A virtual tactile sensing suit for humanoids based on dynamic equations and internal sensors

Salman Faraji and Auke Jan Ijspeert
Ecole Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland
salman.faraji@epfl.ch

1 Summary

In this article, we propose a multi-staged algorithm to detect the magnitude, direction and location of a single external force applied to a humanoid robot while performing dynamic tasks. We use contact force and joint torque sensors as well as IMU to estimate accelerations and build the equation of motion. Then using a search process and based on Jacobian decomposition, we analytically find the point on the whole body which can best account for the error observed in the equation of motion. The method can provide reasonably stable and consistent estimations, even during fast dynamic motions.

2 Introduction

Humanoid robots are very complex machines with many degrees of freedom, actuators, electronics and possibly perception devices. They normally have up to 7 degrees of freedom in each limb which makes a long chain of actuation and sensing devices. Apart from mechanical and cabling issues, it is very difficult to design proper covers for these chains to protect the electronics and fine mechanical parts from external damage. On the other hand, since applications that require human-robot interaction are becoming more and more popular, it becomes necessary to equip the robots with sensory devices that capture dynamics information including contact forces, torques, accelerations or tactile forces. In addition to foot-contact sensors used for locomotion control and tactile sensors in fingers used for manipulation, joint torque sensors are also becoming popular in more recent humanoids (Colasanto et al., 2012). Dynamics sensory information can help to implement an active compliance control on the real robot to safely interact with humans. Dynamics information can also have other applications like identification of the internal model (Traversaro et al., 2015) or external forces (Colomé et al., 2013).

In human robot interaction, it is also important to sense external forces with unknown location. This can happen during interaction with kids or elderly. This task can be handled in two different ways: manufacturing very fine tactile surfaces (Noda et al., 2012) or using internal joint torque information to estimate the external force at known (Le et al., 2013) or unknown locations (Likar and Zlajpah, 2014). The first category of physical sensors provide more precise information, but practical implementation, analysis of data, cabling, range and direction of forces and their additional weight are yet challenging concerns. The second category however uses internal information and virtually implements a tactile surface. But detecting multiple forces and general observability regarding the available number of internal sensors are not yet investigated in the literature.

In this article, we propose a new algorithm to detect a single external force of unknown location on a humanoid robot during dynamic motions. The novel part of our algorithm is to find the force location, given the complex geometry of body links. The magnitude and direction of the external force can already be estimated using the equation of motion and contact force sensors like (Kaneko et al., 2012). To determine locations, the method proposed in (Likar and Zlajpah, 2014) uses an optimization process and approximates the complex geometry of body links with cylinders. In our method however, we decompose the unknown Jacobian of the force application point. By approximating geometries with ellipsoids, we analytically solve the resulting equations to find the force location which is faster than optimization computationally. We also use advanced estimators to determine the floating based accelerations, to be used in the equation of motion.

In the next section, we describe the algorithm, then demonstrate few snapshots of force/location estimation and finally conclude the paper with advantages and limitations of our method.

3 Methods

The proposed method is essentially built upon the assumption of single external force. It also relies on existence of contact force sensors, joint torque sensors and an IMU on the pelvis which is mainly important during dynamic motions. At each time-step, the algorithm takes the following steps:

1. Using IMU and joint encoders, determine the full state vector, its first and second derivatives.
2. Building equations of motion using estimated accelerations, measured joint toques and contact forces. There would be an error vector e, associated to a $J^T F_{ext}$ where both the Jacobian and force are unknown. However F_{ext} directly appears on floating based equations, where associated block of J^T is a unity matrix.
3. Search over all body links: consider a point on the surface of each link and decompose its Jacobian into the

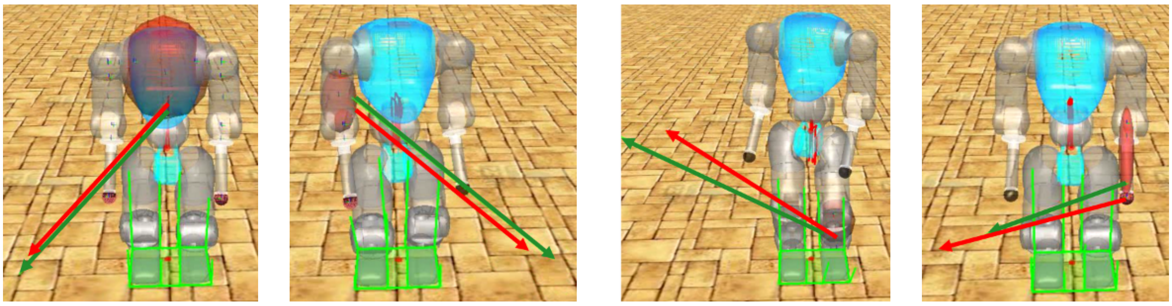

Figure 1: Snapshots of force estimation performance for a 30kg robot performing squatting and yaw motions. Forces are about 10N applied in different directions to various links on the robot. Red arrows show the actual force while green arrows show the estimation. The associated body link is also shown by the approximate red ellipsoid.

known Jacobian of body-link mass-center and an unknown shift. Solve $J^T F_{ext} = e$ with ellipsoid equation using pseudo-inversion to find the shift vector which goes from body-link mass-center to its surface.

4. Score each link based on the error of pseudo-inversion and pick the link with minimal error.

This algorithm is very fast, just requiring to find zeros of a second-order polynomial for each link.

4 Results

We test the algorithm during in dynamic conditions, i.e. squatting and turning around the yaw axis. Figure.1 demonstrates detection of four different external forces and their associated body links. Due to geometry approximations and the difficulty of estimating full-body accelerations, the output of the algorithm might not be stable, jumping between different links. But if accelerations are not too large, detecting forces on bigger body-links or those located far from the pelvis (in terms of the number of joints in between) seems more stable.

We also consider the full estimator with another weaker version in which accelerations are disabled. The latter static algorithm performs equally good in static postures, but largely fails to estimate external forces when the robot is moving. Overall, the performance highly depends on accelerations in dynamic cases. Of course even with the full estimator, having more accelerometers on the robot at different locations can improve the performance

5 Discussion

The proposed algorithm estimates both force and location together which is an advantage. Compared to force estimation on manipulators in static cases, we tackle two other important problems which are floating-base and acceleration estimation during dynamic motions. Overall, this algorithm can be very useful in human-robot interaction where putting physical sensors on body surfaces greatly increases hardware complexity. The proposed virtual tactile suit however only benefits from the existing sensory data. It is computationally very fast, but requires another high level filtering method to stabilize the resulting estimation. It should be noted that the performance can be highly improved by adding more accelerometers on the body and considering precise geometry of the links. We plan to apply this method on the real robot as well as using a similar idea for model refinement. Such method can also be useful when the robot wants to carry some unknown object.

6 Acknowledgments

This work was funded by the WALK-MAN project (European Community's 7th Framework Programme: FP7-ICT 611832).

References

Luca Colasanto, Nikos G Tsagarakis, and Darwin G Caldwell. In *Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS & EMBS International Conference on*, pages 688–694. IEEE, 2012.

Adria Colomé, Diego Pardo, Guillem Alenya, and Carme Torras. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, pages 3535–3540. IEEE, 2013.

Kenji Kaneko, Fumio Kanehiro, Mitsuharu Morisawa, Eiichi Yoshida, and Jean-Paul Laumond. In *Advanced Motion Control (AMC), 2012 12th IEEE International Workshop on*, pages 1–6. IEEE, 2012.

Dinh Phong Le, Junho Choi, and Sungchul Kang. In *Control, Automation and Systems (ICCAS), 2013 13th International Conference on*, pages 1794–1798. IEEE, 2013.

Nejc Likar and Leon Zlajpah. *International Journal of Advanced Robotic Systems*, 11, 2014.

Tomoyuki Noda, Takahiro Miyashita, Hiroshi Ishiguro, and Norihiro Hagita. *Human-Robot Interaction in Social Robotics*, page 183, 2012.

Silvio Traversaro, Andrea Del Prete, Serena Ivaldi, and Francesco Nori. In *Robotics and Automation (ICRA), 2015 IEEE International Conference on*, pages 2105–2110. IEEE, 2015.