Identifying Unmodelled Dynamics in Contact Tasks in Industrial Robotics

Zaviša Gordić, Kosta Jovanović

***Abstract*—The intention of this paper is to propose and discuss different approaches to identifying unmodelled dynamics found in tasks performed by industrial robots. Unmodelled dynamics, forces and torques found in contact tasks cause deviations of joint currents and/or torque measurements from their expected values. Correct classification of these deviations and their distinction from collision-induced disturbances is of outmost importance for a reliable collision detection algorithm. Prospects and concerns of different approaches which can help make this distinction are discussed in terms of their reliability, applicability, and versatility. All approaches rely on information which is possible to obtain from industrial robots with closed architecture using standard commands and without any alteration to their control structure.**

***Index Terms*—Unmodelled Dynamics; Physical Human-Robot Interaction; Collision Detection; Industrial Robots.**

I. Introduction

The current situation and future market trends show the increase in demands for more complex, highly customizable and small batch production. Large companies with installed robots and automation are finding it difficult to adapt their production which was suited to low-mix and medium to large batch production, performing repetitive and tedious tasks in areas isolated from human workers because of safety regulations. On the other side, most of customization and small batch production is predominantly performed by human workers in SMEs who are in a constant struggle to keep up with increased demand for higher and more efficient output and reduced costs. The answer to many of the demands is to facilitate interaction of human workers and robots to synergize best of their advantages and achieve unrivalled dexterity, efficiency, and production costs.

The topic of Physical Human-Robot Interaction (pHRI) has been the subject of numerous research, both in field of collision detection [1]-[15] and safety considerations [16]-[18]. One of the main topics within pHRI is the collision detection, as the innermost level of protection which ensures safety of the worker during human – robot collaboration [2],[6]. A lot of research has been done in this field, with very good results in sensitivity and reliability, regardless of whether an industrial [10]-[12] or a collaborative robot is used [1]-[7]. Most of the related work has utilized model-based collision detection, which requires an accurate model of the robot, but there are also solutions which do not require dynamic model [4]-[5],[12]. While these collision detection algorithms can achieve good performance, most of them were tested in tasks which do not require physical contact of the robot with surroundings. The exception to this pattern can be found in strictly repetitive tasks [12], or in work with detection of intentional human contact through use of filtering [10]-[11],[15]. However, in the latter, the detected intentional contact was detected only on the dynamics of change in robots' joint measurements, and used to bring the robot into compliant state, rather than to continue to identify collisions during a task. In other cases where such contact was allowed, it was predominantly through use of force/torque sensors mounted between the robot tool and the flange of the robot [10]-[11]. The force/torque sensor enables the algorithm to compensate for and to distinguish intentional contact and unmodelled dynamics of the tool and/or load from collisions. However, force/torque sensor mounted between the robot's flange and its end-effector is only able to detect forces/torques at the end of kinematic chain. Therefore, this solution can only be used as a supplement to an existing collision detection algorithm, since collisions may occur at any point between the robot base and its end effector, which would otherwise not be registered by the sensor. Furthermore, such solution is often not suited for the production environment, and therefore robots must rely on their intrinsic sensors.

For industrial robots, which are predominant in production environments, internal sensors include joint position encoders and joint current measurements, based on which joint torques can be estimated. In both cases, detected deviations from the expected values of joint currents/torques originating from intentional contact or unmodelled dynamics can be difficult to distinguish from those originating from collisions, which was recognized in [14]-[15],[19]. This fact combined with necessity to react in shortest amount of time may lead to either high false alarm occurrence frequency or compromised worker safety. Having in mind that the worker safety must be ensured at all times, the effort must be directed into finding a way to reduce the frequency of false collision detections.

The intention of this paper is to propose and discuss different approaches to reaction to unexpected deviations and their proper classification. The main idea is that the intentional deviations can be recorded and integrated into collision detection algorithm, while all deviations different from them should be classified as collisions.

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Following a brief introduction to the topic in the First Section, measurement signal properties are discussed in the Second Section. The section presents major attributes related to the nature of the signal and observations based on measurement on an industrial robot performing contact and manipulations tasks.

The Third Section proposes and discusses different approaches to choosing the appropriate signals and ways in which they can be utilised in order to make the distinction between the intentional actions of the robot and the real collisions. The section also discusses how signals can be used to mark the beginning and the end of the deviation as well as how kinematic parameters can be used to refine and improve the decision making.

Conclusion and discussion of the paper is provided in the Fourth Section along with directions for future research.

II. Measurement Signal Properties

Based on the International Robotics Federation, robot installations in 2018 were beyond 400.000 units per year, and most of the robots installed around the world are applied in different fields of industrial production [20]. Therefore, vast majority of the installed robots are 5-7 axis articulated or 4 axis SCARA configuration industrial robots. Unlike collaborative robots which are just starting to make entry into manufacturing environments, industrial robots were not initially intended to work with humans in their workspace. To enable them to collaborate with humans, existing sensors must be utilized. The signal based on which collisions are detected is typically a measurement of joint current values. This signal may be available in form of signed or absolute values of joint currents, or as joint torque values estimated using measurements of the current. Consequently, regardless of the form in which the signal is provided, its properties remain the same, and the following analysis is valid for all of them.

One of the most important properties of the signal is related to the time domain repeatability of the current measurement. In previous work related to collision detection [12],[19], it was explained that industrial robots typically do not have a possibility to run parallel processes, but instead emulate this behaviour by swiftly jumping from one routine to another. This fact causes slight deviation of time instants in which identical command will be executed within a repetitive cycle. This also includes the motion commands, which consequently leads to the situation in which measurements from consecutive cycles of the identical movement do not match in time domain, as illustrated on Fig. 1.

The second observation related to the nature of the measurement signal of current/torque is the irregular occurrence of peaks, as shown on Fig. 2. The occasional appearance of peaks in measurement is related to the fact that currents/torques are dependant on speed and acceleration in each joint [13],[15]. Due to the fact that industrial robots possess only position measurements from encoders, speed and acceleration are calculated numerically as derivatives and double derivates of position measurements. Depending on the actual dynamics of the position change in relation to the sampling rate, these numerical derivations may result in values which do not correspond accurately to the actual dynamics of the robot [15]. Although these numerical values may differ from real values, they are absolutely adequate for the proper functioning of the robot due to robot’s inherent actuators and structural inertia which filter out the high frequencies of the control signal. However, from the standpoint of observation of signal deviations, these peaks may be mistaken for unexpected external forces. The peaks must not be filtered out because they may contain important indications of a collision or other real external force/torque which are of importance for the collision detection algorithms and worker safety.

Repeatability of the measurement shape and values for identical movements is one of the most important aspects related to the identification of signal deviations. This signal property should be observed from the perspective of the robot itself i.e. its actuators, and from the nature of the desired contact task. At this point, a distinction must be made between deviations caused by unmodelled dynamic properties of the end effector attached throughout the duration of the task on one side and, on the other side, forces/torques exerted or endured by the end effector or dynamics originating from the objects the robot manipulates or interacts with. While the former are generally very easy to determine or automatically estimate even by the built-in functionalities featured in most industrial robots, the latter can be a big issue to quantify and describe in an adequate way.

Previous work has shown that measurement shape and values which originate from the robot itself performing a non-contact task are very repeatable and dependable. However, it was demonstrated that repeatability is not guaranteed for all kinds of contact tasks. For example, while pick and place generally generate predictable and repeatable measurement values for the identical movement, the same cannot be guaranteed for snap fit and spring latch assembly, as shown on Fig. 3 and 4. These two assembly tasks are highly dependent on the repeatability of the object of the assembly and its accurate positioning prior to the assembly process. Different stiffnesses of the springs in spring latch assembly, or slightly altered position of the snap fit object result in significant differences of the measurement signal, as shown on Fig. 3. While the general shape of the deviation from values without contact are similar in shape, the intensities may vary significantly.

From the aforementioned observations, it is possible to understand that industrial robots with closed control architecture pose a unique set of challenges when it comes to detecting deviations from their expected joint current values. When these challenges are viewed from the perspective of collision detection, it should additionally be noted that all signal processing and decision making must be made in very short amount of time in order to make timely reactions of the robot and prevent injury or damage.

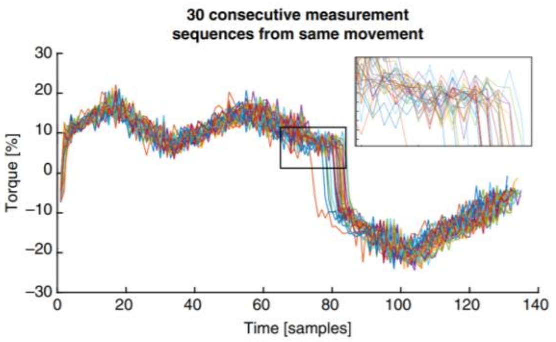

Fig. 1. Measurements from 30 consecutive executions of the same movement [12] show time domain related differences in recorded signal caused by the differences in sampling instants. Signals have slightly different lengths, and they are shifted in time for up to 13 samples or just under 10% of the total length of the signal.

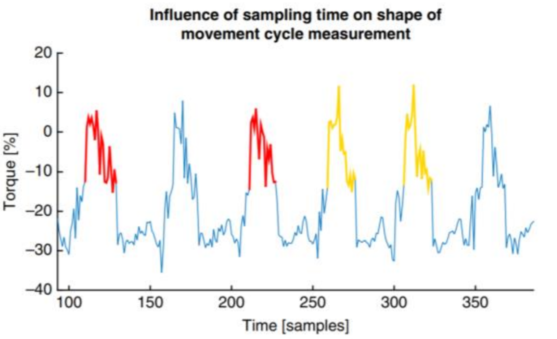

Fig. 2. Unpredictable occurrence of peaks due to differences in sampling instants [12]. The six shown periods of the signal represent six successive cycles of the same motion task. Peaks marked in yellow and red show biggest effects of the issues related to numerical position derivation.

III. Suggested Approaches

The observations from previous section lead to a conclusion that some types of contact tasks are difficult to predict in their intensity and shape, and therefore difficult to distinguish from collision-induced deviations and numerical anomalies. Additional difficulty is that distinction must be made with first samples of deviation in order to minimize the consequences of potential collision.

The presumption for all approaches presented in this paper is that robot performs more or less repetitive tasks in cycles, which is the case in vast majority of tasks for industrial or collaborative robots alike. Therefore, the idea is to record the deviation(s) occurring in one cycle of the robot task while operating in a controlled and supervised environment without collision occurrence. The recorded deviation can be used to extract and generalize certain features of the cycle that can be used as indicators of when and in which shape and intensity to expect deviation originating from an intentional and desired action of the robot in future cycles. With this approach, any deviation from the values of the recorded deviation should be considered as a collision.

To be able to distinguish unmodelled dynamics and forces/torques caused by intentional contacts from those originating from a collision, it is important to know two things. First – the shape and intensity of deviation originating from the unmodelled action, and second – when to expect it and for how long.

To aid in this matter, it is needed to consider which information from the robot, and in which capacity, can be used to complement the measurements of currents/torques.

When various brands and generations of industrial robots, as well as the general logic behind control algorithms are considered, other signals readily available on industrial robots can be identified.

One widely available signal that can be used to aid in this matter is the position measurement either in joint space or in external space, mostly described in Cartesian frame. For robots which can provide only joint position measurements, it is possible to use an automatic procedure to identify kinematic parameters [21] of the robot and provide external frame coordinates using direct kinematics calculations. Position and/or orientation of the flange in external frame, the operating plane, or any other of kinematics-related parameters can have a potential to be used as an indicator of when to expect the start and/or end of deviation. Even more importantly, kinematic parameters can be placed into context of estimating the changes in overall shape of the deviation.

Another option is to use output signals used by the robots to interact and control external entities. These signals can be of good use if it is directly and unambiguously related to the action which causes deviation. One such example can be the output which controls the gripper, since as long as the gripper is closed, the load is connected to the robot, and its influence is present. From the moment the gripper is opened, the load is released, and the deviation is not expected.

The aforementioned types of signals can be used effectively not only to help predict the start and end of the deviation, but also to assist in determining the changes of the shape of deviation caused by the change in robot's posture.

When it comes to the shape of deviations, the recorded deviation is only valid for the identical movement to the one during which it was recorded. Changing the robot movement, the weight distribution of the manipulated object or some other parameter from the cycle in which the deviation was recorded would result in changes to its shape, as illustrated on Fig. 3 and 4. While the overall shape is similar, some levels, peaks or other shape features may be different. To enable matching of the recorded deviation with the one under new conditions, it is needed to predict how it would change.

One way of determining the possible variations to the shape of deviation caused by the possible differences between the cycles of the task execution is to use mostly analytical approach. Forces and/or torques affecting the robot while performing contact tasks can generally be divided into tasks where predominant deviations from the expected values originate from weight and inertia of the manipulated object and those whose origin can be related to the forces/torques the robot itself and/or robot's end-effector exert on an external entity.

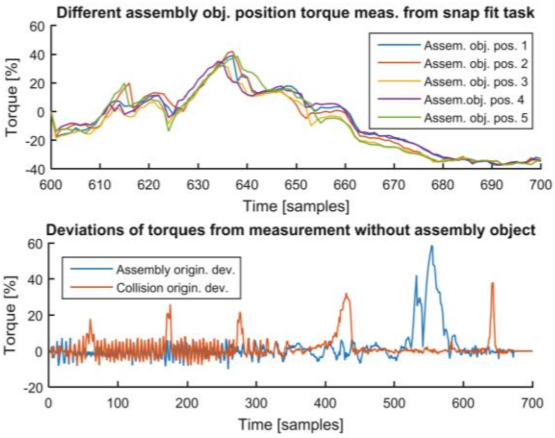

Fig. 3. Deviations of the torque measurement during snap fit assembly task [19]. (upper) Differences in positioning of under 1mm caused that some deviations have additional peaks at sample time 615. (lower) Deviation signal from the snap fit assembly task compared to collision-induced deviations shows great similarity.

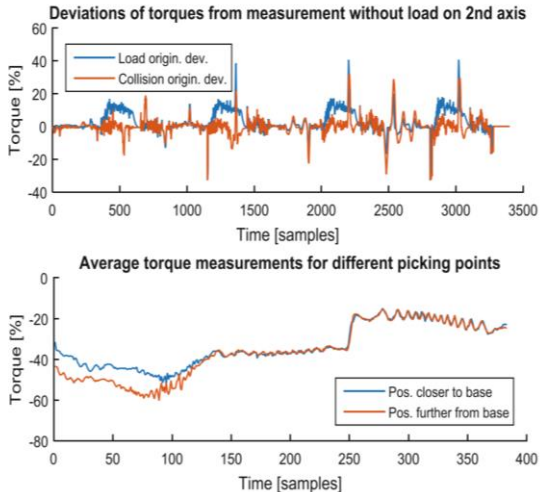

Fig. 4. Deviations caused by unmodelled load during manipulation task[19]. (upper) The deviations of the torque measurement due to unmodelled load compared to collision-induced deviation. While the nature of deviations is different, the intensity can in some cases be comparable. The first two periods of the signal correspond to cycles with picking points closer to the robot's base, while second two periods correspond cycles in which picking points were further away. (lower) Differences in distance of the picking points from the robot's base has caused differences in part of the deviation. From time sample 142, the deviations start to match because that part of the trajectory was common to both cycles of the repetitive task.

For the first group of forces/torques, the spatial configuration of the robot and dynamics of its transition to another configuration is the predominant factor which influences the shape and intensity of the deviation. When the robot is stationary, these deviations are constant, with exception to short transient periods, for example in liquids container manipulation, and reflect onto non-vertical axis. Tasks which belong to this group include typically manipulation actions such as pick and place, loading/unloading, machine tending, palletizing, and packaging.

For the second group, the direction of the exerted force/torque is relative to the orientation of the flange of the robot. The shape and intensity of the deviation is projected onto individual robot joints depending on their orientation relative to the flange, while its dependence on the robot movement is negligible. Robot tasks which belong to this group include screwing, drilling, polishing, riveting, various types of assembly without adhesives or material depositing, probing, friction welding etc.

There are tasks which are a combination of the previous two groups. Most of these comprehensive tasks can be divided into smaller sub-tasks, in order to subject them to the aforementioned division. For tasks where decoupling according to the division is not feasible, the deviation will be a resultant of the individual deviations from the two groups.

With the aforementioned considerations and division in mind, it is possible to understand how the recorded shape of the deviation may evolve due to changes in robot movement and posture. For the analytical approach, it is necessary to use knowledge of robot kinematics to reconstruct the general direction and intensity of the external force/torque relative to any relevant section of the robot. Then, it would be needed to calculate how it would project on individual joints in another configuration, and how the dynamics of the robot manipulator would affect it. If estimation of the changes of the deviation shape and its projection is not feasible, it is possible to use measures of curve similarity, as presented in [22]-[25], or with some modifications, mostly related to real-time application. The positive side of the analytical approach is that it is a verifiable and understandable and transparent process, which is a desirable trait for all matters related to collision detection. Furthermore, the process does not need a vast training set, or a lot of time to set up. The downsides are its complexity, and the fact that it is difficult to completely automate or make user friendly for operators with non-expert knowledge.

An important aspect related to the analytical approach is that it requires additional logic to determine when the deviation is expected to occur, and when to end. This information can in some cases be extracted by observing the kinematic parameters. As mentioned earlier, it is necessary to find a good correlation and a certain repetitive pattern in kinematic parameters such as constant height, position or orientation, geometrical surface/line to which the robot arrives just before the action which causes the deviation starts or just before it ends, This may prove to be an extremely challenging matter, considering the entire spectrum of tasks that a robot may be required to perform, and having in mind that setup phase should be as brief as possible. Of course, if the number of different positions to which a robot should arrive to perform the action that causes the deviation is finite and known in advance, this information could be incorporated into the algorithm.

As mentioned earlier, observing the output signals of the robot or other devices that trigger the actions causing deviations is available, it should be taken into consideration whenever possible.

Another approach to estimating the changes in shape of the recorded deviation would be to use Artificial Neural Networks (ANN). ANNs are able to process a large amount of input data and to find connections and correlations that work well, and that would otherwise remain unused. Research [4],[25] has shown that ANNs can be quite successfully trained to extrapolate and predict joint currents/torques of the robot performing new tasks. This can be done with or without knowledge of kinematic parameters of the robot, and with various other information provided by the robot itself or some of the external entities related to the action that causes the deviation. Following the same logic, it is reasonable to assume they could predict not only the shape of deviation, but maybe also when to expect it, and for how long. To the best knowledge of the authors, the latter has not been a subject of research in any related field, and therefore it can only be assumed based on the general capabilities of ANNs. The problem to this approach, however, is common to many tasks involving ANNs, and that is training. Generally speaking, ANNs require a lot of input data, and a lot of time to process all information and make appropriate connections. For all the material needed for the training, supervised measurements must be made, which is at least impractical from the implementation and exploitation point of view. Moreover, having in mind the high variability of possible contact tasks and types of external contact forces, it may be difficult to be certain of whether a representative training set has been acquired. Although it was shown in [4],[25] that the desired signals originating from the robot itself and all permanently attached entities can be predicted with high certainty, generally speaking the task space is quite unique for each individual application, and the variations in external forces must be well studied for each application. Finally, the biggest issue with ANNs is that the user is never absolutely sure how certain values are predicted, and how reliable they are. For collision detection, this is a huge problem, since reliability must be ensured and provable.

It is evident that both the analytical and ANN approach have prospects and concerns, some of which are complementary. A hybrid approach might be the needed solution which would combine the transparency and verifiability of the analytical approach with the ANNs' flexibility and ability to find hidden connections between inputs. Kinematics model of the robot combined with the current/torque measurements in joints can be used to reconstruct the profile of the deviation in Cartesian space. After the shape of deviation is determined, it can be described as a parametrized curve. Points of interests on this curve can be determined from several samples using Eigenvalues of the measurement set. Then, algorithm such as Active Shape Modelling can be used in conjunction with ANNs to determine the relation of the kinematic parameters with the shape of the deviation curve. Simultaneously, ANNs can find the best indicators of when the deviation may occur within the cycle. The algorithm could evaluate its estimation and indicate to the operator when the satisfactory level has been reached. Even after the adequate success rate of the estimations has been reached, the estimation could get better over time with increase of training and evaluation samples.

Hypothetically, the hybrid model could offer a good solution to the problem of distinction between intentional contacts and collisions. Potentially, it could be improved by incorporating a model of a collision-induced deviation. However, collisions come in different shapes and intensities, and so do the contact task-induced deviations, and there is not a single solution for all tasks. Nevertheless, the proposed approach offers another way to overcome the issues of false alarms occurring in robot contact tasks with unmodelled dynamics and forces/torques.

IV. Discussion and Conclusions

Joint work of human workers and robots is a logical and desirable trend with increasingly more foothold in reality. Enabling industrial robots with closed control architecture to adapt to current and future needs for pHRI would enable faster adoption of robotization primarily in manufacturing SMEs and provide them the tools to be more competitive and productive. The main precondition to enabling robots for pHRI is to enable them to detect collisions with their surroundings and therefore prevent human injury. One of major obstacles in efficient and reliable collision detection is telling apart intentional, but unmodelled dynamics and forces/torques occurring in contact tasks from real collisions. As a contribution to this goal, this paper suggested and discussed approaches to making this distinction, regardless if it is applied combined with model or non-model-based collision detection algorithms. Although intended for industrial robots as implementation platforms, suggested approaches can be implemented also on collaborative robots, regardless of their configuration and number of axis.

The analysis of the signal properties of currents/estimated torques, based on which the decision making is predominantly made, pointed out some of the main attributes and issues from the measurement point of view. The signals were observed and discussed from the perspective of their dynamics, repeatability, and similarity with collision–induced deviations. Measurement results from [19] were used to demonstrate signal properties from various contact and manipulation tasks. They demonstrated how unmodelled load, distance from the robot base and positioning repeatability of parts manipulated by the robot influence on the measured signal.

To achieve better distinction between intentional contact tasks and collisions, additional signals were considered to complement the current/estimated torque signal.

As a most widely available and useful signal, joint or external frame positions can be used to indicate when the section of the task which contains unmodelled dynamics and/or forces/torques will start and end. This functionality requires some previous knowledge which can be obtained through generalization of performing the desired task with human supervision. Both robot flange/end effector position and orientation as well as joint positions can be used to make the generalization. The generalizations can be made using different parameters and making the correlation between them. Parameters which show greatest level of correlation between the different cycles of task execution can be used as good indicators of when to expect the deviations.

Furthermore, it was suggested that with prior knowledge of the kinematic parameters of the robot, it is possible not only to indicate when the unmodelled part of the task will start and end, but also to approximate how the deviation from expected values will evolve depending on the robot joint movement. To this end, three different approaches to estimating the shape of the deviation were considered in general.

The first approach was based on analytics, and its general properties were discussed without going into particularities, along with its advantages and disadvantages. It was pointed out that knowledge of robot's kinematic parameters can also be used to determine the correlation of the robot flange orientation and orientation of the axis most affected by the deviation. The approach based on ANN was also generally discussed in terms of its applicability in collision detection and its prospects and concerns. Finally, it was suggested that a hybrid method might be the best solution for the application in the relevant field.

It was noted that outputs used to activate/deactivate external tools or devices were suggested to be used in tasks where they are available and directly related to the desired tasks. These signals can be used to indicate start of a task section with unmodelled forces/torques and possibly influence the thresholds for collision detection. In many cases, such signals can be used to mark the ending of the task section with unmodelled dynamics and restore detection thresholds.

The considerations and discussion presented in this paper were presented as a general guideline for addressing the aspect of pHRI which is often neglected, yet very important for good quality collision detection. Future work will involve further elaboration and design of deviation detection, estimation and distinction rules in accordance to results presented in this paper and previous research [12],[19],[21].

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