Abstract — This letter considers control of a radially symmetric tripod friction-driven robot. The robot features 3 servo motors mounted on a 3-D printed chassis 7 cm from the center of mass and separated 120 degrees. These motors drive limbs, which impart frictional reactive forces on the body. Experimental observations performed on a uniform friction surface validated a mathematical model for robot motion. This model was used to create a gait map, which features instantaneous omni-directional control. We demonstrated line following using live feedback from an overhead tracking camera. Proportional-Integral error compensation performance was compared to a basic position update procedure on a rectangular course. The controller reduced path error by approximately 46%. The error compensator is also able to correct for aerodynamic disturbances generated by a high-volume industrial fan with a mean flow speed of $5.5 \text{ms}^{-1}$, reducing path error by 65% relative to the basic position update procedure.

I. INTRODUCTION

The vast majority of studies on biological and biomimetic locomotion — aquatic, terrestrial, or aerial — have focused on body types exhibiting bilateral symmetry. This has provided substantial insight into the underlying dynamics, effective gait patterns, and motion control for bilateral actuation. However, few studies have considered locomotion and control for radially symmetric bodies. Radial symmetries are particularly common in aquatic locomotion. Examples include many members of the phyla Cnidaria (e.g., swimming medusae, or jellyfish; [1]) and Echinodermata (e.g., crawling organisms such as sea stars, brittle stars, and sea urchins; [2], [3]). The goal of this paper is to provide physical insight into the crawling locomotion of organisms with radial symmetry, in conjunction with an even distribution of sensory and actuation systems across all limbs [10], ensuring that there is no preferred locomotion direction relative to body orientation. Finally, having multiple radially-distributed limbs also creates more contact points for adhesion, which becomes important in the case of resisting exogenous forces like fluid forcing.

Some previous studies have also developed radially symmetric bioinspired robots to investigate these body plans. A pentaradial five degree-of-freedom (DOF) robot was recently shown to adapt to limb amputation and retain the ability to translate in a specified direction [6]. In an earlier study, a pentaradial robot with six actuators in each limb was developed [11]. Genetic algorithms were then used to identify optimal gait sequences for this robot from block simulations of a brittle-star model in a physics engine. This effort showed that neither bilateral nor radial symmetries were locally optimal for translation. Instead, a complex writhing motion was shown to be most effective. Finally, tripod robots with wheels attached, otherwise known as trident snake robots, have been studied for path planning, geometric control, and optimal control [12], [13], [14], [15]. Other researchers have focused on the development of soft radially-symmetric robots employing pneumatic actuation [16], shape-memory-alloy actuation [17], and electric field manipulation [18] to yield greater geometric adaptability in complex, unstructured environments.

In this paper, we develop and test a minimally-actuated friction driven tripod (Fig. 1). We develop a controller...
that allows this robot to translate in any direction, independent of the current state. We also show that the resulting gait map is not very sensitive to the friction coefficient at the contact points. We demonstrate effective curve following in experiments. Further, we implement an error compensator that reduces path error substantially relative to a basic position update procedure and makes locomotion robust to aerodynamic disturbances.

II. ROBOT AND DYNAMICAL MODEL

A. Robot Design and Characterization

The tripedal robot, shown in Fig. 1 and Fig 2, was designed to approximate the size and geometry of natural sea stars [19]. The robot has limbs of length \( l = 7.5 \text{cm} \) evenly distributed around a central structure, attached at an effective radius of \( R = 5 \text{cm} \). Three Hitec HS-5646 submersible servo motors are mounted onto a photopolymer UV-cured support frame to actuate the limbs. The specific actuation patterns were designed to minimize material so that the inertial contribution of the limbs (88g) could be negligible when compared to the more massive central structure (800g). The total robot mass is \( M = 888 \text{g} \). The power source and Arduino-based control system were stored externally and connected to the robot via a central cable to reduce mass and ease waterproofing.

Disposable tape strips were attached to the contact points to distribute the normal forces and tune friction. For the model validation experiments shown in Fig. 3 the contact points were covered with 600-grit sandpaper. Additional validation tests (not shown here) were also carried out with a lower friction polymer tape contacts. The experiments described in this letter were conducted with the robot moving on a sheet of white drafting paper (to ease motion tracking) layered onto a 6.35mm-thick leveling mat that was stretched across an optical table. The kinetic friction coefficients, \( \mu \), for the polymer-paper and sandpaper-paper contacts were measured by releasing a known mass, \( m \), from rest on a slope with angle \( \beta \), and measuring the velocity achieved by the mass, \( V \), after traveling a distance \( \Delta x \) down the ramp. Frictional energy loss was estimated from these measurements using the relation

\[
\Delta E_f = mg\Delta x \sin \beta - \frac{1}{2}mV^2, \tag{1}
\]

in which the first term on the right-hand side is the change in gravitational potential energy for the sliding mass, and the second term is the gain in kinetic energy. Assuming that the frictional loss can be modeled as \( E_f = \mu N \Delta x \) where \( N = mg \cos \beta \) is the normal reaction force acting on the mass, the kinetic friction coefficient can be estimated via the relation

\[
\mu = \frac{\Delta E_f}{\Delta x mg \cos \beta}. \tag{2}
\]

For the sandpaper-paper contact, the friction coefficient was estimated to be \( \mu = 0.85 \pm 0.043 \). For the polymer-paper contact, the coefficient of friction was estimated to be \( \mu = 0.33 \pm 0.012 \).

To ensure that the observed robot motion was purely due to limb actuation, we made sure that the dynamic effects due to imperfections in table leveling and tension in the cable tether were negligible. An electronic leveling tool showed that the optical support table where the robot motion was recorded had a tilt no greater than 0.2°. For a maximum tilt of 0.2°, the in-plane force due to gravity is

\[
F_{incl} = Mg \sin(0.2\pi/180) \approx 0.0035Mg \tag{3}
\]

Assuming that the normal force at each of the three contact points is on average \( Mg/3 \), the friction force at each contact point for the sandpaper-paper case is

\[
F_f = \mu \frac{Mg}{3} = 0.29Mg. \tag{4}
\]

In other words, for this high-friction case, the in-plane friction force at each contact is roughly two order of magnitude larger than the total force due to tilting. Similarly, cable tension was measured using a hanging scale and found to be negligible compared to the total weight of the system. Thus, cable tension is not expected to play a dynamic role either.

B. Physics-Based Model

The mathematical model is based on conservation laws for linear and angular momentum with a nonlinear frictional forcing. The model assumes that the translational inertia and rotational inertia for the limbs are negligible relative to those for the more massive central structure. The friction forces are assumed to act at the point of contact at the end of each robot limb (see Fig. 2).

To model the friction force, we use a simplified version of the Coulomb friction law in which no distinction is made between static and kinetic friction [20], [21]. Specifically, the friction force, \( \mathbf{F}_f = [F_{f,x}, F_{f,y}] \), acting at the contact point at the end of each limb in the \( x-y \) plane, \( \mathbf{r}_i = [r_{ix}, r_{iy}] \), is modeled as

\[
\mathbf{F}_f = -\mu N_i \frac{\mathbf{r}_i}{|\mathbf{r}_i|}. \tag{5}
\]
Here, \( N_i \) is the normal force at contact point \( i \), \( \mu \) is the measured kinetic friction coefficient, and \( \mathbf{r}_i = [r_{i,x}, r_{i,y}] \) is the velocity of the contact point at the end of each limb. Note that \( \mathbf{r}_i \) and \( \mathbf{r}_j \) can be expressed in terms of the robot state vector, \( \mathbf{z} = [x, \dot{x}, \xi, \phi] \), the actuation angles and rotation rates, \( \phi_i \) and \( \phi_r \), and the geometric constants, \( R \) and \( l \), using simple trigonometric relations (see Fig. 2). Normal forces are computed by combining a vertical force balance \((N_1 + N_2 + N_3 = Mg)\) with torque balances about the robot center of mass:

\[
\begin{bmatrix}
1 & 1 & 1 \\
r_{1,x} - x & r_{2,x} - x & r_{3,x} - x \\
r_{1,y} - y & r_{2,y} - y & r_{3,y} - y
\end{bmatrix}
\begin{bmatrix}
N_1 \\
N_2 \\
N_3
\end{bmatrix}
= \begin{bmatrix}
Mg \\
0 \\
0
\end{bmatrix}.
\]  

(6)

The second and third lines in the equation above ensure that there are no net torques about the robot center-of-mass due to the normal forces.

Under the assumptions stated above, conservation laws for linear momentum in the horizontal plane can be expressed as

\[
M \ddot{\mathbf{x}} = \sum_{i=1}^{3} F_{i,x}
\]

and

\[
M \ddot{\mathbf{y}} = \sum_{i=1}^{3} F_{i,y},
\]

respectively. The conservation law for angular momentum can be expressed compactly as

\[
J \ddot{\xi} = \sum_{i=1}^{3} (\mathbf{r}_i - \mathbf{x}) \times \mathbf{F}_i,
\]

where \( J \) represents the rotational inertia, which is estimated from the mass distribution of the central support structure.

The system of ordinary differential equations shown in (7)(9) is solved numerically to yield predictions for robot translation (\( \mathbf{x} \)) and rotation (\( \xi \)) using the MATLAB \texttt{ode45} algorithm for an adaptive time-step 4th-order Runge-Kutta solver. Recall that the location of the contact points relative to the robot center, \( \mathbf{r}_i - \mathbf{x} \), depends on the limb angles, \( \phi_i(t) \) (Fig. 2). Therefore, the prescribed actuation angles \( \phi_i \) appear directly in all three conservation laws via the friction terms dependent on \( \mathbf{r}_i \) and \( \mathbf{r}_j \). Also, keep in mind that these model simulations involve no tuning parameters. All geometric and dynamic variables appearing in the governing equations (e.g., \( M, J, l, R, \mu \)) are obtained from independent measurements.

C. Model Validation

Model validation tests demonstrated that the robot can rotate and translate independently. These motions can be achieved with sinusoidal actuation at the limbs. If two limbs are in anti-phase, and the third limb is motionless, the robot translates in the direction of the inactive limb, as shown in Fig. 3(a),(b). Here, the active limbs were prescribed to move sinusoidally with amplitude \( 30^\circ \) and frequency \( f = 1 \) Hz. If all three limbs are actuated with the same amplitude and frequency, but with a phase shift of \( 120^\circ \) relative to one another, the robot rotates in place as shown in Fig. 3(c),(d). Note that these experiments also confirm that the mathematical model adequately reproduces the dynamics of the physical system for the high-friction contact. We also observed close agreement between model predictions and experimental results for the low-friction polymer-paper contact surface with \( \mu = 0.33 \pm 0.012 \) (not shown here). This modeling framework is used for gait and control design in the following section.

III. GAIT AND CONTROL DESIGN

A. Omnidirectional Gait

The predictive model showed that an omnidirectional gait would allow for immediate translation in any direction. This new gait was a variation of the previously introduced translational gait. As previously explained, when two limbs operate in anti-phase to one another, and the third limb is inactive, the robot translates in the direction of the inactive limb. However, simulations show that sinusoidal actuation of the inactive limb produces translation at a non-zero angle relative to the previously inactive limb. This angle of translation, \( \theta \) varied depending on the amplitude, \( \alpha \) of the previously inactive limb’s sinusoidal motion. In this new gait, the previously inactive limb is defined as the \( \alpha \)-limb because the amplitude of its sinusoidal motion is \( \alpha \). The other two limbs operate in
anti-phase to one another, with constant amplitude sinusoidal motion. Simulations generated a map of sinusoid amplitude to angle of translation, $M$ (Fig. 2).

Importantly, because of the radial symmetry of the model, any limb can be made the $\alpha$-limb, allowing the model to translate in any direction from any initial configuration. This is why the mapping is only plotted for $\theta \in [0, 60^\circ]$. This is discussed further below in the context of controller design. This framework, coupled with feedback control, was then used to demonstrate path following capabilities in simulations and experiments. Both the robot and simulation experiments update the position gait parameters every cycle.

B. Gait Map

Open loop simulations with $\alpha \in [0, 30^\circ]$ and with non-$\alpha$ limb amplitudes $30^\circ$ generated $M$. A maximum value of $\alpha = 30^\circ$ was selected due to limitations of the physical model. Over the course of a trial, $\alpha$ was held constant, and the resulting translation angle $\theta$ was measured relative to the model reference frame for each cycle of motion. The $\theta$ values of each cycle were then averaged over the entire trial. This averaging produced the average angle of translation, $\theta_{avg}$. There was minimal variation in $\theta$ after the first two cycles of motion, which was consistent across friction coefficients.

This procedure was repeated in three different different friction environments: $\mu = [0.33, 0.59, 0.87]$. These values were selected based upon the friction coefficient values tested with the physical robot. There was little variance in the mappings generated from these three environments, $M_{0.33}$, $M_{0.59}$, and $M_{0.85}$. As a result, we assumed a universal mapping, $M_{avg}$, to provide sufficient accuracy independent of friction magnitude. Fig. 3 shows this averaged map obtained using the predictive model (red curve), together with $\theta$ measurements made in experiments using the tripod robot (blue symbol).

Map insensitivity to friction was further evaluated using the predictive model. During this study, the model was run through a randomly generated course, in three different friction environments, described by $\mu = [0.33, 0.59, 0.85]$. The model completed the course, in each environment, using all four maps, $M_{0.33}$, $M_{0.59}$, $M_{0.85}$, and $M_{avg}$. Using total time to complete the course as a performance metric, $T_c$, there was $<1\%$ variation amongst all four maps. As a result, $M_{avg}$ was used in all simulations and physical robot experiments, regardless of the friction environment.

C. Controller Design

Fig. 5 provides a schematic overview of the feedback tracking procedure implemented in the experiments. The position vector $x = [x, y, \xi]$ and trajectory $s$ are inputs to the gait mapping implemented in MATLAB. The outputs of the MATLAB block are the gait parameters $a = [a_1, a_2, a_3]$ defining the sinusoidal motion of each limb:

$$\phi_i = a_i \sin(2\pi ft).$$

In the expression above, $f$ is the frequency of limb oscillation, which was set to 1 Hz in both the simulations and the experiments. The limb angle $\phi_i$ can be visualized in Fig. 2. One of the values of $a$ is set equal to $a$ in the MATLAB block, indicating that limb will be the $\alpha$-limb. Here $a_1$ refers to limb 1 of the robot, $a_2$ to limb 2, and $a_3$ to limb 3. The selection of limb numbering is arbitrary, as long as the attachment point of limb 1 is used to define the rotation of the robot relative to the global reference frame. Note that a negative value of $a_i$ implies that the limb is running in anti-phase with a limb that has a positive value of $a_i$. Table 1 shows the $a$ vector for differing translation directions. The full range of desired translation directions, $\theta \in [0^\circ, 360^\circ]$, is split into six different zones spanning 60° to take advantage of the symmetry of the robot. The $\alpha$-limb varies in these different zones. In each zone, the map $M_{avg}$ is used to prescribe the value for $\alpha$ needed.

The MATLAB control block used to prescribe gait parameters in the simulations and experiments is described further in Fig. 6. The inputs to this block, $s$ and $x$ are used to determine the desired angle of translation, $\theta_D$. A simple PI error controller was implemented in an attempt to reduce steady-state error, where $e$ is the error signal, $K_P$ is the proportional gain, $K_I$ is the integral gain, and $T_s$ is the duration, in seconds, of a cycle step, $k$.
based upon the robot’s distance from the “ideal path” is used to calculate $\alpha$. The PI controller outputs an adjusted desired frictional coefficient between the surface and the robot. This model facilitates generation of a gait-map which accurately reproduces motion for a friction-driven tripod robot. The gait selection block uses $\theta_{df}$, along with the average gait map, $M_{avg}$, to select $\alpha$ and create $a$. Depending on $\theta_{df}$, one of the six zones listed in Table I is selected and the mapping $M_{avg}$ is used to calculate the value of $\alpha$ needed. The gait parameter vector $a$ sent to the limbs is then structured according to Table I.

The gait selection block in Fig. 6 uses $\theta_{df}$ and $M_{avg}$ to select $\alpha$, and structure $a$ for the next cycle of locomotion. However, since the $M_{avg}$ is a discrete mapping generated from a limited set of simulations, a linear interpolator is implemented to make the map “continuous”. In addition to this interpolation, all input angles to the block must be parsed, so that the correct limb is selected to move sinusoidally in anti-phase. As noted earlier, the zone framework shown in Table I is used to select the correct limb configuration depending on the desired translation angle.

IV. PATH FOLLOWING DEMONSTRATION

To illustrate path following capabilities in simulation and experiments, a rectangular path specified by 4 target points was used (see Fig. 7). In the physical experiments, we used a surface with an unknown friction coefficient between the low-friction polymer-paper case ($\mu = 0.33$) and the high-friction sandpaper-paper case ($\mu = 0.88$) to demonstrate the friction-independence of $M_{avg}$. In addition, an industrial floor fan was used to generate wind flow across the test surface to study the effect of aerodynamic disturbances on path following capabilities. A Protmex 6252A handheld anemometer measured wind speed at both ends of the testing platform. The edge located closest to the fan had a flow speed of $6.4 \pm 0.2 \text{ms}^{-1}$ and the edge furthest from the fan had a flow speed of $4.5 \pm 0.2 \text{ms}^{-1}$. Thus, there were significant velocity gradients across the surface, making for a complex flow field.

In the numerical simulations, aerodynamic drag was modeled as $F_d = (1/2) \rho C_d A_d v^2$ where $\rho$ is the density of air, $C_d$ is a drag coefficient, $A_d$ is the frontal area of the robot, and $v$ is wind speed. The drag coefficient was assumed to be $C_d = 1$, corresponding roughly to the drag coefficient of a cubic bluff body. The frontal area for the robot was estimated to be $A_d = 0.02 \text{m}^2$. The wind speed was set at $v = 5.5 \text{ms}^{-1}$, an average of the velocities measured at each end of the test section. This model, of course, is a significant oversimplification, where the flow field is assumed uniform and constant, there are no ground effects, the drag coefficient does not change with position, and there are no lift effects.

Proportional gain was $K_p = 15 \text{deg cm}^{-1}$ for rapid correction to path deviations, and integral gain was $K_i = 1 \text{deg cm}^{-1}$ to reduce steady-state error. We selected these values based on experimental tuning with an update rate of $f = 1 \text{Hz}$ (i.e., every actuation cycle for the limbs). From Fig. 7(a) it can be seen that, without proportional-integral (PI) error compensation, the robot does not follow a straight line. This is likely a result of error from unmodeled disturbances in $M_{avg}$, imperfections in robot manufacturing, error in gait execution, imbalance from cable tether, and experiment surface inhomogeneity. Fig. 7(d) shows that the PI error compensator corrects for this unmodeled drift. Fig. 7(b),(c) shows the effect of wind in the environment on path following without PI error compensation. The robot is particularly sensitive to wind speed angled at $25^\circ$ with respect to the x-direction, where deviations from the nominal trajectory are amplified. The PI controller successfully compensates for this in Fig. 7(f). Note that the simulation results shown Fig. 7 are in reasonable qualitative agreement with the experimental tracks for the cases with background flow.

Table II shows two performance metrics for the tracking experiments: cumulative path following error $\Delta = \sum |e|$ (m), where $e$ is the perpendicular distance to the nominal path, and the completion time $T_c$ (s). In all flow environments, $\Delta$ is reduced by implementation of the PI error compensator. For example, $\Delta$ is reduced by over 65% for the cases with flow in the x-direction. However, $T_c$ increases with added control for both the no flow and angled flow cases. This is because the robot spends time correcting its trajectory rather than going directly to the way points. A time-optimal path in the presence of flow is not straightforward, and is a topic of further investigation.

Another demonstration of robot path following capability is provided in Fig. 7 which shows that complex curved paths can be tracked by placing intermediate target points. For this figure, we show tracking with no error compensation using the standard $M_{avg}$ map.

V. CONCLUSIONS

We have shown that a momentum-conservation model can accurately reproduce motion for a friction-driven tripod robot. This model facilitated generation of a gait-map which predicted that the robot can translate in any direction independent of the current state. Open loop experiments con-
and consider locomotion on heterogeneous surfaces. This study shows how a minimally actuated, radially symmetric robot can achieve path following by exploiting asymmetrical gait patterns. Future work will target time-symmetric robot can achieve path following by exploiting asymmetrical gait patterns. Future work will target time-optimal path following in the presence of background flows and consider locomotion on heterogeneous surfaces.

Fig. 7. Four points are used for the robot to trace a square path in the presence of a variable wind flow field where (a)-(c) are without error compensation, (d)-(f) are with PI error compensation. (a),(d) Plots are without wind flow, (b),(e) plots are with 0° wind flow, and (c),(f) plots are wind flow at 25° with respect to the x-direction. Blue markers show experimental measurements while red curves show simulation results.

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