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Dead Reckoning of a Skid Steer Mobile Robot using Fuzzy

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Abstract

In the context of autonomous navigations, controlling a four-wheel skid steer mobile robot is quite a challenge. Position estimation using odometric systems tend to give a rather poor estimation of position when implemented on it. In this paper, a fuzzy logic approach is described in order to minimize the position and orientation errors caused by odometric problems. The fuzzy logic maps the inputs heading and distance errors determined by the odometry readings to the outputs of translational and rotational speed of the mobile robot. Through experimental results, the effectiveness of the designed controller has been proven to compensate the position and orientation errors by almost 100 percent.

Keywords: Skid Steering Mobile Robot, Odometric Problem, Intelligent Control.

1. Introduction

Wheeled skid-steering drive configurations are found in many all-terrain vehicles, such as loaders, farm machinery, mining and military. This traction scheme is useful for off-road mobile robots [1], with field applications such as planetary exploration [2], land-mine detection [3] and rescue mission [4]. Furthermore, commercial robotic research platforms also employ this locomotion system.

Skid-steering configuration is based on controlling the relative velocities of left and right side drives; similarly to differential drive wheeled system. However, since all wheels are aligned with the longitudinal axis of the vehicle, turning requires wheel slippage. Therefore, this locomotion scheme poses difficulties when addressing motion control and odometry.

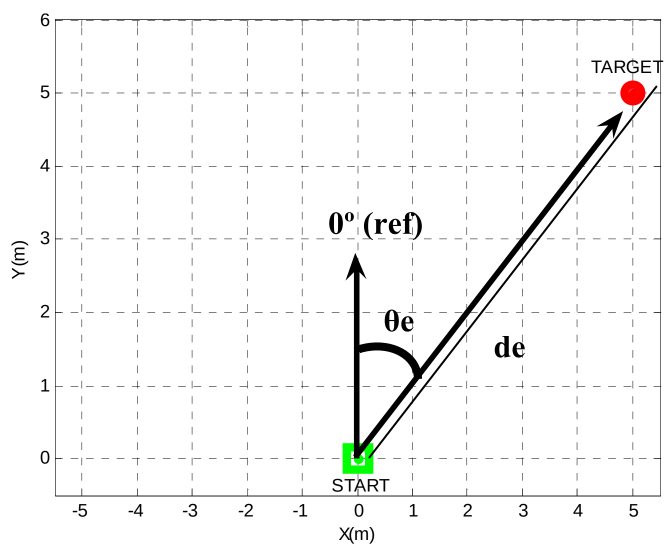
Nevertheless, it is not easy to find work reporting on this problem. Additional internal sensor, such as gyro-scopes [5], inertial units [6] or a small passive trailer with encoders [7] can be applied to detect heading changes that are not sensed by the motor encoders. Some authors have studied kinematics as the relation of linear and angular velocities with the position of the robot [8-9]. However, these do not consider major skid effects, which arise at a lower level, in the relation between drive velocities and robot velocities. Moreover, kinematics equivalences between skid-steering and differential-drive vehicles have been proposed for tracked vehicles. A simple experiment to directly obtain a symmetric model was presented in [10]. A fuzzy logic approach becomes more attractive in this work as a controller framework in order to establish a motion control for a difficult skid-steer mobile robot navigation based on odometry readings.

The computation loads of typical fuzzy inference systems are relatively light. As a result, fuzzy control permits intelligent control to be made in the real-time implementation, thus allowing smooth and uninterrupted motion.

2. Input and output selection

For the fuzzy inputs, heading angle and distance errors (θ_e,d_e) as depicted in Figure 1 can be obtained either from the vision-based technique or directly computed from the position estimation technique (dead reckoning). In the application where the vision sensor is used, (θ_e, d_e) is obtained over the conventional image processing method, that is, through colour detection and edge segmentation method [11] and real-time image processing method [12]. However, images are prone to noise due to inconsistent illumination in the environment and the computation loads are expensive. Therefore, to avoid the computational loads of image processing and its uncertainties, (θ_e,d_e) parameters are directly computed based on the dead reckoning technique where the initial actual position of the robot can be established. Moreover, it is granted that the dead reckoning method are more stable and less susceptible to image uncertainties.

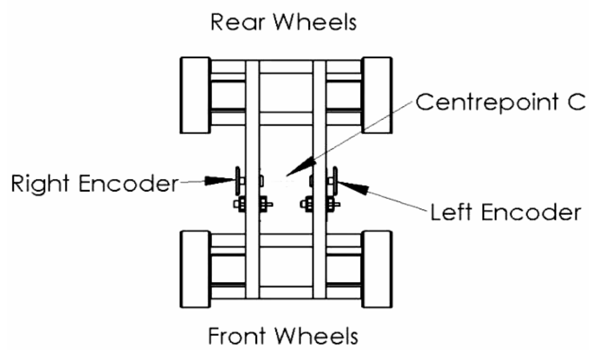
Figure 1: An example of the navigation strategy.



Dead reckoning is the most widely used technique for estimating the position of a mobile robot, taking into account prior position and amount of distance travelled. Using geometric equations [13], it is straight forward to compute the momentary position of the vehicle to a known starting position. In [14], encoders are usually attached directly to motors or wheels but this strategy proved unreliable to be used in skid-steer configurations. When wheels are over accelerated, encoders lose current information that can cause inaccurate readings for actual position. For this reason, in [7], their idea to use the design of a basic encoder trailer was introduced. However, there is no guarantee of achieving good accuracy even if it has been calibrated and the idea itself is not practical to be implemented.

In our design, two flexible arm-wheeled are mounted underneath in the centre of the robot as depicted Figure 2. The design has succeeded in providing continuous data even if the wheels are over accelerated. As a result, poor accuracy of dead reckoning technique could be minimized.

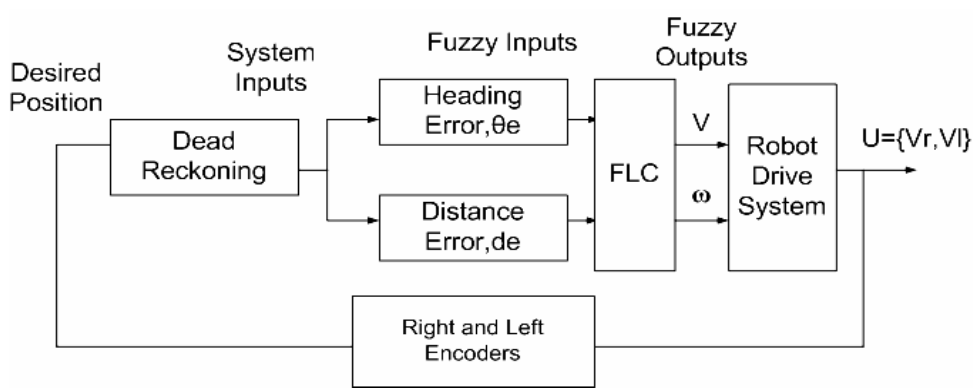
Figure 2: Mobile robot with custom-equipped encoders



3. Fuzzy Controller Design

Fuzzy logic unlike classical logic is tolerant to imprecision, uncertainty, and nonlinearity. In the context of mobile robot navigation, a fuzzy logic-based system has the advantage in that it allows an intuitive nature of rule-based navigation to be easily modelled using linguistic terminology [15]. The block diagram of the overall structure of the control system is shown in Figure 3. It consists of three parts i.e. the system inputs, fuzzy inputs and fuzzy control outputs. The system inputs part can be treated as a pre-processing module where the calculations of the current position and heading angle error are determined by using dead reckoning technique. Crisp values from the calculation are sent to the fuzzy controller as fuzzy inputs i.e. heading error (θ_e) and distance error (d_e). The fuzzy controller formulates the control outputs as translational velocity (v) and rotational velocity (ω). These outputs from fuzzy are chosen as the manipulated analogue voltage to the both sides motor. The voltage variations are fed to the right and left motors of the robot represented by V_r and V_l.

Figure 3: Structure of the proposed control system

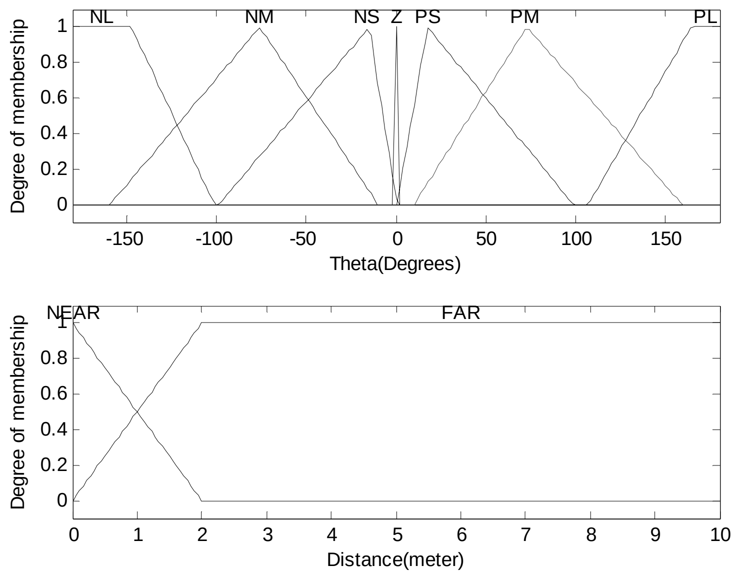


The fuzzy logic controller accepts two inputs (θ_e ,d_e) and returns (v,ω) out from the controller. The fuzzy controller infers the inputs to determine an appropriate analogue signal ranging from 0 to 5V. Appropriate output voltages are sent to control the relative velocities of left and right side drives. The input parameters are fuzzified to degrees of membership by a look up in one or several membership functions. The fuzzification process thus matches the inputs with the conditions of the rules to determine how well the condition of each rule matches that particular input instance. Fine-tuned membership functions consisting of triangular and trapezoid shapes have been adopted for design simplicity. Chosen membership functions are empirically derived based on extensive experiments. The membership functions design for the input and output are depicted in Figure 4. Linguistic input variables consist of Positive Large, Positive Medium, Positive Small, Zero, Negative

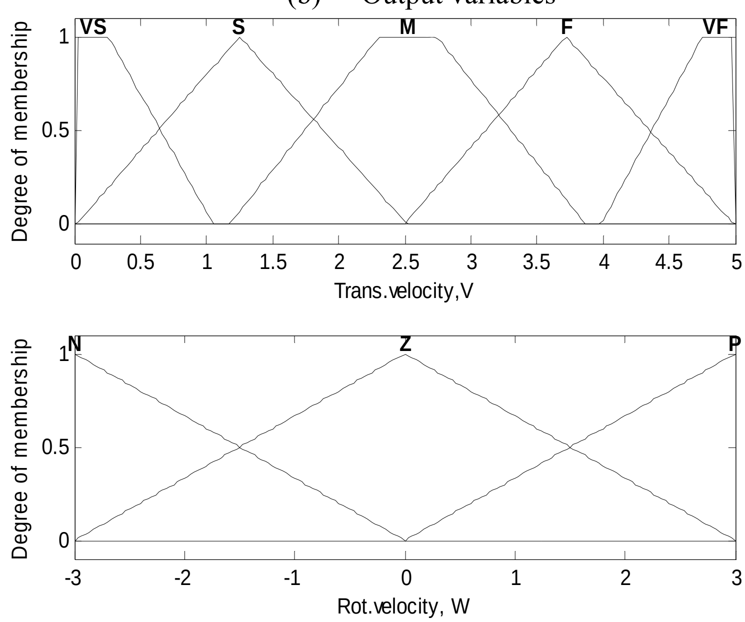
Small, Negative Medium and Negative Large for heading error while NEAR and FAR for distance error.

Figure 4: Fine-tuned membership fuzzy sets

(a) Input variables

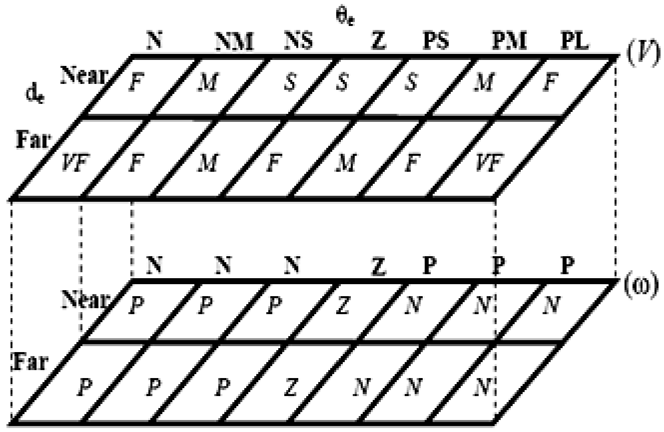


(b) Output variables



In the case of output variables, the linguistic fuzzy sets are Very Slow, Slow, Moderate, Fast and Very Fast for the translational velocity while Negative, Zero and Positive for rotational velocity. The inference rule base has 28 rules for formulating the control output of the fuzzy controller. Figure 5 shows the fuzzy associate memory where the overall rules are formulated by experience.

Figure 5: Fuzzy Associative Memory



The whole rules set are complete, consistent and continuous. However, not all rules are fired at one time of inference process. The control action is defined in term of IF-THEN rules. By taking the Min-Max inference method [16], the examples of fuzzy rule extraction are:

1. **IF** (θ_e) is Positive Large and (d_e) is Far **THEN**
   v is Very Fast and ω is Negative
2. **IF** (θ_e) is Negative Small and (d_e) is Near **THEN**
   v is Slow and ω is Positive

Using the fuzzified input data, the fuzzy sets associated with the output actions are determined by inferring from each fired fuzzy rule. The deffuzzification method used to compute the crisp control actions to both sides' motors is the centre of gravity [16].

4. Experimental Results

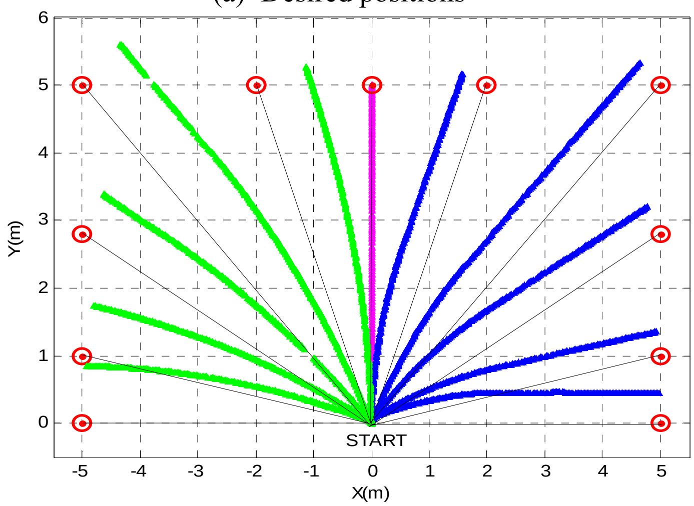
A series of experiments was conducted in an indoor controlled environment using the proposed method. The dimension of the environment is 12x12(m). The maximum speed is up to 0.57m/s. Data acquisition is done in Labview and a Matlab control algorithm is called in Labview. The crisp control actions V_r and V_l are calculated in every 50ms time step. The results are directly recorded through the reading from the experimental. In the experiment, the robot is to reach the desired positions from a start position (X_0, Y_0, θ_0) in minimal travel time. θ_0 refers to a reference. The purpose of the experiment is to tune the fuzzy controller. The desired position is chosen to be within approximately 5 meters around the robot with various heading angles including a straight line. Although the size of the environment is quite spacious, the range of 5 meters is adequate for tuning purposes. At this point, the robot heads directly toward the goals from its original position until it has autonomously reached the desired position; experiment is repeated up to five trials.

Trajectories and various orientation errors are plotted in Figure 6. These figures demonstrate the traveled paths and its set of orientation errors before the fuzzy controller is fully optimized. The trajectory is obtained after plotting the information from the real-time execution via odometric sensors.

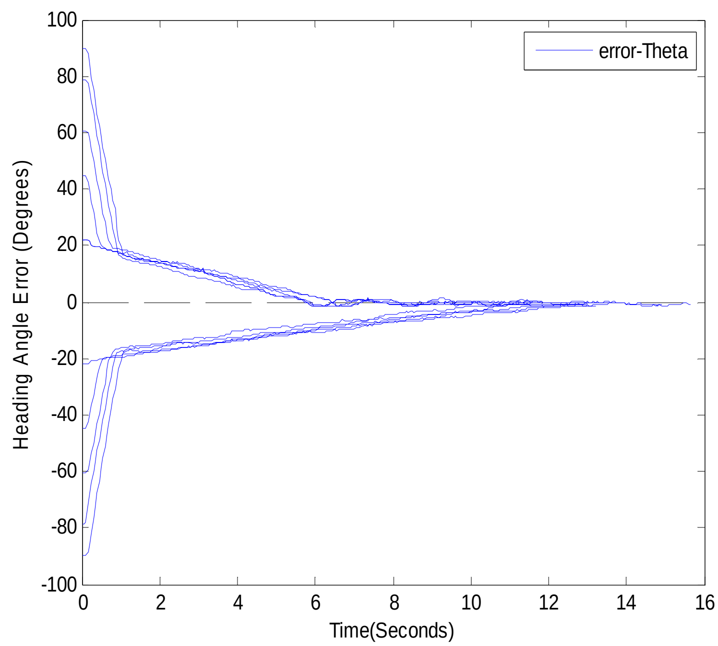
The robot runs five times covering the range of various desired positions and heading angles. The cyan-line refers to a straight path. Note that the fuzzy controller is totally reliant on the odometric information only. Figure 6a displays the trajectories of the paths with respect to the desired positions. The black solid-line refers to actual trajectories. It is obvious that position errors are still large and inaccurate since the controller has no ability to compensate or minimize the errors. None of these trajectories show that the robot has reached the desired position precisely, i.e., each trajectory is out of the actual trajectory except for the straight path. In Figure 6b, it can be seen the inconsistency pattern of the output responses and these show that the fuzzy controller performance is not good to be applied in robot navigation. Each plot shows very fast rise time which is within 0.3 seconds; however the responses did not touch the reference line within the range of ±20°. This is unacceptable to prove a good side of the controller. Basically, fuzzy rules are reformulated based on experiment experience.

Figure 6: Travelled paths

(a) Desired positions



(b) Orientation errors



Result shown in Figure 7 is the performed trajectories after the controller was successfully tuned. It shows very smooth trajectories of the travelled paths right after the tuning is done. Each run has shown the ability of the robot to navigate from the starting point to desired positions accurately. The controller has minimized unwanted lateral skidding that causes the encoder readings to be inaccurate.

For simplicity, Figure 8 shows the output response of orientation errors only for the selected heading angle; -90° and 80°. For the plotted orientation errors, both angles have recorded acceptable minimum errors during the runs. Orientation errors are rapidly compensated and remain very small in the range of ±1°. Figure 8 has recorded better results in comparison with Figure 6 in term of data consistency. Figure 8 shows the errors in orientation are overlap in such a way that the fuzzy controller performs very consistent through the whole runs. The change of membership functions and its rules have shown the effectiveness of the tuning strategy and the heading angle is controlled with a fuzzy logic controller which minimizes the heading angle error.

Figure 7: Robot's paths with fully-tuned controller

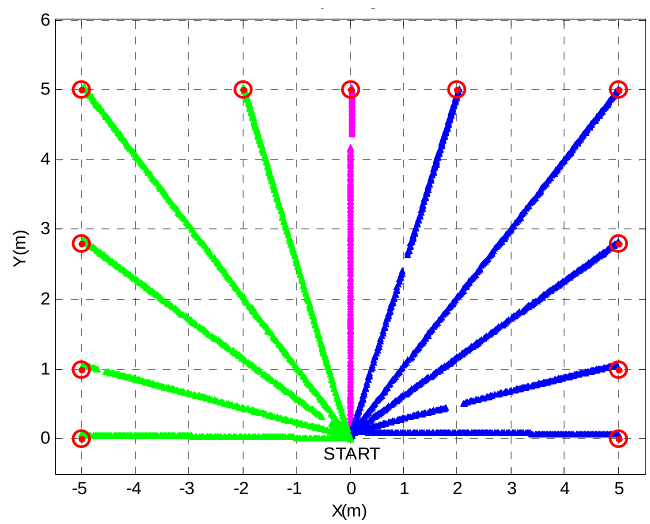


Figure 8: The orientation errors; (a)-90° and (b) 80°.

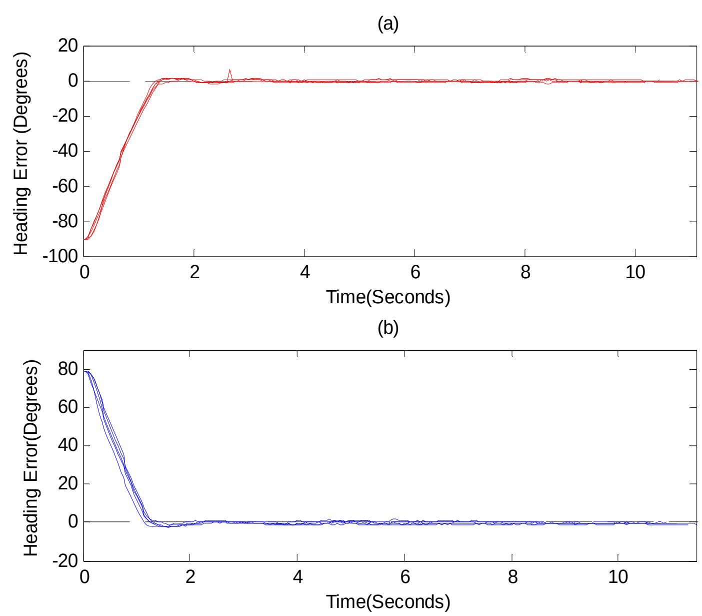
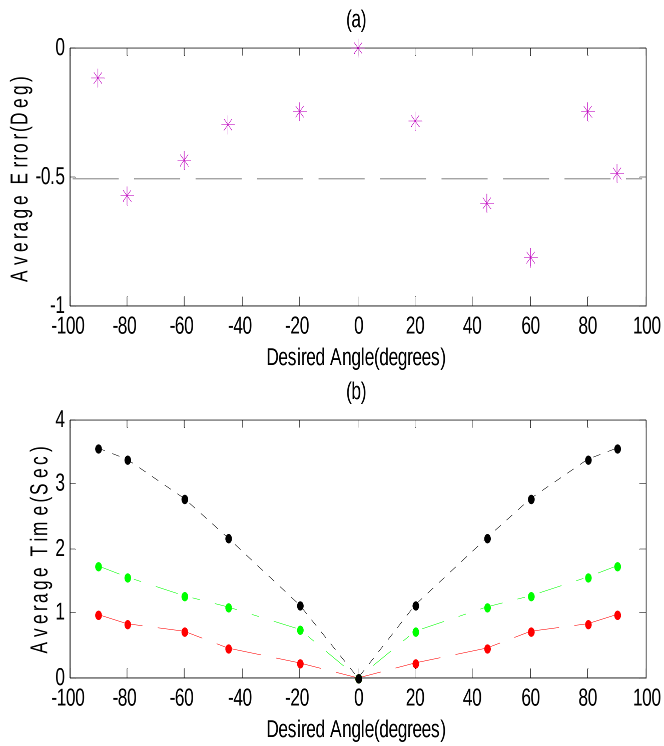


Figure 9 shows the plot of the average error in orientation, rise time (tr), peak time (tp) and settling time (ts) for five consecutive runs. The desired heading angles are {-90,-80,-60,-45,-20, 20, 45, 60, 80, 90} degrees. As shown in Figure 9a, the plotted data is scattered in the range of less than one degree which is precise. The results obtained fall within the satisfactory range, indicating that heading control has been achieved.

Figure 9:(a) Average data of the orientation error
(b) Average time, --- t_r, --- t_p and --- t_s



It is worth noticing that most of the plotted data lies within less than a half degree which is significantly considered precise. The fuzzy controller has performed very well to compensate and minimize the orientation errors with the aid of effective fuzzy rules. However, the result yields significant bias only in the negative range. This is possibly because of an insufficient number of data and this result could be more precise for 50 to 100 trials. Another possible reason could be the alignment of mechanical structure of the robot. All results are obtained by reading the data directly from the real-time experimental work only. Therefore, if the work was based on simulation, more than 100 trials could easily be conducted. In Figure 9b, it can be seen that the pattern of t_r, t_p and t_s are symmetrical, consistent and tend to be almost linear.

In addition, t_r, t_p and t_s are dramatically increased as the desired heading angle is increased. According to Figure 9b, the average data of the rise time for all heading angles is plotted below one second which is good in term of controller performance. The average peak time is also considered fairly good as the overshoot is settled in a very short time. On the other hand, after assessment the averages settling time for all desired orientations are long but still considered acceptable results. Here, the fuzzy algorithm has proven the effectiveness of the inference rules and the controller provides consistent result in either positive or negative region.

5. Conclusion

The paper has proposed a method for establishing real-time motion control and dead-reckoning of wheeled skid-steer mobile robot without modelling of mobile robot kinematics. The FLC fuzzified two inputs (θ_e ,d_e) and returned (v,ω) as the outputs. The FLC infers the inputs to determine appropriate output voltages that were sent to control the relative velocities of left and right side drives. The inference rule base has 28 rules for formulating the control output of FLC. Experimental results showed the effectiveness of the proposed FLC in term of minimizing the error of orientation and the accuracy of the final position are relatively high. Results also showed the ability of FLC to track as well as minimizing the position errors. The proposed methodology could be possibly extended to apply a neuro-fuzzy in the auto-tune scenarios where the hybrid controller can track a dynamic moving target.

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