# Bioinspired Direct-Drive Legged Robot:

# Design Optimization of 5-bar Parallel Linkage Using OpenMDAO

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## ABSTRACT

The develop of quadrupedal robots and adaptable system control is becoming an increasing topic with the growing demand for using robot to explore unknown, hazardous environment. In this project, we aim to improve the mobility of quadruped by lowering the inertia effect of parallel linkage limbs, namely, optimizing the length of the linkage to reduce the mass. However, there is a trade-off between the linkage length and the working space. We thus define an adjustable end-effector trajectory as our minimum working space basing on some of the leading-edge quadrupedal robot, ex: Stanford Doggo [1], Ghost Minitaur [2] and MIT Cheetah [3][6]. To make both ends meet, we implement OpenMDAO [4], which is an open-source framework for efficient multidisciplinary optimization, to produce our optimal design of parallel linkage.


## I. INTRODUCTION

*Model*- Our unit model is a five-bar parallel linkage (Fig. 1,2) controlled by one ODrive BLDC controller, which contains two Quanum brushless DC motors, two primary aluminum links $L_1$ and two secondary links $L_2$ with all revolute joints. Also, we set the distance between two brushless motor as $w$. This distance is a critical value which demonstrates that the geometry is five-bar mechanism when it is nonzero. Overall, we studied the goal trajectory generated by the toe tip of secondary links and define its position as $(x, y)$.

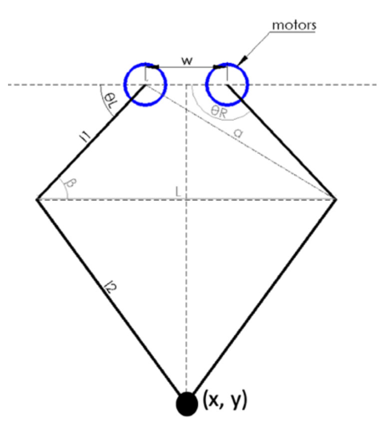


Fig. 1: Schematic draw

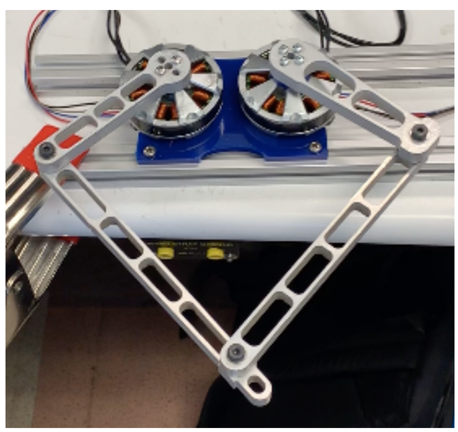

Fig. 2: Five-bar linkage design

| Design values | |
|---|---|
| $L_1(m)$ | 0.09 |
| $L_2(m)$ | 0.16 |
| $w(m)$ | 0.07 |
| $\theta_L$ | $0^{\circ} \sim 90^{\circ}$ |
| $\theta_R$ | $90^{\circ} \sim 180^{\circ}$ |

*The end-effector trajectory*- To generate a proper trajectory which defines the minimum and necessary workspace, we chose several state-of-the-art quadruped studies as our references for gait development. Inspired by the open loop trajectories mentioned in Ghost Minitaur [2] and Stanford Doggo [5], we then obtained a successful approach utilized piecewise sinusoidal function as shown below. (Fig. 3) $Swing\ phase$ is the portion when the end effector is off the ground (the yellow portion) and $stance\ phase$ is the part during it contacting to the ground (the purple portion). Also, the distance between touch down and lift off point defines the step length $L$. Overall, the design flexibility is excellent that the gait can be easily modified by varying the relative amplitudes, frequencies and step length.

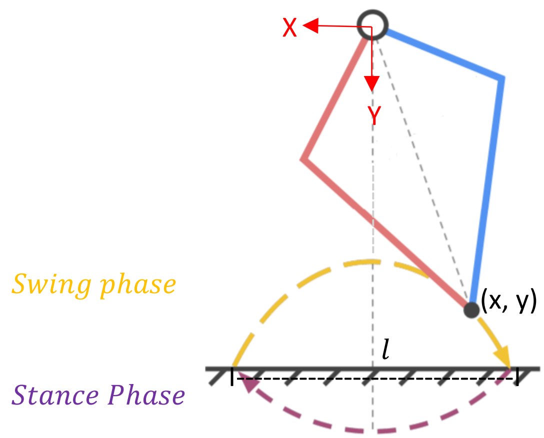

Fig. 3: Piecewise sinusoidal end effector trajectory

In practice, the end effector is constantly contacting to the ground during the stance phase and external force is applied to it. To assure that the design trajectory is closer to the ideal shape, we need to assign more control points to the *stance phase* than *swing phase*. Thus, we define some certain number of control points in each gait cycle. $ST\%$ and $SW\%$ is the percentage of control points during stance and swing phase. Also, they satisfy the following equation:

$$ST\,\% + SW\,\% = 1$$

Therefore, the sinusoidal trajectory points can be defined as following:

$$P\% = \ Current\%$$

$$l\ =\ Design\ Step\ Length$$

$$t =\ Stance\ Phase\ Amplitude$$

$$w = Swing\ Phase\ Amplitude$$

$$h = Robot\ Stance\ Height\ from\ the\ Ground$$

$if\ (P\% \leq ST\%)$

$$x = -\left({}^{l}/_{2}\right) + \left({}^{P\%}/_{ST\%}\right) * l$$

$$y = t * sin\left(\pi * {}^{P\%}/_{ST\%}\right) + h$$

$else$

$$x = \left({}^{l}/_{2}\right) + \left(P\% - {}^{\mathrm{ST}\%}/_{SW\%}\right) * l$$

$$y = -w * sin\left(\pi * \left(P\% - {}^{\mathrm{ST}\%}/_{SW\%}\right)\right) + h$$

## II. METHOD

*Structure of optimization system-* Aiming to build up multi-terrain adaptable quadruped, we look forward to the solution that increases the robot mobility and efficiently addresses the obstacles while traversing real world terrains. Therefore, the ideal of lowering the inertia effect of leg assemble while presenting the gait seems to be theoretically feasible. The following flow chart clearly illustrates the process of design optimization using gradient-base algorithm.

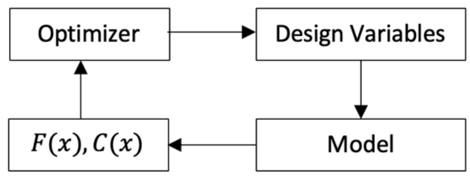


Fig. 4: Flow chart of optimization process

We can significantly lower the inertia effect $I = \int \rho r^2 dV$ by reducing length and mass simultaneously. (Fig. 4) In our case, length of the primary $L1$ and secondary link $L2$ are the objects. The kinematics of the five-bar mechanism can be easily derived from Forward Kinematics ($Fk$). Thus, the linkage length $L1, L2$ and motor angles $\theta_L, \theta_R$ are the design variables that form the optimization model. On the other hand, we choose the objective function $F(x)$ equals the total length of primary $L1$ and secondary link $L2$. The constraint function $C(x)$ is the minimum workspace defined by piecewise sinusoidal trajectory. (Fig. 6) Lastly, we select the $IndepVarComp$ and $ExplicitComponent$ class in Python, which are OpenMDAO frameworks, to configure our gradient-base optimizer.

$$(x, y) = Fk(L1, L2, \theta_L, \theta_R)$$

$$F(L1, L2) = L1 + L2$$

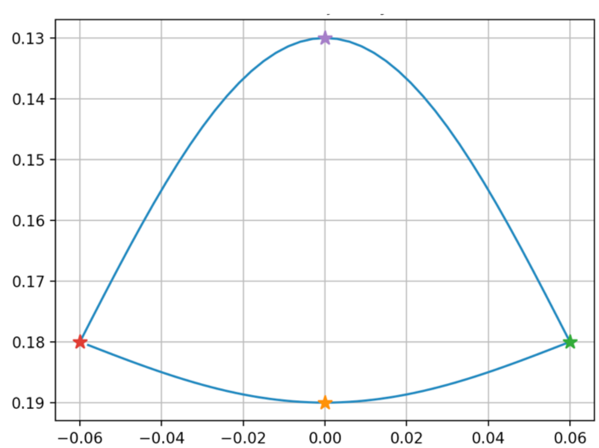


Fig. 5: The piecewise sinusoidal end effector trajectory

| Gait geometry | |
|---|---|
| Stance Phase Amplitude ($t$) | 0.01 |
| Swing Phase Amplitude ($w$) | 0.05 |
| Step Length ($l$) | $0.12\ m$ |
| Stance Height ($h$) | $0.18\ m$ |

$IndepVarComponent$ *set up-* All the independent variables $L1, L2, \theta_L, \theta_R$ are defined as independent outputs inside this component. The initial length of primary link $L1 = 0.09m$ and secondary link $L2 = 0.16m$. For the motor angles $\theta_L, \theta_R$, the left angle is usually around $0^\circ \sim 90^\circ$ and the right one is around $90^\circ \sim 180^\circ$. To avoid reaching the singular point, we set up a $2^\circ$ offset which shrank the working angle a little bit.

$ExplicitComponent$ *set up-* In this project, Forward Kinematics ($Fk$) and $objective\ function$ $F(x)$ are defined by using $ExplicitComponent$, which means all the output variables are explicit. We not only need to specify each input and output, but also the partial derivatives of outputs with respect to the inputs. In each optimizing iteration, more specifically, we define $L1$, $L2$ are input scalars ($L1 \in \mathbb{R}, L2 \in \mathbb{R}$) and $\theta_L, \theta_R$ are input vectors ($\theta_L \in \mathbb{R}^n, \theta_R \in \mathbb{R}^n$), where $n$ is the number of control points.

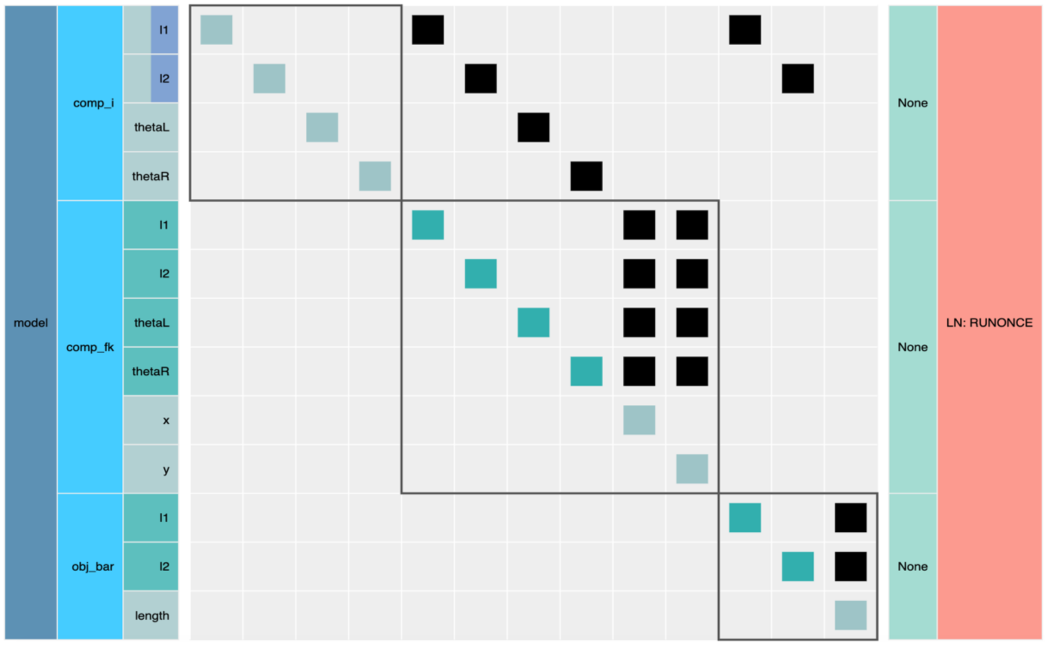


Fig. 7: Model tree of the optimization process using OpenMDAO

## III. RESULT

| | Initial values | Optimal values | Optimal values* |
|---|---|---|---|
| Primary link, $L1$ $(m)$ | 0.09 | 0.0578 | 0.0608 |
| Secondary link, $L2$ $(m)$ | 0.16 | 0.1548 | 0.1562 |
| Total length $(m)$ | 0.25 | 0.2126 | 0.2171 |

Fig. 8: Comparison between initial & optimal values

*Result analysis*- The optimization algorithm we used, which is called Sequential Least Square Programming (SLSQP), is the Han–Powell quasi–Newton method with a BFGS update of the B–matrix and an L1–test function in the step–length algorithm. From the optimal values shown above, the primary link $L1$ decreases the length by 35.78% and the secondary link $L2$ decreases the length by 3.25%. The total length is therefore decrease by 14.96%. However, given that we need to avoid reaching the singular point, a $5.4^{\circ}(\approx 0.03\pi)$ offset is applied to the working angle. The actual working angle of the left motor is $0^{\circ} \sim 84.6^{\circ}$ while the right one is $95.4^{\circ} \sim 180^{\circ}$. After implementing the offset, we get the new optimal values*. The primary link $L1$ decreases the length by 32.45% and the secondary link $L2$ decreases the length by 2.38%. The total length therefore decreases by 13.16%.

*Evaluate the inertia*- To calculate the inertia of primary and secondary link, we use the moment of inertia of rigid bar rotate about one end $I_{end}$ for both link and parallel axis theorem for secondary link:

$$I_{end} = {}^{1}/_{3} * mL^2$$

$$I_z = I_{center} + md^2$$

$$I_{center} = {}^{1}/_{12} * mL^2$$

From above equations, the inertia of primary link $I_{end\_1}$ decreases by 69.18%, and the inertia of secondary link $I_{end\_2}$ decreases by 45.34%. Overall, the total inertia of the leg assembly decreases by 48.42%.

## IV. CONCLUTION

*In terms of inertia-* According to the above result, primary link $L1$ decreases the length by 13.63 times larger than secondary link $L2$. The significant reducing of primary link length is the root cause that improves the mobility of our 5-bar parallel linkage mechanism. On the other hand, applying the safety offset to the working angle only causes a 1.8% difference in decrease of total length, which means the offset is not only necessary but also light-harmful to the optimization result.

*Out of the picture-* We look forward to torque and power optimization of the motors in the next stage of this project, since the kinematic model of our 5-bar mechanism is all set in the optimization framework from now on. In addition, OpenMDAO framework is born to cope with multidisciplinary design optimization. Implementing motor torque analysis and power consumption aspect to original model would be relatively easy and helps determine a more comprehensive optimization result.

## V. ACKNOWLEDGEMENT

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