A Laser-based Dual-arm System for Precise Control of Collaborative Robots

João Silvério and Sylvain Calinon

Abstract—Collaborative robots offer increased interaction capabilities at relatively low cost but, in contrast to their industrial counterparts, they inevitably lack precision. Moreover, in addition to the robots’ own imperfect models, day-to-day operations entail various sources of errors that, despite small, rapidly accumulate as tasks change and robots are re-programmed, often requiring time-consuming calibrations. These aspects strongly limit the application of collaborative robots in tasks demanding high precision such as watch-making. We address this problem by relying on a dual-arm system with laser-based sensing to measure relative poses between objects of interest and compensate for pose errors coming from robot proprioception. Our approach leverages previous knowledge of object 3D models in combination with point cloud registration to efficiently extract relevant poses and compute corrective trajectories. This results in high-precision assembly behaviors. The approach is validated in a needle threading experiment, with a $150\mu$m thread and a $300\mu$m needle hole, and a USB insertion task using two 7-axis Panda robots.

I. INTRODUCTION

In recent years, small parts assembly has become a popular research topic in robotics [1], [2]. With the advent of collaborative robots, such as the Franka Emika Panda robots in Fig. 1, this research direction gains special relevance. As safe, compliant and affordable platforms, collaborative robots often rely on torque control and less costly designs when compared to their industrial counterparts. This comes at the expense of precision, which is especially noticeable in tasks where tolerance is in the sub-millimeter range, such as needle threading (Fig. 1). Indeed, despite having good repeatability, the accuracy of most collaborative robots does not allow them to rely on proprioception alone for this kind of tasks (Fig. 2). With the dynamic nature of modern factories, in which collaborative robots are meant to excel, and all the associated perception and re-programming, it becomes clear that robust solutions for manipulating small parts are required.

A popular approach to circumvent imperfect proprioception is to combine control with sensory feedback. This type of approach takes inspiration from how humans, who have centimeter-level repeatability, perform manipulation tasks by incorporating feedback from vision [3] or touch [4]. In high-precision manipulation tasks, tactile feedback is often poor (e.g. needle threading), undesirable (e.g. small components are often fragile) or unreliable (due to low magnitude of the forces involved). Hence, visual or spatial perception are the most promising types of feedback. Here, we propose a dual-arm solution with laser scanning to address the precision problem. The general idea (detailed in Section III) is to have one arm responsible for manipulation (e.g. assembly, insertion) while the other measures the poses between the object being manipulated and the part where it will be placed (e.g. thread tip and needle hole in Fig. 1). Having the relevant poses, a low-amplitude relative trajectory that compensates pose errors is computed and applied to the manipulator such that the object pose is corrected, resulting in high-precision assembly behaviors. Our approach leverages previous knowledge of the objects’ 3D models in combination with registration of high-resolution point clouds (we use a laser scanner with a reference $1.5\mu$m depth resolution and 2048 points/profile along the $x$-axis) to efficiently extract relevant poses. For this aspect, we argue that exploiting previously available CAD models, similarly to [2], [5], [6], can have a strong practical impact in high-precision manipulation for collaborative robots. In summary, this paper advances the state-of-the-art in four main ways by:

1) introducing a novel approach to perform sub-millimeter insertion tasks using collaborative robots;
2) relying on laser scanning in the $\mu$-meter range;
3) being a dual-arm approach, which provides the possi-
To model relevant objects. Interestingly, Tamadazte for registration. When not available, we use the and rely on CAD models to obtain reference point clouds.

Recent work from Roveda et al. on 6D pose estimation [6] brings forward the insight that CAD-based methods are well suited for dynamic scenarios, such as Industry-4.0-type plants where appropriate lighting is often not guaranteed and where objects often have little texture. Similarly to our work, [6] relies on point cloud registration to find object poses, however at a much larger object scale. We follow their insight and rely on CAD models to obtain reference point clouds for registration. When not available, we use the sensing arm to model relevant objects. Interestingly, Tamadazte et al. [5] also proposed a CAD-model-based tracking method, but applied to visual servoing (without point cloud registration). Their micro-assembly approach is, however, not trivial to extend to dynamic environments like the ones we envision.

Our approach can be seen as a form of visual servoing where the sensory feedback is not provided continuously but every time a new scan is performed. Due to the low amplitude of the corrective trajectory that is computed, proprioception errors do not accumulate to a degree where the task is compromised. Additionally, the fact that the computed trajectory is relative, i.e., computed between two object poses represented in the same reference frame, alleviates the need for very precise calibrations. The distinguishing feature of our work on the sensing side is the very precise point clouds that we operate on, which come from the use of a high-resolution laser line scanner [13]. Depth sensing is a popular approach to modeling objects of various sizes, e.g. bridges [14] or daily-life objects [15]. We here study the applicability at much lower scales.

Finally, we highlight the high reproducibility of this work. By using popular collaborative robots, commercially available sensors, benchmark tools [2] and common daily-life objects (e.g. needles, threads), our results are easy to replicate when compared to other works on the topic that require more specialized robots, objects and setups, e.g. [5], [7], [12].

III. PROPOSED APPROACH

A. Overview

The proposed approach revolves around the setup in Fig. 1. In that figure we see one robot holding a high-resolution laser scanner and another holding a thread. Throughout the paper we will refer to the former as the sensing arm and the latter as the assembling arm. While in Fig. 1 the assembling arm is holding a thread, generically this can be any object that needs to be inserted/fit into another object. We will assume that the action that the assembling arm must perform comes down to an insertion (threading, assembly or other).

Figure 3 gives an overview of our method. Both arms start with the knowledge of the insertion pose, \( p_{ins} = [x_{ins}^T, q_{ins}^T]^T \) where \( x_{ins} \in \mathbb{R}^3, q_{ins} \in S^3 \). This pose represents an initial guess about where the insertion will take place in the robot workspace and is used to bring the laser scanner close enough that a point cloud of both the object to be inserted and its counterpart (where it will be inserted) can be collected. Both \( p_{ins} \) and the initial poses of both arms (see first two boxes in Fig. 3) can be collected beforehand, e.g. by kinesthetic teaching.

Once the scanner is close enough to the insertion pose, a point cloud \( P_{scan} \) is collected. This point cloud can contain sub-point-clouds that correspond to both the object to be inserted and the insertion target (e.g. a thread and a needle). With \( P_{scan} \), point cloud registration is performed (fourth box in Fig. 3), against a reference point cloud \( P_{ref} \), from which the poses of the object to be inserted \( p_{obj} \) and the insertion target \( p_{ins} \) are extracted. With \( p_{obj} \) and \( p_{ins} \), a trajectory that brings the end-effector to the final insertion pose is computed and sent to the assembling arm to be tracked (last two boxes in Fig. 3). Since the resulting trajectory will have a very low amplitude, any modeling errors that might exist are unlikely to accumulate enough to compromise the insertion.

The approach that we propose is both modular and generic by design. For instance, any box in Fig. 3 plays a distinct role that depends only on the completion of the previous one in the chain. Additionally, we impose no constraint on how each module is implemented, e.g. the specific motion of the sensing arm or the registration algorithm. Next, we describe our proposed implementations and a few considerations.

B. Scanning

The sensing arm is responsible for obtaining a high-resolution point cloud \( P_{scan} \) of both the object to be inserted and the part where it will be inserted (both assumed rigid enough not to deform significantly during insertion). Note
that there is the possibility to run multiple scans with different poses if necessary (e.g. for improving \( P_{\text{scan}} \)). An important aspect to consider is the transformation between the sensor frame and the robot base. Here we used the technical drawing from the sensor manual as an initial transformation that we refined using [16]. It should be noted, however, that the typical concerns with the precision of the calibration are alleviated in our approach, since we rely on a relative trajectory, represented in the reference frame of the initial object pose (Section III-D).

C. Point cloud registration

From \( P_{\text{scan}} \) we estimate \( p_{\text{obj}} \) and \( p_{\text{ins}} \). For this we rely on point cloud registration. Note that, with a high-resolution laser scanner such as the one we use, the point density will be very high. This is crucial for high-precision insertions. Similarly to [6] we pre-process \( P_{\text{scan}} \) as a means to remove noise and keep only the most important points. We also need the original point clouds of the objects whose pose we intend to discover, which we refer to as \( P_{\text{ref}} \). One way to obtain \( P_{\text{ref}} \) is by scanning objects beforehand and storing their point clouds. However, as highlighted in [2], in many automation processes the CAD models of the objects are readily available. We propose to use them whenever possible to obtain \( P_{\text{ref}} \). A myriad of tools exist for converting CAD models to point clouds. Here we used Blender [17].

For pose estimation, we used Algorithm 1: a combination of RANSAC [18], for a coarse initial registration of \( P_{\text{scan}} \) and \( P_{\text{ref}} \), and ICP [19], for refining the result. Particularly, we relied on their implementations from the Point Cloud Library (PCL) [20]. From the end-effector pose, we compute a prior on the manipulated object orientation \( q_0 \) that we use to filter out possible poor matches from RANSAC. For objects that are not attached to the robot, other heuristics can be used to compute \( q_0 \) (e.g. a prior on pointing heuristics). When poor registration from RANSAC occurs, which can hinder ICP performance, it is most often a consequence of orientation mismatches. In order to quantify these, we compute an orientation error \( d_\phi(\hat{q}, q_0) \) [21] between the RANSAC-estimated orientation \( \hat{q} \) and \( q_0 \). We then evaluate it against a threshold \( \rho_{\text{rot}} \) (set loosely enough to only reject unrealistic matches) to keep or reject the registration. Finally, we define a threshold \( \rho_{\text{ICP}} \) to stop the algorithm when the distance between point clouds is small enough. Both thresholds are chosen empirically. In Algorithm 1, \( f, P, p \) denote fitness scores, point clouds and poses, respectively. Only the outputs of RANSAC() and ICP() that are relevant to the approach are indicated in rows 4 and 6.

D. Trajectory planning and insertion

Using Algorithm 1 we obtain the poses \( p_{\text{ins}}^* \) and \( p_{\text{obj}} \). After knowing these poses we use spline interpolation to compute a corrective Cartesian trajectory for the assembling \( \{p_1, \ldots, p_T\} \), where \( T \) is the time horizon, that compensates insertion pose errors. Since \( p_{\text{ins}}^* \) and \( p_{\text{obj}} \) are represented in the same reference frame (the one of the sensing arm), a trajectory that connects the two poses is relative in nature, i.e. it can be applied as an offset so that the robot moves incrementally from its current state. One positive side effect is that the need for a very precise calibration of the sensor (as well as between the robot’s bases, which here was manually estimated) is considerably alleviated. In this work we used spline interpolation to plan relative trajectories but more elaborated techniques can equally be applied if required.

IV. EXPERIMENT I - NEEDLE THREADING

We applied the proposed approach to a needle threading experiment, a scenario that demands high precision.

A. Setup

The experimental setup is shown in Fig. 1. The assembling arm holds a thread that is to be inserted in the needle hole. Our evaluation considers three different aspects: initial conditions, testing settings and threading strategies. Initial conditions refer to the robot configuration before it starts moving towards the needle. Testing settings correspond to

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**Algorithm 1: Pose estimation via point cloud registration.**

**Input**: Point clouds \( P_{\text{scan}}, P_{\text{ref}} \); thresholds \( \rho_{\text{ICP}}, \rho_{\text{rot}} \), a prior on the object orientation \( q_0 \)

**Output**: Pose of scanned object \( \hat{p} = [\hat{x}^T \hat{q}^T]^T \)

1. filter and downsample \( P_{\text{scan}} \); \n2. initialize ICP best fitness score \( f_{\text{ICP}} = 1e6 \); \n3. while \( f_{\text{ICP}} > \rho_{\text{ICP}} \) do \n4. \( \hat{p}, \hat{P} \leftarrow \text{RANSAC}(P_{\text{scan}}, P_{\text{ref}}) \); \n5. if \( d_\phi(\hat{q}, q_0) < \rho_{\text{rot}} \) then \n6. \( f_{\text{ICP}}, p_{\text{ICP}} \leftarrow \text{ICP}(P_{\text{scan}}, \hat{P}) \); \n7. if \( f_{\text{ICP}} < f_{\text{ICP}}^* \) then \n8. \( f_{\text{ICP}}^* \leftarrow f_{\text{ICP}} \); \n9. \( \hat{p} \leftarrow p_{\text{ICP}} \); \n10. end \n11. end \n12. end
different needle poses. Threading strategies pertain to the robot configuration when inserting the thread and whether or not it uses sensory feedback. We now elaborate on these.

a) Initial conditions: Every time the robot performs an insertion, regardless of the threading strategy and final needle pose, it starts the motion at one of ten previously recorded joint configurations \( q^{(1)}, \ldots, q^{(10)} \). These were recorded such that the position of the end-effector at each joint configuration \( q^{(i)} \) is further away from the insertion pose than the previous, i.e., \( \| x^{(i)} - x_{\text{ins}} \| > \| x^{(i-1)} - x_{\text{ins}} \| \), \( i = 2, \ldots, 10 \), where \( x^{(i)} = f(q^{(i)}) \) is the end-effector position and \( f(\cdot) \) is the forward kinematics function.

b) Testing settings: We report results for three different needle poses (Fig. 4). Testing the approach with different needle poses allows us to evaluate its robustness when task conditions change. At the scale of this task, variations such as the ones in Fig. 5, which seem negligible in typical robotics conditions, can cause a strong impact on performance and are worth investigating. Prior to evaluations on any given needle pose, we performed an insertion on that needle and stored the pose of the assembling arm \( p_{\text{ins}} \) and the robot joint configuration. For each needle pose we compared three different threading strategies.

c) Threading strategies: We categorize threading strategies by whether the robot uses the laser scanner (insertion with sensory feedback) or not ( proprioception only). In the latter case, we further break down the evaluation into which of two possible configurations, IC1 and IC2 (Fig. 5), the robot uses during insertion. The null space of the task was used to bias the inverse kinematics (IK) solution to stay close to IC1 or IC2. The difference between IC1 and IC2 is that the former is the configuration of the robot during the recorded insertion and the latter is the configuration obtained by taking IC1 and adding \( \sim \pi/2 \) to the first joint (the rest of the joints seen in Fig.5b adapt accordingly so that the robot can accomplish the task). We hypothesize that IC1 will yield the best results in terms of accuracy, when compared to IC2, since it entails the least joint displacements with respect to when \( p_{\text{ins}} \) was recorded. In other words, IC2 will result in higher pose errors (more failed insertions). Specifically, the compared strategies were:

1) **Proprioception only + IC1.** The robot threads the needle using proprioception only and IC1 (Fig. 5a).

2) **Proprioception only + IC2.** The robot threads the needle relying on proprioception and IC2 (Fig. 5b).

3) **Insertion with sensory feedback (laser scanner).**

   The robot threads the needle using IC2 as null space configuration and compensates for insertion pose errors using sensory feedback as per Section III.

B. Hardware and control

In our experiments we used a Micro-Epsilon LLT3000-25/BL laser scanner [13] attached to the left robot arm. We operated the scanner at its reference resolutions of 1.5\( \mu \)m (depth) and 12\( \mu \)m (x-axis, 2048 points/profile). Moreover, in the needle threading experiment we used a 150\( \mu \)m-width thread and a needle with a hole width in the range 300 – 350\( \mu \)m along the smallest axis. Notice both the low scale and tolerance of this insertion task.

As robot platform, we used two 7-DoF Franka Emika Panda arms. The repeatability of the Panda arm, as reported by the manufacturer, is 0.1mm. To the best of our knowledge there is no official value for accuracy. In order to ensure the highest possible precision we used position control.

C. Results

Here we describe the obtained results from each strategy. All the reported results can be seen in the supplementary videos, which are found at https://sites.google.com/view/laser-cobots/.

a) **Insertion with proprioception only and IC1:** This strategy is aimed at testing the accuracy of the Panda robot. Given \( p_{\text{ins}} \), the robot is commanded to reach that end-effector pose, starting from different poses in the workspace. Table I shows the obtained success rates for this strategy (first row). The results show that, on average, for the considered starting poses, the robot managed to thread the needle 70% of the times. Figure 6 further elucidates the outcome. It is clear that, as the initial poses are farther and farther away from the insertion pose, the success rate decreases. This is likely due to a combination of the wider range of joint motions

| Table I: Success rates from needle threading experiment. Each number corresponds to 10 insertion attempts. |
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| **Strategy** | **Setting** | **Total** |
| Proprioception only + IC1 | Needle 1 | Needle 2 | Needle 3 | Total |
| Proprioception only + IC1 | 50% | 60% | 70% | 60% |
| Proprioception only + IC2 | 0% | 0% | 0% | 0% |
| With laser scanner | 100% | 100%† | 90% | 96.7% |

† Includes 2 failures that were successful upon re-scanning.
required to reach the insertion pose (and the small errors that are accumulated during the motion).

b) Insertion with proprioception only and IC2: The results showed that threading is never successful when the insertion joint configuration differs from the original one by a non-negligible amount (see Table I, second row). The third row in Fig. 6 is clear in this aspect, with the thread always ending up either below or before the needle. The arguments given in the previous paragraph hold for this case as well. Here, since not only the starting poses, but also the insertion configuration differs by a significant amount, the previous observation is amplified.

c) Insertion with laser scanner: Finally, using the proposed approach with laser scanning, the previous results were considerably improved. As seen in Table I insertion success rates reach values closer to 100%. In this scenario, the robot was commanded to thread the needle, by first using its proprioception alone as in the previous cases. Once it failed the insertion, the sensing arm performs a scan to obtain a point cloud of the needle and the thread. Using this point cloud it runs Algorithm 1 to find the needle pose. Figure 7 shows an example of a scan. Notice the high density of the cloud, for such a small object. The device resolution proves essential for this sort of tasks. In the bottom-right corner of the image we can see a small point cloud, which corresponds to the thread tip. In our experiments we selected the tip manually on the GUI, but this step can alternatively be automated, similarly to how the needle pose is found. With the needle pose and the thread tip, the robot computes a low amplitude trajectory that compensates for the pose error, ensuring insertion. It is worth pointing out that the results in the third row of Table I include two attempts where the robot initially failed the insertion but, upon a re-scan, succeeded. Indeed, by bringing sensory feedback into the loop, one is able not only to detect errors but also to correct them. The bottom row of Fig. 6 shows 5 out of 10 successful insertions for the needle 2 setting.

V. EXPERIMENT II - USB CABLE INSERTION

In a second experiment we used the NIST Task Board 1 [2] to study the insertion of a USB cable into a socket (Fig. 8). This time we obtained both socket and plug point clouds from their CAD models, made available by NIST. Similarly to Section IV, we computed success rates for 10 insertions, where the robot started at 10 different pre-recorded poses. Note that success rates are one of the performance metrics proposed in [2]. We considered two different robot configurations IC1 and IC2 following the same convention as in Section IV. In this case, we evaluated the approach
TABLE II: Success rates for 10 USB insertions.

| Strategy                   | Total |
|----------------------------|-------|
| Proprioception only + IC1  | 90%   |
| Proprioception only + IC2  | 0%    |
| With laser scanner         | 100%  |

Fig. 8: USB insertion setup with the NIST Task Board 1.

Fig. 9: Front and side view of the USB plug registration. White: Scanned point cloud $P_{\text{scan}}$. Green: Point cloud $P_{\text{ref}}$, obtained from the CAD model (here aligned with $P_{\text{scan}}$ after Algorithm 1). Since the plug was scanned from the front, we relied on a subpart of the whole CAD model.

for one single socket pose. Both socket and USB plug are scanned and registered in order to compute $p_{\text{obj}}$ and $p_{\text{ins}}$. Videos of the experiment are also available at https://sites.google.com/view/laser-cobots/.

Table II shows the obtained success rates. As in the needle scenario, all evaluations consisted of reaching a pre-recorded successful pose $p_{\text{ins}}$. Notice how the success rate is especially high, compared to the previous experiment, when the robot stays close to the joint configuration that performed the original insertion (IC1). This is likely due to the tolerance being higher in this setup. Nevertheless, as in the previous case, when changing the joint angles by a larger amount (IC2) the performance rapidly deteriorates.

In practical scenarios, the results will fall somewhere in between the two cases: neither is the joint configuration likely to be extremely different from the original one, nor is it likely to be very close. For example, offsetting the socket pose and $p_{\text{ins}}$ by the same amount (without recording a new $P_{\text{ins}}$) is enough for the robot to complete the task with a different configuration.

Figure 9 shows typical point clouds obtained during the experiment. The high resolution once again stands out. The registration results were particularly robust in our evaluations, which is attested by the 100% success rate with the laser scanner (last row of Table II).

VI. DISCUSSION

The results in Sections IV and V show that the insertion performance improves as feedback from the laser scanner is considered by the assembling arm. This is especially noticeable in the needle threading task where the tolerance is very low, as the width of both the thread and needle are in the μ-meter scale. Note that in the experimental evaluations only position correction was required by the tasks. However, in some insertion tasks, orientation tolerance might also be low. Correcting for both position and orientation has two main difficulties: 1) finding the orientation of the grasped object with respect to the robot end-effector can be non-trivial and 2) correcting for orientations often entail large joint displacements that lead to pose errors even after correction. One possible way to use our approach in those scenarios is to split the insertion into different phases, where the position and orientation errors are corrected sequentially.

Another aspect that is worth mentioning is related to the fact that the scanning arm is, itself, a collaborative robot. Hence it has the same proprioceptive limitations as the assembling arm. For this reason, it is recommended to minimize the amplitude of joint motions during scans, so as to mitigate kinematic errors as much as possible (which could lead to inaccurate point clouds). In most small part assembly scenarios, these should indeed be small as the objects themselves are small. Our experimental results show that, for the scales considered, no problems occurred. However, when scaling up or using more complex scanning trajectories, meticulous kinematic planning (e.g. using noisier joints less) might be handy. Devising new techniques in that direction could benefit both arms in their roles.

VII. CONCLUSIONS

We proposed a solution that enables collaborative robots to perform high precision tasks. We have shown that, using our approach, a Panda robot could insert a 150μm thread into a 300μm needle hole with a success rate close to 100%. The approach consists of a dual-arm system where one arm controls the motion of a high-resolution laser scanner while the other performs the insertion. It relies on the registration of scanned point clouds to find poses of objects of interest and plan an insertion trajectory that corrects initially imprecise ones. It is particularly well suited to low-volume, high-mixture manufacturing scenarios, where collaborative robots are meant to excel regardless of object scale.

In future work we plan to extend the approach to consider the end-effector and object orientations, and perform insertions in optimal ways by relying on model predictive control formulations on Riemannian manifolds [22]. We also plan to fully benchmark the approach following [2]. The possibility to use other benchmarks [1] will also be studied.
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