An Approach for Estimation of Swing Angle and Digging Depth During Excavation Operation

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Abstract -

This paper discusses the estimation of the swing angle and digging depth during the excavation operation. The ability to calculate the excavator's productivity is an essential step toward autonomous excavators. The swing angle and digging depth have significant effects on the excavator's productivity and must be taken into account for the productivity estimation. Two approaches are proposed to estimate these variables. The first method estimates the swing angle using cabin encoder measurements. The local minimum and maximum points are found, and then Otsu's method is exploited to detect the points that are representative of scooping and dumping positions. The second method utilizes the bucket position to estimate the digging depth. The bucket position is calculated using Inertial Measurement Units (IMUs) measurements and the forward kinematics of the excavator. Otsu's method is used to distinguish the local minimum points that are representative of the digging depth during the operation. Moreover, the algorithms are computationally efficient. Finally, the performance of the proposed methods is studied using real measurements. The results show that the methods can effectively estimate the swing angle and digging depth under different working conditions such as various materials, swing angles, and digging depths.

Keywords -

Excavator; Swing Angle; Digging Depth; Productivity; Otsu's method

1 Introduction

Heavy-duty mobile machines (HDMMs) play significant roles in the world and are exploited in many fields such as construction, forestry, and mining industries. These industries are one of the highly increasing industries and have significant challenges such as lack of skilled human operators, high productivity, harsh environment, and safety [1]. It has been analyzed that the 5% to 10% of direct costs in building projects and up to 40% of direct costs in highway construction projects are related to equipment costs [2]. These industries are highly competitive, and companies must try to improve their products to remain in business against other competitors. In order to reduce costs, the effects of the challenges, and also to increase the productivity of mobile machines, autonomous HDMMs are one main solution. Proposing one autonomous method for all HDMMs is highly complicated since there are a lot of mobile machines in different sizes, shapes, and functions [3].

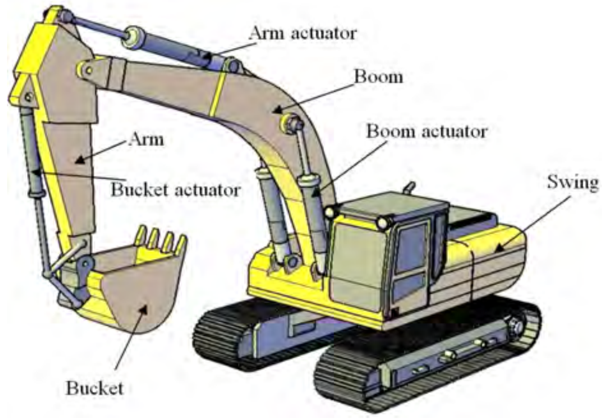

Figure 1. A typical hydraulic excavator and its different parts [4].

1.1 Excavator's Productivity

There are different types of HDMMs, and the hydraulic excavator is one of the most used machines in this field. The excavator is a human-operated machine that is mostly driven by using a hydraulic system. Fig. 1 shows a typical hydraulic excavator. The excavator is one of the primary earth-moving machines in various construction projects such as the construction of highways, airports, industrial and residential buildings. Almost all construction projects require various types of excavation work [5]. An excavator is a multi-functional machine that can easily do different tasks such as dig & dump, trenching and leveling cycles, and utilize different tools. The traveling body, swing body, and front digging manipulator are three main parts of the hydraulic excavator. The manipulator consists of three links: boom, arm, and bucket. The links are manipulated by hydraulic cylinders. Also, the excavator has revolute joints between the swing body, boom, arm, and bucket [6].

The ability to calculate the productivity of hydraulic excavators during different operations can be an essential step toward autonomous excavators. Monitoring the productivity of excavators can reduce the operation time, fuel consumption, and optimize the planning and working parameters. Also, the estimation of the excavator's productivity has major effects on the management and economic aspects. The performance of excavators highly depends on the skills of the human operator, therefore a method for productivity monitoring is significantly required. In addition, human operators can improve their skills by using feedback from the excavator's productivity. Furthermore, since the excavator has repetitive duty cycles, a slight improvement in the operation cycle time or fuel efficiency can bring about huge improvements in the overall performance [3].

Generally, the quantity of material and the operation cycle time are the main factors for the productivity of most cyclical types of machinery. The excavator's productivity means the quantity of transferred material per unit of time. The quantity can be the weight or volume of material. This is the simplest definition of the excavator's productivity. There are different parameters and working conditions such as the swing angle, digging depth, size of the excavator, bucket capacity, dumping conditions, type of materials, weather conditions, and operator's skill that can significantly increase or decrease the productivity of the excavators [6]. Dig & dump duty cycle is one of the most important tasks in different construction projects. This duty cycle consists of four main sub-tasks: 1) digging, 2) swinging loaded, 3) dumping, and 4) swinging empty. Digging depth and type of material are two of the essential factors in the digging sub-task. When the soil becomes harder or the location of material gets deeper, it takes longer to fill the bucket. Moreover, the swing angle is another variable that can increase or decrease the time of swinging loaded/empty and subsequently the overall cycle time [7, 8]. Also, the cycle time is highly dependent on the machine's size because small machines can cycle faster than large machines. Another challenge is continuous variations in environmental and load conditions. These variations can substantially change the productivity of excavators. Furthermore, the cycle time can be influenced by dumping conditions. There are different dumping conditions such as trucks in various sizes, and large or small dump targets [9].

1.2 Literature Review

Publications show the prediction of productivity is done by analyzing the effects of different parameters. Thereby the use of special datasets and methods of companies' handbooks is common. In [10], the authors proposed a deterministic multiple regression model to predict the excavator's cycle time as a measure of productivity. The machine's weight, swing angle, and digging depth are inputs or predictor variables in the regression model. The dataset was obtained from companies' performance handbooks. In [11], the authors propose an artificial neural network by using the same dataset of [10]. The proposed ANN has a higher performance than the MR model in [10]. In [12], an artificial neural network combined with queuing theory is designed to predict the productivity of earthwork machinery including several excavators and haulers. Because of the lack of real data, a computer simulation is utilized to generate data. In [13], the operator competence is presented as a modifying factor in the productivity estimation. The authors model the operator competence and then analyze the effects of this variable on the productivity estimation. In [14], a deep neural network (DNN) model is presented to predict the productivity of excavators by using telematics data. Deep neural networks require a huge dataset and have a high computational load. These challenges can limit the efficiency and practicability of the model. In [15], different deterministic productivity estimation methodologies are introduced and compared with each other. It has been studied that the productivity of the excavator is highly influenced by the swing angle and digging depth. The methods shown only try to approximately predict the operation cycle time, and subsequently, the excavator's productivity and cannot calculate the productivity in real time. These methods are very dependent on datasets and cannot be used for different machines, job conditions, and operators. The most significant challenge is that these methods cannot estimate the swing angle and digging depth, and these parameters should be anticipated by managers or operators at the beginning of operations. During the operation, the swing angle and digging depth change and the assumption of constant values for these variables cannot be a correct solution. Furthermore, these methods cannot be easily utilized for different duty cycles such as trenching.

1.3 Objectives

The focus of this paper is to propose novel frameworks to estimate the swing angle and digging depth during the dig & dump duty cycle. There are several methods to calculate the excavator's productivity, and all of them highly depend on the swing angle and digging depth. These variables can significantly affect the operation cycle time and subsequently the productivity of the excavator. In conventional methods, managers consider only constant values as the swing angle and digging depth at the beginning of operations, but in the proposed algorithm, these variables

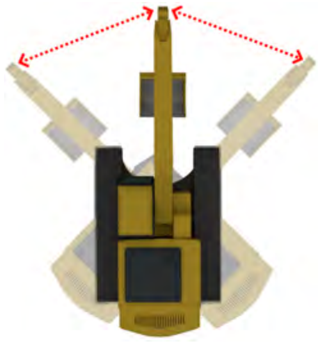

Figure 2. A visualization of swinging movements.

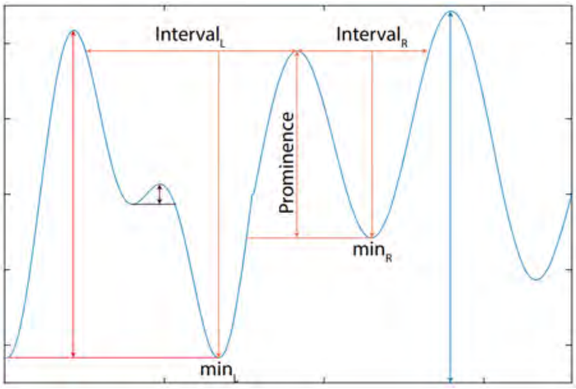

Figure 3. The prominence value [16]

are not considered constant values. In the paper, the swing angle and digging depth are estimated based on the measurements from the excavator and are updated during the operation. The presented algorithms are computationally efficient and use common sensors such as the incremental encoder and Inertial Measurement Units (IMUs) that are affordable and can be easily installed on different excavators. Also, the method can be easily utilized for different duty cycles and also extended for other heavy-duty machines. Currently, there is no automated algorithm for the swing angle and digging depth estimation in commercial automated machine guidance systems. The proposed method can be an interesting feature for the new generation of excavators' automated machine guidance systems. The information about the swing angle, digging depth, and productivity estimation can be utilized as feedback to analyze and improve the skill of human operators in machine guidance systems. Furthermore, the excavator's productivity can be used for the optimization of worksites.

This paper is organized as follows: the methods to estimate the swing angle and digging depth are introduced in Section 2. Section 3 briefly describes the collected datasets and measurements in the experiments. The results of the methods are explained in Section 4. Finally, Section 5 concludes the paper.

2 Methodology

The estimation of swing angle and digging depth is certainly required to calculate and analyze the excavator's productivity during different operations and conditions. In Sections 2.1 and 2.2, two methods are proposed to estimate the swing angle and digging depth, respectively. The proposed methods use measurements from common sensors in the excavator and also are computationally efficient.

2.1 Swing Angle

The swing angle can significantly affect the operation cycle time during the dig & dump duty cycle. In this paper, a novel framework is proposed to estimate and update the swing angle by using the measurement of the cabin encoder. The swinging movements are shown in Fig. 2. Measurements of the cabin encoder during the previous T seconds are considered as input data in this algorithm. The length of the input vector is equal to $T \times f_s$, where f_s is the sampling frequency of measurements.

Firstly, a moving average filter is used to reduce the effects of noises and sudden movements and variations. In this filter, each element of the output is computed by using an equal number of input data on either side of the central value. Actually, the number of samples in one sliding time window is equal to $T_{filter} \times f_s$, where T_{filter} is the length of the sliding time window.

Secondly, local minimum and maximum points are detected to specify the scooping and dumping positions. A prominence value is defined for each local minimum or maximum point. In fact, the prominence of a local minimum point (or a valley) determines its depth compared to other local minimum points. To calculate the prominence of a local minimum point, a horizontal line from the local minimum point is extended to the left and right of the point. Where the horizontal line intersects the data can be another local minimum point or the end of the data. The intersections are outer end-points of the left and right intervals. In the next step, the highest peaks in both the left and right intervals are found, and only the smaller peak is considered. The vertical distance between the local minimum point and the peak is called the prominence value. Also, there is a similar definition for the prominence of local maximum points. The prominence of a local maximum point (or a peak) specifies the height of the point with respect to the other local maximum points. To calculate the prominence of a local maximum point, firstly a horizontal line from the local maximum point is extended to the left and right of the point. The intersections of the line with data can be another peak or the end of data. The intersections specify outer end-points of the left and right

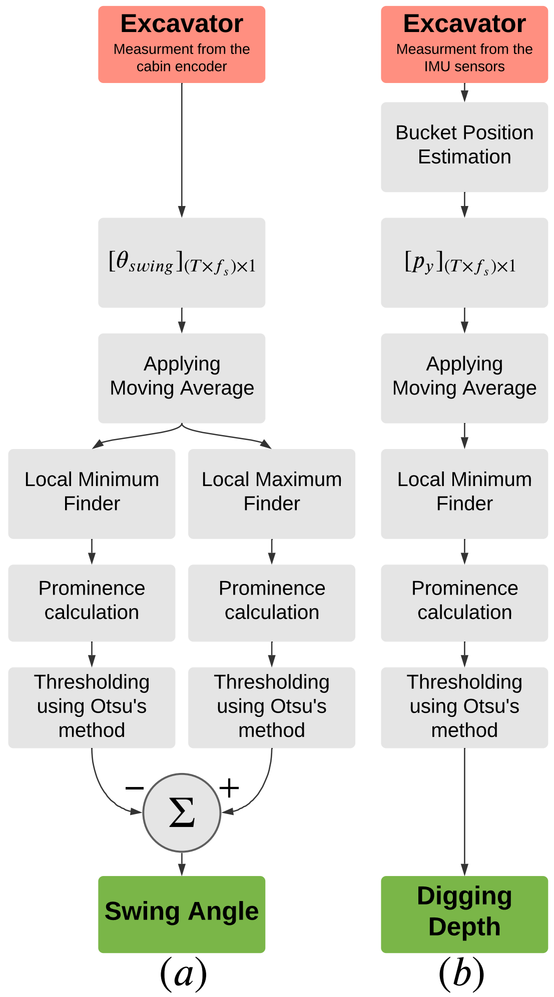

Figure 4. The flowcharts of the proposed methods: (a) swing angle estimation, (b) digging depth estimation.

intervals. After that, the lowest valleys in both the left and right intervals are detected, and only the larger valley is taken into account. The prominence is defined as the vertical distance between the valley and the local maximum point [17]. Fig. 3 shows an example for the prominence calculation of a local maximum point. Firstly, a horizontal line from the local maximum point is extended to the left and right of the peak. The left interval lies between the peak and crossing due to another peak, and the right interval lies between the peak and crossing due to another peak. The lowest points on the left and right intervals are shown by min_L and min_R, respectively. The reference level (highest minimum) is min_R. The prominence is the vertical distance between the reference level and the local maximum point.

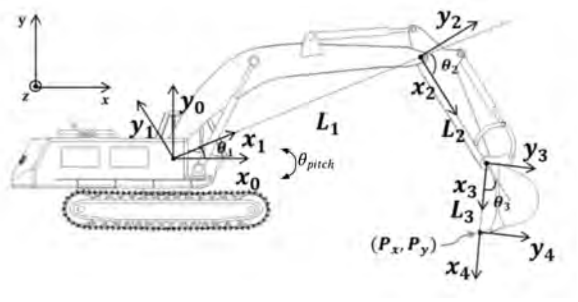

Figure 5. The forward kinematics of the excavator [19].

Probably, all local minimum or maximum points are not acceptable and cannot be considered as the scooping or dumping positions. Otsu's method is exploited to automatically distinguish the valid local extremum points. Otsu's method is an optimum thresholding method by maximizing the variance between classes. This method is mainly used for image segmentation [18]. Finally, Otsu's method diagnoses the valid local extremum points that are representative of the scooping and dumping positions based on their prominence values. The swing angle is defined as the difference between the minimum and maximum angles. The flowchart of the proposed method is presented in Fig. 4.

2.2 Digging Depth

The digging depth is another essential parameter that must be taken into account for the productivity analysis. In this paper, the digging depth is estimated based on the bucket position. The position of the bucket is calculated by using the forward kinematics of the excavator and measurements from four Inertial Measurement Units (IMUs) that were installed on the different parts of the excavator such as the swing body, boom, arm, and bucket. In this part, the swing of the cabin is not considered since it does not have any effect on the digging depth. The axis and frame of forward kinematics of the excavator based on the two-dimensional space is provided in Fig. 5. The endpoint position of the excavator is calculated by using the following equations

$$P_x = L_1 \cos(\theta_{pitch} + \theta_1) + L_2 \cos(\theta_{pitch} + \theta_1 + \theta_2) + L_3 \cos(\theta_{pitch} + \theta_1 + \theta_2 + \theta_3) \quad (1)$$

$$P_y = L_1 \sin(\theta_{pitch} + \theta_1) + L_2 \sin(\theta_{pitch} + \theta_1 + \theta_2) + L_3 \sin(\theta_{pitch} + \theta_1 + \theta_2 + \theta_3) \quad (2)$$

where P_x and P_y are x and y-components of the bucket position, respectively.

Figure 6. The excavator used in the data collection phase. In the picture the cabin (1.), boom (2.), arm (3.) and bucket (4.) are highlighted with red boxes.

Figure 7. The configuration of the sensors on the excavator [20].

The estimation of digging depth is performed by using the y-component of the bucket position. This algorithm is similar to the swing angle estimation approach introduced in Section 2.1. In each iteration, the length of input data is equal to $T \times f_s$. Firstly, a moving average filter is utilized to reduce the effects of noises and meaningless movements, and variations of the bucket. Secondly, to find the depth of digging, local minimum points are detected. There are a lot of local minimum points that are not representative of actual digging depth. Otsu's method is applied to the prominence values of local minimum points to find the valid local minimum points. The flowchart of the presented method is shown in Fig. 4.

3 Data Collection

In this paper, the dataset was collected from a Komatsu PC138US excavator. The crawler excavator used in the experiments is shown in Fig. 6. Although this excavator is old, it has been well-maintained, and it is in good condition. The inspection and maintenance are performed every 500 working hours. The operating weight of this medium-rated excavator is $14000Kg$ and has a standard mono boom, arm, and bucket. The bucket is attached to the arm by using a quick coupler, and also, the excavator has a tiltrotator. The heaped capacity of the bucket is $0.37m^3$ based on the standard of the Society of Automotive Engineers (SAE). The MathWorks Simulink model was used to collect data from the excavator. Measurements of different sensors are transmitted over the controller area network (CAN) bus. The model is connected to the CAN bus utilizing a Kvaser leaf light CAN to USB interface. The sampling frequency f_s is equal to $200Hz$. The Inertial Measurement Units (IMUs) and an incremental encoder are utilized to measure the orientation and rotation of moving parts of the excavator. The configuration of the sensors on the excavator is shown in Fig. 7. The data collection was done in a private worksite where there was no active construction work in the worksite. In fact, there is no unexpected factor that suddenly stops the operation. In the experiments, the dig & dump duty cycle is done by an inexperienced operator, and also two types of materials such as sand and rough gravel are used to show the robustness of the methods. The dig & dump duty cycle is one of the main tasks in all worksites, and it comprises four sub-tasks such as filling the bucket, swinging loaded, dumping, and swinging empty. The operator has practiced less than 30 hours to drive the excavator which this factor can bring about more vibrations and meaningless movements of the excavator and subsequently can increase the challenges of swing angle and digging depth estimation. There are two different scenarios in the dataset. The duration of each scenario is approximately 6 minutes. The start and end positions in both scenarios are near the digging position. In the first scenario, the type of material is rough gravel, and the swing angle of operation is around 60°. In the second scenario, the type of material is sand, the swing angle is approximately 120°, and the digging depth is higher than in the first scenario. To increase the digging depth in the second scenario, the excavator goes on top of a small pile to reach a higher position.

4 Results

The performance of the proposed methods is illustrated by using real measurements. The algorithm was implemented using MathWorks Matlab R2021a on a laptop with a 1.8 GHz Intel Core i7 CPU and 16 GB of RAM. The proposed algorithms are computationally efficient. The average required time for the computation at each time step in the swing angle and digging depth estimation algorithms are 0.0034 and 0.0024 seconds, respectively. The length of input data T is equal to 60 seconds. The output variables such as the swing angle and digging depth are updated in each iteration. The updating rate can easily change based on the application and final goal. Firstly, the performance of the swing angle estimation is analyzed

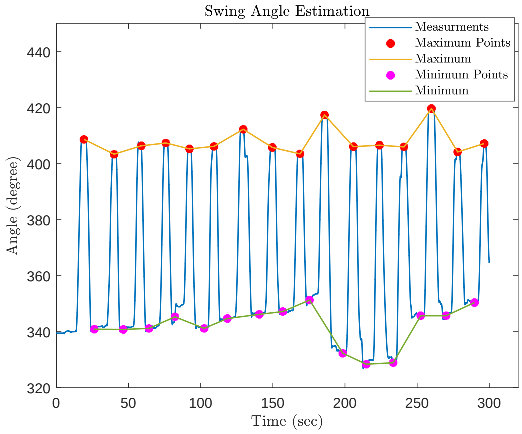

Figure 8. The estimation of maximum and minimum boundaries in the first scenario.

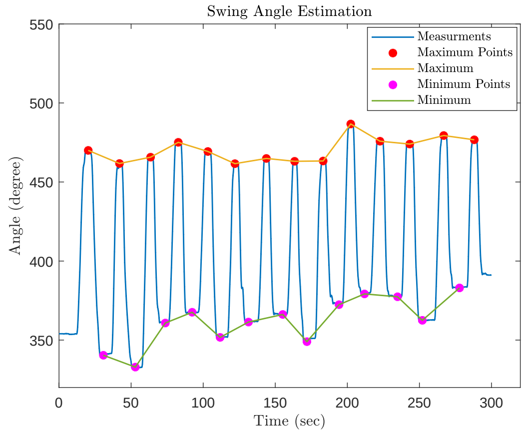

Figure 10. The estimation of maximum and minimum boundaries in the second scenario.

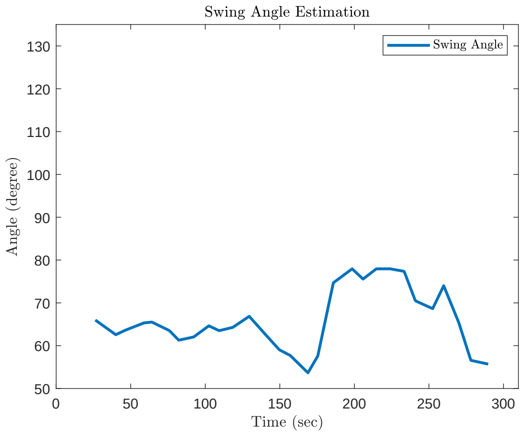

Figure 9. The estimation of swing angle in the first scenario.

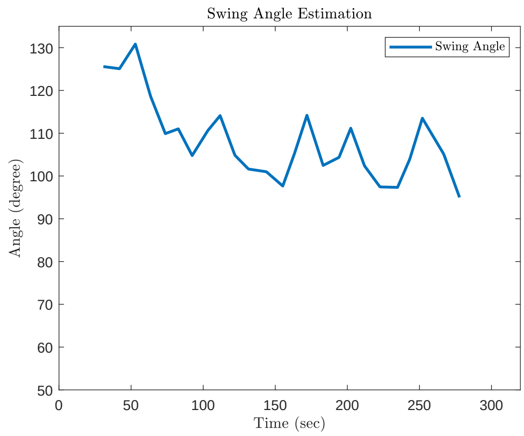

Figure 11. The estimation of swing angle in the second scenario.

in two scenarios. In the algorithm, the length of the time window in the moving average filter T_{filter} is equal to 5 seconds. In the first experiment, the dig & dump duty cycle with a swing angle of 60° is done, and the type of material is rough gravel. The results of the method are shown in Fig. 8 and Fig. 9. The results show the method efficiently estimates the swing angle and can track the changes during the operation. Moreover, the method is evaluated by using another experiment. In the second experiment, the swing angle is approximately 120°, and the type of material is sand. The results are presented in Fig. 10 and Fig. 11. The method can effectively estimate the swing angle.

In the next phase, the performance of the digging depth estimation is investigated in two scenarios. In this algorithm, the length of the time window in the moving average T_{filter} is equal to 2.5 seconds. In the first experiment, the digging depth is lower than in the second experiment. The type of used material in this experiment is rough gravel, and the swing angle is approximately 60°. The estimation of digging depth is shown in Fig. 12. The method can estimate the digging depth, and it is robust against sudden movements of the bucket. In the second experiment, the type of material is sand, and the swing angle is approximately 120°. The result is shown in Fig. 13. The algorithm accurately estimates the current digging depth based on the bucket position. The results prove the presented methods can easily be utilized for real-time productivity estimation of excavators in different working conditions.

5 Conclusion

In this paper, two novel frameworks are presented to estimate the swing angle and digging depth of the dig &

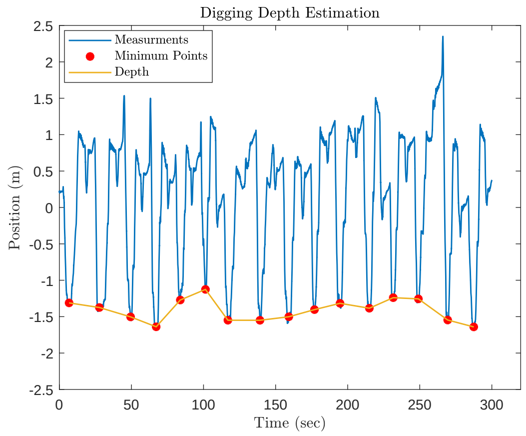

Figure 12. The estimation of digging depth in the first scenario.

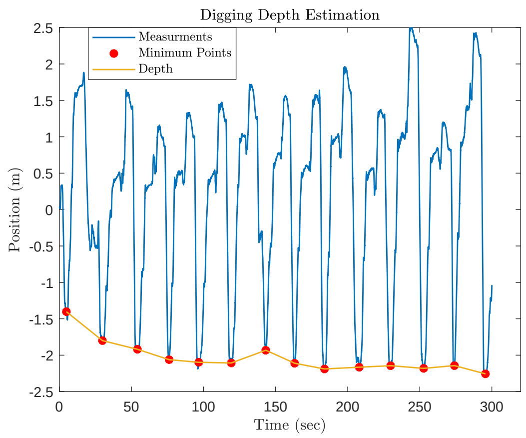

Figure 13. The estimation of digging depth in the second scenario.

dump duty cycle in real time. These variables have significant effects on the excavator's productivity and must be taken into account. Firstly, an algorithm is proposed to estimate the swing angle using the cabin encoder measurements. A moving average filter is used to reduce the effects of noises and sudden movements of the cabin, and then local minimum and maximum finders are utilized to find the extremum points. Afterward, Otsu's method is exploited to find the extremum points that are representative of scooping and dumping positions. Secondly, a similar approach is proposed to estimate the digging depth during operations based on the bucket position. The bucket position is calculated by using the measurements of IMU sensors and the forward kinematics of the excavator. After using the moving average filter, the local minimum points of the bucket position are found, and then Otsu's method is used to recognize the local minimum points that are representative of the digging depth. Finally, the methods are tested by using the collected dataset in a private worksite. The dataset includes two scenarios including different materials such as sand and rough gravel, different swing angles, and digging depths. The results prove the methods can be used in the productivity estimation of excavators.

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The MORE project is an innovative European Industrial Doctorate (EID) research and training programme that tries to answer the challenges of heavy-duty mobile machines (HDMMs). The MORE project contributes to the development of state-of-the-art HDMMs by proposing effective solutions driven by digitalization and Artificial Intelligence (AI). There are eight researchers in the MORE project that work on three main work packages: 1) Process, 2) Machine, and 3) Control. In the process work package, we investigate a set of tasks that are performed by a machine or machines to achieve the purpose of work [21].

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