1. Record Nr. TD20028262

Autore	ZEESTRATEN, MARTINUS
Titolo	Programming by Demonstration on Riemannian Manifolds [Tesi di dottorato]
Editore	Università degli studi di Genova, 2018-02-06
Lingua di pubblicazione	Inglese
Formato	Tesi di dottorato
Livello bibliografico	Monografia
Note	diritti: info:eu-repo/semantics/openAccess In relazione con info:eu-repo/semantics/altIdentifier/hdl/11567/930621

Sommario

This thesis presents a Riemannian approach to Programming by Demonstration (PbD). It generalizes an existing PbD method from Euclidean manifolds to Riemannian manifolds. In this abstract, we review the objectives, methods and contributions of the presented approach. OBJECTIVES PbD aims at providing a user-friendly method for skill transfer between human and robot. It enables a user to teach a robot new tasks using few demonstrations. In order to surpass simple record-and-replay, methods for PbD need to ‘understand’ what to imitate; they need to extract the functional goals of a task from the demonstration data. This is typically achieved through the application of statisticalmethods. The variety of data encountered in robotics is large. Typical manipulation tasks involve position, orientation, stiffness, force and torque data. These data are not solely Euclidean. Instead, they originate from a variety of manifolds, curved spaces that are only locally Euclidean. Elementary operations, such as summation, are not defined on manifolds. Consequently, standard statistical methods are not well suited to analyze demonstration data that originate fromnon-Euclidean manifolds. In order to effectively extract what-to-imitate, methods for PbD should take into account the underlying geometry of the demonstration manifold; they should be geometry-aware. Successful

task execution does not solely depend on the control of individual task variables. By controlling variables individually, a task might fail when one is perturbed and the others do not respond. Task execution also relies on couplings among task variables. These couplings describe functional relations which are often called synergies. In order to understand what-to-imitate, PbDmethods should be able to extract and encode synergies; they should be synergetic. In unstructured environments, it is unlikely that tasks are found in the same scenario twice. The circumstances under which a task is executed—the task context—are more likely to differ each time it is executed. Task context does not only vary during task execution, it also varies while learning and recognizing tasks. To be effective, a robot should be able to learn, recognize and synthesize skills in a variety of familiar and unfamiliar contexts; this can be achieved when its skill representation is context-adaptive. THE RIEMANNIAN APPROACH In this thesis, we present a skill representation that is geometry-aware, synergetic and context-adaptive. The presented method is probabilistic; it assumes that demonstrations are samples from an unknown probability distribution. This distribution is approximated using a Riemannian GaussianMixtureModel (GMM). Instead of using the 'standard' Euclidean Gaussian, we rely on the Riemannian Gaussian— a distribution akin the Gaussian, but defined on a Riemannian manifold. A Riev mannian manifold is a manifold—a curved space which is locally Euclidean—that provides a notion of distance. This notion is essential for statistical methods as such methods rely on a distance measure. Examples of Riemannian manifolds in robotics are: the Euclidean spacewhich is used for spatial data, forces or torques; the spherical manifolds, which can be used for orientation data defined as unit quaternions; and Symmetric Positive Definite (SPD) manifolds, which can be used to represent stiffness and manipulability. The Riemannian Gaussian is intrinsically geometry-aware. Its definition is based on the geometry of the manifold, and therefore takes into account the manifold curvature. In robotics, the manifold structure is often known beforehand. In the case of PbD, it follows from the structure of the demonstration data. Like the Gaussian distribution, the Riemannian Gaussian is defined by a mean and covariance. The covariance describes the variance and correlation among the state variables. These can be interpreted as local functional couplings among state variables: synergies. This makes the Riemannian Gaussian synergetic. Furthermore, information encoded in multiple Riemannian Gaussians can be fused using the Riemannian product of Gaussians. This feature allows us to construct a probabilistic context-adaptive task representation. CONTRIBUTIONS In particular, this thesis presents a generalization of existing methods of PbD, namely GMM-GMR and TP-GMM. This generalization involves the definition ofMaximum Likelihood Estimate (MLE), Gaussian conditioning and Gaussian product for the Riemannian Gaussian, and the definition of ExpectationMaximization (EM) and GaussianMixture Regression (GMR) for the Riemannian GMM. In this generalization, we contributed by proposing to use parallel transport for Gaussian conditioning. Furthermore, we presented a unified approach to solve the aforementioned operations using aGauss-Newton algorithm. We demonstrated how synergies, encoded in a Riemannian Gaussian, can be transformed into synergetic control policies using standard methods for LinearQuadratic Regulator (LQR). This is achieved by formulating the LQR problem in a (Euclidean) tangent space of the Riemannian

	manifold. Finally, we demonstrated how the contextadaptive Task-Parameterized Gaussian Mixture Model (TP-GMM) can be used for context inference—the ability to extract context from demonstration data of known tasks. Our approach is the first attempt of context inference in the light of TP-GMM. Although effective, we showed that it requires further improvements in terms of speed and reliability. The efficacy of the Riemannian approach is demonstrated in a variety of scenarios. In shared control, the Riemannian Gaussian is used to represent control intentions of a human operator and an assistive system. Doing so, the properties of the Gaussian can be employed to mix their control intentions. This yields shared-control systems that continuously re-evaluate and assign control authority based on input confidence. The context-adaptive TP-GMMis demonstrated in a Pick & Place task with changing pick and place locations, a box-taping task with changing box sizes, and a trajectory tracking task typically found in industry
Localizzazioni e accesso	http://memoria.depositolegale.it/*/http://hdl.handle.net/11567/930621