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MOBILE SERVICE ROBOTS LOCAL PATH PLANNING USING ENERGY EFFICIENT DYNAMIC WINDOWS

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ABSTRACT

This paper presents an energy-efficient local path planner for unidirectional battery-powered mobile robot navigation in dynamic situations. The suggested technique adds a cost function based on energy usage to the Dynamic Window Approach (DWA). An on-the-fly trained linear regression model is used to forecast the projected energy usage during planning. On a mobile robot platform, empirical findings demonstrate a 9.79% reduction in energy usage compared to the DWA technique.
Key Words: DWA, algorithm,

1. INTRODUCTION

Energy efficiency is a major goal for any technical system. Challenges like global warming and sparsity of fuel sources increase the importance of this topic. In the context of a mobile robot as a product, this goal has to be transformed into the economic system as described by Luhmann (1994). It is possible to transfer this into a more product focused interest: Energy efficiency leads to battery power saving. A system that drains less current from its battery can potentially run longer. The aspect of an increased battery life is a competitive advantage.

This paper focuses on energy efficiency in robot naviga- tion. The topic of path planning is well studied from a theoretical point of view. This led for example to the popular graph search algorithms like A* Hart et al. (1968) and Dijkstra Dijkstra (1959). The practical use of path planning for omni-directional mobile robots demands the additional consideration of energy efficiency as an opti- mization criterion. A short path length is necessary for an energy efficient route but it is not sufficient because the energy consumption also depends on the velocity profile.

A practical approach is the analysis of motor control in terms of energy efficiency by Trzynadlowski (1988); Barili et al. (1995); Sheta et al. (2009); Zhao et al. (2013). Similar studies on non mobile robotic arms are: Katoh et al. (1994); Shiller (1996); Verscheure et al. (2008). In contrast, this approach considers energy efficiency on a higher level of robot motion as mobile robot navigation has a higher dimensional search space which needs to be considered. The additional dimensions are based on the mobility of the robot. Kim and Kim conducted research on energy-efficient solely transitory trajectories for three omniwheeled robots using an analytically optimised algorithm in 2005, 2008, and 2014. This research takes things into account since energy consumption, particularly for larger robots, relies on how rotations and curved trajectories are executed. Similar robots were employed by Mei et al. (2004, 2005, 2006) to study energy efficiency in terms of exploration, search, and deployment. As a subproblem of exploration and other top-level robot operations, point-to-point navigation is the subject of this study as opposed to those other activities.

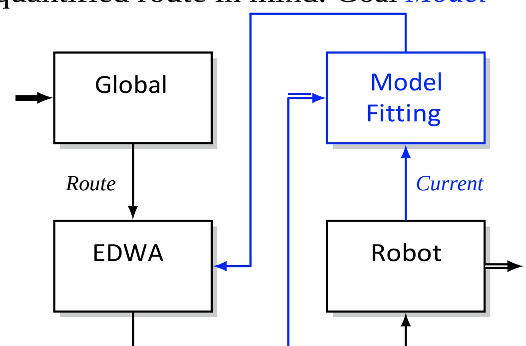
Similar to the energy model mentioned in this work, Liu and Sun (2011, 2012, 2014) employed it, but they saw energy efficiency as a global planning problem and extended the A* algorithm to it. This method, in contrast, addresses it as a local planner issue since the robot must be capable of quickly adapting to changes in the environment. Global considerations would become outdated as a result of these developments, which would cause the robot to abandon the global plan.

The next section of this paper explains which general considerations have been made. It describes basic factors which influence the energy consumption of a mobile robot. In Section 3 the main contribution of this paper, the developed Energy Efficient Dynamic Window Approach (EDWA) algorithm which is an extension of the Dynamic.

Window Approach (DWA) planner is introduced. It also covers the linear model that is used and discribes the use of linear regression to fit the model. Empirical results with the Mecanum wheel based AuckBot are presented in Section 4.

2 .ENERGY CONSIDERATIONS

This is a general consideration of the factors which in- fluence the energy consumption of a mobile robot. The aspects are defined platform independent. They are gener- ally applicable to any holonomic mobile robotic platform. All the mentioned aspects are explained with a quantified route in mind. Goal *Model*



Often navigation is defined to be time optimal (see Shiller (1996)). In contrast, this paper solely speaks about energy optimization because time optimality is for all practical robots considered to be a necessary condition of energy efficiency. This is mostly due to idle currents which are consumed by a robot even without motion. That idle current consumption means a robot spending less time to reach its goal potentially needs less energy than one taking more time.

Route Length

A basic requirement for a planned route regards the length. The path from the current position (s) to the goal (e) over all length segments dL_i should be as short as possible. Any additional length would require more energy.

Smoothness of Motion

The mathematical notion of smoothness is defined as the existence of derivatives in a possibly high order. This should be a goal for a robots trajectory, since jerky motion can create vibrations which result in energy loss (see Rao (2007)). This is taken into account by the inclusion of the acceleration into the cost function. Which is described in Subsection 3.5. Higher order derivatives are currently not considered because data for those are expected to have high noise and it is therefore unlikely to create any benefit.

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ENERGY EFFICIENT DYNAMIC WINDOW APPROACH

The creation of a energy efficient local planner is stud-

min dL_i

$i=s$(1)ied by the creation of a model based cost function that

evaluates potential trajectories in terms of their expected energy consumption. The model on which this cost func-
In the presented architecture (see Figure 1) this require- ment is met by the global planner which uses the previ- ously mentioned Dijkstra (1959) algorithm. Also the local planner which is proposed here, prefers short trajectories as described later.

Pose Efficiency

A robot has a set of possible movement poses C, which have different energy consumptions E. It is a goal to move for as many route sections dL_i as possible in an efficient pose p.

$$\min_{p \in C} \sum_{i=s}^{e} E(dL_i, p) \qquad (2)$$

For most configurations this is mainly influenced by the robots heading angle. For example, in the case of a Mecanum wheeled robot the amount of wheel slippage varies for different directions of movement. In this ap- proach this aspect is taken into account by the splitting of the motion into the two planar Cartesian components. This way the model can include information about the advantage of one direction of movement over another.
tion is based is fitted dynamically using online data. The architecture necessary for this setup is described in the following Subsection.
Architecture
To be able to include the necessary modules a specific architecture is designed. Figure 1 shows the general struc- ture of the used architecture. The left boxes symbolize the basic planner infrastructure, consisting of a *Global Planner* which receives the current goal as input and produces a route from the robots current position to this goal. This route is input for the *EDWA Planner* as local planner which is intended to make the robot follow this route. This is where the cost function described in Subsection 3.5 is implemented. The velocity commands are sent to the robot using the *Robot Driver* module which is where the electri- cal current consumed by the robots motors is measured as well. This data is used by the *Model Fitting* component together with the velocity commanded to the robot to fit a model to this data, which is described in Subsection 3.6. This model is fed back to the *Local Planner* to be used for planning.

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The setup consisting of global planner, local planner and robot driver is popular in robot navigation. This approach 01adds a component for the model fitting (see blue highlights in Figure 1) and extends the local planner component.

Dynamic Window Approach

The base algorithm used as local planner for this paper is the Dynamic Window Approach introduced by Fox et al. (1997). It can be summarized to three steps:

(1) Creation and simulation of a number of possible trajectories based on the robots current dynamic state. Excluded are such trajectories that lead to obstacles or exceed configuration speed constrains. All possible trajectories lay in this dynamic window.

(2) Evaluation of the created trajectories based on certain cost functions concerning the distance from the path and the goal as well as the heading towards the goal.

(3) Execution of the best trajectory i.e. the one with the lowest overall cost. Which makes the robot move in this trajectory.

The DWA was chosen as it is readily expandable by the inclusion of additional cost functions. The discrete creation of any potential trajectories makes it possible to evaluate those as hypotheses. Because the basic concepts of obstacle avoidance and path following are already included into the algorithm, those aspects do not need to be considered any further.

Energy Analysis

To integrate an estimate of energy consumption into the DWA planner, a model of the energy consumption of the robot was developed. The model is based on three types of energy in the system which is partially motivated by Liu and Sun (2014):

(1) **Electric Energy** E_{el} depending on Voltage U, cur- rent I at the time t:

$$E_{el} = U \cdot I \cdot t \qquad (3)$$

For the idle current which is present independent of robot motion.

Motor Magnetization

- Motor Saturation
- Motor Resistance
- Battery Resistance
- Electronics Heat Radiation
- Ground Friction
- Bearing Friction
- Wheel Slippage
- System Vibrations

Model Definition

The model is defined based on the robotic energy analysis. It is dedicated to make a prediction of the estimated energy consumption of any given trajectory.

The speed of the robot in x,y-direction, yaw rotation $[v_x \quad v_y \quad v_\theta]$ and the accelerations $[\dot{v}_x \quad \dot{v}_y \quad \dot{v}_\theta]$ build the model vector X. With the model parameter vector β the predicted current consumption I_t is defined as:

$$I_t = [1 \; |v_x| \; |v_y| \; |v_\theta| \; |\dot{v}_x| \; |\dot{v}_y| \; |\dot{v}_\theta|] \cdot \beta^T = X \cdot \beta^T (7)$$

This predicts the current for one discrete section of trajec- tory.

The energy for the whole trajectory E_{traj} is given consid- ering the constant supply

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voltage U and time slot length t. With traj being the summation over the whole trajectory.

$$E_{traj} = (I_t \cdot t) \cdot U \quad (8)$$

traj

Energy Efficient Cost Function

Based on the defined model of the energy consumption of a trajectory the following calculation for the trajectory cost is performed. This is calculated for each trajectory generated by the DWA as described in Subsection 3.2. The cost component for the trajectory energy C_{Et} is based on the trajectory length l_t and the number of samples in this trajectory n.

(2) **Frictional Energy** E_{fric} depending on speed v,

frictional constant C and the distance s: $CEt = \frac{1}{l} \sum (X \cdot \beta^T) \cdot (n-1)$ (9)

$E_{fric} = F_f \cdot s = v \cdot C \cdot s$ (4) The friction in the whole system is considered as being depending on speed of movement.

(3) **Acceleration Energy** E_{acc} depending on accelera-tion a and the accelerated mass m: traj

The consideration of only trajectory costs would lead to mostly slow movements of the robot, if this is considered energy efficient. To additionally make a prediction for the remaining route, the following route energy cost

C_{Er} is $EaccF_a$

$\cdot s = a \cdot m \cdot s$ (5).

The distance s is assumed to be constant on short distances. The increase of kinetic energy is considered using the acceleration of the system.

It assumes no further acceleration during the path. It therefore assumes the speeds at the end of this trajectory as constant and the mean over x and y-direction $\overline{v}$.

for a trajectory E_{traj}:

$$Etraj = Eel + Efric + Eacc \quad (6)$$

$CEr = r1$ T l

$-\, l\, ([1\ |v_x|\ |v_y|\ |v_\theta|\ 0\ 0\ 0] \cdot \beta)\ l_r\, \overline{v}$ (10) $\frac{}{t}$.

The trajectory energy in this setup is measured electric energy similar to (1).

This model includes also further energy forms and lossesThe previously defined cost functions in (9) and (10) are combined and weighted in respect of the trajectory length l_t and route length l_r.

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that are either constant, speed proportional or acceleration proportional. Therefore, it does not consider components of the following losses that are not proportional to motion: $C = \frac{l_t C_{Et} + C_{Er} \cdot (l_r - l_t)\ E}{l_r}$

Model Fitting

The performance of the previously mentioned cost function depends on the model parameter vector β. This setup includes a feedback of this model parameter from a model fitting component. This is visualized in Figure 1. Input to the model fitting component is the velocity command and the measured overall motor current I_m.
To fit the model, a basic linear regression approach is used. In this the model error J is defined as:

$$J = \sum_{o} (X \cdot \beta^T - I_m)^2 \qquad (12)$$

Waypoint B

Waypoint A

This is calculated as sum over a number of o previous measurements to be robust and independent of sudden changes.
For every new measurement the gradient grad is calculated based on the partial derivative of the model.

$$\text{grad} = (X \cdot \beta^T - I_m) \cdot X \qquad (13)$$

And the model parameter is updated accordingly.

$$\beta = \beta - \alpha \cdot \text{grad} \qquad (14)$$

A basic linear regression approach would require the learning rate α to be scalar. Instead this setup uses a variable learning rate approach which is described below.

Variable Learning Rate

If the previously mentioned model update (14) uses a scalar learning rate, it would produce unwanted behavior due to irregular presence of input data. As the acceleration data input is produced numerically based on past measure- ments, it is only available if the speed command changes. In contrast, the idle current is evaluated (see (7)) for every iteration. This would lead to a relatively fast convergence of the parameter vector component that is concerning the idle current and to a comparatively slow convergence of those components concerning other inputs.
To compensate these asymmetries the concept of variable learning rates is introduced (similar to Bowling and Veloso (2002)). A custom learning rate is calculated for every input feature. The α vector entry number i is defined as α_i. It is based on the length of the buffer of previous measurements used in (12) and the number of nonzero occurrences of the respective feature i during this buffer o_{Xi}. The regular learning rate, which would be used in a
regular linear regression is included as α_0.
drive motor has been equipped with one sensor that tracks its current consumption. The results of the sensors are summed to build the input for the model fitting component.

The tests were performed using the ROS Navigation Stack (see Marder-Eppstein et al.

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(2010)) which was set up for this robot. The source of both the test setup and the presented algorithm is available online [1].

Test runs were performed in the environment shown in Figure 2. The test space is a research laboratory which represents a partially dynamic situation. During the measurements small sections of the surroundings were changed due to moved furniture or moving people. This is consid- ered a realistic setting, since a mobile robot can not expect a fully static environment.

The robot was commanded to navigate back and forth between the waypoints A and B. The routes between the waypoints had an average length of 6.95 meters, depending on the path chosen by the robot. It required the robot to perform more than π radians of rotation for most of the trips. This is considered a representative navigation task, since it had a length that is long enough to contain both acceleration and constant speed sections. The goals were also chosen for the route to contain both rotational and transitory sections which represents a good combination of possible practical usage scenarios.

4.2 Energy Consumption

$\alpha_i = \alpha_0 \boldsymbol{Xi}$(15)

The main result is a comparison between the planner

with the cost function described in this paper and the

If for example the feature would hold a nonzero value half of the time, this factor would be 2 α_0. Experiments show that α_0 = 0.01 leads to useful results. For more experimental data see Subsection 4.3.

RESULTS

4.1 Setup

The previously described planner setup was tested using a Mecanum Wheel based platform as described by Xie et al. (2015). The existing robot was expanded using current sensors to measure current of each motor. Eachtraditional DWA algorithm. 10 trips were evaluated per configuration. Mutual constrain of the compared configurations is the duration to reach the goal. The configura- tions are tuned to meet this constraint, so as to make both current consumptions comparable. The results in Figure 3 show a 9.79% mean energy reduction by using the EDWA algorithm.

The compared setups are tuned to take the same time to reach the goal. This is done by altering the constrains on maximum velocity separately for both setups.

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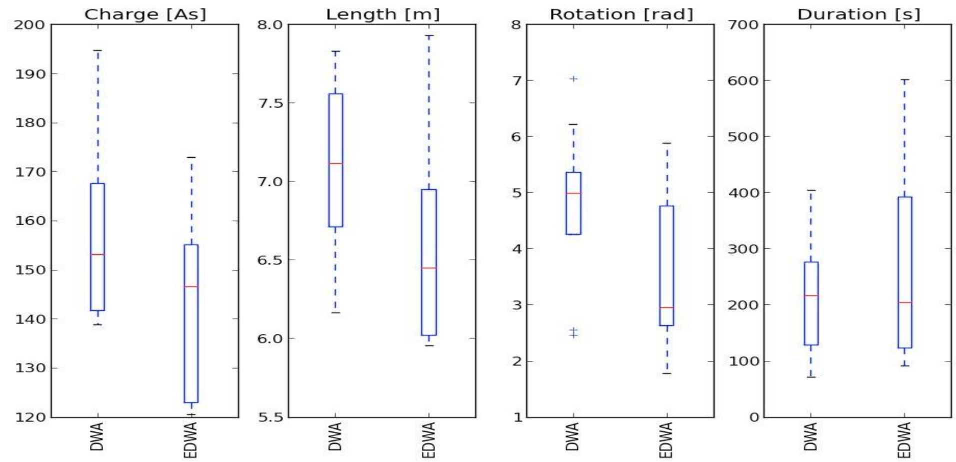

Fig. 3. Box plots indicating charge, length, rotation and duration of the test runs. Every value allows comparison between DWA and EDWA test setups.

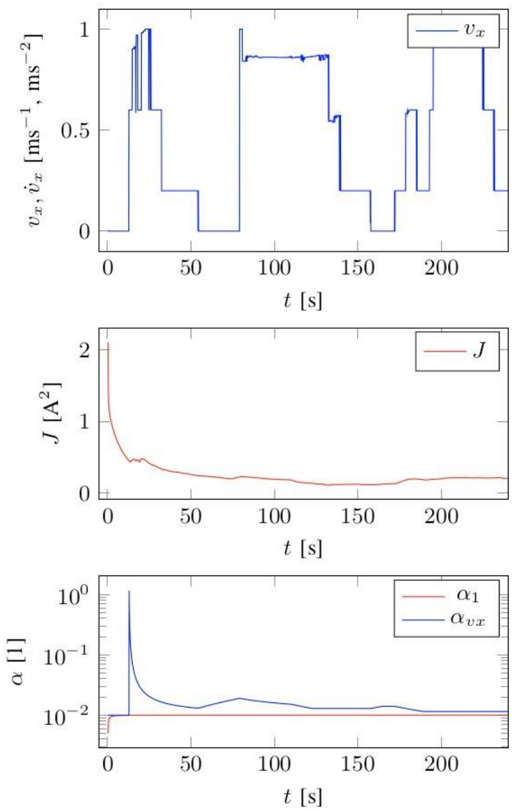

Fig. 4. Plot illustrating the model fitting on recorder d
ata: Speed in x-direction; error of the model while learning; Variable Learning Rates for the model

energy comparison has the unit of electrical charge, since the consumed current was multiplied by the time to make it comparable. The results show that all measured metrics have a big variance which is due to the dynamic environment and the robot choosing small path alterations for every trip.

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4.3 Variable Learning Rate

Using recorded data the convergence of the model using the variable learning rate was tested. By watching the model error it is possible to determine whether the model converges to a solution. This was mostly done to monitor the values of the variable learning rate.

Figure 4 shows in the top section a measurement of the speed in x-direction. The middle section shows the model error decreasing as the model diverges. The bottom section shows the variable learning rates for the speed data entry and the idle current. It is visible that the speeds learning rate changes with the availability of corresponding data. The higher peak at the beginning of the data is due to the zero velocity at the beginning at the measurement. As the time elapses more non-zero measurements are included into the calculation which lets the variable learning rate decrease.

1. CONCLUSIONS

The practical optimization criteria for mobile robot navigation is energy consumption. It is demonstrated how several aspects are important for the energy efficiency of mobile robot navigation. Therefore, no straightforward, one-dimensional optimization can be used to tackle the issue.

It has been shown that the EDWA algorithm saves 9.79% energy in comparison to a DWA setup, while reaching thegoal in the same time and on the same global route. High variance in results indicates potential for improvements of energy savings.

The Variable Learning Rate approach proofs to handle such data well. It is capable of handling unsynchronized occurring data. The currently used model fitting setup is configured to also adopt to changes of the platform physics. If for example a robot in logistics would be equipped with this algorithm, it would handle additionally carried weight energy efficiently. This adaptability can be proven experimentally in future.

REFERENCES

1. Barili, A., Ceresa, M., and Parisi, C. (1995). Energy-saving motion control for an autonomous mobile robot. In , *Proceedings of the IEEE International Symposium on Industrial Electronics, 1995. ISIE '95*, volume 2, 674–676 vol.2. doi:10.1109/ISIE.1995.497266.

2. Bowling, M. and Veloso, M. (2002). Multiagent learning using a variable learning rate. *Artificial Intelligence*, 136(2), 215–250. doi:10.1016/S0004-3702(02)00121-2.

3. Dijkstra, E.W. (1959). A note on two problems in connex- ion with graphs. *Numerische Mathematik*, 1(1), 269– 271. doi:10.1007/BF01386390.

4. Fox, D., Burgard, W., and Thrun, S. (1997). The dynamic window approach to collision avoidance. *IEEE Robotics Automation Magazine*, 4(1), 23–33. doi:10.1109/100.580977.

5. Hart, P.E., Nilsson, N.J., and Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. *Systems Science and Cybernetics, IEEE Transactions on*, 4(2), 100–107.

6. Katoh, R., Ichiyama, O., Yamamoto, T., and Ohkawa, F. (1994). A real-time path planning of space manipulator saving consumed energy. In , *20th International Confer- ence on Industrial Electronics, Control and Instrumen- tation, 1994. IECON '94,*

volume 2, 1064–1067 vol.2. doi:10.1109/IECON.1994.397938.
7. Kim, C.H. and Kim, B.K. (2005). Energy-Saving 3- Step Velocity Control Algorithm for Battery-Powered Wheeled Mobile Robots. In *Proceedings of the 2005 IEEE International Conference on Robotics and Au- tomation, 2005. ICRA 2005*, 2375–2380. doi:10.1109/ ROBOT.2005.1570468.
8. Kim, H. and Kim, B.K. (2008). Minimum-energy trans- lational trajectory planning for battery-powered three- wheeled omni-directional mobile robots. In *10th Inter- national Conference on Control, Automation, Robotics and Vision, 2008. ICARCV 2008*, 1730–1735. doi:10. 1109/ICARCV.2008.4795788.
9. Kim, H. and Kim, B.K. (2014). Online Minimum- Energy Trajectory Planning and Control on a Straight- Line Path for Three-Wheeled Omnidirectional Mobile Robots. *IEEE Transactions on Industrial Electronics*, 61(9), 4771–4779. doi:10.1109/TIE.2013.2293706.
10. Liu, S. and Sun, D. (2011). Optimal motion planning of a mobile robot with minimum energy consumption.
11. In *2011 IEEE/ASME International Conference on Ad- vanced Intelligent Mechatronics (AIM)*, 43–48. doi:10. 1109/AIM.2011.6027010.
12. Liu, S. and Sun, D. (2012). Modeling and experimental study for minimization of energy consumption of a mo- bile robot. In *2012 IEEE/ASME International Confer- ence on Advanced Intelligent Mechatronics (AIM)*, 708– 713. doi:10.1109/AIM.2012.6265887.
13. Liu, S. and Sun, D. (2014). Minimizing Energy Consump- tion of Wheeled Mobile Robots via Optimal Motion Planning. *IEEE/ASME Transactions on Mechatronics*, 19(2), 401–411. doi:10.1109/TMECH.2013.2241777.
14. Luhmann, N. (1994). *Die Wirtschaft der Gesellschaft*. Suhrkamp Verlag, Frankfurt am Main, 6 edition.
15. Marder-Eppstein, E., Berger, E., Foote, T., Gerkey, B., and Konolige, K. (2010). The Office Marathon: Robust navigation in an indoor office environment. In *2010 IEEE International Conference on Robotics and Au- tomation (ICRA)*, 300–307. doi:10.1109/ROBOT.2010. 5509725.
16. Mei, Y., Lu, Y.H., Hu, Y., and Lee, C. (2004). Energy- efficient motion planning for mobile robots. In *2004 IEEE International Conference on Robotics and Au- tomation, 2004. Proceedings. ICRA '04*, volume 5, 4344–4349 Vol.5. doi:10.1109/ROBOT.2004.1302401.
17. Mei, Y., Lu, Y.H., Hu, Y., and Lee, C. (2005). A case study of mobile robot's energy consumption and conservation techniques. In , *12th International Conference on Advanced Robotics, 2005. ICAR '05. Proceedings*, 492–497. doi:10.1109/ICAR.2005.1507454.
18. Mei, Y., Lu, Y.H., Lee, C., and Hu, Y. (2006). Energy- efficient mobile robot exploration. In *Proceedings 2006 IEEE International Conference on Robotics and Au- tomation, 2006. ICRA 2006*, 505–511. doi:10.1109/ ROBOT.2006.1641761.
19. Rao, S.S. (2007). *Vibration of Continuous Systems*. John Wiley & Sons.
20. Sheta, M.A., Agarwal, V., and Nataraj, P.S.V. (2009). A new energy optimal control scheme for a separately ex- cited DC motor based incremental motion drive. *Inter- national Journal of Automation and Computing*, 6(3), 267–276. doi:10.1007/s11633-009-0267-4.
21. Shiller, Z. (1996). Time-Energy Optimal Control of Ar- ticulated Systems With

Geometric Path Constraints. *Journal of Dynamic Systems, Measurement, and Con- trol*, 118(1), 139–143. doi:10.1115/1.2801134.

22. Trzynadlowski, A. (1988). Energy optimization of a certain class of incremental motion DC drives. *IEEE Transactions on Industrial Electronics*, 35(1), 60–66. doi:10.1109/41.3063.

23. Verscheure, D., Demeulenaere, B., Swevers, J., Schutter, J.D., and Diehl, M. (2008). Time-energy optimal path tracking for robots: a numerically efficient optimization approach. In *in Proceedings of The 10th International Workshop on Advanced Motion Control*, 727–732.

24. Xie, L., Scheifele, C., Xu, W., and Karl A. Stol (2015). Heavy-Duty Omni-Directional Mecanum- Wheeled Robot for Autonomous Navigation. In *IEEE/IES International Conference on Mechatronics 2015*.

25. Zhao, Y., Wang, Y., Bortoff, S., and Ueda, K. (2013). Real- time energy-optimal trajectory generation for a servo motor. In *American Control Conference (ACC), 2013*, 1165–1170. doi:10.1109/ACC.2013.6579993.