Design of an intelligent, vision-based guidance approach for industrial robots using Model Predictive Control

Bishoy Gerges (Engineering & Material Science, German University in Cairo, Egypt), **bishoy.yassa@student.guc.edu.eg**
Prof. Frank Schrödel (Automation Technology & Robotics, Schmalkalden University of Applied Sciences, Germany), **f.schroedel@hs-sm.de**

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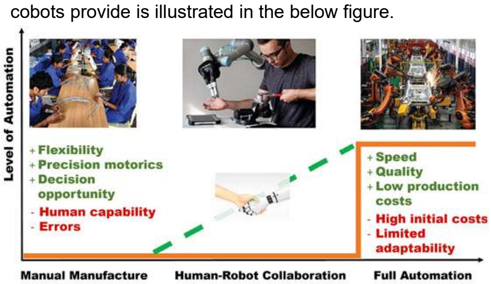
Industrial robots can replace many of human workers' jobs on site providing high accuracy and productivity. Typical tasks are ones that involve dealing with heavy loads, operating in poses unrealizable by the worker or tasks that require handling dangerous, toxic or hot substances. There are tasks where collaboration between humans and robots can be established and is sometimes necessary. Such robots that collaborate with humans in industrial sectors are called "collaborative robots", "robotic assistants" or "cobots. This collaboration provides the advantage of having the flexibility of human workers together with precision and repeatability of robots in a certain task. This perfect balance which cobots provide is illustrated in the below figure.



Literature Review

In general, it may not be possible to derive the optimal robot motion in a given specific time due to the complex constraints which require iterative differential solving algorithms. In literature, a large number of approaches for trajectory generation has been extensively studied. A classical example of graph search-based approaches for trajectory generation are A*-like methods, see e.g. [1]. The incremental property of the search algorithm results in an exponential growth of the computational complexity. To reduce the calculation complexity, some extensions regarding merging graph search algorithms with grid-based environment clustering are under evaluation. Potential Field approaches for trajectory generation like [2] are real-time capable. However, often they select local minima as optimal solutions and they can not handle kinematic boundary constrains. That's why, they create no feasible solutions, especially in high-dynamic scenarios. One very active field of research for trajectory generation is based on MPC in which the robot's planning problem is formulated into a finite horizon model-based constrained optimization problem, see [3], [4], [5]. Certainly, feasibility and computational complexity is a major issue for real-time applications. Another common category of trajectory planning algorithms is sampling-based, see [6], [7]. These methods generate a large set of candidate trajectories by utilizing deterministic or stochastic sampling of the state space. Thereafter, the best sub-optimal solution among these candidates is executed. The drawback of these methods is that the optimality of the resulting trajectory relies on generating a high number of samples, which may also not allow real-time applications. In previous work, an MPC based trajectory planning strategies is utilized, because this provides the capability to handle nonlinearities, operating constraints as well as predictions during the control design.

Problem Statement

In our research, we enable a full responsive collaboration between a cobot and human worker in a certain task through optimal motion planning. This approach allows not only ensuring the safety of the worker but it takes into consideration environmental and system constrains as well. This is achieved by designing a Model Predictive Controller (MPC) that optimally controls the path of the robot that meet the safety, system and environmental constraints in real time. Safety constraints includes the allowable distance between the worker's hand and the robot. System constraints can include maximum control effort that the robot motors can achieve. Obstacles or barriers that the robot may collide with during motion can be considered as environmental constraints. Perception of these safety constraints was achieved by using computer vision. Cameras were used to receive the distance between the worker's hand and the tool center point (TCP) of the robot. After that, the MPC could run an optimization problem that met the above-mentioned constraints.

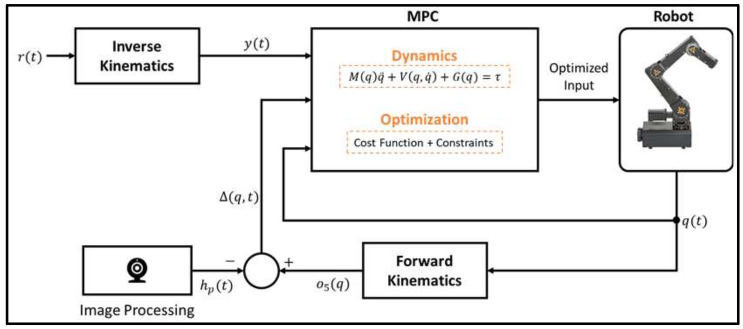


Fig. 1: Guidance Concept.

Methodology

The position of the human hand, denoted by h_p, is tracked in the task space via image processing. The feedback from the robot encoders, defining its configuration, is passed into the forward kinematic model to get the position of the robot end-effector in the task space, o_5. By getting these two positions, the distance between the robot end-effector and the human's hand is obtained. The safety feature is imposed by constraining this distance while solving the Optimal Control Problem (OCP) of the MPC. The inverse kinematic model of the robot is used to transform the reference trajectory from the task space to joint space. The dynamic model of the robot is exploited by the MPC during solving the OCP to predict and optimize the behavior of the robot while achieving the defined constraints. This guidance concept is illustrated in Fig. 1. The used robot is a low-cost 5-DOF industrial robot manufactured by Igus GmbH [8]. Model predictive control uses the dynamic model of the robot to predict its future behavior and optimize it based on a cost function while satisfying a set of constraints. The MPC formulation to control the Igus robot is designed to be:

$$\underset{\bar{u}(\cdot)}{\text{minimize}} \quad \int_0^{T_p} \left\| \begin{bmatrix} \bar{x}(t) \\ \bar{u}(t) \end{bmatrix} - \begin{bmatrix} y(t) \\ u^{ref} \end{bmatrix} \right\|_W^2 \mathrm{d}t + \|\bar{x}(T_p) - y_N\|_{W_N}^2 \quad \text{(a)}$$

$$\text{subject to} \quad \bar{x}(0) = x(0) \quad \text{(b)}$$

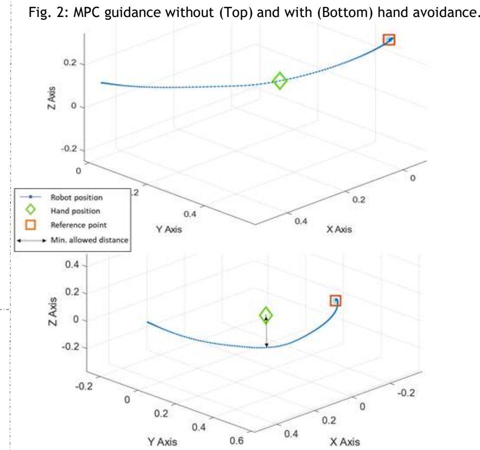
$$\dot{\bar{x}}(t) = f(t, \bar{x}(t), \bar{u}(t)), \quad \forall t \in [0, T_p] \quad \text{(c)}$$

$$\bar{x}(t) \in \mathcal{X}, \quad \forall t \in [0, T_p] \quad \text{(d)}$$

where T_p is the prediction horizon, $x(.)$, $\bar{x}(.)$ and $\bar{u}(.)$ are the vectors of the system states, system estimated states and estimated inputs respectively. $y(.)$ and u^{ref} are the references for the states and the control inputs respectively. y_N is the states reference at the end of the prediction horizon. (c) is the dynamic equations of the system. W and W_N are the weighting matrices for the stage cost and the terminal cost respectively. (d) represents the constraints imposed on the states including the safety constraint involving the distance, $\Delta(x)$, between the human's hand and the robot end-effector $\Delta_{min}(x) \leq \Delta(x)$.

Results

Fig. 2: MPC guidance without (Top) and with (Bottom) hand avoidance.



The hand position is treated as an online variable so that the constraint distance, Δ is variable. Two tests were conducted in the task space without and with defining a safe distance constraint where the MPC is given a desired final position to be reached by the robot. In both tests, the MPC guides the robot towards the final position, as seen in Fig.2. However, in the first test the robot collides with the human hand while in the second test the robot avoids the human hand maintaining the minimum safe distance.

Conclusion

In this paper, a protective separation distance has been calculated and maintained between the robot and the human operator during the experiment, thus enabling a collaborative environment in which both human and robot can work without having collision or clamping risks between the robot gripper and the operator's hands. Using an MPC for trajectory planning to achieve this target has been shown to be effective where a work area is described as a set of constraints under which the MPC guides the robot during a certain task.

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