ONLINE ESTIMATION OF WHEEL SINKAGE AND SLIPPAGE USING A TOF CAMERA ON LOOSE SOIL

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Abstract
A prominent concern with wheeled mobile robots that travel on loose and rough terrain is that they may get stuck in soil and experience a sharp increase in wheel sinkage and slippage. Various analyses of wheel–soil interaction mechanics have been conducted to study this issue. Several studies have been carried out for the online estimation of wheel sinkage and slippage using image processing. However, these image-based online estimation methods are greatly affected by target environment conditions such as lighting and reflectance. In contrast, a ranging sensor that provides three-dimensional point cloud data performs better at estimation even in an uncertain environment. This study proposes an online sinkage/slippage estimation method using a time-of-flight (ToF) camera that can measure the distance from a target object. Sinkage/slippage estimation of the traveling wheel on loose soil is experimentally demonstrated by attaching the ToF camera on the side of the wheel. The experimental result showed that most of the wheel sinkage could be estimated to within ±1 mm absolute error using point cloud data; traveling velocity and slip ratio of the wheel could be estimated for a resolution of less than 1 mm/s and less than 3.9% absolute error, respectively.

Keywords: Online estimation, Sinkage, Slippage, Lunar/planetary exploration rover

1. Introduction
Lunar or Martian surfaces are covered with fine regolith, gravel, and rocks. In the past, lunar/planetary exploration missions have mainly adopted unmanned mobile rovers with rigid metallic wheels for locomotion. A wheel-based mechanism excels in mobility performance and is mechanically simple.

However, wheels experience sinkage and slippage, particularly when traversing over loose soil. These phenomena adversely affect the operation of the robot. For unmanned missions, the worst-case scenario is that the wheel buries itself in loose soil and renders the rover stranded; wheel sinkage and slippage cause this scenario. Several studies have been performed on mechanistic improvements and motion control to reduce wheel slippage. Designing larger wheels and using plate-like lugs or grousers on the wheel surface were some of the effective mechanistic improvements (Sutoh et al., 2013, 2012).

Getting stuck in loose soil is accompanied by a sharp increase in wheel sinkage and slippage, as shown in Fig. 1. To avoid this scenario, each wheel of the rover needs to independently estimate its traveling conditions in rough terrain. One goal of this study is therefore to aim at the development of a new intelligent wheel system that can achieve an online estimation of wheel sinkage and slippage. This study focuses on the mechanics of wheel–soil interaction and reviews a key mechanical relationship between the contact forces acting on the wheel from the soil, the wheel sinkage, and the slippage.

In the field of terramechanics, contact forces such as a normal force and drawbar pull were modeled based on the normal and shear stress distributions generated at the contact patch between the wheel and soil. However, these conventional models target heavyweight vehicles such as large-scale construction machines, agricultural vehicles, and...
military vehicles. Thus, small and lightweight vehicles such as lunar/planetary exploration rovers are out of scope for these models. Therefore, detailed measurements of the stress distributions generated beneath a wheel were carried out to re-model the stress distributions for small rovers; a novel stress measurement system to measure three-dimensional stress distributions at the contact patch was developed. In the measurement system, a six-axis force and torque sensor is attached inside the wheel, which can measure the stresses over a specific sensing area on the wheel surface using a specialized contact-part. Three-dimensional stress distributions with the angle of wheel rotation were obtained by integrating several measurement results. The measurements showed precise stress distributions; their validity was discussed by analyzing the equilibrium of wheel weight and the resulting normal force (Higa et al., 2015).

Previous studies by the same authors confirmed stress distribution to be influenced by wheel sinkage, slippage, and terrain conditions, and to acquire different characteristics. If the force acting on the wheel could be estimated, it would be possible to estimate terrain conditions and wheel sinkage/slippage as well. However, the measurement method used for three-dimensional stress distribution cannot always measure the entire stress distribution throughout wheel rotation. Hence, it is difficult to apply this method to robotic rover missions in which the continuous online estimation of the sinkage and slippage is based on on-board measurement. Therefore, to realize the online estimation of wheel conditions (e.g., forces and torques, wheel sinkage, and wheel slippage) in the actual environment, a novel stress distribution model based on three-dimensional stress measurements is required.

Iagnemma et al. (2004) addressed the online estimation of terrain parameters by reflecting the force acting on the wheel, into the conventional model. This study was accomplished by sensing the torque and reaction forces applied by the terrain on a mobile robot. Nagatani et al. (2009) accurately estimated the drawbar pull by directly measuring the normal stress distribution beneath the wheel using pressure sensor arrays on its surface. These related studies show that direct measurement of the forces and torques acting on the wheel is more effective for performing better-wheeled mobility on an unknown rough terrain. Therefore, this study proposes an intelligent wheel that can online estimate the force/torque acting on the wheel and the wheel sinkage and slippage. The aim is to prevent the rover from getting stuck by implementing velocity distribution control using intelligent wheels. Development of a measurement system that allows for an online estimation of wheel sinkage and slippage is addressed, as a first step towards implementing the smart wheel.

This paper first describes the concept of an intelligent wheel system. Next, a single wheel testbed that is developed for comprehensive wheel traveling experiments on loose soil is presented. Finally, the estimation results of wheel sinkage/slippage using a time-of-flight (ToF) camera, which can measure the distance from a target object, are presented based on traveling experiments. The ToF camera-based method achieves better estimation on loose soil, and so it can be used for various field robot applications.

2. Concept of Intelligent Wheel System

Figure 2 shows a conceptual diagram of an intelligent wheel system. The intelligent wheel is composed of a wheel (with a rotary motor for driving it), a ToF camera, and a six-axis force-and-torque (F/T) sensor. A ToF camera was used for online estimation of wheel sinkage and slippage. The ToF camera outputs point cloud data of distance between the sensing IC of the ToF camera and a target object. The cost of calculating the distance is low because of an onboard processor specialized to perform a distance calculation. The ToF camera can also capture an 8-bit/16-bit monochrome image. Hence, wheel slippage estimation is performed based on the optical flow technique. The intelligent wheel can measure forces and torques via one six-axis F/T sensor attached on a wheel’s rotation axis, and one between the wheel and its driving motor. A more accurate estimation of the wheel and terrain conditions can be achieved by combining the rover attitude data measured from an IMU (Internal Measurement Unit) inside the rover.
The intelligent wheel system developed in this study estimates the forces/torques acting on the wheel by using the F/T sensor data. Moreover, it allows for estimation of wheel sinkage and slippage online throughout its travel via the ToF camera that is attached on the outside of the wheel.

This paper focuses on online wheel sinkage/slippage estimation for the intelligent wheel.

3. Single Wheel Testbed

A single wheel testbed was developed for performing comprehensive traveling wheel experiments on loose soil. Figure 3 shows an overview of the single wheel testbed. The size of the testbed, which includes the sandbox, is 2.50 m in length, 1.05 m in width, and 1.25 m in height. The length, width, and height of the sandbox are 1.6 m, 0.3 m, and 0.2 m, respectively. In the laboratory, there are two sandboxes of the same size, filled with Toyoura standard sand and lunar regolith simulant. The traveling experiment can be performed on a different soil simply by replacing the sandbox.

The testbed is composed of a longitudinal unit, restricted to move in a horizontal traveling direction via a linear guide, and a vertical unit restricted to free vertical motion via a linear shaft. The testbed is designed based on static structure analysis so that a wheel weight of 100 N can be applied. In the testbed, a wheel diameter of 250 mm can travel on test soil up to 85 mm in sinkage. Furthermore, the wheel load can also be adjusted by the load canceller mechanism.

The longitudinal unit is connected to a conveying motor that creates horizontal movement via timing pulleys and belt. The conveying motor and timing pulleys are inter-connected via a removable shaft coupling. Therefore, two traveling conditions can be simulated: forced slip by the conveying motor, and free slip by constant traction load. In the latter case, a traction rope is also connected to the timing belt, and several traction loads are hooked up for simulating traveling conditions.
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Figure 4 shows the system diagram of the single wheel testbed. The wheel is turned by a rotary DC motor with a harmonic drive gear with a final gear ratio of 750:1. The wheel motor is connected to a micro-controller via a motor driver, and can produce constant wheel rotational velocity through a feedback controller. The vertical unit is conveyed by the conveying motor or by the traction load in the horizontal direction. The conveying motor is also connected to a micro-controller via a motor driver for maintaining constant horizontal traveling velocity. Wireless serial communication using the XBee modules is used for sending commands and receiving the data between PC and the microcontroller of the vertical unit. The linear encoder of the vertical and longitudinal unit counts wheel sinkage and wheel’s travel distance, respectively. The measurement data obtained by the linear encoders is used for ground truth of the wheel trajectory and not utilized for online estimation.

4. Online Estimation of Wheel Sinkage

Nagatani et al. (2010) studied a visual odometry system using a telecentric camera on loose soil. The wheel sinkage/slippage estimation based on image processing by captured images on the side surface of the traveling wheel were also studied (Milella et al., 2006; Reina et al., 2006). Image-based estimation of the soil’s physical properties is very sensitive to environmental conditions such as intensity of light. An estimation of wheel sinkage more robust against such environmental uncertainties can be achieved by using a ToF camera because it provides three-dimensional point cloud ranging data. This section presents an online wheel sinkage estimation using a ToF camera towards the development of the intelligent wheel.

4.1 Wheel Configuration

Figure 5 shows the test wheel utilized in this study. The wheel weighs 50 N and is connected to a DC motor via the timing belt. The wheel is also controlled so that its rotational velocity is kept constant by a micro-controller. The wheel diameter and width are 250 and 100 mm, respectively. A ToF camera (CamBoard pico flexx) produced by PMD Technologies AG is attached to the side position of the wheel, as shown in Fig. 5. Traveling experiments are carried out for online estimation of wheel sinkage. The ToF camera can sense 100 mm in depth as its minimum ranging distance. The point cloud ranging data can be obtained by utilizing an infrared light flashed from the camera. It was also connected via USB to an operating PC.

Estimation system is developed on the operating PC using a virtualized Ubuntu with Intel Core i7-3632QM CPU (2.20 GHz x 4) processor and 8 GB of RAM is allocated to the virtual machine (Ubuntu). Sinkage calculation is performed on the system using the point cloud data received from the ToF camera. Maximum frame rate of the ToF camera is 45 Hz. The sinkage is performed at an interval of 5 Hz due to the wheel’s slow velocity.
4.2 Experimental Conditions

This study used the following procedure to estimate wheel sinkage using the three-dimensional point cloud data:

1. Extract point cloud data in the region of interest using a Pass Through filter.
2. Down-sample the point cloud data using a Voxel Grid filter.
3. Calculate the arithmetic mean of the point cloud data.
4. Calculate wheel sinkage from the geometric relationship between the origin coordinate of ToF camera and the wheel.

Wheel sinkage calculated by the estimation method was compared with the ground truth measured by the linear encoder of the vertical unit. Here, the target circumferential velocity at the wheel rim was controlled to be 20 m/s. A comparative analysis of wheel sinkage was performed under three different slip ratios: 0%, 40%, and 80%. The slip ratio $s$ is introduced as an evaluation index:

$$s = \left(1 - \frac{v_x}{r \omega}\right) \times 100.$$  \hspace{1cm} (1)

where $v_x$ is the traveling velocity of the wheel, $r$ is the wheel radius, and $\omega$ is the wheel’s angular velocity.

Slip ratio is defined as the ratio between the actual traveling velocity and the circumferential velocity of the wheel. In the general case of a driving wheel, the slip ratio becomes a positive value from 0 to 100 expressed as a percentage. The value $s = 0 \, [\%]$ corresponds to the case of the wheel traveling without any slippage, and $s = 100 \, [\%]$ is a case in which the wheel slips completely and is getting stuck.

Fine lunar regolith simulant (FJS-1 (Kanamori et al., 1998)) was used as the test soil. The soil in the sandbox was mixed loosely and then made flat before each traveling experiment. The optical reflection of FJS-1 is smaller, compared to Toyoura standard sand.

4.3 Results and Discussions

Figure 6 shows the resulting point cloud data of the ranging distance obtained by the ToF camera. The blue region was extracted by procedures 1 and 2. Figure 7 also depicts the time histories of the estimation results of wheel sinkage over the wheel traveling time and the ground truth measured by the linear encoders of the vertical unit. The results confirm that estimated sinkage was better matched with ground truth under all slip conditions. Although the maximum estimation error was less than 2 mm, most estimation errors were less than $\pm1$ mm. In the sinkage estimation method using the ToF camera, the average value of the point cloud data in the extracted region (shown as the blue area in Fig. 6) was calculated. A probabilistic filtering approach will be employed to achieve a more accurate estimation.
5. Online Estimation of Wheel Slippage

Online estimation of wheel slippage is one of the key technical challenges for a wheeled mobile robot traveling on loose soil. The ToF camera provides an 8-bit monochrome image in addition to point cloud ranging data. The image can also be obtained by the use of infrared light. Thus, the image obtained by the ToF camera is not influenced by environmental lighting conditions but cannot discriminate color information of target objects. The image size is 224×171 pixels. Although this is a low-resolution camera, it is enough to track soil particles at close-range from the wheel. The wheel slippage was estimated by applying an optical flow technique to the images.

5.1 Estimation Method of Wheel Slippage

According to the definition of wheel slip ratio in Eq. (1), the circumferential velocity of the wheel can be calculated by the wheel radius and encoder of the wheel motor. For an estimate of the wheel traveling velocity, the actual traveling velocity of the wheel under several slip ratios is required. Although the ToF camera provides the point cloud data, it is difficult to estimate the wheel traveling velocity using that data. To estimate the wheel traveling velocity using the point cloud data, apparent features in the target environment are essential. Therefore, an estimation method was proposed for the wheel traveling velocity that applied an optical flow technique to the monochrome images.

In general, two typical optical flow techniques can be used. One is the sparse optical flow technique (e.g., the Lucas-Kanade algorithm (Bouguet, 2000; Lucas and Kanade, 1981)), and the other is the dense optical flow technique (e.g., the Farneback algorithm (Farnebäck, 2003)). The former techniques preliminarily detect features of an image and then track the movement of each feature. The method has the advantage of low calculation cost. However, feature extraction becomes more challenging for a ToF camera because it flashes an infrared light when obtaining images. Therefore, the latter method was used for slippage estimation. Although the latter method has a higher calculation cost because of the need to calculate all pixels by averaging a group of pixels, such a concern emerges only when using high definition images. To reduce the calculation cost, the wheel traveling velocity was estimated as follows:

1. Mask the image by a region of interest.
2. Calculate optical flows using the Farneback algorithm.
3. Display the results in the image by averaging 12×12 pixels.
4. Calculate the traveling velocity by inputting the distance to the soil surface.
5. Calculate the wheel slippage based on Eq. (1).

The experiments were carried out under the same conditions as the experiments for wheel sinkage estimation. The ground truth data of the wheel slippage was measured by the encoders of both the wheel motor and the conveying motor. These motors were controlled to have constant rotational velocity during the experiments. A central region of the image was used to reduce image distortion. The averaging sinkage value at the central region was also applied.
5.2 Calculation of Traveling velocity

The optical flow algorithm provides the travel distance using two images. It is necessary to know the actual length of each pixel to calculate the traveling velocity \( v_x \). The actual length of each pixel can be obtained by the relationship between the view angle and the resolution of the ToF camera. The traveling velocity is calculated as follows:

\[
v_x = z_d \tan \left( \frac{\theta_H}{2} \right) \cdot \frac{2}{n_H} \cdot \frac{\Delta x}{\Delta t} \tag{2}
\]

where \( z_d \) is the distance between the origin of the ToF camera and the soil surface, \( \theta_H \) is the viewing angle in the horizontal axis of the ToF camera, \( n_H \) is number of horizontal pixel of the image, \( \Delta x \) is average travel distance provided by an optical flow, and \( \Delta t \) is interval time between each image.

The monochrome image provided by the ToF camera calculates the traveling velocity at a 5 Hz frame rate. However, to account the loss of received data during the experiment, most estimates are provided at approximately 1 Hz. The computation frequency is sufficient due to the wheel’s slow velocity.

5.3 Results and Discussion

Figure 8 shows a snapshot of the optical flow technique for \( s = 0 \text{ [%]} \). The result confirmed that the soil particles were better tracked based on the optical flow. Each line shows the distance between two images and each plot shows the current position of the tracked pixel block. Therefore, this result shows that the soil moves to the left of the image.

Figure 9 depicts the estimates of the traveling velocity of the wheel in steady state over travel time. Each black line shows the time histories of the ground truth data by the linear encoder. Each plot shows the time histories of the estimated traveling velocity. Most of the estimates vary quantitatively but reflect their qualitative tendency. Table 1 lists median values of each estimated traveling velocity and their absolute errors. This study performed experiments under forced-slip control. In other words, the constant traveling velocities listed in Table 1 were set forcibly. The results show that the absolute errors between the target velocity and estimated velocity are less than 0.7 mm/s. It can thus be concluded that traveling velocity can be estimated with a resolution of the order of 1 mm/s.

Figure 10 shows the estimated slip ratios of the wheel, which were calculated in Eq. 1 by inputting the estimated traveling velocity shown in Fig. 9. The median value of each estimated slip ratio under the steady state condition was calculated to validate the estimated wheel slippage. Table 2 lists median values of each estimated wheel slippage and their absolute errors. Although estimated traveling velocity under large slip ratio was less accurate, the absolute errors of each slip ratio are less than 3.9%. In particular, under a small slip ratio, the absolute error was 1.4%. It can therefore be concluded that wheel slippage can be estimated precisely, and the proposed method is validated for the online estimation of wheel slippage.
6. Conclusion

This study performed an online estimation of wheel sinkage and slippage using only a ToF camera as the first step in the development of an intelligent wheel. The estimation results showed that most of wheel sinkage could be estimated to within ±1 mm absolute error using a ToF camera that has millimeter-order space resolution. Traveling velocities of the wheel were also estimated to within 1 mm/s. Wheel slippage was estimated to within an absolute error of 3.9%.

For future work, the attachment position of the ToF camera will be examined to enhance estimation accuracy. In addition to this, a six-axis F/T sensor will be introduced to the wheel, and an attempt will be made to estimate terrain conditions or soil characteristics by measurement of force and torque data acting on the wheel’s rotational axis.

Nomenclature

\( s \) Slip ratio \( [%] \)
\( r \) Wheel radius \( [\text{mm}] \)
\( v_x \) Wheel traveling velocity \( [\text{mm/s}] \)
\( \omega \) Wheel angular velocity \( [\text{rad/s}] \)
\( z_d \) Distance to the soil surface \( [\text{mm}] \)
\( \theta_H \) Horizontal view angle \( [\text{°}] \)
\( n_H \) Number of horizontal pixel of the image \([-]\)
\( \Delta x \) Average distance \( [\text{mm}] \)
\( \Delta t \) Interval time \([\text{s}]\)

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References


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<td>Target slip ratio [%]</td>
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