A Highly Dynamic Gait for Extremely Challenging Terrain

One of the most difficult challenges for quadruped robots is walking on very uneven terrain. The problem becomes even more complicated with additional moments upon adding a payload or a robotic arm, which may cause it to become unstable. Moreover, developing a generalized controller that can operate in any terrain is a difficult task. Fankhauser et al. [1] made a controller for rough terrain but used a single gait, causing the motion to be slow. My research will primarily focus on the development of the dynamic gait generator to traverse highly challenging terrains, during the 4–6-month project period.

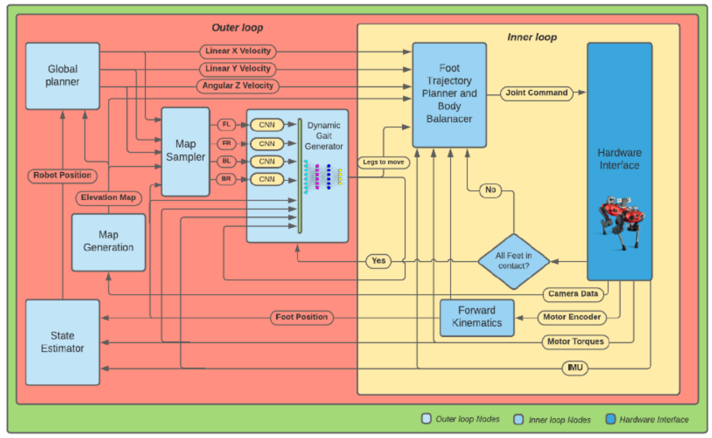

Fig. 1. Block diagram representing the control scheme for quadruped robots on very uneven terrain with a dynamic gait.

The backbone of this control scheme is the elevation map created by the map generation node, as shown in Fig. 1., using the techniques by Fankhauser et al. [2]. The produced map follows the robot and spans 5-6 meters in front, 1-2 meters to the sides, and 1-2 meters to the back, providing useful terrain information for the subsequent nodes. Using a window around the commanded velocities, a region of space is identified and sampled from the elevation map for each leg. This region is converted into a four-channel 50x50 pixel array, where each pixel reflects the size of the robot foot. A value of 0 indicates that the region is not a viable foothold in the first channel, and 1 indicates that it is viable. The remaining channels represent the possible foot's X, Y, and Z positions in relation to the robot's body center. The 4-channel pixel maps are processed through separate CNNs (Convolution Neural Networks) to construct weights distinct to each leg. The CNNs' features are flattened and merged with motor torques, IMU, and foot positions. The above information allows us to determine the robot's body orientation, current feet locations, and probable footholds after motion. The neural network would then be able to decide the legs to be moved. Using reinforcement learning and a very close robot model representing a quadruped in the actual world will train the network. Following that, the final policy is applied to the robot and fine-tuned in the real world, as shown by Smith et al. [3].

The trajectory generator receives the output from the dynamic gait generator. It plans an approximate motion path using a fixed equation of motion for the legs, such as a cubic spline. Using the elevation map, the planner calculates a path that avoids the obstacles in the original course, resulting in an irregular path. When going along such routes, the system may become unbalanced. This instability can be corrected by moving the legs on the ground to retain the center of mass within the support polygon created—simultaneously avoiding collisions with any other obstructions. Using the tractrix equation, the legs can avoid these obstacles, proven effective for a redundant serial robot in 3D space [4]. Because this application may not be a one-to-one match between a quadruped and a serial robot, some tweaking to the equations will be required to make it work.

The last step would be for the quadruped to autonomously move to its goal using the global planner, which considers the commanded goal location and current robot position from the state estimator to calculate linear X, linear Y, and Angular Z velocity with respect to the body, as shown in Fig. 1. These commands can be delivered manually during the early phases of development by replacing the global planner and state estimator with a joystick interface. The controller described above should be able to navigate exceedingly difficult terrains and support payloads as well as a robotic arm if added. On the other hand, because we have elevation maps and trajectory planning, there may be some computing issues when using this strategy. For faster computation, voxel-based elevation maps can substitute the 3D point clouds when generating the map.

References

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