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REVIEW OF VIBRATION-BASED SURFACE & TERRAIN CLASSIFICATION FOR WHEEL-BASED ROBOT IN PALM OIL PLANTATION

Bukhary Ikhwan Ismail
Senior Staff Researcher, Industrial Autonomy, IoT Systems, MIMOS Berhad, Kuala Lumpur, Malaysia
ikhwan.ismail@mimos.my

Hishamadie Ahmad
Senior Engineer, Industrial Autonomy, IoT Systems, MIMOS Berhad, Kuala Lumpur, Malaysia
hishamadie.ahmad@mimos.my

Shahrol Hisham Baharom
Staff Engineer, Industrial Autonomy, IoT Systems, MIMOS Berhad, Kuala Lumpur, Malaysia
shahrol.baharom@mimos.my

Muhammad Nurmahir Mohamad Sehmi
Engineer, Industrial Autonomy, IoT Systems, MIMOS Berhad, Kuala Lumpur, Malaysia
nurmahir.sehmi@mimos.my

Mohammad Fairus Khalid
Principal Engineer, Industrial Autonomy, IoT Systems, MIMOS Berhad, Kuala Lumpur, Malaysia
fairus.khalid@mimos.my

Abstract

Palm oil can grow in almost flexible topography. On flats, slopes, hilly, or undulating areas and whether on inland or reclaimed coastal areas. This makes the palm oil plantation environment unique with various soil types & surfaces. Each surface has a unique physical characteristic that directly influences the driving, handling, power efficiency, stability and safety of a robot. A mobile robot should have knowledge not limited to obstacles, but also the surface that the robot traverses to estimate wheel slippage and apply corrective measures. This paper discusses the harshness factors in palm oil plantation estates and the effects on wheel traction. We then present our review of several vibration-based surface classification techniques. Based on our survey, a combination of multimodal sensory for surface classification is more suitable to identify surfaces and terrain in palm oil plantations.

Keywords

Robot, Surface Classification, Terrain Classification, Vibration, Palm Oil, Plantation

1. Introduction

Malaysia's RM67.74 billion palm oil (PO) industry relies heavily on foreign labour, especially in the infield plantation sector. Since the Covid-19 pandemic and Movement Control restrictions, estates are short of workers. Palm oil production output and export were affected significantly in Malaysia. Harvesting and evacuation of fresh fruit bunches are activities in the estate that require a high number of foreign workers (Deraman et al., 2013). Both activities represent about 60% of the total work operation and account for 15% of the fruit production cost. Improving mechanisation and automation in these areas can increase production output as well as reduces the dependency on foreign labour.

Our goal is to introduce an autonomous wheel robot to assist in infield operation. To navigate in a harsh estate environment, we need a mobile robot that can traverse through harsh surface and terrain settings. This paper describes our survey in surface classification techniques for the wheeled-based robot. We organise the paper as follows. Section 2 discusses the palm oil plantation's environmental harshness and challenges. Section 3 describes the environmental parameters that will affect the robot. We described surface vibration classification processes in

Section 4. Section 5 provides a survey on the state-of-the-art techniques for surface detection, specifically vibration-based classification.

2. The Harsh Plantation Environment

We can describe the harshness of the plantation estate environment in multiple factors. Surface or soil in estates varies from clay, silt, sand, gravel, asphalt, peat or man-made trunk road mix with chemicals and additives as shown in Figure 1. Each soil has different water retention, coarseness, float and machine traverse-ability. Clay soil has high water retention, because of small particles and water easily trapped between them. After the rain, the water is absorbed slowly into the soil making it prone to water puddling and flooding as shown in Figure 2. Sandy soil has poor water retention, and after rain, it would quickly seeps through the soil. Peat soils as shown in Figure 3: Infield with semi-compost material, are very spongy and have very high floatation (Woittiez, 2022). It is common for the estate ground covered with low grass or small to medium shrubs or vegetation as shown in Figure 4. For a robot to manoeuvre successfully, we must take into consideration of multiple surfaces and their characteristics.

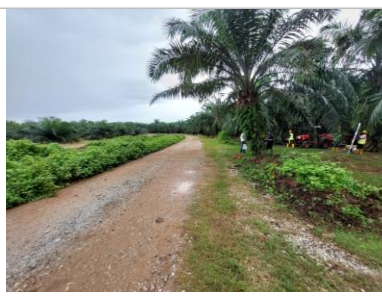
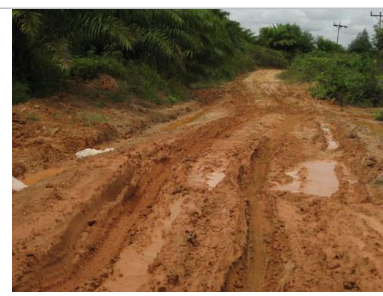
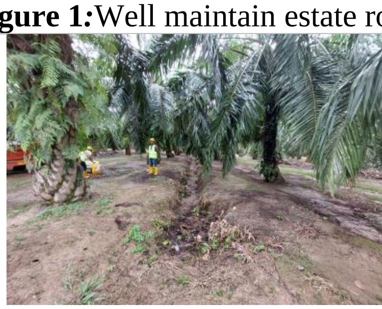
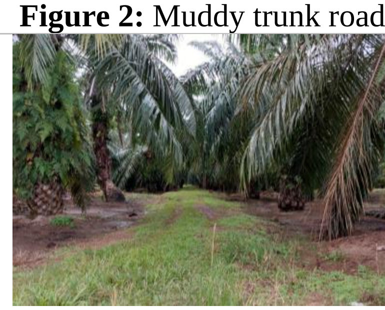
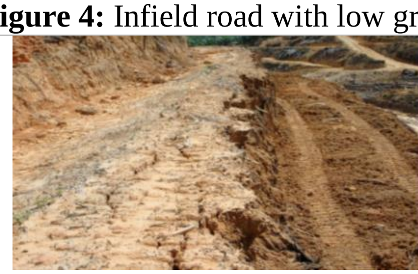
 **Figure 1***:*Well maintain estate road	 **Figure 2:** Muddy trunk road
 **Figure 3**: Infield with semi-compost material	 **Figure 4:** Infield road with low grass
	

Figure 5: Terrace design on hilly terrain(Fair, 2020)	**Figure 6:** Terrace Close-up (Fair, 2020)

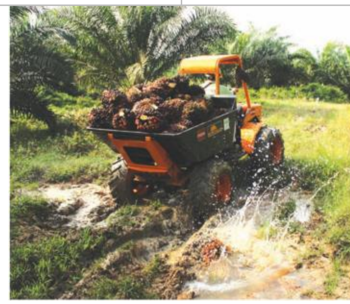


Figure 7: Rhyno Transporting FFB (Deraman et al., 2013)

(Source – Figures 1 & 2 https://www.sustainableagriculture.eco, Figures 3 & 4 Sime Darby Plantation – Carey Island, Figures 5 & 6 - https://www.eco-business.com

Terrain or relief are vertical and horizontal dimensions of the land surface. Factors such as slope, elevation and orientation describe the terrain feature as shown in Figure 5 & Figure 6. It dictates the movement of water, making certain soil wet or dry. Unlike other crops, e.g., rapeseed, soy, and corn; the land is flat. For mechanisation in PO to be effective, it needs good harvesting paths to carry out infield operations. Without it, accessibility to the machine will be limited, especially in areas of steep terrains and pockets of hill locks.

Malaysia is a tropical climate with high rain all year long. The monsoon season is from November to February and is prone to flooding. Heavy rain and high humidity change the surface characteristic. Some estates have natural clay soils. During the dry season, it is compact, and during the wet season, the clay particle swells by absorbing water. It causes the clay bond to fail and break the road surface and possibly form potholes as shown in Figure 2 and Figure 7. These potholes are dangerous to vehicles carrying heavy loads. Estate in Lahad Datu Sabah for example, typically have sandy soil with poor clay content and very low moisture instead (Shuib et al., 2020).

PO plantation estate is extremely large. For example, a single division of estate has 2413 hectares with 236,727 palm oil trees, with an average of 98 trees per hectare (Myspatial Sdn. Bhd.). 61% of palm oil is owned by large private estates. Another 39% are owned by 300,000 small to medium farmers (Khalid et al., 2021). The sheer size of the plantation requires a long-operation machine. Palm oil trees can produce fruit for up to 20-30 years. Old plantations or even small estates might not have proper topological planning for water flow on slopes and plains. Thus, prone to water puddling and challenging for any machine to operate. Figure 5 shows proper terracing on the hillside.

PO is planted about 20 feet between each other. After a certain age, the fronds provide a thick canopy. GPS or RTK solution might be hard to pinpoint any mobile robot's location. If the canopy percentage is over 60%, locking the location coordinate will not be workable (Aini et al., 2014). Cellular signal is weak in most remote areas. With no significant landmark or marker makes it is hard to navigate.

When any of the parameters changes, wheel traction and traversability of a mobile robot will be affected. Thus, having infield information about the environment and surroundings, i.e., surface and terrain information is important for the robot to navigate properly.

3. Mobile Robots in Harsh Environment

Conventional motion control systems and motion planning strategies deal with smooth surfaces and terrain. It is imperative to detect the topology and its surfaces to determine the best possible route. Profile that comprises parameters such as speed, torque, braking, and cornering can be customised to suit individual surfaces and environments.

3.1. Requirement of Autonomous Robot in Plantation

While there is plenty of robotic form factor e.g., legged, track-based but they lack the range and support infield operation. It may be challenging for certain terrain and soil condition i.e., peat soil & muddy surfaces. Track-based vehicles provide better traction and floatation on soft peat soil. But limited in range and speed. Wheeled robots are among the popular design in an autonomous robot system. It has an advantage over other designs because of the distance it can cover, ease of manoeuvrability and suitability for palm oil estate operation. Here we list some requirements for a wheeled robot: -

- Support infield operations - Requires acceptable carrying and towing load capacity. The robot must be flexible to attach common agricultural fixtures, e.g., bin, sprayer, hook, and grabber.
- Surface & terrain traversability - good traction wheels & more than 15% climbing degree ensure the traversability of the robot on steep terrain.
- Cost-effective - 30% of PO estates are owned by small to medium farmers. The solution must be cost-effective and accessible to them.
- Support large estate - Palm oil estate is large in land area. Operational distance, time and robot maximum speed play a crucial role for a medium to a large estate.

3.2. Effects of Harsh Landscape on Wheel Traction

A harsh topological landscape and a multitude of surfaces make it challenging for any machinery on the plantation. The harsh environments cause farmers to use different transportation depending on surface conditions and weather. To support infield transportation, machinery is preferred to increase efficiency. But where the path is inaccessible, wheelbarrows and animal-driven carts, i.e., using buffalo, are still being used (Deraman et al., 2013) (Muhamad & Aziz, 2018). To have better floatation on peat soil and challenging terrain, several vehicle configurations use wide tires, rubber track or a combination of both e.g., Beluga or Rhyno, as shown in Figure 7. The effects of insufficient traction can be described: –

- Insufficient traction will cause the vehicle to slip, drift, over or under-steer and even dig the soil. It can lead to topple or fall, which poses a safety issue to the mobile robot and its surrounding.
- If speed is not suitable for the current road condition, safe braking distance may compromise.
- Without proper traction compensation, wheel slips will occur, which leads to inefficient energy usage.
- Shifted weight during operation can affect the vehicle's centre of gravity and each wheel has a different traction requirement.

To improve traction, some strategies can mitigate the issues: -

- Suitable tire profile, width and tire pattern for sufficient surface contact. Reducing tire pressure also helps to increase traction (Muhamad & Aziz, 2018).
- Distributing weight evenly and proper vehicle centre of gravity on flat or steep terrain increases wheel traction.
- Incorporating a control system can detect tire slippage and adjust the motor speed, torque, and braking profile accordingly.
- Other non-trivial systems that can help tractions are a tire monitor which keeps track of pressure, tire load, wear and tear, puncture and even temperature. This gives additional inputs to the robotic system to react accordingly. To counter harsh conditions, an adaptive suspension can be used for the vehicle.
- If the terrain and surface classification knew beforehand, the system can navigate and pass through with a certain degree of certainty to decide or find an alternate route.

4. Surface Classifications

Surface classification can be categorised by visual and non-visual techniques. In this paper, we focus on the latter. Non-visual surface identification uses haptic or accelerometer-based sensors. It's usually a simple sensor, with non-complex data output. Since the data is not complex like vision-based data, the processing requirement is low. The hardware form factor is usually small, robust, rugged and maintenance-free suitable for outdoor usage. One of the biggest differences compared to the visual sensor counterpart is, the non-visual system detects "as it happens". To have a "just-in-time" reaction, the overall solution, i.e., algorithm or communication bus must be executed in real-time. The operation speed of the robot plays a role in how fast the algorithm is needed to identify and classify the surface.

4.1. Vibration-based Surface Classification

When the vehicle is in motion, surface unevenness produces a vibration signature. Some motion sensors that can be used are vibration-specific sensors, gyroscope, or acceleration values in IMU sensor. One study was conducted using a tactile metal probe touching the surface and the metal rod attached to the IMU. This gives a direct profile of the surface, rather than being dampened by vehicle suspension mechanisms or tires (Giguere & Dudek, 2011). The z-axis of the accelerometer, which is a vertical movement of the robot, would be the point of interest. Some experiments combine gyroscope data and IMU for surface classification (M. Concon et al., 2021).

Based on our literature review, it is common to constant certain parameters. For example, vehicle dimension (length, width) and operational variable (speed, velocity and trajectory). Several works experiment on variable speed and manoeuvrability, i.e., cornering, acceleration or de-acceleration. Training the classifier with these data would be closer to real-life applications. Multiple external factors affect the robot's vibration: -

- Anatomical of the robot i.e., robot length, width, ground clearance, suspension system, tire dimension and profile.
- Application use cases - of the robot to support various infield operations. The mounting of different extensions might dampen or amplify vibration.
- Vehicle in motion - speed and velocity. Many surface identification and classification experiments stick to one speed across the different surfaces for ease of the experiment. Different speeds give different amplitudes of collected acceleration signals.(Sattar et al., 2018) argues at high speeds, the output discrimination between normal road and pothole

regions was difficult. Some collect multiple speeds. e.g., 15, 30, 60km/h and normalised to a single value (Sattar et al., 2018) while others collect and test the classification accuracy at multiple speeds (Bai et al., 2019). (Yi et al., 2015) Introduce a lookup table by categorising speed into different ranges. Each event is then indexed according to the ratio of standard deviation in which the event had been detected.

- Wear and tear of components - over time, any joint or moving mechanical parts, e.g., tire, suspension, steering, may deteriorate. Vibration might increase or new vibration is introduced due to mechanical failure. It is imperative to take into consideration future work enhancement.

4.2. Classification Techniques

There are two common techniques for vibration-based classification. First is feature engineering. It identifies and selects distinct vibration feature patterns and trains the model. Second, is feature learning. It trains the classifier model using raw data instead of extracting vibration features.

Good classification depends on good-quality data. Usually, filters are applied to remove noise that distorts parts of the signal. For example, a high-pass filter is used to spot low-frequency evidence such as speed change and vehicle manoeuvring, which have lower frequencies than road surface anomalies (Sattar et al., 2018). Some remove data outliers by applying *Median Absolute Deviation* (MAD) (Sayed et al., 2018). If possible, the vibration that originates from the robot itself, i.e., motor vibration, suspension or transmission, be removed.

It is a common practice where data will be chunked into predetermined segments. Each segment can comprise X number of data points and each segment overlaps by e.g., 20% or 50% between the previous segment. Studies show that the number of data points per segment affects the accuracy of the model and the training time (Sattar et al., 2018), (Concon et al., 2021), (Giguere & Dudek, 2011). If the segment to large, accuracy will not increase. To determine the most effective classifier algorithms parameter such as accuracy, speed of identification, and training time is often compared.

In Feature Engineering, raw data is labelled according to the surface. Then the data is split into short segments. A common method for extracting interesting features is from time or frequency domain analysis. For the time domain; mean, variance, skewness, kurtosis, and the fifth moment can be used. For the Frequency domain, PSD, FFT or the sum of the higher half of amplitude. Some argue that time-domain analysis is better than the frequency domain. Frequency analysis tends to ignore important cues in the phase spectrum, which would not be good for surface detection (Giguere & Dudek, 2011).

Feature Engineering relies heavily on the accurate vibration pattern of the surface. Instead of extracting features, end-to-end learning can learn unique feature representations directly from the raw data. Usually, the algorithm uses deep learning techniques that require high computing processing during training. But training can be done offline on the cloud for example and does not affect the mobile robot computation. In table 1, we surveyed several research works that classify surfaces based on vibration profile. In the table below, we discuss the methods and their accuracies.

Table 1: *Vibration-based Surface Classification Review*

Surfaces	Method	Accuracy	Comments
Wood, carpet, concrete, gravel, tiles	(Concon et al., 2021) Uses lateral, longitude, vertical acceleration, and angular velocities as data input with minor pre-processing. Data is segmented into 1.5 seconds or 75 samples per window with an overlap of 20% to conserve the temporal dependencies between time steps. Use deep learning to train the classifier; LSTM, 1D convolutional Network and Convolutional Neural Network LSTM (CNN-LSTM)	CNN-LSTM provides the highest accuracy - 98.49% out of all classifiers they tested.	A small-scale robot was used that might not reflect the actual robot form factor for our case. The method is easy to replicate.
Packed/loose gravel, sand, sparse/tall grass, asphalt	(DuPont et al., 2008) Tested with varying window sizes to tune classification accuracy. The experiment was conducted on a robot equipped with a shock absorber and at different speeds. Data is processed using FFT and trained using a Probabilistic Neural Network	Confidence level of 90-100% for various terrains.	The author noted that an additional wheel sensor to get wheel slippage can improve classification accuracy.
Grass, tile, carpet, terrazzo, gravel,	(Giguere & Dudek, 2011) A small vacuum-like robot was used. The accelerometer is attached to a metal tactile rod that touches the ground surface. The	For 1 and 4-second windows, the learning accuracies range from 89.9% to 94.6%.	The author claims using a tactile probe that touches the surface will provide a more accurate

wood, pack dirt.	surface was classified using Artificial Neural Network		representation of the surface. For our outdoor robot, we foresee issues in the durability and applicability of the probe.
brick, flat, soil, cement, sand	(Bai et al., 2019)Tested two robot platforms (Clearpath Jackal & Blue Whale XQ) at multiple speeds. It extracts features from FFT and uses a deep neural network based on Multilayer Perception for training the classifier.	Up to 98% accuracy for both mobile robot platforms at 6 different speeds ranging from 0.2m/s to 0.6 m/s	Testing the classification method at two different platforms and multiple speed proofs is valuable for real-life use cases.
bedrock, soil and sand targeting for Mars exploration	(Otsu et al., 2016) uses vibration sensors and onboard video capture to learn from onsite experience through self-supervised learning. For vision, it uses the colour feature and vibration data uses the Wavelet power spectrum feature. It is noted that visually similar terrain may differ from mechanical vibration. It employs co- and self-training to train two classifiers, vision and vibration separately and re-train them iteratively on each other's output. For co-training, it uses SVM.	Up to 82 % of accuracy.	Since the planetary rover has not gone to any planet before, thus training data are not available beforehand. Rovers need to learn quickly from their own experience in the early phase of surface operation. The approach might be suitable for harsh palm oil estate conditions.
To check road condition.	(Sattar et al., 2018) comparative studies of detecting road unevenness using built-in sensors in the smartphone. To check road	Since it is a comparison study for other work, the	It gives us an idea of how to do surface classification even

Either manmade or road damage.	surface anomalies such as potholes, cracks, and bumps as the car passes over. It reviewed two types of sensors to collect vibration from phones. Accelerometer and gyroscope. The identifies the use of threshold-based, machine learning (SVM, K-Means Clustering, Linear Regression, and others) and Dynamic Time Wrapping Approach in several works.	results vary from 60 to 90% accuracy.	by using smartphones.
Asphalt, tile cobble, gravel concrete, artificial grass, plastic.	(Mei et al., 2019) Vibration signal from accelerometer by subtracting gravitational acceleration and splitting the signal into segments. Each segment contains a 50% overlap of successive segments. Uses One Dimensional Convolutional LSTM (1DCL) to learn spatial and temporal features of the vibration data.	using 1 Dimension Convolutional Layer (1DCL) with an accuracy of 80.18%	Vibration collected on the dampened signal due to tire and suspension provides a real implementation of attaching the IMU to the vehicle. It tested feature engineering and feature learning. Based on their experiment, feature learning has better accuracy.

(Source: Authors' Illustration)

5. Discussion and Conclusion

Surface detection is one aspect of inputs for autonomous robots to decide on better traction, safety and optimal navigation. Based on our survey, relying solely on vibration data might not be sufficient. We can add additional inputs, such as vision to detect surfaces and border identification to have better classification accuracy (Gonzalez & Iagnemma, 2018; Masha & Burke, 2021). We can further enhance this with a multi-modal approach, which fuses robot position information with wheel slippage information.

Tropical weather in Malaysia is hot, rainy, or highly humid. Each weather changes the soil characteristics and affects wheel traction. It is possible to include weather data and data from humidity sensors in the current environment. Historical knowledge on the previous traverse path can be stored for future reference too. These additional data can help robots decide on navigation tasks or to estimate the surface condition.

In future, we would like to study the combination of vibration sensors with vision such as feature extraction & colour. The robot must be able to traverse a multitude of surfaces and terrains. Our research was done during the pandemic. Access to the palm oil plantation estate was restricted. Our understanding of the palm oil plantation estate surfaces and terrain characteristics was limited to literature and online sources. It is possible that we may miss out on important points and observations. We need to do an up-close site visit at the plantation estate, to study the environment and infield plantation operations to have a better understanding to design our mobile robot.

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