Collision Detection for a Mobile Robot using Logistic Regression

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Abstract: Collisions cannot be entirely avoided during normal operation of an autonomous mobile robot. Therefore, mobile robots need to detect collisions and react appropriately when they happen. We investigate whether logistic regression on acceleration data can be used for collision detection. We have collected training data from an acceleration sensor during normal driving behavior of a small mobile robot. Collisions were manually marked by a human operator. Accelerations occurring in a direction opposite to the current direction of motion are more likely to be actual collisions. Hence, we combine accelerometer data and motor commands in the logistic regression model. The trained model was able to detect 13 out of 14 collisions on a separate test set with no false positives.

1 INTRODUCTION

A mobile robot can be equipped with a number of different sensors, e.g. infrared, sonar, laser range sensors or a camera, which allow him to move around in arbitrary environments (Corke, 2011; Jones and Flynn, 1993; McKerrow, 1991). Irrespective of the type of sensor used, collisions may occur for a number of different reasons: sensors may not fully cover the entire environment of the robot, some obstacles may be invisible to a sensor or sensor data processing may be too slow such that the data is already outdated by the time the collision occurs. It may also happen that the robot collides with an obstacle and then becomes stuck. If a robot becomes stuck, high stall currents may be applied to the motors. These high currents may cause damage to the robot if applied for long time periods. Detection and handling of different types of collisions is essential for a mobile robot in a real life environment.

With this contribution we use logistic regression (Hosmer Jr. et al., 2013) to predict collisions from data measured by an accelerometer on a mobile robot. Logistic regression and perceptron like neural networks are quite similar and both can be used for classification tasks. Dreiseitl and Ohno-Machado (2002) have compared both methods in the context of medical data classification. However, logistic regression can of course also be used for various tasks in robotics. Dorigo and Schnepf (1993) have used genetics-based machine learning for behavior-based robotics. They trained a robot to follow a light point and to avoid hot or dangerous objects.

Several researchers have used an accelerometer for collision detection. Na et al. (2005) have used acceleration sensor data for collision recognition for small scale fish robots. They have used fuzzy logic to estimate collision angles. He et al. (2007) apply a median filter to a running window of consecutive acceleration data and then compute the standard deviation. Finally a threshold is used to detect collisions. Nadarajan and Sridharan (2010) used acceleration and gyroscope data to detect instability in a NAO robot. They have used a support vector machine for classification. Moorits and Usk (2012) used accelerometer data for collision detection in navigational marine buoys.

Vail and Veloso (2004) have used decision trees for surface identification with a legged robot. McMahan et al. (2012) have shown that it is possible to use accelerometer data for localization of contact points on a robot arm. A multi class support vector machine was used for classification. Wisanuvej et al. (2014) use multiple accelerometers distributed along a multi-jointed robot arm for localization of collisions. They also propose to use this data for identification of materials the arm collided with and even for environment mapping. Speleers and Ebner (2019) have evaluated three different methods for collision detection using an acceleration sensor on a mobile robot: a simple threshold on the acceleration signal, a running median filter and a frequency based averaging filter.

Apart from mobile robotics, acceleration sensors are also used in the car industry to deploy airbags (Chan, 2000). Today, ordinary smartphones also contain acceleration sensors. Hence, these phones can also be used for vehicular collision detection (Lundsgaard and Grivas, 2006). Once a collision has been detected, they can also be used to notify emergency responders (Barfield, Jr. and Welch, 2016; Mane and Rana, 2014; Thompson et al., 2010).

2 COLLISION DETECTION

A simple yet efficient method for collision detection using acceleration data is to simply compare the acceleration data provided by the sensor with a threshold. If the acceleration is larger than a certain threshold and does not occur in the direction the robot is moving to then a collision has been detected. However, in practice it is quite difficult to use this method if the acceleration data occurring due to normal movement of the robot has a similar magnitude. This is especially the case for small robots which may be deployed in peoples homes. Also, small objects on the ground may also cause peaks in the acceleration data. However, if the objects are small enough for the robot to drive over then we would like to ignore such small "collisions". If the robot is driving over rough terrain, we may obtain an oscillating signal which may make it difficult to extract obvious peaks for collision detection.

Apart from collision detection we may also want to classify the type of collision which occurred. A collision against a table leg, human foot or a small object on the ground will result in different acceleration data. This data could be used to classify the type of collision. However, a simple threshold will not be sufficient for this kind of classification task. Learning algorithms allow for automatic classification of collision data. No manual tuning of parameters is required.

3 ROBOT ARCHITECTURE

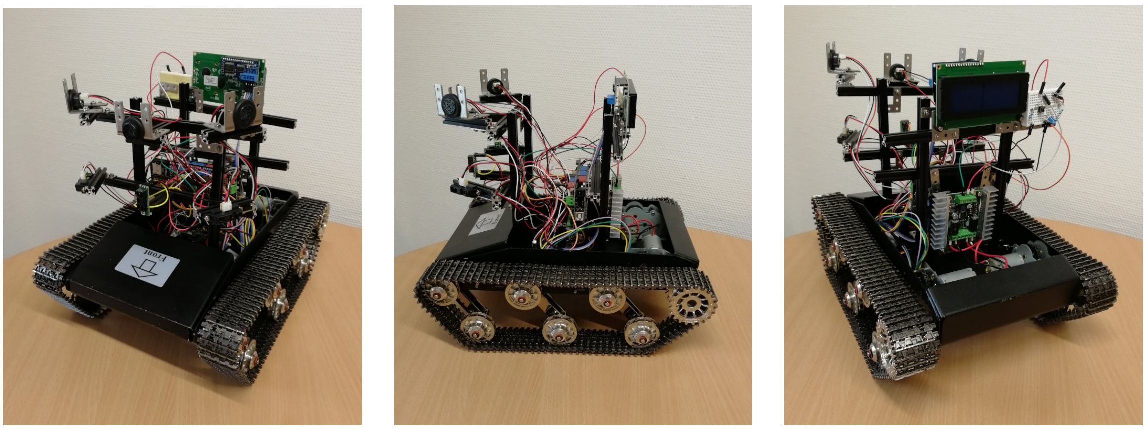
For our experiments, we have used the Dagu Robot (dagurobot.com) T'Rex Tank chassis (Fig. 1). The tracked tank chassis is driven by two motors via a Sabertooth 2x12 motor controller. The robot is powered by 11.1V LiPo battery. An Arduino Mega 256 micro controller was used to control the robot. The robot was equipped with three Sharp analog infrared sensors. One was oriented towards the front, the other two at an angle of approximately 30° pointing slightly sideways. The two sideway sensors (GP2Y0A21) could measure distances within the range $10-80$ cm. The frontally oriented sensor (GP2Y0A60) could measure distances within the range $10-150$cm. A 2x20 LCD was used to display debug information. A BNO055 sensor (Bosch Sensortec GmbH, 2006) was used to provide 3-axis acceleration data. This sensor was mounted approximately at the center of the robot.

The sharp infrared distance sensor provides analog output. This output is read at a rate of approximately 40Hz by the Arduino micro controller. The two lateral sensors are used to implement a corridor following behavior which allows the robot to wander around. The frontally oriented sensor is used to detect obstacles in the robot's path. If the distance measured by the frontally oriented sensor is less than 15cm, then we stop the robot, drive backwards for 1000ms, turn the robot by 180° and then continue with normal driving behavior.

4 CENTERING BEHAVIOR

Normal driving behavior uses the data from the left and right sensors to center the robot inside a corridor. This behavior is similar to the way honeybees process optical from their left and right eye (Lehrer et al., 1988; Srinivasan, 1992a,b). Behavior-based control algorithms have been shown to be very effective for robot control (Arkin, 1998). Several researchers have built robot behaviors based on this type of processing using optical flow (Coombs et al., 1998; Coombs and Roberts, 1992; Santos-Victor et al., 1993, 1995). If the optical flow on the left hand side is larger compared to the right hand side, then the robot will turn to the right. If the optical flow on the right hand side is larger compared to the left hand side, then the robot will turn to the left.

Instead of working with laterally oriented cameras it is also possible to process optical flow from a monocular camera. Ebner and Zell (2000) have used a foveated camera and extracted optical flow from the left and right peripheral visual areas. Optical flow was computed in ego motion complex logarithmic space. The ego motion complex logarithmic mapping is taken around the focus of expansion instead of the center if the image. Hence, optical flow due to the angular velocity of the robot is compensated for. Once this compensation is done, the optical flow from the peripheral areas on the left and right hand side is proportional to the inverse distance of the viewed objects. Again, this distance information can



(a) (b) (c)

Figure 1: Dagu Robot T'Rex Tank chassis with Sabertooth 2x12 motor controller. The robot is equipped with three frontal IR sensors. The three ultrasonic range sensors are not used. (a) front (b) side (c) rear.

be used for a centering behavior as described above.

Here, we are not using optical flow for the centering behavior. Distances are readily available from the Sharp distance sensors. Let s_l and s_r be the distance measurement from the two sensors facing towards the left and right side respectively. The difference between the two sensors is used to set the angular velocity $\dot{\alpha}$ of the robot.

$$\dot{\alpha} = \tau(s_l - s_r) \tag{1}$$

where τ is a scaling parameter. For our experiments, we have used $\tau = 0.05$.

To drive our robot, we need to specify the power applied to the left and right motors through the Sabertooth motor controller. Let m_l be the power applied to the left motor and let m_r be the power applied to the right motor via the motor controller. Let m_0 be the power applied to both motors to achieve a desired forward velocity. The desired rotational velocity is simply added to the left motor value and subtracted from the right motor value.

$$m_l = m_0 + \dot{\alpha} \tag{2}$$

$$m_r = m_0 - \dot{\alpha} \tag{3}$$

A positive angular velocity will make the robot turn right while a small angular velocity will make the robot turn left. This simple method will center the robot inside a corridor. If an obstacle is sensed towards the left side of the robot then the robot will turn to the right side and vice versa.

5 LOGISTIC REGRESSION FOR COLLISION DETECTION

We use logistic regression for collision detection. Logistic regression is a statistical model for dependent binary variables (Dreiseitl and Ohno-Machado, 2002; Hosmer Jr. et al., 2013). Our binary output variable will take on the value 0 if no collision has occurred and 1 if a collision has occurred. We would like to estimate the probability that a collision has occurred based on acceleration sensor data.

Let $a_x(t)$, $a_y(t)$ and $a_z(t)$ be the acceleration data in cm$/s$ measured by the accelerometer (the component due to gravity is automatically removed by the sensor). It is assumed that we have $a_x(t) = a_y(t) = a_z(t) = 0$ at rest. The sensor was mounted such that the x axis points to the left and the y axis points backwards. Let $m_l(t)$ and $m_r(t)$ be the power applied to the two motors. This data is obtained with a frequency of approximately 125 Hz. Each data point $p(t)$

$$p(t) = (a_x(t), a_y(t), a_z(t), m_l(t), m_r(t)) \tag{4}$$

consists of the data measured by the accelerometer as well as the power applied to the motors.

The deceleration due to a collision usually spans multiple data points. Using more than a single data point allows for more reliable collision detection. Let W_i be n consecutive data points obtained during time $t_{i+n-1} - t_i$.

$$W_i = (p(t_i), \ldots, p(t_{i+n-1})) \tag{5}$$

Let o_i be our binary output value with $o = 1$ if a collision has occurred during the time period from t_i to t_{i+n-1}. We want to estimate the probability $P(o = 1|W)$. According to our logistic regression model, we have

$$P(o = 1|W) = \sigma(\theta_0 + \theta W) \tag{6}$$

for a sigmoid function $\sigma(x) = \frac{1}{1-e^{-x}}$ and parameters θ and θ_0. The vector W contains $5n$ values. Logistic regression essentially tries to compute a hyperplane to separate areas inside this vector space where a collision has occurred from areas where a collision has not occurred. We need to compute the weight vector θ and bias θ_0 from the available training data. The software package R (The R Development Core Team, 2008) was used to obtain the logistic regression model. We have used the function `glm` (generalized linear model) with default parameters except for the parameter family which was set to binomial.

The training data is recorded via the serial Arduino interface during normal operation of the robot. The data points $p(t_i)$ are obtained at a rate of 125 Hz. In order to apply logistic regression, we also need to obtain ground truth data when a collision has happened. We have connected an external button to the Arduino. This button is pressed by a human operator whenever a collision has happened. Let $c(t) = 1$ if the button was pressed and $c(t) = 0$ otherwise. The button press occurs approximately at the time of the collision. However due to various reasons (operator pressing too early to after a slight delay), this data is only approximately correct. Hence, we first correct all collision data $c(t)$ using an R-script and then compute the time of the collision during post processing.

We take the button press as the approximate time when a collision has happened. Some collisions may have been marked before the actual event has happened and some have been marked after the event has happened. Therefore, we search for a peak in the magnitude of the acceleration data. If $c(t) = 1$, then all data points within a window of b_s time steps before and b_s time steps after time t are considered. If $c(t) = 1$ for several consecutive time steps, then we obtain a window that will contain more than $b_s + b_s + 1$ data values. Let t_m be the time step where the magnitude of the acceleration was at a maximum. We then set all values within $[t - b_l, t + b_r]$ to 1. Let $\tilde{c}(t)$ be this modified collision data. Preliminary experiments have shown that the parameters $b_s = 6$, $b_l = 6$ and $b_r = 12$ work particularly well. The reason for assuming that the collision is centered around the maximum is because a collision frequently results in a quick impulse followed by a slower decline.

Using all recorded data points $p(t)$ and associated ground truth collision data $\tilde{c}(t)$, we create overlapping windows of size $n = 19$. Subsequent windows have an offset of one data point. We compute the probability P' that a collision has occurred during a window W as the fraction of values $\tilde{c} = 1$ to the total number of data points, i.e.

$$P'_i = \left(\sum_{j=0}^{n} \tilde{c} \right) / n \tag{7}$$

Using $n = 19$ we obtain $P'_i = 1$ if a collision event is completely contained within this window. The regression model has been trained using these windows with associated P'_i. All data was recorded while the robot was driving around in an office environment.

Using the trained regression model, we are able to detect collisions by processing a window of 19 consecutive data points. The model will compute a probability that a collision has occurred. We apply a threshold of 0.95 to this probability, i.e. a collision only occurs if the output of the mode is 0.95 or larger. If a collision has been detected, we locate the data point t_m whose magnitude of the acceleration is at a maximum. We then compute the motor power by taking the maximum acceleration during the collision. Let $a_{\max}$ be this maximum. Values larger than 8 are limited to 8. This limits the rotational velocity of the robot. The motor power is set to

$$m_l = -m_0 - s a_{\max} \tag{8}$$

$$m_r = -m_0 + s a_{\max} \tag{9}$$

using $m_0 = 50$ and $s = 8$. The parameters were manually set based on preliminary experiments. The setting is maintained for a time of 1000 ms. This will result in a motion that is opposite to the one that lead to the collision. For example, if the robot bumped into a chair leg with his front left corner then it will set back by turning to the left. This will allow the robot to avoid the chair leg when moving forward again.

6 EXPERIMENTS

Acceleration data obtained during a collision with a chair leg is shown in Fig. 2. The collision is clearly marked by the peak in the data along the y axis. Apart from this peak along the y axis, we also see considerable accelerations occurring along the x and z axis of the robot. This is due to the robot moving sideways and downwards (the tracks are spring mounted to the robot). Due to this type of behavior it is best to consider all three axes when determining whether or not a collision has occurred.

Fig. 3 shows the collision data while the robot was moving upward on a ramp. The robot was colliding with a chair leg. Peak acceleration also occurred along the z direction. However, the peak is not as high in the previous data. When the robot reaches the bottom of the ramp, we also obtain large oscillations along the y direction. However, these data points should not be interpreted as a collision.

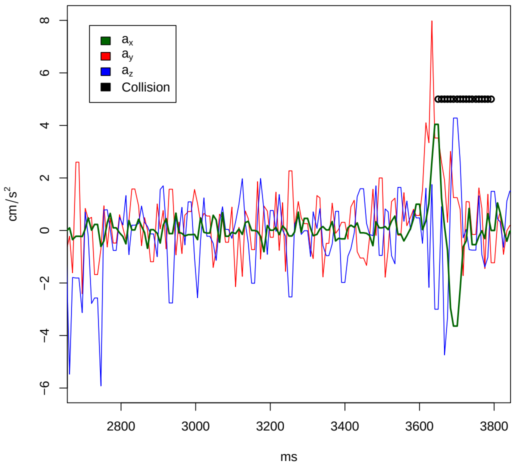


Figure 2: Acceleration data a_x, a_y and a_z obtained from the robot while bumping into a chair leg. The time of collision was marked manually by a human operator.

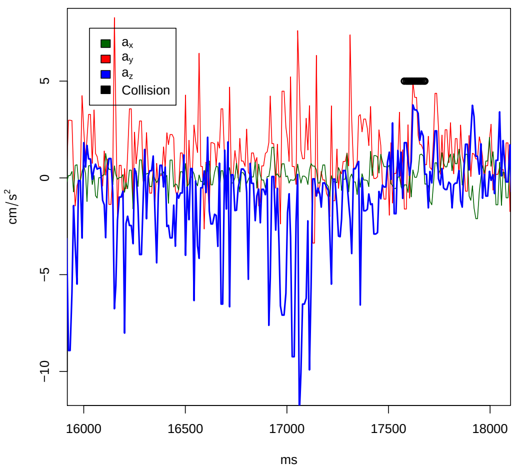


Figure 3: Acceleration data a_x, a_y and a_z obtained from the robot while it was moving upward on a ramp and then bumping into a chair leg. The time of collision was marked manually by a human operator.

It is quite difficult to devise an algorithm which will detect both types of collisions that we have analyzed here (colliding with a chair leg on the ground and colliding with a chair leg on a ramp). Apart from these two types that we have seen so far, many different collision types can occur in practice. A learning algorithm has the advantage that we only need to collect collision data for various situations as well as data from normal driving behavior when no collisions occur. The learning algorithm will then optimally tune its parameters to the given data.

Logistic regression allows us to detect collisions by learning from a training data set. Our training data set contains 27 collisions where the robot was level and colliding with a chair leg (collision of type A). It also contained 14 collisions where the robot was moving upward on a ramp and colliding with a chair leg (collision of type B). The remaining training data was recorded during normal driving behavior of the robot on the ground. Sometimes the robot was also driving over small objects. These objects provide for variations in the collision data. However, they should not be considered as collisions. The small objects on the ground should result in variations during normal driving behavior in order to make the collision detection algorithm more robust. Our training set consisted of a total number of 22105 data points (21014 for normal driving behavior, 859 for type A collisions 232 for type B collisions) with associated binary data (collision/no collision). Since each window contained 19 data points and we have used overlapping windows, we obtained 20996 windows from normal driving behavior, 841 windows from type A collisions and 214 windows from type B collisions.

We then tested the robots ability to detect collisions on a test data set shown in Fig. 4. This data set consists of 14 collisions. It was recorded while the robot was moving around on the floor. It collided with a table chair (7 times, type A collision). The robot was also moving upward on a ramp and then collided with a table chair (7 times, type B collision). Only one of these 14 collisions was not correctly classified as a collision. Table 5 summarizes our results. Our model did not recognize one collision of type A. This may have been the case because the robot collided with the chair leg at an angle that was not sufficiently well represented by the available training data. Collision detection results are also shown in Fig. 4. Actual collisions have been marked manually by a black circle. Whenever our model predicted a collision, a green circle is shown in the plot.

In order to further improve collision detection, it would of course also be possible to learn collision detection models separately for different types of collisions. Once these separate models have been learned, they could be combined in a final processing stage. However, this approach could result in over-training of certain collision types. Collisions that do not occur during training will probably not be detected.

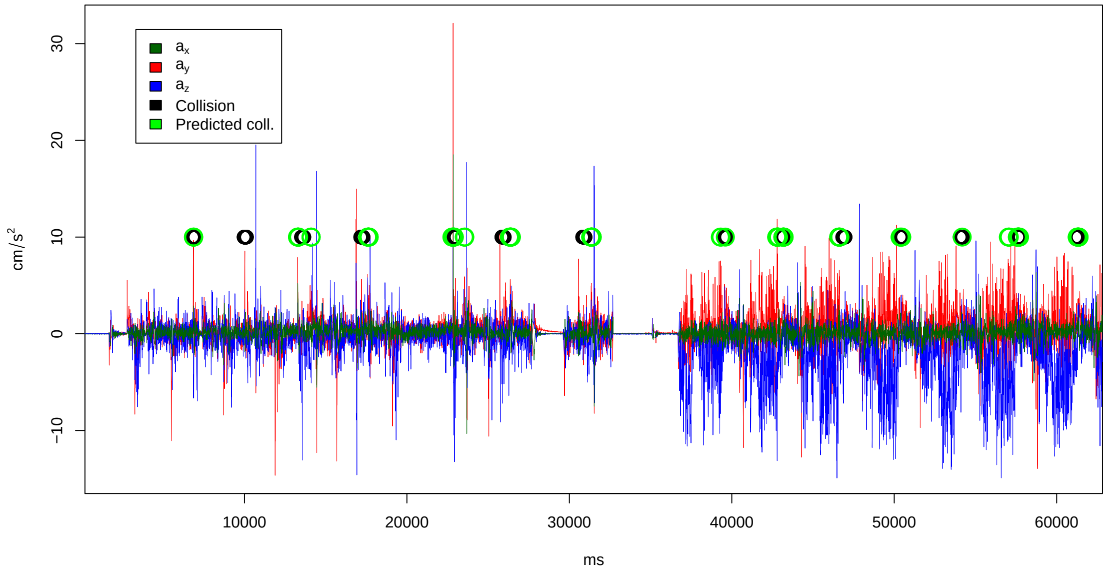


Figure 4: Test data set with 14 collisions. Acceleration data a_x, a_y and a_z together with manually marked collisions (black circles). Predicted collisions have been marked by a green circle. Only one of the collisions has not been detected by the model.

Figure 5: Collision data was gathered during normal driving behavior. Two types of collisions were recorded: Type A collisions (table chair) and type B collisions (table chair while robot was moving on a ramp).

	type A	type B
collisions (training set)	27	14
collisions (test set)	7	7
recognized collisions (test set)	6	7

7 CONCLUSION

We have used logistic regression for collision detection of a mobile robot. The robot was equipped with an accelerometer. Our model was based on 19 successive data points obtained at a rate of approx. 125 Hz. Each data point consisted of the acceleration values along the three axes of the robot together with the power supplied to the robot's motors. A training data set was obtained by letting the robot drive around inside an office environment and then marking collisions manually. Out of 14 collisions in the test set 13 were detected. Thus, logistic regression appears to be a promising method for collision detection using an acceleration sensor on a mobile robot. The advantage of using logistic regression compared to a simple threshold on the acceleration data is that the method can be easily tuned to detect certain types of collision by simply recording training data. Currently, training has to take place off-line. Extending the method to an on-line learning paradigm would be desirable.

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