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CoLLaboratE

Co-production CeLL performing Human-Robot Collaborative AssEmbly

D4.3 – Teaching by kinesthetic guidance

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Abstract:

The present document is a deliverable of the CoLLaboratE project, funded by the European Commission's Directorate-General for Research and Innovation, under the Horizon 2020 Research and innovation programme (H2020). This public deliverable presents the outcome of the CoLLaboratE consortium's research on the field of teaching by kinesthetic guidance. Kinesthetic guidance lowers the barrier of the adoption of cobots in industry by allowing non-experts to program a robot by demonstration. The deliverable describes a number of novel tools for effectively teaching and properly encoding complex motion patterns that can be generalized spatiotemporally. They provide for haptic inspection to facilitate kinesthetic teaching and introduce novel movement primitives that correctly encode the demonstrated motion, spatially generalize it, generate the reverse motion and incorporate uncertainties by exploiting time-independent probabilistic formulations.

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EXECUTIVE SUMMARY

This document is a deliverable of the CoLLaboratE project that briefly present the outline of the results of Task 4.2 "Teaching by kinesthetic guidance". The objective of this task is to design a framework for teaching by demonstration utilizing kinesthetic guidance, a basic component for collaborative assembly operations and collaborative object handing. The encoding of the teaching is based mainly on the widely used methodology of Dynamic Movement Primitives (DMP) while Gaussian Mixture Models are also utilized to exploit probabilistic approaches.

Initially, a novel control scheme for facilitating the human during the procedure of kinesthetic teaching is presented, by enabling the haptic inspection and allowing task modifications. Moreover, trajectory modifications are also addressed by a novel incremental policy refinement so that modifications can be made in several sequential steps, shortening the time necessary for the deployment of robot tasks by re-using existing similar policies.

In addition, novel DMP formulations for accurate encoding of the learned motion and generalizing the learned kinematic behaviour in space are proposed. In particular, a novel DMP formulation for the orientation part of the demonstrated movement is developed that alleviates oscillatory behaviors observed with the classical formulation; moreover, a DMP formulation that globally scales the path so that the demonstrated 3D path pattern is preserved is also developed avoiding path pattern distortions during scaling that are present in classical formulations.

Driven by the benefit of reverse motion execution, such as retracting from a target in cluttered spaces, a novel reversible DMP formulation is developed that preserves the DMP properties and also allows easy teaching of new velocity profiles along the encoded path.

Apart from the deterministic DMP methods, a probabilistic encoding method is presented that exploits time-independent probabilistic formulations. Such an approach allows encoding of the variations among multiple demonstrations, which are utilized to facilitate partial re-demonstration via kinesthetic guidance of the most uncertain segments of a task.

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Abbreviations and Acronyms

Partner's short name	Partner's full name
AUTH	ARISTOTLE UNIVERSITY OF THESSALONIKI
CERTH	CENTRE OF RESEARCH AND TECHNOLOGY HELLAS
ARMINES	ASSOCIATION POUR LA RECHERCHE ET LE DEVELOPMENT DES METHODES ET PROCESSUS INDUSTRIELS
JSI	INSTITUT JOZEF STEFAN
IDIAP	FONDATION DE L'INSTITUT DE RECHERCHE
UNIGE	UNIVERSITA DEGLI STUDI DI GENOVA
KU Leuven	KATHOLIEKE UNIVERSITEIT LEUVEN
LMS	UNIVERSITY OF PATRAS
CRF	CENTRO RICERCHE FIAT SOCIETA CONSORILE PER AZIONI
BOR	BLUE OCEAN ROBOTICS
ASTI	AUTOMATISMOS Y SISTEMAS DE TRANSPORTE INTERNO SA
KOL	KOLEKTOR ORODJARNA NACRTOVANJE IN IZDELAVA ORODIJ TER ORODJARSKE STORITVE D.O.O.S
ARCELIK	ARCELIK A.S.
ROMAERO	ROMAERO S.A.

Abbreviation	Definition
WP	Work Package
D	Deliverable
EC	European Commission
EU	European Union
PbD	Programming by Demonstration
DMP	Dynamic Movement Primitives
VF	Virtual fixture
DS	Dynamical System
GAS	Globally Asymptotically Stable
BGMM	Bayesian Gaussian mixture models
FS	Frenet-Serret

1 RESULTS OF T4.2

The task T4.2 – "Teaching by kinesthetic guidance" aimed to develop a framework that enables non-experts to teach tasks to a robot kinesthetically in a collaborative manner (Objective 2 of the project). The kinesthetic teaching is one of the Programming by Demonstration (PbD) means that are developed in WP4 for intuitive robot programming, also including a visual demonstration approach (T4.1) and an augmented reality mobile interface (T4.3).

1.1 OUTLINE OF RESULTS

During kinesthetic teaching/guidance, the operator physically interacts with the robot and moves it while it is in gravity compensation mode, demonstrating the desired motion. This motion is then encoded utilizing Dynamic Movement Primitives (DMP) either in the joint or in the Cartesian space [1], [2], [3]. Although the DMP encoding and reproduction of the Cartesian position of the robot's end-effector is straightforward, utilization of the dominant DMP formulation for end-effector orientation encoding may produce undesired oscillations during reproduction that cannot be predicted in advance. This result is a direct consequence of the dominant formulation. To resolve this problem, AUTH developed a DMP variant for encoding and reproducing orientation trajectories to be fed to a robot's controller, which preserves all DMP properties while accurately, reproduce the demonstrated trajectory without any oscillations.

Kinesthetic teaching becomes more effective if the learned trajectory can be inspected by the operator before execution and corrected or modified. Aiming to reduce the human's cognitive and physical load during this procedure, a method was developed by AUTH that utilizes virtual fixtures and DMP to assist the teaching and modification of a task by haptic feedback in the form of generalized forces. Thus even a non-expert operator is expected to easily guide the robot along the learned trajectory verifying that the task has been encoded correctly. The operator can further make modifications to a task segment by penetrating the virtual fixtures. Trajectory modifications are also addressed by a novel incremental policy refinement developed by JSI so that modifications can be made in several sequential steps shortening the time necessary for the deployment of robot tasks by re-using existing similar policies. Collaborate use cases involve assembly operations where complex trajectories are usually present and the above methods are aimed at facilitating kinesthetic teaching in most of them.

The ability of DMP for spatio-temporal generalizations during autonomous execution come with shortcomings regarding the spatial scaling preservation of the demonstrated 3D path pattern as the scaling of each coordinate is traditionally performed separately. To alleviate associated problems, a DMP formulation was developed by AUTH that scales the path globally according to the task. This formulation is particularly useful in the foreseen use-cases of the CoLLaboratE project where the robot, after the initial demonstration, needs to generalize to different targets. Some examples include the different placement targets for the PCB's in Arcelik use-case, new riveting locations in ROMAERO use-case, multiple picking and placement positions in the KOLEKTOR use-case and, finally, different windshield presentation positions associated with the anthropometry of the operator who will subsequently perform inspection and assembly.

DMP are executed to generate reference trajectories usually for forward motions. However, there is a need in many tasks for reverse motion (reverse DMP execution) to allow accurate retraction from targets in cluttered spaces like in the foreseen ROMAERO use case or in the case of assembly/disassembly operations. As classical DMP formulations do not support reversibility, a novel reversible DMP formulation was developed by AUTH that achieves reversibility, preserving existing DMP properties and having additional favorable properties that allow easy teaching of new velocity profiles along the encoded path.

In many robotic applications requiring generalization and adaptation, probabilistic approaches have been shown to provide a more flexible framework than its deterministic counterparts. CoLLaboratE provided also a complementary movement primitive solution using Gaussian Mixture Models. In particular, IDIAP developed time-independent Bayesian Gaussian mixture models (BGMMs) to encode movements in action-state level. The main advantage of the proposed approach in the teaching perspective is that it allows partial demonstrations via kinesthetic guidance by exploiting time-independent probabilistic formulations. The user can demonstrate some trajectories and add more to correct or precise some critical parts of the movement. The robot can also inform the teacher about the parts of the movement where it has the most uncertainty about and can request a new full or partial demonstration around those regions.

Many of the aforementioned methods have already been combined into an integrated solution for assisted kinaesthetic teaching in the CoLLaboratE project. The integrated solution enables an intuitive kinaesthetic teaching procedure that allows the haptic inspection and partial modification of the kinematic behaviour, with the learned kinematic behaviour a) being accurately reproduced, b) retaining its original pattern when scaled in space and c) being reversible.

1.2 Contribution

In PbD the robot is taught based on demonstrations performed by the human teacher, a procedure which reduces the time and effort required by the user, as compared to classical code-based robot programming. PbD does not require the employment of a robot programming expert and its associated cost which is of particular importance for the deployment of co-bots by SME's. While the most natural way to demonstrate a task is by capturing the motion of the manual operation via external sensors [4], the demonstrated trajectory may not be directly useful for the robot. Even if the robot is kinematically similar to human arms, the gripper is usually very different to the human hand. This affects considerably the grasping, motion trajectory and picking and placing strategy. In the Arcelic use case for example, the human re-grasps the board to easily place it on the TV case. In kinesthetic teaching the user must guide the robot and its end-effector to demonstrate the task and hence the demonstrated trajectory can be directly encoded and reproduced by the robot during execution. As kinesthetic teaching is less natural to direct human demonstration, assistive tools are needed to facilitate a non-robot-expert to perform the demonstration. The encoding of the demonstrated data is also important so that they can be generalized properly to different locations velocities and task variants. A number of novel methods have been developed within the CoLLaboratE project regarding both the above aspects in view and motivated by the foreseen use cases.

In some cases, the kinematic behavior can be learned utilizing only one demonstration, however, cases such as task variations or inappropriate spatial generalization may require the re-demonstration of the task multiple times. In such cases, we can see the whole procedure of kinesthetic teaching as a bi-directional communication, in which the robot communicates what is already learned to the human, while the human instructs any corrections or modifications of the task. The quality of this communication plays a crucial role on the reduction of the cognitive and physical load of the human-teacher and time required for the teaching. There are many works in the literature that tackle the problem of kinesthetic teaching in such a way. The most common approach is the one in which the autonomous task execution and the adaptation/learning takes place simultaneously [1], [3], [5], [6], [7], [8], [9]. In such a way, the human can observe the already learned kinematic behavior, which is executed in real time by the robot, and she/he has to intervene the execution at the appropriate time instance in order to correct or modify the behavior. That means that the human has to synchronize with the robot, which may impose a high cognitive load to the user. For reducing this cognitive load, our research team initially proposed a passive control scheme which imposes penetrable virtual fixtures inducing a non-linear stiffness around the already learned path of the robot, communicating only the spatial properties of the kinematic behavior [10]. Utilizing this control scheme, the human-teacher has the ability to haptically inspect and validate the path of the already learned kinematic behavior and modify any segments of it, by penetrating the virtual fixture (VF), reducing, in this way, the time required for modifications. However, the control scheme of [10] does not communicate temporal properties and no haptic cues are provided during the demonstration of the modified segment. Thus, the human is unaware of the already learned behavior when performing a modification, and therefore the human has to explore the task space in order to return within the virtual fixture.

The proposed solution developed in the CoLLaboratE project, is based on our previous work [10], but has been enhanced in [11] with the following additional properties: a) not only the spatial, but also the temporal properties of the already learned motion are haptically communicated to the human-teacher, b) the proposed virtual fixture is based on a novel artificial potential field which is designed to provide haptic cues both during the inspection and the modification of the learned kinematic behavior. Due to these additional properties, the time and effort required for the kinesthetic teaching is significantly reduced.

In robotics, it is frequently necessary to adapt the existing policy to a new context. Although autonomous learning can be applied for this task, it is often more efficient to adapt the existing policy by utilizing kinesthetic guidance. Doing so, it is essential that we do not always demonstrate the policy over and over again from the beginning, but only gradually correct and refine the existing policy. This issue is efficiently addressed by incremental learning. More importantly, we can change the trajectory in a natural way at different speeds, with the robot moving along the currently learned trajectory in both directions, back and forth. The natural way means that the robot is guided by pushing along the existing trajectory, and at the same time, we change the position and orientation only where it is necessary. Complex trajectories can be learned by demonstrating only the motion's spatial part at any speed and finally demonstrating the desired speed profile.

To this end, we have developed an active learning mode where compliant control is defined according to a trajectory defined using Frenet Serret (FS) formulas [12]. This notation allows us to completely separate the task's spatial and temporal components and teach them separately or together. In doing so, we use a trajectory record with Cartesian DMPs, which we had to modify accordingly to support reversibility. We achieved this with two sets of nonlinear forcing terms and defined the conditions for switching between them [13]. When learning by pushing a robot, the DMP phase must follow the actual path. The phase is updated either by force in the tangential FS frame or by an error in this direction. As the phase update relates to the admittance or impedance force guidance, it can affect the closed-loop stability of the learning when the robot is in contact with the environment.

Within the CoLLaboratE project, a novel incremental learning formulation is developed in [14], which supports DMPs' reversibility, learning in multiple phases, and separating spatial and temporal scaling. Independent learning of spatial and temporal component is supported by the utilization of a second-order canonical system driven by the user's force along the encoded path. Thus, the user is allowed to concentrate during the first phase in teaching a path as slowly as required not to compromise accuracy while velocity profile teaching in the second phase is facilitated by robot motion evolving only along the learned path. In the paper, we also tackled the stability issues of learning in a physically constrained environment. Moreover, we statistically evaluated the benefits of the developed incremental learning against the classical kinesthetic teaching.

According to kinesthetic teaching, the demonstrated motion has to be encoded by the system that generates the motion, which in turn should be able to be generalized for any initial state and any given target. To encode the demonstrated motions and generalize them to kinematic behaviors, the most popular approaches involve the utilization of Dynamical Systems (DS) with parameters learned to optimally reflect the set of demonstrated motions. The most commonly used dynamical systems for PbD are the Dynamic Movement Primitives (DMP) [2], [3] and Gaussian Mixture Models [15]. Both dynamical systems involve function approximation methods, most commonly utilizing a weighted sum of Gaussian base functions, with the weights of those functions being the parameters which encode the kinematic behavior. DMPs have a number of useful properties including robustness to perturbations; they allow spatial and temporal scaling via a non-explicit time representation and can be manipulated to adapt to different situations via coupling terms during the execution of the movement [16], [17]. When used in Cartesian space the issue of orientation representation arises since it is known that unlike the position there is no minimal representation of orientation that is singularity free. Minimal representations introduce artificial discontinuities that should be avoided. Orientations are defined in the $SO(3)$ group, which is a three-dimensional manifold that can be represented by rotation matrices and quaternions. In the field of robotics, quaternions are generally preferred over rotation matrices, as they require less parameters and have been used in many applications [18], [19], [20]. The generalization of the DMP framework to orientation trajectories with quaternion representations has been introduced by Pastor et al. [21] and expanded by Ude et al. [22]. The approach in [21] usually leads to slow convergence as pointed out in [22]. In contrast, faster convergence characterizes the formulation proposed in [22]. Since its publication, this formulation has been the dominant approach for orientation DMP robot learning and control. However, when producing the orientation reference with this formulation, undesired oscillatory behaviors may arise because unlike the formulation in position, the dominant approach for orientation DMP does not yield a linear tracking system.

The research conducted in the CoLLaboratE project led to an improved DMP formulation for encoding orientation trajectories, presented in [23], which alleviates the aforementioned problems.

An essential feature of PbD is the ability to generalize to new environments. Human environments are characterized by perpetual modifications and unpredictable alterations. Any learned kinematic behavior must be able to be scaled both spatially and temporally, as well as be robust to perturbations. Despite their favorable properties, the spatial scaling of the classical DMP formulation in [3] is performed separately for each coordinate and hence it is frame dependent. As a consequence, 3D path patterns may be significantly distorted when scaled spatially with the classical DMP formulation in cases the initial and goal value are close to each other along one coordinate as the scaling is amplified in this coordinate. Moreover, one cannot encode or execute trajectories when one coordinate has the same initial and goal value. The biologically-inspired DMP formulation [16], alleviates some of the spatial scaling problems of the classical formulation but loses its global scaling property, as pointed out in [21].

Distortion of 3D path patterns is undesirable in some tasks for example those involving planar paths and tasks executed over a workbench with orientation constraints. Generalizing a planar task using the classical DMP formulation may lead to the violation of the plane constraint. Tasks executed over a workbench, usually have orientation constraints associated with the workbench's normal vector. Generalization using the classical DMP can also lead to the violation of these constraints, and even generate a trajectory which penetrates the workbench surface. Such tasks are typical in the CoLLaboratE project, as in the use cases of ARCELIK and KOLEKTOR.

The research conducted in the CoLLaboratE project led to a novel formulation that is presented in [24], for encoding a trajectory in the Cartesian space which produces reasonably scaled trajectories globally, maintaining the learnt characteristics. It is shown that spatial scaling is problematic in both the original and biologically-inspired DMP formulations. The proposed formulation remedies this problem by appropriately rotating the executed trajectory according to the task and scaling its magnitude to alleviate frame dependency.

For many tasks, reverse execution could enable automatic derivation of certain required operations from their forwards counterparts. For instance, in assembly tasks a reversible model could be used for assembling and disassembling a workpiece. More generally, when performing any task that involves reaching, like a handover, a placing or an insertion task etc, the reverse motion could be used for the retraction, saving the effort of explicitly encoding and programming the backward motion. This becomes even more useful in reaching targets through cluttered environments like in the ROMAERO use case. Reversibility can also prove really effective and practical for recovering from errors during the execution of a task. These errors could originate from faulty or noisy sensor measurements or could be attributed to disturbances. Using reverse execution, the robot can temporarily back out of an erroneous situation by tracing back to a previous point, after which the execution can be automatically retried. Such a property may be useful in the KOLEKTOR use-case by teaching the extraction of the winding (disassembly) and reverse the motion for assembly. As classical DMP do not support reversibility, the authors in [25] propose a non-linear dynamical system, which achieves partial reversibility if the solution stays within a region and becomes unstable beyond. As the solution cannot be guaranteed to stay within the permitted region, the authors finally resort to the use of two separate forcing terms to ensure global stability.

Demonstrating a desired trajectory using kinesthetic guidance can prove quite cumbersome, as one has to pay attention to guide the robot accurately along the desired path while at the same time imposing a desired speed of execution (velocity profile). This places a lot of cognitive load to the user and can deteriorate the quality of demonstration. This is an acute problem in tasks where accuracy in the demonstrated path is of great essence. To address this need, a two phase learning approach for path and velocity profile teaching has been initially proposed in [12] where Frenet-Serret frames were utilized to impose low stiffness along the direction of motion and higher in the perpendicular axes to constrain the motion along the desired path in the second phase. An iterative procedure to determine the phase value at each control step is involved. As a result, a lot of computations and parameter tuning is involved.

Within the CoLLaboratE project, a novel DMP formulation is developed [26], which achieves reversibility and supports two phase learning, sharing all the favourable properties of classical DMP, such as spatial and temporal scaling, GAS, robustness to perturbations and on-line adaptation via the addition of coupling terms. In the second phase, learning is supported by the utilisation of a second order canonical system driven by the user's force along the encoded path. Thus, the user is allowed to concentrate during the first phase in teaching a path as slowly as required not to compromise accuracy while velocity profile teaching in the second phase is facilitated as robot motion could only evolve along the learned path.

Many robotic applications require encoding movements in a probabilistic way to cope with its deterministic counterpart's limitations such as generalizations to via-points, capturing local synergies between different state variables and direct adaptive compliance exploiting the correlations [27], [28]. Although the state-of-the-art DMP provides a robust and accurate way of reproducing demonstrations, with many capabilities improved in this deliverable, complementary probabilistic solutions are necessary to address uncertainties. With the motivation to extend the applicability of the approaches developed in CoLLaboratE to different range of scenarios in human-robot collaboration, IDIAP worked on alternative, but complementary movement encoding frameworks. Note that the methods developed by IDIAP in this deliverable can be seen as an alternative to DMP, but they can also be used in combination with DMP to increase its capabilities [29], [30].

Within the CoLLaboratE project, IDIAP developed time-independent control policies in [31], based on Bayesian Gaussian mixture models (BGMMs) to encode movements in action-state level. Complete time-independence, encoding of the probabilistic relation between the control command and the state of the robot and local synergies captured by the covariance matrices are examples of the complementary properties desired to address our motivation. In the teaching perspective, the main advantage of the proposed approach is that it allows partial demonstrations via kinesthetic guidance. The user can demonstrate some trajectories and add more to correct or precise some critical parts of the movement. The robot can also inform the teacher about the parts of the movement where it has the most uncertainty about and can request a new full or partial demonstration around those regions.

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