Hexapod Gait Control Through Internal Model Belief Update

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1 Introduction

Gait is a common locomotion strategy for legged animals where a repetitive sequence of leg movements results in motion. Assuming the predictive coding theory, the agent continually represents its beliefs about the gait state in a state estimation [1]. In *Internal Model* (IM) principle, the state is predicted from efference copy by a *Forward Model* (FM) that can be further utilized for motor control [2]. However, in gait dynamics, the sensory state depends on the sequence of the previous motor commands, which makes the sensory-motor dynamics challenging to model.

Physiological evidence shows that animal gaits are correlated with the *Central Pattern Generator* (CPG) activity [3] that is hypothesized to estimate the motion phase [4]. The CPG can then be considered a part of the FM that predicts the sensory state for each particular phase.

We propose a biomimetic controller combining the CPG with the predictive coding theory. The state estimation is updated by fusing sensory observation with the CPG-based FM predictions. The estimated state is compared to the given reference value, and the difference is backpropagated through FM updating the gait; see Fig 1. We test the proposed gait controller on a real hexapod walking robot Daisy by HEBI Robotics, where the robot performs various motion behaviors and navigates toward the goal location.

2 Method

Let the gait dynamics be described in C discrete *motion phases*. We denote ν_m^ϕ the motor command for the m-th effector at the motion phase ϕ, and similarly γ_n^ϕ be the value of the n-th sensory modality at the phase ϕ. We define *motor embedding* as a sequence of the motor commands $\nu = (\nu^\phi)_\phi^C$, where $\nu^\phi = (\nu_m^\phi)_m^M$. Similarly, we define *sensory embedding* $\gamma = (\gamma^\phi)_\phi^C$, where $\gamma^\phi = (\gamma_n^\phi)_n^N$. The agent updates its belief about the *gait* $\bar\nu$ minimizing the difference between *sensory reference* γ^* and *sensory estimate* $\bar\gamma$.

We model the sensory estimate $\bar\gamma$ as value maximizing posterior sensory state probability given the *sensory observation* $\hat\gamma$ and *predicted motion consequence* provided by the FM $F : (\nu,\phi) \to \gamma^\phi$

$$\bar\gamma_n^\phi = \arg\max_{\gamma_n^\phi} P(\gamma_n^\phi | \hat\gamma_n^\phi, F(\bar\nu,\phi)_n). \tag{1}$$

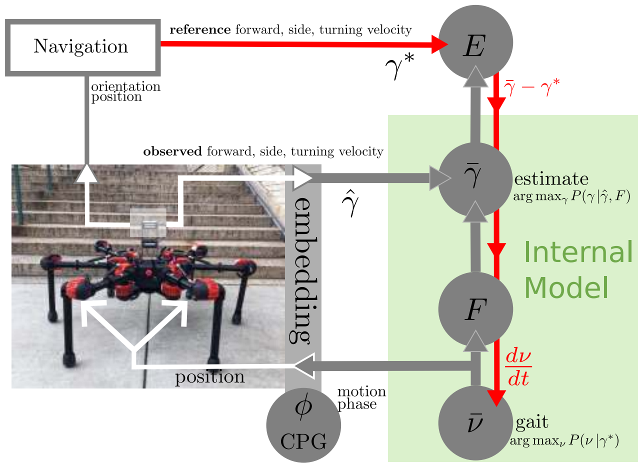


Figure 1: Schema of the proposed controller coupled with the hexapod walking robot Daisy. The controller commands the joint angles, while the sensor-motor loop is closed by the tracking camera Intel RealSense T265 providing a relative localization of the robot.

The gait $\bar\nu$ is then the most probable motor embedding given the sensory estimation being equal to the reference value

$$\bar\nu_m^\phi = \arg\max_{\nu_m^\phi} P(\nu_m^\phi | \bar\gamma = \gamma^*). \tag{2}$$

Assuming naive Bayes, uniform prior distribution, and normal likelihood distribution, we reformulate the posteriors in (1) and (2) into a log-likelihood form, from which we derive the update rules

$$\frac{d\bar\gamma_n^\phi}{dt} = \frac{\hat\gamma_n^\phi - \bar\gamma_n^\phi}{\Sigma^{\hat\gamma|\bar\gamma}} + \frac{F(\bar\nu,\phi)_n - \bar\gamma_n^\phi}{\Sigma^{F|\bar\gamma}}, \tag{3}$$

$$\frac{d\bar\nu_m^\phi}{dt} = \sum_\varphi^C \sum_n^N \frac{\gamma_n^{\varphi *} - \bar\gamma_n^\varphi}{\Sigma^{\gamma^*|\bar\nu}\Sigma^{F|\bar\gamma}} \frac{\partial F}{\partial \nu_m^\phi}, \tag{4}$$

with likelihood variances $\Sigma^{\gamma|\bar\gamma}, \Sigma^{F|\bar\gamma}$, and $\Sigma^{\gamma^*|\bar\nu}$ for observation, prediction, and reference, respectively.

The forward model F is an ensemble of C linear regressors $f_\phi : \nu \to \gamma^\phi$ switched by a motion phase: $F(\nu,\phi) = f_\phi(\nu)$. For the presented early results of the proposed approach, the motion phase is tracked by a model of the unperturbed CPG: $\Phi(t) = tT^{-1}$ that switches the phases $\phi(t) = \arg\min_i ||iC^{-1} - \Phi(t)||; i = 1 \ldots C$ with the period T.

3 Results

The ability of the studied control schema to model the gait dynamics and its usability to locomote was empirically examined on a real hexapod walking robot Daisy. During the control, we expect that if the reference value is above the observed value, we measure the growth of the observed value; $\gamma^* - \hat{\gamma} \approx \frac{d\hat{\gamma}}{dt}$. The expectation is tested in the navigation setup, where the sensory references γ^* are generated with respect to (w.r.t.) robot's distance and orientation to the goal location. If the observed sensory values change positively correlates with the reference-observation difference, the robot should approach the goal location.

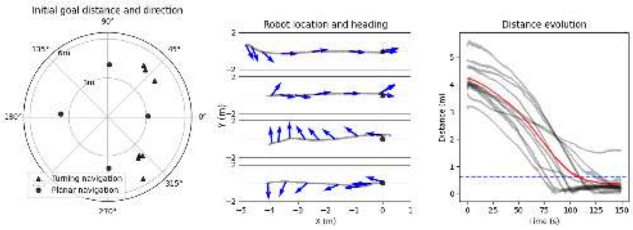
The six-legged robot is actuated by 18 controllable joints, and the mounted T265 provides relative localization. With six motion phases, $C = 6$, the motor embedding is a sequence of six joint angle commands $\bar{\nu} \in \mathscr{R}^{6\times18}$ that change the position w.r.t. the robot's default position, which is depicted in Fig. 1. The observed sensory modalities are planar and turning velocities embedded into the sensory observation $\hat{\gamma} \in \mathscr{R}^{6\times3}$. The sensory observations are fused with the FM predictions into estimate $\bar{\gamma}$ using the update rule (3). The angle commands $\bar{\nu}$ are updated by (4), where both update rules are calculated using the Euler method with the step size set to 0.001.

The FM used in the proposed controller, shown in Fig. 1, is trained in two iterations. The training dataset is built by drawing 1400 random gaits from the normal distribution $\nu_m^\phi \in \mathcal{N}(0, 0.2)$ and recording the sensory observation. The dataset is used to learn the initial FM $F^{(1)}$, and the robot is tasked to move forward, resulting in an initial gait $\nu^{(1)}$. In the second motion babbling iteration, the random gaits are drawn from $\nu_m^\phi \in \mathcal{N}(\nu_m^{\phi,(1)}, 0.2)$, and the second FM $F^{(2)}$ is trained. The second iteration FM, $F^{(2)}$, was able to walk the robot forward in all five experimental repetitions.

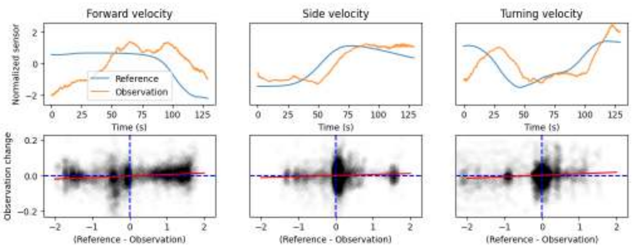
The controller with the trained FM is deployed with either of two navigation methods: (i) *Turning navigation*, which generates turning and forward velocity references towards the goal location; and (ii) *Planar navigation*, which generates forward and side velocity references towards the goal location. The robot approached the goal location from eleven initial positions and orientations shown in Fig. 2a and exhibited motions sideways, forward, backward, and left-right turning. The navigation setup generated sensory references and observations from which we measured the positive correlation between the reference difference and observation change Fig. 2b.

4 Discussion and Conclusion

The measured results corroborate the expectation that the proposed gait controller causally entangles the sensory reference with the sensory observation. If true, the entanglement is propagated through a single FM implemented as the CPG-switched linear regressors, providing complex motion behaviors by controlling 18 joints of the hexapod walking robot. The trained controller adjusted the gait motion and navigated the robot toward the requested target location using forward, side motion, and turning. In our future work, we plan to utilize the presented probabilistic formulation by tracking the FM prediction confidence and combining several other FMs. The proposed approach will allow the gait controller to scale incrementally and improve its performance over multiple scenarios.



(a) Navigation setups



(b) Sensory reference and observation

Figure 2: (a) Eleven experimental runs with different initial distances and directions to the goal located at coordinates $[0, 0]$. Four measured paths with the robot heading are shown in the middle. All, except the run with $180°$ initial direction, runs were observed to reach the goal vicinity of 0.6 m where the robot stayed. (b) The top row shows examples of the sensory observation and reference measured during the experimental runs. The bottom row shows the least-square linear fit to 142 098 measured data points with the coefficients 0.0085, 0.0056, and 0.0083 for forward, side, and turning velocity, respectively.

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