

On the Comparative Analysis of Locomotory Systems with Vertical Travel

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Abstract

This paper revisits the concept of specific resistance, ε , a dimensionless measure of locomotive efficiency often used to compare the transport cost of vehicles [6], and extends its use to the vertical domain. As specific resistance is designed for comparing horizontal locomotion, we introduce a compensation term in order to offset the gravitational potential gained or lost during locomotion. We observe that this modification requires an additional, experimentally fitted model estimating the efficiency at which a system is able to transfer energy to and from gravitational potential. This paper introduces a family of such models, thus introducing methods to allow fair comparisons of locomotion on level ground, sloped, and vertical surfaces, for any vehicle which necessarily gains or loses potential energy during travel.

1 Introduction

Specific resistance, a dimensionless measure of locomotive efficiency, has often been used as a comparison of transport cost for both biological and engineered systems. In the robotic domain, where locomotion may include significant vertical motion, such as in the case of climbing robots, unmanned aerial vehicles, etc., the transport cost may include significant amounts of changing gravitational potential, not accounted for in calculations of specific resistance. In this paper, we provide motivation to extend this measure of transport cost to the vertical domain and apply models of locomotive efficiency in the presence of changing gravitation potential to several mobile robotic systems.

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Gravitational potential has been considered with specific resistance, but always assuming a perfect efficiency of conversion. McGeer’s unactuated gravity walker, for instance, uses the work performed by gravity to determine a specific resistance of $\varepsilon = 0.02$ [11], while similar, actuated bipedal machines inspired by passive dynamics have achieved similar, albeit slightly higher, values, $\varepsilon \approx 0.05$ [4]. The mismatch between the purely mechanical and the electromechanical systems suggests that additional inefficiencies are present, and must be considered when considering gravitational potential on actuated systems.

The need for a specific resistance calculation invariable to the slope of locomotion is apparent when considering the growing literature of climbing robots. While specific resistance has been compared for a variety of ground vehicles—an exhaustive comparison at time of publication is in [8]—no similar comparison has been performed for climbing robots. With dynamic and efficient climbers [3, 5, 10], as well as various other robots that climb on a variety of surfaces at differing speeds [13, 1, 9], we believe the lack of a formal comparison to be something that needs addressing in the climbing robot community. This paper outlines a methodology by which specific resistance can be applied to climbing robots—even those that only climb on sloped surfaces rather than vertical, such as in [2, 5]—and compared to other climbing robots as well as to the growing list of ground robots covered in work such as [8].

When considering level ground robots that occasionally encounter sloped surfaces and hills, our compensated specific resistance is also of use. We have applied automated tuning algorithms to allow a robot to learn efficient locomotion strategies by evaluating specific resistance [15]. A shortcoming of this approach is the need for level ground on which to tune behaviors. With a gravity-compensated calculation of specific resistance, we can apply our methods to a variety of terrain geometries, rather than being limited to level ground only. Additionally, with more and more accurate models of a robot’s motion while changing elevation, it is possible to apply compensated specific resistance as a near instantaneous measure of locomotive efficiency, thus providing even greater feedback to systems such as automated tuning algorithms.

2 Technical Approach: Specific Resistance in the Vertical Domain

Specific resistance is defined as the power required to keep a vehicle in motion, divided by the weight times the velocity of travel:

$$\varepsilon = \frac{P}{m g v} \quad (1)$$

A mass in a frictionless environment requires no additional power to keep itself moving, thus a “perfect” specific resistance has the value $\varepsilon = 0.0$. Dissipative effects—friction, impacts, and any inefficiencies—result in lost energy during locomotion, all of which specific resistance reflects in a single dimensionless measure. Using the Hamiltonian of a system, the sum of kinetic (T) and potential energy (V_g for gravitational, V_p for power plant energy), we can account for these dissipations:

$$\mathcal{H}(t) = T(t) + V_g(t) + V_p(t) \quad (2)$$

Due to dissipation, $\mathcal{H}(t)$ will be monotonically decreasing over time, $\frac{d}{dt}\mathcal{H} < 0$. Considering specific resistance on level ground ($\frac{d}{dt}V_g = 0$) and at near-constant speed ($\frac{d}{dt}T \approx 0$), we directly correlate any “drain” of energy, the derivative of the Hamiltonian, to the measured power plant output $P = -\frac{d}{dt}V_p$. The power measured at the power plant, therefore, is a fair measure of the dissipative energies, and thus is reflected as the numerator of (1).

A system that travels vertically, however, must perform work with or against gravity, $\frac{d}{dt}V_g \neq 0$, which should therefore be taken into account in the calculation of specific resistance. A simple solution is to offset the output of the power plant with any gravitational power, $\frac{d}{dt}V_g$. Doing this, however, complicates our notion of specific resistance, compounding a mere measurement of power and velocity into a model of the interaction of the various energy sources. The simplest version would contain a numerator of $P - m g v \sin(\theta)$, where θ is the angle of motion relative to horizontal, thus offsetting electrical power with gravity. This modification, however, assumes perfect conversion between power plant and gravitational potential. We introduce an additional term in our model, $\beta(\theta) \in C^\infty[S^1, R^+]$, to reflect a conversion efficiency. Higher values of β indicate that the power plant must output greater amounts of energy per unit energy of gravitational potential. Our new equation for compensated specific resistance, $\hat{\varepsilon}$, is a model of the interaction of θ with the measured ε , and, by compensating for gravitational potential, will produce near constant results over a range of angles:

$$\begin{aligned} \hat{\varepsilon}(\theta) &= \frac{P - \beta(\theta) m g v \sin(\theta)}{m g v} \\ &= \frac{P}{m g v} - \beta(\theta) \sin(\theta) \end{aligned} \quad (3)$$

With a model rather than a simple measurement, we propose fitting functions for $\beta(\theta)$, which we initially perform for a constant value of $\beta(\theta) = \beta_0$. For robots on slopes and vertical terrains, this requires at least two differently sloped surfaces in order to perform a fit.

To provide a simple example noting the chiefly linear nature of gravity’s interaction with power consumption, we consider the case of a ball rolling on a flat surface. In absence of all other dissipative forces, we consider a ball in

motion subject to only gravity and rolling resistance. In the case of rolling on a purely horizontal surface, the ball will be decelerated by the force of rolling resistance, defined as the coefficient of rolling C_{rr} , multiplied by the normal force.

$$f_{rr} = C_{rr} m g \quad (4)$$

On a surface angled at θ degrees, the body is affected by both gravity and rolling resistance. While rolling resistance decreases in either positive angles or negative angles, it does so with the $\cos(\theta)$ from the normal force. The gravitational force directed along with motion, however, changes with $\sin(\theta)$, and is thus linear when considering our model of specific resistance. The following equations sum up the forces affecting the ball’s motion.

$$f = f_g + f_{rr} \quad (5)$$

$$f_{rr} = C_{rr} m g \cos(\theta) \quad (6)$$

$$f_g = m g \sin(\theta) \quad (7)$$

Fig. 1 shows modeled data using basic assumptions of ball mass (1 kg), radius (0.1 m), velocity ($1 \frac{m}{s}$) and coefficient of rolling resistance ($C_{rr} = 0.15$, a value typical of a tire on pavement), over a range of angles from -90° to 90° . As seen, the gravitational force dominates the “power” measurement (estimated from additive and dissipative forces on the ball), and a linear fit is relatively adequate.

3 Experiments and Results

We experimentally test our calculation of $\hat{\varepsilon}(\theta)$ by applying differently configured robots to surfaces at varying slopes. We make use of both a RHex hexapedal robot [12], and a similar, but smaller EduBot machine [14], including a modified version of EduBot with wheels rather than legs.

We ran an EduBot robot with wheels on a variety of sloped surfaces found on the Penn engineering campus, testing both up and down at angles of 2.9° , 3.8° , and 4.5° , as well as on horizontal ground, during which we collected power and velocity data. A plot of how the specific resistance measurement is affected by θ is shown in Fig. 2. A linear fit of ε , assuming $\beta(\theta) = \beta_0 = 1.28$, is shown. If we were to apply this value of β_0 to the equation for $\hat{\varepsilon}(\theta)$, we could produce a model that achieves near-constant values over a wide range of slope angles.

A second dataset comes from experiments that have been performed on the RHex robot, with which we have tuned gaits for rugged, sandy terrains. In this experiment, shown in Fig. 3, the robot was run 70 m both up and

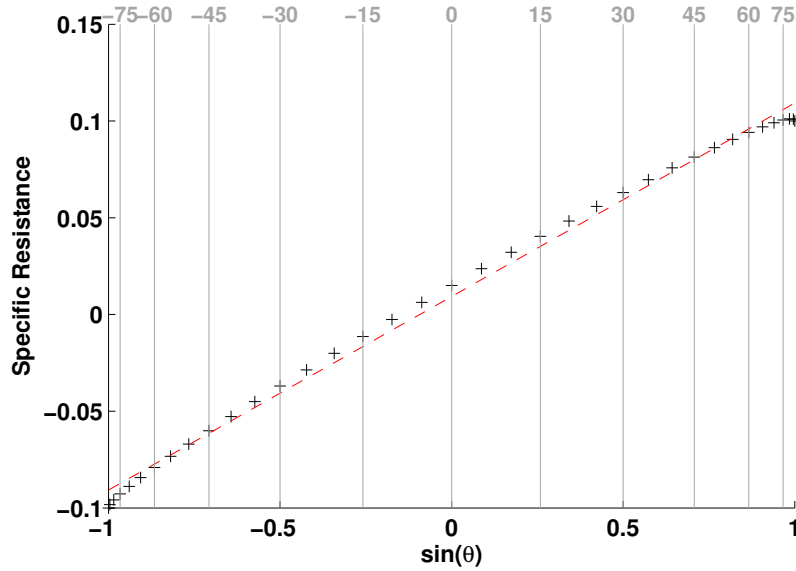


Fig. 1: A simple model of a rolling ball on an angled surface. The force due to gravity dominates the power, thus specific resistance follows a close-to-linear curve through a wide range of angles. $\hat{\varepsilon}(0) = 0.093$ and $\beta_0 = 0.1$.

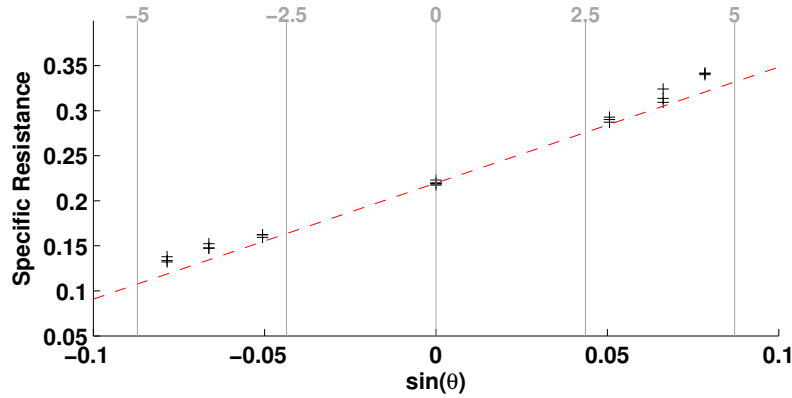


Fig. 2: Effect of slope angle, θ , upon the measured specific resistance, ε . A wheeled vehicle is run on various sloped surfaces (typical length of 10 m), from which we fit a linear model, $\hat{\varepsilon}(0) = 0.23$, and $\beta_0 = 1.28$. While the horizontal axis is $\sin(\theta)$, angles in degrees are marked as well as vertical gray lines.

down a sandy road inclined at approximately 3° , while power and GPS data were collected. While the GPS provides only an extremely noisy measurement of travel, the data shows overall differences in both power consumption and velocity, when averaged out on the different slopes. Applying our methods, we compute $\beta_0 = 3.04$ for this scenario, indicating that, for RHex on sandy, loose-packed surfaces, we achieve a lower efficiency at converting into potential energy, not surprisingly, than for the wheeled machine on smooth, inclined surfaces.

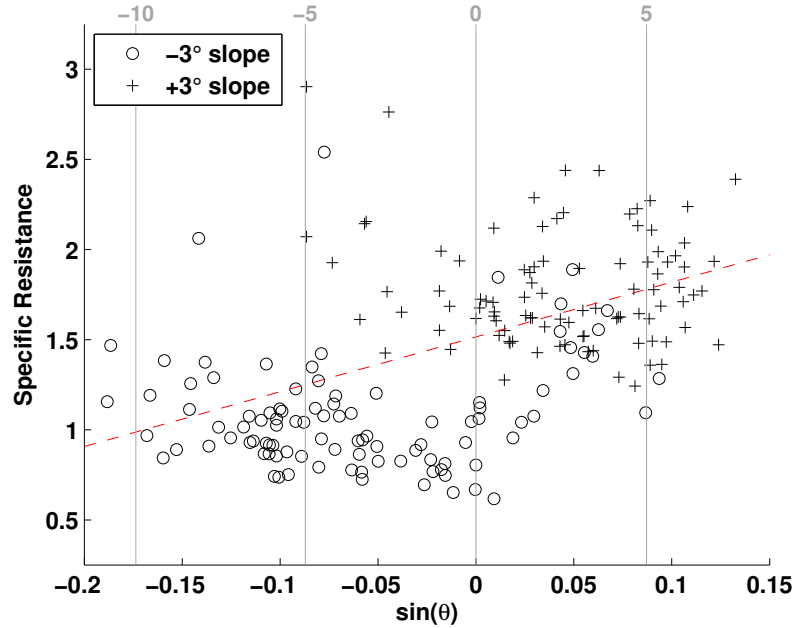


Fig. 3: The RHex robot was run up and down a rugged, sloped road. From the noisy measurements of a GPS, we compute a fit for ε , in which $\hat{\varepsilon}(0) = 1.52$ and $\beta_0 = 3.04$. Vertical gray lines note angle in terms of degrees.

4 Experimental Insights

Specific resistance abstracts away the details of locomotion into a single number. Similarly, our compensated version simplifies additional details of locomotion, most importantly, the manner in which a system interacts with gravitational potential, into a simple model of energy efficiencies, $\beta(\theta)$.

The physics of gravity, and how gravity interacts with power consumption, dictates that measurements of ε will be continuous with respect to θ , thus locally linear, allowing us to compute a value of β_0 and normalize specific resistance with our compensated version, $\hat{\varepsilon}(\theta)$. How locally linear the function is, however, is also of importance, as all vehicles eventually have angles at which their locomotion mechanisms no longer work as expected, necessitating a complicating move away from a constant $\beta(\theta)$ to higher order polynomials.

Anecdotally, early results with a legged robot show that the gait can have a large effect on the local linearity of ε . Some gaits, perhaps poorly tuned ones, exhibit worsening dynamics—and inefficient locomotion—as the slope changes. Other gaits exhibit decent linear fits over a wide range of slopes, much like the wheeled platform previously described.

With respect to climbing robots, our equation for $\hat{\varepsilon}$ is immediately applicable to behaviors on vertical terrain, even if such behaviors do not necessarily translate onto horizontal surfaces. By collecting data over a range of surface angles (and over a wide range, due to the fact that $\sin(\theta)$ changes slowly for angles approaching 90°), we can apply compensated specific resistance to experimental data from that of climbing robots.

We study the fitting of a linear model to the application of a robotic wall climbing machine. One version of the RiSE V2 robot, weighing 5.17 kg (noticeably heavier than prior description in [13] due to the recent addition of body actuation and sensor payloads), was tested on an angled stucco surface, ranging in angles from 60° to 80° in order to collect power information. The robot used an alternating tripod gait in an open-loop fashion, in order to provide as fair of a comparison as possible amongst various angles. Fig. 4 shows box-and-whisker plots of the specific resistance values at different angles, along with a locally linear fit.

Comparing to data presented in [8], the RiSE climbing robot’s performance, with a compensated specific resistance of 23.05 while climbing at an overall average of 2.2cm/s , is similar to quasi-static walking robot, not surprising as this version of RiSE is a quasi-static climbing robot. Future work intends to pursue similar comparisons for dynamic and fast climbing robots such as those described in [3] and [9].

Depending upon surface type and locomotion behavior, the locally linear fit may be insufficient to describe specific resistance’s relationship with gravity, such as when the challenge of a sloped terrain is too great for a mobile robot. An example of this is provided in Figs. 5-6. In a set of experiments conducted on an angled hill in a desert terrain, the X-RHex robot [7], an updated version of the RHex robot, was commanded to successively hike up and then down an angled hill. In a first set of experiments, the robot’s gait was commanded open-loop, shown in Fig. 5. In a second experiment, Fig. 6, the gait was modulated by the pitch angle of the robot while climbing, as anecdotal results indicate that RHex-style robots perform suitably better when an open-loop gait is offset by the pitch of the hill, thus keeping the legs under the robot’s body.

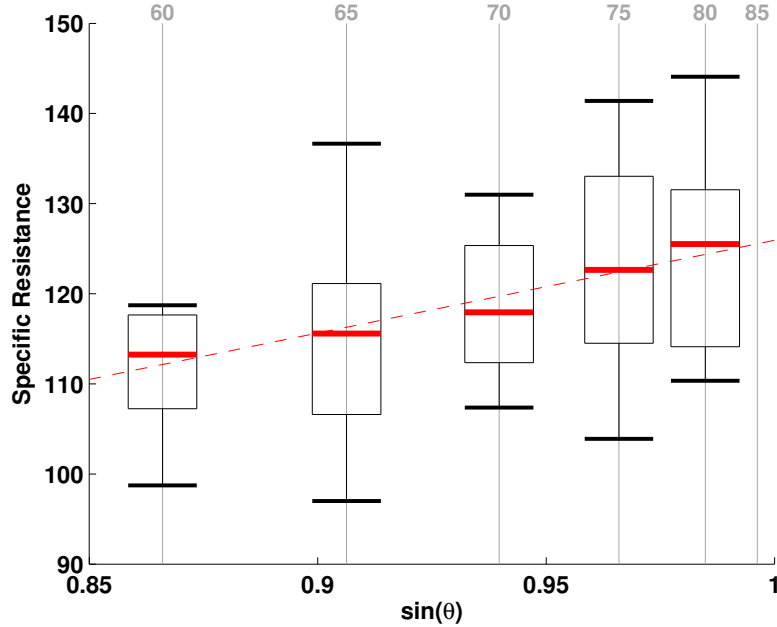


Fig. 4: Upon fitting a linear segment to experiments conducted with the RiSE climbing robot, we obtain the following values: $\hat{\varepsilon}(0) = 23.05$ and $\beta_0 = 102.9$. Vertical gray lines mark surface angle, in degrees.

The robot with pitch offset enabled for its gait consumes significantly less power to climb uphill, maintaining a suitably linear fit of specific resistance during hill climbing. Without pitch offset, the specific resistance is better described as a higher order polynomial, with a quadratic fit shown in Fig. 5.

5 Conclusions and Future Work

We have presented a modification to the calculation of specific resistance in order to take into account changes in gravitational potential during locomotion. By comparing data from several platforms, we have shown locally linear models to provide, in several cases, good methods for comparing locomotion on variously angled surfaces, while also suggesting that, in other cases, higher-order models are required.

The non-linearities sometimes encountered with our models are to be expected, and we believe they will be quite useful for behavior testing. The compensated version of specific resistance can be used to provide a near-

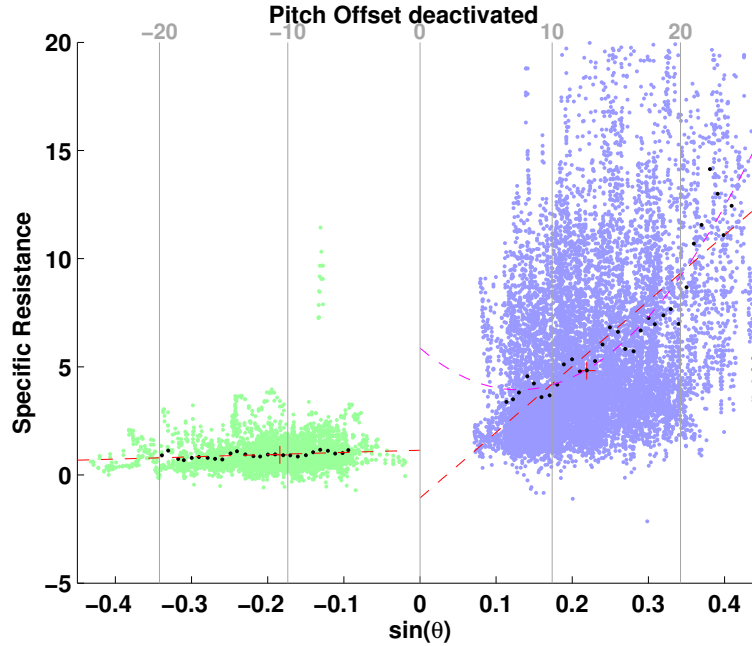


Fig. 5: X-RHex uses an open-loop gait to climb and descend an angled surface. While downhill locomotion (left-hand side) provides sufficiently good locomotion, the uphill locomotion (right-hand-side) gets dramatically worse with higher angle slopes. Both linear and locally quadratic line fittings of the raw data are shown.

constant value of locomotive efficiency over a range of locomotion scenarios on horizontal or sloped terrain. As such, noting highly non-linear events during locomotion can be useful, as they may allow a robot to easily realize times at which its behavioral strategy may be insufficient and should be changed due to changes in the surface and slope. Additionally, ranges of linearity for given platforms or locomotion styles may provide arguments for various gaits or methods of locomotion over others, depending upon performance.

Additional future work will continue the collection of data regarding climbing robots, tested over a wide variety of angles, in order to provide comparisons amongst many climbing platforms, in addition to the existing literature of level ground robot comparisons.

Lastly, we intend to test the application of this method to automated behavior tuning across a wide range of surface angles, to test whether our compensated version of specific resistance provides a better instantaneous measure of locomotive efficiency.

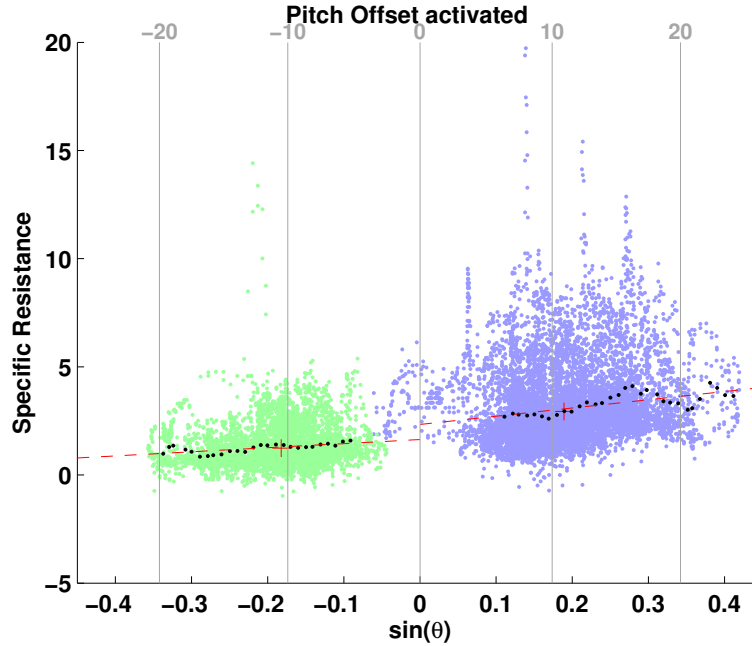


Fig. 6: In a second experiment, X-RHex uses a gait in which the robot’s legs are commanded to stay centered underneath the robot’s body, based upon the slope of the hill measured from an IMU. While going uphill (right-hand side) the robot maintains a nicely linear fit of specific resistance, indicating suitably good locomotion.

Acknowledgments

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References

1. Asbeck, A.T., Kim, S., Cutkosky, M.R., Provancher, W.R., Lanzetta, M.: Scaling Hard Vertical Surfaces with Compliant Microspine Arrays. *International Journal of Robotics Research* **25**(12), 1165–1179 (2006). DOI 10.1177/0278364906072511
2. Bretl, T., Rock, S., Latombe, J., Kennedy, B., Aghazarian, H.: Free-climbing with a multi-use robot. In: *International Symposium on Experimental Robotics* (2004)
3. Clark, J., Goldman, D., Lin, P., Lynch, G., Chen, T., Komsuoglu, H., Full, R., Koditschek, D.: Design of a bio-inspired dynamical vertical climbing robot. In: *Robots: Science and Systems*. Atlanta, GA (2007)

4. Collins, S.H., Ruina, A., Tedrake, R., Wisse, M.: Efficient bipedal robots based on passive-dynamic walkers. *Science* **307**, 1082–1085 (2005)
5. Degani, A., Shapiro, A., Choset, H., Mason, M.T.: A dynamic single actuator vertical climbing robot. In: *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 2901–2906 (2007)
6. Gabrielli, G., von Karman, T.H.: What price speed? *Mechanical Engineering* **72**(10), 775–781 (1950)
7. Galloway, K.C., Haynes, G.C., Ilhan, B.D., Johnson, A.M., Knopf, R., Lynch, G., Plotnick, B., White, M., Koditschek, D.E.: X-RHex: A highly mobile hexapedal robot for sensorimotor tasks. Tech. rep., University of Pennsylvania (2010)
8. Gregorio, P., Ahmadi, M., Buehler, M.: Design, control, and energetics of an electrically actuated legged robot. *IEEE Transactions on Systems, Man, and Cybernetics* **27**, 626–634 (1997)
9. Haynes, G.C., Khripin, A., Lynch, G., Amory, J., Saunders, A., Rizzi, A.A., Koditschek, D.E.: Rapid pole climbing with a quadrupedal robot. In: *IEEE International Conference on Robotics and Automation*, pp. 2767–2772 (2009). DOI 10.1109/ROBOT.2009.5152830
10. Jensen-Segal, S., Virost, S., Provancher, W.: Rocr: Energy efficient vertical wall climbing with a pendular two-link mass-shifting robot. In: *IEEE International Conference on Robotics and Automation* (2008)
11. McGeer, T.: Passive dynamic walking. *International Journal of Robotics Research* **9**(2), 62–82 (1990)
12. Saranli, U., Buehler, M., Koditschek, D.E.: Rhex: A simple and highly mobile hexapod robot. *International Journal of Robotics Research* **20**(7), 616–631 (2001). DOI 10.1177/02783640122067570
13. Spenko, M.J., Haynes, G.C., Saunders, J.A., Cutkosky, M.R., Rizzi, A.A., Full, R.J., Koditschek, D.E.: Biologically inspired climbing with a hexapedal robot. *Journal of Field Robotics* **25**(4-5), 223–242 (2008). DOI <http://dx.doi.org/10.1002/rob.v25:4/5>
14. Weingarten, J.D., Koditschek, D.E., Komsuoglu, H., Massey, C.: Robotics as the delivery vehicle: A contextualized, social, self paced, engineering education for life-long learners. In: *Robotics Science and Systems Workshop on "Research in Robots for Education"* (2007)
15. Weingarten, J.D., Lopes, G.A.D., Buehler, M., Groff, R.E., Koditschek, D.E.: Automated gait adaptation for legged robots. In: *IEEE International Conference on Robotics and Automation*, vol. 3, pp. 2153–2158 (2004)