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Speed Control of BLDC Motor to Ensure Safe and Efficient Navigation of a Mobile Robot using Machine Learning

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ABSTRACT

The use of autonomous vehicles has been increasing in various applications such as driving, outdoor field work (agriculture, mining industry and others), terrain classification, environmental monitoring and among others. The fundamental task of traverse ability for safe and efficient navigation of these vehicles is determining the level of roughness of terrains it travels. The proposed model implements the use of simpler method using inertial sensors to estimate the type of terrain. Existing dataset were used for terrain classification. A simple Adam classifier is implemented in MATLAB environment. The classified terrain is mapped to respective speed based on the type of terrain in order to avoid abrupt movements and the disturbance over terrain changes. The proposed model incorporates a controller, which regulates the speed according to terrain identified by the algorithm in Simulink environment. The accuracy of classification is found to be 98%, which is more compared to previous model described in literature.

Keywords: Machine Learning, Adam Optimizer, BLDC Motor speed control

1. INTRODUCTION

The demand for Autonomous Vehicles (AVs)has grown in past decades. Automation has become one of the requirements in today's world. Minimizing human efforts, fuel usage, increasing work efficiency are some of the advantages that can be listed. Brushless DC motor (BLDCM) has been widely used in fields such as aerospace applications, automobile industry, robotics, medical instruments and electric vehicle applications etc. Because, it has many predominant features such as higher efficiency, less maintenance, high torque to weight ratio, higher power density and easy to control over a wide range of speed. For BLDC motors to be used more frequently, optimal position control is necessary for high efficiency, accuracy, and dependability.

A well-functioning robot has a noticeable effect on climbing hilly roads, by the increased average speed achieved with them, thereby eliminating the 'groan' issue when gradient factor comes in. When users supply enough push, he can climb maximum gradient even, which is only achievable through cars or motorbikes. But when users apply frequent brakes on rough roads or climbing hills the power consumed is more. Also, there are chances of irregular navigation and loss of balance.

The previous study emphasizes that. load has a noticeable impact on the dynamic. performance of the system by taking in the computation of the friction coefficient and moment of inertia of a BLDC motor with load at various load levels [1]. This research talks about the PID controller parameters and tuning methods used. The simulation model of BLDC motor gives the information about the machine ratings and the feedback logic of the hall sensors. Terrain features, navigation and motion planning difficulties of autonomous vehicles play a critical role in robotic navigation. proprioceptive sensors like IMUs provide. indirect information about. the ground, which is why they. are less frequently used. For making decisions, a combination of a Bayesian optimization method with a Gaussian Process model is suggested [2]. Only inertial data is used to classify the terrain, and this data is mostly affected by the agents. velocity on the signal's spectrum frequency content as measured by its accelerometer sensors. The prediction model that makes use of the nonlinear regression, support vector machine, and neural network machine learning capabilities in MATLAB is shown in the article [3]. There are various techniques that can be explored. Since there are versatile and useful set of tools available in MATLAB machine the simulation can be performed here. There are many methods discovered to identify terrains such as Soft Foot-Q robotic technique which again involves IMU sensor [4]. This kind of haptic based terrain classifications are only suitable. to legged robots, such as humanoid robots, hexapod robots, dog-like. robots, and crawling robots. To validate the readings and estimation various techniques have been proposed given in [5]. The co- and self-training approaches are used as a classifier. Four-wheeled test rover operating in terrain similar to that of Mars, including bedrock, soil, and sand, validated the proposed method. A method for gathering information from nine different indoor surface types utilizing simply an IMU sensor mounted on an industrial trolley. with silent wheels is explained in [6]. Their main contributions are the release of the most comprehensive dataset for indoor surface categorization to date. Another method suggested a feature-temporal semi-supervised extreme learning machine (FT-S2ELM) [7]. The feature-temporal similarity matrix can better explain the relationships of the samples with the addition of temporal smoothness, allowing for improved classification of data close to class boundaries. There is also a terrain classification can also be based on 3-D vibrations induced in the rover structure by the wheel-terrain interaction and using sensors from legged walking robots [8]-[9]. The rover's inertial measurement unit is first used to determine the acceleration data for the three directions. The properties of the recognized terrain's vibrations are then discovered. Random forests have been tested for surface recognition; in this work the true performance was calculated using dataset from the indoor surfaces. a distributed semi-flocking control mechanism based on local sharing of information is suggested and solved in [10]. Their suggested control protocol incorporates a terrain adaptation force and a navigation objective selection technique to solve this issue. When compared to the most advanced flocking-based control protocols, the work on tough terrains shows that the suggested control protocol can achieve better performances in both area coverage and target tracking while using less energy.

So, identifying and classifying the surface is very important for smooth movement of mobile robots. Literature review shows that the SVM algorithm used for terrain classification gives an accuracy about 80%. The scope of improving the efficiency has to be explored with different classifier algorithms. The main objective of paper is to develop a simulation model for analysing the effect of various terrain on speed control of BLDC motor control and to classify the terrain of mobile robot by machine learning technique. In the following sections describe the use of Adam optimizer as a classifier for terrain classification and steps to implement this algorithm in MATLAB2022a. The BLDC motor speed control simulation was done in Simulink. Finally the simulation results have been discussed along with the accuracy.

2. BLDC Motor Simulation Model

The closed loop speed.control of BLDC motor is constructed in Simulink environment as shown in figure 3.6 BLDC motor is similar to PMSM, but the back emf waveform is trapezoidal in shape. The specifications of BLDC motor are seen from the Table 1,

Table 1 – BLDC Motor Specifications.

Parameters	**Values**
Rated Voltage	24 V dc
Number of poles	8
Rated Speed	4000 rpm
Rated Torque	0.125 Nm
Torque Constant	0.036 Nm/A
Moment of Inertia	48 $e^{-7}\ kg - m^2$
Friction coefficient	$1e^{-5}\ Nm - sec/rad$

A 150V DC is applied to BLDC motor through a switch controlled by a timer. The gates of respective switch in inverter are controlled based on the states of hall sensor signals. The three-phase outputs of inverter are applied to stator windings of BLDC motor. The speed is fed back and the error signal is calculated, i.e., difference between desired and actual is given as an input to Proportional-Integral (PI) controller. The controller is tuned to find and proportion and integral constant. The Hall effect sensors give out the position of the rotor. Based on these values the gating pulses are applied. The load torque is taken as 5Nm. The gating pulses are applied to each of the MOSFETs in every leg as seen in figure Fig 2a.

Hall sensor output from the motor is taken to calculate the respective position. Fig 2b. This is compared to find out which device should turn on during the interval of time. Later these signals are fed to each of the MOSFETS. The more detailed description is given in later pages.

The base speed and time constant are calculated from the electromagnetic torque and speed responses with no load. The rated torque is calculated using torque response. The coefficient and moment of inertia of a BLDC motor with load arrangement at no load are calculated using the aforementioned equations.

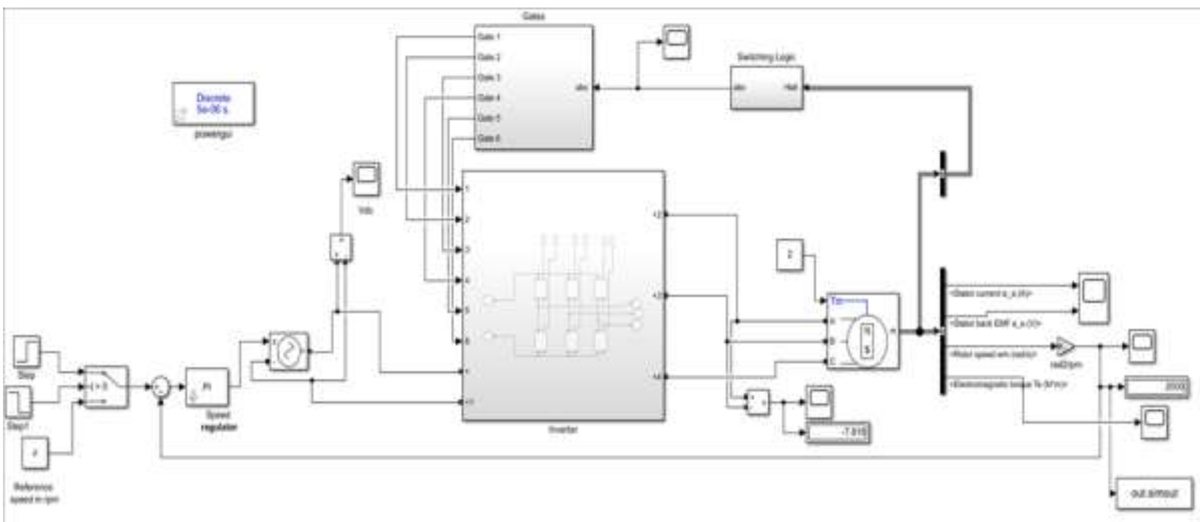

Fig. 1 - Simulink Model of Closed Loop speed Control of BLDC motor.

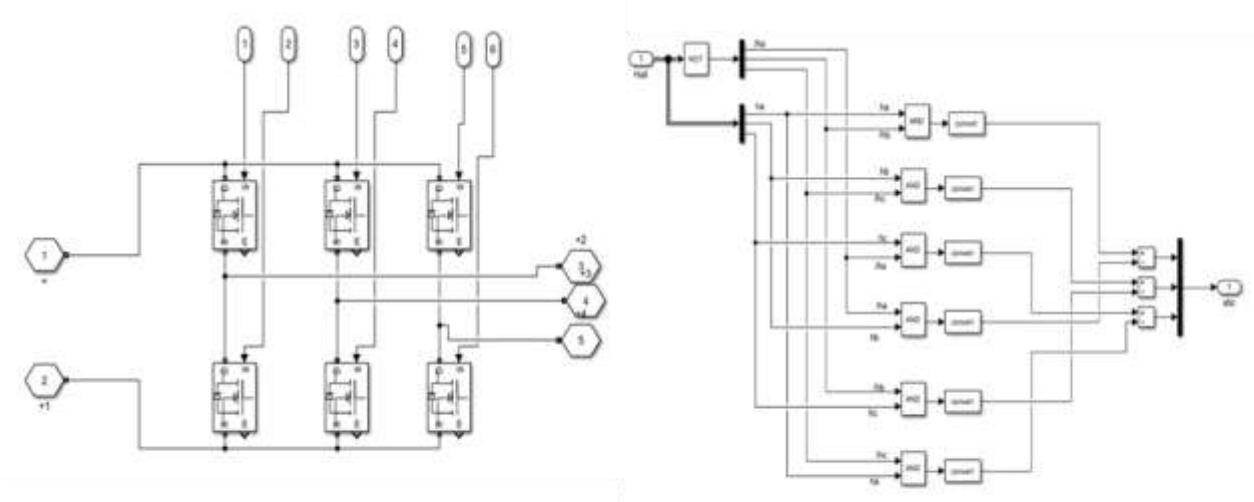

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Fig 2 – (a) Inverter Circuit; (b) Hall Sensor Output.

3. MATLAB IMPLEMENTATION

The basic block diagram of this project is seen in Fig 3a. The collected data set of terrain classification is taken from. These datasets are downloaded and imported into Matlab2022a environment. The following steps of testing, training and validation of the data is done using Matlab code. Random data from IMU sensor is fed to the trained network. This classifies the terrain using this input data, which is then mapped to safe speed. The predicted velocity is fed to Simulink model of BLDC motor closed loop speed control as reference speed. This is how the speed BLDC motor of mobile robot is controlled depending on the terrain.

The dataset is loaded in Matlab2022a environment and the values are read in table. The labelled data is converted to categorical data type. The data in table is split into for training, testing and Validation. Adam algorithm is used for training the network. When the network is finally trained, random values are passed from 9-axis IMU sensor for identifying the terrain. This value is fed to the Simulink model as a reference speed for the BLDC motor to run. Finally, the accuracy of the model is calculated.

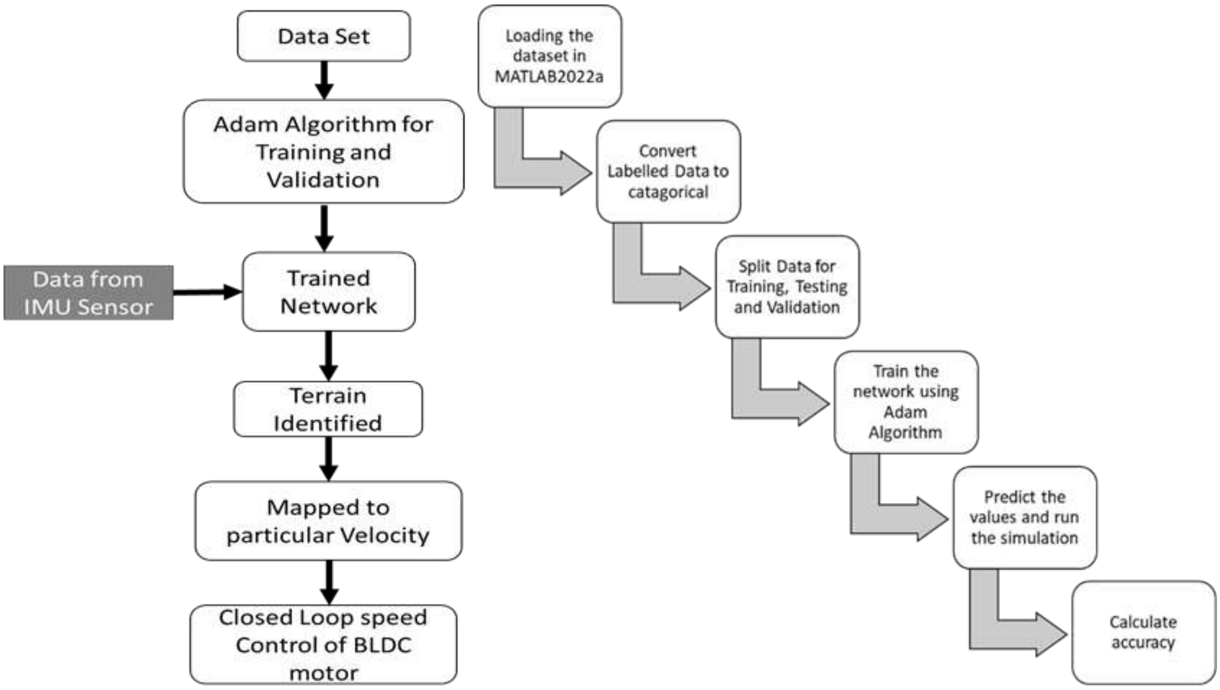

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Fig 3 – (a) Block Diagram; (b) Process Flowchart.

4. Simulation Results

The simulation results from the developed model as well as for the speed control model are demonstrated in the following section.

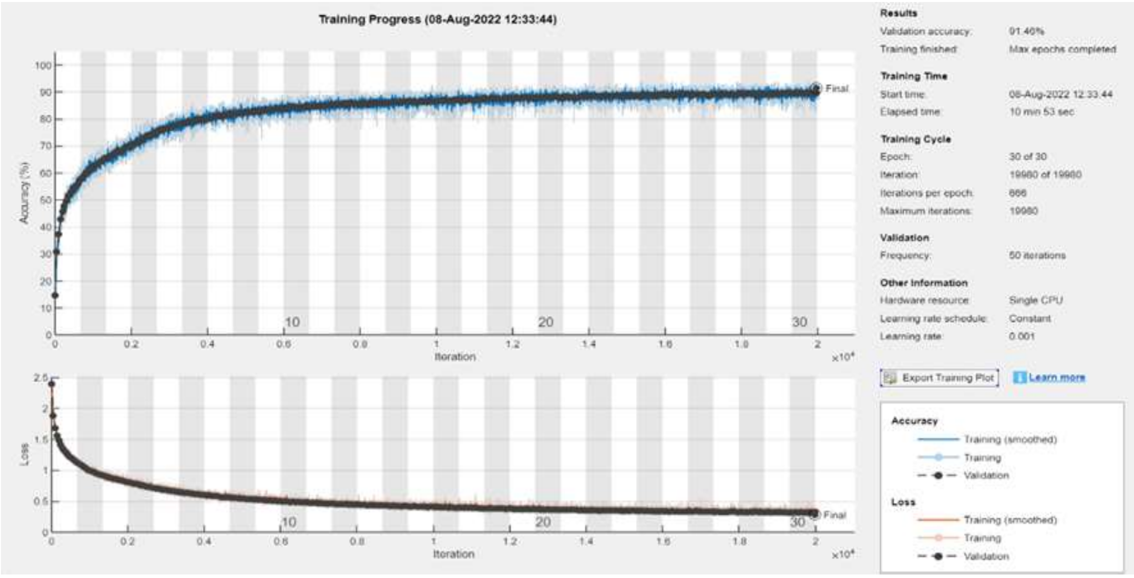

Fig. 4 - Simulink Model of Closed Loop speed Control of BLDC motor.

Figure 4 shows the training progress with the training parameters. This shows the validation accuracy and mini-batch loss which lets to halt training at any point. Since at max epochs is taken as 30 on the account to train the network to be more accurate. The mini-batch size was set to 512, as larger the value, the faster the training. Learning rate is another major parameter to control the speed of training but since larger value will decrease its accuracy it was set to 0.01.

As seen from Fig 5 the confusion Matrix shows the maximum numbers on diagonal. It is a plot between actual and predicted out values. Information concerning class labels and anticipated class labels can be found in a confusion matrix. The confusion matrix's (i,j) entry, in general, represents the number of samples whose anticipated class is j and whose known class label is i. The diagonal elements represent observations that have been successfully categorized.

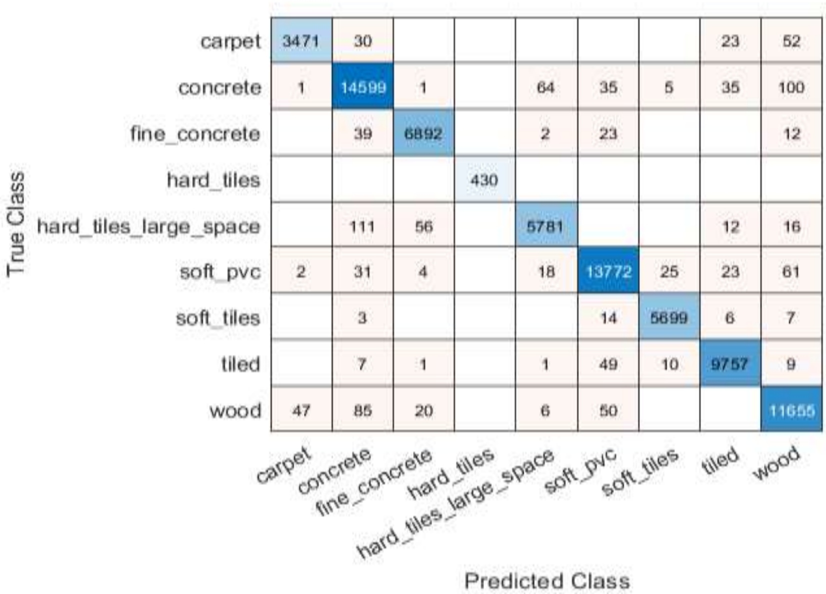

Fig. 5 – Confusion Matrix.

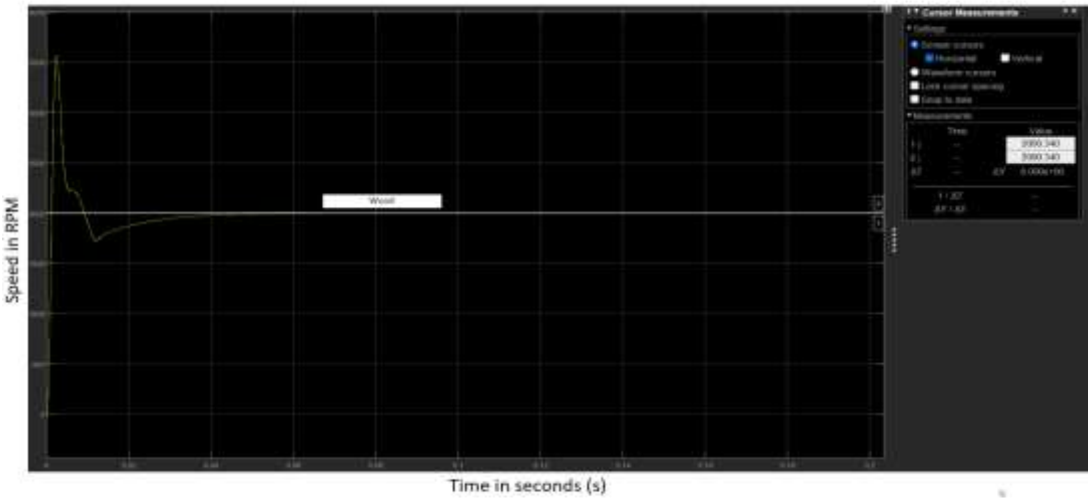

Fig. 6 – Simulink output for terrain Identification.

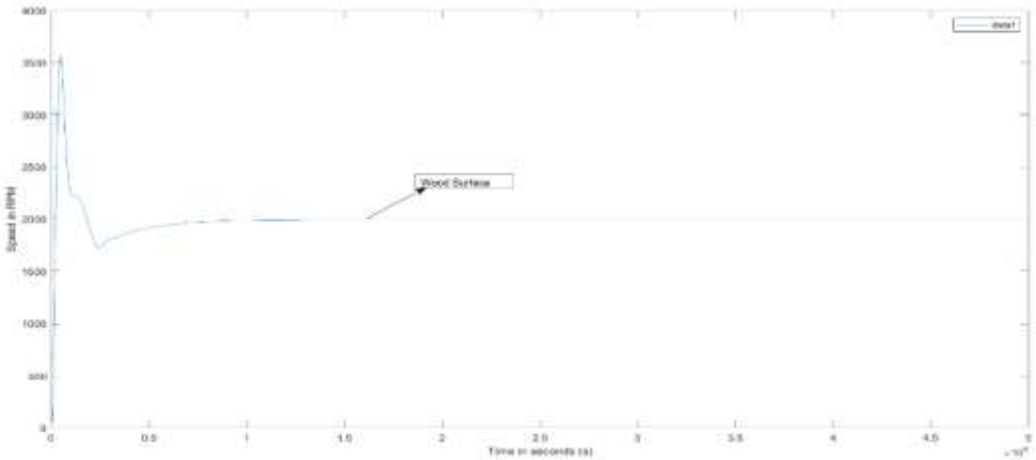

Fig. 7 – Matlab2022a output for terrain Identification.

Fig. 6 shows the simulation output of speed control loop of BLDC motor. The speed is mapped to 2000 rpm as the terrain identified is wood. This is set as a reference to get an error signal. Similarly the simulation is run through the Matlab code and the values obtained from the model is plotted against time series. This results in the Fig 7.

5. CONCLUSION

If the Mobile robot adapts its own motion considering the terrain level of roughness, it can obtain a better navigation and task performances. The classification was done using Adam algorithm with an accuracy of 98.5%. The training progress and suitable parameters were used to obtain higher accuracy. Similar approach can also be used in other applications such as eelectric Wheel Chair, Agriculture and Mining Industry and for Efficient Navigation of autonomous vehicles. Incorporating other features from the terrain, for example the slope, and use such identification for path planning, decision making strategies and optimizing the robot's navigation is the further study that can be carried on.

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