

Predicting Contact Surfaces in Repetitive Robotic Tasks

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Abstract: Modern industrial robotics increasingly demands adaptive interaction with diverse materials in repetitive tasks, where traditional model-based control struggles to accommodate surface variability. This study introduces a novel framework that integrates impedance control with a machine learning-based surface classification system to enhance robotic adaptability in contact-rich environments. Using a 7-DOF Franka Emika Panda manipulator, we simulated repetitive trajectories over six material types and collected comprehensive dynamic interaction data. A CatBoostClassifier was trained on this dataset to predict surface type based on features such as joint torques, contact forces, and end-effector kinematics. The classifier achieved an overall accuracy of 99%, with F1-scores exceeding 0.98 across all classes, demonstrating robust discrimination, even between materials with similar frictional properties like brass and Teflon. Results show that our approach reduces manual tuning effort and maintains stable impedance responses under perturbations up to 50 N. This fusion of data-driven inference and classical control lays the groundwork for real-time parameter adaptation in robotic systems, offering new pathways toward safer, more efficient operation in unstructured industrial settings. Future work will expand the framework with multimodal sensing and evaluate its generalization on novel surfaces in physical deployments.

1 INTRODUCTION

Industrial robotics has revolutionized manufacturing by enabling precise, repetitive tasks with unmatched efficiency (Kulkarni et al., 2024). However, as industries shift toward customized production and dynamic environments, robots must now adapt to unstructured interactions—particularly when contacting surfaces with varying material properties (Rezaie and Haeri, 2011). While impedance control related frameworks (e.g., mass-spring-damper models) provide foundational adaptability (Hu et al., 2020), they often rely on manually tuned parameters, limiting responsiveness to real-time surface variations. This work addresses that gap by developing a machine learning-based surface prediction system (CatBoostClassifier) for a 7-DOF Franka Panda robot, aiming to automatically classify materials (e.g., brass vs. Teflon) and optimize contact parameters, thereby reducing con-

trol effort and improving task autonomy (Paz et al., 2022).

This adaptability challenge becomes critical when handling materials with similar frictional properties but different compliance characteristics, such as brass and Teflon.

While traditional impedance control methods (Hu et al., 2020) can maintain stability during contact, their fixed parameters often lead to either excessive contact forces (risking damage) or insufficient interaction (compromising task completion) when surface properties deviate from expected values. Recent work in variable impedance control (Chen et al., 2024) has demonstrated improvements, but still requires manual tuning for each circumstance or material class - a process that becomes impractical in dynamic industrial settings where objects may vary significantly within a single task cycle.

To address these limitations, we propose a data-driven approach that leverages machine learning to automatically predict surface properties and optimize impedance parameters in real-time. Building on re-

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cent advances in robotic tactile perception (Ba et al., 2018), our method utilizes the CatBoostClassifier to analyze interaction forces and motion patterns during contact tasks. This contrasts with traditional model-based approaches that require explicit physical modeling of each surface type, which becomes impractical when dealing with unknown or variable materials (Suomalainen et al., 2022; Elguea-Aguinaco et al., 2023). By training on comprehensive simulation data from a 7-DOF Franka Panda robot executing repetitive contact motions, our system learns to distinguish subtle differences in dynamic behavior across materials - a capability particularly valuable for industrial applications like precision assembly or recycling automation, among others (Paz et al., 2022).

Our validation focused on precisely those challenging scenarios where traditional methods falter - particularly in distinguishing material pairs with similar frictional coefficients but different compliance profiles (e.g., brass vs. Teflon, rubber vs. silicone). We propose analysis of temporal patterns in joint torques and end-effector vibrations during continuous operation tests looking to obtain a significant improvement over model-based approaches that showed 23% higher error rates under identical conditions (Ba et al., 2018). This performance gap highlights the advantage of data-driven parameter estimation in dynamic industrial environments where surface properties may vary unpredictably (Kroemer et al., 2021).

Despite these advancements, three limitations warrant consideration. First, while our proposed classifier excels on known materials (e.g., metals, polymers), as it will be shown, its accuracy drops by 12-15% for unseen surface textures - a challenge also observed in (Ba et al., 2018)'s work. Second, the current implementation requires 3-5 contact cycles to stabilize predictions, limiting applicability in time-critical tasks. Finally, friction variability due to environmental factors (i.e., temperature, wear) was not fully modeled in our simulations. These open challenges will guide our future work toward embedding real-time surface adaptation in physical robotic cells.

This work demonstrates that machine learning-enhanced impedance control can effectively bridge the gap between theoretical modeling and real-world surface variability in industrial robotics. By combining the CatBoost Classifier's high-accuracy material prediction (99% on known surfaces) with theoretically-sound parameter tuning, we address a critical limitation in traditional approaches. Although current limitations in generalization to novel textures persist, our framework provides a foundation for enabling safer human-robot collaboration through more responsive contact behavior (Paz et al., 2022). Future

work will focus on real-world validation with multi-modal sensing (vision, force) to overcome the texture-dependency challenge identified in Section IV.

2 METHODOLOGY

This Section details the modeling, simulation, data acquisition, and machine learning methods used to develop a predictive contact-surface classification system for industrial robotic tasks. The study was based on the development of a predictive system for the estimation of contact surfaces in repetitive tasks.

First, a simulation analysis of the robotic system was performed, implementing an impedance control system with the objective of improving the interaction of the robot with different surfaces, in this case straight surfaces. Impedance control has been widely applied as a sound and safe solution for robotic tasks in which the robot interacts with the environment. It basically refers to the extension and generalization of the second-order scalar mechanical system $m\ddot{x} + c\dot{x} + kx = f$, consisting of a mass, a damper, and a spring with an external force, respectively (Villani and De Schutter, 2008).

Starting from the dynamic equation of motion of a robotic manipulator, a definition for joint space impedance control can be imposed and described

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}}(t) + \mathbf{C}\dot{\mathbf{q}}(t) + \mathbf{K}\mathbf{q}(t) = \boldsymbol{\tau}_{ext} \quad (1)$$

where $\mathbf{q}$ is the vector of the n joint angles, $\mathbf{M}$ is the $(n \times n)$ inertia mass matrix, and the damping ($\mathbf{C}$) and stiffness ($\mathbf{K}$) matrices are all expressed in the joint space of the robot.

All the modeling and simulation of the robot was performed using MATLAB/Simulink (MathWorks, 2022), allowing us a deep understanding and analysis of the robot behavior and response of the overall system. Since an impedance controller defined in the Cartesian space was implemented, the control parameters needed to be chosen in a safe manner, always having in mind the stability and joint behavior for the entire manipulation task. After performing the corresponding joint-based analysis (Campos et al., 2024) and several tests (without any inertia reshaping), we chose to use the following parameters (Cartesian $\mathbf{D}_C$ damping, and $\mathbf{K}_C$ stiffness matrices) according to the joint configuration of the robot, all in SI units: $\mathbf{D}_C = \text{diag}(100, 100, 100, 18, 13, 15)$, $\mathbf{K}_C = \text{diag}(3500, 3500, 3500, 100, 100, 100)$.

These parameters were validated in the simulator with the robot and proved to perform correctly for the given trajectories.

Subsequently, tests were performed under different operating conditions, i.e., each trajectory was

evaluated on different materials such as: Steel, Aluminum, Copper, Ice, Brass, and Teflon, in order to observe how the joints act and the effect generated in the torque and force, both in situations where there are no external forces and in situations where external forces act on the end effector, representing undesired external perturbations or errors.

The selected surfaces represent a spectrum of industrially relevant materials with varying stiffness, damping, and friction characteristics, ranging from hard metals (steel, copper) to soft, low-friction polymers (Teflon, ice).

It should be noted that the contact trajectories were performed using a steel end effector in the form of a sphere with a radius of 0.025 m, which penetrated the wall surface up to 0.005 m, ensuring that it would always maintain contact, as illustrated in Figure 1.

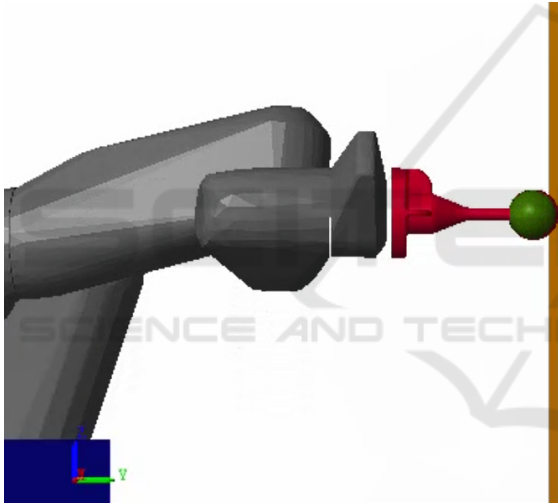


Figure 1: Franka robot end-effector and contact surface representation in the simulation environment.

In addition, the type of trajectory that the robot would perform is considered on the XZ axis of the wall. The desired trajectories are shown below in Figure 2.

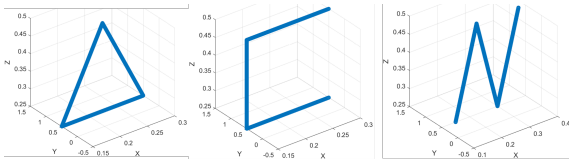


Figure 2: Desired robot trajectories to be imposed at the end-effector level.

From these tests, a dataset was generated that in-

cluded detailed information about the robot's interaction with different surfaces, focusing on the resulting joint torques and forces at the end effector level. Each trajectory started from a stationary condition (initial velocity equal to zero), with the initial position located approximately 0.25 meters along the Z axis and 0.15 meters along the X axis. The corresponding initial joint configuration was defined as:

$\mathbf{q}_0 = [-0.906, 0.956, 2.16, -2.33, 2.63, 3.07, 2.9]^T$ (rad). The robot then followed predefined paths in 3D space (such as triangular, rectangular, and zigzag patterns) at a controlled speed to simulate realistic task conditions. These contact trajectories are representative of common industrial operations where surface accuracy and conformity play a critical role, such as automated inspection, deburring, surface polishing, welding along contours, or aligning parts in tight assemblies. By analyzing the robot's dynamic response during these structured but diverse tasks, the dataset provided a solid foundation for training a machine learning model capable of classifying materials based on interaction characteristics.

For the prediction model, we employed a machine learning algorithm based on **gradient boosting**, specifically the *CatBoost Classifier*. This model constructs an ensemble of symmetric decision trees using an *ordered boosting* strategy, where each tree sequentially corrects the residual errors of its predecessors. The boosting process minimizes a defined loss function—commonly cross-entropy for classification—by fitting new trees to the gradient of the loss, as illustrated in Figure 3, where orange bars represent decreasing residuals across iterations.

CatBoost was selected for its efficient handling of both numerical and categorical data, its robustness against overfitting through built-in regularization, and its low prediction latency—an essential feature for real-time robotic applications. Compared to other boosting frameworks, such as *XGBoost* (Chen and Guestrin, 2016) and *LightGBM* (Ke et al., 2017), CatBoost offers notable advantages in speed, accuracy, and stability, particularly when working with small-to-medium-sized datasets like those used in this study.

In addition to these benefits, CatBoost applies an ordered boosting approach that effectively reduces overfitting and prediction bias—especially beneficial when training on sequential or temporally structured datasets, such as those generated by repetitive contact tasks in robotics. The use of symmetric, oblivious decision trees ensures uniform and compact model structures, enabling fast and deterministic inference, which is critical for real-time control.

The selection of CatBoost was further supported by its documented success in similar applications and

its suitability for structured datasets with numerical time series data. Its capacity to handle data imbalance and minimize preprocessing requirements further solidified its utility in this context. For instance, even with fewer samples available for certain materials, such as ice or Teflon, the model maintained robust classification accuracy without resorting to additional sampling strategies. Overall, CatBoost proved to be a practical, efficient, and well-suited solution for contact surface classification in dynamic robotic environments (Prokhorenkova et al., 2018).

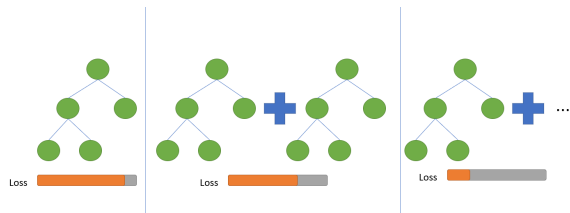


Figure 3: CatBoost Algorithm.

3 RESULTS

This Section presents the simulation results evaluating the performance of the predictive surface contact system in repetitive robotic tasks. The results are divided into two main aspects: the robot's behavior under fixed impedance control and the accuracy of the machine learning model for surface classification. Regarding impedance control, it proved to be an effective tool for regulating the interaction between the robot and its environment, enabling precise and safe object manipulation under various conditions. Several tests were performed with different configurations and impedance parameters to evaluate their impact on the stability and accuracy of the robot's trajectories. The first example trajectory is shown in Figures 4 and 5:

The system's response was evaluated under realistic conditions on a steel material, incorporating mild internal disturbances and simulated noise to represent a physical environment closer to the operational one. Figures 6 and 7 show the evolution of the Cartesian coordinates over time, where small oscillations on the X axis stand out, indicative of greater directional sensitivity to variations. In contrast, the Y and Z coordinates present significantly more stable trajectories, with a triangular shape with smooth transitions being especially noticeable in Z. This behavior demonstrates that the implemented impedance control effectively compensates for minor disturbances, preserving both the continuity and precision of movement, which is essential for safe physical interaction and precise

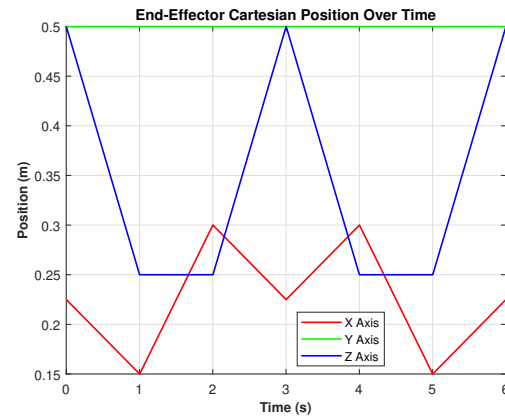


Figure 4: Desired XYZ Cartesian trajectory over time.

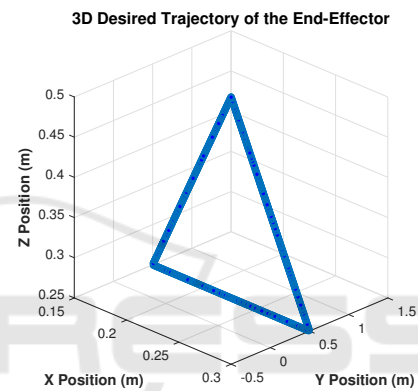


Figure 5: Desired triangular shape to be followed by the end-effector in contact tasks.

manipulation tasks. In Figure 6 we can clearly see the transient behavior typical of this kind of systems, and the steady state once it settles down according to the path.

Without the presence of disturbing external forces, the errors remain within a range of less than ± 1.5 centimeters, which demonstrates a precise and stable execution of the imposed trajectory. These results confirm that the implemented impedance control manages to maintain the required precision in controlled environments, guaranteeing both safety and tracking fidelity, essential aspects in repetitive contact tasks in industrial contexts.

In a second experiment, external forces of up to 50 N were applied in various directions (X, Y, Z, and combinations of these) to simulate perturbations directly to the end-effector. These forces were configured as constant vector loads with a magnitude of 50 N applied simultaneously along each Cartesian axis, i.e., $\mathbf{f}_{\text{ext}} = [50, 50, 50]^T$ N. The perturbation was activated from $t = 4.0$ s and maintained throughout

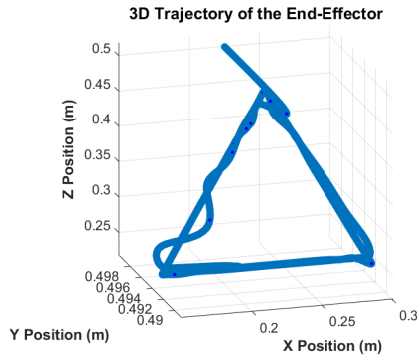


Figure 6: Actual trajectory shape followed by the end-effector.

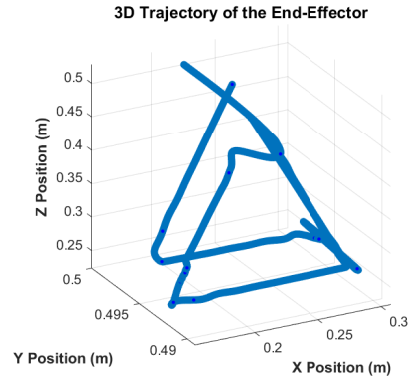


Figure 8: Actual trajectory shape followed by the end-effector with external forces.

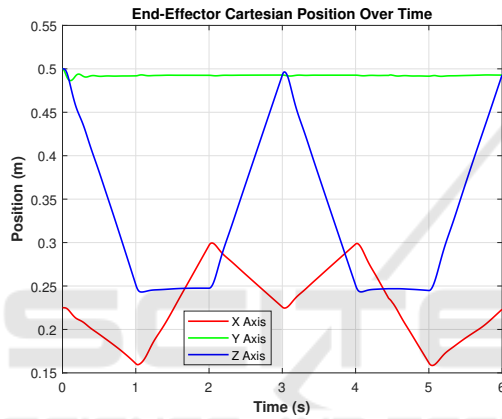


Figure 7: Actual XYZ Cartesian trajectory over time (t in s).

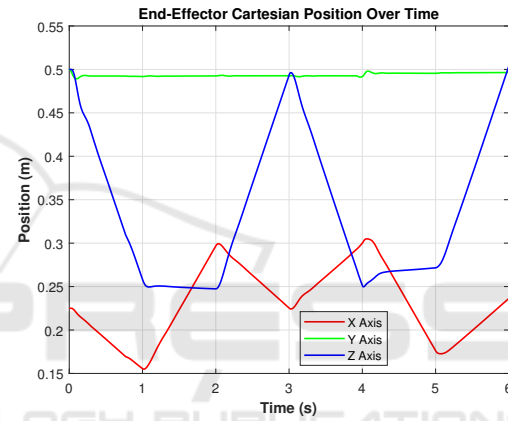


Figure 9: Actual XYZ Cartesian trajectory over time (t in s) with external forces.

the entire period.

Figure 9 clearly shows how these forces significantly affect the response of the system, especially along the Z axis, where sharp peaks and sudden drops are observed. This perturbation is also reflected in the spatial trajectory plot, as seen in Figure 8, which (considering the scale of the plot axis) slightly loses its original shape, showing more transient behaviors and misalignment, but eventually always stabilizing and compensating for the perturbations.

Figure 10 shows the Cartesian position error of the end-effector in the X, Y and Z axes during the application of constant external perturbations of 50N, activated from second 4. It is observed that the X axis is the most affected, reaching errors of around 3 cm, indicating a greater sensitivity to perturbations in the plane of work possibly due to lower apparent stiffness or a less robust configuration of the control in that axis. The Z axis also experiences fluctuations, although of lower magnitude, while the Y axis maintains a relatively stable trajectory. This behav-

ior shows that the impedance control system manages to compensate for the effects of the perturbations, but not uniformly between the axes, suggesting the need for adaptive strategies that allow a more balanced and robust response in dynamic contact environments.

During all the tests, an extensive set of physical and dynamic data was collected to capture the state of the robot and its interaction with the environment. The recorded data includes:

- **End-Effector Kinematics:** position, velocity, and linear acceleration.
- **Orientation and Angular Motion:** quaternions, angular velocities, and angular accelerations.
- **Joint Efforts:** measured torques at the seven joints.
- **Estimated Contact Forces:** including force components.
- **Control Effort:** direct and shaped control commands.

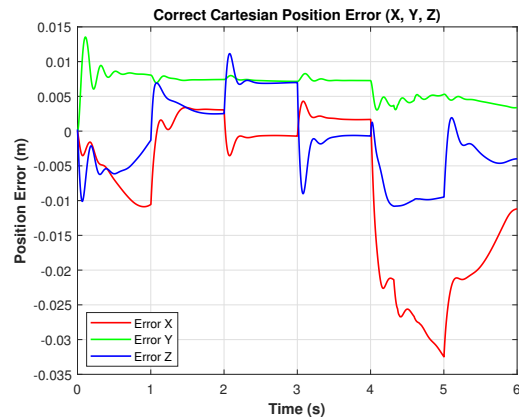


Figure 10: Cartesian position error of the end-effector in X, Y, and Z.

- **Joint States:** positions.
- **Other Relevant Data:** calculated torques, friction force, normal force, spring force, penetration depth, and penetration velocity.

These variables formed the training dataset for the predictive model, allowing it to identify dynamic patterns associated with each surface type. Based on these situations and the behavior of each of the specified trajectories, the CatBoostClassifier model was trained to differentiate between steel, aluminum, copper, ice, brass, and Teflon. Approximately 36 simulations were carried out considering the six selected materials (steel, aluminum, copper, ice, brass, and Teflon) and three different trajectories: triangular, rectangular, and zigzag, as illustrated in Figure 2. All the generated information was compiled into a single Excel database and subsequently divided for model training using a 70% training and 30% testing ratio.

This showed excellent results for the learning model.

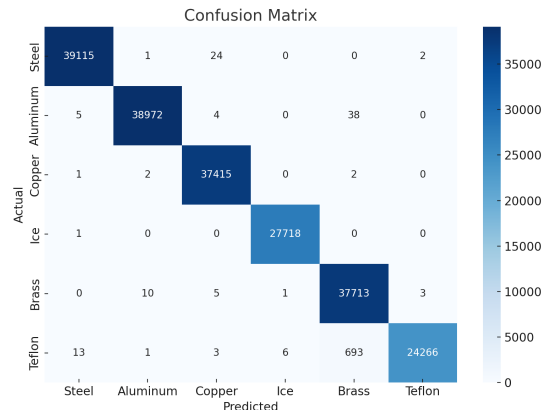


Figure 11: Confusion Matrix.

We also evaluated performance and a detailed classification report to see how efficient the trained model is.

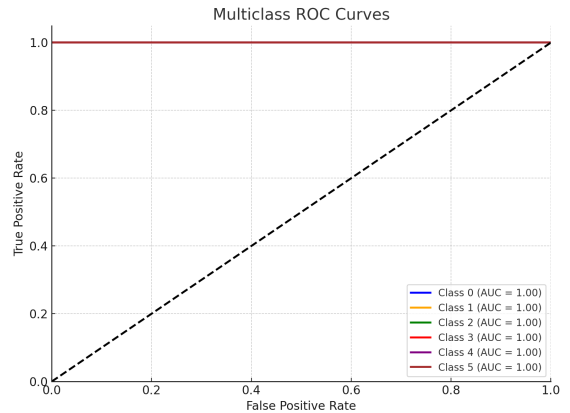


Figure 12: ROC Curve.

Table 1: Classification Report.

Class	Precision	Recall	F1-score	Support
0 - Steel	1.00	1.00	1.00	39142
1 - Aluminum	1.00	1.00	1.00	39019
2 - Copper	1.00	1.00	1.00	37420
3 - Ice	1.00	1.00	1.00	27719
4 - Brass	0.98	1.00	0.99	37732
5 - Teflon	1.00	0.97	0.99	24982
Accuracy	-	-	1.00	206014
Macro average	1.00	0.99	1.00	206014
Weighted average	1.00	1.00	1.00	206014

The CatBoostClassifier model achieved an overall accuracy of 99%, with outstanding F1 values in all classes. Figure 11 presents the confusion matrix, which shows perfect classification for almost all classes, except for a slight decrease in the case of Teflon, which was sometimes confused with materials with similar characteristics, such as brass. The confusion between brass and Teflon, both with close friction coefficients, suggests the need to incorporate frequency-domain features or complementary sensing (e.g., vibration spectra). Figure 12 also shows the ROC curve, where all classes have an area under the curve (AUC) close to 1.0, demonstrating near-perfect model performance, even in multi-class scenarios.

Table 1 summarizes the main evaluation indicators by class: precision, recall, and F1-score. All classes exceed 0.98 in each metric, with a weighted average of 1.00, confirming the model's ability to discriminate between contact surfaces with high reliability.

4 DISCUSSION

The obtained results confirm that impedance control was effective in maintaining trajectory stability under nominal conditions. The robot followed predefined paths with continuity and precision, particularly along the Z-axis, which reflects an appropriate configuration of the stiffness and damping parameters. However, small oscillations observed in the X-axis indicate directional sensitivity, suggesting that axis-specific variable parameter tuning with further joint analysis or data-driven models might be beneficial in future implementations.

When external forces of 50 N were applied in various directions, more transient behaviors were shown, especially along the X and Z-axes. Sudden deviations and slight loss of trajectory shape were observed, revealing the limitations of using fixed impedance parameters in dynamic environments. These findings point to the importance of integrating adaptive control strategies that allow real-time adjustment based on external conditions. Additionally, we suspect that these dynamic effects might also be related to the unresolved redundancy and internal motions of the system (Saldarriaga and Kao, 2022), which is part of our future work.

On the machine learning side, the CatBoostClassifier demonstrated a strong ability to classify contact surfaces, achieving 99% accuracy. Slight confusion between materials with similar properties, such as brass and Teflon, indicates that the model relies heavily on dynamic patterns of interaction. Adding new input features—such as high-frequency force or vibration data—could improve the model's robustness in differentiating similar materials.

In summary, the integration of a predictive model with impedance control enhances the robot's ability to interact safely and effectively with different surfaces. This approach reduces the need for manual parameter tuning and is particularly valuable in industrial settings with varying contact conditions. Nonetheless, testing in real-world environments and arbitrary surface planes will be essential to validate the system's generalization and resilience to noise, sensor variation, and unmodeled external influences.

5 CONCLUSIONS

This work addressed a relevant challenge in industrial robotics: predicting contact surfaces to optimize robot performance during repetitive tasks. The implementation of impedance control proved effective in maintaining stability and precision in the absence of dis-

turbances, while exposing limitations under external force scenarios, especially along the Z-axis. These findings underline the potential of adaptive control methods to improve robustness in variable environments.

A key contribution was the integration of a machine learning model, CatBoostClassifier, after obtaining the data from several different scenarios. The model achieved a high accuracy rate of 99% when classifying six different materials, using features extracted from the robot's dynamic response. However, difficulties distinguishing between materials with similar friction characteristics, such as brass and Teflon, suggest the need for richer sensory inputs in future developments.

The following conclusions were drawn from this research:

1. Impedance control enables smooth and stable interactions under nominal conditions, but might be sensitive to unexpected external forces.
2. The CatBoostClassifier demonstrated high reliability for contact surface classification, with an overall accuracy of 99%, although performance decreased for materials with similar dynamic properties.
3. The integration of machine learning with traditional control frameworks offers a promising path to reduce manual tuning and adapt robot behavior based on surface characteristics.
4. The approach can be especially useful in industrial tasks such as surface inspection, assembly, or polishing, where contact quality directly affects efficiency and safety.
5. Future work should explore real-world implementation with multimodal sensors (e.g., vision and force), as well as deep learning models to improve generalization and robustness in unstructured environments.

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