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Neural Networks Terrain Classification using Inertial Measurement Unit for an Autonomous Vehicle

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Abstract: This research is focusing on the terrain classification using data from an Inertial Measurement Unit acquired during vehicle motion. The proposed classifier is different from the vibration-based classifier in the fact that it uses the relationship between different axis of input as well as the spectral information to classify the difference between terrains. The data from the Inertial Measurement Unit (IMU) are three axes acceleration and three axes angular velocity. The acquired data are preprocessed and filtered by fuzzy rules, then classified by a neural network into 5 categories: flat plane, rugged terrain, grassy terrain, incline plane and unclassified. The trained networks were experimentally validated with 100 samples in each category. The result shows that the proposed classification method can classify a flat plane, rugged terrain, and incline plane 100% correctly. For grassy terrain, it can be classified correctly about 80%.

Keywords: Neural Network, Terrain Classification, 6 DOF Inertial Measurement Unit.

1. INTRODUCTION

Currently, technology related to an autonomous vehicle has been widely discussed. The terrain classification is one of the features needed in a navigation or a localization system for an autonomous vehicle. Most researches in terrain classification focused on the technique that required an input from a camera such as works by Talukder et al. (2002) [1] and Larson, Voyles & Demir (2004) [2]. The other approach is to use multiple sensors including odometry sensor, Inertial Measurement Unit together with range sensor such as works by Ojeda et al (2005) [3]. Brookes, Lagnemma and Dobowsky (2005) [4] suggested the method of terrain classification based on vibration measurement from an accelerometer using the linear discriminant analysis for the planetary exploration rovers.

2. TERRAIN CLASSIFICATON

Output data from IMU consists of AccX (x-axis acceleration), AccY (y-axis acceleration), AccZ (z-axis acceleration), Roll (x-axis angular velocity), Pitch (y-axis angular velocity) and Yaw (z-axis angular velocity).

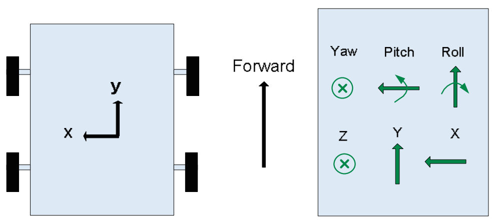


Fig. 1 The car axes.

According to Fig. 1, the car moved forward along the y-axis. The x-axis and the z-axis were the directions that it moved horizontally and vertically, respectively. As the car travelled on four kinds of terrain, flat plane, rugged terrain, grassy terrain, and incline plane, the output data from IMU was considered. While the car was moving, the acceleration data became quite noisy, thus less reliable for terrain classification. However, when traveling on grassy terrain, y-axis acceleration output magnitude was quite small when compared with the other terrains. Moreover, Roll (y-axis angular velocity) was the important variable for terrain classification. For flat plane, Roll magnitude and its variance were small, but for rugged terrain, the variance of Roll was quite large. For grassy terrain, Yaw and AccY were considered as these two signals were small in magnitude, and when the car moved on incline terrain, the result of Roll magnitude output was very small. Thus, 5 signals including running average of AccY, running average of Roll, running average of Pitch, running average of Yaw, and running standard deviation of Roll, were used as inputs of fuzzy logic filtering stage.

3. SYSTEM DESIGN

A localization system for a vehicle is usually done by analyzing and determining the relationship between various kinds of sensor measurements. As each sensor have its own behavior, advantages, and drawbacks. Therefore, the more data fusion from multi-sensor, the more accurate position estimation. The designed position estimation algorithm can be seen in Fig. 2. GPS and rear wheel encoder were used as inputs of position estimation using Extended Kalman filter with multiple models switching. The multiple models are designed according to the kinds of terrain that the vehicle travelled on, which consist of flat plane, rugged terrain, grassy terrain, and incline plane. In each case, the data from IMU are different, and the estimated state variables change according to the terrain. This paper focused on terrain classification using fuzzy neuron method. The outputs from IMU were statistically preprocessed and filtered by the fuzzy logic, and the outputs from the fuzzy stage were then fed as the input to neural network for terrain classification.

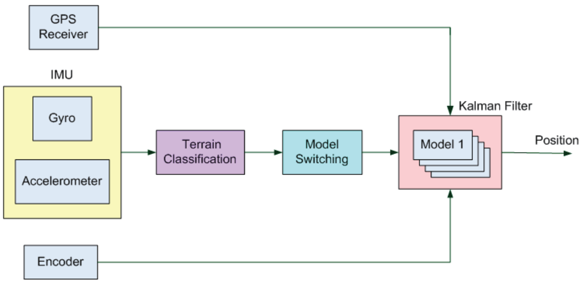


Fig. 2 Position Estimation Algorithm.

4. The Experimental Platform

The radio control car that was used as the experimental vehicle is shown in Fig. 3.

Fig. 3 The radio control car was used in the experiment.

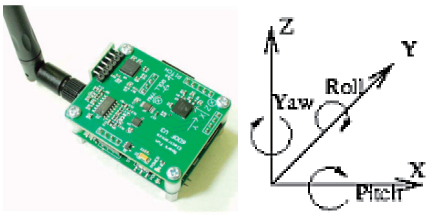


Fig. 4 The 6-DOF Inertial Measurement Unit (IMU).

A six-degree of freedom Inertial Measurement Unit (IMU), shown in Fig. 4, was attached to the car. The IMU consists of three axes of acceleration (AccX, AccY, and AccZ) and three axes of angular velocity (Roll, Pitch, and Yaw).

4.1 Data Collection

The vehicle was controlled via a remote control to travel on four different kinds of terrains, which are flat plane, rugged terrain, grassy terrain, and incline plane, as could be seen in Fig. 5. For each terrain, the car moved straightforward with 1 m/s velocity for 2 meters long. The IMU was set to measure acceleration and angular velocity at 50 Hertz, or every 20 milliseconds. The data was collected 10 times for each kind of terrains. These data was then used as train set and test set for the terrain classification module.

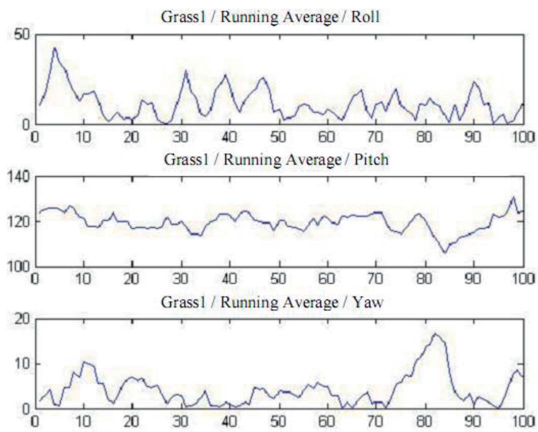
a b

c d

Fig. 5 Four kinds of terrains in the experiment. a) flat plane, b) rugged terrain, c) grassy terrain, d) incline plane.

4.2Preprocessing data

After acquiring data from sensor, they were then statistically preprocessed. As there are 10 data sets for each terrain, 5 data sets were used as training data, and 5 data sets were used as testing data for the classification process from the data acquired by the IMU. According to the output data set from IMU, 4 types of signal were collected, which are AccY, Pitch, Roll, and Yaw. For AccY, its unit was converted from 10 bit binary to m/s^2 with range of 2g sensitivity. For Pitch, Roll, and Yaw, their units were converted from 10 bit binary to degrees per second. The absolute values of these data were preprocessed by the running average as shown in Fig. 6. Finally, there were 5 kinds of data, running average (with 5 data points window) of AccY, Pitch, Roll, Yaw, and the running standard deviation of Roll, that were inputs of the fuzzy logic.



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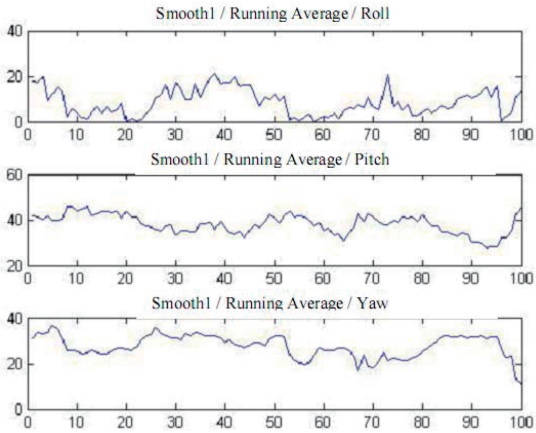

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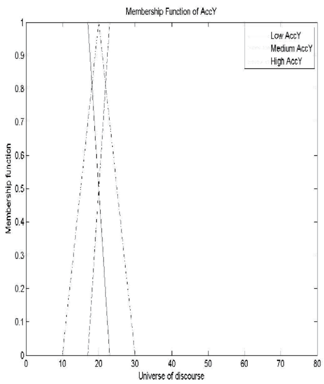
Fig. 6 The data were preprocessed by the running average. a) Graph of the running average of Roll, Pitch, and Yaw on grassy terrain. b) Graph of the running average of Roll, Pitch, and Yaw on flat plane.

4.3 Fuzzy Logic Filter

Fuzzy logic was designed to filter the data from IMU after preprocessing, which were the running average of Roll, Pitch, Yaw, AccY, and running standard deviation of Roll before feeding into neural network as the inputs. The fuzzy rules were designed with Mamdani-Min implication and Max-Min composition. The output fuzzy rules of AccY and SD Roll were defined as 2 types. For Pitch and Yaw, their output fuzzy rules were defined as 4 types. The output fuzzy rules of Roll could be defined as 3 types. The defuzzifier was designed with the method of Center of Area (COA). Running average of AccY was fuzzified into low AccY, medium AccY and high AccY. Running average of Roll was fuzzified into very low Roll, low Roll, medium Roll, high Roll, and very high Roll. Running average of Pitch was fuzzified into low Pitch, medium Pitch, and high Pitch. Running average of Yaw was fuzzified into very low Yaw, low Yaw, medium Yaw, high Yaw, and very high Yaw. Standard deviation of Roll was fuzzified into low SD Roll, medium SD Roll, and high SD Roll. The membership functions of inputs were shown in Fig. 7.



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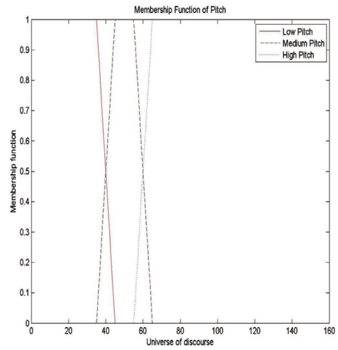

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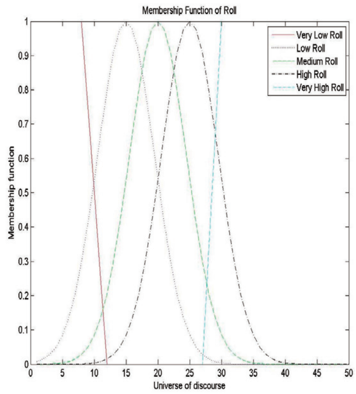

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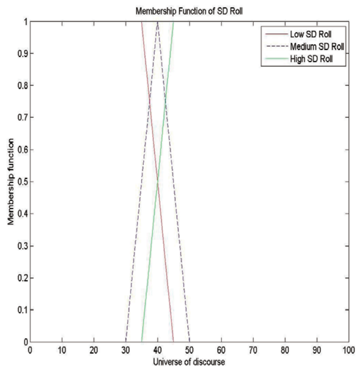

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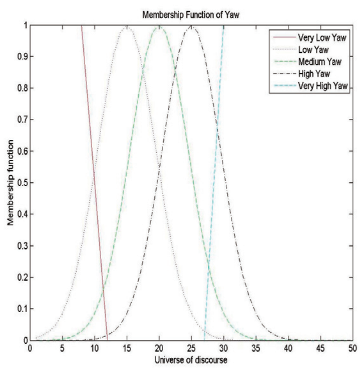

e

Fig. 7 The input membership function of the designed fuzzy. a) Running average of AccY, b) Running average of Pitch, c) Running average of Roll, d) Running SD of Roll, e) Running average of Yaw.

The output fuzzy rules were defined as

AccY
IF AccY is low THEN AccY is 1 ELSE
IF AccY is medium or high THEN AccY is 2

Roll
IF Roll is very low THEN Roll is 1 ELSE
IF Roll is low or medium THEN Roll is 2 ELSE
IF Roll is medium or high THEN Roll is 3 ELSE
IF Roll is very high THEN Roll is 4

Pitch
IF Pitch is low or medium THEN Pitch is 1 ELSE
IF Pitch is medium THEN Pitch is 2 ELSE
IF Pitch is medium or high THEN Pitch is 3

Yaw
IF Yaw is very low THEN Yaw is 1 ELSE
IF Yaw is low or medium THEN Yaw is 2 ELSE
IF Yaw is medium or high THEN Yaw is 3 ELSE
IF Yaw is very high THEN Yaw is 4

Roll SD
IF Roll SD is low THEN Roll SD is 1 ELSE
IF Roll SD is medium or high THEN Roll SD is 2

4.4 Neural Network

The feed forward neural network was used in the classification with 5 inputs from the preprocessing stage and the fuzzy filter including the running average of AccY, Pitch, Roll, Yaw and the running standard deviation of Roll which has already filtered into a discrete level. The neural network had 1 hidden layer, 10 hidden nodes and 5 outputs, flat plane, rugged terrain, grassy terrain, incline plane, and unclassified, as shown in Fig. 8. The neural network was trained off-line using 5 sets of 100 samples for each category and the learning constant was 0.2. The target output was set as 1 of C representation.

Flat plane	10000
Rugged terrain	01000
Grassy terrain	00100
Incline plane	00010
Unclassified	00001

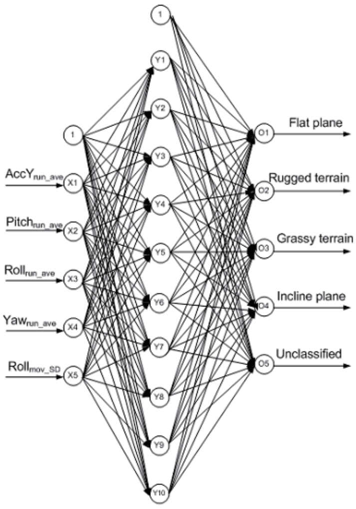

Fig. 8 Structure of the neural networks used for terrain classification.

5. EXPERIMENTAL RESULT

After training the neural network, we obtained the appropriate weights. These weights were used in testing the neural network. The 5 data sets of 100 samples for each category (the test set) were tested as the input of neural network. Each sample of data would correspond to one output. All samples were tested and the number of samples of 5 classified output types including flat plane, rugged terrain, grassy terrain, incline plane and unclassified within 100 data points were counted. The classified terrain is chosen according to the terrain type that gained the maximum percentage after omitting samples that classified as unclassified type. The result can be seen in table 1 shown below. The percentage of maximum output of 4 terrains that was selected as the final output are shown in the last column of table 1 as flat plane, rugged plane, grassy terrain, or incline terrain.

Table 1. The result of terrain classification from neural network.

Terrain	% Flat plane	% Rugged terrain	% Grassy terrain	% Incline plane	Classification
Flat plane					
1	75.84	0.09	0.00	24.08	Flat plane
2	92.35	0.11	0.00	7.53	Flat plane
3	81.68	0.09	1.49	16.73	Flat plane
4	81.63	0.11	0.00	18.26	Flat plane
5	85.01	0.08	4.85	10.05	Flat plane
Rugged terrain					
1	0.07	85.30	14.30	0.34	Rugged terrain
2	0.67	72.02	15.65	11.66	Rugged terrain
3	0.66	87.13	5.54	6.67	Rugged terrain
4	0.15	99.35	0.01	0.49	Rugged terrain
5	12.87	73.57	8.67	4.89	Rugged terrain
Grassy terrain					
1	0.00	8.76	91.24	0.00	Grassy terrain
2	97.52	0.41	0.05	2.01	Flat plane
3	45.74	0.08	53.46	0.71	Grassy terrain
4	34.81	0.11	50.00	15.08	Grassy terrain
5	96.74	0.98	0.24	2.04	Flat plane
Incline plane					
1	5.35	0.36	0.00	94.28	Incline plane
2	9.02	0.22	0.00	90.76	Incline plane
3	33.50	0.63	0.00	65.87	Incline plane
4	5.55	0.38	0.00	94.06	Incline plane
5	3.66	0.80	0.00	95.54	Incline plane

The result in Table 1 showed that the proposed classification method can classify a flat plane, a rugged terrain, and an incline plane 100% correctly. The grassy terrain can be classified correctly about 60% of the test samples.

6. CONCLUSION

The terrain classification is one of the features needed in a navigation or a localization system for an autonomous vehicle. This paper focused on the terrain classification using data from an Inertial Measurement Unit (IMU) acquired during vehicle motion. The output data from the IMU are three axes acceleration and three axes angular velocity. The acquired data are statistically preprocessed and fuzzified by fuzzy rules, then classified by a neural network into 5 categories: flat plane, rugged terrain, grassy terrain, incline plane and unclassified. The result showed that the proposed method can classify flat plane, rugged terrain, and incline plane 100% correctly. For grassy terrain, it can be classified correctly about 80%. The proposed terrain classification method will be incorporated into the position estimation algorithm for the autonomous vehicle system.

7. ACKNOWLEDGEMENT

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8. REFERENCES

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