Advances in Robotics Research
Advances in Robotics Research

Theory, Implementation, Application
Preface

This book is a collection of scientific papers presented at the German Workshop on Robotics—a convention of researchers from academia and industry working on mathematical and algorithmic foundations of robotics, on the design and analysis of robotic systems as well as on robotic applications. As a new event of the Deutsche Gesellschaft für Robotik (DGR, German Robotics Society), the workshop took place at the Technische Universität Carolo-Wilhelmina zu Braunschweig on June 9-10, 2009.

Covering some of the most important ongoing robotics research topics, this volume contains 31 carefully selected and discussed contributions. All of them were presented at the workshop that was attended by 80 researchers representing a wide range of research areas within robotics. The papers are organized in ten scientific tracks: Kinematic and Dynamic Modeling, Motion Generation, Sensor Integration, Robot Vision, Robot Programming, Humanoid Robots, Grasping, Medical Robotics, Autonomous Helicopters, and Robot Applications. Two invited talks by Antonio Bicchi and Atsuo Takanishi presented surveys of research activities in the fields of human-robot interaction and humanoid robotics.

The Program Committee was comprised of Karsten Berns, Oliver Brock, Wolfram Burgard, Martin Buss, Thomas Christaller, Rüdiger Dillmann, Bernd Finkemeier, Martin Hägele, Bodo Heimann, Dominik Henrich, Gerd Hirzinger, Alois Knoll, Helge-Björn Kuntze, Gisbert Lawitzky, Jürgen Roßmann, Roland Siegwart, Markus Vincze, and Heinz Wörn. After an extensive review and discussion process, the committee met at February 17, 2009, and composed the scientific program from a pool of 49 submissions.

Organizing scientific conventions with a high level of originality cannot be performed by individuals alone. One always has to intercommunicate, to discuss, to exchange knowledge and experiences—to work together. Without the help of many people, the organization of the meeting would not have been possible. This includes all Program Committee members as well as all technical reviewers. A special word of thanks goes to Ilona Engel for her great and diligent support during all stages of the organization and, in particular, for the work she did during the workshop. Ralf Westphal organized the Web site in an excellent way, and he was responsible for the registration procedure. Regarding design and layout of all handouts, Simon Winkelbach was our design specialist for all issues concerning the workshop. The greatest word of thanks is—of course—due to all authors and participants of the German Workshop on Robotics. Finally, we would like to acknowledge the financial support of the Technische Universität Carolo-Wilhelmina zu Braunschweig and the KUKA Roboter GmbH.

Braunschweig
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Torsten Kröger
Friedrich M. Wahl
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Joint Dominance Coefficients:
A Sensitivity-Based Measure for Ranking Robotic Degrees of Freedom

Klaas Klasing, Dirk Wollherr, and Martin Buss

Abstract. Many robotics applications require a weighting scheme for individual degrees of freedom in a kinematic linkage. Such schemes are used for example in path and motion planning algorithms to penalize large end-effector movements or scale distance computations for the retrieval of nearest neighbors. Most often, the weights are manually picked and heuristically adjusted for specific linkages. In this paper we propose joint dominance coefficients as a universal tool for estimating the influence of each degree of freedom of a robot on the overall robot displacement. The measure is easy to compute, converges quickly and can be applied to any kind of parameterized kinematic linkage, including tree-structured and closed kinematic chains. A mathematical derivation is provided along with application examples for various robotic linkages. The results show that the method accurately and reliably yields the desired weights.

1 Introduction

Most robotics applications involve kinematic linkages with several degrees of freedom (DoF). These DoF arise from revolute or prismatic joints that connect the robot links. The overall geometry of the robot is usually parameterized by the DoF of the base link (movement of the robot base) and the joint values (angles for revolute joints, distances for prismatic joints), which describe the robot configuration. A central question for many applications is how the overall robot displacement depends on the degrees of freedom of the robot. Such a dependency measure is useful for example in the context of path and motion planning applications, where DoF that cause larger displacements must be penalized by corresponding weights.

While for prismatic DoF there is a linear relationship between parameter change and robot displacement, for revolute DoF the overall displacement is a nonlinear
function of the robot configuration. As an example, consider a 20-link serial kinematic chain with equally long links connected by revolute joints. When the chain is fully extended, an angular change in the first joint has a much larger influence on overall robot displacement than the same angular change applied to the 19th joint in the chain. However, for a configuration in which the robot is ‘folded’ to its minimal expansion, for both the first and the 19th joint an angular change has the same effect on overall displacement. The influence of each DoF on robot displacement is therefore configuration dependent. The question addressed in this paper is whether there is a practically feasible way of assessing the influence of each DoF over all possible robot configurations.

The measure presented in the following provides an automated numeric procedure for assigning a weight to each degree of freedom that correctly captures the overall influence of the respective DoF on the robot displacement. To the best of our knowledge there exists no method that is able to generically derive meaningful coefficients similar to those obtained by our approach.

The remainder of this paper is structured as follows: Section 2 briefly reviews existing related methods. Section 3 presents prerequisites, a derivation of joint dominance coefficients as well as an efficient way to calculate the coefficients in practice. Section 4 demonstrates the application of the method to a number of different kinematic linkages. A discussion of the results and the applicability of the method is given in Section 5.

2 Related Work

The problem of weighting the links in a kinematic linkage is equivalent to the problem of scaling an underlying distance metric. In the field mechanism design finding suitable distance metrics for specific linkage topologies is an active research topic [1, 2]. In the context of sampling-based path planning suitable distance metrics are relevant for effective sampling [3], nearest neighbor searching [4] and local planning [5]. All of these works are related in that they try to provide a consistent and meaningful notion of distance within the topology defined by the linkage. In contrast, this paper is not concerned with deriving new metrics for specific linkages. Instead it aims to provide a universal numeric measure for each DoF in a linkage, which can then be used to adjust a given metric.

The proposed coefficients can also be used for the analysis of kinematic linkages. In this respect they are loosely related to swept volume [6, 7], which represents a powerful tool for analyzing the reachable workspace of a kinematic linkage. However, for the simple purpose of finding suitable weights for specifying DoF displacement influence, swept volume methods are somewhat of an overkill. While weights similar to the coefficients proposed in this paper could be derived from swept volume methods for many linkages, these methods are computationally expensive and require detailed geometric considerations. In contrast, the proposed joint dominance coefficients only need a parametrization of the forward kinematics as well as a number of representative points on the linkage. Although
only moderately sized tree-structured linkages are examined in this paper, the sampling-based nature of joint dominance coefficients makes them perfectly suitable for closed-loop parametrizations, such as [8], as well as systems with many DoF. In both cases analytical derivation of similar coefficients from swept volume quickly becomes infeasible because of the complexity increase.

Joint dominance coefficients are also loosely related to the individual Lipschitz constants that can be used to bound robot displacement for iterative collision checking [5]. While our approach provides an average value per DoF, the Lipschitz constants represent an upper limit for displacement on a per-DoF basis. To our knowledge there exists no automated generic procedure for deriving these constants; in fact in most path planning applications that utilize iterative collision checking, the DoF scaling is usually hand-tuned until certain displacement constants seem to be met.

3 Methodology

In this section the concept of joint dominance coefficients is derived and a method for efficient calculation of the coefficients is presented.

3.1 Distance Metrics

In the following we will assume that a robot \( \mathcal{A}(q) \) has \( n \) degrees of freedom that are parameterized by a vector \( q \in \mathbb{R}^n \), \( q = [q_1 \ldots q_n] \). The geometry of the robot \( \mathcal{A} \) is defined over either \( \mathbb{R}^2 \) or \( \mathbb{R}^3 \). The set of all possible robot configurations makes up the so-called configuration space \( \mathcal{C} \), or simply C-space [9, 5]. Each DoF is assumed to be bounded by joint limits \([q_i,\min, q_i,\max]\).

A central prerequisite for all research methods that utilize the configuration space of a robot is a notion of the distance between two configurations \( q \) and \( q' \). For many applications a simple Euclidean distance in joint space

\[
\rho_E(q,q') = \| q - q' \|_2
\]

works sufficiently well for the purposes of nearest neighbor searching, uniform sampling of configurations etc. However, if the linkage contains many revolute joints, the metric does not respect the topology of the configuration space and for many pairs of configuration \((q,q')\) does not reflect the actual displacement of the robot in the world.

A much better measure is provided by the so-called robot displacement metric [5]

\[
\rho_D(q,q') = \max_{a \in \mathcal{A}} \{ \| a(q) - a(q') \| \}
\]

\(^1\) For \( n + 1 \) links attached by \( n \) revolute joints the configuration space has the topology of an \( n \)-dimensional torus.
that yields the maximum distance that any point on the robot $A$ has been displaced. Unfortunately, $\rho_D(q,q')$ cannot be efficiently computed for generic kinematic linkages in practice, however, as we shall see in the following, it is possible to find efficient approximations.

### 3.2 Derivation of the Joint Dominance Coefficient Vector

To distinguish between the ‘importance’ of different degrees of freedom, a so-called joint dominance coefficient for each DoF/joint is proposed. This coefficient reflects how much a given degree of freedom influences the overall average displacement of the robot.

Fig. 1 Several representative points on a kinematic linkage can be used to approximate the robot displacement metric.

For simplicity of derivation consider the serial kinematic linkage depicted in Figure 1. Let the position of the end effector (in orange) with respect to frame 3 be denoted by $3^p e$. The values of the rotational joints $2^\text{nd}$ will be denoted by $q_1$, $q_2$, and $q_3$, and the corresponding homogeneous transformation matrices $T_1(q_1)$, $T_2(q_3)$, and $T_3(q_3)$. Then, the position of the end effector in world coordinates is given by

$$0^p e = 0^T_1 \cdot 1^T_2 \cdot 2^T_3 \cdot 3^p e = f(q). \quad (3)$$

The local sensitivity of the end effector position $f(q)$ with respect to the value of the $i$th joint $q_i$ is – for a given configuration $q^* = [q_1^*, \ldots, q_{i-1}^*, q_i, q_{i+1}^*, \ldots, q_n^*]$ – given by

$$\left. \frac{\partial f(q)}{\partial q_i} \right|_{q^*} = f'(q_i) \bigg|_{q^*}. \quad (4)$$

Note that the sensitivity derivative is a vectorial function of $q_i$. Taking the Euclidean norm of this vector to obtain its magnitude and integrating over the joint limits of the respective joint $q_i$ yields

$$\sigma_i(q^*) = \int_{q_{i,\text{min}}}^{q_{i,\text{max}}} \left\| f'(q_i) \big|_{q^*} \right\|_2 \, dq_i, \quad (5)$$

2 All derivation steps hold for prismatic joints as well as for more complicated tree-structured linkages, too.
Joint Dominance Coefficients

which is a scalar measure that indicates how much \( q_i \) influences end effector displacement over its joint range. Two further adjustments are necessary to obtain a meaningful coefficient for the entire configuration space: Firstly, sensitivity is a local measure that may drastically differ for different configurations. Since the goal is to have one coefficient per joint for the entire configuration space, the overall measure is aggregated by randomly sampling \( n_s \) configurations \( q_j^* \), where \( j = 1, \ldots, n_s \). The average influence of joint \( q_i \) on the end effector position is then given by

\[
\sigma_i = \frac{1}{n_s} \sum_{j=1}^{n_s} \int_{q_{i\min}}^{q_{i\max}} \left\| f'(q_i) \left| q_j^* \right\|_2 dq_i. \tag{6}
\]

Secondly, a good displacement metric should not only take into account the end effector, but essentially the movement of any link on the robot. The robot displacement metric from (2) would be an ideal measure for this but is hard to calculate in practice. We therefore propose to use a collection of \( n_p \) representative points \( p_1, \ldots, p_{n_p} \) on the robot for expressing the overall displacement. Obviously, the position of each point is calculated from a sequence of transformation matrices and can be represented by corresponding functions \( f_1(q), \ldots, f_{n_p}(q) \). Such points would usually be chosen at the robot base, at the origin of each coordinate frame and at each end effector. For the simple robot from Figure 1 all highlighted points would be chosen as representative points.

Then, the overall displacement between two configurations \( q \) and \( q' \) is expressed by the new metric

\[
\rho_P(q, q') = \sum_{i=1}^{n_p} \left\| f_i(q) - f_i(q') \right\|_2. \tag{7}
\]

Therefore, the overall average influence of a given joint on the robot displacement from (7), which we call joint dominance coefficient, is given by

\[
\sigma_i = \frac{1}{n_s} \sum_{j=1}^{n_s} \sum_{k=1}^{n_p} \int_{q_{i\min}}^{q_{i\max}} \left\| f'(q_i) \left| q_j^* \right\|_2 dq_i. \tag{8}
\]

When calculated for each joint, the resulting vector \( \sigma = [\sigma_1 \cdots \sigma_n] \) of joint dominance coefficients should be normalized to obtain

\[
\sigma^* = \frac{1}{\|\sigma\|_2} - \sigma = \frac{1}{\|\sigma\|_2} \begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{bmatrix}. \tag{9}
\]

This joint dominance coefficient vector indicates what percentage of the overall average displacement of a robot is caused by each degree of freedom.
3.3 Calculation of the Joint Dominance Coefficient Vector

In a practical implementation, the calculation of the partial derivatives $f'(q_i)$ as well as the analytical evaluation of the integral would require a symbolic math engine. Although the derivatives exhibit a certain structure and can be broken down into a finite series of $\sin$ and $\cos$ expressions that stem from the transformation matrices, arbitrary kinematic linkages may still cause arbitrarily complex symbolic terms that need to be integrated. For efficient calculation of $\sigma$ it is therefore desirable to have a numeric approximation of (8). Such an approximation can be achieved in two steps: Firstly, the derivative is substituted by a difference quotient, and secondly the integration is replaced by a summation. To this end each degree of freedom is gridded at a certain resolution and $n_r$ samples $q_i,1,\ldots,q_i,n_r$ are placed evenly between $q_i,\text{min}$ and $q_i,\text{max}$, i.e. $q_i,1 = q_i,\text{min}$ and $q_i,n_r = q_i,\text{max}$. For notational feasibility, let $q(i,k,l)$ denote the kth randomly generated configuration vector for which the $i$th entry (corresponding to the $i$th DoF) has been set to $q_i,l$. Then the resulting term for the approximated joint dominance coefficient is

$$\hat{\sigma}_i = \frac{1}{n_s} \sum_{j=1}^{n_p} \sum_{k=1}^{n_s} \sum_{l=1}^{n_r-1} \left\| f_j(q(i,k,l)) - f_j(q(i,k,l+1)) \right\|_2. \quad (10)$$

Since the vector is normalized in the end and $n_s$ is the same for all degrees of freedom the factor $\frac{1}{n_s}$ can be dropped. After rearranging the order of summation, one obtains

$$\hat{\sigma}_i = \sum_{j=1}^{n_s} \sum_{k=1}^{n_r-1} \rho_P(q(i,j,k),q(i,j,k+1)), \quad (11)$$

where $\rho$ is the displacement metric from (7).

To summarize, $\hat{\sigma}^*$ is calculated by generating $n_s$ random configurations, computing – for each configuration – the displacement $\rho_D$ between each two consecutive configurations spaced at $n_r$ even steps in $[q_i,\text{min},q_i,\text{max}]$ for the $i$th degree of freedom, adding all displacements for each $i$ and finally normalizing the vector. Note that the estimation has a runtime complexity of $O(n \cdot n_s \cdot n_r)$ and thus is linear in the number of DoF.

3.4 Remarks

Several remarks are in order for the chosen way of calculating the coefficients. Firstly, the algorithm relies on random sampling to aggregate the local sensitivity-based measures to an overall measure for the entire configuration space. Random sampling was preferred over sampling on a grid, because the number of samples on a grid increases exponentially with the number of DoF. In fact this is the same problem that led researchers to turn to sampling-based path planning as a means for solving high-dimensional planning problems. Consequently, much the same
requirements apply for the sampling sequence. Since we try to achieve a fairly uniform covering of the configuration space with a finite number of $n_s$ samples, the sampling sequence should be dense [5]. For our purposes we used uniform random sampling in the hypercube bounded by the individual $[q_{i,\text{min}}, q_{i,\text{max}}]$. A deterministic (quasi-random) alternative would be the use of Halton points [10]. Since the number of samples is known beforehand it is also possible to use Hammersley points [11] or lattice sampling [12].

A second remark concerns the convergence of the computation. A detailed proof is omitted due to space constraints but can be constructed along the following lines: The integral in the inner term of (8),

$$
\int_{q_{i,\text{min}}}^{q_{i,\text{max}}} \| f'(q_i) \|_{q_i} \, dq_i,
$$

has been replaced by its Riemann sum in (10), which implies asymptotic convergence as $n_r$ grows. The convergence of the overall coefficient with growing $n_s$ then depends on the continuous differentiability of the configuration space manifold, and the denseness of the sampling sequence. An empirical study of the convergence is presented in the following section, which allows for specifying recommended values for $n_r$ and $n_s$.

### 4 Application to Kinematic Linkages

To evaluate the meaningfulness of the proposed coefficients, the method was applied to the four kinematic linkages depicted in Figure 2. All of them represent robots in a

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Admissible DoF ranges for each robot.</th>
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<tr>
<td>Robot</td>
<td>DoF</td>
</tr>
<tr>
<td>---------</td>
<td>-----------</td>
</tr>
<tr>
<td>simple3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
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<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4,5,6</td>
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<tr>
<td>crab11</td>
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</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4,6,8,10</td>
</tr>
<tr>
<td></td>
<td>5,7,9,11</td>
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<td>tree11</td>
<td>1,3,4,5,6,8,9,10,11</td>
</tr>
<tr>
<td></td>
<td>2,7</td>
</tr>
</tbody>
</table>
Fig. 2 Four robots used for evaluation: (a) A simple robot with 3 DoF (b) A snake robot with 6 DoF (c) A crab-like robot with 11 DoF (d) A tree-like robot with 11 DoF.

Fig. 3 Joint dominance coefficients of the four robots. Translational and rotational DoF of the base link have the strongest influence (a), (b), and (c). For each DoF the coefficient nicely reflects the position in the kinematic tree and the available joint range.
2D world. Their respective degrees of freedom are marked by the numbered circles. The simple3 robot in Figure 2(a) can move in the horizontal direction and actuate its rotational joints. Both the snake6 robot and the crab11 robot can translate and rotate freely in the plane and actuate all indicated degrees of freedom. The tree11 robot has a fixed base, but can actuate any of its revolute joints.

Table III lists the admissible range of each DoF for all four robots. The translational DoF were constrained to the ranges usually used in planning scenarios, i.e. the size of the workcell the robot would move in.

The joint dominance coefficient vectors of the four robots are shown in Figures 3(a)-(d). The coefficients were calculated with $n_r = 20$ and $n_s = 100$. Quite clearly, the values nicely reflect the overall influence of each DoF. The translational DoF of the base dominate because they cause the largest displacement, regardless of the remaining configuration. After that, the rotation of the base has the greatest influence, followed by the hierarchy of the individual DoF in the kinematic tree.

Figure 4 shows the value of the first joint dominance coefficient $\hat{\sigma}_1^*$ of the crab11 robot plotted over different values of $n_r$ and $n_s$. It can be seen that the value converges quite quickly in $n_r$ and decently fast in $n_s$. For $n_r \geq 10$ and $n_s \geq 50$ the value remains invariant in the first three significant digits. Individual simulations over $n_r$ and $n_s$ for the other robots showed the exact same convergence behavior.

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3 Equivalent results would be obtained for a 3D world, as the displacement is measured by the sum of Euclidean distances and the joints are assumed to have only one revolute or prismatic DoF each.

4 Since the algorithm uses random sampling, each value was averaged over 20 runs. The variance was observed to converge proportionally with the mean.
5 Conclusion

In this paper we have presented Joint Dominance Coefficients, a novel numeric procedure for estimating the influence of each DoF in a kinematic linkage on the overall displacement. The algorithm makes use of random sampling in the configuration space to assess the displacement caused by a change in each DoF over its range. The method was observed to converge quickly and yield meaningful weights for various tree-structured kinematic linkages.

The presented applications mainly stem from our involvement with sampling-based path planning. In fact the proposed method was developed to overcome the repeatedly encountered problem of manually having to pick suitable weights for a given linkage; however, we expect that it can be useful far beyond the domain in which we have examined it. Future research could aim at extending the method to the mentioned Lipschitz constants or to providing coefficients for dynamic constraints, i.e. maximum joint velocities.

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References

Learning Kinematics from Direct Self-Observation Using Nearest-Neighbor Methods

Hannes Schulz, Lionel Ott, Jürgen Sturm, and Wolfram Burgard

Abstract. Commonly, the inverse kinematic function of robotic manipulators is derived analytically from the robot model. However, there are cases in which a model is not a priori available. In this paper, we propose an approach that enables an autonomous robot to estimate the inverse kinematic function on-the-fly directly from self-observation and without a given kinematic model. The robot executes randomly sampled joint configurations and observes the resulting world positions. To approximate the inverse kinematic function, we propose to use instance-based learning techniques such as Nearest Neighbor and Linear Weighted Regression. After learning, the robot can take advantage of the learned model to build roadmaps for motion planning. A further advantage of our approach is that the environment can implicitly be represented by the sample configurations. We analyze properties of this approach and present results obtained from experiments on a real 6-DOF robot and from simulation. We show that our approach allows us to accurately control robots with unknown kinematic models of various complexity and joint types.

1 Introduction

Robotic manipulators typically require a Cartesian controller that maps the three-dimensional world space coordinates to joint configurations. The equations for the inverse kinematics can analytically be derived in advance when a robot model is available. Careful parameter calibration then ensures high accuracy in positioning tasks.

In the emerging field of home robotics, robots are likely to be assembled without surveillance of an engineer, meaning that no accurate construction model is available at design time. Further, home robots need to operate for extended periods of