Bayesian Contact State Segmentation for Programming by Human Demonstration in Compliant Motion Tasks

Wim Meeussen, Johan Rutgeerts, Klaas Gadeyne, Herman Bruyninckx, Joris De Schutter
Department of Mechanical Engineering, K.U.Leuven, Belgium

I. MOTIVATION, PROBLEM STATEMENT, RELATED WORK.

This paper presents a contribution to *programming by human demonstration* [3], [14], in the context of *compliant motion* [4] tasks in which an object held by a manipulator moves in contact with an environmental object, as shown in Fig. 1. Major challenges in the automatic translation from a human compliant motion demonstration into an executable compliant motion robot program are: (i) to recognize the *contact formation* (CF) to which the human demonstration is currently subjected, (ii) to estimate the geometric parameters of that contact formation, and (iii) to detect when exactly the human demonstration execution changes between two CFs. Initial research on the identification of CFs focused mainly on two different approaches: (i) ad hoc identification strategies that exploit geometric knowledge of the contacting objects, but that have a very poor stochastic foundation (e.g. [1], [7]) and (ii) Hidden Markov Model based (hence stochastic) solutions to assembly problems that can recognize CF transitions very fast but only with limited allowed uncertainty (e.g. [6], [12]).

Slaets et al. [13] presented some results in the field of compliant motion that go a bit beyond the scope of this paper: they build a geometric model of an unknown environment from a given number of primitives, while this paper starts from a known parameterization of a geometric model. However, their approach is based on the Non-Minimal State Kalman Filter [9], [11], and is only valid if the estimation has converged to a unimodal Gaussian before a contact transition. They only allow new contact constraints to be added gradually, and no contact constraints to be removed. Recently Gadeyne et al. [8] developed a *particle filter* [5] approach to estimate, simultaneously, geometric parameters of a *known* geometric model and to recognize contact transitions. Their approach is able to estimate (continuous) geometric parameters with a large uncertainty, and simultaneously recognize (discrete) contact transitions in an experiment consisting of six possible and initially known CFs.

This paper generalizes and scales the approach of Gadeyne et al. to allow *all possible contacts* between two polyhedral objects. To cope with this increased complexity, an improved prediction step is used, based on the topological information contained in a contact state graph, [15], [16], and the relative pose of the contacting objects. This paper also presents efficient algorithms for the pose and consistency measurement equations [2], [10], that reduce the numerical cost and allow the estimators to discriminate in *realtime* between 245 different CFs, in an uncertain environment.

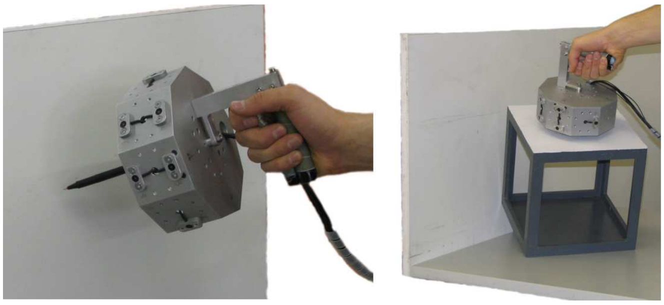

Fig. 1. To program a compliant motion task, a human manipulates an object in contact with its environment through a sequence of contact formations.

II. TECHNICAL APPROACH

The estimation problem for compliant motion tasks, consists of two connected sub-problems: the recognition of the (discrete) CF and the estimation of (continuous) geometric parameters. This requires a hybrid *Probability Density Function* (PDF), containing both continuous and discrete unknown variables. While Kalman filters cannot cope with the cross-dependency between discrete and continuous variables, using a hybrid PDF, particle filters can. The approach in this paper is based on particle filters, which estimate the discrete CF and continuous geometric parameters in two steps. In the first step the system model makes a prediction for the next CF and the geometric parameters. In the second step the measurement model corrects this prediction based on sensor data from the human demonstration.

A. System Model – Prediction

The system model predicts the next CF out of hundreds of theoretically possible next CFs, using the topological information from the objects' contact state graph. The contact state graph represents all possible CFs between two objects, and connects two CFs when a direct transition between them is possible, without going through any other CF. An example of an automatically generated contact state graph is shown in Fig. 2. The use of this topological information drastically reduces the number of possible CF transitions.

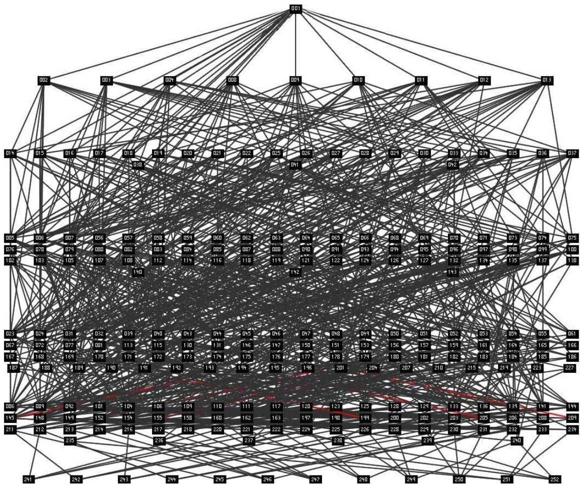

Fig. 2. This automatically generated contact state graph shows all possible contact formations (nodes) and transitions between neighboring contact formations (arcs).

B. *Measurement models – Correction*

Two different measurement models are used to correct the predicted CF and geometric parameters. The first model is based on the pose (position and orientation) measurement between the manipulated object and its environment, and the second model is based on the wrench (force and torque) and twist (translational and rotational velocity) measurements.

The pose measurement model expresses that when the manipulated object is in contact with the environmental object, the distance between the objects at the contact points should be zero, hence closing the kinematic chain between the objects. The distance between the objects at non-contact points should be greater than zero, expressing that the objects do not penetrate nor contact. The decomposition of a general CF into the lower level *elementary contacts* (ECs) allows the automatic generation of the pose measurement equation for different CF models.

The wrench-twist measurement model expresses the consistency between the constraints imposed by the first order contact kinematics of an ideal frictionless contact and the wrench and twist measurements. The first order kinematics are represented by a wrench space and a twist space. The wrench space represents all possible wrenches that can be applied between the contacting objects at the current pose. The twist space represents all possible instantaneous twists that maintain the contact. The measured wrench (twist) is consistent with the wrench (twist) space, when it is possible to represent the measured wrench (twist) as a linear combination of the wrench (twist) space vectors.

III. RESULTS

A 13-dimensional hybrid joint density PDF is used, consisting of a 12-dimensional continuous parameter and a 1-dimensional discrete state. The continuous parameter contains geometric parameters that represent the pose of the environmental object relative to a world reference, and the pose of the manipulated object relative to the demonstration tool used by the human demonstrator to interact with the manipulated object. Hence the geometry of the objects is assumed to be know; only the pose is subject to uncertainty. The discrete state contains the CF between the manipulated object and the environment, and can be any of the hundreds of CFs in a complete contact state graph. The proposed algorithms are very efficient and capable of processing $90,000$ particles[1] per second, on a 2 $[GHz]$ AMD 64 laptop, sufficient for realtime discrimination between hundreds of CFs and estimation of uncertain geometrical parameters. This performance is achieved by:

- assuming probabilities to be independent,
- not calculating or only approximating probabilities that are not relevant,
- developing numerically efficient algorithms, and
- choosing easy to evaluate PDFs.

The evaluation of the pose measurement model normally requires the computation of a distance at all possible ECs between the contacting objects. Per CF in the contact state graph there are several ECs, therefore, the total number of possible ECs is typically in the range of 10^2 to 10^3. In this paper only the distances at ECs that are relevant in the current CF are calculated. These are the distances at the ECs of the current CF, as well as the ECs directly adjacent to the current CF. When objects are far apart, the distance between them is approximated by the distance between spherical boundary boxes.

The evaluation of the wrench and twist measurement model normally requires the calculation of three singular value decompositions (SVDs). In this paper we present an efficient algorithm that reduces the numerical cost to only one SVD. The importance of reducing the number of SVDs required becomes clear when using profiling tools. Reducing the number of SVDs from 3 to 1 decreased the computational cost of the overall filter with 55%. Using the efficient algorithm still 60% of the overall computation time is spent on this one SVD.

IV. EXPERIMENTS

In the presented experiments, a human manipulates a cube in an environment consisting of two perpendicular faces, using a demonstration tool, as shown in Fig. 1. During the demonstration, sensors mounted on the demonstration tool measure its pose, twist and contact wrench. The initial uncertainty on the planes is represented by a uniform distribution with a width of 15 $[mm]$ on the x and y positions, 130 $[mm]$ on the z position of the planes and 0.5 $[rad]$ on the roll-pitch-yaw orientation of the planes. There are 245 possible CFs between the cube and the planes, and there is initially no contact between the objects.

The demonstration guides the object through a sequence of contact formations, which includes different estimation "challenges":

- adding contact constraints (CF_1 to CF_2 to CF_3),
- removing contact constraints (CF_5 to CF_6),
- adding many contact constraints at once (CF_6 to CF_8),

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[1] processing one particle includes a prediction step, two correction steps and the overhead of the particle filter such as re-sampling.

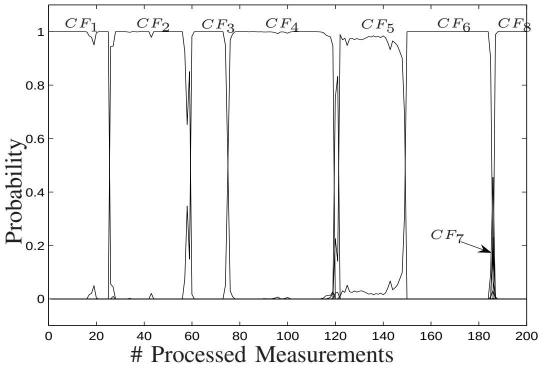

Fig. 3. The CF evolution of a human demonstration where a cube is manipulated in contact with two perpendicular faces. The evolution is shown by the probability of each CF.

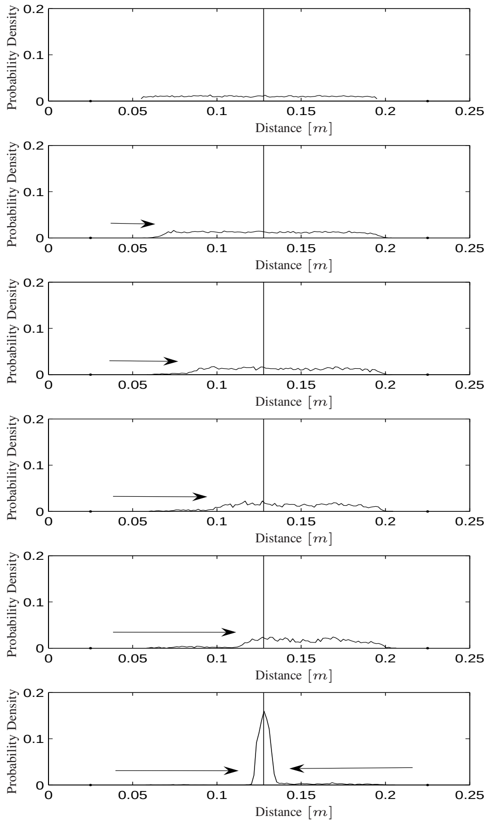

Fig. 4. The time evolution of the probability density on the position of a plane, when approaching the plane with a cube. The probability density decreases gradually when the object approaches. The last figure shows how the probability density suddenly decreases when the cube makes contact with the plane.

- removing many contact constraints at once (CF_4 to CF_5), and
- contacts with the two planes simultaneously (CF_4).

Fig. 3 shows the evolution of the estimated probability on each of the 245 CFs, but only a few CFs have a probability greater than zero. The estimators successfully recognize the CF that was demonstrated as the most likely CF.

Fig. 4 shows the time evolution of the uncertainty on the continuous position of the plane. Initially the position is represented by a uniform distribution, indicating that there is no knowledge about its position. When the cube approaches the plane, the probability decreases on the left side of the distribution. This shows that the cube “penetrated” one of the possible positions of the plane without detecting a contact, thus proving that possible position invalid. This evolution continues until the cube makes contact with the plane. The CF transition is detected due to the inconsistency between the measured wrench and the assumed no-contact CF. The knowledge about the new CF allows accurate estimation of the position of the plane, also decreasing the probability on the right side of the uniform distribution.

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