Fusing Optimal Odometry Calibration and Partial Visual Odometry via A Particle Filter for Autonomous Vehicles Navigation

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Abstract— *Autonomous vehicles are increasingly becoming ubiquitous in the 21st century; they find application in agriculture, industry, airplanes, cars, service robotics, and others; in order to display autonomous guidance, a vehicle needs to estimate its position and orientation relative to an arbitrary coordinate system; to do so, several sources of information can be used, including images, global positioning systems, inertial measurements or odometry, each according to the application; methods, such as Kalman Filter can be used to combine the several sources of information; however, the more accurate each source of information is, the better the estimation of vehicle position and orientation will be; therefore, the calibration of the parameters of the odometrical systems in autonomous terrestrial vehicles is a must; visual guidance is also an important technology used for vehicle guidance. In this paper, it is presented an off-line method for odometry calibration using a genetic algorithm and the fusion of odometry data with heading information from camera data; a particle filter is used to fuse the data from the optical encoder and the camera. This method was tested in an Automated Guided Vehicle (AGV) with tricycle topology, demonstrating high accuracy in position estimation and guidance through arbitrary paths.*

Keywords— Autonomous Guided Vehicle (AGV).

I. INTRODUCTION

Autonomous vehicles are a relatively new technology with hundreds of potential applications in many aspects of the human life [1]; they have the potential of becoming the everyday driver of the people, and also the automatic guided vehicles AGV of the new generation industrial plant, not requiring magnetic tracks under the floor to follow a predetermined path; they exhibit the capability of interpreting data from sensors to determine their current position with respect to a predefined coordinate frame, responding at any time to the question where am I? [2]; the pose of a vehicle is comprised of the x,y coordinates of its position plus the heading or yaw angle [x, y, Ɵ]. When two different sensors provide information from the same variable, it is necessary to decide at which extent one is more reliable than the other in order to provide a weighted estimate of the variable; such is the working of the Kalman Filter [3]. Sources of the same variable are, for instance, an inertial measurement unit (IMU) [4] providing yaw rate information -which integrated over time provides yaw angle- and optical encoder ticks which can be counted and the count converted into the yaw angle of the vehicle whose wheels they are attached to.

A navigation strategy, or algorithm, is usually required to move the vehicle from one point to another; the navigation algorithm is fed with the current position and a next desired position, and its outputs convey the commands to motors in charge moving and steering the vehicle. Again, the accuracy of the movement of the vehicle depends on the accuracy of the pose estimation; this leads us to the conclusion that among the first work to be done is to accurately estimate the pose of vehicle in order to provide reliable autonomous guidance.

Odometry, refers to the measurement of the distance traveled by a wheel as it turns over the terrain; when it comes to vehicles, three and four wheeled vehicles use odometry in at least, two opposite wheels simultaneously. Usually, an optical encoder is used to measure, in ticks, the advance of the wheel; the encoder ticks can be easily converted to the distance traveled by the wheel using a simple formula that assumes the radius of the wheel to be constant; however, systematic and non-systematic factors contribute to provide errors in the measurement of the pose of the vehicle, including unequal wheel diameter, misalignment of wheels, limited encoder resolution, travel on uneven floors, wheel slippage, and others; therefore, it is necessary to calibrate the odometry minimizing the impact of the unwanted errors already mentioned.

Visual odometry (VO) is the process of estimating the movement of a vehicle using images from a camera(s) attached to it; it is based on the incremental estimate of the position of the vehicle through examination of the changes in the images from onboard camera(s); like terrain odometry, VO needs to be calibrated; however, the advantage of VO with respect to terrain odometry is that it is not affected by wheel slippage or uneven terrain. In VO, the vehicle motion between the current and previous images is computed from monocular or stereo images [5]. The main components of a VO system are: image feature detection, feature matching, and motion estimation.

Fusing data is the process of using noisy data from two or more sources related to one variable (one-dimensional) or more (n-dimensional). Typical fusing data techniques are the Kalman Filter for linear and gaussian systems and its variants, Extended Kalman Filter and Unscented Kalman Filter, for non-linear system. Kalman Filters are a kind of stochastic observers [6]. Particle filters (PF) is another valuable technique for sensor fusion; PF are useful when dealing with non-linear systems.

Visual odometry, Kalman filter and Particle filters (PF) are described elsewhere in the literature of the topic, therefore they will not be described here in more detail.

II. SYSTEM DESCRIPTION

In this research a tricycle topology vehicle was used. Here is described the architecture and operation principles of the approach presented in this paper for autonomous vehicle guidance; the proposed method is comprised of two stages: calibration (off-line) and operation. The calibration stage is depicted in figure 1.

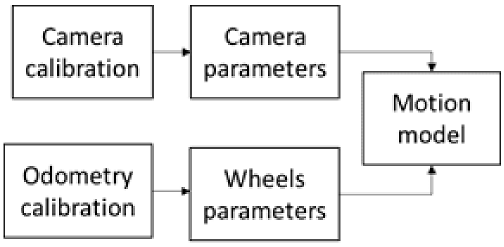

FIGURE 1: Off-line calibration

Calibration stage. In this stage, two procedures are developed; the first is camera calibration; here, the extrinsic and intrinsic parameters are found using typical methods; the second procedure is odometry calibration; as mentioned earlier, the odometry is calibrated in an evolutionary manner using a genetic algorithm; details can be found in [7]; in brief, the steps for odometry calibration are:

a) **Data gathering:** Consists of obtaining encoder pulses as the vehicle moves on predefined linear and curved paths; paths ranging from 1.5 to 3 meters are used and are very attractive when compared to more complex calibration paths presented in the literature [8]. Initial and final positions as well as encoder pulses are recorded.

b) **Evolutionary calibration:** The data recorded is used in a genetic algorithm, whose parameters can be found in Table 1. The aim of using a genetic algorithm is to find the calibration constants [k1, k2] and separation between wheels b, which are part of the kinematic model that will be described here later.

The parameters of the camera as well as the effective radius of the wheels are put together in a motion model, basically the kinematic model of the tricycle topology vehicle [9] and the camera model. It should be noticed that the modeling approach can be applied to other vehicle topologies.

In the case of the camera model, it is required to compute only one parameter: the yaw angle; therefore, it is a partial visual odometry approach. This reduces the computational complexity of the image processing operation of the system. The algorithms related to the calibration state where developed using Matlab®.

TABLE 1
GENETIC ALGORITHM PARAMETERS FOR ODOMETRY CALIBRATION.

Parameter	Value
Population	50 individuals
Mating	Roulete
Selection	Elitist, 2 individuals
Cross-point	Scatter
Mutation	Gaussian
Restrictions	3.0e-4 < [k1, k2] < 4.5e-4 0.35 > b > 0.39 (m)
Goal	To minimize pose error
Stop criterion	150 generations

The kinematic model of the tricycle topology is as follows:

$$\Delta s_l = \frac{2\pi r_l . pl_l}{R} = pl_l . k_1 \tag{1}$$

$$\Delta s_r = \frac{2\pi r_r . pl_r}{R} = pl_r . k_2 \tag{2}$$

$$\Delta\theta = (\Delta s_r + \Delta s_l).b \tag{3}$$

$$\Delta u_{x,y} = \frac{\Delta s_r + \Delta s_l}{2} \tag{4}$$

$$\theta_1 = \theta_0 + \frac{\Delta\theta}{2} \tag{5}$$

$$x_k = x_{k-1} - \Delta u_{x,y} . sin\theta_1 \tag{6}$$

$$y_k = y_{k-1} - \Delta u_{x,y} . cos\theta_1 \tag{7}$$

Where:

pl_l, Count of encoder pulses from the left, rear wheel.

pl_r, Count of encoder pulses from the right, rear wheel.

k_1, Odometric compensation constant of the left wheel.

k_2, Odometric compensation constant of the right wheel.

R, Optical encoder resolution (pulses per revolution).

2.1 Operation stage

Figure 2 shows the operation stage; when tracking a specific path, the vehicle moves forward and produce encoder pulses from both rear wheels; at the same time, the camera captures images. From one current image and the previous, the digital image processing step computes θ (the yaw angle). As can be seen, two versions of θ are at the disposal of the particle filter; each computation of the particle filter produce the estimated version [x', y', θ'], which is the best estimate (in an optimization sense) of the pose of the vehicle.

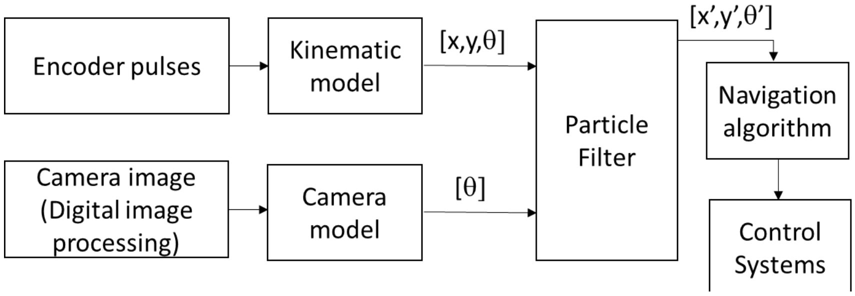

FIGURE 2: Operation stage of the vehicle.

2.2 Implementation

The system described in the previous section was implemented according to the following:

Physical system: A three-wheeled vehicle, shown in Figure 3. Front wheel steering.

Vehicle main-board: Jetson-nano, NVIDIA. With camera, artificial vision enabled.

Software: Embedded linux. OpenCV.

Control Systems: Microcontrollers and DSP based. Digital PID control.

Motor: DC type, both motion and steering.

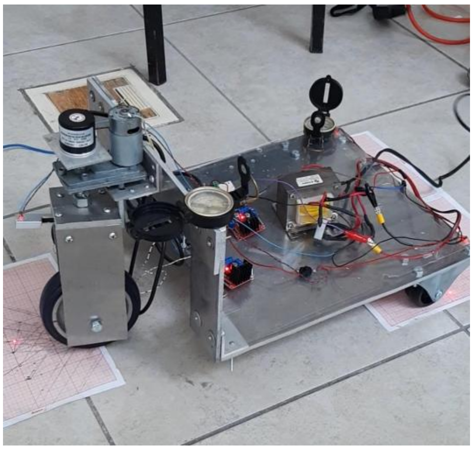

FIGURE 3: Vehicle used showing the tricycle topology.

III. RESULTS

To test this approach to autonomous vehicle navigation, the odometry calibration was carried out using calibration 15 runs of trajectories similar to the one shown in Figure 4. The genetic algorithm produced k_1=3.9447008587e-004, k_2= 3.9698427203e-004 and b= 0.3688034 as the calibrated parameters for the set of equations 8 through 7. The camera parameters are shown in the calibration matrix Q:

$$Q = \begin{bmatrix} 436.5401 & 0 & 206.2603 \\ 0 & 436.0246 & 151.2045 \\ 0 & 0 & 2 \end{bmatrix} \tag{8}$$

To test the system a set of irregular shaped trajectories was designed and programmed to be followed by the vehicle; for comparison purposes, three scenarios were tested:

a. Using uncalibrated odometry parameters,

b. Using only calibrated odometry parameters,

c. Using calibrated odometry and visual odometry with particle filter.

The results of autonomous path tracking are shown in Table 2. Asterisks denote that the task could not be completed by the vehicle. The trials were executed in a controlled environment, with uneven floor but not abrupt changes. The error reported is the mean error value of 10 trials at each scenario.

IV. DISCUSSION

It is evident that the worst-case response was the one of no calibration at all. Here, the only trajectory completed by the vehicle was of 22 meters long, but with a large error, up to about 12%. This is due to the fact that uncalibrated data produce a rapidly growing accumulation of error. It was observed a variable deviation of the vehicle from the predefined trajectory, which implies that it is most likely the dominant error, was due to random or non-systematic errors.

When using only terrain odometry calibrated parameters, a remarkable improvement was obtained, reducing the error dramatically with respect to the uncalibrated scenario; the computed calibration parameters using the genetic algorithm were capable of significantly reduce the error, although it is not clear at what extent the reduced error was of the type systematic or non-systematic.

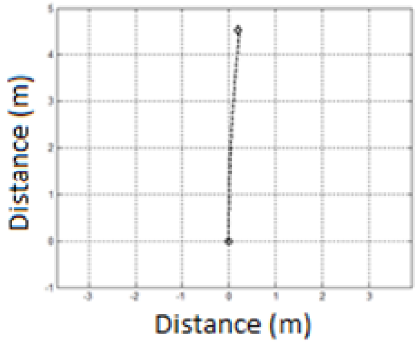

FIGURE 4: Example of calibration trajectory

TABLE 2
RESULTS OBTAINED IN 4 TRAJECTORIES.

Scenario	Length (m)	Absolute Error (%)
Uncalibrated odometry	22	12.242
	47	*
	100	*
Odometry calibration only	22	0.234
	47	0.333
	100	*
Odometry calibration + VO + PF	22	0.1025
	47	0.1236
	100	0.592

Finally, the full approach introduced here clearly separates from the other two scenarios since the vehicle was capable of successfully complete a 100 meters long trajectory. When compared to the two previous scenarios it showed to be remarkable better. To ensure success of the PF, the calibration data was used to simulate it and varying levels of noise were introduced to both, the calibration data and a simulated version of the θ yaw angle from the camera. Other approaches in literature reported similar results but using a more complex framework or tested on shorter trajectories.

V. CONCLUSION

This paper presents an approach to the problem of autonomous vehicle guidance; the use of optimization in a first stage of odometry calibration is one of major steps towards a real-world applicable system because it helped to reduce systematic and non-systematic errors, as seen in Table 2.

Combining data from the odometry system and the camera with the particle filter, as shown in Figure 2, significantly supported the dramatic reduction in the percentage of error shown as compared to the simple use of odometry calibration. Although many sophisticated algorithms have been published in the past and recent years, including auto-calibration and pose, they are complex and computational expensive, a key difference with the approach presented here. It is not discarded as future work to include some continuous optimal calibration method during the operational stage of the vehicle.

Finally, the goal of this project is to produce industrial grade AGV autonomous systems, so the efforts in such direction will continue from these research groups.

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REFERENCES

[1] R. Kümmerle, G. Grisetti, and W. Burgard, "Simultaneous calibration, localization, and mapping," in IEEE International Conference on Intelligent Robots and Systems, 2011, pp. 3716–3721.

[2] L. Feng, J. Borenstein, and H. Everett, "'Where am I?' sensors and methods for autonomous mobile robot positioning. TR UM-MEAM-94-12," 1994.

[3] G. Fu, J. Zhang, W. Chen, F. Peng, P. Yang, and C. Che, "Precise Localization of Mobile Robots via Odometry and Wireless Sensor Network," Int. J. Adv. Robot. Syst., vol. C, p. 1, 2013.

[4] J. Borenstein, H. R. Everett, L. Feng, and D. Wehe, "Mobile robot positioning: Sensors and techniques," J. Robot. Syst., vol. 14, no. 4, pp. 231–249, 1997.

[5] D. Scaramuzza and F. Fraundorfer, "Visual Odometry : Part I: The First 30 Years and Fundamentals," IEEE Robot. Autom. Mag., vol. 18, no. 4, pp. 80–92, 2011.

[6] P. Zarchan and H. Musoff, Fundamentals of Kalman Filtering: A Practical Approach, Third. Reston, VA: American Institute of Aeronautics and Astronautics, Inc., 2013.

[7] D. E. Goldberg, Genetic Algorithm in Search, Optimization, and Machine Learning. Addison Wesley Publishing Company, 1989.

[8] J. Borenstein, "UMBmark: a benchmark test for measuring odometry errors in mobile robots," Proc. SPIE, vol. 2591, pp. 113–124, 1995.

[9] J. C. Martínez-romo et al., "Genetic Optimization for Odometry Calibration of Tricycle Topology mobile robots," pp. 1–20, 2016.