Journal of Oil Palm Research
DOI: https://doi.org/10.21894/jopr.2024.0008

AUTONOMOUS HARVESTING ROBOT FOR OIL PALM PLANTATION: A REVIEW

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ABSTRACT

Due to the continuous labour crisis, the oil palm industry in Malaysia has lost an estimated worth of RM10.46 billion unharvested fruit in the first five months of the year 2022. A robotic system in automating the harvesting process of the oil palm fresh fruit bunches (FFB) is proposed to solve the existing problems related to oil palm harvesting and further enhances the development of oil palm harvesting technologies. This article aims to review the six identified key technologies for solving the technological challenges in the development of this robotic system. The key technologies are as follows: (1) oil palm ripeness detection; (2) oil palm cutting mechanism; (3) tree climbing mechanism; (4) motion trajectory planning for fruit harvesting manipulator; (5) localisation; (6) navigation and obstacle avoidance. Six criteria for successful implementation of the proposed harvesting robot are discussed followed by recommendations on the type of technology used. The integration of these technologies as a complete robotic system is analysed. Prediction on the trend of technological development in oil palm harvesting is discussed.

Keywords: climbing mechanism, oil palm harvesting mechanisation, motion trajectory planning, navigation, ripeness detection.

Received: 28 May 2023**; Accepted:** 17 November 2023**; Published online:** 23 January 2024.

INTRODUCTION

Overview of Oil Palm Industry

The oil palm industry is one of most significant commodity crops in Malaysia, with exports totalling more than RM64.84 billion in 2019 (Parveez *et al.*, 2020). With estimated oil palm plantation area of 5.9 million hectares, the industry is working harder than ever to address concerns about sustainability and safety that have been raised on a worldwide scale. Furthermore, the oil palm plantation in Malaysia is accountable for the employment of 428 000 workers as of May 2017 (Tang and Al Qahtani, 2019). According to Meijaard *et al.* (2020), palm oil is subjected to about 40% of the present global yearly demand for vegetable oil for use in food and fuel. Therefore, improving the overall efficiency in oil palm industry will provide huge positive impact to the world.

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Problems Related to Oil Palm Harvesting

Labour shortage. According to FMT Reporters, (2022), the oil palm plantation was short of 28 940 workers, each of whom could pick two tonnes of fresh fruit bunches (FFB) every day. Due to the continuous labour crisis, the oil palm industry in Malaysia has lost an estimated worth of RM10.46 billion unharvested FFB from January to May of year 2022. In Malaysia, foreign workers make up more than 75% of the total workforce in oil palm plantations (Channel News Asia, 2022). The difficulty in hiring foreign workers, particularly those from Indonesia, occurs because of immigration restrictions brought on by COVID-19 pandemic.

The work environment in oil palm plantations is considered as 4-Ds (dirty, difficult, dangerous, demeaning) by Malaysians (SOPPOA, 2021). According to the study conducted by Bhuanantanondh *et al.* (2021), 88% of oil palm harvesting workers suffered a prevalence of musculoskeletal disorders (MSDs) in year 2020. The most affected body parts of MSDs for oil palm harvesting workers include the lower back, shoulder, neck, upper back, and hand. The common risk factors of MSDs in oil palm harvesting include lifting and carrying heavy FFB, extended or repeated stooping, and repetitive muscle movements. Moreover, the lack of ergonomics in the oil palm harvesting process has caused high rates of developing MSDs on workers in oil palm plantations as compared with other agricultural sectors (Bhuanantanondh *et al.*, 2021).

Most oil palm plantations have uneven terrain, which is usually located in rough and sloping areas (Sowat *et al.*, 2018). Therefore, accessibility by workers to the oil palm plantation is the biggest factor limiting the use of mechanised harvesting equipment. Therefore, manual labour harvesting is still regarded as the most effective choice.

FFBs of tall oil palm trees are difficult to harvest. The older oil palm trees can grow up to 20 m in height (Britannica, 2021). Highly skilled workers are required to harvest the FFB at this height. Despite the high yield of these older oil palm trees, it is claimed to be not economical to harvest them. Therefore, the tall oil palm trees will be left unharvested in the plantation and pending to be replanted. This issue has been solved by planting the dwarf variant of the oil palm, which can grow up to 6 m in height (Bernama, 2021). However, replanting the oil palm trees takes time and there is still large percentage of tall oil palm tree that remains unharvested.

Trends in Development of Oil Palm Harvesting Method

Malaysia has progressed through several harvesting technologies, from manual to semi-mechanised to fully mechanised. The manual harvesting process is usually done by using two types of tools: Chisel and sickle. Chisels are normally used for harvesting FFB from shorter trees, which are below 3 m in height. For taller trees, a sickle with long pole is used. Handling these tools, especially those with long flexible pole, is a very difficult and dangerous task (Sowat *et al.*, 2018). Therefore, the workers must possess exceptional tool handling skills in addition to having sufficient energy to complete the cutting task for taller oil palm trees.

To solve the issues related to manual harvesting, semi-mechanised tools are developed which are more economical and efficient. The Cantas motorized cutter was developed by the Malaysian Palm Oil Board (MPOB), capable of harvesting FFB at 4.5 - 6.0 m in height (Zahid and Firdaus, 2018). Cantas enables 37% faster cutting than using a traditional manual sickle with pole, while productivity increased from 4.19 to 11.60 t FFB/day (Sowat *et al.*, 2018). Although Cantas had demonstrated to boost harvesting effectiveness, however this technology possesses various limitations. Firstly, the maximum reach for Cantas is only 6.0 m while the height of oil palm trees can go up to 20.0 m. Secondly, the workers using this mechanised cutter are exposed to a high magnitude of vibrations. Exposure to these vibrations for an extended period may cause the development of Hand-Arm Vibration Syndrome (HAVS), affecting the health of the workers (CCOHS, 2017).

Source: Shuib *et al.* (2011)

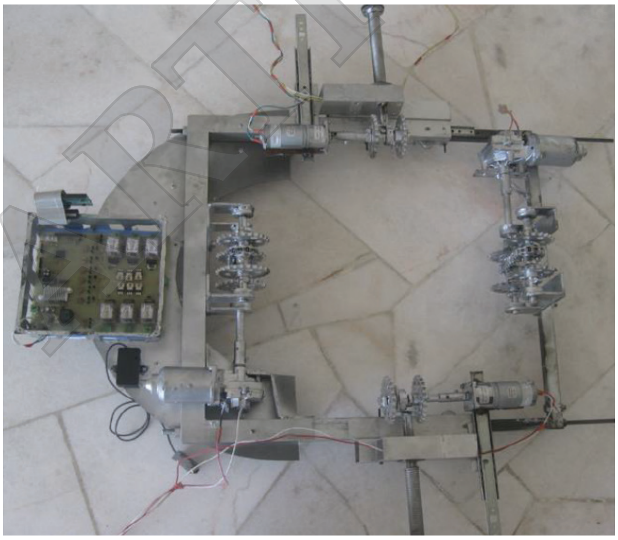
Figure 1. FFB harvesting operation with Cantas motorised cutter.

Other than semi-mechanised harvesting, there are several attempts that have been made on fully mechanised harvesting techniques. One of the techniques is using a harvesting machine with a cutting mechanism mounted to the end effector of a boom (Sowat *et al.*, 2018). These cutting mechanisms included hydraulic scissors, circular blades and wire-cutting mechanism. The boom of the harvesting machine was mounted onto a tracked vehicle powered by a 31.5 hp diesel engine with a loading capacity of 500 kg (Shuib *et al.*, 2011). This technique achieved the productivity of harvesting 4 to 6 t FFB/ day. However, it had a limited maximum height that the cutting mechanisms could reach. Increase in the maximum reach would require the use of longer boom, which would be heavier, larger in size and less cost-effective. Moreover, the relatively large size of the vehicle also caused accessibility issues, especially on narrow and rough terrain. Furthermore, heavy vehicles, which are 10 to 30 t in weight, often cause soil compaction when running through the oil palm estate (Sowat *et al.*, 2018). This would in turn degrade the soil quality and reduce the crop yields.

Source: Shuib *et al.* (2011)

Figure 2. Fully mechanised harvesting machine.

Another approach to fully mechanised harvesting is by using a tree climbing robotic harvester (Shokripour *et al.*, 2010). This climbing robot was designed to be as light as possible, hence, reducing the amount of energy required to reach the top of the tree as shown in *Figure 3*. Further details on the tree climbing mechanisms are discussed under the "*Tree Climbing Mechanism*" section. The advantage of using climbing robot in oil palm FFB harvesting is that it can reach the top of the oil palm tree regardless of the height, which solves the limitations of other harvesting methods. According to Sowat *et al.* (2018), the current climbing robots could only climb trees with smooth surfaces. However, oil palm trees are usually full of frond stubs, which is the results of pruned fronds and forms irregular surface on the entire trunk. Hence, a reliable tree climbing mechanism for oil palm tree has not been fully developed to this date.



Source: Shokripour *et al.* (2010)

Figure 3. Oil palm climbing robot.

Research Problem

A robotic system in automating the harvesting process of the oil palm FFB is proposed to further enhance the development of harvesting technologies and solve the existing problems. The technological challenges for developing this robotic system are discussed as follows.

Difficulty of a mobile robot to manoeuvre autonomously in oil palm plantation. The terrain of oil palm plantations can be categorised into four major types: Flat, hilly, peat and sandy (Teoh, 2000). The hilly terrains are less accessible to the mobile robot especially on wheels or tracks due to the limited climbing angles. Besides, the terrains with peat soil are soft, damp, and uneven. This will cause the mobile robot to have a high chances of getting stuck when manoeuvring through this area. Moreover, the existence of largely grown vegetation on the ground in oil palm plantations will cause difficulty for sensors to detect the available path.

Inaccuracy of existing robot localisation technology for oil palm plantation. Localisation refers to the ability of the robot to determine its location on the plantation. Most of the existing robot localisation technology revolves around the use in urban areas (Georgiev and Allen, 2004), unmanned aerial vehicles (Back *et al.*, 2020) or ships (Medina *et al.*, 2018). Since the working conditions of these areas differ from the oil palm plantation, direct implementation of the existing localization techniques will cause incompatibility and inaccuracies in the result. Therefore, adaptation and modification of these localisation techniques are required before implementing them in the oil palm plantation.

Non-robust climbing mechanism for climbing robot to move up and down the oil palm tree. Most of the existing climbing mechanisms are designed for climbing trees with relatively circular shape of trunk. Furthermore, these mechanisms are very limited to climbing the trees with a specified range of diameter. Since the trunks of oil palm trees have irregular shapes and the diameter variation is relatively large between each tree, the existing tree climbing mechanisms are not robust enough to be implemented for the oil palm tree (Tan *et al.*, 2014). Therefore, modifications and improvements to the existing climbing mechanisms must be made so that it is feasible to be used on oil palm trees.

Non-existence of robotic harvesting manipulator that can detect and harvest the oil palm FFB autonomously. As discussed earlier, all the existing solutions for oil palm harvesting require manpower to harvest manually or operate on the semi-mechanised equipment. Thus, high labour cost is still required for oil palm harvesting. This problem can be solved by implementing the state-of-the-art robotic manipulator technology such that robots are used to harvest the oil palm FFB autonomously, hence, minimising the labour cost.Inaccuracy of ripeness classification for oil palm FFB in field conditions. Human judgement is the current way of determining the oil palm FFB ripeness in the plantation. As the judgement varies between individuals, there is a lack of consistency in the classification of oil palm FFB ripeness (Rismen *et al*., 2020). Furthermore, there is a lack of existing research on the development of techniques that can classify the FFB ripeness with high accuracy and consistency in the field conditions.

Purpose of this Review

Six key technologies are identified to solve the technological challenges stated in previous section. These technologies are (1) oil palm ripeness detection; (2) oil palm cutting mechanism; (3) tree climbing mechanism; (4) motion trajectory planning for fruit harvesting manipulator; (5) localisation; and (6) navigation and obstacle avoidance. The aim of this article is to review the state-of-the-art development of these key technologies towards the development of autonomous robots for harvesting oil palm FFB. Besides, a set of criteria for the successful implementation of these technologies will be discussed. Further analysis is conducted on the integration of these technologies as a complete robotic system followed by predicting the trend of technological development in oil palm harvesting.

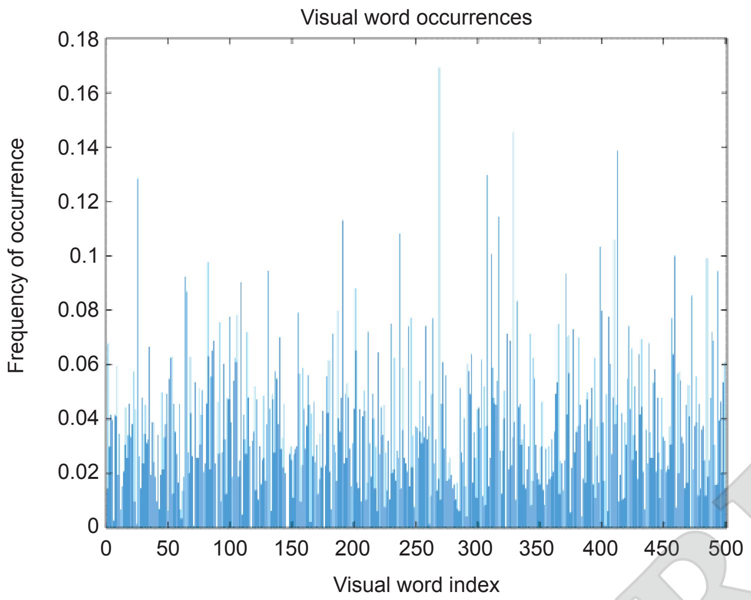
KEY TECHNOLOGIES ON AUTONOMOUS OIL PALM HARVESTING

Oil Palm FFB Ripeness Detection

In general, the ripeness of the oil palm FFB can be classified into five categories: Unripe, underripe, ripe, overripe, and rotten. The ripeness level has significant relationships with the quality and oil content of the oil palm FFB. The oil content of the FFB is highest at the ripe stage while it reduces when reaching the overripe stage. Therefore, it is crucial to determine the FFB ripeness and only harvest the ripe FFB to ensure the maximum quality and yield of palm oil.

Dan *et al.* (2018) proposed a technique of identifying the oil palm FFB ripeness through Raman spectroscopy. This technique worked by measuring the vibrational characteristics of molecules while exposing the oil palm FFB samples with laser light. The result from this study showed that the Raman intensity at identified wavenumbers was the highest at the ripe stage, with the trend of increasing value from unripe to ripe stage, then decreasing from ripe to rotten stage. Raj *et al.* (2021) further implemented this finding with the use of machine learning methods to classify the ripeness automatically. This research achieved a classification accuracy of 100% by using fine k-nearest neighbours (KNN) classifier. One of the advantages of using Raman spectroscopy to determine the oil palm FFB ripeness was that it can provide sensitive, fast, and significant amounts of data for classifying the fruit ripeness level. However, the results obtained from this study were done in a controlled environment, where the outcome was not verified under field conditions. Furthermore, using Raman spectroscopy to classify the oil palm FFB ripeness requires the fruit to be sliced before measuring the Raman intensity, which is impractical to use in field conditions.

The oil palm FFB ripeness can also be classified through image analysis methods. According to Shuwaibatul *et al.* (2019), the ripeness stages of oil palm fruit could be classified by using colour features and bag of visual words (BOVW). In the colour features method, the image dataset was segmented by using the K-mean clustering algorithm to filter out the fruit and spikes from the image. Hue measurements from the segmented images were used as the input feature for support vector machine (SVM) to classify the ripeness of oil palm FFB. The BOVW method used the speeded up robust features (SURF) algorithm to convert the images into feature vectors. The BOVW was formed after clustering the feature vectors by using K-means Clustering algorithm. The BOVW was the frequency representation of the visual word occurrences in an image as illustrated in *Figure 4*. The SVM classifier was developed to classify the oil palm FFB ripeness based on the extracted BOVW feature. This study obtained average classification accuracy of 57% and 70% by using the colour features and BOVW methods respectively. Using the image analysis method to classify the oil palm FFB ripeness has the advantage of relatively long-distance classification. Besides, preparation of the oil palm fruit samples was not required in this method. However, the classification accuracy of this method was relatively low as the classification algorithms were sensitive to ambient light when taking the images.



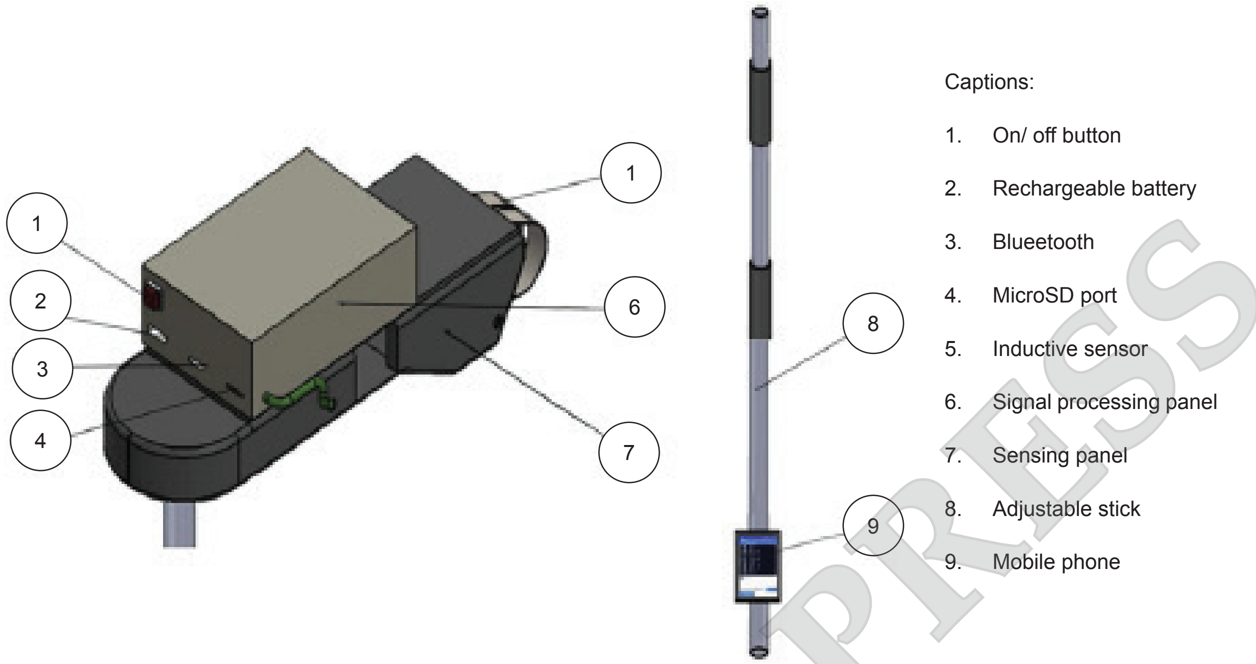
Source: Shuwaibatul *et al.* (2019)

Figure 4. Histogram of visual word occurrences used in the bag of visual word method.

According to Herman *et al.* (2020), the ripeness of oil palm fruit could be classified by using computer vision based on deep learning and visual attention techniques. The residual attention mechanism allowed the classification algorithm to recognise small details between images. Combining the residual attention mechanism with deep learning techniques, the proposed model was called ResAtt DenseNet. This paper utilised a Ten Crop pre-processing method to increase the number of images in the dataset, by cropping each image from different orientations with horizontal flipping. This technique achieved the test F1 score of 0.6929. This technique had higher classification accuracy compared to the machine learning method based on colour features and BOVW. However, deep learning algorithms are more computationally complex than machine learning algorithms.

Other than computer vision-based classification, Rismen *et al.* (2020) proposed a technique for identifying and forecasting the oil palm ripeness by using an inductive sensor system as shown in *Figure 5*. The inductive sensor was used to obtain the resonant frequency data for the target oil palm FFB. Discriminant analysis algorithm was applied to classify the fruit ripeness based on the sampled resonance frequency values. It was found that the value of resonant frequency decreased as the fruit ripened. Therefore, the age of ripeness of the fruit from anthesis could be estimated by using polynomial regression. This research successfully achieved the test result of 100% classification accuracy and 13.45 days of root-mean-square error in estimating the age of ripeness. Using inductive sensor to classify the oil palm FFB ripeness had higher classification accuracy over the other classification methods. Besides, this method was non-invasive, where the fruit sample was not damaged when detecting ripeness. Since the inductive sensor provided continuous range of resonant frequency data, estimation of the age of fruit ripeness could be achieved through regression technique, solving the limitation of machine vision techniques. One of the disadvantages of using inductive sensor was the relatively low sensing range, where the sensor must be physically in-contact with the fruit.

Tuerxun *et al.*, 2020 proposed the use of optical sensors to detect the ripeness of oil palm FFB. This method used light emitting diode (LED) to emit light at different wavelengths towards the FFB. The spectral data of the reflected light from the FFB was captured by the optical spectrometer. By using the Lazy KStar classifier, this research achieved 63% of classification accuracy. Setiawan *et al.*, (2019) obtained a better result of 88.2% accuracy by using a similar approach but the accuracy was determined based on oil content measurement rather than grader evaluation. Therefore, the results obtained from Setiawan *et al.* (2019) had higher validity as grader evaluation tends to be inconsistent. Besides, KNN and discriminant analysis algorithm were used as the classifiers in this research, while both obtained the same classification results. Using optical sensors to detect the ripeness of oil palm FFB has the advantage of non-destructive testing, where the FFB is not damaged in the detection process. However, the accuracy of classification might be affected by external lighting especially when implementing under field conditions.



Source: Rismen *et al.* (2020)

Figure 5. Inductive sensor system to detect the oil palm FFB ripeness.

TABLE 1. SUMMARY OF REVIEW ON OIL PALM FFB RIPENESS DETECTION

Author	Detection technique	Classifier type	Predictors	Accuracy (%)	F1 score
Raj *et al.*, 2021	Raman spectroscopy	KNN	4 peak intensity and 2 peak positions at different wavenumbers	100.0	-
Shuwaibatul *et al.*, 2019	Computer vision	SVM	BOVW	70.0	-
Herman *et al.*, 2020	Computer vision	ResAtt DenseNet	RGB value	-	0.69
Rismen *et al.*, 2020	Inductive sensor	discriminant analysis	Resonance frequency	100.0	-
Tuerxun *et al.*, 2020	Optical sensor	Lazy KStar	Reflected light spectrum	63.0	-
Setiawan *et al.*, 2019	Optical sensor	KNN and discriminant analysis	Reflected light spectrum	88.2	-

Oil Palm Cutting Mechanism

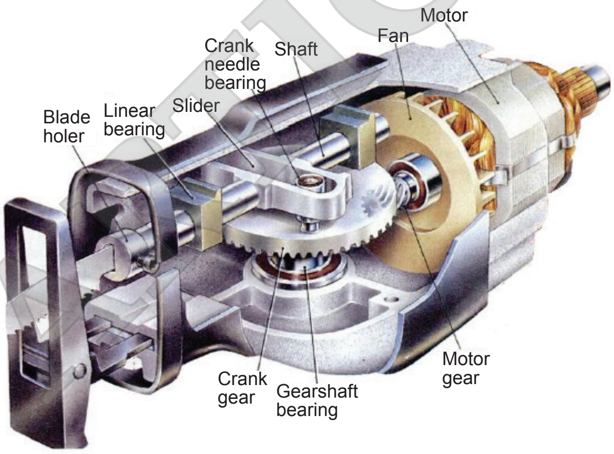
During the harvesting process, the oil palm FFB may be located behind the fronds and obstruct the reach of the cutting mechanism. Therefore, the fronds must be trimmed before the cutting mechanism can reach the FFB. The design of the cutting mechanism must serve two purposes: Trimming the fronds and harvesting the FFB.

Shuib *et al.* (1988) developed an oil palm FFB harvesting machine with scissor and grapple mechanisms as shown in *Figure 6*. The scissor mechanism was used to cut the fruit bunch while the grapple mechanism held the fruit bunch to prevent it from falling. Both mechanisms were hydraulically powered. Using scissor cutting mechanism to harvest the oil palm FFB had the advantage of low mechanical vibration compared to the reciprocating mechanism. Besides, there was no reaction force induced on the manipulator during the cutting process, minimising the risk of damaging the mechanism of the manipulator. However, this mechanism was relatively heavy as the structure must be rigid enough to withstand the high cutting force on the fruit bunch.

Source: Shuib *et al.* (2011)

Figure 6. Oil palm FFB harvesting machine with grapple and scissor cutting mechanism.

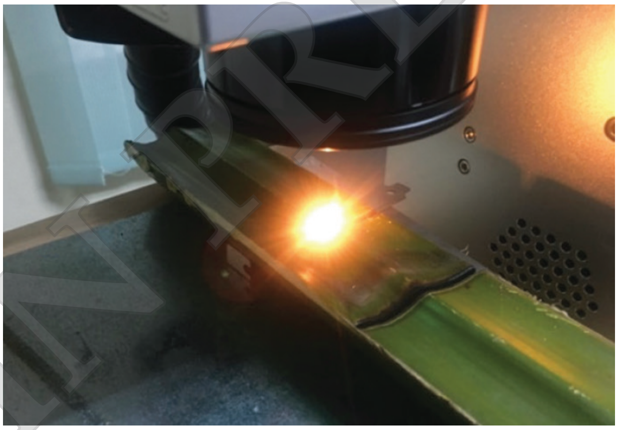
The cutting mechanism for harvesting oil palm FFB could be done by using a cutting blade with a reciprocating mechanism (Shokripour *et al.*, 2012). This mechanism replicated the back-and-forth motion of conventional hacksaw to cut the fruit bunch. This reciprocating motion was produced from a rotary motor with gear mechanism as shown in *Figure 7*. Using reciprocating cutting mechanism had advantage of smaller blade size which made it easier to be aligned properly to the target during the cutting process. However, the reciprocating motion caused intense vibration on the manipulator, potentially damaging the mechanism over time and reducing the accuracy of the cut.



Source: Shokripour *et al.* (2012)

Figure 7. Reciprocating mechanism with saw blade.

Azaman *et al.* (2022) had proposed a method for harvesting the oil palm FFB by using pulse fibre laser system. This method worked by emitting a 50 W laser beam at frequency of 500 kHz and focal length of 63 mm at the target object. This method achieved the average cutting time of 342 s on cutting the oil palm frond, which was very long compared to other cutting mechanisms. Moreover, a small scale of combustion on the palm fronds surface was observed during the cutting process, indicating the possibility of the frond to catch fire. The use of laser cutting method had the advantage of requiring lesser mechanical parts, reducing the weight and maintenance needed. Besides, no vibration would be induced on the manipulator during the cutting process. This research shows a promising alternative method for cutting the oil palm FFB, where the use of higher power laser can further reduce the cutting time.



Source: Azaman *et al.* (2022).

Figure 8. Laser cutting process of oil palm frond in laboratory condition.

Tree Climbing Mechanism

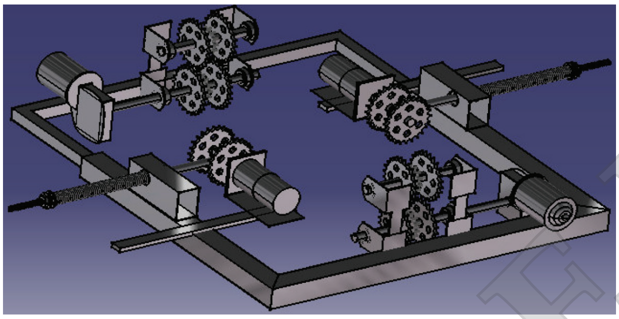
The use of harvesting machine with boom to reach the top of the oil palm tree has limitations on the maximum vertical reach due to instability. While increasing the maximum vertical reach, the weight of the harvesting machine must be increased to ensure stability. Therefore, it is not feasible to use the harvesting machine with boom for taller trees. This issue can be solved by using tree climbing robot to reach the top of the oil palm tree.

Shokripour *et al.* (2010) designed a four-wheeled climbing robot for oil palm tree as shown in *Figure 9*. This robot utilised passive spring mechanism to ensure the wheels were clamped tightly on the tree. The clamping force on the wheels could be calibrated manually by using the lead screw to adjust the initial position of the wheels. Sprockets were used as the wheels to increase the adhesion on the tree. This climbing mechanism required a control system to balance the tilt angle of the robot on the tree. This could be achieved by controlling the individual motor on each side of the wheels. The advantage of using this climbing mechanism was that it can climb

TABLE 2. SUMMARY OF REVIEW ON OIL PALM CUTTING MECHANISM.

Author	Cutting method	Advantages	Limitations
Shuib *et al.*, 1988	Hydraulic scissor	• Low mechanical vibration. • No reaction force induced on the manipulator.	• Entire structure of mechanism is relatively heavy.
Shokripour *et al.*, 2012	Reciprocating blade	• Small blade size. • Easy to align the blade to the target.	• Causes intense vibration on the manipulator.
Azaman *et al.*, 2022	Pulse fibre laser	• Requires fewer mechanical parts. • Relatively lightweight. • No vibration induced on the manipulator.	• Very slow cutting speed. • Potentially cause fire on the target object.

up and down the tree relatively fast while the entire robot was relatively lightweight. However, this climbing mechanism requires the operator to assemble and calibrate the robot on the tree manually, which is impractical for autonomous harvesting.

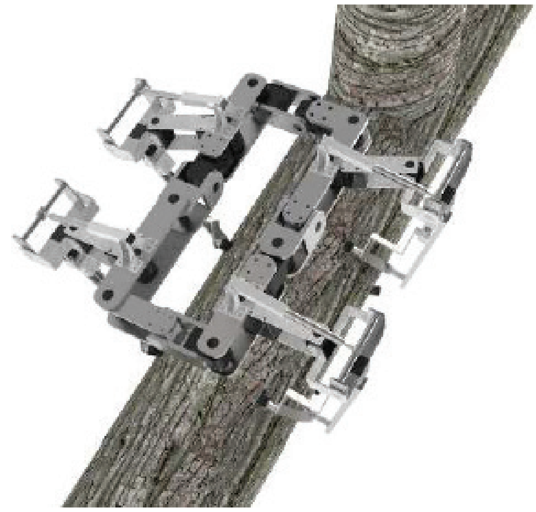


Source: Shokripour *et al.* (2010)

Figure 9. Four-wheeled climbing robot for oil palm tree.

Mustapa *et al.* (2018) developed a spiral tree climbing robot for pole-like tree. This robot had three modules: Steering, driving and support module. The steering module consisted of two motors to change the angle of the driving module. The driving module had two wheels with springs inside the shaft for clamping the wheels on the tree. The support module consisted of four-ball castors to guide the movement of the robot. The advantage of using spiral tree climbing mechanism was that it allows the robot to rotate around the tree, allowing the manipulator with a cutting mechanism to harvest oil palm FFB around the tree. Besides, the use of a support module eliminated the need to use active control system for balancing the tilt of the robot. However, this climbing mechanism required the operator to assemble and calibrate the robot on the tree manually, which was impractical for autonomous harvesting.

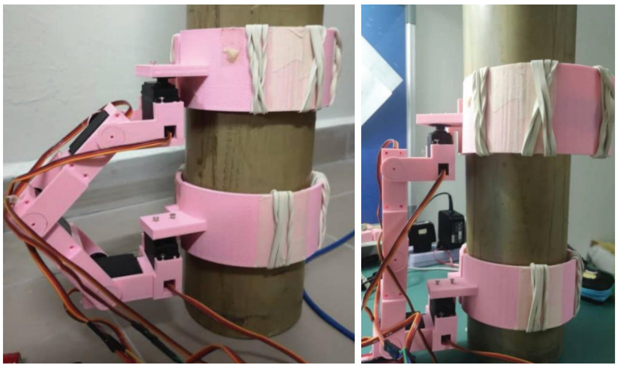
Bionic climbing robot inspired by primates had proven to have more flexibility than wheel-based climbing robot (Wang *et al.*, 2020). This climbing robot composed of four legs and a body frame as shown in *Figure 10*. The four legs were designed to realise the motion of clamping and loosening on the tree. A total of eight degree-of-freedom (DOF) was required to imitate the tree climbing posture of the primate. The actuators of this robot were coordinated based on the forward and inverse kinematics mathematical models. By tuning the mathematical models, this climbing mechanism could be applied to trees with different diameters, increasing the flexibility of the climbing mechanism. However, it required a complex control system as compared with wheel-based climbing mechanisms. Besides, the climbing speed of the bionic climbing robot was slower than wheel-based climbing robot.



Source: Wang *et al.* (2020)

Figure 10. Climbing robot inspired by primates.

Khairam *et al.* (2021) developed a clamp-based pole climbing robot as shown in *Figure 11*. This robot consisted of three parts: Top clamp, bottom clamp, and body. The two clamps opened and closed to tighten and loosen the grip on the pole respectively. The body of the robot consisted of three servo motors. These servo motors were coordinated with a control system to realise the upward and downward movements of the robot. The advantage of using clamp-based climbing mechanism was that the robot can be attached and detached to and from the tree easily as compared with wheel-based mechanism. However, this mechanism had issues where the clamps did not adhere properly to the tree due to the absence of spring mechanism. Besides, the climbing speed of the clamp-based climbing robot was slower than wheel-based climbing robot.



Source: Khairam *et al.* (2021)

Figure 11. Low-cost pole climbing robot.

Motion Trajectory Planning for Fruit Harvesting Manipulator

The motion trajectory planning is a crucial technology in enabling precise and efficient movements of the robotic manipulator for harvesting the oil palm FFB. The motion trajectory planning algorithm must be able to identify the fronds that obstruct the cutting path of the FFB. Hence, trimming of the fronds can be conducted, if necessary, before harvesting the FFB.

One of the motion trajectory planning methods for fruit harvesting manipulators was an improved multi-objective particle swarm optimisation (GMOPSO) algorithm (Cao *et al.*, 2021). This method was divided into three steps: Path planning, B-spline parameterisation, and trajectory optimisation. The optimised rapidly exploring random tree (RRT) algorithm was used to produce the path points to be taken by the manipulator. The generated path points were connected by using multiple sections of B-spline curve to create a smooth motion trajectory. To ensure the generated trajectory meets the dynamic and kinematic limitations of the manipulator, the pulsation, energy consumption, and motion time of the manipulator must be optimised. This could be achieved by using the proposed GMOPSO algorithm to obtain the Pareto optimal solution set. This algorithm was used to solve all the constraints and optimise the trajectory taken by the manipulator. This method achieved 96.67% success rate in harvesting apples with an average motion time of 25.5 s.

Tang *et al.* (2020) proposed a path planning method for picking citrus fruits by using an improved immune algorithm (IIA). This method used a binocular camera to detect the location of the target fruits. The proposed IIA method was used to plan the optimised path for harvesting multiple fruits detected from the binocular camera. The IIA algorithm was an improvement of basic immune algorithm (BIA), which was an optimisation algorithm inspired by the biological immune system. BIA could obtain a global optimal solution with high probability, making it suitable for generating the shortest path on multiple target fruits. However, BIA had long runtime. To reduce the runtime, IIA algorithm combined the tabu search strategy with BIA algorithm. This reduced the runtime by 21.49% as compared with the BIA algorithm. However, since then the number of ripened oil palm FFB that present at the same time on a tree is usually not more than two, and the implementation of a path planning algorithm on multiple fruits are not required.

TABLE 3. SUMMARY OF REVIEW ON TREE CLIMBING MECHANISM

Author	Climbing mechanism	Advantages	Limitations
Shokripour *et al.*, 2010	Wheel-based with four wheels	• Relatively fast in climbing speed. • Entire climbing mechanism is relatively lightweight.	• Requires an active control system to balance the tilt angle of the robot, increasing complexity.
Mustapa *et al.*, 2018	Wheel-based with two wheels and support modules	• Relatively fast in climbing speed. • Allows the robot to rotate around the tree.	• The climbing mechanism is more complex.
Wang *et al.*, 2020	Bionic climbing mechanism inspired by primates	• Very flexible, can be applied on trees with different diameters.	• The climbing mechanism is very complex. • Slower climbing speed than wheel-based climbing mechanism.
Khairam *et al.*, 2021	Clamp-based with top and bottom clamps	• Can be attached and detached to and from the tree easily.	• Has issues where the clamps do not adhere properly to the tree. • Slower climbing speed than wheel-based climbing mechanism.

Therefore, a simpler path planning algorithm can be used for harvesting oil palm FFB to further reduce the required runtime.

You *et al.* (2020) proposed a motion planning framework capable of sequencing cut points while avoiding obstacles in real-time. This method used an RGB-D (Red Green Blue-Depth) camera to map and construct a 3D representation of the tree. The cut points for trimming the tree were manually selected by a human operator. The motion of the manipulator was generated by using Fast Reliable and Efficient Database Search Motion Planner (FREDS-MP) framework. The FREDS-MP framework precomputed the motion trajectories into a database. The precomputed motion trajectories were used to further optimise the trajectory while moving the manipulator in real-time. This method had achieved overall success rate of 75% on tree pruning tasks. However, the requirements of pre-mapping and manual cut point selection were impractical for the autonomous harvesting process.

Wang *et al.* (2022) proposed a trajectory planning method based on offline and online smoothing algorithms. The collision-free trajectory was initially generated by using sample-based planners, which represented the paths with segmented polygonal lines. These segmented paths caused the manipulator to stop at the vertex, causing jerky motion and reducing the motion speed. This problem could be solved by smoothing the trajectory. The proposed offline smoothing algorithm utilized short-cutting heuristic method to generate collision-free trajectory, described by using cubic polynomial functions. The trajectory was generated based on the kinematic constraints of the manipulator. This method can also be used in online smoothing, where the trajectory is optimised in real-time during execution. However, it was found that the short-cut construction in online smoothing might fail due to insufficient computational iteration, resulting in the jerky movement of the manipulator. Therefore, hardware with higher computing speed is required for online smoothing.

Localisation

Localisation refers to the process by which the robot determines its position and orientation within the oil palm plantation. This technology is an important component of navigation, ensuring that the robot is harvesting the targeted oil palm tree at the right location. Robot localisation typically involves using various sensors and algorithms to estimate the position of a robot relative to a known or previously mapped reference point.

According to Georgiev and Allen, (2004), a combination of Global Positioning System (GPS), digital compass and odometry were used for real-time localisation in open-space outdoor environments. An extended Kalman filter was used to estimate the location of robot by combining these sensors data obtained in real-time. This technique strongly depended on the quality of the absolute position obtained from the GPS. Therefore, the reduction in GPS quality would reduce the accuracy of estimating the robot location. To solve this limitation, a visual pose-estimation algorithm was proposed to produce a more accurate estimation of the location of the robot. This technique used the linear features of the surrounding image obtained from a camera to compute the pose of the robot. This could be achieved by matching the linear features with the environmental model consisting of a database of small-scale facade models. By combining the GPS, compass and odometry localisation with the visual pose-estimation technique, this research was able to achieve the mean error of 0.2865 m relative to the exact location of the robot. However,

TABLE 4. SUMMARY OF REVIEW ON MOTION TRAJECTORY PLANNING FOR FRUIT HARVESTING MANIPULATOR

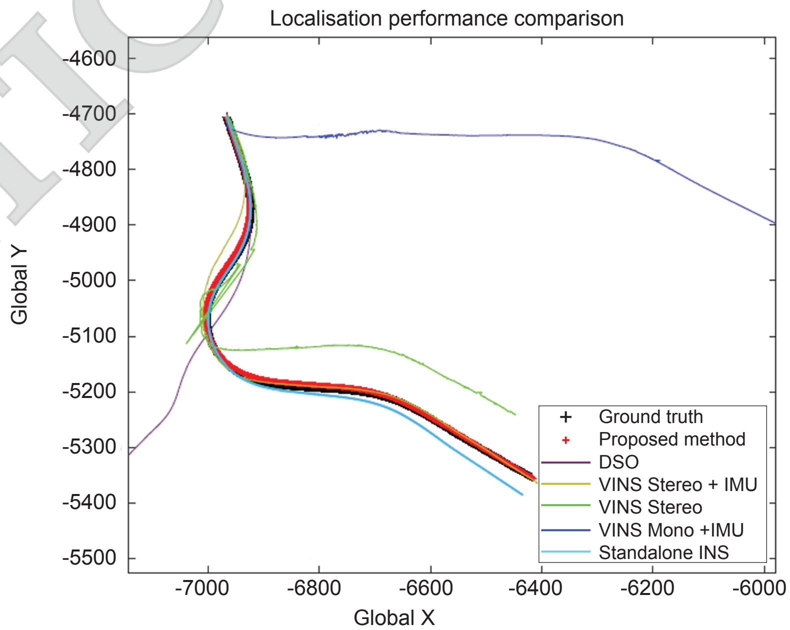
Author	Path finding algorithm	Trajectory optimisation algorithm	Findings
Cao *et al.*, 2021	Rapidly exploring random tree (RRT)	Improved multi-objective particle swarm optimisation (GMOPSO)	• Able to optimise pulsation, motion time and energy consumption of the trajectory based on kinematic constraints of the manipulator. • Achieved 96.67% success rate on harvesting apple with the average motion time of 25.5 s.
Tang *et al.*, 2020	Improved immune algorithm (IIA)	-	• Reduces the runtime by 21.49% as compared with the BIA algorithm. • Able to provide path planning for harvesting multiple fruits.
You *et al.*, 2020	Fast Reliable and Efficient Database Search Motion Planner (FREDS-MP)		• Requires pre-mapping of the tree structure. • Achieved overall success rate of 75.0% on tree pruning tasks.
Wang *et al.*, 2022	Sample-based planners	Smoothing algorithm based on short-cutting heuristic method	• Able to generate collision-free trajectory based on the kinematic constraints of the manipulator. • Can plan trajectory in real-time to avoid collision on dynamic obstacles.

the requirement of an environment model reduced the feasibility of applying this technique to different environments.

Hamer and Dandrea, (2018) proposed a localization system using an Ultra-Wideband (UWB) Network. This method enabled numerous robots to localise themselves simultaneously within a defined area. This could be achieved by equipping the area with a stationary radio modules network, which is also called as anchors, synchronised with a distributed clock synchronisation scheme. An algorithm was also developed by utilising the time-difference of arrival (TDOA) concept to allow both the transmitting anchors and receiving robots to determine their location within the area. The TDOA algorithm worked by computing the time difference in receiving data packets from multiple anchors, which is proportional to the distance of robot between each of the anchors. This localisation technique had achieved the localisation error range of ±100 mm on the horizontal plane. One of the advantages of this localisation technique was that it allows multiple robots to locate themselves independently and anonymously. However, the actively transmitting anchors required power supply to operate, which was not available across the oil palm plantation.

Another global localisation method for mobile robots is to use radio frequency identification (RFID) technology (Tao *et al.*, 2020). This method combined phase difference and readability information from RFID signals to allow mobile robots to determine their position and attitude angle within an area. This could be done by installing two RFID reader antennas on the mobile robot and distributing RFID reference tags on the floor in a square pattern. One of the advantages of this localisation method was the high positioning accuracy, with an average precision of 5.9 cm. Besides, this method also allowed the mobile robots to determine their orientation with mean accuracy of 2.1°. One of the limitations in this localisation method was that it requires the RFID reference tag to be placed with a fixed pattern across the floor, which was impractical for outdoor environments.

To further improve the dead reckoning localisation based on inertia navigation system (INS), Jeon *et al.* (2021) had proposed a learning-based lane detection model to aid in the localisation of the vehicle. This technique worked by combining the sensor data obtained from INS with the lane detection network. The INS system provided the position, velocity and heading of the vehicle, while the lane detection network obtained the feature points describing the lane positions. An unscented Kalman Filter (UKF) was being used to combine the INS and lane points data to estimate the location of the vehicle. This research also compared the proposed method with other localisation methods as shown in *Figure 12*, showing promising results of the proposed method on estimating the vehicle location in GNSS denied area. This localisation technique could effectively minimise the error drifting problem found in standalone INS, hence, providing a more accurate estimation of the robot location. Furthermore, a learning-based lane detection model increased the robustness of the system and allowed the system to be implemented on different road geometry and environments. However, this method did not include the localisation based on rolling and pitching motion of the vehicle, which might cause errors in the localisation results.



Source: Jeon *et al.* (2021)

Figure 12. Comparisons of the localisation methods.

The proposed method is lane-aided dead-reckoning system, being compared with other systems such as direct sparse odometry (DSO), Visual-aided Inertia Navigation System (VINS) with stereo and monocular vision and standalone INS based dead reckoning system.

Navigation and Obstacle Avoidance

The navigation and obstacle avoidance allow the robot to maneuverer through the oil palm plantation autonomously with the desired path while avoiding the obstacles. There are several approaches to navigation and obstacle avoidance in autonomous systems such as sensor-based, map-based, hybrid and machine learning-based navigations. The processes of navigation and obstacle detection involve mapping, localisation, path planning, obstacle detection and control.

The generation of the shortest path for mobile robot navigation while avoiding obstacles could be done by using improved breadth first search (Tripathy *et al.*, 2021). This technique worked in a grid-based environment where the mobile robot was localised by using RFID tags placed equally in a square grid. Greedy algorithm was used to trace out the shortest and most optimal path found from the breadth first search technique. This technique allowed the mobile robot to move in four directions: Up, down, left, and right. The advantage of using this technique for navigation and obstacle avoidance was that very less computational power was required to determine the shortest and most optimal path. However, since that the mobile robot could only move in four directions, the motion of the mobile robot was not optimised especially on areas with multiple turning points.

To solve the inflexibility of grid-based environment, Ajeil *et al.* (2020) had proposed a navigation algorithm that worked in both static and dynamic environments. This algorithm was a hybrid of Particle Swarm Optimisation with Modified Frequency Bat algorithm (Hybrid PSO-MFB). The Modified Frequency Bat (MFB) algorithm worked by mimicking the echolocation behaviour of microbats during its search operation, where path searching was done by altering pulse rates and loudness of sound emission. The Particle Swarm Optimisation (PSO) algorithm helped to optimise the path generation process during navigation. Therefore, combining MFB with PSO could balance the exploration and exploitation process when generating the path for navigation. As a result, the Hybrid PSO-MFB algorithm had outperformed the MFB algorithm in terms of path optimization. However, the computational complexity was higher for Hybrid PSO-MFB algorithm than MFB algorithm.

Back *et al.* (2020) had proposed a vision-based trail detection navigation and obstacle avoidance technique. This technique worked by combining together three methods: Trail following, disturbance recovery and obstacle avoidance. The trail following method worked by using two convolutional neural networks (CNN), one for determining the head direction of mobile robot while the other detected the lateral position offset of the mobile robot from the trail. The disturbance recovery method was used when the mobile robot loses track of the trail due to disturbances. This method utilised the past outputs from the CNN to control the heading direction of the mobile robot for recovering back to the trail. Besides, the proposed obstacle avoidance method worked based on optical flow estimation with CNN. The advantage of using this technique for navigation

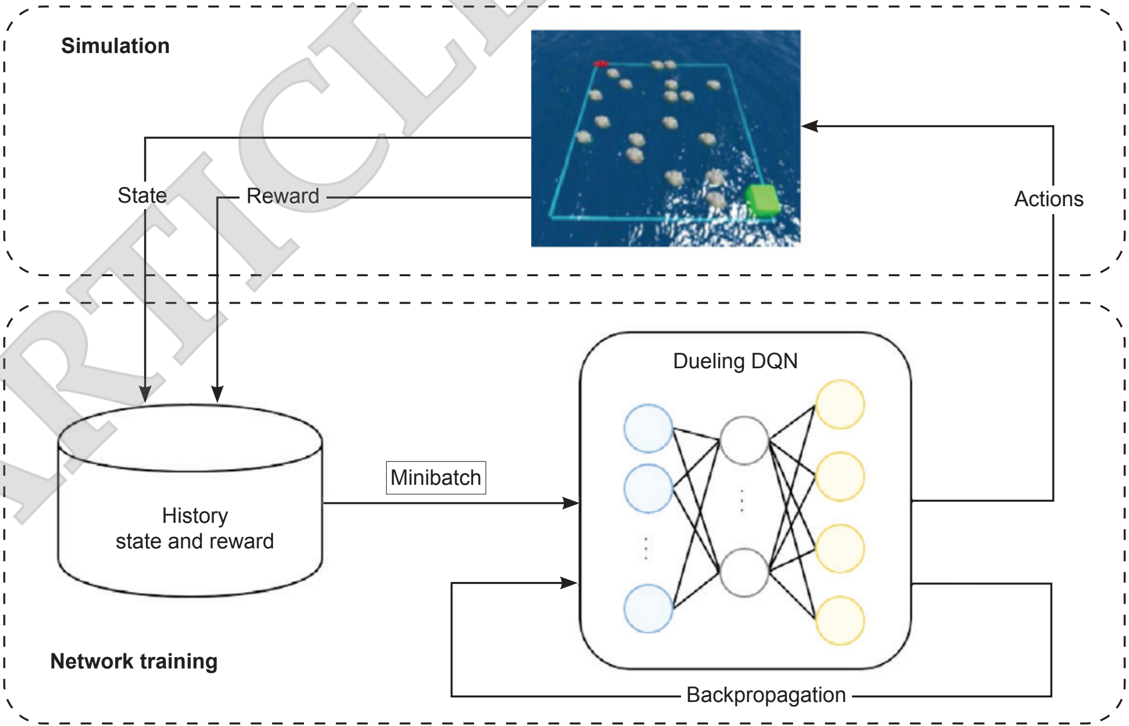
TABLE 5. SUMMARY OF REVIEW ON LOCALISATION

Author	Localisation technique	Advantages	Limitations
Georgiev and Allen, 2004	GNSS, odometry and visual pose estimation	• Obtain relatively accurate localisation with the mean error of 0.2865 m. • Can be used on areas where the GNSS signal is lost.	• Requires the preparation of environment model before using, reducing the feasibility for using on different environments.
Hamer and Dandrea, 2018	Ultra-wideband (UWB) network	• Allows multiple robots to locate themselves independently and anonymously.	• Requires power supply for multiple active transmitting anchors.
Tao *et al.*, 2020	Radio frequency identification (RFID)	• High positioning accuracy, with average precision of 5.9 cm. • Can determine the orientation of the robot with mean accuracy of 2.1°.	• Placing RFID reference tags across the floor is impractical for outdoor environment.
Jeon *et al.*, 2021	Inertia navigation system (INS) with learning-based lane detection model	• High localisation accuracy on GNSS denied area. • Can be implemented on different road geometry and environments.	• Rolling and pitching motion of the vehicle may cause errors in the localisation results.

and obstacle avoidance was that the computational cost is relatively low as the whole system could be implemented in a low power single-board computer. However, this technique only worked in known and trained environments, which was not robust to be applied in complex environments.

Other than deep learning, deep reinforcement learning (DRL) method called Autonomous Navigation and Obstacle Avoidance (ANOA) was proposed by Wu *et al.* (2020). The DRL algorithm worked by exploring the environment based on rewards mechanism to optimise the actions for completing the tasks. ANOA was based on Q-learning, where the algorithm learns the value of an action to estimate obtainable rewards known as Q values. The Q values were used for discrete decision making on controlling the mobile robot. The ANOA deep reinforcement learning framework is shown in *Figure 13*. Comparing with different Q-learning algorithm such as deep Q-network (DQN) and Deep Sarsa, ANOA used a duelling DQN which was proven to be the fastest in optimising the actions. In contrast with ANOA, heuristic-based navigation methods such as path planning and swarm intelligence algorithms were computationally slow and unable to avoid dynamic obstacles in real-time. However, Wu *et al.* (2020) had noted that implementing the DRL methods from simulation to real world was difficult as the algorithm tended to be overfitted to the simulated environment when training, which led to poor generalisation.

To solve the problem associated with poor generalisation of deep reinforcement learning (DRL) in navigation, Liu *et al.* (2021) proposed a self-improving navigation technique called lifelong learning for navigation (LLfN). To improve the navigation results in different environments, gradient episodic memory (GEM) was used when training the DRL model. GEM algorithm prevents catastrophic forgetting of the DRL model, which is the result of overwriting old knowledge when adapting to the new environment. GEM works by ensuring the update process of the navigation model will not increase the loss of previous tasks. The training process was done on three different simulated environments. The training result had shown that LLfN was capable of learning in new environments while avoiding catastrophic forgetting. In comparison with LLfN, the Sequential Training technique had shown improvement of navigation performance in present environment but reduced the previous ones. Therefore, LLfN technique had proven to be effective in multiple environment usage without the need of additional parameter tuning and calibration. However, this technique increased the total time required for training the navigation model as compared with Sequential Training.



Source: Wu *et al.* (2020)

Figure 13. Block diagram of the ANOA algorithm.

TABLE 6. SUMMARY OF REVIEW ON NAVIGATION AND OBSTABLE AVOIDANCE

Author	Methodology	Dynamic obstacle avoidance	Findings
Tripathy *et al.*, 2021	Path finding using improved breadth first search with RFID tags distributed equally in a square grid for localisation.	No	• Very less computational power is required. • Allows the mobile robot to move in only 4 directions, which is not optimised for environment with multiple turning points.
Ajeil *et al.*, 2020	Hybrid PSO-MFB	Yes	• Outperformed the MFB algorithm in terms of path optimisation. • The computational complexity is higher for hybrid PSO-MFB algorithm than MFB algorithm
Back *et al.*, 2020	Deep learning based on vision-based trail detection navigation and obstacle avoidance	Yes	• Can be implemented in a low power single-board computer. • Computational cost is relatively low. • Only works in known and trained environments.
Wu *et al.*, 2020	Deep reinforcement learning using duelling deep Q-network	Yes	• Proven to be the fastest in optimising the actions compared to deep Q-network and Deep Sarsa. • Algorithm tends to be overfitted to the simulated environment when training, which leads to poor generalisation.
Liu *et al.*, 2021	Deep reinforcement learning with self-improvement technique	Yes	• Proven to be effective in multiple environment usage. • Increases the total time required for training the navigation model.

DISCUSSION

The use of autonomous robotic system in harvesting oil palm FFB is proposed to solve the existing problems in harvesting operation. A successful deployment of this robotic system requires solving all the technological challenges as stated in this review. This can be achieved by implementing and integrating the six identified key technologies.

Criteria for Successful Implementation on the Key Technologies

To further assist on the future research in this proposed robotic harvesting system, a set of criteria for successful implementation of these key technologies are discussed in this section.

The harvesting robot must have the capability to detect the ripeness of the oil palm FFB accurately with minimal human supervision. This process is crucial as the detection result is required for the robot to decide which oil palm FFB to harvest. Besides, the detection result can also be used by the robot to locate the position of the fruit for planning the motion trajectory and harvest the FFB. As reviewed in the previous section, the existing methods for identifying the ripeness of oil palm FFB can be categorised into four types: Raman spectroscopy, computer vision, inductive sensor, and optical sensor. Based on the advantages and limitations of these methods, the use of computer vision is recommended due to the relatively long sensing range.

The harvesting robot must be equipped with an efficient cutting tool to harvest the oil palm FFB. Since that the kinematics of the robotic manipulator are different from human body, the cutting tool must be redesigned to fit the usage for the robotic manipulator. This is essential to increase the cutting efficiency and maximise productivity of the harvesting robot. The existing cutting mechanisms are chisel, sickle, mechanised chisel, mechanised sickle, reciprocating saw, scissor, and laser. Modification and experimentation on these cutting tools are required to find the best fit of use on the robotic manipulator.

The harvesting robot must have a motion trajectory planning algorithm to control the robotic manipulator on harvesting the oil palm FFB. The motion trajectory of the robotic manipulator highly depends on the position and orientation of the fruit on the tree, type of cutting tools being used and the mechanics of the robotic manipulator. Therefore, the motion trajectory planning algorithm used must be robust to be used in different situations and configurations. The existing motion trajectory planning methods are mainly based on optimisation techniques such as improved multi-objective particle swarm optimisation (GMOPSO) algorithm, improved immune algorithm (IIA), Fast Reliable and Efficient Database Search Motion Planner (FREDS-MP) framework, and motion smoothing algorithms. Adaptation of these algorithms based on the configuration of robot is required to ensure the motion trajectory for harvesting the oil palm FFB is optimised.

The harvesting robot must have the ability to climb up and down the oil palm tree efficiently. Since the oil palm trees can grow up to an average height of 15 m, it will be impractical for the robot to harvest the fruit with structural support from the ground level due to instability. Therefore, the use of climbing mechanism is recommended for the robot to reach the top of the tree. This is because the climbing mechanism allows the robot to utilise the tree trunk as the structural support, hence, minimising the vertical reach required for the robotic manipulator. The existing tree climbing mechanism are categorised as follows: Clamp-based, wheel-based, and bio-inspired climbing mechanisms. The major challenge on implementing these climbing mechanisms on oil palm tree is the existence of frond base on the tree trunk. The frond base reduce the roundness and smoothness of the tree trunk, which increases the complexity of the climbing mechanisms required to move up and down the tree effectively. Removal of the frond base from the tree trunk is recommended to overcome this challenge.

The harvesting robot must be able to determine its location in the oil palm plantation. The ability of the robot to localise is crucial such that the robot will not move randomly in the oil palm plantation. Furthermore, it allows the robot to harvest the oil palm FFB within the plantation with a planned path for maximising productivity. The existing technologies for robot localisation are global navigation satellite system (GNSS), inertia measurement unit (IMU), radio frequency identification (RFID), visual odometry and active beaconing system. Each of these localisation technologies have their own advantages and limitations, implementing a combination of these technologies is recommended.

The harvesting robot must be capable of maneuverer through the oil palm plantation autonomously while avoiding obstacles. This allows the robot to harvest the oil palm FFB from tree to tree without the need for human supervision. There are several approaches to navigation and obstacle avoidance in autonomous systems such as sensor-based, map-based, hybrid and machine learning-based navigations. The sensor-based navigation and obstacle avoidance uses various sensors, such as cameras, lidars, and radars, to perceive the environment and detect obstacles in the path of the robot. The map-based navigation and obstacle avoidance technique uses a pre-built map of the environment to plan a path that avoids obstacles. The hybrid navigation and obstacle avoidance technique use both sensor-based and map-based navigation. Machine learning-based navigation and obstacle avoidance use machine learning algorithms to train robots to navigate through the environment and avoid obstacles. Since that the trees are planted in a grid manner, hybrid navigation and obstacle avoidance is recommended.

Interconnectivity Between the Key Technologies as a Complete System

The proposed robotic system must be integrated with the six key technologies to achieve autonomous harvesting process. Localisation provides the essential spatial awareness required for the robot to pinpoint its exact position within the oil palm plantation. This positional data is then employed by navigation systems to plan optimal paths, enabling the robot to move from tree to tree efficiently. The obstacle avoidance technology ensures the navigation path remains clear and collision-free. Besides, having a robust climbing mechanism allows the robot to reach the top of the tree efficiently. After climbing to the top of the tree, the ripeness detection technology allows the robot to identify and distinguish ripe FFB from unripe ones accurately. After the ripe FFB is detected, the robotic manipulator with cutting tool can harvest the FFB with the right trajectory by implementing the motion trajectory planning algorithms. Finally, the robot climbs down the tree and the harvesting process repeats.

The use of Robot Operating System (ROS) as the middleware to integrate the robot control is recommended. ROS is widely used in complex robotic systems due to its versatility, modularity, and robustness. It provides a framework that simplifies the development and integration of various components within a robot, making it easier to implement the six key technologies as a complete system.

Prediction on the Trend of Technological Development in Oil Palm Harvesting

Driven by the need to increase efficiency, reduce labour costs, and address various challenges in the oil palm plantation, the use of autonomous harvesting robots can serve as the long-term solution to these problems. This solution is feasible based on the following arguments.

Increased adoption of artificial intelligence and machine learning. These technologies will enable the harvesting robots to better understand their environment, make real-time decisions, and adapt to changing conditions.

Advancements in sensor technology. The cost of sensors, including LiDAR, cameras, GPS, and other environmental sensors, is steadily decreasing. This reduction in sensor prices makes it more economically viable to equip the harvesting robots with the necessary sensing capabilities, enabling robots to navigate, perceive their surroundings, and make informed decisions more effectively.

Improved battery technology. Battery technology is a crucial factor in the development of autonomous harvesting robots, as they need reliable power sources for extended operation in the field. Advances in battery technology, including higher energy densities, faster charging, and longer lifespans, will lead to robots with extended runtimes and reduced downtime for recharging or battery replacement.

Increasing computing power. The increase in computing capabilities enables robots to process larger volumes of data and perform complex computations in real time. It also facilitates the use of more sophisticated artificial intelligence algorithms, allowing robots to adapt and make decisions more rapidly and accurately.

CONCLUSION

To solve the existing problems related to oil palm harvesting, a robotic system in automating the harvesting process of the oil palm FFB is proposed. The technological challenges for developing this robotic system are (1) difficulty of a mobile self-driving unit to manoeuvre autonomously in oil palm plantation; (2) inaccuracy of existing robot localisation technology for oil palm plantation; (3) non-robust climbing mechanism for climbing robot to move up and down the oil palm tree; (4) non-existence of robotic harvesting module that can detect and harvest the oil palm FFB autonomously and (5) inaccuracy of ripeness classification for oil palm FFB in field conditions.

Six key technologies for developing this robotic system are reviewed. These technologies include: (1) oil palm ripeness detection; (2) oil palm cutting mechanism; (3) tree climbing mechanism; (4) motion trajectory planning for fruit harvesting manipulator; (5) localisation; (6) navigation and obstacle avoidance. Future work for implementation and integration of these key technologies onto oil palm harvesting process are necessary to further enhance the development of oil palm industry.

Six criteria for successful implementation of the proposed autonomous robotic system in harvesting oil palm are discussed. Recommendations on the technology used for fulfilling these criteria are made. Interconnectivity between the key technologies as a complete system is analysed. The trend of technological development in oil palm harvesting is predicted.

ACKNOWLEDGEMENT

The authors would like to acknowledge Asia Pacific University of Technology and Innovation for supporting the publication of this review article. Special thanks to Mr. Dennis Tan for providing important ideas and feedback to make this review article a success.

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