Proceedings of 2016 IEEE
International Conference on Mechatronics and Automation
August 7 - 10, Harbin, China

A Framework of Teleoperated and Stereo Vision Guided Mobile Manipulation for Industrial Automation‡

Fei Chen†, Boyang Gao, Mario Selvaggio, Zhijun Li and Darwin Caldwell
Department of Advanced Robotics
Istituto Italiano di Tecnologia (IIT)
Via Morego 30, 16163, Genova, Italy
{fei.chen†, boyang.gao, mario.selvaggio, zhijun.li}@iit.it
{darwin.caldwell}@iit.it

Keith Kershaw, Alessandro Masi, Mario Di Castro and Roberto Losito
Engineering Department
European Organization for Nuclear Research (CERN)
1211 Geneva 23, Switzerland
{keith.kershaw, alessandro.masi, mario.di.castro}@cern.ch
{roberto.losito}@cern.ch

***Abstract*—Smart and flexible manufacturing requests the adoption of industrial mobile manipulators in factory. The goal of autonomous mobile manipulation is the execution of complex manipulation tasks in unstructured and dynamic environments. It is significant that a mobile manipulator is able to detect and grasp the object in a fast and accurate manner. In this research, we developed a stereo vision system providing qualified point cloud data of the object. A modified and improved iterative closest point algorithm is applied to recognize the targeted object greatly avoiding the local minimum in template matching. Moreover, a stereo vision guided teleoperation control algorithm using virtual fixtures technology is adopted to enhance robot teaching ability. Combining these two functions, the mobile manipulator is able to learn semi-autonomously and work autonomously. The key components and the system performance are then tested and proved in both simulation and experiments.**

***Index Terms*—mobile manipulation, stereo vision, teleoperation**

I. INTRODUCTION

Modern manufacturing style, namely Industry 4.0 or Intelligent Manufacturing [2], requires the shift in paradigm from massive production to customized production and further to massive customization. The production in wage-intensive countries have created needs for flexibility, dexterity and cost-efficiency, especially in the field of automation and robotics. However, the industrial robots today are mainly assigned to do repetitive and dirty works without much flexibility or even intelligence. The gap between the requirement and reality introduces industrial level mobile manipulation robotic technology featured with task flexibility and robotic mobility and learning ability [3]. Mobile manipulation is a widespread term used to refer to robotic systems consisting of one or two robot arms mounted on a mobile platform, which allows robot performing tasks with locomotion and manipulation abilities. Starting from 1980s, the development of mobile manipulator has been experienced several stages focusing on different key components in both hardware and software. During that period, many mobile manipulators have been developed: MORO [4], Rob@Work [5], Little Helper [6], PR2 [7], TUM Rosie [8], KUKA OmniRob and KMR iiwa are the most representative mobile manipulators (Fig. 1).

(a) KUKA OmniRob (b) KUKA KMR iiwa

Fig. 1. Industrial mobile manipulator: two representative generations of KUKA mobile manipulator.

This new manufacturing style has greatly expanded the basic function of an industrial mobile manipulation robot. For example, this robotic mobile manipulation system can be easily reconfigured by nonspecialist personnel to perform autonomous/semiautonomous tasks in the unstructured environment. Implementing a high performance teleoperation capability can also enhance remote maintenance work experience, allow safe teaching and learning for robot by teleoperation demonstration, and recover from the event of unforeseen problems.

Therefore, autonomous mobile manipulator can be characterized by:

- *Autonomy*: It is an independent system and can operate fully automatic, and can also be teleoperated when human cannot intervene.
- *Adaptation and Safety*: It is able to work in typical structured industrial environments but also unstructured human dynamic environment, as it can avoid situations that harms people, objects and/or itself.
- *Perception and Learning*: It is capable of collecting information about the environment, and accordingly moves either the whole or part(s) of itself around, and in extension is able to perform versatile manufacturing operations

‡The work leading to this publication has received funding from the European Union's Seventh Framework Programme under grant agreement no. 608849 EuRoC [1].

at different workstations taught by human operators.
- *Collaboration*: It can communicate and collaborate with other robots or human operators.
- *Dexterity and Reconfiguration*: It is able to grasp and manipulate the target objects and quickly reconfigured to new tasks procedures.

Significant progress has been made in recent years in advancing the state-of-the-art in such kind of mobile manipulator. Technologies, e.g. image (RGBD point cloud) guidance based navigation [9], teleoperation [10] and collision free motion planning for grasping/manipulation, have been widely studied and applied on robotic mobile platforms [11]. As a representative of modern industrial mobile manipulator, KUKA OmniRob is chosen as the experimental prototype to carry out many European robotic projects, such as First-MM [12], TAPAS [13], and VALERI [14] targeting robust mobility and dexterous manipulation in shop floor logistics and automation, in home assistance and disaster response and rescue. Results from these challenges and projects reveal that the research into and application of mobile manipulation is the logical integration of manipulation, navigation, perception, teleoperation and learning. Although important progress has been made, there is still much work to do, e.g. the software developed for one case is not easily transferred to other cases. It is still inconvenient to program or teach a robot. It is therefore necessary to extend mobile manipulation application with respect to several key robotic technology.

- **Manipulation**: Use cases, particularly those in industry, have shown that robots usually undertake simple tasks e.g. clamping, delivering and peg-in-hole. It is unusual to see a robot perform more complicated tasks e.g. using tools or performing in hand manipulation of small or non-prehensile objects. Modern manufacturing industry requires that robots are able to manipulate various components and perform various tasks.
- **Perception**: It is still very challenging to recognise objects, especially under poor or unstable light conditions. In such cases, the robot should be able to detect and generate accurate 3D maps of the target region and precisely plan the object approaching, grasping and manipulating motion.
- **Navigation**: Currently commercial robot platform can locate accurately using SLAM. But when addressing simultaneous navigation and manipulation, the movement of the platform and the robot are still isolated given enough working space. The application of whole body motion control, the control of complete kinematic chains, is still not well investigated to extend the robot ability. This is especially important when the robot is working within a very restricted environment, or needs additional support e.g. force, velocity to manipulate objects. As a result, the robot should be able to navigate and locate itself providing additional degrees of freedom while the robot arm is move.
- **Teleoperation and Learning**: In extreme cases where humans cannot intervene, limited consideration has been paid to the development of an automated intelligent fault diagnosis and error recovery ability. In other cases emphasizing strict safety consideration, robot teaching by teleoperation for robot to perform the task is not well exploited as well.

The mobile manipulator as the original contribution presented in this work, namely autonomous mobile manipulation system (IIT-AutoMAP [15]) is built based on KUKA KMR iiwa (a.k.a., KUKA MIIWA or DLR-MIIWA [17], a successor to KUKA OmniRob [16]) industrial manipulator by integrating new hardware and software functional modules. IIT-AutoMAP demonstrates a framework for converting traditional industrial mobile manipulator into intelligent and user friendly mobile manipulator (Fig. 2) by integrating stereo vision and teleoperation functions. This mobile manipulation system is particularly beneficial for industrial inspection and maintenance tasks which require robot with semi-autonomy and full-autonomy abilities. This work focuses on the concepts, ideas and working principles of industrial mobile manipulator, based on a proof-of-concept philosophy. We also choose some typical industrial scenario to demonstrate the use of IIT-AutoMAP.

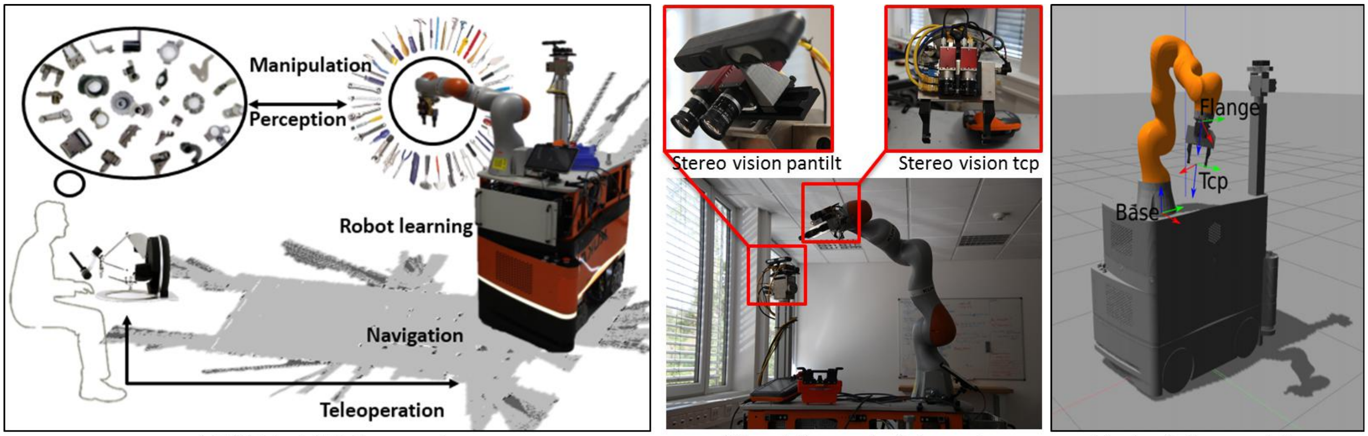
II. System Description

A. Hardware components

In general, IIT-AutoMAP KUKA MIIWA mobile manipulator is composed of a KUKA LBR iiwa collaborative arm mounted on a KUKA KMR platform (Fig. 3). LBR iiwa lightweight robot is an intelligent, industrial production assistant for the manufacturing processes and enables safe human-robot collaboration (HRC). Work can be partially automated, for example, to support the human operator, particularly at ergonomically unfavorable workstations.

The Mecanum wheels enables MIIWA to move in all directions, shorten throughput times and reduce non-productive time in the manufacturing process. The extended working range opens up a wide range of options for entirely new production concepts and increased cost-effectiveness in the form of reduced logistics costs. With the omnidirectional wheel technology, the KMR iiwa moves safely to the desired position with the speed of $4m/s$ ahead or sideways and $2m/s$ diagonally. Even in confined spaces, it achieves positioning accuracy of up to $\pm 1mm$. MIIWA makes it possible to utilize the efficiency and reliability of modern robotic technology for large-area automation solutions in the logistics sector. The integrated laser scanner monitors the work environment, while the integrated control software for navigation and motion enables reliable and flexible work sequences.

Two sets of stereo vision systems are mounted on the platform to provide the main perception function for the robot. One is mounted on the end-effector with the gripper focusing the manipulated object, named stereo vision TCP. The other one is set up on the platform to monitor the working environment, named stereo vision Pantilt. This system setup provides high quality point cloud data and color image and



(a) IIT-AutoMAP concept (b) mobile manipulator setup (c) simulation model

Fig. 2. Concept and setup of IIT autonomous mobile manipulation system (IIT-AutoMAP)

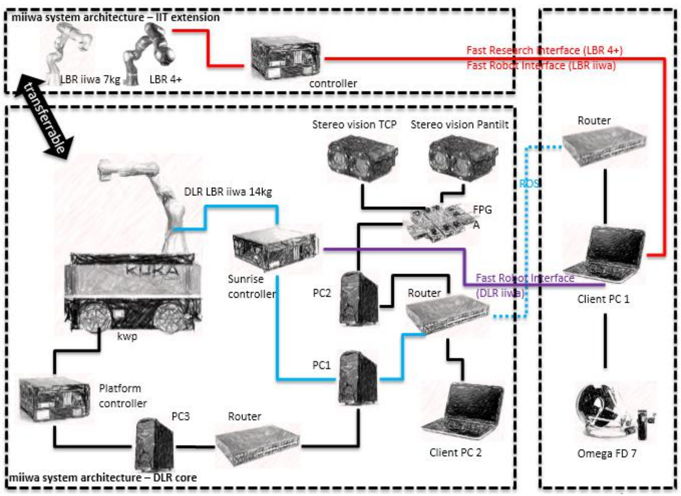


Fig. 3. IIT-AutoMAP hardware communication diagram

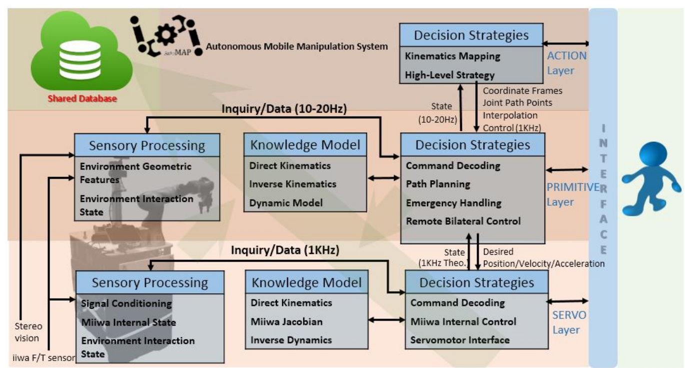


Fig. 4. IIT-AutoMAP software communication diagram

allows the robot to maximize the chance of identifying the object regardless of the occlusion (Fig. 2-b).

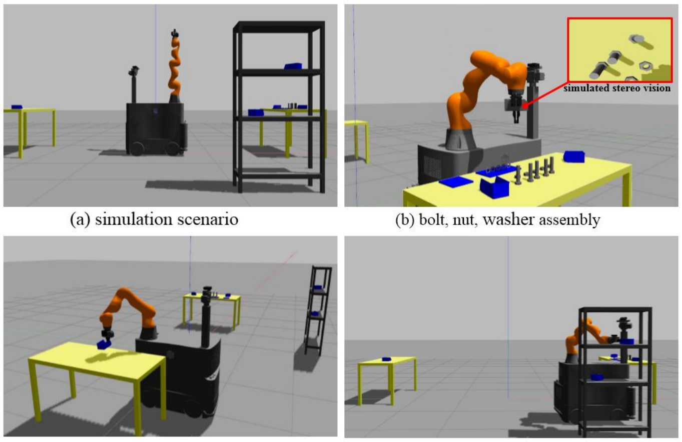
B. Software functions

The primary aim of the work is to apply state-of-the-art technologies to solve new and challenging assembly problems in a semi-structured environment. A number of key enabling technologies will be reshaped to solve generic assembly problems (Manipulation, perception and navigation) and then specifically tailored (Teleoperation and learning) to address the end-user problem (Fig. 4).

Robotic manipulation, particularly referring to grasping and in-hand manipulation, involving basic assembly operations using customized or commercial tools, is one of the most important tasks to be tackled in this project. The robot should be able to navigate autonomously or semi-autonomously (remotely controlled), creating a map using its inbuilt simultaneous localization and mapping (SLAM) function. A perception module for image guided path and motion planning and intelligent object detection is a key link to other modules, connecting with the SLAM module, as well as object identification and the object pose estimation module. A teleoperation function will be integrated to the MIIWA mobile manipulator using user-friendly haptic devices, Omega 7. This will permit a human to teach the robot the assembly skill needed to conduct the subtle manipulation. Moreover, in some emergency situations, a technician can always take over the control to help the robot recover from error or danger. Recent robot learning technology for remote control is also exploited. Based on the previous work about robot learning on various industrial applications, e.g. valve turning [12], contact perception [13] using KUKA robots, we apply both trajectory and force in the robot teaching framework to enhance learning effectiveness in assembly tasks [14] and even optimizing its behaviour [15]. For these activities, we also develop ROS/Xenomai based communication software which is proven to be very effective under industrial environment.

C. Simulation setup

For the purpose of quickly prototype and test of the system a simulation environment has been set (see Fig. 5). The teleoperation system has been simulated using ROS [18] and Gazebo dynamic simulator [19]. Both the robot and the parts of the simulated environment have been modeled in 3D and the CAD models have been imported in the using URDF files. Masses and inertia of the industrial parts have been computed according to relative material properties through MeshLab [20]. By using appropriate plugins, Gazebo can



(a) simulation scenario (b) bolt, nut, washer assembly (c) SLC pick and place from table (d) SLC pick and place from shelf

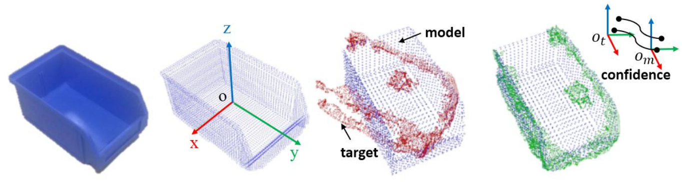
Fig. 5. Simulator setup with robot and its working environment. *Due to the length of the paper, the simulation results will be demonstrated in presentation.*

outputs eye-in-hand camera images and force/torque sensor values at robot wrist through standard ROS topics. In this way, the human operator can teleoperate the robot, as explained in previous sections, using the haptic device and passivity controller whose code has been wrapped into ROS nodes. In this work, algorithms related with teleoperation and stereo vision has been first tested and proved in simulation and then implemented in the real robotic platform.

III. System development

A. Stereo Vision and Perception

It is a key ability for the robot to be able to detect and localize the tools and items in the working area. The recent release of affordable depth cameras such as Microsofts Kinects has lately significantly boosted both the development of new methodologies and the implementation of tools to tackle such tasks. However its infrared based solution has restricted its application into only in-house environment where the infrared reflection is stable. Other different technologies have been proposed to implement reliable 3D vision for autonomous systems. Time of flight (ToF) cameras [21], and more in general LIDAR systems, actively project light rays on the scene and rely on measurements on the reflected light (phase shift or time) to reconstruct the 3D scene. This approach generally provides accurate depth estimation independently of lighting conditions. However their expensive cost also prevent them to be largely adopted in factory. As factory environment usually offers favorable and invariant lighting conditions, and color based robot vision is favored. Therefore it is reasonable to build the industrial vision solution based on stereo vision and disparity matrices (Fig. 2-b). Its main principle is like the human vision, correspondences from two distinct views are computed, and the relative misalignment among features in the frames is exploited to recover the depth information. Stereo vision requires heavy processing to compute disparities and can be affected by adverse lighting conditions, but offers acceptable results at a very low power consumption and little expense [22].



(a) A blue SLC (b) Point cloud model (c) Matching with ICP (d) Successful match

Fig. 6. An example of SLC pose estimation based on PCD using ICP.

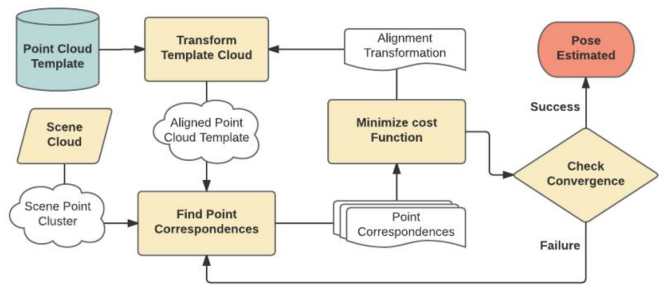


Fig. 7. A complete object recognition procedure using ICP.

We improve the algorithm proposed in [23] [24], where disparity matrices are computed through pixels-wise semi-global matching basing on mutual information, namely iterative closest points (ICP) algorithm. Fig. 6 shows its working concept on a industrial simple load carrier (SLC). As ICP works on point to point correlations, real sensor data makes it impossible to find perfect correspondences, and hence can lead the algorithm to convergence on a sub-optimal (and hence wrong) solution. This problem has been addressed in literature with many interesting variations and extensions. The high modularity of the algorithm (each of the algorithm steps, points selection, point matching and error minimization, can be treated independently, and refined even further) made it possible to develop different approaches for each step, and combine them according to the dataset to maximize performance [25] (Fig. 7).

In order to evaluate and compare the results of our corrections, we needed to define a confidence metrics. We used an approach based on Euclidean distance between matching points. We define the confidence of a given registration as the inverse of the average squared Euclidean distance among each pair of matching points:

$$Confidence = \frac{n}{\sum_{i=0}^{n} Euclidean(p_i^m, p_i^t)^2} \quad (1)$$

where n is the number of correspondences, p_i^m the i-th point of the model cloud, and p_i^t the i-th point of the target cloud. This solutions allows the system to easily compare results of the registration and safely select the best correction.

As explained in the previous sections, the main drawback of ICP is a blind convergence over the closest minimum of the objective function, which is not guaranteed to be the correct solution. In order to verify the correctness of an alignment, some further knowledge about the objective function is needed. We define as Alignment Space the set of admissible poses of the template cloud respect to the scene frame. As the objective

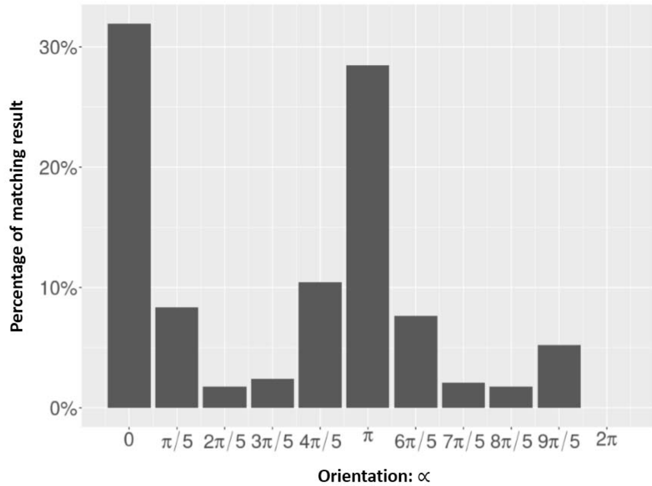


Fig. 8. Error pattern transformation histogram for SLC recognition

function depends on the template pose, each minima will correspond to a particular pose in the alignment space. Once identified the optimal solution, a transformations between each local minima and the global one can be computed. We consider this procedure as a learning process of the error patterns present in the alignment space. We introduce the Error Pattern Transformation (EPT) to correct the error. For each local minimum, EPT is defined as the transformation matrix transforming the wrong alignment into the correct one. EPTs represent the relative poses of the minima in the alignment space, and are hence dependent only on template and target structures. This means that once computed, they maintain their validity for each scene, assuming that the target cloud in the scene is similar enough to the estimate used. After bring the final solution in the neighborhood of the correct alignment. The system can then apply each EPT to the registration output, and use the validation metrics to evaluate all the transformed poses. If one of such poses features an higher level of confidence respect to the registration output, the algorithm had actually converged on a local minima, and the correct solution is retrieved.

Figure 8 shows a EPT for SLC detection. Histograms representing the frequency of convergence of the ICP algorithm over solutions within the given intervals of α with bin size of $\pi/5$. The vertical axes depict the frequency of convergences obtained for each given orientation interval over the whole training set. From this figure, it shows the presence of minima around the optimal ($\alpha = 0$) and the main sub-optimal ($\alpha = \pi$) solutions.

B. Teleoperation and Human-Robot collaboration

We define the human-robot collaboration models to combine teleoperation and full autonomy by integrating the inputs from both human and autonomous agents with autonomous task configuration [26]. It has been shown that a human operator teleoperating a robot can overcome challenging tasks thanks to the ability of sensing the remote environment through force feedback. It is well known that the delay makes the closed loop force reflection unstable or even data acquisition impossible

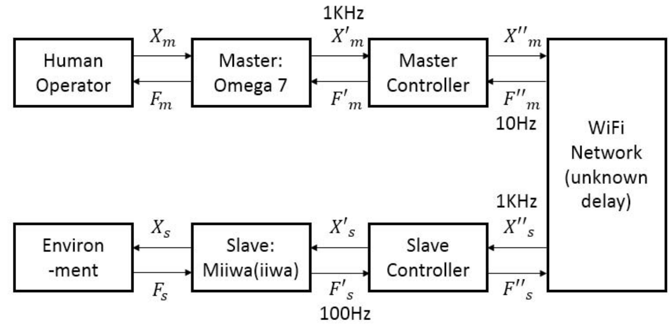


Fig. 9. Bilateral control scheme

with the classical bilateral control scheme (Fig. 9). To this end various passivity based control scheme have been proposed which can reduce the transparency of the system in pursuit of stability. However when the complexity of the task or the degree of redundancy of the slave robot gets higher shared and supervisory control can be adopted to help the operator to handle such complex situations. Shared control has the purpose of enhancing the human experience in teleoperating slave robot mainly through the use of virtual fixtures. Virtual fixtures help the human operator to perform safe and precise movement which are essential in many robotics application such as robotic surgery.

Teleoperation systems are composed of master and slave sides, represented by n-degree-of-freedom impedance/admittance controlled robots which, separately, behave as passive decoupled mechanical systems. Once these systems are connected in feedback, if the delay with which they exchange information is negligible the overall system can be considered stable, otherwise passivity preserving controller has to be considered.

In order to enhance the performances of a teleoperation system, guidance constraints imposed an additional force on the master side. These can help to keep the teleoperated slave robot moving along a desired path or towards a target zone while leaving ultimate control to the user. For the purpose of proofing system stability in such conditions, every physical system can be modeled as a two port Hamiltonian mechanism. Formally, it can be represented as:

$$\begin{cases} \dot{x} = [J(x) - R(x)]\frac{\partial H}{\partial x} + g(x)u \\ y = g^T(x)\frac{\partial H}{\partial x} \end{cases} \tag{2}$$

where $x \in \mathbb{R}^n$ is the state and $H(x) : \mathbb{R}^n \to \mathbb{R}$ is the Hamiltonian function, namely the sum of system stored energy. Moreover, J represents the internal coupling, R the internal dissipation, $g(x)$ the input matrix, u the input and y the system response. It can be shown that for a two port Hamiltonian system passivity condition with respect to $u^T y$ can be written as:

$$u^T y = \dot{H}(x) + \frac{\partial^T H}{\partial x} R(x) \frac{\partial H}{\partial x} \geq \dot{H}(x) \tag{3}$$

The effect of additional forces at the master side associated with active constraints has been demonstrated not to influence passivity condition. In this case the term u in Eq. (2) in presence of virtual fixtures can be specialized as

$$u = F_{ext} + F_{fb} + F_{vf} \quad (4)$$

where F_{ext} is the force exchanged with the human operator, F_{fb} the force feedback and F_{vf} represents the additional guidance force of the virtual fixtures. In particular, the term F_{fb} is the force coming from the slave side and depends on the adopted teleoperation scheme, such as position-position or position-force, while F_{vf} is computed by a suitable constraint enforcement method, in our case using artificial potentials.

Regardless of the geometric primitive used for describing a virtual fixture, a constraint enforcement method has to be applied to provide external supporting force to the master. Various kind of constraint enforcement method have been proposed in the past for different kind of geometric primitives: attractive potential field, initially used in teleoperation by [27] and other assembly case [28], are used throughout this work.

By choosing appropriate gains the operator moves freely when is position is away from the parts, while an increasing force is applied to the master side as soon as the corresponding robot position is going to approach a part. From a mathematical point of view this can be seen as:

$$P(x) = \sum_{i=0}^{n} e^{-(x-x_{0i})} \quad (5)$$

$$F_{vf} = -\frac{\partial P}{\partial x} = -\sum_{i=0}^{n} \frac{x - x_{0i}}{\|x - x_{0i}\|} e^{-(x-x_{0i})} \quad (6)$$

where x is the current robot position, x_{0i} is the position related to each object present in the scene, n is the number of object in the scene with an associated potential, P represent the sum of potential functions and F the total force to be opportunely rendered on the haptic device. It is trivial to understand that the force felt by the human operator only increase when approaching to the target making him/her free to move unconstrained in the remaining part of the environment.

IV. Experiments

A. SLC recognition and pick-place experiment

The stereo camera system in this work is composed of two Allied Vision Mako $G-125C$ cameras which provide 1.2 Megapixel ($1292X964$) frames at $30fps$. We demonstrate the comparison of standard, 2D constrained ICP, and 2D constrained ICP with EPT based correction. The algorithms have been evaluated on the task of estimating the pose of a blue SLC (Fig. 6). We create the dataset based on the observational data recorded and apply it when evaluating the algorithm performances.

We define the accuracy of a given algorithm on a given training sample as the percentage of correct convergences over all the 72 initial alignments. We consider correct all the alignments for which the translational error and the rotational error (respect to the sample ground truth) are respectively inferior to 0.3 cm and 0.03 rads. Table I shows the results obtained by the different algorithms with similar performance. On the observational data, 2D-ICP showed an higher average performance, but the correct convergences did not exceed 50% for either of the two algorithms. The EPT based algorithm, on the other side, gave better results, as it managed to correctly recover the optimal alignment for each of the testing samples with any initial alignment. Even for the observational set, where testing and training samples featured structural differences and (even if slightly) different morphology of the objective function, the accuracy was still 100%.

TABLE I
Algorithms performance

Observational Set		STD-ICP	2D-ICP	EPT-ICP
Samples	1	48.62	48.62	100.00
	2	38.89	40.28	100.00
	3	37.50	51.39	100.00
	4	45.83	44.44	100.00
	Average	**42.71**	**46.18**	**100.00**

Figure 10 shows the experiment that the IIT-AutoMAP robotic manipulator can successfully detect, recognize and grasp the SLC from the shelf through all trials.

B. Bolt pick-place by teleoperation experiment

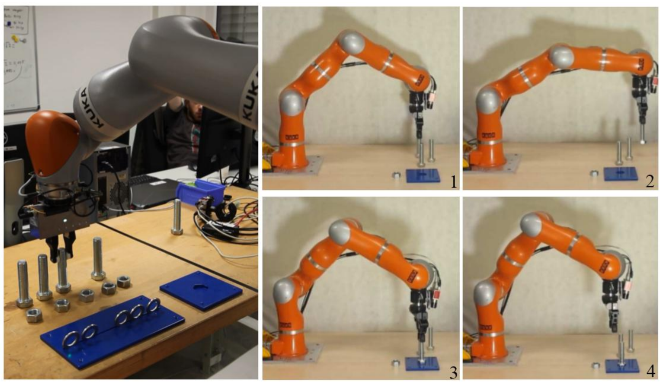
The system hardware consists of a KUKA LWR 4+ slave robot teleoperated by via a Force Dimension Omega 7 master device. A force-torque sensor is mounted on the robot end effector. It is sampled at 1 kHz, and a low pass filter with cutoff frequency fc = 100 Hz is used for filtering the force signal. Two computers running Linux Ubuntu are used: one of these is connected to the stereo vision cameras and receives signals via Ethernet communication, the other one is connected to the Omega via USB and the robot via Ethernet. These two laptops are exchanging information by means of TCP/IP socket.

KUKA LWR 4+ and one computer are connected through Fast Research Interface. The Fast Research Interface Library [29] runs on a remote computer which is connected to the KRC (KUKA Robot Controller) via ethernet connection. This subsystem runs at $5ms$ for testing purposes, even though it can be operated up to a frequency of $1kHz$. The robot is commanded in cartesian impedance mode with stiffness $K = [2500\ 2500\ 2500\ 300\ 300\ 300]$ and damping ratio $D = [0.7\ 0.7\ 0.7\ 0.7\ 0.7\ 0.7]$, along and about the x, y, and z axes. The function that deals with socket communication has been implemented in a separate thread in order to avoid the influence on the teleoperation loop. The Omega 7 device sends haptic device pose, velocities and forces at high frequency. Before sending position commands to the robot, the haptic device position and orientation are opportunely mapped and scaled to match the desired robot movement space. Energy tank based control approach [30] is used for stabilizing force feedback loop between master and slave.

The specific evaluation procedure adopted in this work to demonstrate the validity of the proposed approach consists in detecting bolts in the scene and opportunely place one of them in a fixture (also detected and associated with an artificial potential). The operator teleoperates the robot using haptic device receiving force feedback from the force torque sensor and images from the stereo camera system. When the system

(a) initial position (b) adjust platform (c) approach object (d) pre-grasp (e) grasp (f) post-grasp

Fig. 10. A vision guided SLC pick up experiment



(a) experiment on IIT-AutoMAP (b) key step demonstration with KUKA 4+ arm

Fig. 11. A virtual fixture guided bolt pick up experiment

starts, both the robot and the haptic device poses are recorded in order to compute their offset transformation matrices. It allows to start from generic initial pose of master and slave. The bolts are randomly placed in the scene can be recognized by the vision. Once the parts are in the field of view of the cameras, their position are calculated in the stereo camera reference system. These positions are used to generate virtual fixtures required as described in the previous sections.

In this experiment, one bolt from the scene is grasped and placed in the fixture (Fig. 11-b). The starting pose of the robot allows the operator to clearly see the parts placed in the scene. When the system starts, the operator is attracted towards all the parts. When one bolt is grasped, the system is triggered by closing of the gripper and the artificial potentials associated with other bolts become repulsive, bringing the operator away from them during the following path. This allows the operator to safely approach the fixture and place the bolt.

Figure 12 shows the geometric path of the robot, the time series of the components, and the magnitude of the force due to the virtual fixture, recorded at the master. When the operator starts moving around $2sec$, the magnitude of the force increases because of the attractive force from the bolt the robot is going to grasp. Then the robot reaches, after around $5sec$, the top of the bolt and successfully grasps it (Fig. 12-a,b,c). In the following phase the forces start from a slightly greater value because, as soon as a bolt is grasped, the potential associated with the other bolts are switched to repulsive. This makes the operator moving away from other objects under the driving of an attractive force towards the fixture pose. Finally, around 20 seconds, the magnitude of force starts increasing again when the robot is approaching the target region and goal pose.

Considering that the force received by the operator is approximately $10N$, the presence of the virtual fixture does not deteriorate the transparency of the overall teleoperation system. In fact, during the holding or placing phase, the force coming from the active constraint never exceeds the 10% of the external force coming from the environment. It has to be pointed out that the force values in the previous diagrams represent the force after the passivity controller. This prevents the released energy from being larger then the injected one keeping the system stable.

V. Conclusion and Future Works

In this research, a stereo vision system providing qualified point cloud data of the target object is presented. A modified and improved iterative closest point algorithm is applied to recognize the targeted object greatly avoiding the local minimum in template matching. Moreover, a stereo vision guided teleoperation control algorithm using virtual fixtures technology is adopted to enhance robot teaching ability.

This system with its expected performance will have a major impact on safety and manufacturing. The technology and systems developed in this work will be readily transferable to the maintenance of thousands of key components along the Large Hadron Collider (LHC) within the European Organization for Nuclear Research (CERN) and more widely to other external scientific and industrial facilities having hostile and unstructured working environment.

To this end, future work will focus on the robot teaching and learning for carrying out various tasks.

References

[1] B. Siciliano, F. Caccavale, E. Zwicker, M. Achtelik, N. Mansard, C. Borst, M. Achtelik, N. O. Jepsen, R. Awad, and R. Bischoff, "Euroc-the challenge initiative for european robotics," in *ISR/Robotik 2014; 41st International Symposium on Robotics; Proceedings of*. VDE, 2014, pp. 1–7.

[2] K. Schwab, "The fourth industrial revolution," in *World Economic Forum, Geneva*, 2016.

[3] M. Hvilshøj, S. Bøgh, O. Skov Nielsen, and O. Madsen, "Autonomous industrial mobile manipulation (aimm): past, present and future," *Industrial Robot: An International Journal*, vol. 39, no. 2, pp. 120–135, 2012.

[4] J. Schuler, *Integration von Förder-und Handhabungseinrichtungen*. Springer-Verlag, 2013, vol. 104.

[5] E. Helms, R. D. Schraft, and M. Hägele, "rob@ work: Robot assistant in industrial environments," in *Robot and Human Interactive Communication, 2002. Proceedings. 11th IEEE International Workshop on*. IEEE, 2002, pp. 399–404.

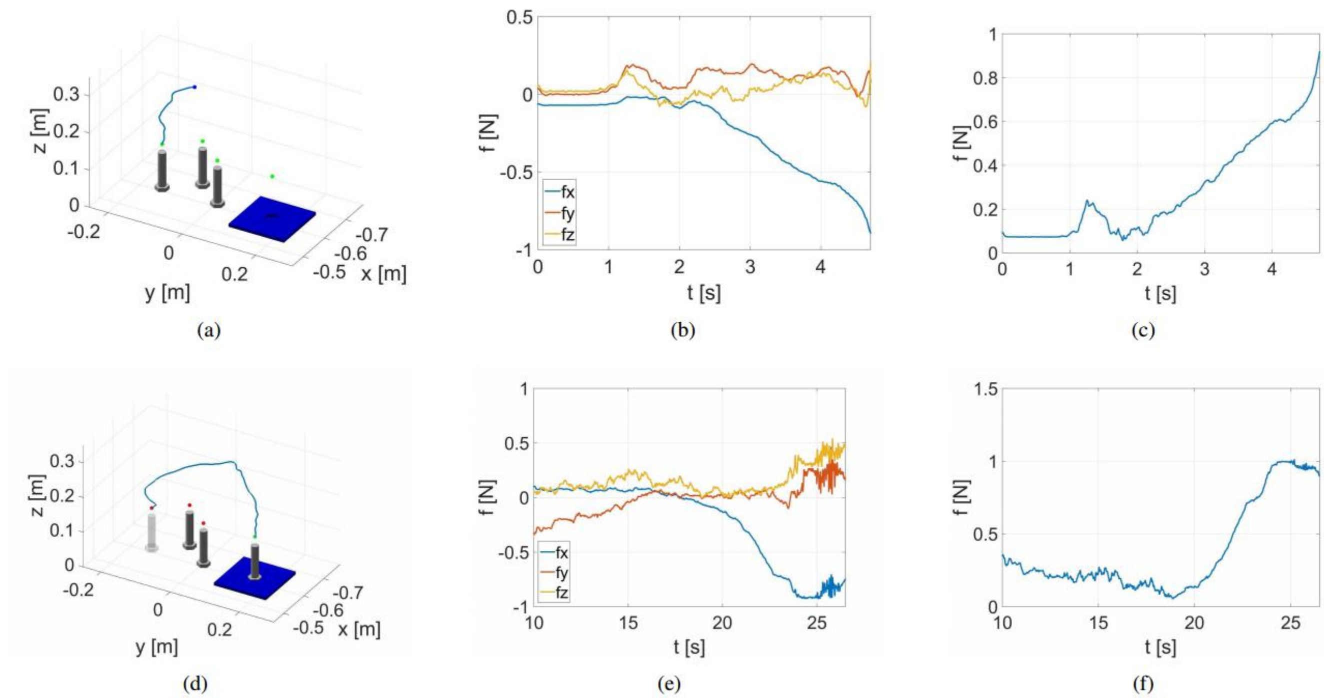


Fig. 12. A stereo vision guided bolt pick up experiment: (a), (b) and (c) are depicted respectively the geometric path followed by the robot, the components of the force rendered by the haptic device, and the force magnitude. (d), (e) and (f) the same data relative to the moving and placing phases

[6] M. Hvilshøj, S. Bøgh, O. Madsen, and M. Kristiansen, "The mobile robot little helper: concepts, ideas and working principles," in *Emerging Technologies & Factory Automation, 2009. ETFA 2009. IEEE Conference on*. IEEE, 2009, pp. 1–4.

[7] *Willow Garage, "Willow Garage", 2010. Available: $https://www.willowgarage.com/pages/pr2/$.*

[8] *TUM-Rosie, "TUM-Rosie", 2011. Available: $http://ias.cs.tum.edu/robots/tum-rosie/$.*

[9] J.-A. Meyer and D. Filliat, "Map-based navigation in mobile robots:: Ii. a review of map-learning and path-planning strategies," *Cognitive Systems Research*, vol. 4, no. 4, pp. 283–317, 2003.

[10] P. F. Hokayem and M. W. Spong, "Bilateral teleoperation: An historical survey," *Automatica*, vol. 42, no. 12, pp. 2035–2057, 2006.

[11] S. Chitta, E. G. Jones, M. Ciocarlie, and K. Hsiao, "Mobile manipulation in unstructured environments: Perception, planning, and execution," *Robotics & Automation Magazine, IEEE*, vol. 19, no. 2, pp. 58–71, 2012.

[12] *First-MM, "Flexible Skill Acquisition and Intuitive Robot Tasking for Mobile Manipulation in the Real World", 2007-2013. Available: $http://www.first-mm.eu/$.*

[13] *TAPAS, "Robotics-enabled Logistics and Assistive Services for the Transformable Factory of the Future", 2007-2013. Available: $http://www.tapas-project.eu/$.*

[14] *VALERI, "validation of advanced, collaborative robotics for industrial applications", 2007-2013. Available: $http://www.valeri-project.eu/$.*

[15] *AutoMAP, "Autonomous Mobile Manipulation System", 2014-2017. Available: $http://www.euroc-project.eu/index.php?id=automap/$.*

[16] *KUKA miiwa, "KUKA KMR iiwa", Available: $http://www.kuka-robotics.com/en/products/mobility/KMR_iiwa/$.*

[17] A. D?mel, S. Kriegel, M. Brucker, and M. Suppa, "Autonomous pick and place operations in industrial production," in *Ubiquitous Robots and Ambient Intelligence (URAI), 2015 12th International Conference on*, Oct 2015, pp. 356–356.

[18] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, and A. Y. Ng, "Ros: an open-source robot operating system," in *ICRA workshop on open source software*, vol. 3, no. 3.2, 2009, p. 5.

[19] N. Koenig and A. Howard, "Design and use paradigms for gazebo, an open-source multi-robot simulator," in *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, vol. 3. IEEE, 2004, pp. 2149–2154.

[20] P. Cignoni, M. Corsini, and G. Ranzuglia, "Meshlab: an open-source 3d mesh processing system," *Ercim news*, vol. 73, no. 45-46, p. 6, 2008.

[21] L. Li, "Time-of-flight camera–an introduction," *Technical White Paper, May*, 2014.

[22] B. Tippetts, D. J. Lee, K. Lillywhite, and J. Archibald, "Review of stereo vision algorithms and their suitability for resource-limited systems," *Journal of Real-Time Image Processing*, vol. 11, no. 1, pp. 5–25, 2016.

[23] H. Hirschmüller, "Accurate and efficient stereo processing by semi-global matching and mutual information," in *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, vol. 2. IEEE, 2005, pp. 807–814.

[24] F. Pomerleau, F. Colas, R. Siegwart, and S. Magnenat, "Comparing icp variants on real-world data sets," *Autonomous Robots*, vol. 34, no. 3, pp. 133–148, 2013.

[25] S. Rusinkiewicz and M. Levoy, "Efficient variants of the icp algorithm," in *3-D Digital Imaging and Modeling, 2001. Proceedings. Third International Conference on*. IEEE, 2001, pp. 145–152.

[26] F. Chen, K. Sekiyama, F. Cannella, and T. Fukuda, "Optimal subtask allocation for human and robot collaboration within hybrid assembly system," *Automation Science and Engineering, IEEE Transactions on*, vol. 11, no. 4, pp. 1065–1075, 2014.

[27] N. Turro, O. Khatib, and E. Coste-Maniere, "Haptically augmented teleoperation," in *Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference on*, vol. 1. IEEE, 2001, pp. 386–392.

[28] F. Chen, P. Di, J. Huang, H. Sasaki, and T. Fukuda, "Evolutionary artificial potential field method based manipulator path planning for safe robotic assembly," in *Micro-NanoMechatronics and Human Science, 2009. MHS 2009. International Symposium on*. IEEE, 2009, pp. 92–97.

[29] G. Schreiber, A. Stemmer, and R. Bischoff, "The fast research interface for the kuka lightweight robot," in *IEEE Workshop on Innovative Robot Control Architectures for Demanding (Research) Applications How to Modify and Enhance Commercial Controllers (ICRA 2010)*. Citeseer, 2010, pp. 15–21.

[30] M. Franken, S. Stramigioli, S. Misra, C. Secchi, and A. Macchelli, "Bilateral telemanipulation with time delays: A two-layer approach combining passivity and transparency," *Robotics, IEEE Transactions on*, vol. 27, no. 4, pp. 741–756, 2011.