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# Potential Function Control for Multiple High-Speed Nonholonomic Robots

Luke Wachter, John Murphy, Laura Ray, *IEEE member*

*Video Abstract* - Many approaches to the formation control problem for multi-robot systems have been proposed. In distributed consensus algorithm methods [1-3], and leader-follower structures [4] the robots are explicitly assigned positions within the desired formation. By contrast, artificial potential function (APF) control [5-9] generally does not specify a formation explicitly but rather drives the robots down the negative gradient of a potential field such that a formation emerges at a global or local minimum. The ad hoc emergence of the formation has several benefits, especially for a fleet of homogeneous vehicles: It allows for spontaneous adaptation of the formation to addition and removal of vehicles, and it allows for truly homogeneous control for each agent since no hierarchy or unique assignment in a constraint graph is needed.

APF methods, however, are generally designed for and tested on robots that approximate fully holonomic double integrator point masses [6-8]. APF methods designed for nonholonomic robots have been limited to robots with single integrator dynamics [9] or to a single robot traveling at low speed [5]. This video presents the results of an effort to adopt APF methods for high-speed, dynamic, nonholonomic robots.

The video describes the experimental testbed: a fleet of inexpensive 4-wheel drive skid-steered robots called Dynabots [10] capable of speeds up to 10 m/s and accelerations of at least 4 m/s$^2$. Three of the Dynabots are shown in Figure 1. These robots fuse GPS and inertial measurement to estimate their own state. They communicate via wireless 802.11b.

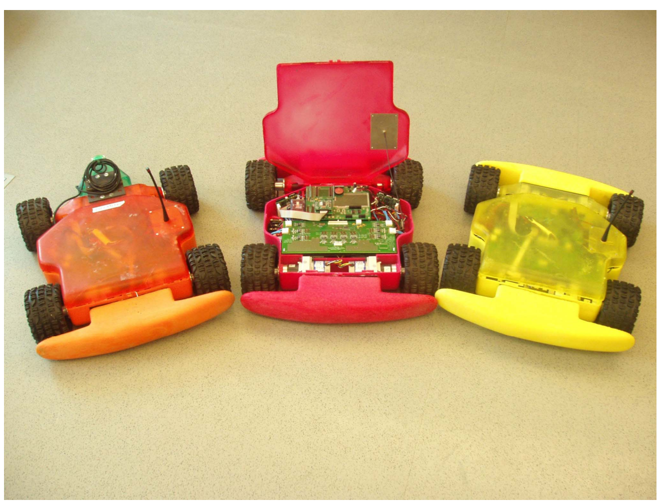

**Figure 1** A fleet of three Dynabots

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L. Wachter is an M.S. degree candidate at the Thayer School of Engineering, Dartmouth College (e-mail: luke.wachter@dartmouth.edu).

J. Murphy is a Ph.D. degree candidate at the Thayer School of Engineering, Dartmouth College.

L.E. Ray is an Associate Professor at the Thayer School of Engineering, Dartmouth College Hanover, NH 03755 USA (603-646-1243; e-mail: lray@dartmouth.edu).

A potential field method developed in [6] is selected for its computational simplicity. In the video, we provide a brief overview of this method, which incorporates radial potential functions centered at each robot and at a virtual leader located at the target position. The potentials described in [6] have been modified with a deadband $c$ chosen to reduce settling time at the expense of increased steady state error. The APF centered at each robot is given by

$$V = \alpha_h \begin{cases} \ln(d) + \dfrac{h_0}{d^2}, d < h_0 \\ \ln(h_0) + \dfrac{1}{h_0}, h_0 < d < h_0 + c \\ \ln(d-c) + \dfrac{h_0}{(d-c)^2}, d > h_0 + c \end{cases},$$

where $d$ is the distance from the robot, $\alpha_h$ is the controller gain, and $h_0$ is the equilibrium distance. The potential centered at the virtual leader is of the same form but with different choices of $\alpha_h$ and $h_0$. The control force on each robot is the negative gradient of the sum of the potentials from all other robots and from the virtual leader. The overall effect of the combination of potentials is to maintain separation between robots while driving the fleet toward the virtual leader. The control force $F_p$ from the APF is mapped to the Dynabot's left and right side wheel torque inputs, $\tau_r$ and $\tau_l$, respectively, by

$$\tau_r + \tau_l = KF_p \cos(\phi_e) - Cv$$
$$\tau_r - \tau_l = K_\phi \phi_e - C_\phi \dot{\phi}_e$$

where $\phi_e$ is the difference between the direction of the commanded force and the robot's current bearing, $v$ is velocity, $K_\phi$ and $K$ are proportional gains and $C$ and $C_\phi$ are derivative gains.

A field test with three Dynabots demonstrates that the mapping above successfully brings the fleet of robots into position around a goal location, marked in the video by a flag. However significant oscillation near the equilibrium is observed, which degrades the system settling time. At issue is selecting an appropriate system damping: a small damping coefficient $C$ results in high top speeds away from the virtual leader but leads to oscillation near the equilibrium, while a large $C$ suppresses oscillation at the expense of lower top speed initially. A nonlinear distant-dependent damping term is introduced in order to address this issue:

$$C_d = C\left(\alpha + \frac{h_0}{d + \beta h_0}\right)$$

which provides a minimum damping of $C\alpha$ when the robot is far from the virtual leader and elevated damping as the robot nears its target. Figure 2 shows how nonlinear damping improves system performance by reducing settling time compared to the system with constant damping coefficient. When the constant damping coefficient is selected to match the nonlinear damping term in the far-field, the system suffers from reduced settling time due to oscillations about the equilibrium. In this case, the distance-dependent damping term provides a 46% reduction in 2% settling time. When the constant damping coefficient is selected to match the nonlinear damping term at the equilibrium, the initial performance is sluggish. In this case, the nonlinear damping provides a 30% reduction in 2% settling time. The video demonstrates the application of the distance-dependent damping with a single robot trial in which the robot reaches 6 m/s but still arrives at its final position and stops with a minimum of oscillation.

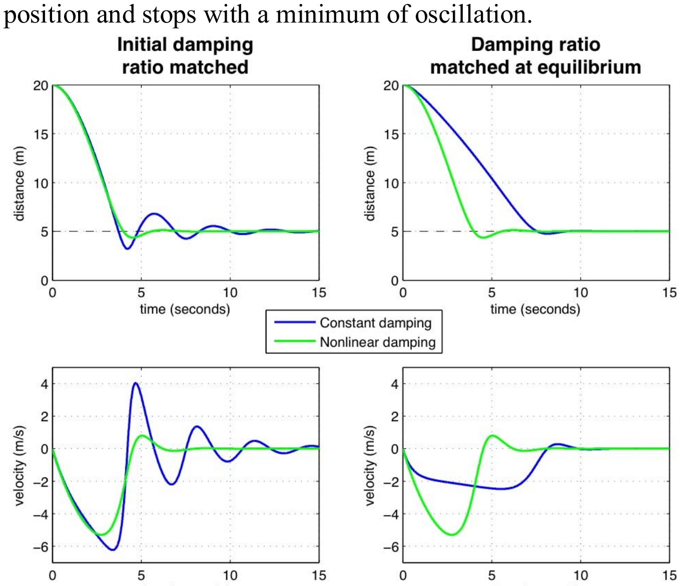


**Figure 2** Comparison of transient response of a single robot with constant damping and distance-dependent damping coefficients

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