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Mihaylova, L.S., Lefebvre, T., Staffetti, E. et al. (2 more authors) (2002) Contact Transitions Tracking During Force-Controlled Compliant Motion Using an Interacting Multiple Model Estimator. Information & Security. 114 - 129 . ISSN 1311-1493

CONTACT TRANSITIONS TRACKING DURING FORCE-CONTROLLED COMPLIANT MOTION USING AN INTERACTING MULTIPLE MODEL ESTIMATOR

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1. Introduction

In different robot operations the manipulator has to interact with the environment through the manipulated object and modify its trajectory depending on the contact forces that arise. These force-controlled operations are called *compliant motion tasks*. Force control is required due to the fact that small errors in the models can generate high forces on the manipulator. For other tasks, such as cutting, welding or polishing, the robotic manipulator has to apply a given force to execute correctly the task. In all cases the manipulator is moving an object in contact with the environment through a sequence of contact configurations. In this paper the objects involved in the compliant motion are supposed to be rigid and polyhedral. The path of the manipulated object is a sequence of contact configurations. The configurations can be grouped into a subsequence of configurations equivalent from a topological point of view, i.e., in which the same elements of the manipulated object are in contact with the same elements of the environment. In this context each class of equivalence is called *contact formation* (*CF*).[5]

This work assumes uncertainties in the position and orientation of both the manipulated object and the environment. In practice, besides these model uncertainties other sources of uncertainties are present such as friction, sensor noises, geometrical uncertainies such as burrs, or unexpected events. The focus here is on the detection of the current CF and the instant of transition between the CFs.

Encoders, mounted at the robot joints, supply information about the end-effector location and motion, and a force sensor, mounted at the robot wrist, gives information about the interaction with the environment. This information is also used to estimate the uncertain geometric parameters. In Bruyninckx *et al.* [2] a possible architecture of an autonomous assembly system is proposed. It is pointed out that such a system needs a high-level planner (responsible for planning, re-planning and on-line error recovery), a low-level module (responsible for sensing and the execution of the planned action), and a medium-level module (for estimation and monitoring).

This work presents and generalizes results reported earlier.[9] The possible CFs are described by different models and, with them, an Interacting Multiple Model (IMM) estimator is implemented. Its performance is investigated and evaluated by experiments with real data of different type: velocities and forces. Other works treat force-controlled compliant motion tasks.[3,4,7] Thus, the problem of estimating first-order geometric parameters and monitoring contact transitions has been approached through single-model Extended Kalman Filters (EKFs), run in parallel for the known different CFs.[3] The Summed Normalized Innovation Squared (SNIS) test has been used as an indicator of the transitions between the CFs. One solution to the estimation of the geometric parameters for one CF was proposed on the basis of iterated EKF.[7,8]

The remaining parts of this article are organized as follows. In section 2 the problem of contact transitions' tracking during force-controlled compliant motion is formulated as a state estimation problem of *hybrid systems*. Section 3 gives the state and measurement equations of a compliant motion with subsequent CFs, namely those of moving a cube into a corner. Section 4 describes an Interacting Multiple Model estimator and its connection with the planning part. Section 4 yields performance analysis for the cube-in-corner assembly with experimental data involving a KUKA-IR 361 robot. The final section provides concluding remarks. Short guiding rules for the Jacobian matrices computations of the measurement and closure equations are given in the Appendix.

2. Problem formulation

During the compliant motion different CFs occur. They can involve, for instance, a contact between an edge of the manipulated object and a face of the environment (edge-face contact), a face of the manipulated object and a face of the environment (face-face contact), and so on (Figure 1). To estimate the unknown geometric parameters and track the transitions between CFs, the manipulated object and the environment are considered as a stochastic hybrid system with continuous and discrete uncertainties. The state-space equations are of the form

$$x_{k+1} = f(x_k, m_k) + g(m_k, \eta_k), \tag{1}$$

$$h_k(x_k, m_k, z_k, \xi_k) = 0, \tag{2}$$

where $x_k \in \mathbb{R}^{n_x}$ is the system state vector, estimated based on the measurement vector $z_k \in \mathbb{R}^{n_z}$; m_k is the modal state, corresponding to the CF. The measurement equation is in implicit form,[3,10] in which h_k is a function of both the estimated variables and the measured data z_k. The additive system and measurement noises $\eta_k \in \mathbb{R}^{n_\eta}$ and $\xi_k \in \mathbb{R}^{n_\xi}$ are mutually independent, white with zero mean and covariances Q_k and $R_{z,k}$, respectively. The functions f, g and h are nonlinear and remain unchanged during the estimation procedure.

In this paper the focus is on the detection of the current CF and the instant of transition between the CFs. It is supposed that the changes between the CFs are modeled by a first-order Markov chain with initial and transition probabilities, respectively

$$P\{m_{j,0}\} = \mu_j(0), \tag{3}$$

$$Pr\{m_{j,k+1}/m_{i,k}\} = \pi_{ij,k}, \tag{4}$$

where

$$\sum_{j=1}^{N} \pi_{ij,k} = 1,\ i = 1, ..., N$$

and $\pi_{ij,k}$ is the transition probability from CF m_i to CF m_j. At the same time, the unknown geometric parameters of the manipulated object and of the environment are estimated.

The solution to the state estimation problem with unknown model (1)-(2) can be provided by Bayesian sub-optimal MM estimators, between which the Interacting Multiple Model (IMM) filter has proven to be one of the most efficient schemes. Within the framework of the MM estimation the lack of knowledge about the exact model is replaced by a discrete set of models $\mathbb{M} \triangleq \{m_1, m_2, \ldots, m_N\}$, each of them describing possible modes/regimes, here different CFs. With the models several Kalman filters are run in parallel. The IMM estimator calculates the state estimate as a probabilistically weighted sum of the state estimates $\hat{x}_{j,k/k}$ from the Kalman filters with the mode probabilities $\mu_{j,k}$, namely [1]

$$\hat{x}_{k/k} = \sum_{p_{j,k} \in \mathbb{M}} \hat{x}_{j,k/k} \mu_{j,k} \tag{5}$$

and the associated covariance matrix accordingly.

Usually the constructed models for the unknown system modes/ regimes are multiple system models (1). This paper considers tracking task, where the modes, i.e. the CFs

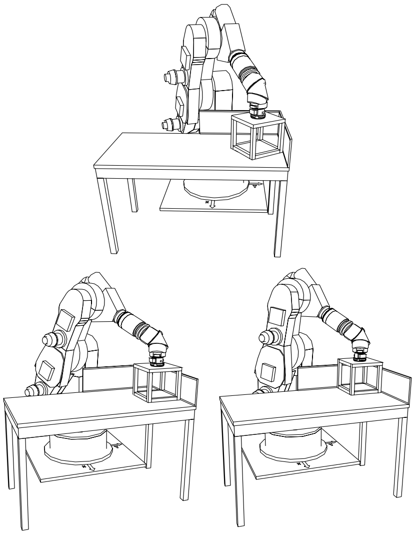

Figure 1: Robot placing a cube in a corner.

are described through several nonlinear measurement models (2), subject to nonlinear kinematic constraints, called closure equations. [3,8]

3. State and measurement equations

The system equation describes the positions and orientations of the manipulated object and the environment and it is linear.

State equation. The system model is of the form

$$x_{k+1} = x_k + \eta_k. \tag{6}$$

The estimated states are geometric grasping and environment parameters (positions and orientations). The state vector $x_k = (x_k^{mo^T}, x_k^{env^T})^T$ comprises a part $x_k^{mo} = (x_k^m, y_k^m, z_k^m, \theta_{x,k}^m, \theta_{y,k}^m, \theta_{z,k}^m)^T$, referring to the manipulated object, and a part $x_k^{env} = (x_k^e, y_k^e, z_k^e, \theta_{x,k}^e, \theta_{y,k}^e, \theta_{z,k}^e)^T$, referring to the environment. These positions and orientations do not change during the task execution, i.e. the states are *static*. Four reference frames are considered (Figure 2): $\{$w$\}$ is the *world* frame, $\{$g$\}$ is a frame on the *gripper* of which the position and orientation with respect to the world frame $\{$w$\}$ are exactly known (through the position kinematics of the robot), $\{$m$\}$ is a frame fixed to the *manipulated* object, $\{e\}$ is a frame fixed to the *environment*. x_k^{mo} are considered with respect to $\{g\}$, and x_k^{env} relative to $\{w\}$.

Measurement equation. The sensor measurements are translational and angular end-effector velocities, v_k and ω_k, together with contact forces and moments, f_k and m_k, measured by a force/torque sensor. They are grouped in the *twist* $t_k = (v_k^T, \omega_k^T)^T$, *wrench* $w_k = (f_k^T, m_k^T)^T$ and measurement $z_k = (t_k^T, w_k^T)^T$ vectors. Measurement equations are derived for each CF from the reciprocity condition. [3]

This condition states that any twist of the manipulated object is reciprocal to any wrench of the modeled wrench space (spanned by the basis G_i) and that any wrench is reciprocal to any twist of the modeled twist space (spanned by the basis J_i). Index i refers to the i-th CF. Then Eq. (2) acquires the form

$$h_{i,k} = \begin{pmatrix} G_{i,k}^T(x_{i,k})\, t_k \\ J_{i,k}^T(x_{i,k})\, w_k \end{pmatrix} = 0. \tag{7}$$

Both G_i and J_i contain trigonometric functions (sines and cosines) of the estimated states, such that the measurement functions [8] are nonlinear. To every CF correspond different twist and wrench bases. The models in Eq. (7) are very distinct, which is appropriate for using the multiple-model approach to solve the problem. Equation (7)

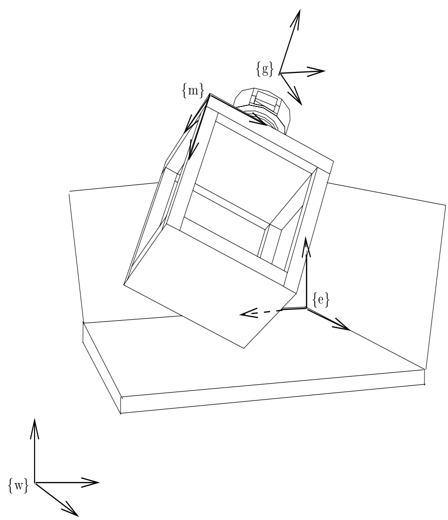

Figure 2: Frames.

is linearized for each CF around the current predicted state estimate $\hat{x}_{i,k+1/k}$. For the computation of the derivative of $h_{i,k}(.)$ with respect to the estimated variables, the partial derivatives of $J_{i,k}$ and $G_{i,k}$ are needed (See the Appendix).

Closure equations. The occurrence of a CF yields additional information for the state variables. The so-called kinematic closure equations [3]

$$c_i(x_{i,k}) = 0 \tag{8}$$

describe additional *nonlinear constraints* that relate different configuration variables (of the manipulated object and the environment) for each CF. The closure equations are models of the contacts obtained as a composition of basic contacts (vertex-face and edge-edge) between polyhedral objects. For instance, the *edge-face* contact between the cube and the environment is described by means of two vertex-face contacts, the contact between two faces of the object is described as a composition of three vertex-face contacts, and so on.

For each CF, the closure equation is applied once. Its corresponding EKF uses as initial state estimate and covariance matrix the ones obtained from the EKF based on the measurement equation. The state estimate and its covariance matrix, computed by the closure equations, are given to the interacting step of the IMM algorithm.

4. IMM estimator for transition and CF monitoring

The number of possible CFs between the manipulated object and the environment is generally high.[5] A set of mutually *exclusive* and *exhaustive* hypotheses is constructed to describe all possible CFs of the manipulated object from one place to another. For the case in which the manipulated object is a cube and the environment is a corner this number is 249.[12] In the planner,[12] a graph is constructed so that its nodes correspond to the possible CFs and its arcs to the transitions between them. Given the path of the motion and the level of uncertainty about the geometric parameters, it is possible to eliminate from the set of hypotheses those CFs whose distance d from the nodes of the path is higher than a given threshold d_{max}.[13] The distance d is the minimum number of arcs of the CF graph that are between two nodes. In this way, a relevant amount of CFs can be eliminated [2,5] and the number of hypotheses considerably reduced. Here it is assumed that the hypothesis H_0 corresponds to the case of completely constrained object. Hypotheses $H_i, i = 1, \ldots, N$ describe all other CFs. With the models for each CF and its EKFs, an IMM estimator is implemented. So, the CFs can be monitored on-line, using the information provided by the IMM mode probabilities.

The nonlinear character of the measurement equations requires the use of EKFs or other nonlinear filtering techniques that do not require computation of derivatives. [6]

The present work estimates the state vectors through EKFs. Each EKF is of the form

$$\hat{x}_{i,k+1/k+1} = \hat{x}_{i,k+1/k} + K_{i,k+1}\nu_{i,k+1}, \tag{9}$$
$$\hat{x}_{i,k+1/k} = \hat{x}_{i,k/k}, \tag{10}$$
$$P_{i,k+1/k} = P_{i,k/k} + Q_{i,k}, \tag{11}$$
$$K_{i,k+1} = -P_{i,k+1/k}H^T_{x_i,k+1}S^{-1}_{i,k+1}, \tag{12}$$
$$P_{i,k+1,k+1} = \Gamma_{i,k+1}P_{i,k+1/k}\Gamma^T_{i,k+1} + K_{i,k+1}R_{i,k+1}K^T_{i,k+1}, \tag{13}$$
$$S_{i,k+1} = R_{i,k+1} + H_{x_i,k+1}P_{i,k+1/k}H^T_{x_i,k+1}, \tag{14}$$

where

$$\begin{aligned}\Gamma_{i,k+1} &= I + K_{i,k+1}H_{x_i,k+1},\\ R_{i,k+1} &= D_{i,k+1}R_{z,k+1}D^T_{i,k+1},\\ H_{x_i,k+1} &= \partial h_i/\partial\hat{x}_{i,k+1/k},\ D_{i,k+1} = \partial h_i/\partial z_{k+1},\\ \nu_{i,k+1} &= h_i(\hat{x}_{i,k+1/k}, z_{k+1}).\end{aligned}$$

$\hat{x}_{i,k+1/k+1}$ and $\hat{x}_{i,k+1/k}$ are, respectively, the filtered and predicted state vectors, $K_{i,k+1}$ is the EKF gain matrix, $P_{i,k/k}$ is the estimation error covariance matrix, $\nu_{i,k+1}$ is a “pseudo-innovation” process [10] and $S_{i,k+1}$ - its covariance matrix. I denotes the identity matrix.

The Appendix presents guiding rules for the computation of the Jacobian matrices for the measurement and closure equations. Lefebvre and coauthors provide detailed derivation of the measurement models (models of different CFs). [8]

5. Performance analysis on a cube-in-corner assembly

The proposed approach is applied to a cube-in-corner assembly system (Figure 1). The experimental data are obtained with a KUKA-IR 361 industrial robot. The cube is mounted directly on the robot without flexibility between them. The measurements are taken at a frequency of 10 Hz. The experimental data (Figures 3-6) correspond to the three CFs of the cube-in-corner assembly (Figure 1): $k \in [0, 220]$ is the face-face and edge-face contact, $k \in [221, 450]$ is the two face-face contact, and $k \in [450, 545]$ is the three face-face contact (completely constrained case). In the test a path with three CFs is used. In the IMM the hypotheses are: H_0 - three face-face contact, H_1 - two face-face contact, H_2 - face-face and edge-face contact. The noise covariance matrices Q and R_z

$$Q = diag\{5, 5, 5, 0.001, 0.001, 0.001, 1, 1, 1, 0.001, 0.001, 0.001\},$$

$$R_z = diag\{0.05, 0.4, 1.96, 4\cdot10^{-7}, 5\cdot10^{-6}, 9\cdot10^{-8}, 0.06, 0.009, 0.008, 150, 87, 51\}$$

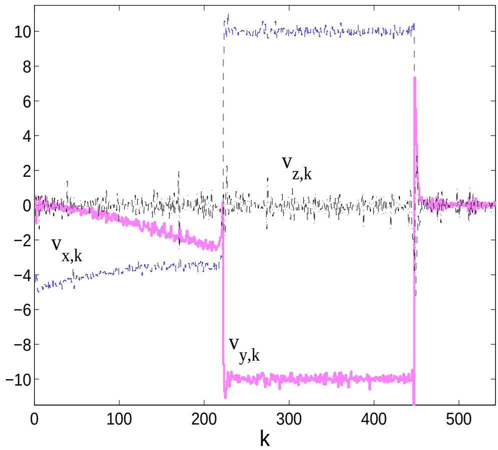

Figure 3: Measured translational velocities.

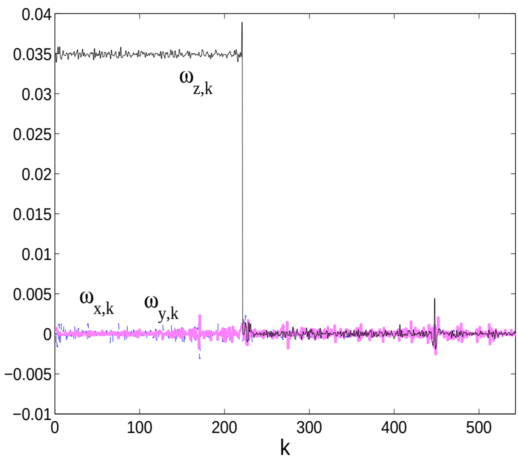

Figure 4: Measured angular velocities.

are the same for all EKFs. The units of the elements of Q are mm^2 and rad^2, respectively for the positions and angles, and those of R_z are $(mm/sec)^2$, $(rad/sec)^2$, N^2, $(Nmm)^2$ for the measured velocities, forces and moments. The system noise covari-

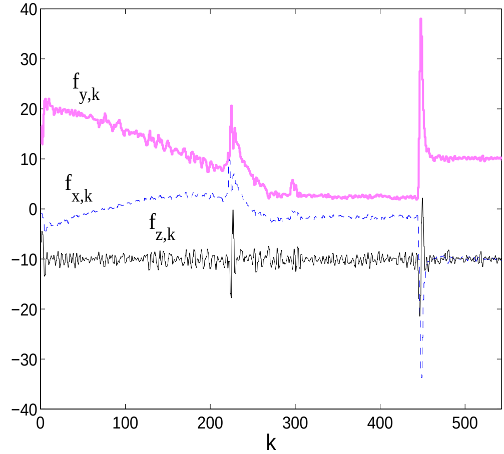

Figure 5: Measured forces.

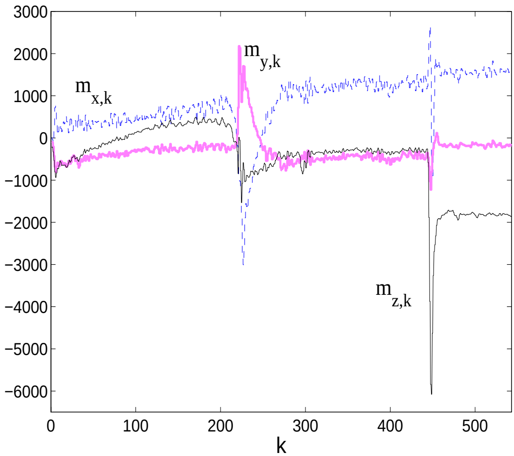

Figure 6: Measured moments.

ance matrix Q reflects the presence of linearization errors, whereas the measurement noise covariance for the used sensors is known. The IMM transition probability matrix

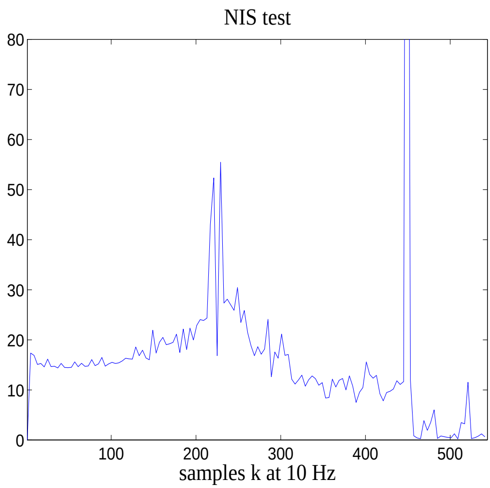

Figure 7: Normalized Innovation Squared test.

and the initial probability vector are chosen as follows:

$$Pr = \begin{pmatrix} 0.98 & 0.01 & 0.01 \\ 0.01 & 0.98 & 0.01 \\ 0.01 & 0.01 & 0.98 \end{pmatrix}, \mu_0 = \begin{pmatrix} 1/3 \\ 1/3 \\ 1/3 \end{pmatrix}.$$

Due to a lack of information, equal initial probabilities are assigned to all CFs.

It is obvious from Figure 8 that, based on the IMM probabilities, the contact transitions can be detected on time. After the change a small period is needed and the algorithm resolves the "competition" between the CFs. This is reflected also in the Normalized Innovation Squared (NIS) test,[1] $\epsilon_k = \nu_k S_k^{-1} \nu_k$ (Figure 7) and in the peak estimation errors. In the periods of transitions the estimates are not reliable. The estimation error $e_k = \hat{x}_{k/k} - x_k$ of the positions and orientations is presented in Figures 9-12. The NIS test (Figure 7) and the mode probabilities (Figure 8) contain information about the type and instants of contact transitions. By the IMM approach the CFs and the transitions between them are detected on-line and, at the same time, the unknown parameters of the manipulated object and the environment are estimated. So, both modes detection and estimation are performed automatically. In earlier works of the research team [7,8] the detection of the CFs was performed from the information of the SNIS test of independently working EKFs and their residual errors. Of course, the computational cost is proportional to the number of the EKFs (the number of CFs). The IMM filter, implemented in the present paper, is with a *fixed structure*, i.e. with preliminary

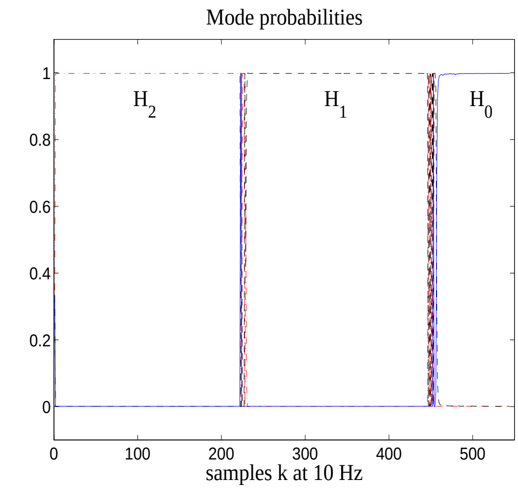

Figure 8: IMM mode probabilities.

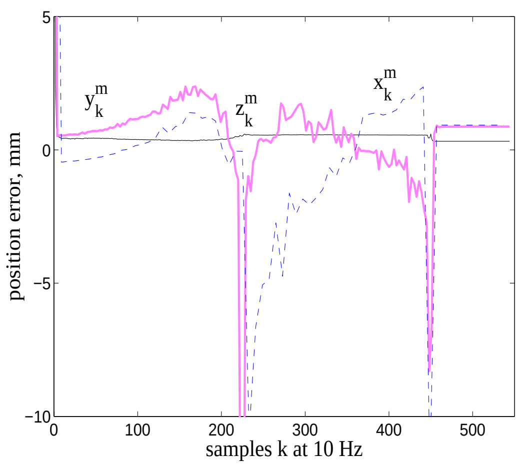

Figure 9: Error e_k in positions of the cube.

determined set of models. When the estimation block is connected with the planning part,[5,12,13] the estimator can receive from the graph of the planner information about the next neighboring CFs. Based on this graph structure of the CFs, *variable structure*

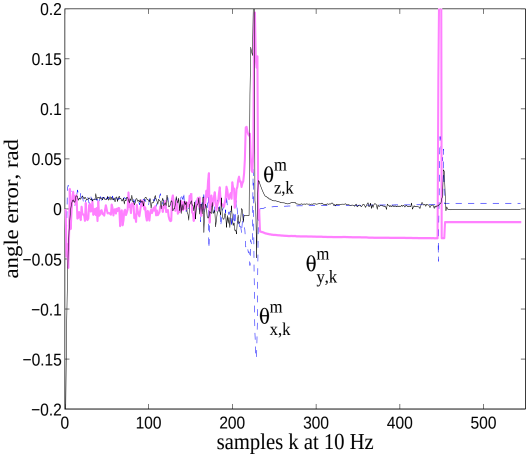

Figure 10: Error e_k in orientation angles of the cube.

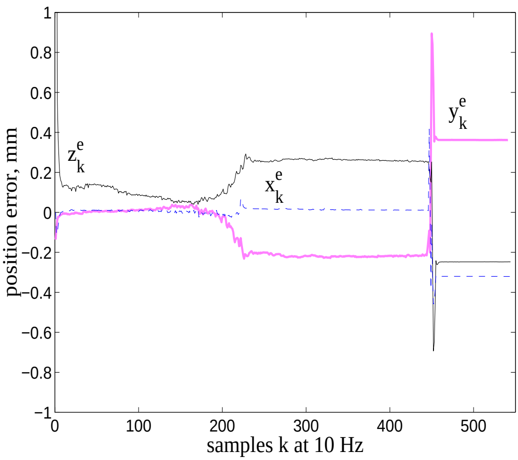

Figure 11: Error e_k in positions of the environment.

IMM estimators (with time varying set of models) can be designed.

Extensions to cases with time-varying geometric parameters of the manipulated object and the environment can be performed by analogy.

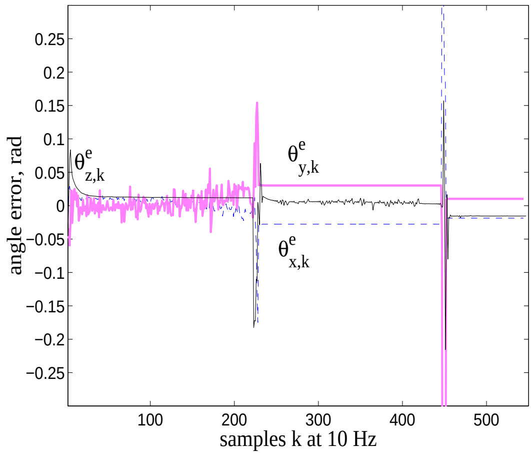

Figure 12: Error e_k in angles of the environment.

6. Conclusions

In this paper a general approach to contact transitions detection and estimation of uncertain geometric parameters (positions and orientation angles) is proposed for force-controlled robotic tasks in which a robotic manipulator moves an object in contact with the environment, both rigid and polyhedral.

The possible CFs are described by different measurement equations, whereas the system equation is known. An IMM estimator is implemented and its performance is evaluated by real sensor data (linear and angular velocities, forces and moments). The IMM probabilities and the normalized innovation squared test permit to monitor the occurring CFs. The experimental assembly of moving a cube into a corner demonstrates high estimation accuracy and quick detectability of the contact transitions.

Appendix. Derivatives Computation

The computation of the measurement and closure equations is based on the screw-transformation matrices,[3] that are functions of the rotational matrices between the different frames.[3,4] The partial derivatives are found from Eq. (7) and have the form

$$\frac{\partial h_{i,k}}{\partial x_{i,k}} = \begin{pmatrix} \partial(G_{i,k}^T(x_{i,k}))/\partial \mathrm{x}_{i,k}^{mT} & \partial(G_{i,k}^T(x_{i,k}))/\partial \mathrm{x}_{i,k}^{eT} \\ \partial(J_{i,k}^T(x_{i,k}))/\partial \mathrm{x}_{i,k}^{mT} & \partial(J_{i,k}^T(x_{i,k}))/\partial \mathrm{x}_{i,k}^{eT} \end{pmatrix},$$

$$D_{i,k} = \partial h_{i,k} / \partial z_k = \begin{pmatrix} G_{i,k}^T & 0 \\ 0 & J_{i,k}^T \end{pmatrix}.$$

The matrix derivatives are computed according to the rules for matrix calculus operations proposed by Vetter.[11]

Acknowledgement

Herman Bruyninckx and Tine Lefebvre are, respectively, Postdoctoral and Doctoral Fellows of the Fund for Scientific Research-Flanders (F.W.O–Vlaanderen) in Belgium. Lyudmila Mihaylova is a Postdoctoral Fellow at Katholieke Universiteit Leuven, on leave from the Bulgarian Academy of Sciences. Financial support by the Center of Excellence BIS21 grant ICA1-2000-70016 and the K. U. Leuven's Concerted Research Action GOA/99/04 are gratefully acknowledged.

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