State Estimation of a Walking Humanoid Robot

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1 Motivation

We compare two approaches to Kalman filter (KF)-based state estimation for humanoid robot in dynamic walking: model based on center of mass (COM) translation and model based on limb motions in the joint space. We refer the first model as the *LIPM KF model*, and the second one as the *Planar KF model*. Both models are shown in Fig. 1

Walking control strategies can be developed based on simplified models. For example, the Linear Inverted Pendulum Model (LIPM) is often used to generate a COM trajectory that satisfies the Zero Moment Point (ZMP) constraint. In reality, these simplified approaches may not be appropriate as the actual dynamics of the robot are very complex. For instance, the upper body rotation should be modeled by angular momentum and cannot be modeled by a point mass, and motion in the lateral and sagittal directions are coupled in 3D rather than decoupled. Given these discrepancies, an interesting question is - what is the appropriate model to use for humanoid walking state estimation? Does modeling the rotation of the upper body help state estimation and control of humanoids? What about even more complex models based on additional links?

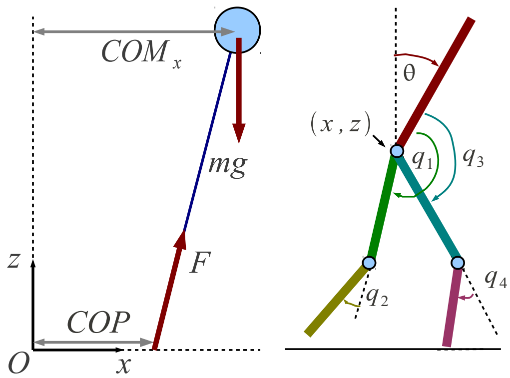

Figure 1: The LIPM model (left) and the Planar Model (right). In the LIPM model, the location of COP is determined by vertical force distribution under each foot

2 Related Work

In computer vision, KFs using physics based models have been applied to tracking human body [1]. Recently, [2] studied standing balance for a humanoid with unknown modeling errors. In this work, the robot is modeled by a LIPM and the Extended Kalman Filter (EKF) is used. A H_2-norm optimal filter was introduced in [3] to estimate the pose and velocity of the links of a humanoid robot. This work assumes that the motion model is linear and all external forces are known. In quadrupedal [4] and hexapedal [5] robot locomotion state estimation, hybrid EKFs are developed and model transitions are determined by inertial sensors or leg configuration sensors. Sliding model observers for a five-link biped robot are designed and experimented to estimate the absolute orientation of the torso during the single support phase [6][7].

3 Our Approach

Among the issues associated with state estimation of humanoid walking, two difficult ones are how to handle *contact state* and how to use *force sensing*.

The issue with contact state is that different contact states correspond to different dynamic models, making the walking system hybrid in nature. For example, in bipedal walking, the three basic dynamic models are double support, single support on the left and right foot; furthermore, the feet can either stick or slide with respect to the supporting surface. One way to handle hybrid system state estimation is to use Multiple Model Adaptive Estimation [8]. Knowing when to switch models is essential for this type of estimators to work. We try to avoid explicit model switching by using force sensor measurement.

The sensors equipped on the robot are potentiometers measuring joint angles and load cells measuring joint torques, the force/torque sensors to measure the contact force and torque under each foot, and an IMU mounted on the torso to measure the linear accelerations and angular velocity of the torso in torso coordinates. The force/torque sensor measurements are used in several different ways in state estimation. In the LIPM KF model, the data are used to compute the center of pressure (COP), and to tune the process noise parameters; in the Planar KF model, they are used as control inputs to the dynamics, and to select the measurement equations.

4 Simulation Results

Before working on the robot data, we simulate a normal speed forward walking using a five-link planar humanoid model for 6 seconds, and perform Kalman Filtering on the simulated sensor data. The results are shown below. In

Fig. 2, we plot COM position x_{com} in blue, left foot position x_L in green and right foot position x_R in red. The solid lines are ground truth from simulation, dashed lines are estimation from the Planar KF, and dotted lines are estimation from the LIPM KF. Both estimates drift away from the ground truth, and the LIPM KF diverges faster than the Planar KF. Fig. 3 shows the total error between COM and COP defined by

$$error = [(x_{com} - x_{cop})_{est} - (x_{com} - x_{cop})_{true}] \tag{1}$$

where the subscript "est" stands for "estimated". Both filters reach a minimum error in double support phase, and the Planar KF in general performs better than the LIPM KF in estimating the relative horizontal position. We notice the constant offset in Planar KF error trace due to measurement biases. Both KFs can estimate horizontal COM velocity, the results compared to the ground truth are shown in Fig. 4. The Planar KF clearly outperforms the LIPM KF in this situation, mainly due to torso rotating around the hip joint during walking, and the LIPM KF does not take this into account. It reveals the limitation of over simplified models in predicting complex dynamic behaviors.

Besides above comparisons of both KFs, we also show the estimated internal joint positions and velocities by the Planar KF in Fig. 5 and Fig. 6. It appears from these figures that the modeling error can not be eliminated without being explicitly addressed in the filter.

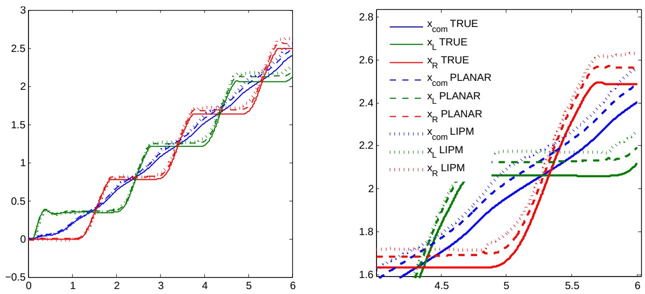

Figure 2: COM and feet positions, from ground truth, Planar KF and LIPM KF; figure on the right is a blowup view of the plot on the left

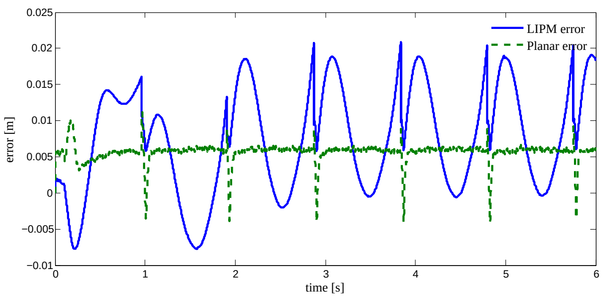

Figure 3: Total position error on $x_{com} - x_{cop}$

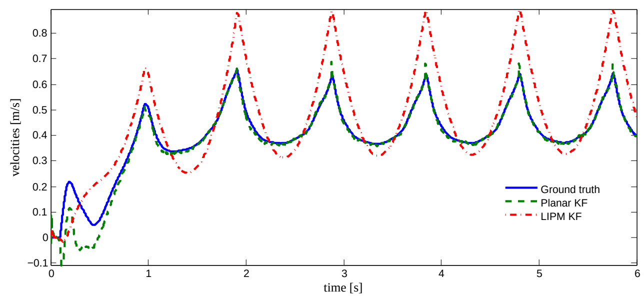

Figure 4: COM horizontal velocity, ground truth, Planar KF and LIMP KF

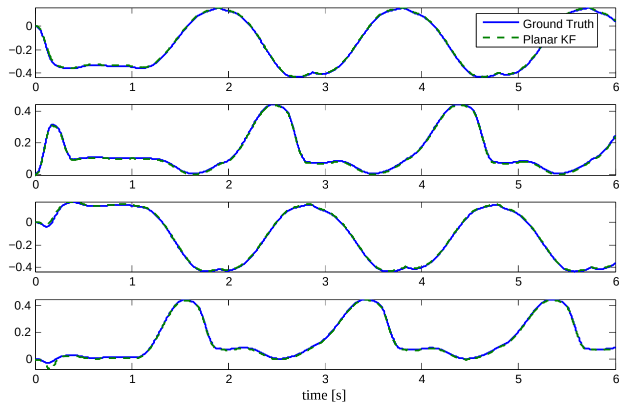

Figure 5: Joint positions from Planar KF and ground truth. From top to bottom: left hip, left knee, right hip, right knee

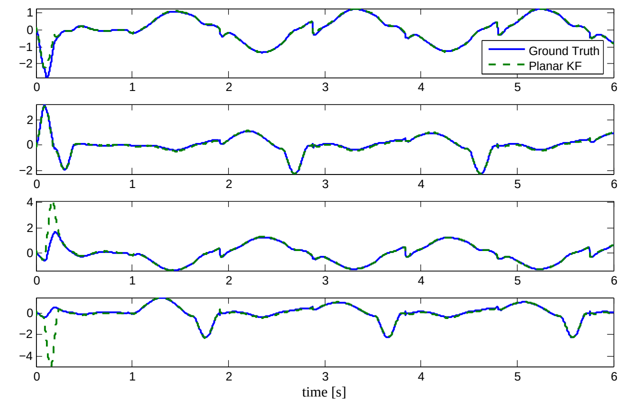

Figure 6: Joint velocities from Planar KF and ground truth. From top to bottom: left hip, left knee, right hip, right knee

The comparison in simulation indicates that the Planar KF outperforms the LIPM KF on estimating COM position/velocity. Another advantage of the Planar KF is it also estimates joint velocities.

5 Open questions

- Are there better ways to fuse force sensor data?
- Are there better ways to fuse the accelerometer data?

- What can we do to better predict contact state?

References

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