ConFusion: Sensor Fusion for Complex Robotic Systems using Nonlinear Optimization

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Abstract—We present ConFusion, an open-source package for online sensor fusion for robotic applications. ConFusion is a modular framework for fusing measurements from many heterogeneous sensors within a moving horizon estimator. ConFusion offers greater flexibility in sensor fusion problem design than filtering-based systems and the ability to scale the online estimate quality with the available computing power. We demonstrate its performance in comparison to an iterated extended Kalman filter in visual-inertial tracking, and show its versatility through whole-body sensor fusion on a mobile manipulator.

I. INTRODUCTION

Sensor fusion is a valuable tool in the roboticist’s toolbox. As the complexity and state dimensionality of robots increase, information from numerous sensors must be considered to determine the full state of the robot for use in motion control. While general methods for sensor fusion are well-established, the design and implementation of state estimators for complex robots is tedious, making it difficult to easily add and remove sensors or to investigate alternative state representations for different tasks. In this work, we look to develop a framework for online sensor fusion that supports a wide range of robots and sensors and provides the flexibility and modularity necessary to easily build and evaluate state estimators for complex robots.

This paper introduces ConFusion, an open-source C++ package for online sensor fusion. ConFusion implements a moving horizon estimator (MHE) to optimize over a sliding batch of states to generate high-accuracy robot state estimates for use in real-time control systems. The effort required to implement a sensor fusion problem is no more than would be required for an extended Kalman filter, but ConFusion’s batch-based approach and use of nonlinear optimization provides more flexibility in terms of state estimator design and the ability leverage additional computing resources to improve estimate quality by optimizing over a larger batch of states. Our modular framework allows for the easy incorporation of new sensors and estimated parameters and the ability to easily run offline batch calibration problems using the same state and measurement models.

II. PRIOR WORK

Most robotic systems today use filter-based sensor fusion algorithms for generating real-time state estimates for use in motion control. Extended Kalman filters (EKF) are popular for their very low computational overhead, low memory requirements, and ease of implementation [1], [2], [3], [4]. In systems where non-linearities and non-uniform noise distributions are more dominant, other types of filters like the unscented Kalman filter (UKF) and particle filter are often used [5], [6]. Filter-based sensor fusion has multiple well-known weaknesses, though. The sequential process-then-update nature of filtering schemes places restrictions on the structure of the sensing system, since the use of an explicit process model, which models the evolution of the complete state from one time instance to the next, is required [7] and multiple and asynchronous process measurements cannot be directly incorporated. Additionally, since all measurements are processed sequentially, with the information provided by each measurement summarized by its immediate update to the state, estimate errors can bias the influence of future measurements and future measurements cannot be used to retrospectively improve the accuracy of past estimates.

More complex sensor fusion schemes facilitate the improvement of estimates after future measurements have been received. Fixed-lag smoothers achieve this by iteratively taking forward and backward recursive passes over a batch of states which slides over time. Fixed-lag smoothers still enforce the restrictions in sensing system structure mentioned above, however. MHEs maintain an active batch of estimated states whose parameters are optimized simultaneously at each time-step. This allows the estimate of the state at a certain time to be repeatedly improved as the state marches back through the estimated batch of states. MHEs have been previously shown to outperform EKFs in monocular SLAM [8] and in monitoring chemical processes [9]. In a previous work, we showed that they can also provide...
smoother predictive estimates for use in high-frequency real-time robot controllers [10]. In [7], the two-state implicit filter is proposed to relax the sensing system design constraints imposed by filter-based approaches. The proposed filter is very similar to a MHE with a batch size of two, though updates to the estimated parameters are obtained using a recursive-style solver with worse performance in the presence of non-linearities than the solvers typically employed in MHEs. In [11], an open source MHE implementation is presented that was developed to maximize computational efficiency through automatic code generation and the use of specialized solvers. It was developed for applications with very limited computational resources and it is not clear how effective it would be for use in complex robotic systems. It also does not provide the full flexibility in sensing system design offered by MHEs because it runs an EKF at the front of the optimized batch of states to perform marginalization.

The biggest downside of using MHEs for online state estimation is their high computational cost relative to filter-based methods. Over the last 10 years, multiple open-source packages for non-linear-least-squares optimization have been developed to support bundle adjustment and simultaneous localization and mapping (SLAM) applications [12], [13], [14]. While these solvers were not developed with online usage in mind, their scalability and computational efficiency make them valuable tools in online applications as well. Okvis is a point-feature-based online visual-inertial odometry system that uses the Ceres Solver [13] for non-linear-least-squares optimization in a MHE [15]. The sensor fusion algorithm employed is very similar to the one presented here, though we generalize it to support the fusion of an arbitrary number of general sensors and process models. iSAM2, also designed for SLAM applications, takes a different approach and estimates the full state history over time by efficiently factoring the probabilistic constraints between estimated parameters as they are induced by measurements over time [16]. While this method works well in SLAM problems, where links between states and landmarks are relatively sparse over time, it is not clear how it would transfer to more general sensor fusion problems for robot state estimation, where links between states and other estimated parameters are often persistent.

III. CONTRIBUTIONS AND PAPER STRUCTURE

The main contributions of this work are as follows. We present a general framework for online sensor fusion that allows for the easy incorporation of additional sensors, multiple non-synchronized process measurements, and which can leverage additional computing resources to improve estimate quality. Our C++ implementation is made available open-source online.

Additionally, we demonstrate a novel state estimator for mobile manipulation using dual visual-inertial sensors at the robot’s base and end-effector, showing that the additional sensors improve localization accuracy versus ground truth measurements.

This paper is structured as follows. The theory of the underlying sensor fusion problem used in ConFusion is presented in Section IV. The software structure and features of ConFusion are explained in Section V. Experimental results using ConFusion for visual-inertial tracking and whole body state estimation of a mobile manipulator are presented in Section VI. Finally, conclusions and an outlook to future work are given in Section VII.

IV. MOVING-HORIZON ESTIMATION

We consider the problem of estimating the state of a robot at discrete instances of time \(x_t\) given a heterogeneous set of measurements. Measurements provide either information about the state of the robot at a specific time instance (such update measurements are written \(u_t\)) or information relating the time evolution from one state instance to the next (a chain of such process measurements linking states \(x_t\) and \(x_{t+1}\) is written \(\tilde{p}_{t:t+1}\)). In addition to the state of the robot, time-invariant (or static) parameters \((s)\) are also estimated. These might be sensor intrinsic or extrinsic calibrations, or in the case of robot localization, the position of stationary references in the robot’s environment. Update and process models of the following form are used to relate measurements received to the estimated parameters.

\[
u_t = g(x_t, s) \quad x_{t+1} = h(x_t, p_{t:t+1}, s)
\]

The \(g\) and \(h\) functions typically only involve a subset of the state and static parameters and can be non-linear in the estimated parameters and measurements. The Markov property is implicitly assumed, as process chains can only link successive states. Otherwise, no specific structure is assumed for these models, though the full observability of the estimated parameters is required from the full set of active measurements and models to achieve good estimator performance.

Considering a batch of \(N\) states, determining the optimal set of parameters can be formulated as a least-squares problem of the following form.

\[
\{x^*_t_{0:N}, s^*\} = \arg \min_{x_{0:N}, s} \left[ \frac{1}{2} \sum_{t=0}^{N} \|u_t \otimes g(x_t, s)\|^2_{W_u} + \sum_{p \in \mathcal{P}_{t-1:t}} \|p \otimes h(x_{t-1}, \tilde{p}, s)\|^2_{W_p} \right]
\]

The first term in the function being minimized captures any prior knowledge about the initial value of the first state and static parameters \((x_{0}, s)\). We use the notation \(\|a\|^2_B = a^T B a\). When assuming that uncertainty in the initial state and the update measurement noise are normally distributed, the weighting matrices of the prior knowledge and update measurement residuals are chosen to be the inverse covariance of those quantities. Assuming normally
distributed process noise, the weighting for the process chain residuals is the inverse covariance of the state resulting from forward propagating the estimate of the preceding state (starting with no uncertainty on the preceding state) through the process measurements. With these choices for the weighting matrices, this sum-of-squares cost function is therefore made up of unit-less terms, each representing a probabilistic quantity. We use $\Box$ operators here to indicate that the distance between any non-Euclidean quantities (e.g. for parameters representing rotations in 3d space) is computed in the tangent space centered at the current value of those quantities.

Equation (1) is solved iteratively using nonlinear least squares optimization. At each iteration, all of the residuals are linearized about the current value of the estimated parameters. If we define $x$ to be the a stacked vector of all of the estimated state and static parameters, $e_i = W^{\frac{1}{2}} f_i(x)$ such that $e_i^T e_i = \| f_i(x) \|^2_W$, $e = [e_0^T, ..., e_{m-1}^T]$, and $J = \frac{\partial e_i}{\partial x}$, the right side of (1) can be approximated as a linear least squares problem,

$$\arg\min_{\delta x} \| J \delta x + e \|^2,$$

where we now consider solving for the optimal increment to apply to the estimated parameters, e.g. $x' = x \Box \delta x$. When over-parameterized variables are being estimated, $\delta x$ is defined in the tangent space of the current estimate. By defining $H = J^T J$ and $b = -J^T e$, solving (2) is equivalent to solving the so-called normal equations of the problem, $H \delta x = b$. Since $H$ is inherently sparse due to the assumed Markov property, this equation is solved at each iteration using sparse Cholesky factorization. The Levenberg-Marquardt algorithm is used to provide more robustness in optimization than the Gauss-Newton algorithm, while achieving convergence in fewer iterations than gradient descent [17]. Evaluating the individual residuals is done in parallel over a user-specified number of threads, though solving the normal equations at each iteration is done from a single thread.

In the presence of outlier measurements or non-normal noise distributions, the squared residual terms can be enclosed in a loss function (e.g. Huber loss) to decrease their influence in the presence of large residual values. This results in a robustified iteratively re-weighted least squares optimization problem.

### A. Marginalization

It is not feasible to solve (1) continuously online since the number of estimated parameters grows linearly over time. To deal with this, measurements are removed (or marginalized) out of the problem once their influence on the estimated parameters becomes sufficiently small. The information contained in the marginalized measurements is approximated in what we call the prior constraint. This residual function relates the remaining estimated parameters to the values at the time of marginalization. The MHE optimization problem considering a receding horizon (or batch) of $N$ states is

$$\{ \hat{x}_{t_i:t_i+N}, s^* \} = \arg\min_{\hat{x}_{t_i:t_i+N}, s} \| e_{\text{prior}}(\hat{x}_{t_i}, \hat{x}_{t_i}, \hat{s}, s) \|^2 +$$

$$\sum_{j=i}^{i+N} \left( \sum_{u \in \mathcal{U}_{t_j}} \| u - g(x_{t_j}, s) \|^2_{W_u} \right) +$$

$$\sum_{j=i}^{i+N} \left( \sum_{\tilde{p} \in \mathcal{P}_{t_{j-1}} \setminus \delta} \| x_{t_j} - h(x_{t_{j-1}}, \tilde{p}, s) \|^2_{W_{\tilde{p}}} \right),$$

(3)

Estimated parameters are marginalized out of the problem using block Gaussian elimination on the normal equations of the underlying least squares problem. To marginalize out some subset estimated parameters, $x_{\mu}$, we first extract the portion of the problem that is directly dependent on $x_{\mu}$. All cost functions which contain an element of $x_{\mu}$ are computed and linearized, generating the Jacobian of this sub-problem ($J_{\mu}$). All of the estimated parameters which appear in this sub-problem but are not being marginalized, $x_{\lambda}$, will be constrained by the resulting prior constraint after marginalization. Once computed, the Jacobian of the sub-problem is reordered with $x_{\mu}$ in the left-most columns and the associated $H_m = J_{\mu}^T J_{\mu}$ and $b_m = -J_{\mu}^T e_{m}$ are computed. The normal equations of the sub-problem can be written

$$\begin{bmatrix} H_{\mu\mu} & H_{\mu\lambda} \\ H_{\lambda\mu} & H_{\lambda\lambda} \end{bmatrix} \begin{bmatrix} \delta x_{\mu} \\ \delta x_{\lambda} \end{bmatrix} = \begin{bmatrix} b_{\mu} \\ b_{\lambda} \end{bmatrix}.$$

The Schur complement is taken to isolate $\delta x_{\lambda}$ as

$$\begin{bmatrix} H_{\mu\mu} & H_{\mu\lambda} \\ 0 & H^* \end{bmatrix} \begin{bmatrix} \delta x_{\mu} \\ \delta x_{\lambda} \end{bmatrix} = \begin{bmatrix} b_{\mu} \\ b^* \end{bmatrix}$$

where

$$H^* = H_{\lambda\lambda} - H_{\lambda\mu} H_{\mu\mu}^{-1} H_{\mu\lambda}$$

$$b^* = b_{\lambda} - H_{\lambda\mu} H_{\mu\mu}^{-1} b_{\mu},$$

and $\delta x_{\lambda}$ can now be found independent of $\delta x_{\mu}$.

The resulting prior constraint is formulated as

$$e_p = J_p (\hat{x}_{\lambda} - x_{\lambda}) - (J_p^T)^T b^*,$$

where $\hat{x}_{\lambda}$ is the value of the remaining parameters linked to the prior sub-problem at the time of marginalization. $J_p$ is obtained from $H^* = J_p^T J_p$ via LU decomposition and $(J_p^T)^T$ is computed using the Moore-penrose pseudo-inverse. When taking the Schur complement, $H_{\mu\mu}$ is inverted using Cholesky decomposition. While this marginalization scheme allows any measurements to be marginalized from the problem at any time, our MHE implementation only considers the marginalization of the measurements linked to one or more states at the front of the optimized batch of states. The problem structure before and after marginalizing out the measurements connected to a state is shown graphically in Fig. 2.

In the case that new static parameters are being continuously added to the problem over time, e.g. while performing SLAM in unknown environments, the prior constraint will
should first create a derived version of the StateMHE problem. To set up a sensor fusion problem the user into base classes representing the different components of a source online fusion framework, called ConFusion, is made available open-source. ConFusion abstracts a sensor fusion problem model, for re-use and encourage users to contribute new measurement models to build up a library of models over time.

All optimized parameters, whether as a part of the state or a static parameter are of type Parameter. Over-parameterized quantities can be assigned a local parameterization. A local parameterization is specified by ⊟ and ⊞ operations, which project estimates between global and local space. We provide local parameterizations for quaternions and fixed-yaw orientations (for use in defining gravity-aligned reference frames) for general usage. All parameters can be configured to be optimized or constant at any time during operation by simply setting a flag. This can be useful if a static parameter should be first refined during an initialization phase and then fixed for long-term operation.

To run a sensor fusion system online, measurements simply need to be passed into an instance of a ConFusor, which then handles creating new states, attributing the received measurements to those states, and building and solving the MHE problems repeatedly over time. Measurements can be added from one or more threads other than that which is running the estimator. The ConFusor provides functions to marginalize out the measurements connected to some desired number of states at the front of the optimized batch, to remove static parameters from the prior constraint, and to stop and restart tracking as desired. In this way, the user can control the size of the sensor fusion problem without having to manipulate the internal MHE problem structure.

A class called the BatchFusor is additionally provided to run batch (or bundle adjustment) problems over a sequence of states, which were either cached while running a ConFusor online or immediately created from a set of measurements. This can be used to periodically run offline calibration runs on longer trajectories where the observability of system calibration parameters is ensured.

ConFusion essentially wraps around the Ceres Solver [13] to support online sensor fusion. ConFusion was designed to expose the Ceres Solver API to the greatest extent possible so that its flexibility can be leveraged by the user and so that users already familiar with it can quickly get up and running. ConFusion therefore allows the user to utilize Ceres’ utilities for residual auto-differentiation, loss functions, and the wide range of supported non-linear solvers.

It is often difficult to debug sensor fusion systems because small implementation errors can cause the sensor fusion problem to quickly explode without a clear indication of what the cause was. For this reason, ConFusion provides some tools for diagnosing problems and analyzing system performance. Diagrams showing the links between parameters and residuals can be automatically generated, allowing the user to check that measurements are being linked to the expected parameters. Fig. 3 shows a diagram drawn by ConFusion for the mobile manipulator state estimator described in Section VI.B. ConFusion also comes with a general utility for logging estimated parameter values and residuals over time for analysis and scripts to easily plot the logged data in Matlab.

https://bitbucket.org/tsandy/confusion

Fig. 2. Diagrams showing the structure of a MHE problem before and after marginalization. Estimated parameters are drawn as squares, residuals as circles, and marginalized parameters as diamonds. Drawn edges represent the dependence of residuals on the connected parameters.

also grow over time. To control the size of the prior constraint, static parameters can be factored out of the prior constraint when desired. This is similarly done by applying the Schur complement to the \( H^* \) and \( b^* \) computed in the previous marginalization step, but reordered such that the parameters to be removed appear in the left-most columns. As was done in our previous work in object-based SLAM [18], the parameters of the first state which are linked to the prior constraint can be similarly factored out of the prior constraint to allow sensor fusion to be stopped and re-started while maintaining the accumulated relative certainties in the static parameters in a probabilistically consistent way.

V. SOFTWARE STRUCTURE

Our C++ implementation of the proposed MHE sensor fusion framework, called ConFusion, is made available open-source online. ConFusion abstracts a sensor fusion problem into base classes representing the different components of a MHE problem. To set up a sensor fusion problem the user should first create a derived version of the State class which specifies the parameters that make up each instance of the state. The user must define how the first state is initialized given an initial set of measurements and how a new state should be initialized from the previous state and a set of new measurements.

The user should implement measurement models for the update measurements and process chains used in the sensor fusion problem, inheriting from the UpdateMeasurement and ProcessChain base classes, respectively. We provide a set of measurement models, including our IMU process chain model, for re-use and encourage users to contribute new features.

https://bitbucket.org/tsandy/confusion
VI. EXPERIMENTS

We demonstrate the performance of ConFusion through two sets of experiments. First, we compare the performance of ConFusion to that of an iterated extended Kalman filter (IEKF) on the visual-inertial tracking of a sensor-head and show the impact of batch size on the resulting real-time estimate accuracy and smoothness. Second, we show the extendability of ConFusion by performing whole-body sensor fusion on a mobile manipulator using visual and inertial sensors on both the base and end-effector of the robot and the manipulator kinematics. Our visual-inertial sensor heads are comprised of an Xsens MTi-100 inertial measurement unit (IMU), delivering accelerometer and gyroscope measurements at 400 Hz, and a PointGrey Blackfly monochrome camera providing images at 10 Hz and 5 mega-pixel resolution. As visual references, we use stationary AprilTag [19] fiducial markers. Experiments were run using a standard laptop (Intel i7-4800MQ). In both data-sets, we compare the estimated trajectories to ground truth measurements captured with a Leica Tracker, which provides full pose measurements of a tracked frame at 50 Hz and with a nominal accuracy of less than 0.1 mm and 0.02 deg.

A. Visual-Inertial Tracking

In this section, we show the performance of ConFusion in visual-inertial tracking. This analysis extends that from our previous work [10] to consider the case of tracking multiple tags and the impact batch size has on performance. The reader is referred to that paper for the sensor models and conventions employed here.

Fig. 4 shows the accuracy of the estimated IMU pose in the presence of aggressive motions using different sensor fusion schemes. The estimates consider an online mapping scenario with no prior knowledge of the fiducial marker poses. To simulate the generation of real-time estimates for use in robot motion control, the estimates were generated by playing back the recorded data in real-time, generating the estimates online, and then forward-propagating them through the more recent IMU measurements up to the time of the most recent IMU measurement. The frame offsets which fit the generated trajectories to the ground truth data were calibrated in a batch problem using all of the measurements in the dataset. It can be seen that the MHE estimates generated by confusion are both more accurate and smoother than those of the IEKF. Although the rotational error is higher when using a bigger batch size, we believe this is caused by a small shift in the estimator’s global frame during operation, causing a
misalignment with the ground truth measurement system. The bottom subplot shows the consistency of the real-time forward-propagated position estimates. This is computed as the difference between the delayed estimate from ConFusion and forward-propagated estimate from the same time. This shows how well the IMU process model and estimated intrinsic parameters fit the true evolution of the sensor-head motion. Once again, you see that the ConFusion estimates outperform the IEKF. A video showing these estimated trajectories is included in the attached video.

Fig. 5 shows how the estimator performance is impacted by the batch size and number of cores used for computation in ConFusion. You can see that the tracking accuracy increases with batch size up to some point, and then slightly decreases. This shows the trade-off between using a larger batch to decrease the estimate errors incorporated into the prior constraint over time, and the increased computation time, and therefore latency in the generated estimates, for use in real-time applications. We believe that the small rise in rotational error with batch size is once-again due to the misalignment with the calibrated offset to the ground truth system and does not reflect a true degradation in accuracy. The third subplot shows the average computation time for building and solving the MHE problems and performing marginalization. With each number of threads, the batch size was increased until the computation time (along with image pre-processing time) started to overrun the image frame rate. You can see that increasing the batch size has a nearly linear impact on the computation time, showing that the sparsity of the system Jacobian in effectively being leveraged to improve computational efficiency. The use of additional cores allows for the usage of a bigger batch of states, though the impact decreases with larger batch sizes since the solver step of the algorithm only uses a single thread. Finally, the bottom subplot shows the root-mean-square (RMS) value of the same consistency measure introduced in the previous paragraph. The use of a larger batch does indeed have a smoothing effect, improving the consistency measure by more than 10 percent. This is important for use in real-time control systems as any inconsistency in the generated real-time estimates is seen as an additional disturbance by the robot’s control system.

B. Mobile Manipulator Whole-Body State Estimation

We next consider the problem of estimating the state of a mobile manipulator. We use a new robot, called IFmini (Fig. 1), which consists of a 6 degree of freedom hydraulically actuated manipulator, designed and built by the Italian Institute of Technology [20], mounted on top of a four wheeled differential drive base, called the Supermegabot by Inspectorbots. IFmini is a more dynamic, albeit smaller, successor to the In situ Fabricator (IF), designed for performing building construction tasks directly on the construction site [21].

https://youtu.be/MhNJBG0WqUc
In the interest of performing dynamic manipulation tasks with high accuracy, we would like to estimate the pose and velocity of IFmini’s end-effector within its environment. For use in control, these estimates should be available at high rate and with minimal latency. To support whole-body model-based control, it is desirable to additionally estimate the pose and velocity of the base. Here we show that we can generate accurate real-time estimates of the base and end-effector states using ConFusion. Building on our past results [10], the consistency of our MHE estimates allows for the accurate forward propagation of our state estimates through the IMU measurements up to real time for use in control.

In order to support whole-body sensor fusion, and also to evaluate which sensors are most valuable for generating high-accuracy real-time estimates, we have equipped IFmini with a camera and IMU on both the base and end-effector. In this configuration, the robot state is simply two times the state considered for visual-inertial tracking in the previous section, with both cameras localizing the robot within the same map. We additionally fuse joint angle measurements and a model of the arm’s kinematics to relate the relative poses of the base and end-effector as an additional update measurement. The relative pose of the arm’s base frame with respect to the base IMU, the relative pose of the arm’s end-effector with respect to the end-effector IMU, and the joint angle biases for the middle four arm joints are additionally used as static parameters to align the sensors with the arm kinematic model. Although ConFusion supports solving for these parameters online, we find that it is most effective to calibrate them separately in a batch problem and leave them fixed during online operation. This ensures that their values do not over-fit configuration-specific errors within the sensing system (e.g. camera intrinsic calibration inaccuracy) while the robot is stationary.

Fig. 6 shows the real-time end-effector pose estimate error versus ground truth while undergoing whole body motions. Estimates were processed using different combinations of sensors, as shown in Table I. All estimates were generated using a batch size of 8 running on three threads. Once again, estimates were forward propagated up to the time of the most recent IMU measurement to simulate real-time operation on the robot. The sensor extrinsics, offsets to the ground truth measurement frames, and a map of the fiducial marker poses was first calibrated in a batch problem on a different dataset then held constant for this experiment. The performance of the state estimator running on the robot in real-time and being used to close an end-effector task-space motion control loop, is shown in the accompanying video.4

The flexibility of ConFusion allows these different sensor configurations to be used simply by changing an enumeration specifying which sensors are active. The same state representation is used even though, in configuration 1, the entire base state was not estimated and, in configuration 2, the base states have no linked process measurements but are only linked to the rest of the problem through the update measurements and static parameters. This flexibility would not be possible in a filter-based framework.

We observe that the usage of the additional sensors on the base of the robot improves the estimator accuracy. With visual-inertial sensing on the end-effector alone, there are portions of the trajectory where no fiducials are visible (e.g. 8-10 sec), resulting in large errors due to uncorrected drift. Using the camera mounted on the robot base provides an additional viewpoint for viewing the fiducials, making it more likely that visual references are always seen. The use of the base camera and arm odometry also makes the extrinsic calibration of the cameras with respect to the manipulator and the joint angle biases immediately observable from the observation of the same reference in both cameras. Adding a second IMU on the base further improves estimator accuracy. Since the base IMU constrains the evolution of the base portion of the state, it appears that its usage helps resolve small mismatches between the camera model and calibration inaccuracies in the two cameras as observed fiducials move to different regions of the image plane.

VII. Conclusion

In this paper, we have presented ConFusion, a software package for online sensor fusion for robotic systems. We have demonstrated its ability to generate more accurate

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4Biases for the joints closest to the base and end-effector are not considered because they are compensated for in the relative poses of the IMUs with respect to the manipulator.

[https://youtu.be/MhNJBG0WqUc]
estimates than filtering-based approaches, leverage additional computing resources to improve estimator performance, and support complex sensor setups on mobile robots. As future work, we plan to investigate ways to parallelize the linear solver step in the MHE optimization problem and more principled strategies for determining when measurements and parameters should be marginalized out of the problem. With regard to the IFmini system, we plan to use the demonstrated state estimator to guide the execution of dynamic high-accuracy manipulation tasks and to investigate if the articulated dual-camera setup can be used to improve mapping and localization accuracy for natural-feature-based SLAM.

ACKNOWLEDGEMENT

We would like to give special thanks to Prof. Andreas Wieser and Robert Presl for providing and operating the Leica Tracker for acquiring ground truth measurements. This research was supported by the Swiss National Science Foundation through the National Centre of Competence in Research Digital Fabrication (Agreement #51NF40.141853) and a Professorship Award to Jonas Buchli (Agreement #PP00P2_138920).

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| Clg. | EE Cam | EE IMU | Base Cam | Base IMU | Odometry | Pos [m] | Rot [rad] |
|------|--------|--------|----------|----------|----------|---------|----------|
| 1    | X      | X      |          |          |          | 0.070   | 0.010    |
| 2    | X      | X      | X        |          | X        | 0.036   | 0.0084   |
| 3    | X      | X      | X        | X        | X        | 0.030   | 0.010    |

TABLE I

The sensors used in the tests plotted in Fig. [6] are shown, as well as the root-mean-squared position and rotation errors over the plotted interval.