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SIMPLE YET EFFECTIVE TECHNIQUE FOR ROBUST REAL-TIME INSTABILITY DETECTION FOR HUMANOID ROBOTS USING MINIMAL SENSOR INPUT

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Legged locomotion of autonomous humanoid robots is advantageous but also challenging since it inherently suffers from high posture instability. External disturbances such as collisions with other objects or robots in the environment can cause a robot to fall. Many of the existing approaches for instability detection and falling prevention include a large number of sensors resulting in complex multi-sensor data fusion and are not decoupled from the walking motion planning. Such methods can not simply be integrated into an existing low-level controller for real-time motion generation and stabilization of a humanoid robot. A procedure that is both easily implementable using a minimal number of affordable sensors and capable of reliable detection of posture instabilities is missing to date. We propose a simple, yet reliable balance control technique consisting of a filtering module for the used data from two-axes-gyroscopes and -accelerometers located at the trunk, an instability classification algorithm, and a lunge step module. The modules are implemented on our humanoid robots which participate at the yearly RoboCup competitions in the humanoid kid-size league of soccer playing robots. Experimental results show that the approach is suited for real-time operation during walking.

Keywords: balance control; legged locomotion; posture instability; reflex motion.

1. Introduction

The Zero-Moment-Point (ZMP) (Ref. 1) is an often used dynamic stability criterion, particularly in conventionally built humanoid robots such as Honda's Asimo. However, this criterion can describe the large versatility of human bipedal locomotion only to a small extent. Impacts or hits against the robot torso are difficult to handle and exceed the limits of what control

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strategies can achieve. As with human beings falling avoidance can then only be achieved by reflex based motions.

Höhn *et al.* (Ref. 2) use pattern recognition to detect and classify instabilities. The classification is based on feature vectors, consisting of the translational/rotational velocities, tilts of the torso and foot, the CoP and the gait phase. In Ref. 3 a similar approach is described, with the difference that five particular reflex motions are hard-coded for an optimal reaction to instabilities. An emergency stopping method, divided into four phases according to the role of the ZMP, is proposed by Morisawa *et al.*[4] In each phase approximate analytical solutions of the Center of Gravity dynamics are used to generate the motion. The above concepts require several sensors and high computational power which is not always available on an autonomous robot. Another approach, coupling walking motion and its stabilization, is proposed by Behnke *et al.*[5] Sensor readings during undisturbed omnidirectional walking are captured and modeled for predefined gait speeds, including means and standard deviations of the tilts about the x- and y-axis and their derivatives. For intermediate walking speeds, a linear interpolation is performed and a stability indicator is computed comparing actual sensor readings to the predefined models. Depending on the indicator strength, one of two reflexes is activated to stabilize the robot. The method requires up to several hundreds of walking experiments.

The goal of this work is to provide a simple control methodology based on sensor data provided by two-axes-accelerometers and -gyroscopes mounted at the hip. The proposed balance control procedure consists of a filtering module based on the Kalman filter for the detection of collisions or impacts, a classification algorithm for the definition of the instability measure, and a stabilization sequence by means of reflex based lunges, leading to the system structure shown in Fig. 1. Our strategy allows to detect instabilities during both walking and special motions such as standing or kicking. The adjustment to special motions requires solely a fine tuning of the degrees of freedom and bounds as presented in detail in the following.

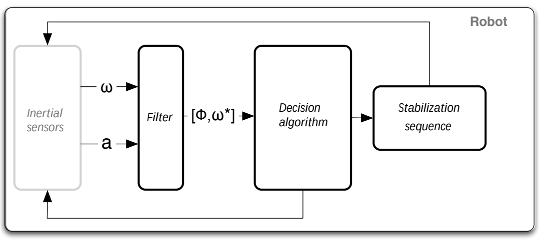

Fig. 1. System structure of our balance control procedure. Angular velocities and accelerations provided by the inertial sensors are denoted as ω and a, respectively. Based on these data the filtering module determines the attitude ϕ and filtered velocity ω^*.

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2. Filtering Module

A problem common to all gyroscopes and accelerometers is that of drift and shock sensitivity, respectively. We use gyroscopes to measure local changes in rotation and accelerometers to measure external forces acting on the robot. In the first part of our methodology we describe the model and measurement for the Kalman filter, and subsequently present the algorithm for determining the attitude ϕ and angular velocity ω^* of the robot in the x- and y-axis.

2.1. *Model*

The gyroscope data is integrated with discrete time steps δt[a] to maintain an ongoing estimate of the orientation of the robot. The correction by the accelerometers, i.e. comparison to the gravity, turned out being sufficient for the compensation of the drift. The system dynamics $\hat{x}_i^- = (\hat{\Phi}_i^-, \hat{\omega}_i^-)^T$ is therefore formulated as follows:

$$\begin{aligned} \hat{\Phi}_i^- &= \hat{\Phi}_{i-1} + \hat{\omega}_{i-1}\delta t\,, \\ \hat{\omega}_i^- &= \qquad \hat{\omega}_{i-1}\,. \end{aligned}$$

2.2. *Measurement*

Assuming that the acceleration of gravity is measured by the accelerometers and not considering the noise, the angle θ for the orientation of the robot can be estimated. When the robot is tilted, the accelerometers measure $\vec{g}^* = \vec{g} + \vec{g}_0$. The projection of $\vec{g}$ on the robot axes reveals the forces g_x, g_y and g_z. The angle is computed as follows:

$$\begin{aligned} \Phi_x &= \arcsin(\tfrac{g_y}{g}) \\ \Phi_y &= \arcsin(\tfrac{g_x}{g}) \end{aligned}$$

with $g = 9.81m/s^2$. For the clarification of the notation, the delivered sensory data is denoted as follows:

- accelerometers: $z_{\tilde{a}_x}, z_{\tilde{a}_y}, z_{\tilde{a}_z}$, and
- gyroscopes: $z_{\tilde{\omega}_x}, z_{\tilde{\omega}_y}, z_{\tilde{\omega}_z}$.

Both information resources, model $\hat{x}_i^-$ and measurement z_i, enable us to optimally estimate the roll and pitch angles. Since the accelerometers do not provide any useful information regarding the yaw angle, we can not

[a] δt is the time step at which new data is available and lasts 10 ms.

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Support Technologies for Mobile Machines

compensate the drift in the gyroscopes by a fusion and therefore do not further consider the yaw angle.

2.3. *Algorithm for Integer Numbers*

By using invariant matrices A and H and constant matrices Q and R which were experimentally determined, and starting with a random error covariance P_0, the Kalman gain can be computed offline. The selection of the scaling factors f_{dt}, f_a, f_ω requires a compromise between accuracy and avoidance of an overflow. For further details we refer to Radkhah *et al.*[6] Expressions in brackets shall signify integer numbers which can be handled more efficiently than floating point numbers by the microcontroller:

Step$_i$: Model (Predict) $\in \mathbb{Z}$

$$\begin{aligned}(f_\omega \cdot f_{dt} \cdot \hat{\Phi}_i^-) &= (f_\omega \cdot f_{dt} \cdot \hat{\Phi}_{i-1}) + \tfrac{(f_\omega \cdot f_{dt} \cdot \hat{\omega}_{i-1})}{f_{dt}} \\ (f_\omega \cdot f_{dt} \cdot \hat{\omega}_i^-) &= (f_\omega \cdot f_{dt} \cdot \hat{\omega}_{i-1})\end{aligned}$$

Step$_i$: Measurement $\in \mathbb{Z}$

$$\begin{aligned}(f_a \cdot z_{\Phi_i}) &= \mp z_{\tilde{a}_i}, \quad \arcsin(x) \approx x \\ (f_\omega \cdot z_{\omega_i}) &= z_{\tilde{\omega}_i}\end{aligned}$$

Step$_i$: Correct (partially $\in \mathbb{R}$ due to K)

$$\begin{aligned}(f_\omega \cdot f_{dt} \cdot \hat{\Phi}_i) = \; & (f_\omega \cdot f_{dt} \cdot \hat{\Phi}_i^-) \\ & + K_{11}\left[(f_a \cdot z_{\Phi_i}) \cdot \tfrac{f_\omega \cdot f_{dt}}{f_a} - (f_\omega \cdot f_{dt} \cdot \hat{\Phi}_i^-)\right] \\ & + K_{12}\left[(f_\omega \cdot z_{\omega_i}) \cdot f_{dt} - (f_\omega \cdot f_{dt} \cdot \hat{\omega}_i^-)\right]\end{aligned}$$

$$\begin{aligned}(f_\omega \cdot f_{dt} \cdot \hat{\omega}_i) = \; & (f_\omega \cdot f_{dt} \cdot \hat{\omega}_i^-) \\ & + K_{21}\left[(f_a \cdot z_{\Phi_i}) \cdot \tfrac{f_\omega \cdot f_{dt}}{f_a} - (f_\omega \cdot f_{dt} \cdot \hat{\Phi}_i^-)\right] \\ & + K_{22}\left[(f_\omega \cdot z_{\omega_i}) \cdot f_{dt} - (f_\omega \cdot f_{dt} \cdot \hat{\omega}_i^-)\right]\end{aligned}$$

Due to the linearization of arcsin the algorithm produces inaccurate results for large angles ($\approx \pm 90°$). For the stability detection, however, this is not relevant since only angles in the interval $[-20°, 20°]$ are essential.

2.4. *Experimental Results*

Fig. 2 shows the accelerometer data on the left and the gyroscope data on the right, both recorded during a walking motion. The accelerometers

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Support Technologies for Mobile Machines

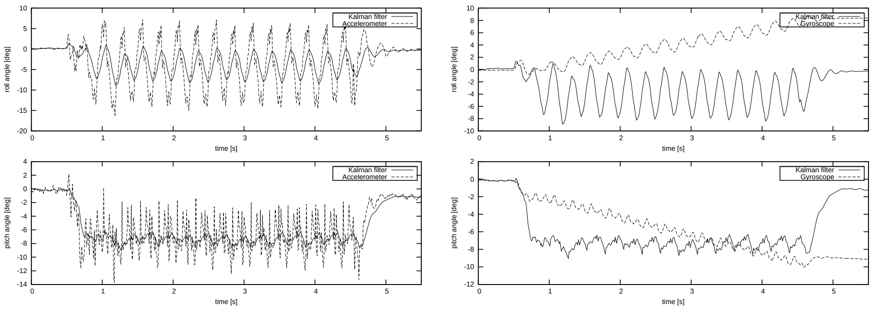

Fig. 2. Determination of the orientation using accelerometers (at the left) and using gyroscopes (at the right) during a walking motion. The accelerometer data is very noisy (dashed line on the left) compared with the filtered data (solid line on the left). Accumulation of the drifts increases the total drift error in the gyro based results (dashed line on the right) compared with the filtered data (solid line on the right).

are highly sensitive to vibrations as can be easily recognized. Hence the measurements are very noisy compared with the results when using the Kalman filter. An alternative determination of the orientation represents the integration of the gyroscopic angular velocities. It can be noted that gyroscopes alone do not provide any reliable information due to the drift.

The Kalman filtering approach proposed in this paper incorporates both accelerometer and gyroscope based data for the computation of the orientation. As expected, this way the drift of the gyroscopes and the shock sensitivity of the accelerometers can be eliminated.

3. Instability Classification

Most important for the detection of an unstable posture is the definition of a stability measure based on the results of the filter module. The purpose of such decision algorithm is the correct triggering of the stabilization sequence.

3.1. *Basic Idea for the Definition of an Instability Measure*

The inputs of the decision algorithm are chosen to be $[\Phi_x,\ \omega_x]$ and $[\Phi_y,\ \omega_y]$. Two independent instability measures based on these inputs will be computed: L_x and L_y for the roll angle and the pitch angle, respectively. These values are then combined to an instability vector indicating the direction and intensity of a shock. Considering that computations are directly to be performed on the microcontroller, a simple basic idea consists of defining

Preprint of paper which appeared in the Proceedings of the
13th International Conference on Climbing and Walking Robots and the
Support Technologies for Mobile Machines

lower and upper bounds for the weighted sum of the angle and velocity:

$$L := \alpha_\Phi \cdot \Phi + \alpha_\omega \cdot \omega$$

with $L \in [L_{min},\ L_{max}]$. The system is defined as stable unless the limits are exceeded. The weights α_Φ and α_ω specify the influence of Φ respectively ω on the measure.

3.2. *Robustness in the Presence of Drift or Incorrect Calibration*

Absolute bounds are always sensitive towards a shift of the measurement data. In order to address this problem, our neutral position N_L is chosen to be a dynamically changing value. It iteratively emerges from averaging instability measures L predicted for the near future:

$$N_{L_i} := (1 - \beta) \cdot N_{L_{i-1}} + \beta \cdot L_i,$$

where $N_{L_0} = 0$ and the weighting factor range $0 \leq \beta \leq 1$. A position that is held for longer time is assumed to be stable and hence becomes the new neutral position N_L. By changing β a compromise between robustness and inactivity of the mean value can be made. In Fig. 3 an example of an incorrectly calibrated accelerometer is given. As can be noticed, after only half a second the correct neutral position is found.

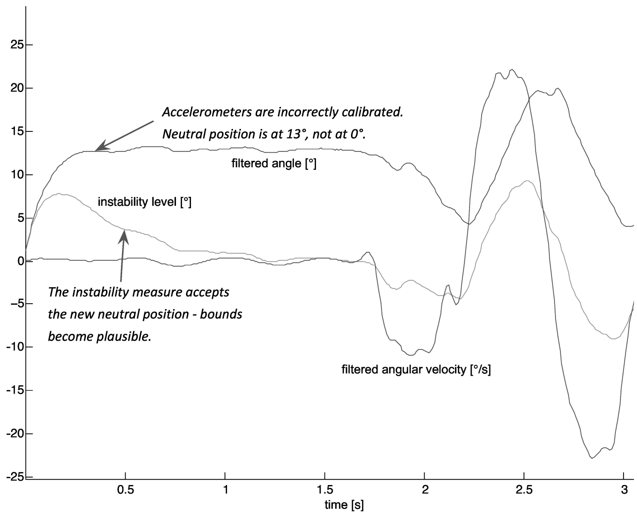

Fig. 3. Estimation of the instability measure in the case of an incorrectly calibrated accelerometer.

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Support Technologies for Mobile Machines

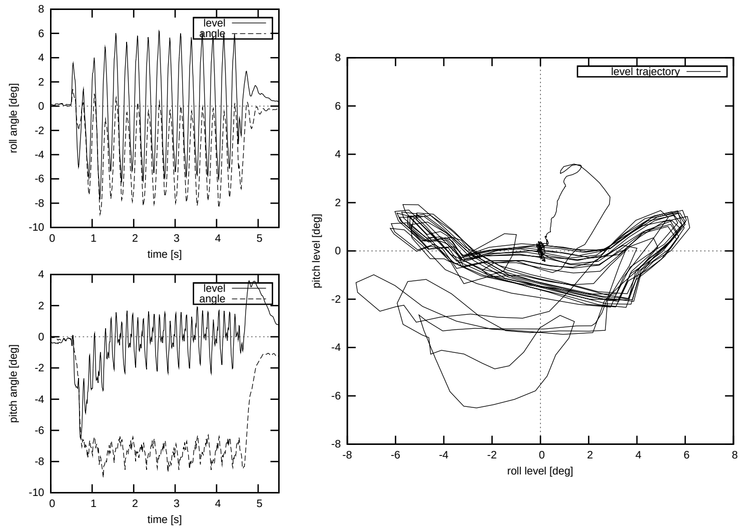

Fig. 4. At the left the instability measures are plotted against the filtered orientations about the x- and y-axis. On the right-hand side the instability measure L_{roll} is plotted against L_{pitch}.

3.3. *Experimental Results*

On the left-hand side in Fig. 4 the instability levels L_{roll} and L_{pitch} are plotted against the roll and pitch angular positions recorded during a walking motion. It is noticeable that the instability measures run ahead of the orientation outputs, but behave like the orientation outputs. Ongoing deflections do not lead to a larger instability measure. Rather they are identified as desired tilts. For instance, during forward locomotion the robots have a visible supine position. The amplitudes in the instability measure are caused only by jerky transitions such as transitions from standing to walking and reverse. A compromise between robustness and inactivity as well as forewarning time and accuracy can be made by tuning the parameters.

The instability measures L_{roll} and L_{pitch} indicate the direction and velocity of a fall. To clarify the entropy of these measures, have a look at the rightmost plot in Fig. 4. It represents the level trajectories around the robot in the bird's-eye perspective. Imagine the robot is standing at the origin of the plot and looking in direction of the positive y(pitch)-axis. To detect an instability, it is sufficient to compute the absolute value of the trajectory vector $(L_{roll}, L_{pitch})^T$ and the difference between its angle and a reference direction such as the robot's viewing direction $(0, 1)^T$. It

Preprint of paper which appeared in the Proceedings of the
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Support Technologies for Mobile Machines

seems to be plausible to set bounds rather on the trajectory vector instead separately on each instability level. The bounds on the trajectory vector certainly require a dynamic treatment similarly to the other parameters discussed above. For instance the robot tends to tilt faster forwards than to fall over to its sides. A higher bound for the measure L_{roll} therefore seems to be recommended.

4. Stabilization Sequence and its Demonstration

The third module is responsible for moving the robot from an unstable into a stable posture. By means of the calculated attitude and velocity of the robot, a new foot position for the swing leg is computed. Using inverse kinematics, a novel stable trajectory for all leg joints can be determined. The demonstration of the correct execution of all modules can be seen in Fig. 5. Further details can be found in Radkhah *et al.*[6]

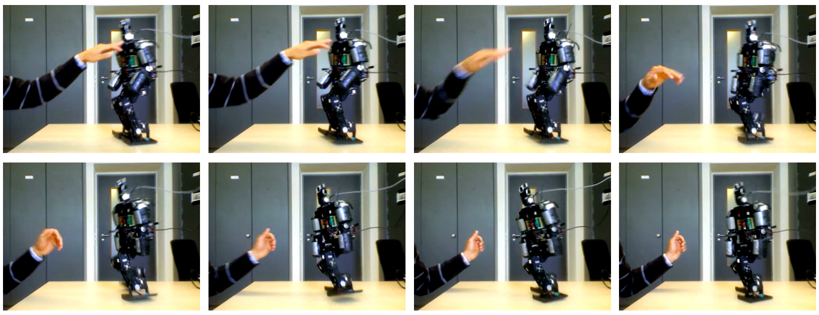

Fig. 5. After being pushed backwards the humanoid robot triggers a stabilization sequence, making a step backward with its right foot to stabilize itself. For further information about our robot system we refer the reader to Friedmann *et al.*[7]

5. Discussion

Compared to existing methods, the approach proposed in this paper is advantageous in several aspects. The following suggestions for extensions are interesting, given more computational power. Also, note that some of the below extensions may complicate the currently well working system unnecessarily.

Preprint of paper which appeared in the Proceedings of the
13th International Conference on Climbing and Walking Robots and the
Support Technologies for Mobile Machines

5.1. *Improving the Kalman Filter*

The application of the Kalman filter offers a few important degrees of freedom and flexibility which can both be used for improvements and extensions of the implementation. The matrices Q and R for the system and measurement uncertainties, for instance, could be adjusted to the posture or locomotion pattern of the robot, i.e. the model should not be trusted, the faster the robot moves. Furthermore, it might turn out necessary to compute both matrices online as soon as they change with each time step. In this case either the computation is completely performed online on the microcontroller or, for simplification purpose, a look-up table for pre-calculated Kalman gains $K_\infty^{(i)}$ for the corresponding Q_i is created.

5.2. *Extension of the Classification Module*

The goal of the second module is defining an instability measure that outputs at each time step the degree of stability of the current posture of the robot. The implementation on the microcontroller requires an efficient determination of the measure. Improvements for this measure include

- extension by transformation and pattern recognition running on a more powerful computer and their evaluation at specific cycles, and
- comparison to visual information retrieved by a camera.

It is also imaginable to integrate a memory for incorporating the previous measures in the current computation of the instability measure. For instance, an unstable attitude should be rated more critical, the longer it is taken up.

5.3. *Improving the Stabilization Sequence*

For the determination of the stabilization sequence it must be noted that truly optimal reaction in each situation can not be realized. The exhausting generation of special actions for the stabilization sequences is a way to respond to many instabilities. Currently, we are working on the smooth run of the strategy during all motions with dynamically changing bounds. In order to support the automatic choice of a stability sequence, it is also possible to memorize the result of a reaction, i.e. to learn from false reactions. A successful reaction, for instance, could result in a better weighting or adjustment of necessary parameters.

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Support Technologies for Mobile Machines

6. Conclusions

During walking, standing and many other intended motions of a humanoid robot, it is desirable to avoid falling, since falling robots might damage themselves or parts of their environment. We proposed a strategy for reliable detection of instabilities and reaction to them. The minimal sensor input is not a limiting factor considering the obtained results. The instability events can be detected by the proprioceptive sensors in real-time. Due to limitations of onboard computational power, the idea of a simple set-up of the hardware and software system for a balance control strategy seems to be justified. Furthermore, decoupling the balance control from the generation of walking motion simplifies its implementation on a real robot platform and allows easy adaption of the system to other robots. Finally, there is no need for installation of further sensors like feet-ground contact force sensors at places that require complicated wiring.

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References

1. M. Vukabratovic and B. Borovac, *Int. J. Humanoid Robotics* **1**, 157 (2004).
2. O. Höhn and W. Gerth, *Int. J. Robotics Research* **28**, 245 (2009).
3. O. Höhn, J. Gacnik and W. Gerth, Detection and classification of posture instabilities of bipedal robots, in *Proc. Int. Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines (CLAWAR'05)*, (London, UK, 2005).
4. M. Morisawa, S. Kajita, K. Harada, K. Fujiwara, K. K. F. Kanehiro and H. Hirukawa, Emergency stop algorithm for walking humanoid robots, in *Proc. IEEE/RSJ Int. Conference on Intelligent Robots and Systems (IROS'05)*, (Edmonton, Canada, 2005).
5. R. Renner and S. Behnke, Instability detection and fall avoidance for a humanoid using attitude sensors and reflexes, in *Proc. IEEE/RSJ Int. Conference on Intelligent Robots and Systems (IROS'06)*, (Beijing, China, 2006).
6. K. Radkhah, D. Scholz, A. Anjorin, M. Rath and O. von Stryk, *Additional Remarks Related to the Paper: Simple Yet Effective Technique for Robust Real-Time Instability Detection for Humanoid Robots Using Minimal Sensor Input*, Tech. rep. TUD-CS-2010-0075, Department of Computer Science (Technische Universität Darmstadt, Darmstadt, Germany, 2010).
7. M. Friedmann, J. Kiener, S. Petters, H. Sakamoto, D. Thomas and O. von Stryk, *Int. J. Humanoid Robotics* **5**, 417 (2008).