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# Development and Validation of a Screw Interlock Recognition Method based on Logistic Regression

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**Abstract**

Conventional robotic screw methods rely on position control and the use of a threshold value, normally a contact force value, to detect the contact between tool and screw, so the nut-runner can be placed correctly on the workpiece. In the case of a dynamic workspace, the variance of the workpiece position will likely cause the nut-runner to be positioned incorrectly and will significantly decrease the success rate of the screw task.

This paper proposes a novel method based on a logistic regression model for flexible Human-Robot-Collaboration (HRC) screw assembly operations in highly dynamic workspaces. The proposed method is part of a screwing strategy based on impedance control and developed for HRC applications. The screwing strategy consists of a spiral movement executed by the robot while approaching the workpiece and it is used as a search procedure to find the screw. The proposed method is used to detect when the tool correctly interlocks with the screw head so the robot can proceed with the screwing process. The goal is to stop the spiral movement timely when the nut-runner has correctly interlocked with the screw head to ensure a successful screw task and avoid potential damage to the nut-runner or the workpiece.

The proposed screw interlock recognition method utilizes a logistic regression model to observe the contact forces between tool and screw head. The learning model is trained using force data collected from experiments and then its feasibility is validated with further testing.



*Keywords:* logistic regression; robotic; impedance control; automated screwing process

## 1. Introduction

Screw tasks are nowadays commonly automated in various industrial branches with the help of robotic systems [1]. In most cases, the automation of screwing processes take place in robotic cells characterized by a strictly controlled environment and, more recently, in collaborative robot workstations [2, 3], which are used mainly for low-torque and non-heavy-duty fastening tasks. Typically, the implementation of Human-Robot Collaboration requires a strictly controlled workspace to operate reliably, where the position of the tool and workpieces are well defined. Such robot workspaces are referred to as static workspaces.

On the other hand, the implementation of robotic screw solutions in workspaces that are not originally conceived for automation, such as manual production lines, remains a topic that is not yet widely explored. The implementation of robotic solutions in such environments is characterized by the presence of disturbances that can be caused by human presence or other sources, such as the design and construction tolerances of the conveyor system in the assembly line. As a result, the position of the workpiece is not constant and can vary in each screwing



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operation [4]. Such workspaces are also known as dynamic workspaces.

Traditional robotic cells rely on position control to perform automated screw tasks, which is unattainable if the workpiece position is not fixed and can vary. There are other control strategies that can compensate for the deviation of the workpiece position. In principle, the contact between screw head and nut-runner can be also seen as a peg-in-hole operation. Numerous peg-in-hole assembly strategies aim to recognize the contact state by observing wrench signals or robot pose so that the robot can react accordingly [5–7].

It is also possible to implement a camera system and use computer vision to determine the position deviation of the workpiece and thus adjust the robot pose [8, 9]. Nonetheless, computer vision techniques like visual servoing cannot react to any position deviation if the camera angle has been obstructed. Furthermore, the position correction from camera systems has innate inaccuracy [10], whereby screw tasks can still fail even after the pose correction.

This paper proposes a screw interlock recognition method that can be implemented for screwing tasks in highly dynamic workspaces. The method, based on logistic regression in combination with impedance control, aims to correctly position the nut-runner on the workpiece despite its position deviation and identify when the nut-runner has correctly interlocked with the screw head. This approach is a follow-up of the automated screwing strategy presented in a previous work [11], where the original screw interlock recognition method based on a threshold value has been replaced by the proposed method based on logistic regression.

## 2. Robotic Screwing Strategy based on Impedance Control

The idea of using active compliance based on impedance control for automated screwing applications is not new. Some robot manufactures have already integrated robotic screwing skills in their portfolio. However, most of these solutions are implemented in applications where the position of the workpiece does not vary and the screwing procedure is performed without external disturbances. Research work has already demonstrated the advantages of using impedance control to counteract any position variation along the screw axis [12, 13]. However, its ability to compensate for position variation on the plane perpendicular to the screw axis is very limited and the use of a threshold value to detect the contact between tool and screw makes them unappropriated for a dynamic environment. In a paper from 2020 [14] the author shows a method of automated unfastening using a cobot and impedance control combined with a spiral movement to align the nutrunner with the hole.

The proposed screwing strategy was conceived for semi-automated assembly processes where the screws are first manually placed in the workpiece and only the tightening process has to be automated. The three phases of the automated screwing strategy: Screw Approach, Screw Interlock as well as Screwing and Tightening are presented in the following chapters.

### 2.1. Screw Approach

In a typical static workspace, the position of the screw is always known and the robot can simply approach it. The same method cannot be implemented in a dynamic workspace due to the variation of the workpiece position. Instead, the robot can only bring the nut runner close to the position of the screw and a search procedure would be necessary in order to approach the screw and place the nut runner correctly on the screw head.

The search procedure consists of performing a spiral movement of the robot TCP to approach the screw head. Such spiral movement is also commonly implemented in peg-in hole assembly operations where impedance control is used. The spiral movement has three important parameters; spiral radius, axial and radial velocity. Under the correct parameters, the spiral movement can compensate for position deviation of the workpiece on the plane perpendicular to the screw axis (Figure 1). However, the spiral movement method can only compensate for position deviation of the screw if it is still located within the radius of the spiral movement.

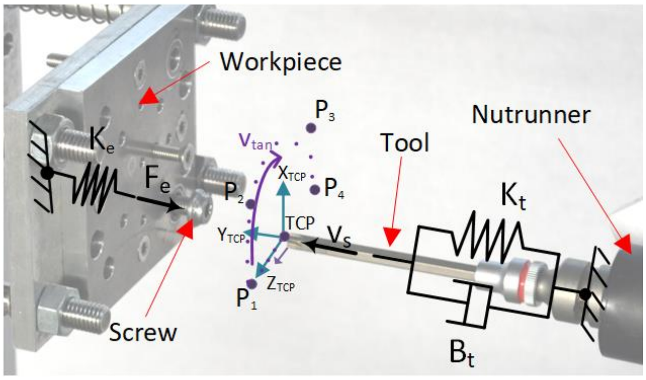


Figure 1 Search procedure: the robotic active compliance mode render a mass, spring (Kt), damper (Bt) system that execute a linear movement (vs) in the screw direction (Ytcp). At the same time, a circular movement (vt) in the XZ plane is performed with the help of teached points (P1- P4). The screw is represented as the environment with a specific stiffness (Ke)

The implementation of impedance control on the screw axis is proposed to compensate for position deviations of the workpiece along this axis. While impedance control is active, the robot behaves compliant and moves along the screw axis until a certain target force is reached.

In summary, the search procedure is a combination of impedance control and spiral movement along the screw axis.

### 2.2. Screw Interlock

Eventually, the nut-runner comes into contact and interlocks with the screw. This is the critical phase of the screw task; the robot must be able to identify when the screw interlock occurs in order to stop the spiral movement. Stopping the spiral movement too early may prevent the screw interlock and ultimately failing the screw task. On the other hand, stopping it too late will leave the robot moving the nut-runner while interlocked with the screw, potentially damaging the robot, the nut-runner, and the workpiece.

*2.3. Screwing and Tightening*

After the screw interlock occurs and the spiral movement stops, the robot proceeds with the screwing process. During the screwing process, the robot further utilizes impedance control along the screw axis to follow the screw movement towards the workpiece. The screwing process finishes with the fastening of the screw using standard built- in torque and angle control functions from the industrial nut-runner controller.

The work presented here focused only on the "screw interlock" phase. The proposed screw interlock recognition method implements a learning model that observes the force progression to identify the screw interlock, which will be discussed in detail in the following chapter.

## 3. Methodology of Screw Interlock Recognition

*3.1. Logistic Regression*

Logistic regression is a supervised learning algorithm that solves binary classification problems [15]. It calculates the probability of one out of two events taking place based on the input of independent variables. A logistic regression model utilizes the following linear function f(x) as its classifier, whereby b0, b1, …, bn is the weight of the classifier and $x_1$, $x_2$, …, $x_n$ are the independent variables.

$$f(x) = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n$$

The probability p(x) whether a set of independent variables belongs to one of the two classes is calculated using the sigmoid function of the linear classifier.

$$p(x) = \frac{1}{(1 + exp(-f(x)))}$$

The model is trained using labeled data from the two possible classes. During the training phase, the model utilizes a solver to determine the best weights for the classifier so that the model prediction is as close as possible to the label of the training data. In this paper, the solver liblinear [16] is utilized to optimize the weights of the classifier. After the model is trained and a set of classifier weights is derived, the model can make predictions regarding new independent variables.

The proposed screw interlock recognition method utilizes a logistic regression model to predict one of two outcomes; whether or not the nut-runner has come into contact and interlocked with the screw. During the screw approach, the robot continuously communicates with the learning model. In each time step, the robot collects the force measurements on the x, y, and z axes within the last second into three vectors (Fx_1s, Fy_1s, and Fz_1s) and inputs them into three separate logistic regression models as the independent variables. The length of these vectors corresponds to how many instances of force values are measured within one second, i.e. the sampling rate.

The learning models on each axis will then calculate the probability that the screw interlock has occurred within these force measurements. The probability values on each axis, which ranges between 0 and 1, are then added together. In case of a successful screw interlock, the contact force on the screw axis (y axis) always rises, since the robot tries to achieve the target force after it comes in contact with the screw. On the other hand, depending on how smooth the screw interlock is, the contact forces on the other two axes may not experience a significant change. In other words, an increase of contact force on the screw axis is a strong indicator that a screw interlock has occurred. Therefore, the probability on the screw axes is given more weight than the other two axes. If the sum of the probabilities on all axes exceeds a certain threshold will stop the spiral movement and proceed with the screwing process (Figure 2). Due to the doubled weight on the screw axis, the value of the sum ranges from 0 to 4.

Typically, in a binary classification problem, the probability threshold is set to 50%. To avoid stopping the spiral movement prematurely, the model must be rather certain that the screw interlock has occurred before it makes a prediction. Therefore, the probability threshold is increased to 75%. Correspondingly, the sum value described previously must exceed a threshold value of 3.

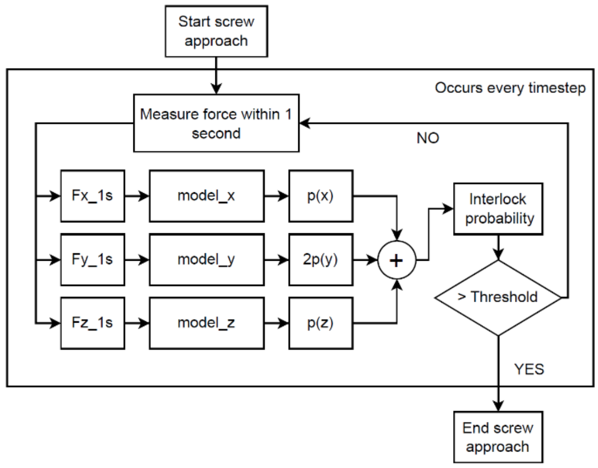


Figure 2 Screw Interlock Detection based on Logistic Regression Model

In this contribution, logistic regression is implemented as the classification algorithm due to its simplicity and low computational cost, which allows a fast calculation in each time step. Naturally, another method can also be utilized in future works to approach this classification problem.

*3.2. Failsafe method*

As mentioned previously, the capability of the spiral movement to compensate for position deviation is limited. The nut-runner will still miss the workpiece if it deviates too much from its supposed location. If the spiral movement successfully finds the screw, the tip of the nut-runner bit will interlock with the drive of the screw. On the other hand, if the spiral movement is unsuccessful, the nut-runner bit will collide with the side of the screw head. In case of such a collision the contact force on all three axes will rise abruptly, especially on the x and z axes, by a significant value. In this instance, the spiral movement shall be stopped immediately to avoid straining the robot and the nut-runner any further.

For this purpose, the maximum contact force on each axis within the last second is observed. If the sum of these forces exceeds a certain threshold at any point during the screw approach, the robot will stop the spiral movement and move back to the starting position.

$$max\left( Fx_{1s}\right) + max\left( Fy_{1s}\right) + max\left( Fz_{1s}\right) \geq Threshold$$

## 4. Experiments

### *4.1. Training the model*

Since logistic regression is a supervised learning model, it needs to be trained with labeled data. For the work presented here, the parameters from Figure 1 of the screw method have been kept constant and only different deviations in the position of the tool relative to the screw have been used to train the model. If the screw axis is collinear with the tool axis, i.e. there is no position deviation, the axis of the spiral movement will coincide with the screw. From each screw task, different portions of the force profile, which represent the screw approach or the screw interlock, are selected and labeled to train the learning model. The model has been trained using data from 20 screw tasks considering position deviations of 2 mm and 4 mm as well as without deviation.

After the model has been trained, its accuracy is tested using new data that was not used for the training process. When the accuracy is sufficient (in this case above 80%), the model is implemented in the actual test bed for validation. The experiment aims to observe the accuracy of the model in identifying successful screw interlock under different uncertainties (different position deviations). Furthermore, the experiment also tests how reliably the failsafe measure can detect a failed screw interlock. A screw task is considered successful under two conditions; the spiral movement must first hit the screw head and the learning model must stop the spiral movement correctly. Therefore, in each test there are four possible outcomes:

- Case 1: The tool hits the screw head and the model stops the spiral movement when the screw interlock has taken place (successful interlock task).
- Case 2: The tool hit the screw head but the model stops the spiral movement incorrectly (unsuccessful interlock task).
- Case 3: The spiral movement misses the screw, and the failsafe method stops the spiral movement correctly (successful failsafe task).
- Case 4: The spiral movement misses the screw, and the failsafe method stops the spiral movement incorrectly (unsuccessful failsafe task).

### *4.2. Test bed*

The equipment for the training, testing and final implementation consists of the following (Figure 3):

- Collaborative robot arm: Universal Robot UR16e
- Nut-runner: Cleco EC 50EAN89JA4 with angular head. Rotation speed: 125 1/s and tightening torque: 10 Nm
- Nut-runner bit: T40.
- Screw: Torx M8 x 30 mm
- Workpiece: metal plate with holes for M8 Screw
- Workpiece holder: Use of springs to simulate a stiffness in the environment of 3.69 N/mm

The logistic regression model is implemented using a python script that is run on an external computer. The acquisition of force measurement between the external computer and the robot controller is realized using a socket connection with an optimized sampling rate of 50 Hz, providing no data loss within the socket connection. The impedance control has been implemented using the inherent active compliance mode of the UR16e controller, defined as "force mode". The parameters of the program and force mode for the automated screwing strategy are the following:

- Target force of the force mode: 8 N in the direction of the scree axis.
- Axial velocity of the spiral movement: 5 mm/s
- Tangential velocity of the spiral movement: 24 mm/s
- Radius of the spiral movement: 5 mm

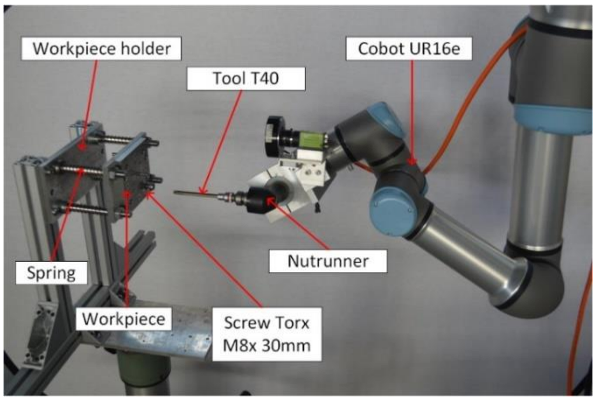


Figure 3 Test bed with Cobot UR16e

## 5. Results

### *5.1. Force Profile Analysis*

This chapter discusses several examples of force profile from the experiments. Figure 4 and Figure 5 present force profiles from two successful interlock tasks. The fourth plot on each figure presents the calculated probability of a screw interlock where the yellow line indicates when the probability threshold is triggered and the spiral movement is stopped.

In the first example (Figure 4), the nut-runner bit interlocks with the screw very smoothly. The contact force on the screw axis ($F_y$) increases very noticeably, while the contact forces on the other two axes barely change during the spiral movement. As the probability threshold is triggered (indicated by the yellow plot), the spiral movement stops while the nut runner bit is interlocked with the screwhead, which causes abrupt changes to the contact forces.

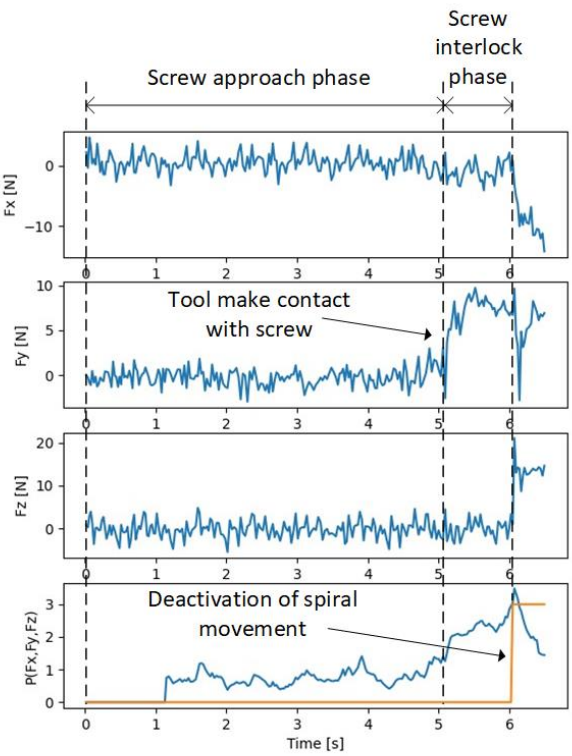


Figure 4 Experiment 1: Force profile of a successful interlock task

Since the force values on the screw axis is given more weight in calculating the screw interlock probability $p_{interlock}$= p(x) + 2p(y) + p(z) (Figure 2), the learning model is still able to make the correct prediction. In the second example (Figure 5), the screw interlock occurred not as smoothly, which results in a noticeable change on the x and z axes. In this instance, the threshold for the screw interlock probability is triggered with a lower contact force on the y axis, compared to the first example. Similar to the previous example, the contact forces abruptly change after the probability threshold is triggered.

*5.2. Validation of the trained Model*

Table 1 presents the number of experiments using different position deviations in which the contact detection method has behaved according to one of the cases described in section 4. Unlike the previous work [11] where a threshold force value could not be implemented and it was necessary to implement a timer to deactivate the search procedure; the new method proposed in this work was successfully implemented, especially for tolerances smaller than 2mm.

Table 1. Experiment Outcomes.

| Deviation | Case 1 | Case 2 | Case 3 | Case 4 |
|---|---|---|---|---|
| 0 mm | 20 | 0 | 0 | 0 |
| 2 mm | 18 | 2 | 0 | 0 |
| 4 mm | 13 | 2 | 5 | 0 |
| 6 mm | 4 | 1 | 15 | 0 |

As expected, the nut-runner always finds the screw under 0-2 mm position deviation. For 0 mm deviation, the screw task has a 100% success rate (i.e. number of experiments that performed according to Case 1). For 2 mm deviation, the spiral movement always finds the screw but there are two occasions where the logistic regression model makes a wrong prediction and stops the spiral movement before the nut-runner interlocks with the screw. The success rate of the spiral movement has decreased to 75% for 4 mm deviation, since the screw is now located further from the spiral movement axis. Furthermore, there are two instances where the model stops the spiral movement too early, resulting in a 65% overall success rate. Starting from 4 mm deviations, the spiral movement does not always find the screw, resulting in a failed screw task. In such instances, the failsafe method always fulfills its objective, stopping the robot movement and moving it back to the start position. A 6 mm position deviation places the screw just outside the spiral movement's circumference, which understandably leads to a significantly lower success rate. In summary, out of 80 screw tasks under different position deviation, the spiral movement can find the screw 60 times. Out of these 60 instances, the spiral movement is stopped by the learning model correctly 55 times, resulting in a 91,67% prediction accuracy.

Although the sampling rate of 50 Hz for the acquisition of the contact forces has proven to be sufficient to stop the spiral motion in time without damaging the hardware. This is an aspect that should be further analyzed. A higher sampling rate would be beneficial to ensure a faster reaction of the system and avoid safety-critical situations. In this contribution, it was not possible to use a higher sampling rate without suffering data loss. This issue will be considered in future work.

## 6. Summary

The work presented is a first evaluation of the feasibility of the proposed screw interlock recognition method that is based on a logistic regression model. The robotic system was able to perform screwing tasks under different position deviations of the screw. The effectiveness of the proposed method to stop the spiral movement in time has been successfully tested and validated, especially for deviations of 2 mm. While this first implementation of the learning model has shown some effectiveness, it still has some limitations:

- Although the validation of the logistic model has presented a good accuracy, the model has been trained by varying only one condition (position deviation).
- The proposed failsafe method is based on a threshold value that has to be estimated by observing several force profiles where the spiral movement fails to find the screw.

Future work will consider the variation of further parameters of the screwing strategy, such as environmental stiffness, screw size, workpiece material, etc., to train the logistic regression model and evaluate its robustness. Even though logistic regression model is intended for binary classification problems, it can be modified for multi-class classification problems by utilizing multiple decision layers. The learning model can be extended to include an additional state, namely when the spiral movement fails to find the screw. This way, the proposed screw method can be simplified using a single learning mode that also covers failed screw interlock.

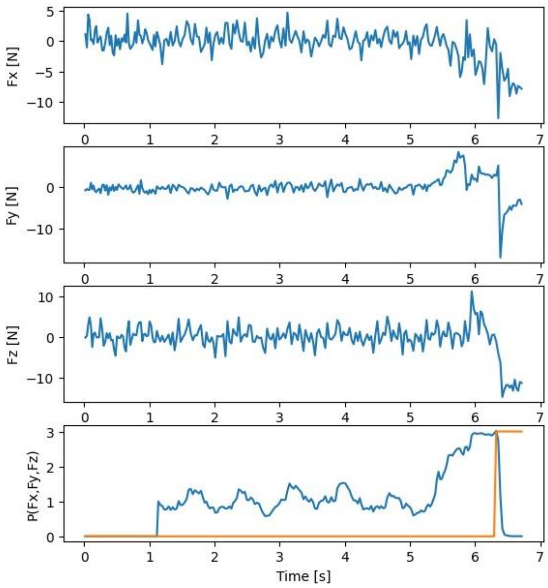


Figure 5 Experiment 2: Force profile of a successful interlock task

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