A Demonstration Tool with Kalman Filter Data Processing for Robot Programming by Human Demonstration

Johan Rutgeerts, Peter Slaets, Filips Schillebeeckx, Wim Meeussen, Walter Verdonck,
Bert Stallaert, Peter Princen, Tine Lefebvre, Herman Bruyninckx, Joris De Schutter
Department of Mechanical Engineering, Katholieke Universiteit Leuven,
Celestijnenlaan 300B, B3001 Leuven (Heverlee), Belgium.
johan.rutgeerts@mech.kuleuven.ac.be

***Abstract*— This paper presents a modular demonstration tool for robot programming by human demonstration and an approach for the calibration of the tool's sensors. The tool is equipped with a wrench sensor, twelve LED markers for fast and accurate six dimensional position tracking with the Krypton K600 camera system, a compact camera and a laser distance sensor. A gripper mechanism is mounted on the tool for grasping and manipulating objects. The design of the tool specifically focussed on the demonstration of compliant motion task, with applications in manipulation and assembly tasks. The calibration approach first uses an Extended Kalman Filter to convert the measured positions of three to twelve visible LED's into the pose of the tool frame relative to the Krypton camera frame. Then, using a Non Minimal State Kalman Filter, the force sensor calibration parameters are calculated, and the orientation of the Krypton camera frame relative to the world frame is defined. This calibration approach is verified in a real world experiment.**

I. Introduction

In *Robot Programming by Human Demonstration* [4], [14], sensor data of a task is gathered while a human operator performs a demonstration. In an interpretation step, a formal task description is deduced from this sensor data. Subsequently, the formal task is executed by the robot, during which new sensor data is gathered, processed and interpreted to cope with possible geometric uncertainties.
Several techniques are possible to perform a demonstration of a robot task:

- *Interaction with the robot:* by moving the robot itself so that it performs the correct motion, possibly using a master–slave system or a joystick.
- *In a virtual environment:* with or without the use of a haptic interface providing force feedback to the demonstrator.
- *By observing human motion:* by letting the demonstrator interact directly with the objects in the environment and observing the relative motions and contacts, using e.g. cameras or other sensors.

This last option requires a demonstration tool [5], [8] that allows us to manipulate the objects and which incorporates the various sensors. This paper discusses the design of such a demonstration tool for compliant motion tasks. First, a general description of the developed tool is given. Then, the Kalman Filter and Non Minimal State Kalman Filter are introduced. These are used in section IV and V to estimate the tool frame and the force sensor calibration parameters.

II. General description

A. Specifications

The developed tool is intended to be used to demonstrate various manipulation and identification tasks, involving compliant motion. This required functionality implies several design specifications:

- *modular gripper:* during the demonstration of a manipulation task, objects must be grasped and released. This implies that the tool is equipped with a gripper. For identification tasks however, a measurement probe is more appropriate. A modular design allows us to switch between gripper and probe, or betweem different grippers for different tasks. All grippers are two-finger grippers which are opened and closed manually.
- *position and force-torque measurement:* the targeted tasks to be demonstrated, are compliant motion tasks. This requires 6D pose measurement (thus position and orientation) and 6D force-torque measurement.
- *small and lightweight:* to allow for easy manipulation of objects, the demonstration tool must be small, so that the manipulated objects are close to the demonstrators hand, and lightweight, for easy movement.
- *room for other sensors:* for further research purposes there has to be room for other sensors, such as a camera and a laser distance sensor.

Concrete values for these specifications are given in table I.

B. Sensors

1) pose measurement: The device used to measure the pose of the tool is the *Krypton K600* camera system, shown in fig. 1. The K600 consists of three calibrated cameras and a number of LED markers. Each LED marker is "fired" separately, and its position is recorded by the three camera's. By means of triangulation, the 3D position of each of the LED markers can

TABLE I

DEMONSTRATION TOOL SPECIFICATIONS

Grasping and manipulating objects	Modular
Easy to use	
Lightweight	500 g
Compact	$30 \times 30 \times 30$ cm
Pose measurement (6 degrees of freedom)	
Position accuracy	1-2 mm
Orientation accuracy	1°
Work volume	order of 1 m^3
Force and torque measurement	
Maximum force	50 N
Maximum torque	2.5 Nm
Extra sensors	
Camera and distance sensor	

be determined. The system is fast and highly accurate, taking measurements at 100 Hz or more, with a volumetric accuracy of 90 μm.

The performance of the Krypton measurement system has been compared to that of the *Ascension Flock of Birds*. This is a magnetic pose measurement device, which implies that its measurements may be influenced by conductive metals in the environment. The distortion on the measurements by e.g. the vicinity of the force-torque sensor in the tool, proved to be too high to be acceptable. Using this sensor to provide relative instead of absolute measurements might be a solution to this problem. For the time being however, the Krypton system is the preferred measurement system and the only system incorporated in the tool.

2) force–torque measurement: The force-torque sensor is the 50M31A from JR3 (their smallest sensor currently available). It has a diameter of 50 mm and a height of 31 mm. The maximum force is 100 N for F_x and F_y, and 200 N for F_z. The sensor is rather big with respect to the tool, but all electronics reside in the sensor itself; the link between the sensor and its interface card is digital.

3) other sensors: The tool provides room for other sensors. At this time, two extra sensors have been mounted: a laser distance sensor and a small camera (however, so far they have not been used in experiments).

C. Design

Fig. 1 shows a CAD drawing of the tool, with the extra sensors mounted. The gripper is at the bottom of the tool. It is manually actuated by a kind of 'bicycle break' mechanism. Key benefits of this approach over e.g. electric actuation is the small size and weight of the mechanism. The gripper is attached to the tool with easily accessible bolts, so that it can be swapped for e.g. a measurement probe.

Above the gripper, four L-shaped profiles are located, to which the LED markers are attached. The L-profiles all have a different orientation, so that at least three LED markers are visible to the Krypton camera in a large range of orientations of the tool with respect to the camera. This is necessary to unambiguously determine the pose of the tool.

The force sensor forms the connection between the bottom part of the tool, with the gripper and the L-profiles, and the upper part, which is held by the human demonstrator.

The mountings for the camera and laser sensor are attached to the upper part of the tool. If desired however, they can easily be removed to reduce weight.

III. Kalman Filter

This section introduces the Kalman Filter, which will be used in section IV and V to estimate the pose of the tool and the calibration parameters of the force-torque sensor.

The Kalman Filter can be used in analytical estimation problems, where the state is estimated of a system with linear process and measurement models and with additive Gaussian uncertainties. The probability density function (pdf) over the state vector is then a Gaussian distribution, which is fully determined by its mean vector and covariance matrix. This mean and covariance are updated analytically with the Kalman Filter algorithm [7], [12].

A. Kalman Filter variants for nonlinear systems

For most nonlinear systems, the pdf cannot be written as an analytical function with a limited number of time-varying parameters. In order to have a computationally interesting update algorithm, the Kalman Filter is used as an approximation. This is achieved by linearisation of the process and measurement models of the system. It also means that the true pdf is approximated by a Gaussian distribution. Different ways of linearisation (different Kalman Filter variants) lead to different results. The best known Kalman Filter variants are the *Extended Kalman Filter* [2], [10], [13], the *Iterated Extended Kalman Filter* [2], [10], [13] and the *Unscented Kalman Filter* [6], [9], [11].

B. The Non-Minimal State Kalman Filter

The *Non-Minimal State Kalman Filter* (NMSKF) [**?**] is an exact Bayesian filter, able to deal with static systems (parameter estimation) with any kind of nonlinear measurement model subject to additive Gaussian measurement uncertainty. The filter can also be applied to a limited class of dynamic systems. The Non-Minimal State Kalman Filter calculates the exact (non-Gaussian) pdf over the state by providing analytical update equations for its sufficient statistics.

An advantage of this filter is its theoretical simplicity for people familiar with the Kalman Filter algorithm. The filter can be interpreted as a Kalman Filter linearizing the process and measurement models in a higher-dimensional state space (hence its name). The "mean vector" and "covariance matrix" of the Gaussian in the higher-dimensional state space are sufficient statistics of the posterior pdf over the original (minimal) state.

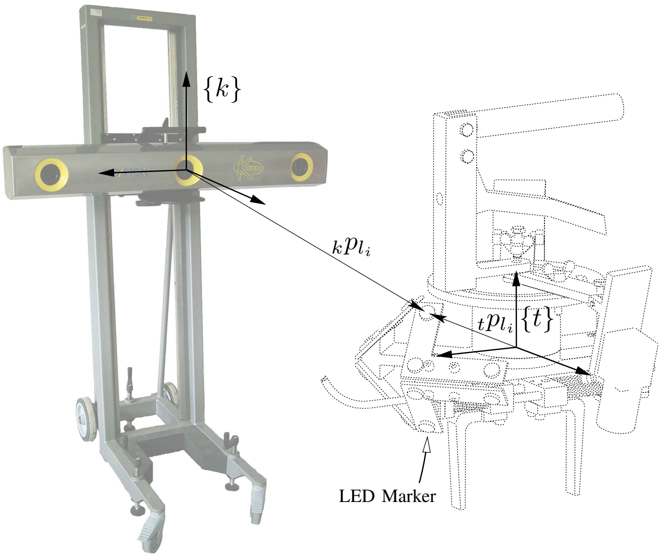

Fig. 1. CAD drawing of the demonstration tool with the Krypton camera system.

IV. Tool frame estimation

A. Problem description

The Krypton K600 system measures the position of a number of LED markers attached to the tool (or in other words, the position of a number of distinct points of the tool). The pose of the tool, i.e. the pose of some reference frame of the tool (the *tool frame*), has to be determined from these position measurements. In order to do this unambiguously, at least three non-collinear LED markers must be visible to the Krypton system. In total, twelve LED markers are attached to the demonstration tool, which results in a great range of poses of the tool with respect to the K600 with at least three visible non-collinear markers.

B. Pose estimation

This paragraph describes how the tool frame is estimated from this varying number of available position measurements.

1) Kalman filter: an iterated extended Kalman filter estimates the tool frame from the position measurements. This allows for a uniform and stochastically correct way of dealing with the changing number of measurements, when different markers become visible or disappear to the Krypton system. Furthermore, the Kalman filter can easily be extended to estimate other characteristics such as the twist of the tool frame, by extending the state vector and adding the corresponding system- and measurement equations.

2) state parameterization: any frame can be fully defined by six parameters. However, every parameterization with only six parameters will have singularities. To avoid these singularities, the homogeneous transformation matrix ${}^t_k\boldsymbol{T}$ is chosen as a non-minimal parameterization for the tool frame(with t and k indicating the tool frame and the Krypton camera frame respectively). It has twelve instead of six parameters, so six constraints must be added, which express the orthonormality of the rotation matrix:

$$ {}^t_k\boldsymbol{T} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & {}_kp_x^{k,t} \\ r_{21} & r_{22} & r_{23} & {}_kp_y^{k,t} \\ r_{31} & r_{32} & r_{33} & {}_kp_z^{k,t} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

$$ = \begin{bmatrix} {}_k\boldsymbol{e}_x^t & {}_k\boldsymbol{e}_y^t & {}_k\boldsymbol{e}_z^t & {}_k\boldsymbol{p}^{k,t} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

with constraints:

$$ {}_k\boldsymbol{e}_x^t \cdot {}_k\boldsymbol{e}_y^t = 0 \quad \Leftrightarrow \quad r_{11}r_{12} + r_{21}r_{22} + r_{31}r_{32} = 0 \quad (3)$$

$$ {}_k\boldsymbol{e}_x^t \cdot {}_k\boldsymbol{e}_x^t = 1 \quad \Leftrightarrow \quad r_{11}^2 + r_{21}^2 + r_{31}^2 = 1 \quad (4)$$

$$ {}_k\boldsymbol{e}_y^t \cdot {}_k\boldsymbol{e}_y^t = 1 \quad \Leftrightarrow \quad r_{12}^2 + r_{22}^2 + r_{32}^2 = 1 \quad (5)$$

$$ {}_k\boldsymbol{e}_x^t \times {}_k\boldsymbol{e}_y^t = {}_k\boldsymbol{e}_z^t \quad \Leftrightarrow \begin{cases} r_{21}r_{32} - r_{31}r_{22} = r_{13} \\ r_{31}r_{12} - r_{11}r_{32} = r_{23} \\ r_{11}r_{22} - r_{21}r_{12} = r_{33} \end{cases} \quad (6)$$

3) measurement equations: for each of the n visible LED markers, the following expression holds:

$$ \begin{bmatrix} {}_k\boldsymbol{p}_{l_i} \\ 1 \end{bmatrix} = {}^t_k\boldsymbol{T} \cdot \begin{bmatrix} {}_t\boldsymbol{p}_{l_i} \\ 1 \end{bmatrix} \qquad \forall i \text{ such that } l_i \text{ visible} \quad (7)$$

These n vector equations are the equivalent of $3n$ scalar equations and form the measurement equations of the Kalman filter. By writing the six constraints (3) – (6) in their implicit form, they can be incorporated in the Kalman Filter algorithm as extra measurement equations for which the measurement is always zero, with very low uncertainty.

4) system equations: in every time step, a new tool frame is estimated from new measurement data. If no estimation of the twist of the tool frame is done, no system update can be performed on the state estimate, other then adapting its covariance matrix to correspond to the maximum tool frame displacement during every timestep.

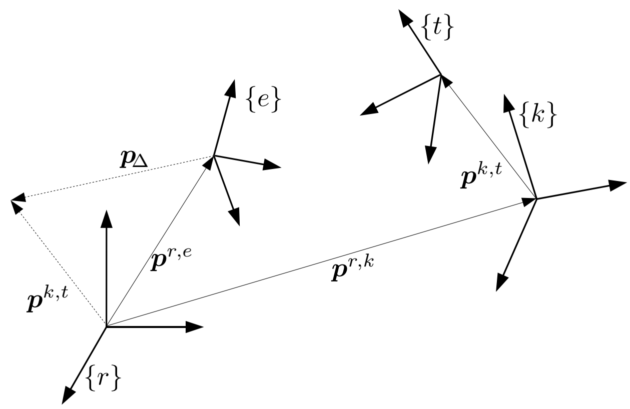

Fig. 2. The frames, relevant to the telemanipulation experiment.

C. Experimental evaluation

As a first application and evaluation of this Kalman filter based tool frame estimation, a teleoperation experiment has been set up. In this experiment, the task is to lift up a crate

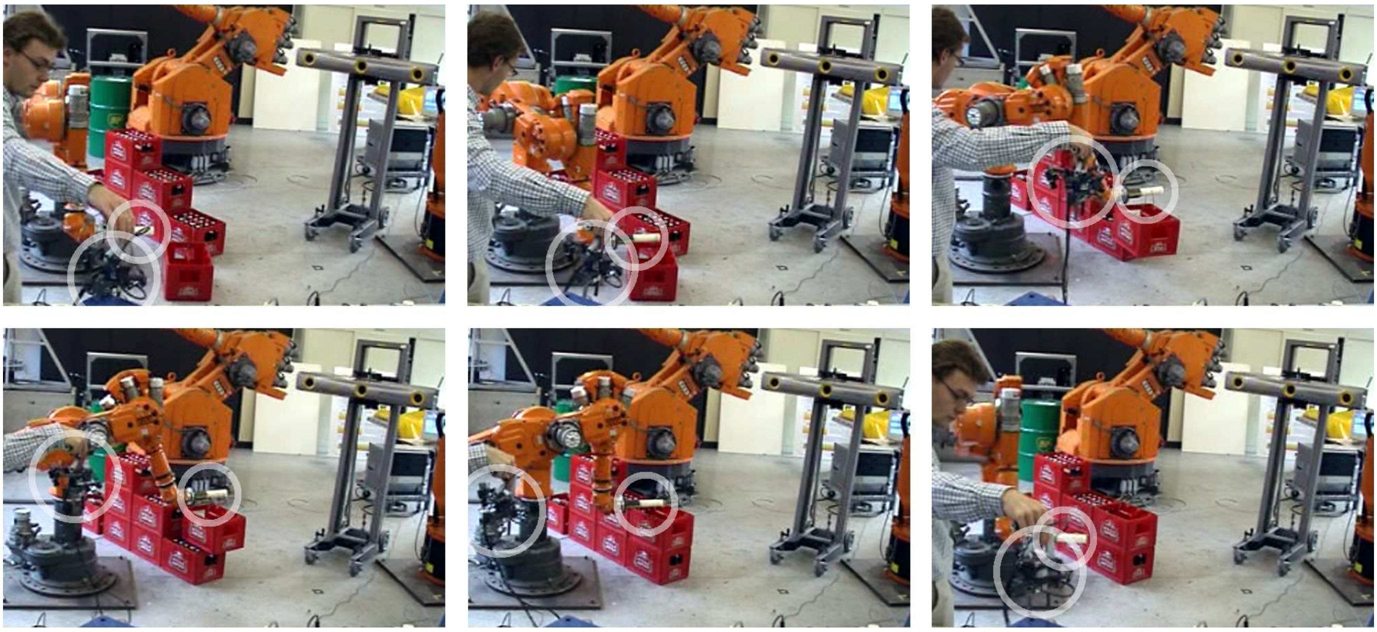

Fig. 3. Left to right, top to bottom: an image sequence, showing the different steps of the telemanipulation experiment. A large circle is drawn around the tool, a smaller circle around the robot end effector. The first picture shows the first phase of the experiment. In this phase, the tool is held still, and the robot rotated around its tool center point to align their respective orientations. The other pictures show the second phase of the experiment: the tool is used in a master–slave configuration, i.e. the robot tracks its motion.

with the robot and and to stack it on top of some other crates. The demonstration tool is used in a master–slave configuration: its position corresponds to the desired position of the robot end effector.

Fig. 2 shows the related frames:

- the robot base frame $\{r\}$,
- the robot end effector frame $\{e\}$,
- the Krypton camera frame $\{k\}$ and
- the tool frame $\{t\}$.

In a first phase, the tool is held still and the initial orientation of the tool ${}^{t}_{k}\boldsymbol{R}_{init}$ is calculated. The robot end effector is then rotated around the tool center point, to align the end effector orientation with that of the tool frame:

$$ {}^{k}_{r}\boldsymbol{R} \cdot {}^{t}_{k}\boldsymbol{R}_{init} = {}^{e}_{r}\boldsymbol{R} \tag{8} $$

In this equation, the rotation matrix of $\{k\}$ with respect to $\{r\}$ is a known constant[1].

To relate the measured tool position $\boldsymbol{p}^{k,t}$ to the desired end effector position $\boldsymbol{p}^{r,e}$, the offset $\boldsymbol{p}_{\Delta}$ between the initial values of $\boldsymbol{p}^{k,t}$ and $\boldsymbol{p}^{r,e}$ is also calculated:

$$ {}_{r}\boldsymbol{p}_{\Delta} = {}^{k}_{r}\boldsymbol{R} \cdot {}_{k}\boldsymbol{p}^{k,t}_{init} - {}_{r}\boldsymbol{p}^{r,e}_{init} \tag{9} $$

This leads to the following relation for the desired end effector position in the second phase of the experiment, during which the tool is moved:

$$ {}_{r}\boldsymbol{p}^{r,e}_{des} = {}^{k}_{r}\boldsymbol{R} \cdot {}_{k}\boldsymbol{p}^{k,t} - {}_{r}\boldsymbol{p}_{\Delta} \tag{10} $$

The desired end effector pose is then given by:

$$ {}^{e}_{r}\boldsymbol{T}_{des} = \begin{bmatrix} {}^{k}_{r}\boldsymbol{R} \cdot {}^{t}_{k}\boldsymbol{R} & {}_{r}\boldsymbol{p}^{r,e}_{des} \\ \boldsymbol{O}_{1\times 3} & 1 \end{bmatrix} \tag{11} $$

Fig. 3 shows a sequence of pictures from the experiment (left to right – top to bottom). It is conducted on a Kuka 361 industrial manipulator, which is controlled by a PC running RTAI/lxrt and the Orocos control software [3].

In the experiment, only six LED markers were attached to the tool, which reduces the movability of the tool, since at all times at least three markers must be visible.

V. Force sensor calibration

A. Problem description

In order to measure the contact forces during compliant motion tasks, a force sensor is integrated in the tool. However, the raw measurement data from this sensor do not correspond to the equivalent wrench of the contact forces, because of the influence of gravity and the offset on each of the six measured components.

To compensate for these effects, in general 10 parameters must be known:

- the six offsets (6 parameters)
- the mass of the gripper and the manipulated object (1 parameter)
- the center of gravity (3 parameters)

To obtain the contact wrench, the offsets and the gravitational force have to be subtracted from the raw measurements, after

[1] If the real rotation matrix of $\{k\}$ with respect to $\{r\}$ is chosen as ${}^{k}_{r}\boldsymbol{R}$, the end effector's and the tool's absolute orientation will be equal. Another possibility is e.g. to choose ${}^{k}_{r}\boldsymbol{R}$ to be the identity matrix. In that case the end effector's relative orientation (with respect to the robot base frame) equals the relative orientation of the tool (with respect to the Krypton camera frame). This approach is used in the experiment and proves to be an intuitive way to control the robot's motion.

transforming the latter from the world frame to the sensor frame. This transformation poses a specific problem. All position measurements are relative to the Krypton camera frame, so in order to do the transformation, the orientation of the vertical axis of the world frame must be known with respect to the camera frame. Since it is difficult to manually align the Krypton camera frame with the world frame, this orientation cannot be measured directly, so two extra parameters are to be determined.

B. State vector estimation

1) Kalman Filter: the proposed solution is to use a NMSKF to estimate the 12 parameters (the state vector). The NMSKF transforms the measurement equation to a higher dimensional non-minimal state space, making the measurement equation linear in the non-minimal state variables. This renders the NMSKF robust to large uncertainties on the state estimate. In this application, this robustness to large uncertainties is needed, since the offsets on the force measurement vary highly, and since the mass of the manipulated object is a priori not known.

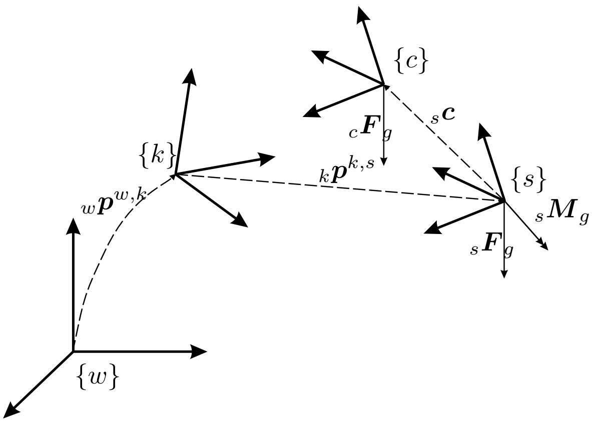

Fig. 4. The frames, relevant to the force-torque calibration problem.

2) Measurement equations: Fig. 4 shows the definition of the relevant frames and vectors:

- $\{s\}$ is the force-torque sensor frame (with fixed pose relative to the tool frame),
- $\{w\}$ the world frame (with Z-axis vertical),
- $\{k\}$ the Krypton camera frame and
- $\{c\}$ is parallel to $\{s\}$, but has its origin in the center of gravity of gripper and manipulated object.

The wrench $\mathbf{w} = [{}_s\boldsymbol{F}_g \ {}_s\boldsymbol{M}_g]^T$ is the wrench as measured by the sensor and $\mathbf{o}$ the offset on this measured wrench (both thus by definition in the origin of and relative to $\{s\}$).

The wrench vector $\mathbf{g}$ is the gravity vector. In $\{c\}$ it is given by:

$$_{\mathrm{c}}\mathbf{g} = \begin{bmatrix}0 & 0 & -mg & 0 & 0 & 0\end{bmatrix}^T \tag{12}$$

This corresponds to a wrench $_{\mathrm{s}}\mathbf{g}$ in $\{s\}$:

$$_{\mathrm{s}}\mathbf{g} = {}^{c}_{s}\boldsymbol{S} \cdot {}_{\mathrm{c}}\mathbf{g}; \qquad {}^{c}_{s}\boldsymbol{S} = \begin{bmatrix} {}^{w}_{c}\boldsymbol{R} & \mathbf{0}_{3\times3} \\ {}^{w}_{c}\boldsymbol{R}\,[{}_c\mathbf{p}^{s,c}\times] & {}^{w}_{c}\boldsymbol{R} \end{bmatrix} \tag{13}$$

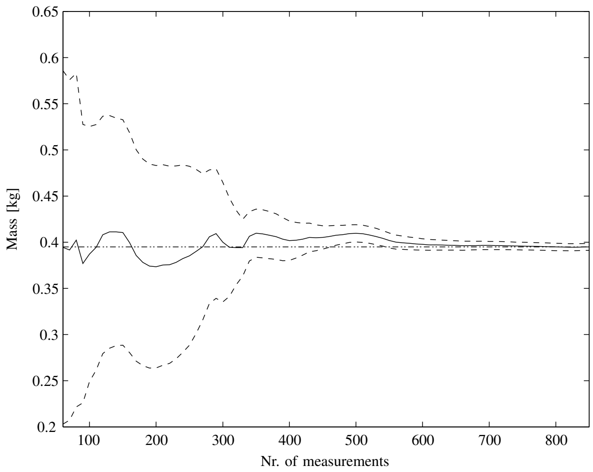

Fig. 5. Estimation of the mass of the gripper. The full line shows the estimate, the dashed lines show the 2σ boundaries.

with:

$$[{}_r\mathbf{p}^{p,q}\times] = \begin{bmatrix} 0 & -{}_rp_z^{p,q} & {}_rp_y^{p,q} \\ {}_rp_z^{p,q} & 0 & -{}_rp_x^{p,q} \\ -{}_rp_y^{p,q} & {}_rp_x^{p,q} & 0 \end{bmatrix} \tag{14}$$

in which ${}_r\mathbf{p}^{p,q} = \begin{bmatrix}{}_rp_x^{p,q} & {}_rp_y^{p,q} & {}_rp_z^{p,q}\end{bmatrix}^T$ is the vector from the origin of $\{p\}$ to the origin of $\{q\}$, expressed in $\{r\}$.

If the tool is moved in free space with only small accelerations, so that the inertial influence on the wrench measurement is negligible, the following measurement equation holds:

$$\mathbf{w} - \mathbf{o} - {}^{c}_{s}\boldsymbol{S} \cdot {}_{\mathrm{c}}\mathbf{g} = \mathbf{0}, \tag{15}$$

since the measured force, compensated for gravity and the offsets, must then be zero. This equation is an implicit and non-linear measurement equation, function of the state and the measurements:

- $\mathbf{w}$ is the measured wrench
- $\mathbf{o}$ is the offset wrench
- ${}^{c}_{s}\boldsymbol{S}$ is both function of state parameters (orientation of $\{k\}$ with respect to $\{w\}$ and position of the center of gravity in $\{s\}$) and of measurements (${}^{t}_{k}\boldsymbol{T}$, estimated from the Krypton measurements as described in the previous paragraph).
- ${}_{\mathrm{c}}\mathbf{g}$ is function of the mass.

C. Experimental evaluation

To evaluate the force sensor calibration procedure, two experiments are conducted. In the first experiment, the sensor is calibrated three times with different masses: the first time without an extra grasped mass, the second time with a grasped mass of 250 g and the third time with a mass of 501 g. Fig. 5 shows the estimation of the mass of the gripper, without extra grasped mass. The estimation yields an estimate of 0.39 kg, with a 2σ interval of 8 g.

Table II shows the results of the estimates in the consecutive experiments. The difference in estimated mass between the

TABLE II

COMPARISON OF THE ESTIMATED PARAMETERS.

Parameter	Estimate		
Grasped mass [kg]	0	0.250	0.501
Estimated Mass [kg]	0.395	0.645	0.899
Rotation x-axis [rad]	-0.033	-0.013	-0.027
Rotation y-axis [rad]	0.009	-0.018	-0.017
c_x [m]	-0.009	-0.005	-0.005
c_y [m]	0.008	0.006	0.003
c_z [m]	0.035	0.057	0.057
Offset F_x [N]	1.57	1.57	1.55
Offset F_y [N]	2.25	2.32	2.36
Offset F_z [N]	0.63	1.03	1.20
Offset M_x [Nm]	-0.202	-0.203	-0.210
Offset M_y [Nm]	0.094	0.089	0.086
Offset M_z [Nm]	-0.068	-0.068	-0.068

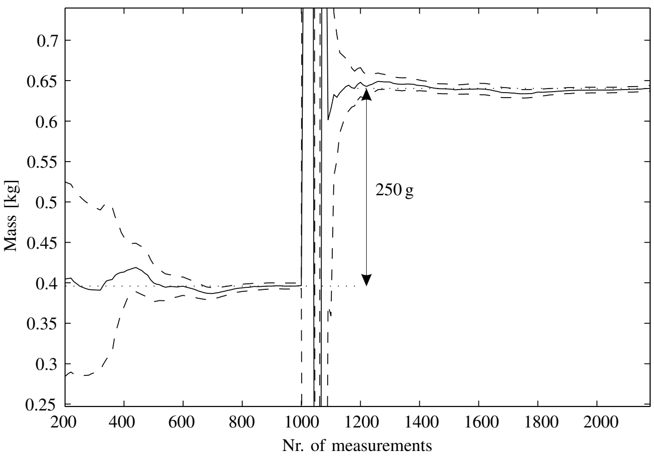

Fig. 6. Estimation of the mass of the gripper. Until measurement 1000, there is no extra grasped mass. An extra mass of 250 g is grasped between measurement 1000 and 1100. The extra mass renders the measurements inconsistent with the current estimate. A consistency test detects this inconsistency and resets the Kalman Filter. From measurement 1100 on, the estimate converges to the correct, 250 g higher, value.

first and the second time the experiment was performed, is exactly 250 g. The difference between the second and the third time is 254 g, with a real value of 251 g. The x- and y-coordinates of the centre of gravity are very small, because of the symmetry of the tool. The z-coordinate is larger and changes because of the change in grasped mass.

In the second experiment, the estimation is started without grasping an extra mass. When the estimates have converged, an object is grasped. The extra mass renders the measurements inconsistent with the current estimate. A consistency test, based on the NIS criterium, detects this inconsistency and resets the estimator. Fig. 6 shows the estimate of the mass. From the beginning until measurement 1000, there is no extra grasped mass. Between measurement 1000 and 1100, an extra mass of 250 g is grasped, which disturbs the estimation. From measurement 1100 on, the estimate converges to the correct, 250 g higher, value.

VI. CONCLUSION

The design of a modular demonstration tool for robot programming by human demonstration and an approach for the calibration of the tool's sensors have been presented. An Extended Kalman Filter is used as a uniform and stochastically correct way to convert the measured positions of three to twelve visible LED markers into the pose of the tool frame. Other characteristics can be estimated by extending the state vector and adding the corresponding system- and measurement equations. A Non Minimal State Kalman Filter is used to calculate the force sensor calibrations parameters. This type of Kalman Filter is robust to large uncertainties on the state estimate. Experiments evaluate the calibration approach. The demonstration tool will be used in our work on robot programming by human demonstration.

ACKNOWLEDGMENT

All authors gratefully acknowledge the financial support by K.U.Leuven's Concerted Research Action GOA/99/04.

REFERENCES

[1] *Int. Conf. Robotics and Automation*, Minneapolis, MN, 1996.

[2] Y. Bar-Shalom and X. Li. *Estimation and Tracking, Principles, Techniques, and Software*. Artech House, 1993.

[3] H. Bruyninckx. Open RObot COntrol Software. `http://www.orocos.org/`, 2001.

[4] J. Chen and Alexander Zelinsky. Programing by demonstration: Coping with suboptimal teaching actions. *Int. J. Robotics Research*, 22(5):299–319, 2003.

[5] R. Hirai, H. Noguchi, and K. Iwata. Human-demonstration based approach to the recognition of process state transitions in insertion of deformable tubes. In *Int. Conf. Robotics and Automation* [1].

[6] S. Julier and J. Uhlmann. A general method for approximating nonlinear transformations of probability distributions. `http://www.robots.ox.ac.uk/~siju/work/work.html`, november 1996.

[7] R. E. Kalman. A new approach to linear filtering and prediction problems. *Trans. ASME J. Basic Eng.*, 82:34–45, 1960.

[8] Ralf Koeppe, Achim Breidenbach, and Gerd Hirzinger. Skill representation and acquisition of compliant motion using a teach device. In *Proc. IEEE/RSJ Int. Conf. Int. Robots and Systems*, Osaka, Japan, 1996.

[9] T. Lefebvre, H. Bruyninckx, and Joris De Schutter. Comment on "A new method for the nonlinear transformation of means and covariances in filters and estimators". *IEEE Trans. Autom. Control*, 47(8):1406–1408, 2002.

[10] Peter S. Maybeck. *Stochastic models, estimation, and control. Vol. 2*. Number 141-2 in Mathematics in science and engineering. Academic Press, Orlando, FL, 1982. Republished by Navtech Press, Arlington, 1994.

[11] J. Uhlmann S. Julier and H.F. Durrant-Whyte. A new method for the nonlinear transformation of means and covariances in filters and estimators. *Trans. on Automatic Control*, 45(3):477–482, March 2000.

[12] Harold Wayne Sorenson. *Kalman filtering: theory and application*. IEEE Press, New York, NY, 1985.

[13] Hisashi Tanizaki. *Nonlinear Filters. Estimation and Applications*. Springer-Verlag, 1996.

[14] Qi Wang, J. De Schutter, Wim Witvrouw, and Sean Graves. Derivation of compliant motion programs based on human demonstration. In *Int. Conf. Robotics and Automation* [1], pages 2616–2621.