Cascade Non-Linear State Estimation for Humanoid Robot Locomotion

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1 Summary

Humanoid robots by mechanical construction have the ability to locomote on various type of terrains. In order to do so, their planning and control frameworks need to be provided with reliable and accurate estimates of the robot's internal state at every time instant.

In our previous work, we proposed a non-linear Center of Mass (CoM) estimator [1] which extends the popular Linear Inverted Pendulum Model (LIPM) based estimators by allowing CoM motion in the vertical axis. Thus, the limiting assumption that the CoM is constrained to lie on a constant height horizontal plane is surpassed and accurate estimates for the full 3-D CoM position and velocity can be obtained. Nevertheless, in our approach all the fused measurements were in the world/inertial frame of reference. To this end, the need of having reliable estimates of the affine transformations which link the supporting foot and the robot's body to the world frame is mandatory.

This work demonstrates a cascade estimation scheme, consisting of two Extended Kalman Filters (EKF), for acquiring low drift state estimates of important quantities commonly used in control loops for either humanoid robot balance or locomotion. First, the humanoid's body position, orientation, velocity, support foot position, and orientation with respect to the world frame, are estimated, yielding in such a way the affine transformations needed by the second part where the 3-D CoM position and velocity is effectively estimated.

The significance of reliable CoM estimates has been demonstrated in the DRC finals by Team WPI-CMU [3], where by utilizing the linear combination of the CoM position and velocity, termed as Capture Point (CP), they were the only team successfully detecting and preventing a fall.

2 Methods

The presented state estimation scheme requires sensors that are commonly available on humanoids nowadays such as joint encoders, an Inertial Measurement Unint (IMU) on the chest, Foot Sensitive Resistors (FSRs) on both feet, and an RGBD camera. Furthermore, the whole scheme, which is illustrated in Figure 1, is based on generic/simplified dynamics, thus it is readily amenable to generalization to other humanoids.

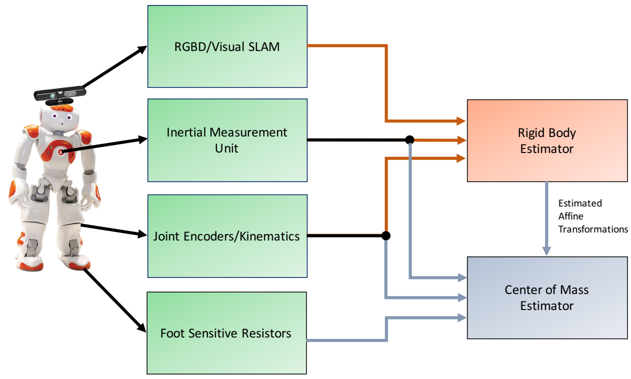

Figure 1: A cascade state estimation scheme that utilizes two EKFs, fusing effectively four different sensing sources, namely RGBD, IMU, joint encoders, and FSRs.

2.1 Rigid Body Motion Estimation

The non-linear estimator presented in [2], which is based on Newton-Euler dynamics of a rigid floating mass, is extended in order to take into account the position and orientation of the supporting foot. The state vector we estimate is the following:

$$\mathbf{x}_t = \begin{bmatrix} {}^b\mathbf{v}_b & {}^w\mathbf{R}_b & {}^w\mathbf{r}_b & {}^w\mathbf{R}_s & {}^w\mathbf{r}_s & \mathbf{b}_\omega & \mathbf{b}_\alpha \end{bmatrix}^\top \tag{1}$$

where ${}^w\mathbf{r}_b$ and ${}^w\mathbf{r}_s$ are the position of the body and support foot with respect to the world frame, $\mathbf{R}_b^w$ and $\mathbf{R}_s^w$ are the corresponding orientations expressed as rotation matrices, ${}^b\mathbf{v}_b$ is the body's velocity, and $\mathbf{b}_\omega$, $\mathbf{b}_\alpha$ are the gyro and accelerometer biases, all expressed in the body frame.

The inputs to the filter are the IMU measurements for the gyro rate ${}^b\omega_b^{\text{imu}}$ and the linear acceleration ${}^b\alpha_b^{\text{imu}}$:

$$\mathbf{u}_t = \begin{bmatrix} {}^b\omega_b^{\text{imu}} & {}^b\alpha_b^{\text{imu}} \end{bmatrix}^\top \tag{2}$$

Since the foot in contact is stationary but can slightly move due to possible slippage, it is proper to model the support foot position and orientation as random walks.

For the update step we fuse the body position and orientation from a visual SLAM algorithm along with the kinematically computed support foot's position and orientation with respect to the body frame:

$$\mathbf{y}_t = \begin{bmatrix} {}^{w}\mathbf{r}_b^{\text{rgbd}} & {}^{w}\mathbf{R}_b^{\text{rgbd}} & {}^{b}\mathbf{r}_s^{\text{enc}} & {}^{b}\mathbf{R}_s^{\text{enc}} \end{bmatrix}^\top \tag{3}$$

Accordingly, the measurement model is also non-linear.

2.2 Center of Mass Estimation

In this section, we extend our non-linear Zero Moment Point (ZMP) based state estimator to account for the angular momentum acting on the body by considering a flying-wheel around the CoM. Since the dynamics are non-linear we make use of an EKF with state:

$$\mathbf{x}_t = [c_x \ c_y \ c_z \ \dot{c}_x \ \dot{c}_y \ \dot{c}_z \ f_x \ f_y \ f_z]^\top \tag{4}$$

where c_x, c_y, c_z and $\dot{c}_x$, $\dot{c}_y$, $\dot{c}_z$ are the 3-D position and velocity of the CoM respectively, and f_x, f_y, f_z are the external forces acting on the CoM.

The input signal is derived from the FSRs and the IMU:

$$\mathbf{u}_t = \begin{bmatrix} z_x^{\text{fsr}} & z_y^{\text{fsr}} & z_z^{\text{fsr}} & f_N^{\text{fsr}} & \dot{\omega}_x^{\text{imu}} & \dot{\omega}_y^{\text{imu}} \end{bmatrix}^\top \tag{5}$$

where z_x^{fsr}, z_y^{fsr}, z_z^{fsr} is the 3-D position of the ZMP, f_N^{fsr} is the vertical resultant Ground Reaction Force (GRF) as measured by the FSRs and $\dot{\omega}_x^{\text{imu}}$, $\dot{\omega}_y^{\text{imu}}$ is the angular acceleration in the x and y axes numerically computed from the IMU and filtered through a low-pass filter.

The measurements fused in the update step are the CoM position, computed from the kinematics and the CoM acceleration, computed from the IMU's body acceleration:

$$\mathbf{y}_t = \begin{bmatrix} c_x^{\text{enc}} & c_y^{\text{enc}} & c_z^{\text{enc}} & \ddot{c}_x^{\text{imu}} & \ddot{c}_y^{\text{imu}} & \ddot{c}_z^{\text{imu}} \end{bmatrix}^\top \tag{6}$$

All quantities needed by the CoM estimator are transformed to the world frame, with the affine transformations estimated by the rigid body estimator.

3 Results

Next, we demonstrate a real-time execution of the presented estimation scheme with our aldebaran NAO v4.0 robot, while walking on a milimeter precision paper. To correctly tune the estimators, we logged IMU raw data for 13 hours and performed an Alan variance analysis to accurately identify the noise parameters of the IMU. As it turned out the IMU is pretty noise, approximately ten times contrasted to commercially available IMUs. The visual measurements for the camera position and orientation were delayed about 190-200ms in the NAO's CPU clock, while the kinematic measurements were available in every control cycle e.g. 10ms resulting in faster filter updates.

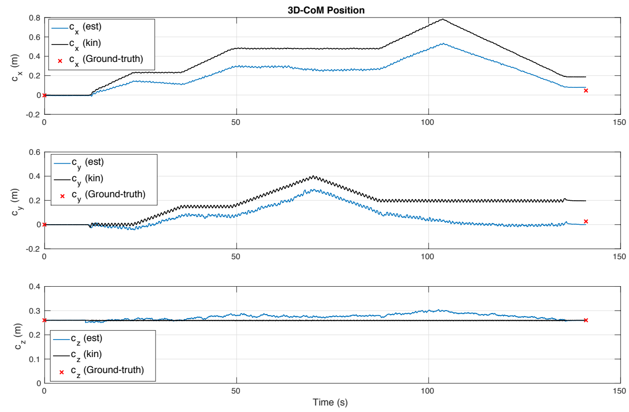

Figure 2: 3-D CoM trajectory, the blue lines indicate the estimated trajectories while the black lines indicate the kinematically computed ones.

In Figure 2, the estimated 3-D CoM trajectory is shown, contrasted to the kinematically computed one. As illustrated in the video (`https://goo.gl/eOqAUN`) and also in the graph, the robot unavoidable drifts while the feet contact the ground. This drift has been captured by the estimation process, resulting in approximately 4.6cm error in the x-axis, 3cm error in the y-axis and 8.5 degrees error in yaw, which is more than satisfactory when taking into account the inaccurate and noisy sensors the NAO robot is equipped with.

4 Conclusion

In this work, we presented a cascade non-linear state estimation scheme which effectively utilizes the joint encoders, the IMU, the FSRs, and an RGBD camera to provide with reliable state estimates for the 3-D body position, velocity and orientation along with the 3-D CoM position and velocity. The aforementioned quantities are commonly used in various humanoid control frameworks, such as the ZMP/CP based control schemes, the Hybrid Zero Dynamics framework and in limit cycle walking.

References

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[3] X. Xinjilefu, S. Feng, and C. Atkeson, "Center of Mass Estimator for Humanoids and its Application in Modelling Error Compensation, Fall Detection and Prevention", *IEEE-RAS International Conference on Humanoid Robots*, pp. 67–73, 2015.