

Real-World Validation of Three Tipover Algorithms for Mobile Robots

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Abstract—Mobile robot tipover is a concern as it can create dangerous situations for operators and bystanders, cause collateral damage to the surrounding environment, and result in an aborted mission. Algorithms have been developed by others to assess the stability of the robot, and many of these algorithms have been demonstrated using simulated data. In order to verify that these algorithms accurately match real-world behavior, we have collected data of a mobile robot tipping over and then compared this data to the stability measures provided by three algorithms: Zero-Moment Point (ZMP), Force-Angle stability measure (FA), and Moment-Height Stability measure (MHS). A small mobile robot platform based on the iRobot PackBot drove a course including ramps and obstacles; an IMU and GPS provided inertial and positional data for the algorithms, and the actual tipover event is determined from video footage of the tests. The average normalized measure at tipover event initiation was found to be 0.665 for ZMP, -0.094 for FA, and 0.023 for MHS, where a value of 1 corresponds to resting stability. Standard deviations were 0.38, 0.84, and 0.67, respectively. The measures show a significant amount of noise, which is likely due to the vibrations caused by movement of the tracks and could be reduced by employing additional filtering during data collection. The preliminary real-world data validates these tipover algorithms as able to assess robot stability, and they can be used as part of a tipover avoidance system.

I. INTRODUCTION

A majority of mobile vehicles are concerned with avoiding tipover (also rollover or overturning), and there are many reasons to avoid robot tipover. It often results in immobilizing the robot until it can be righted by a human or another machine, which may never occur. Tipover can also create dangerous situations for operators and bystanders, and it can cause collateral damage to humans, other robots, or the general surrounding environment. If the robot is carrying a payload, tipover will often result in the physical or functional loss of the payload. Additionally, tipover can result in bending or breaking parts of the robot, requiring expensive repairs.

Mobile robots are given critical tasks and sent on dangerous missions such as search and rescue in collapsed buildings or civilian and military bomb disposal. Such a robot is shown in Figure 1. A tipover can cause a critical mission to be aborted, and in the worst case scenario, this event will place a human in harms way during the robot recovery. While a robot may be able to self-right using its manipulator, these strategies are not necessary if the robot



Fig. 1. A photograph of the modified PackBot Fido from iRobot used in tipover validation tests.

can avoid tipping over. Tipover avoidance requires additional stability measures and control algorithms when the vehicle is remotely or autonomously operated, as is often the case with small mobile robots.

These robots are likely to tipover because they encounter terrain features typically found on roads and paths, which are engineered for larger wheelbase vehicles with human occupants. These terrain features appear larger and steeper to the mobile robots. The mobile robots also typically have a higher relative center of mass due to manipulators or cargo payloads. The lack of a human operator providing an intuitive measure of stability may also cause more tipover events.

Stability measures and algorithms have been developed by others to assess the stability of a robot and predict tipover conditions. They include the Zero-Moment Point, Force-Angle stability measure, and Moment-Height Stability measure. The Zero-Moment Point (ZMP) is a point on the ground where the sum of all the forces and moments acting on the robot can be replaced by a single force [1]. It was originally derived for stabilizing bipedal robots, and it has been adapted many times and applied to mobile robots [2], [3], [4], [5]. The specific implementation of the ZMP algorithm used in this paper is taken from [2] and [3].

A different approach was proposed by Papadopoulos and Rey [6], which they called the Force-Angle stability measure (FA). The FA algorithm measures stability by the angle of the applied force on the center of mass. The angles are referenced to the support polygon, which is a convex polygon derived from the ground contact points of the robot. Building on this idea, Moosavian and Alipour proposed the Moment-Height Stability (MHS) measure [7]. This algorithm accounts

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for the robot's inertia about each axis of the support polygon. It also incorporates an intuitive factor by scaling results by the height of the robot's center of mass.

Recent work using the Lateral Load Transfer (LLT) algorithm has shown relevance for use in large trucks [8] and all-terrain vehicles [9]. It is quite applicable to vehicles with suspensions, but most of the small robots used search and rescue and bomb disposal missions do not have suspensions. In addition, they are likely to tip in any direction, not just laterally. For these reasons, the LLT algorithm was not included in this assessment.

Each algorithm provides a measure of the stability of the robot. Typically these measures are normalized so that a value of one corresponds to the most stable robot position and zero to the stable boundary. Values less than zero correspond to unstable positions. The ZMP is a point on the ground, and must be converted to a measure before it can be normalized [2],

In order to be useful in preventing tipover, these algorithms must be computed on-line, and the results used in the robot control system. All three of these algorithms are capable of on-line computation, and some have used them in this way [10], [4]. However, all of these algorithms and their applications have only been demonstrated using simulations, so it has been difficult to say how they will correspond to actual tipover events.

The algorithms addressed here have been compared by Moosavian and Alipour in [11] using simulated data. They found that some measures are too confident or too restrictive compared to the cluster of other measures. However without real-world data, it is impossible to say whether the outlier or the group is a more accurate measure.

There has been work on using real-world data to evaluate tipover algorithms [12], [13], [14], but it has focused on tractors and did not employ one of these more standard algorithms. Li and Liu used a fuzzy controller for tipover prevention using real-world data [15], but they, too, developed their own stability algorithm. While the work is relevant, none of the algorithms presented here were tested.

There is a need to validate and compare these algorithms using data from real-world tests. Real-world data is invaluable for guiding further refinements and producing accurate measures of mobile robot stability. A full validation of these algorithms requires a large number of trials with a large number of robot platforms. In this work, we have provided preliminary validation data from a single platform and configuration. Additional configurations were not tested because the primary goal of this study was to characterize this particular configuration.

This paper will discuss the methods used: algorithmic assumptions, data collection platform, and scoring system. Then the results of these tests will be presented and discussed. This will be followed by some conclusions about the practical application of tipover algorithms to mobile robots.

II. METHODS

The mobile robot platform was dynamically modeled in software, and the ZMP, FA, and MHS algorithms were coded as described in [12], [6], [11] with some assumptions, which are addressed below. Then the robot was fitted with an inertial measurement (IMU) based data collection system and driven over various obstacles. The data from these tests was then passed to the software to calculate the tipover measures over time. The algorithms can run in real-time, but as they are not being used to control the robot in these tests, they are computed off-line and after the trials. Here we will discuss the key assumptions and algorithm details, the data collection system, and the method for scoring the tipover measures.

A. Algorithms

The robot model and the algorithms are coded using computational engineering software programs MATLAB and Scilab. The following will discuss the assumptions required for implementing the software model of the robot and implementation details relevant to all of the tipover algorithms and details specific to each algorithm.

In modeling the robot, it is assumed to be a simple rectangular prism of uniform density. This first-order model is a good starting point and can be refined if necessary. Additionally, the robot's payload was assumed to be statically fixed to the robot base. While the tipover measures can account for the changing center of mass and inertia tensor, the payload on the real robot was not moving during these tests. The measured mass and mass center from the real robot are used in the models.

It is also assumed that the ground contact points are fixed relative to the robot. Trying to estimate the contact points and the support polygon over the course of a test on rough terrain is very difficult, so we have left that out of our simplified model. In addition, the slip between the robot and the ground is assumed to be zero, testing pure rotational instability. Although slip is likely occurring, it can be left out of the simplified model because the robot's motion is measured by inertial sensors, so slip does not affect the measurements. Additionally, the obstacles and course are rigid, so slip does not change the ground contact points significantly.

It is necessary to discuss some of the implementation details relevant to all of the tipover algorithms. All of the algorithms require the net force and moment wrench acting on the robot to be known. These dynamics must be computed from the input data provided by the IMU system. This was done numerically using the Newton-Euler method as presented in [16].

To reduce the effects of noise on the algorithms, the input data is low pass filtered. A sixth order Butterworth filter with a cut-off frequency of 5 Hz was applied to the roll, pitch, and azimuth data from the IMU and to the velocity data from the global positioning unit (GPS).

In order to compare the tipover algorithms, the measures they provide must be normalized to a common scale. This is done by dividing the measure at the current time by the measure of the stationary robot on a level surface. With this



Fig. 2. A video frame of the robot driving up at 40° ramp during a tipover test.

normalization, it is possible to get measures greater than one and less than zero.

The ZMP does not directly provide a measure of system stability [1], so it has been combined with a potential function to create a stability measure. Since the robot support polygon is a rectangle, the potential function from [3] is used. The FA is implemented as described in [6] without modifications. The MHS was modified from [7] by setting the exponent of the moment of inertia, σ_i , to be -1 instead depending on the sign of the moment about a support axis. This keeps the measure continuous as it crosses the boundary of stability.

B. Data Collection

Real-world data was collected using a remotely controlled robot fitted with a system for measuring the orientation and position of the robot.

The robot platform is a modified PackBot Fido from iRobot (Bedford, Massachusetts, USA). This robot is used by police and military units for bomb disposal missions because it is remotely controlled and portable. A photograph of the modified robot is shown in Figure 1. The modified robot weighs 43.5 kg; it is 69 cm long and 41 cm wide with an average height of 45 cm. The support polygon is a rectangle 51 cm long by 36 cm wide. The center of mass was found by placing the robot in different orientations on a rig whose ground contact forces were measured by four load cells. It was determined to be 22 cm above the ground and 3 cm forward of the center of the support polygon with an accuracy of ± 1 cm in each direction.

A SPAN HG-1700 unit from NovaTel (Calgary, Alberta, Canada) provided the position, velocity, and orientation of the robot. The unit combines IMU gyroscope and accelerometer measurements with absolute position measurements from a GPS. The IMU provides data at 20 Hz with a position accuracy of 1.5 m, a velocity accuracy of 0.02 m/s, an acceleration accuracy of 0.03 m/s^2 , and an attitude accuracy of 0.010° . This data is provided to the algorithms as 3D position and velocity and roll, pitch, and azimuth angles.

Two off-board cameras record the robots movements and are used for determining the time of tipover. The cameras and on-board sensors provide data at 20 Hz.

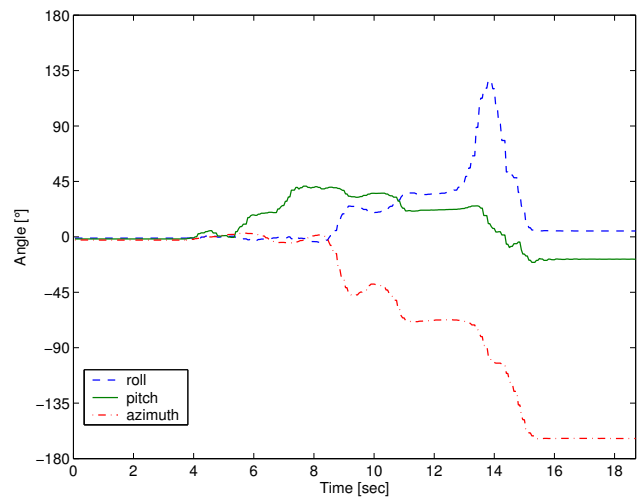


Fig. 3. A plot of the orientation data gathered in a tipover test. This test involved the robot driving up a 40° ramp and traversing it sideways. Tipover begins at 12.45 seconds.

A course with ramps, obstacles, and rubble was set up at SPAWAR Systems Center in San Diego. The ramps varied in slope from 20° to 45° , and the obstacles were boards measuring up to 13 cm square and ditches measuring up to 61 cm across and 15 cm deep. A frame from the video of the robot driving up a 40° ramp is shown in Figure 2.

C. Scoring

We used three methods of scoring the tipover algorithms. The exact time of tipover for each test is determined by observing the video data. The frame where one of the robot tracks visibly loses contact with the ground is considered the actual time of tipover. The first scoring method takes the tipover measure provided by each algorithm at the actual time of tipover. The second method compares the lag time between the actual start of tipover and when the tipover measure crosses zero, the stability boundary. If the measure crosses zero before the start of tipover, then the lag time is measured as a negative value. This is referred to as a lead event, and a positive lag time as a lag event. The third scoring method counts the number of false positives, where the tipover measure crosses zero to a negative value, indicate an unstable situation, and then crosses back to a positive value, indicating a stable situation without the robot tipping.

III. RESULTS

Data was collected from eleven tests, with four of those resulting in tipover and one more where part of the robot contacted the ground but did not fully tip over; therefore five trials provided useful data. Figure 3 shows the orientation of the robot during a test where it drove up a 40° ramp, turned right, and then tipped over while trying to traverse the ramp. One track of the robot loses contact with the ground at 12.45 seconds. The robot continues to tip, as seen by the increase in roll angle. The sudden decrease in roll angle around 14 seconds is where the operator caught the robot and righted it.

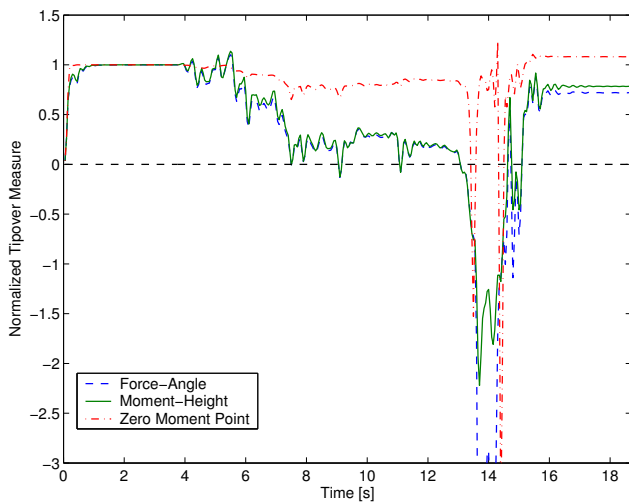


Fig. 4. A comparison of Zero Moment Point, Force-Angle, Moment-Height Stability measures over time for a tipover trial. This is the same trial as in Figure 3. The results have been low-pass filtered at 2 Hz for clarity.

A plot of the tipover measures during this test is shown in Figure 4. The tipover event is recorded by all three measures around 13 seconds, about a half a second after the start of tipover as determined by observing the video. The FA and MHS measures are almost identical except when less than zero. The ZMP measure closer to one until the tipover event is recorded, at which point the ZMP becomes the most negative measure of the three. The scores from this particular test are listed in Table I.

The ZMP has no false positives, meaning that the measure was always greater than zero before the actual time of tipover. The FA and MHS measures cross four times before the actual event. The measures are positive at the actual time of tipover, giving positive lag times.

Figure 5 shows the tipover measures from a similar test to the one shown in Figure 4 except that in this test the robot does not tip over. Again the FA and MHS algorithms track nearly identically, and the ZMP is closer to one. There is more noise in the FA and MHS measures in this test than in the test shown in Figure 4, but the average values look quite similar to the first test before the tipover event.

The average scores from the 5 trials resulting in tipover are listed in Table II. On two of the five tests resulting in tipover, the FA and MHS measures crossed the stability boundary before the start of the actual tipover event. For these lead events, the average lag time was -0.38 seconds. On the other three tests, the measures indicated the unstable situation an

TABLE I
SCORES FROM THE TIPOVER TEST SHOWN IN FIGURE 4

	ZMP	FA	MHS
measure at tipover	0.847	0.179	0.190
lag time [sec]	0.95	0.60	0.60
false positives	0	4	4

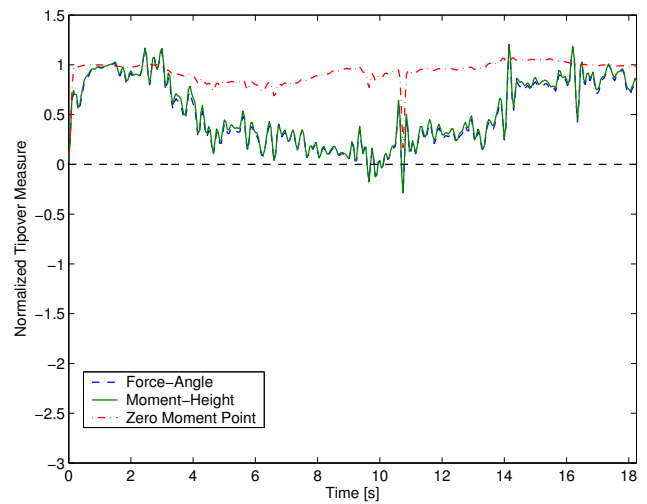


Fig. 5. A plot of the measures data gathered in a tipover test. This test involved the robot driving up a 40° ramp and traversing it sideways. The robot does not tip over, in contrast to Figure 4. The results have been low-pass filtered at 2 Hz for clarity.

average of 0.25 seconds late. The ZMP lagged for all five tests by an average of 0.40 seconds. The ZMP has fewer false positives than the FA and MHS. These results are shown graphically with the bar graph in Figure 6.

IV. DISCUSSION

We chose to evaluate three tipover algorithms for mobile robots. ZMP and FA were chosen because of their wide acceptance and many adaptations. MHS was chosen because it appeared to more closely account for the dynamics of the situation and should thus provide a more accurate tipover measure. Additional algorithms, such as those compared in [7] can be referenced to the three covered here for evaluation. It is also possible to run the data through other algorithms in the future.

Although better differentiation between the algorithms would have been achieved by testing multiple robot platforms in additional configurations, such as adding a moving manipulator, the primary goal of this study was to characterize this particular configuration.

The tipover measures tend to be very noisy, which is probably due to the vibrations caused by the tracks on the rigid obstacles. Additional filtering should reduce this noise; the current implementation only filters the input data to 5 Hz.

TABLE II
COMPARISON OF TIPOVER MEASURES

	ZMP	FA	MHS
measure at tipover	0.665	-0.094	0.023
standard deviation	0.38	0.84	0.67
lead event count	0	2	2
lag event count	5	3	3
lag time [sec]	0.40	-0.003	-0.003
false positives	1.2	5.8	5.8

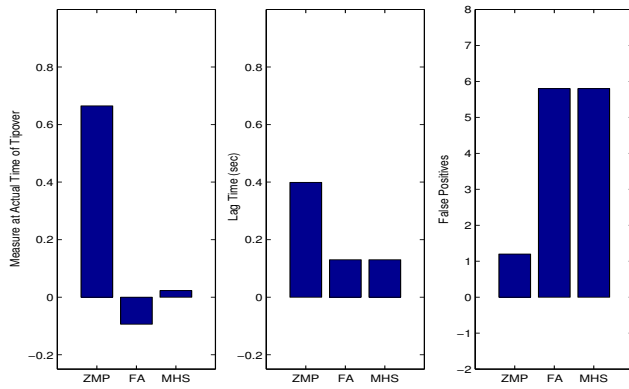


Fig. 6. The average scores for each algorithm. On the left is the tipover measure at the actual time of tipover, where closer to zero or below is better. In the middle are the average lead and lag times, and lower values are better here. The graph on the right shows the average number of false positives. A smaller number is better here to an extent as an algorithm with very low false positives may fail to indicate a tipover event.

Filtering can introduce additional lag, which leaves less time to prevent a tipover if the algorithms are being used as part of an on-line tipover avoidance system. A more complex filtering solution would involve an observer such as a Kalman filter.

Another option for reducing noise in the tipover measures would be to use the data from additional sensors. For example, the IMU measures linear acceleration but does not output these measurements. A direct measurement of linear and angular acceleration would mitigate noise from differentiation.

A perfect tipover measure crosses zero when the robot begins to tip. If the measure crosses after the actual tipover has started, then a control system trying to prevent tipover will have a very difficult task achieving its goal. The greater this lag time, the less useful the tipover measure becomes. On the other hand, if the measure crosses zero before the actual event, then the measure increases its usefulness. One way to achieve larger lead times is to increase the sensitivity of the algorithms. The robot model can be adjusted to increase sensitivity, but it can also incur more false positives, where the algorithm predicts a tipover event which never occurs. Registering too many false positives could paralyze the robot depending on how the tipover avoidance system is implemented.

The results in Table II show that based on the value of the measure at the actual time of tipover, FA tends to be the best measure of tipover stability closely followed by MHS, while ZMP is the worst. Although the average MHS measure is closer to zero, the average ZMP measure is less than zero indicating the unstable situation. These results are a bit surprising, as one would expect that the extra dynamics considered by the MHS would provide a more accurate measure. Yet, considering simple nature of the validation tests, with no manipulator or other changing dynamics beyond gravity and inertial forces, it is likely that the differences between FA and MHS have not been exposed.

It is difficult to address the statistical significance of

these results because of the small number of trials actually resulting in tipover. As with any preliminary study, a significant amount of effort is spent determining the best methods for testing and measuring the necessary parameters. Further studies will be able to address statistical significance as well as the variations in robot platform required for a full validation.

As seen in Figures 4 and 5, FA and MHS track each other almost exactly with the largest differences occurring when the measures are less than zero. In these cases the FA measures indicate lower stability than the MHS measures. The algorithms were initially tested using simulated data inputs and with more complex models. The FA and MHS measures showed obvious differences when the center of mass moved relative to the support polygon. These differences are not seen with the real-world data because the center of mass relative to the support polygon is constant through out the tests.

In Figure 4 it can be seen that both FA and MHS show a significant decrease in stability after the robot makes a turn while on the 40° ramp. At the time of tipover the stability of the robot according to the FA measure has decreased by 82% of the resting stability and 81% according to MHS. In addition, for all five tests, the average stability at the actual time of tipover has decreased by 101% and 98% from resting stability for FA and MHS, respectively. Given these values, a stability margin can be easily constructed, although it will likely depend on the course over which the robot is moving: along ramps or slopes, across ditches or over obstacles, or over a pile of rubble.

The tests in Figures 4 and 5 provide a nice comparison of similar situations with different results. Both tests involve the robot driving up a 40° ramp, turning 90°, traversing across the ramp, and then turning and driving down the ramp. The tipover measures are about the same in each test, so why does the robot tip in one test but not the other? Additionally, the FA and MHS measures in Figure 5 are noisier, but on average slightly lower than those of Figure 4.

The robot is controlled by a human operator, so the turns are not executed exactly the same in the two tests. However, the tipover event happens when the robot is traversing the ramp not turning. The speed of the robot during the traverse is higher for the trial which does not tip, and this is likely reflected in the slightly lower FA and MHS measures. The increased speed seems to have increased the stability of the robot in a way that is not reflected in any of the tipover measures. This could be due to unmodeled dynamics such as friction effects [17] or interactions between the tracks and the ramp surface.

A more refined model should give results that match the real-world behavior more closely than the simple model used here. One of the difficulties in refining the model is accurately determining the inertia tensor for the robot. Each element, from the batteries to the frame to the screws affect the inertia tensor, as does the payload and payload position. It is prohibitive to measure all of these elements, thus some approximation is necessary.

In addition to accurate modeling of the properties of the robot, it is difficult to accurately model slippage and friction effects. The greatest factor in determining slippage is the condition of the ground. Asphalt will have lower slip than loose dirt or dry leaves; the robot is likely to encounter all of these ground conditions during its mission. Even though slip was observed with the real robot, the algorithms assume the ground conditions are perfect with no slip and infinite friction.

The tipover algorithms can be made more sensitive by changing the size of the support polygon. The support polygon is defined by the ground contact points of the robots wheels or tracks. Shrinking the size of the support polygon increases the sensitivity of the algorithms, making the model robot more likely to tip over when subjected to a given force and moment wrench.

Refining the model used by the algorithms will result in more accurate results, but the increased cost in computation and resulting additional lag must outweigh the small increase in accuracy. Given the level of noise from the first difference method of differentiation and from the vibrations of the robot as it moves, any improvement in algorithm accuracy from a refined model could be nullified.

V. CONCLUSIONS

Mobile robot tipover is a concern as it can create dangerous situations for operators and bystanders, cause collateral damage to the surrounding environment, and result in an aborted mission. In order to avoid tipover, algorithms have been developed to assess the stability of the robot. Many of these algorithms have been demonstrated using simulated data. In order to verify that these algorithms accurately match real-world behavior, we have collected data of a mobile robot tipping over and then compared this data to the stability measures provided by three algorithms: ZMP, FA, and MHS.

The three tipover algorithms studied here can be used to assess robot stability with FA and MHS being more effective measures than ZMP. Differences between the FA and MHS measures were not seen, and this is likely due to the simple robot platform, where the center of mass stayed fixed relative to the robot. A full validation is still necessary as this work only addresses a single platform and configuration.

The ideal tipover algorithm indicates the onset of instability at the exact time the robot is starting to tipover, so some method of estimating future data will provide a substantial benefit for avoiding tipover. Creating a stability margin based on the tipover measures can help avoid tipover as well, although unmodeled dynamics, vibrations during robot movement, and noise from sensor measurements may create an overly restrictive margin. A complete tipover avoidance system will also require the development of evasive maneuvers when a tipover event is imminent. These maneuvers will be robot and mission specific.

If noise can be significantly reduced, then the preliminary real-world data suggests that the FA and MHS tipover

algorithms are able to assess robot stability and can be used as part of a tipover avoidance system.

In addition, they can be used to predict the mobility of a mobile robot during the design phase prior to production because the algorithms provide a reasonable measure of stability.

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