know path planning algorithm take this kinematic constrains into account. For manual and manual-assisted driving, the set of maximum velocities is sensed by the driver as a change in the sensitivity of the throttle pedal.
- Generate random tests with combinations of start, goal positions and maximum speeds. Perform at least $N = \frac{n!m}{2!(n-2)!}$ test for each algorithm to evaluate, where $n = \dim(\mathcal{G})$ and $m = \dim(\mathcal{V})$. In our case, we have performed 180 experiments per approach for each driving mode.

During the experiment, all data is logged for computing some metrics. True Positive (TP) experiments imply that the vehicle reaches the goal without collisions. False Positive (FP) experiments imply that the vehicle reaches the goal with collisions or reaches an incorrect goal (localization failures in autonomous driving modes may cause the vehicle to belief that it has reached the goal). Finally, Negative (N) experiments are those where the vehicle gets blocked. That is: doesn't know how to escape from a collision, or doesn't reach the goal within a maximum limit-time T ($T = 500$s. in our case).

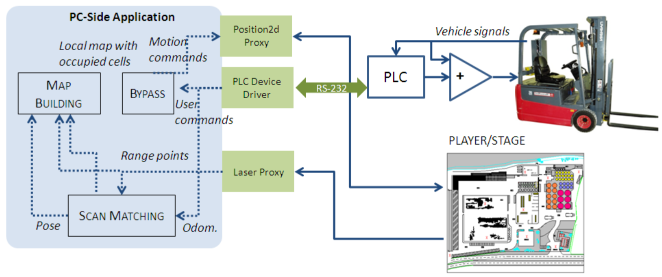
There are several crucial aspects that must be also evaluated: 1) **Robustness**. The higher the percentage of True Positives, the higher the robustness of the approach. In order to increase robustness wider and clearer areas must be followed. 2) **Efficiency** or operability of the vehicle as a measure of mean time, velocity or mean path length 3) **Safety** is terms of average minimum distance to obstacles and risk of collisions, minimum distance to any obstacle for the whole experiment 4) **Comfortability** in terms of the type of described trajectory (bending energy and smoothness) and variations of the acceleration (jerk). All this concepts will be formally defined thereinafter.

Figure 2 show the three different architectures compared in this paper: a) descrived traditional manual driving; b) manual-assisted diving and c) auto guided driving. Using the setup described in Figure 2(a) command signals from the driver affect directly to the vehicle. In Figure **??** several ITS modules modify the user actions so some improvements are introduced to the driving, such as collision avoidance and speed surveillance. In adition, the driver is assisted by vision feedback generated from a map which is already constructed during the experiment. Finally, Figure 2(c) shows the architecture of AGV where an AMCL module is used for estimating the vehicle pose and wavefront planner for globally provide way points. As previously commened it is possible to select between ND and VFH+ as real-time obstacle avoidance technique.

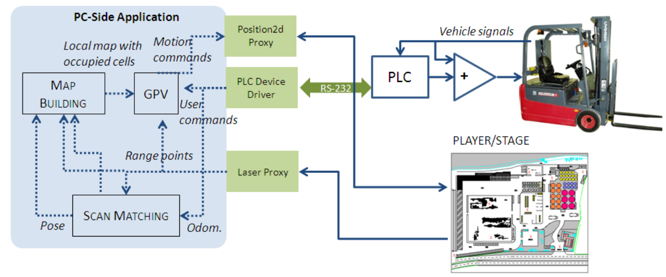
The great amount of experiments required to compute the different metrics has forced us to use Player [33] as simulation platform. By doing that the experiments can be carried out staticly and environments can be generated flexibily defined at a low cost. That is why Player is present in the three set ups. In simulation implemented algorithms and drivers including SICK laser driver have been taken from Player. Manual and manual-assisted driving mode read real data from the PLC and simulated data from Player/Stage v2.0.1, where a factory layout is depicted for a more realistic simulation, as shown in Figure 2(c) (red crosses are start-goal positions). From the Player client point of view, no matter whether the forklift is real or simulated.

Table I contains experimental results in the factory environment previously descrived. It can be appreciated that in manual driving TP (robustness) decreases with increasing velocities, while manual-assisted driving has shown very good performance, at high velocities. In AGV driving, the ND approach shows very high robustness, while VFH+ gives poor results due to the large percentage of Negative experiments That indicates that the VFH+ requires too much time to reach the goal (especially at low speeds) or is not able to reach it (maybe because is blocked after hitting the environment).

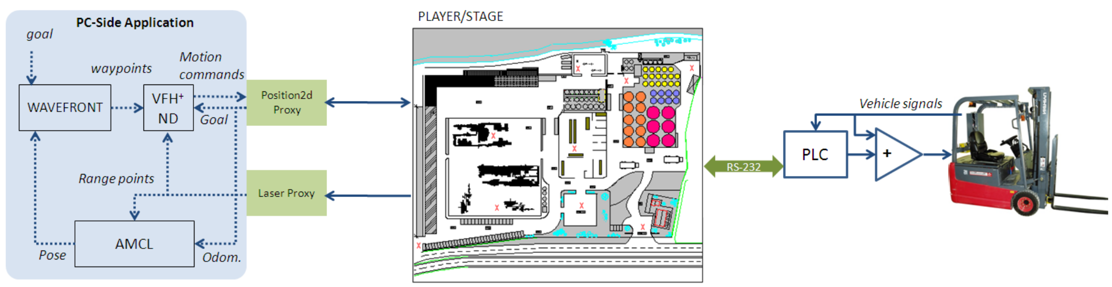
Following the ideas of [37], some metrics have been



(a) Setup for static experiments in manual mode.



(b) Setup for static experiments in manual-assisted mode.



(c) Setup for static experiments in autonomous (AGV) mode.

Fig. 2. Benchmark setup.

TABLE I

ROBUSTNESS OF DRIVING MODES AT DIFFERENT SPEEDS.

Speed $[m/s]$	Case [%]	Mode			
		Manual	Assisted	AGV	
				VFH+	ND
1	TP	97.87	100.00	76.47	89.29
	FP	2.13	0.00	0.00	1.79
	N	0.00	0.00	23.53	8.93
2	TP	94.12	100.00	86.96	100.00
	FP	5.88	0.00	0.00	0.00
	N	0.00	0.00	13.04	0.00
3	TP	96.55	100.00	72.22	100.00
	FP	3.45	0.00	2.78	0.00
	N	0.00	0.00	25.00	0.00
4	TP	82.05	100.00	73.53	100.00
	FP	17.95	0.00	0.00	0.00
	N	0.00	0.00	26.47	0.00
5	TP	54.84	94.12	77.36	80.39
	FP	45.16	5.88	15.09	19.61
	N	0.00	0.00	7.55	0.00

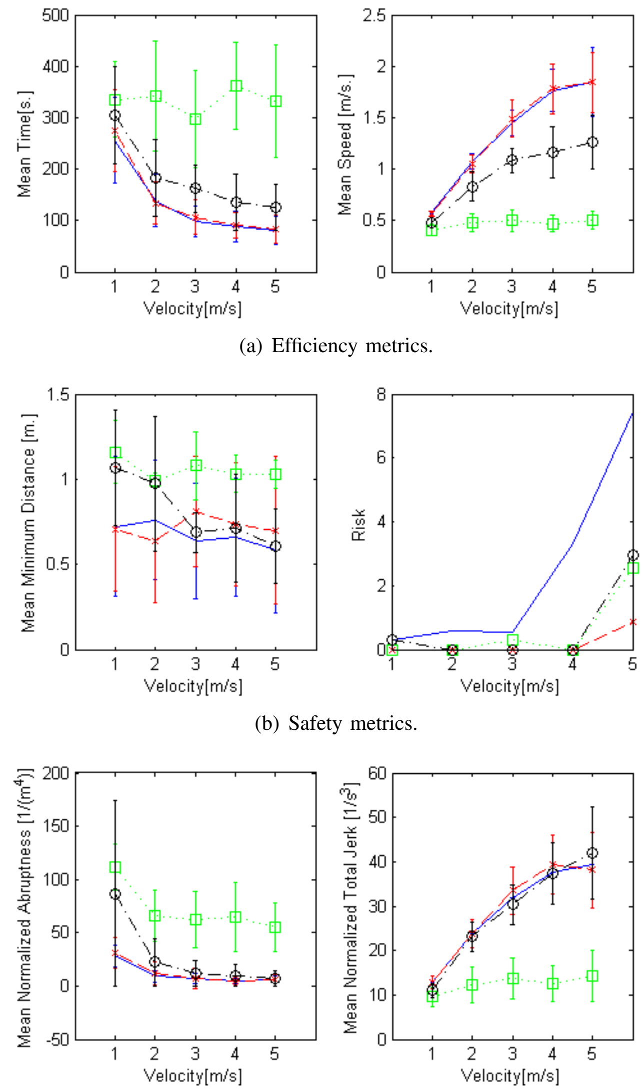
computed in addition to others such as risk and mean square jerk. For the computation of the metrics, only True Positive experiments have been considered, but the risk which takes into account the number of hits on each experiment. The mean time (MT) is $MT = \frac{1}{N}\sum_{i=1}^{N} T_i$, where N is the number of TP experiments for a given speed and approach and T_i the total amount of time to reach the goal. The mean path length (MPL) is $MPL = \frac{1}{N}\sum_{i=1}^{N} PL_i$, where $PL_i = \int_s^g \Phi_i(l)dl$, being $\Phi_i(l)$ the trajectory of the i-th experiment, s the start position and g the goal position. Consequently the mean speed (MS) is $MS = \frac{1}{N}\sum_{i=1}^{N} \frac{PL_i}{T_i}$. The mean average minimum distance (MAMD), is defined as SM2 in [37] $MAMD = \frac{1}{N}\sum_{i=0}^{N}\sum_{j=1}^{N_i} \min(\mathbf{d}_i)$, where N_i are the number of scans taken at the i-th experiment and $\min(\mathbf{d}_i)$ is the distance of the closest obstacle to the vehicle taking into account its shape. The MAMD can be taken as a measurement of how conservative the trajectories are when navigating in the middle of obstacles. In addition, the mean minimum distance (MMD), defined as SM3 in [37] is $MMD = \frac{1}{N}\sum_{i}^{N} \min(\{\mathbf{d}_1, \mathbf{d}_2, ...\mathbf{d}_N\})$, considers the mean of minimum distances of the overall experiment. The risk as defined in [38] is the ratio of number of accidents and the exposure. The exposure (the units or magnitude of the activity in which the accidents occurred) can be defined in multiple ways such as vehicle kilometers, trips, road user hours, etc... For our particular case we have considered MAMD value as exposure, therefore risk (R) is formally defined as $R = \frac{\sum_{i=0}^{N}(\#accidents_i)}{MAMD}$. The bending energy can be understood as the energy needed to bend a rod to the desired shape. The mean total bending energy (MTBE) is defined as $MTBE = \frac{1}{N}\sum_{i=0}^{N}\int_s^g \kappa_i^2(l)dl$, where $\kappa_i(l)$ is the curvature of the trajectory. The smoothness is defined by the square of the change in the curvature, therefore the mean normalized abruptness (MNA) is $MNA = \frac{1}{N}\sum_{i=0}^{N}\frac{\int_s^g(\kappa_i(l)/dl)^2 dl}{PL_i}$. It is interesting to remark that the term smoothness is indeed related with the change of curvature, but we prefer to use abruptness as the inverse of smoothness. Finally, we consider the mean normalized total jerk (MNTJ) which takes into account changes in acceleration or deceleration. MNTJ is defined as $MNTJ = \frac{1}{N}\sum_{i=0}^{N} j_i$, where $\mathbf{j}_i = \sum_{j=1}^{N_i}\sqrt{x_j'''^2 + y_j'''^2}$, being x_j''' and y_j''' the instantaneous Cartesian accelerations of the trajectory.

In table II, we show numerical values for the metrics previously defined. The most relevant metrics have been depicted on figures for clearer comparison. In this sense, Figure 3(a) compares efficiency related metrics: MT, MS; Figure 3(b) compares safety related metrics: MMD, R; while comfort related metrics are depicted in Figure 3(c), MNA, MNTJ.

Figure 3(a) (MS) shows that in manual driving the vehicle

TABLE II
METRICS OF DRIVING MODES AT DIFFERENT SPEEDS.

Speed $[m/s]$	Metrics [%]	Mode Manual	Assisted	AGV VFH+	ND
1	MT $[s]$	255.72	274.58	335.04	304.64
	MPL $[m]$	146.99	154.96	135.09	147.68
	MS $[m/s]$	0.57	0.56	0.41	0.48
	MAMD $[m]$	3.38	3.19	3.12	3.38
	MMD $[m]$	0.72	0.71	1.16	1.07
	Risk	0.30	0.00	0.00	0.30
	MTBE $[m^{-1}]$	13.22	13.49	34.49	33.64
	MNS $[m^{-4}]$	28.51	31.63	111.48	86.98
	MNTJ $[1/s^3]$	12.70	12.86	9.56	10.96
2	MT $[s]$	138.96	134.17	341.88	182.96
	MPL $[m]$	151.05	142.34	157.58	150.48
	MS $[m/s]$	1.08	1.05	0.48	0.83
	MAMD $[m]$	3.40	3.37	3.02	3.40
	MMD $[m]$	0.76	0.64	0.99	0.97
	Risk	0.59	0.00	0.00	0.00
	MTBE $[m^{-1}]$	13.54	14.67	37.08	23.20
	MNS $[m^{-4}]$	9.08	12.12	66.11	22.46
	MNTJ $[1/s^3]$	23.77	23.87	12.36	23.08
3	MT $[s]$	97.69	106.60	296.69	162.75
	MPL $[m]$	142.12	160.58	143.67	176.47
	MS $[m/s]$	1.45	1.49	0.50	1.08
	MAMD $[m]$	3.64	3.43	3.24	3.38
	MMD $[m]$	0.64	0.81	1.08	0.69
	Risk	0.55	0.00	0.32	0.00
	MTBE $[m^{-1}]$	17.68	17.31	31.70	28.02
	MNS $[m^{-4}]$	7.13	7.03	62.85	11.96
	MNTJ $[1/s^3]$	31.90	33.48	13.74	30.31
4	MT $[s]$	88.77	91.06	361.20	134.84
	MPL $[m]$	154.91	163.60	166.67	156.56
	MS $[m/s]$	1.76	1.78	0.47	1.16
	MAMD $[m]$	3.33	3.51	3.16	3.66
	MMD $[m]$	0.66	0.73	1.03	0.71
	Risk	3.30	0.00	0.00	0.00
	MTBE $[m^{-1}]$	18.55	19.30	36.42	25.38
	MNS $[m^{-4}]$	4.65	5.05	65.07	9.88
	MNTJ $[1/s^3]$	37.74	39.36	12.55	37.41
5	MT $[s]$	80.73	84.16	332.98	125.02
	MPL $[m]$	149.44	156.67	161.77	153.70
	MS $[m/s]$	1.85	1.84	0.50	1.26
	MAMD $[m]$	3.35	3.41	3.16	3.51
	MMD $[m]$	0.58	0.70	1.03	0.60
	Risk	7.46	0.88	2.54	2.95
	MTBE $[m^{-1}]$	22.07	20.00	36.67	24.79
	MNS $[m^{-4}]$	5.73	5.51	55.24	6.96
	MNTJ $[1/s^3]$	39.48	38.19	14.32	42.01



(a) Efficiency metrics.

(b) Safety metrics.

(c) Comfort metrics.

Fig. 3. Metrics of manual driving (solid blue line), manual-assisted driving (dashed red line), VFH+ autonomous driving (dotted green line) and ND autonomous driving (dashed-dotted black line)

(with or without assistance) is still much more faster than with autonomous navigation algorithms. In order to avoid obstacles, autonomous vehicles move at lower speeds, which implies more mean time (Figure 3(a), MT). A vehicle running the ND can move faster than VFH+ with very high robustness. The path length is basically the same for all algorithms and speeds which indicates that wavefront planner uses the optimal path (the same path that has been taken in manual driving). Therefore, the efficiency of manual driven approaches is clearly higher. With respect to safety metrics, the MAMD is quite similar in all cases and no significant conclusions can be drawn. However, by taking into account the MMD (Figure 3(b)) we can see that due to the over confidentiality in manual driven approaches provide lower values, which causes more accidents in manual driven (without assistance) approach and therefore the driver takes a higher risk (Figure 3(b), R). Autonomous driving with VFH+ is very cautelous (thus inefficient) navigating not so close to obstacles (in those cases that there were the experiment is a TP). The manual-assisted driving and ND are not so cautelous, but the overall risk is much more lower because they are very robust (containing very few number of accidents or hits). Therefore they can move closer to obstacles but without collisions, so the risk is low. Finally, the comfort metrics indicate that VFH+ autonomous driving approach performs frequent changes on the steering wheel so that the path described by the vehicle is more abrupt (Figure 3(c), MNA). The abruptness of the ND is similar to manual driving modes. On the opposite way, the jerk (Figure 3(c), MNTJ) that the vehicle suffers is higher for ND and manual driving modes than for the VFH+. This is because the VFH+ operates at very low speeds.

IV. CONCLUSIONS

The paper addresses the problem of providing a methodology for benchmarking AGVs moving at industrial environments. For that purpose, the methodology establishes the conditions of how the experiments have to be performed. In order to grade the overall performance, we first define metrics and procedures for quantifying the robustness, efficiency, safety and comfortability, which are fundamental issues in Intelligent Transportation Systems (ITS).

This paper validates the proposed methodology based on four different driving modes (manual without assistance, manual with assistance, ND-base autonomous driving and VFH+ autonomous driving) with a single static simulated scenario interacting with the real forklift in manually driven modes. More than 180 experiments where performed on each driving mode, including 5 different maximum speeds and 9 equally spaced start-goal positions.

As main conclusions, we can clearly see the higher performance of manual-assisted driving with respect to manual driving. Manual-assisted driving is more robust and more safer (takes lower risk) with the same efficiency and comfortability. Another conclusion obtained through the benchmarking methology is that ND performs much more better than VFH+, again is more robust and safer with higher efficiency and comfortability. The main difference between manual driving modes and ND is that manual modes have higher efficiency with similar robustness and comfortability ratios.

In future work, we will extend our results to experimentations, including dynamic scenarios. It will be interesting to highlight the potential benefits of manual-assisted driving against manual driving and also with respect to autonomous AGVs. It is our purpose to grade also the benefits of combining haptic, visual and audio devices in manual-assisted driving.

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