Efficient Navigation of Mobile Robots using Machine Learning Techniques

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Abstract:- Several recent advancements in robotic technology have dealt with the efficient navigation of robot machines. But still many a times it has been observed that the robot fails to walk on a particular type of floor and often falls down. This is probably due to incompatible speed or orientation of robots with respect to the surface on which it is walking. The system presented here deals with the navigation of robots on different kinds of floors using Machine learning and data mining techniques. The system provides an optimum orientation, speed and acceleration values for robots on any particular type of floor so that it can walk smoothly without falling down on the floor. It will also help the robot to decide that which kind of floor is not suitable for them and hence protects them from external damage. It provides the robot with certain values using which it can adjust itself on any type of surfaces. Thus we will be able to develop an intelligent robot which can automatically adjust itself to be able to navigate through any kind of surfaces.

1. INTRODUCTION

In this work, we consider the task of robotic navigation by fetching it the range of values of orientation, speed and acceleration in all the three dimensions according to which the robot needs to adjust itself in order to walk smoothly and swiftly on any kind of surface. We have a dataset which is obtained by testing the movements of robot in different kinds of floors like wooden, carpet, tiles etc. The dataset contains a total of nine features which are used to predict the type of floor on which the robot is walking. We have used Random forest regression technique to predict the type of the floor based on the values of features. Random Forest is an ensemble learning algorithm which uses decision trees to predict the result. At last we consider the average of the results obtained by the specified number of decision trees. Thus we develop a system which is able to predict the type of surface based on the specified features of robot.

2. RELATED WORKS

Several recent advancements have been observed in the field of Robotic Navigation. One of such effort proposed by Sebastian Thrunet al. , [5] includes training the robots about its environment using grid based and topological based approach.HansJacobS Feder et al. ,[6] proposed SONAR technique which is used for adaptive navigation and mapping of mobile robots. Jean-Arcady Meyer et al. ,[7] suggested that neural networks can be used for developing an evolutionary method of navigation in mobile robots. William Benn et al., [8] proposed efficient algorithms of image processing that are used for collision avoidance and obstacle detection in autonomous moving systems and vehicles. While the above methods involves the use of memory, works ofTucker Balch and Ronald Arkin et al. ,[9] have suggested that a reactive navigation strategy can be used using a spatial memory within a schema based motor control model. Research works of David C Conneret al. ,[10] have suggested a method of composing simple control policies which is applicable over a limited region in a way that the resulting composition performs the navigation. Works of Elon Rimonet al. ,[11] suggests a navigation function that connects the kinematic planning problem with the dynamic execution problem in a much efficient way. Some concepts proposed by Erann Gat of Jet Propulsion Labet al. ,[12] suggest heterogeneous ways to enable robots to perform multiple tasks in a noisy and unpredictable environment.Feature Extraction techniques proposed by Savitha G et al. ,[13] provides efficient ways for selecting required features from a given dataset for offline signature verification.Considering all these technical concepts, we have made an attempt to improve the ways of robotic navigation by providing intelligence to the robots.

3. DATASET DESCRIPTION

The Dataset is collected by Inertial Measurement Units Sensors (IMU Sensors) which is embedded in a small mobile robot. The dataset is collected while driving the robot over different floor surfaces and the following measurements are recorded as a table. The figure3.1 illustrates different types of floors which are considered in the dataset.

1. Orientation X :The orientation of robot along horizontal axis.
2. Orientation Y :The orientation of robot along vertical axis on the floor.
3. Orientation Z :The orientation of robot along the upward direction axis over the floor.
4. Angular velocity X: The angular velocity of robot along the horizontal axis.
5. Angular velocity Y: The angular velocity of robot along the vertical axis.
6. Angular velocity Z: The angular velocity of robot along upward axis with respect to the floor.
7. Linear acceleration X: The linear acceleration of the robot along the horizontal direction.
8. Linear acceleration Y: The linear acceleration of the robot along the vertical direction.

9. Linear acceleration Z: The linear acceleration of the robot along the upward direction with respect to the floor.

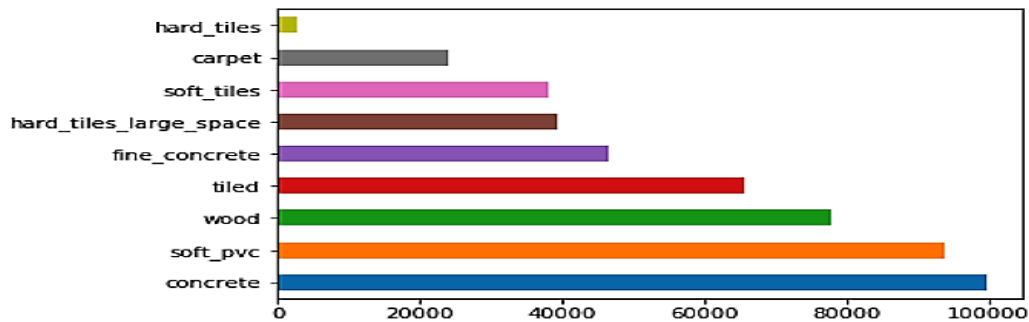10. Surface: The type of surface on which the robot is driving.

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<matplotlib.axes._subplots.AxesSubplot at 0x290b2756e10>
```


Fig. 3.1 Type of Surfaces with its respective number of occurrences in the dataset.

4. METHODS

The work presented here involves five main stages. These stages are :

1. Data Preprocessing
2. Data Cleaning
3. Feature Extraction
4. Model Training
5. Result prediction

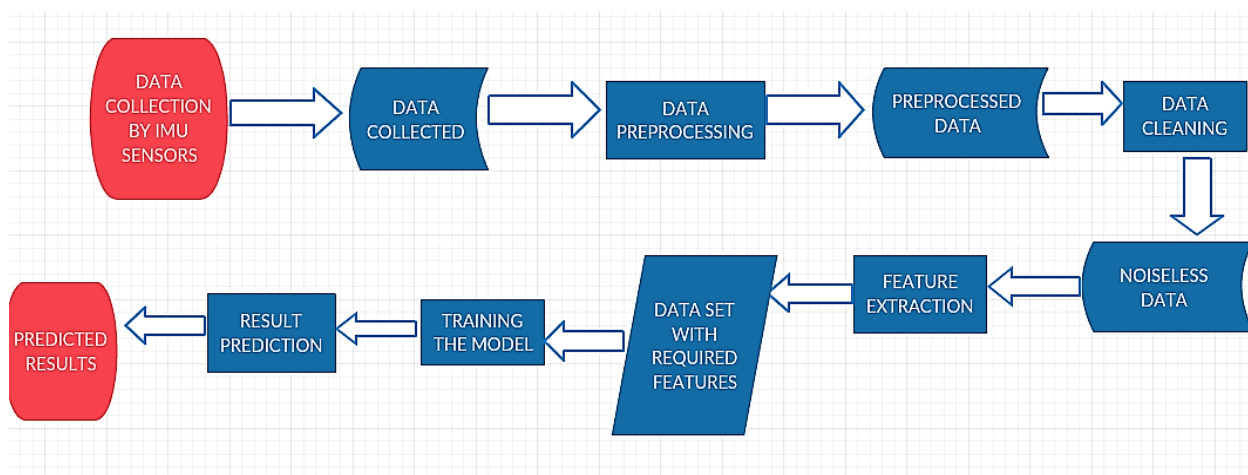The Figure 4.1 Shows different stages involved in getting the desired predictions.

Fig. 4.1 Methods involved in the process.

a. Data Preprocessing

Data preprocessing is a data mining technique which is used to transform the raw data in a useful and efficient format.This is the initial step where the features are first mapped to its corresponding target values by taking the inner join of their rows. Each of the feature row is first mapped to a target value having the name of the floor.

This is followed by encoding the values of target. Since target value is the name of the type of floor which is a non numeric categorical data, we need to encode it to numeric form so that we can use it for performing the prediction. We check the dataset for any missing values. If any missing value is present we will substitute it with mean of values in the case of features data and median in case of categorical target values.Hence we obtain a preprocessed set of data which is suitable for performing data analysis.

b. Data Cleaning

The preprocessed data thus obtained may contain noise which can adversely affect the results. So we need to detect those rows which are not contributing positively towards the prediction. So we use cross validation strategy to find out which rows should be included in our training model to obtain best possible results. In the proposed system we have used K Fold cross validation strategy to remove noise from the dataset. In this cross validation strategy the dataset is divided into K parts. In each of the iteration one of the part is considered as test set and remaining k-1 parts are considered as training set. Then prediction is done and accuracy is shown as the output for each of the K iterations. We will remove those rows for which the accuracy is comparatively lower than others. Hence we obtain a noise free dataset which is further used to train the model and predict the values.

c.   Feature Extraction

Feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non redundant, facilitating the subsequent learning steps, and in some cases leading to better human interpretations.

By analyzing the features, some of the columns like row_id and group_id are only used for mapping the dataset. They can't be used as categorical features as they are just sequence numbers which is used to map feature dataset to target dataset.

Hence, we eliminate such features from our dataset.

The next step is to find the correlation matrix of features. We will check that which of the two features have high correlation value and eliminate one of the features which has least correlation with the target variable. In this way, we will handle multi dimensional collinear features which together contribute to the prediction but individually have low correlation with the target.

The figure 4.2 illustrates a correlation matrix which shows the extent to which the different features are related to each other. Each block in the matrix represents the correlation between its corresponding row and column features.
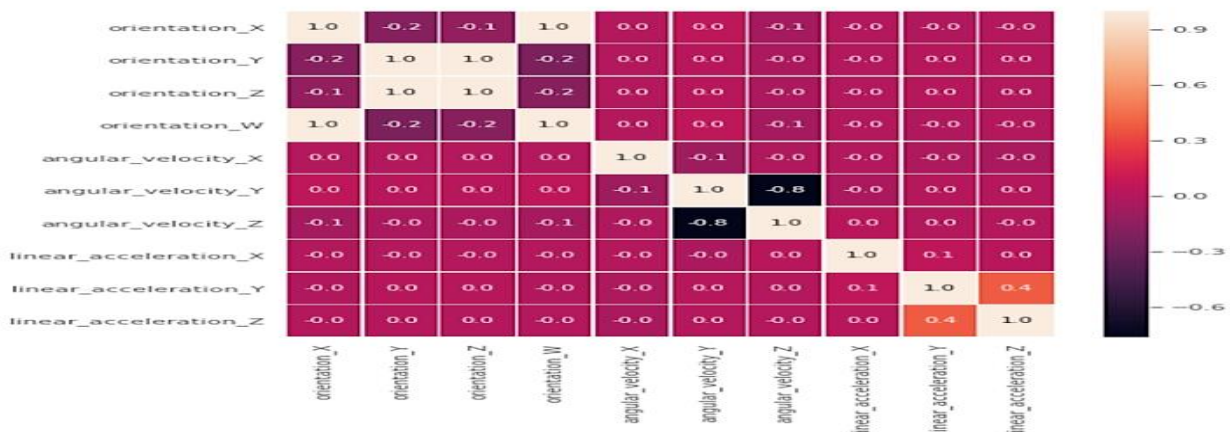

Fig 4.2 Correlation among features

d.   Model Training

Several Machine Learning Algorithms are available which can be used to do prediction as well as classification. The process of selecting suitable algorithm according to the dataset and fitting the data to the model is termed here as Model training.

We will visualize the data and the relation of features with the target value based on which we will select the appropriate algorithm which best fits the dataset.

Based on the visualization plots, we have selected Random Forest Algorithm as our training algorithm

Random Forest

Random Forest or random decision forests are an ensemble learning method for classification, regression and other

tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is mean prediction of the individual trees.

In Random Forest algorithm, Instead of using information gain or gini index for calculating the root node, the process of finding the root node and splitting the feature nodes will happen randomly.

Fig. 4.3 describes the process of Random Forest algorithm where the dataset is taken and different number of trees are built based on random selection of features rather than considering gini impurity value as in decision trees. Then voting is done based on the results obtained from different trees and thus the final output is derived.
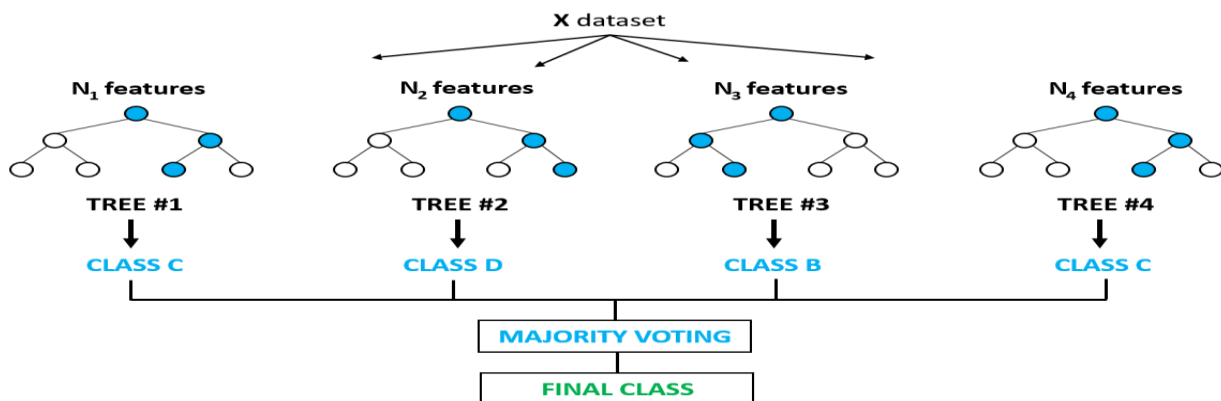

Fig.4.3 Random Forest Algorithm

5. RESULTS AND CONCLUSIONS

This paper addresses the issue of inefficient robotic navigation. The paper provides an efficient method to prevent robots from falling down while moving on the floor by adjusting their orientation, angularvelocity and linear acceleration according to the type of floor. This technique will also help the robot in recognizing their environment and thus incorporating more intelligence and decision making capabilities in it. We predict the type of floor with the help of trained model. The root mean squared error is calculated for the prediction on the dataset which can further be used to enhance the accuracy of the results.

We have used K fold cross validation strategy which is a resampling method used to evaluate machine learning models on a limited data sample. The given data sample is split into K samples and one of these samples is considered as test set and other as training set and its corresponding accuracy is recorded.

The cross validation output is shown in fig. 4.4illustrates the record of accuracy values for different samples in K fold cross validation process.

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0.8851500984251969
[ 48768  48769  48770 ... 487677 487678 487679] [    0     1     2 ... 48765 48766 48767]
0.890255905511811
[    0     1     2 ... 487677 487678 487679] [48768 48769 48770 ... 97533 97534 97535]
0.888307906824147
[    0     1     2 ... 487677 487678 487679] [ 97536  97537  97538 ... 146301 146302 146303]
0.888307906824147
[    0     1     2 ... 487677 487678 487679] [146304 146305 146306 ... 195069 195070 195071]
0.6910269028871391
[    0     1     2 ... 487677 487678 487679] [195072 195073 195074 ... 243837 243838 243839]
0.8089936023622047
[    0     1     2 ... 487677 487678 487679] [243840 243841 243842 ... 292605 292606 292607]
0.8109416010498688
[    0     1     2 ... 487677 487678 487679] [292608 292609 292610 ... 341373 341374 341375]
0.8496965223097113
[    0     1     2 ... 487677 487678 487679] [341376 341377 341378 ... 390141 390142 390143]
0.823490813648294
[    0     1     2 ... 487677 487678 487679] [390144 390145 390146 ... 438909 438910 438911]
0.8463951771653543
[    0     1     2 ... 438909 438910 438911] [438912 438913 438914 ... 487677 487678 487679]
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Since 0.89 is the maximum accuracy achieved , we are selecting its corresponding training set as our train set.

Fig. 4.4 Crossvalidation output.

6. FUTURE ENHANCEMENTS.

We can develop software for ambient navigation of robots and can embed the software in the robot thus providing it more intelligence.We can use reinforcement learning techniques for training the robots to adapt itself according to the environment.We can provide feedback input to the robots using our trained model so that it can learn to walk without falling down for getting the negative feedback. Thus, we can protect robots from falling down while walking which will save the useless expenses and costs involved in its repairing or purchasing.

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