Slip Recovery for Quadruped Robots

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1 Introduction

Being able to detect slippage and deal with it, has become of great importance for legged robots which are meant to traverse unstructured terrains. In particular, a strategy for detecting slippage and recover from it, becomes crucial when constraint inverse dynamics approaches are implemented [1],[3], which rely on the assumption that the stance feet constraints are never violated (e.g. they are not moving).

2 Slip detection

The approaches to address the problem of slip detection, can be grouped into two big families: torque based and kinematic based approaches. The torque based ones require the availability of (at least) a 3-axis force sensor which is usually located at the contact point (e.g. the foot-tip). If the friction coefficient is known in advance, the slippage could simply be detected by checking if the ratio of the tangential/normal forces [2] is within the limit of static friction. When the friction coefficient is unknown, an idea is to check the frequency content of the tangential contact force signal. As a matter of facts, in presence of slippage, a high frequency ripple appears in the force signal due to the local stick-slip phenomena that occur between the contacting surfaces [4], [5]. A shortcoming of this approach is that the force sensor should be rugged enough to withstand the impacts at the contact point (unless intrinsic sensing is used). In addition to this, during locomotion the touchdown event can create discontinuities in the force signal and, unless properly filtered out, jeopardize the detection. A detection strategy based on kinematics looks more promising in the context of legged robots where ground impacts are the order of the day. A kinematic strategy can be implemented at the acceleration, velocity or position level. In [6] Takemura considers slippage as an impulse-like leg acceleration, and has accelerometers attached to the lowerleg links to detect slippage. A drawback of this approach is that, to be able to discriminate the slip acceleration, the motion component generated by the driving torques must be subtracted, and this not an easy task because accelerometers are usually affected by noise and drift. Alternatively, slippage could be estimated at the position level, by checking if the inter-distances between the stance legs is kept constant along the whole duration of a single stance configuration. However, since a velocity error accumulates more quickly than a position error, it is more reasonable to check the slippage at the velocity level. The choice of the frame in which the feet velocities are evaluated, directly affects the robustness of the approach. Indeed, the more intuitive way to detect slippage is to check if the Cartesian velocities of the stance feet are all zero in an *inertial* frame (we only have linear velocities because the robot has point feet). However, this requires an estimation of the robot base linear velocity (the angular velocity can be measured with accuracy by an on-board IMU sensor) which usually is prone to estimation errors and drift. Indeed, the base linear velocity is commonly inferred through leg odometry or kinematic based state estimation techniques [8], which rely on the assumption that none of the feet is slipping. Therefore, a wrong state estimation influences the computation of the feet velocities and this can, on its behalf, result into false positives in the detection of slippage. A more robust approach would be to use only informations that directly come from sensor measurements (e.g. encoders). In particular, the stance feet velocities, if compared in the *base frame*, will have to be all equal in norm and direction. Thus, in a manner similar to what a car ABS braking system is doing, a fruitful strategy is to compare the value of the norm $|v|$ of the velocities of the stance feet v and discriminate the outlier with appropriate statistical tools. A short time integration of the body linear acceleration (IMU) can be helpful to improve the estimation in the case that more than one leg is slipping at a time.

3 Surface normal and friction coefficient estimation

During locomotion there are two types of uncertainties which can cause slippage:

1. on the estimate of the direction of the surface normal $\hat{n}$. This is commonly estimated by vision or by fitting a plane through the stance feet positions (blind terrain detection) [6].
2. on the surface (static/dynamic) friction coefficient μ. In general μ cannot be known in advance and is commonly inferred using euristics based on semantic information coming from vision [9].

We can get useful insights for the estimation of μ and n from the following facts:

1. if unilateral constraints are active (e.g. the legs are always pushing on the ground and the feet are not detaching), the direction of the slip velocity v will always be tangent to the surface. This means the surface normal will have a right angle with the velocity vector v.

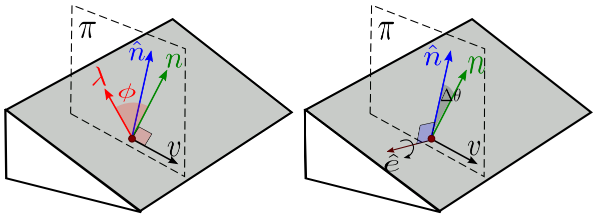

Figure 1: (Left) Vector definitions for slip detection (for a generic leg on a slope). The red dot is the foot location, π is the plane where the ground reaction force λ and the foot velocity vector v lie. n and $\hat{n}$ are the real and estimated normal to the surface. (Right) Slip recovery definitions: $\hat{e}$ is the axis rotation to move $\hat{n}$ towards n while $\Delta\theta$ is the correction angle.

Furthermore, physics tells us that the normal should lie in the plane π passing through the ground force vector λ and the velocity vector v (see Fig. 1(left)). These two facts allow us to easily determine the real normal direction n by geometric computations.

2. during the slipping motion, the ground reaction force vector λ is always lying on the friction cone edge. Therefore, a noise free average of the angular distance ϕ between λ and n, can be a good estimate of the real friction coefficient ($\mu = tan(\phi)$).

4 Slip recovery

When slippage occurs some actions should be undertaken. Earlier works on slip recovery are presented in [6] where a long term strategy aims to change gait frequency and stride length when approaching slippery surfaces. This is feasible only for reactive locomotion approaches on terrain which have limited roughness. On the other hand, when a static walk on a very challenging terrain has to be performed, the occurrence of slippage might result in unrecoverable loss of stability because any other footstep can be infeasible (think about the task of crossing a river). A short term strategy is needed in these extreme cases. We propose a local slip recovery strategy where, after a very short initial estimation phase (to find n and μ), we make the actual surface inclination estimate $\hat{n}$ converge to the real one, according to the following recursive equation:

$$\begin{aligned} \omega(k) &= K(\Delta\theta(k)) \\ \hat{n}(k+1) &= R(\hat{e}(k)\omega dt)\hat{n}(k) \end{aligned} \tag{1}$$

where $\Delta\theta \in \mathbb{R}$ is the angular error between $\hat{n}$ and $n \in \mathbb{R}$ at time k (see Fig. 1(right)). $\hat{e} \in \mathbb{R}$ is the axis perpendicular to both $\hat{n}$ and n, and $R(.) \in \mathbb{R}^{3\times3}$ is the rotation matrix associated to the rotation vector $\hat{e}\omega dt$. K is a scalar gain useful to set the convergence rate and dt is the sampling time. During the correction we continuously send $\hat{n}$ to our body control framework [7] that will optimize the ground reaction forces in order to do not violate the friction cone constraints. If the estimate of the surface normal, for the slipping foot, is set to the appropriate direction (inside the cone), the slippage will naturally end-up after a short transient. Note that we could have sent, since the beginning, the correct value to the body controller, but we implemented a smooth convergence to the real normal n to prevent torque discontinuities.

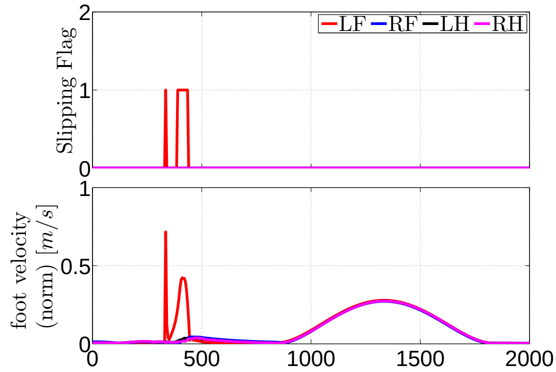

Figure 2: (Upper) LF leg starts slipping around 380ms. (Lower) Plot of the norm of the feet velocities.

5 Results

The proposed approach corrects the estimate $\hat{n}$ of the normal surface to the real value n for a slipping foot. Figure 2 shows that the slippage in the left-front (LF) leg terminates (the norm of the velocity goes back to the values of the other feet velocities) in less than 100ms. This is achieved by exploiting the optimization capabilities of our whole body control framework [7] that will apply forces which satisfy the corrected friction cone constraints.

References

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