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CNNs based Foothold Selection for Energy-Efficient Quadruped Locomotion over Rough Terrains *

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Abstract –When deployed in practical scenario, the legged robot has higher terrain passing ability but is suffering from lower locomotion efficiency than the wheeled robot. In this paper, we present a strategy that can improve the locomotion efficiency for a quadrupedal robot. First, an optimized energy-efficient nominal stance is generated. Second, a Convolutional Neural Networks (CNNs) based and self-supervised foothold classifier is implemented which will guide the robot to form the supporting legs in energy-efficient nominal stance during locomotion. The effectiveness of the present approach is validated on our quadrupedal robot Pegasus in stairs climbing experiment.

Index Terms – Quadrupedal robot. Energy-efficient locomotion. Convolutional Neural Network. Foothold classifier.

I. INTRODUCTION

When interacting with irregular terrains, on one hand, a legged robot has much more excellent traversability than a wheeled machine. However, on the other hand, the locomotion efficiency of the legged robots is very low. Most of the energy is wasted on locomotion other than on performing a mission. Therefore, if deployed in practical applications, one of the most urgent problems that has to be solved is to improve the locomotion efficiency in order to extend operation life on primary tasks.

The strategies for improving the locomotion efficiency of a legged robot can be classified into two categories: First, from the point view of optimized hardware design. Second, through the way of optimizing the control algorithms or locomotion parameters. The design objective of MIT Cheetah Robot [1] is to achieve very high locomotion efficiency. Based on a comprehensive design principle, the robot was equipped with very low inertial legs, high torque density motors and the energy regeneration modules. As a result, the energy loss from the major energy loss modes was minimized and the resulting Cost Of Transport (COT) is 0.51 which rivals running animals in the same scale Partial of the mechanical power generated during locomotion can be temporarily stored and reused to save energy consumption. The elastic elements were widely used on legged robots for energy regeneration. Both the StarlETH [2] and ANYmal [3] quadrupedal robot from ETHZ were equipped with the series elastic actuators (SEA) and have achieved high energy-efficient locomotion. Many legged walkers using passive dynamics [4] locomotion were reported, such as the bipedal robot Ranger [5] can walk with a quite low COT value of 0.19. However, those passive locomotion walkers have very limited movement versatility, thus, difficult to be extensively used in practical applications.

The other way to improve locomotion efficiency is through optimizing the locomotion parameters or the control strategy. The bipedal robot [6] achieved energy-efficient locomotion including running and walking by using the optimal gait parameters. The humanoid robot NAO [7] achieved efficiency dynamic walking with the optimized gait parameters which were identified with policy gradient reinforcement learning approach. The quadrupedal robot StarlETH can locomote efficiently with the help of an adaptive controller that can change the joint motors' torque distribution and feet contact force according to the internal sensor real-time readings. The locomotion efficiency of the quadrupedal robot presented in paper [8] was improved by applying the optimized foot trajectory.

However, the terrain information wasn't taken into account by the above proposed approaches using locomotion parameter optimization. The terrain information is very important heuristic knowledge and can be helpful in improving the locomotion efficiency as well as the mobile stability when the robot is interacting with challenging terrains. The paper [9] presented an energy optimal trajectory generation approach based on the energy heuristic and the terrain map. This energy-based searching approach can minimize the energy loss compared to the traditional distance-based search method. The Hexapod Robot Weaver [10] can auto adapt the gait parameters including stride height, stride frequency and virtual stiffness

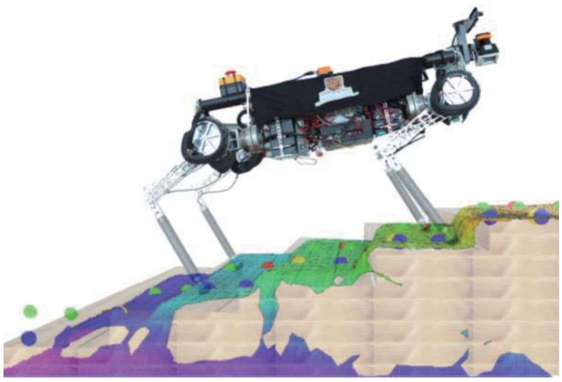

Figure 1. By employing our proposed CNN-based foothold classifier with the terrain map, the quadrupedal robot Pegasus can automatically climb a stairs efficiently.

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according to the real-time terrain information from both of the internal and exteroceptive sensors. As a result, the robot can walk with a low COT value on different rough terrains.

Our proposed method makes full use of the terrain information percept by an exteroceptive sensor such as a Lidar. The generated terrain map is as input to a CNN mode which learns to carefully select the footholds that can form in the optimized energy-saving nominal stance. As a result, the supporting legs are kept in energy-efficient postures during locomotion.

When the robot is dealing with challenging terrain, the foot placement locations should be selected carefully to avoid slippages as well as falls. The strategies for the foothold selection can be divided into three main categories: feature-based, template-based and CNN-based. First, the feature-based approach calculates the foothold traversability score by weighted summation of the terrain geometrical features such as roughness, slope and step height. Most of the legged robots are belonging to this category, such as the six-legged walker Ambler [11] and Lauron IV [12], the quadrupedal robot ANYmal [13], and the biped robot Lola [14], etc. Second, the template-based method learns the weights of the features of the template terrains based on expert demonstration and then uses the learned weights for the foothold selection. The template-based method is successfully applied to the quadrupedal robot LittleDog [15][16] and HyQ [17]. Third, the CNN-based strategy was firstly applied to HyQ [18] on foothold selection. Compared with the traditional Logistic Regressor, the CNN architecture is much more efficient in solving the classification problem while is suitable for real-time running. Furthermore, by using CNNS, the time wasted on manual adjustment of geometrical parameters of different terrains are saved. Another case can be found in [19].

We have implemented our foothold selection module based on the convolutional neural network. The foothold classifier not only takes into account kinematic constraints and terrain constraints but also considers energy-efficiency constraints.

In the following, Section II gives a brief introduction to the hardware architecture and software framework of our quadrupedal robot Pegasus. Section III shows the analysis on energy-efficient stance postures based on experimental results. Section IV introduces the CNN-based foothold classifier that can help our robot to realize energy-efficient locomotion. Section V shows the experimental result on a real quadrupedal robot platform. Section VI discusses the conclusions.

II. SYSTEM OVERVIEW

A. Pegasus Hardware Configuration

Our experimental platform is the quadrupedal robot Pegasus which weighs about 35.2 kg with 1.0 m long and 0.4 m wide. Each leg has three joints (hip, thigh and knee) powered by electric motors shown in Fig. 2. All the algorithms run on an onboard embedded computer (NVIDIA Jetson TX2) running Linux and ROS. To perceive the surrounding terrain information, a rotating lidar (Hokuyo UTM-30LX-EW) is mounted in the front of robot which rotates a full cycle at 1.5 s.

B. Navigation Framework

The robot is expected to navigate to the goal position as efficiently as possible. To achieve this objective, we developed an entire system architecture (shown as Fig. 3) which includes the following modules: localization, perception, mapping, foothold selection, swing-leg trajectory planning and COG trajectory generator.

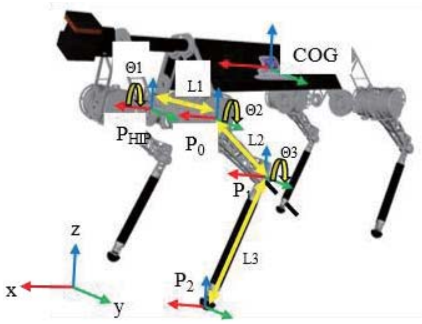

Figure 2. Leg configuration and frame definition of our quadrupedal robot Pegasus. The 3DOF leg joints are defined as hip (roll), thigh (pich) and knee (pitch).

All the modules are designed to cooperate with each other, the system working process is described as below: First, the perception module gets the 3D point cloud of the surrounding terrain from the rotating lidar. Second, the mapping module generates the elevation map with the point cloud. A Robot Operating System (ROS) package [11] was used for elevation mapping. The traversability map is calculated based on the elevation map. Third, the planning module generates the feasible footholds, COG trajectory and swing-leg trajectory based on the maps. Lastly, all the planned footholds and trajectories are transformed to joint motor commands to control the robot walk in stable and energy-efficient locomotion. The

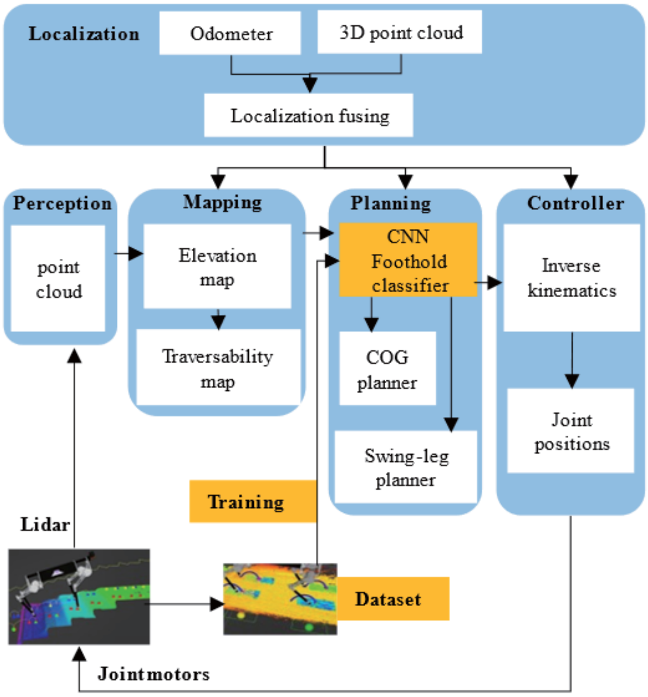

Figure 3. Overview of Pegasus navigation framework.

localization module supplies real-time pose states for the other modules. To correct the accumulated error caused by slippages, we fused the output of the odometer unit and point cloud localization unit as the final pose states.

In the navigation framework, the key module that contributes to achieve energy-efficient locomotion is the CNN-based foothold classifier which includes dataset collecting and training and online inferencing as marked with orange rectangles in Fig. 3.

III. Energy-efficient Nominal Stance

A. *Assumptions*

The objective of this paper is to design a CNN-based foothold classifier that can guide the robot to locomote in an energy-efficient way. Our designed optimization strategy is based on the following assumptions:

1) Hip joint neglected: For our quadrupedal robot Pegasus, there are three motors on each leg, i.e., hip, thigh and knee joint. The robot has the mobile capability in forward direction as well as in lateral direction. However, the lateral workspace is much smaller than the forward one. We will focus on the thigh and knee joint while neglecting the hip joint.

2) Swinging leg neglected: Creeping gaits are preferable for quadruped robot when interacting with challenging terrains with low speed. Locomoting with the creeping gait, the robot can achieve statically stable at most time [20]. We applied a six-creeping gait similar to [21] to our quadrupedal robot. The leg swing sequence is right-hind (RH), right-front (RF), left-hind (LH), left-front (LF). There exist two phases in a full cycle of six-creeping gait, the stance phase and the swing phase. For Pegasus, the power consumption of the swinging leg is much smaller than the supporting legs due to the leg is made of carbon fibre material. Therefore, we only pay attention on optimizing the energy consumption of the supporting legs while neglecting the swing leg'.

Based on the above assumptions, the focus of this paper lies on the energy-efficiency optimization of the thigh and knee joint of the supporting legs.

B. *Energy-Efficient Stance Posture*

For the supporting leg, different postures correspondent to different current values. The larger current value means larger energy consumption. To find the energy-saving postures for a supporting leg, we have launched an experiment on the real robot platform. In this experiment, the robot was commanded to do up and down movement alternately while the four feet stayed in a nominal stance. The current of thigh and knee joint are logged and the total current of each leg is calculated. By analyzing the current data, we found that the total current has the minimum value when the leg is almost bended or nearly stretched. Figure. 4 shows the changing tendency of the total current of the right hind (RH) leg during the up and down movement.

Based on the above experimental results, we can draw the conclusion that the leg should be bended or stretched as much as possible if the most energy-efficient leg posture is demanded. However, when taking into the kinematics and stability into

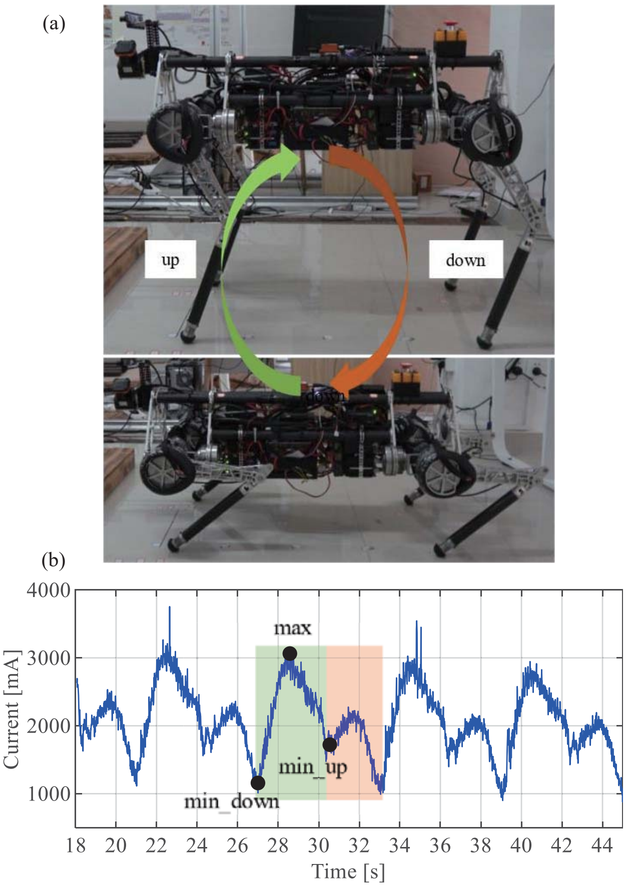

Figure 4. (a) Up and down movement. The minimum and maxmum COG height is 25 cm and 50 cm. (b) The corresponding total current of the right hind leg. The green filled marker corresponds to the up duration while the red one corresponds to the down process in (a), respectively.

account, neither the almost bended nor the nearly stretched posture is allowed. First, considering the passing ability over rough terrains, the COG height should be as high as possible. Second, the completely stretched posture should be avoided to increase the locomotion stability. Therefore, in order to walk efficiently as well as stably, our motion planning strategy prefers a higher COG height (the value is set to 0.48 m in this paper).

C. *Optimized Nominal Stance*

For a quadrupedal robot, the shape of nominal stance is of primary importance in increasing the locomotion stability and moving speed [22]. A nominal stance with parallelogram shape is widely used in statically walking gait. Our robot Pegasus also uses a parallelogram nominal stance which is parameterized with three parameters: stance length (L_{Stance}), stance width (W_{Stance}) and skew (L_{Skew}). The skew parameter plays an import role in helping the robot to move more stable and faster [22]. We experimentally found that our robot can walk more stable and faster if the skew value is set to half of the step length.

As a short conclusion, for our quadrupedal robot Pegasus, we get recommended nominal stance configurations: L_{Stance} =

0.8 m, W_{Stance} = 0.4 m, L_{step} = 0.2 m, L_{Skew} = 0.5*L_{step} = 0.1 m, COG height H_{COG} = 0.48 m.

The goal of the motion planner is to guide the robot to locomote with this recommended energy-efficient nominal stance.

IV. CNN-BASED FOOTHOLD CLASSIFIER

Foothold selection is of primary importance for the quadrupedal robot in successfully walking over rough terrains. Starting from our proposed nominal stance, the purpose of the foothold selection is to find the kinematical feasible footholds to the desired navigation goal. Additionally, when taking the energy-efficiency into account, the candidate footholds have to be able to form in optimized nominal stance to save energy. Compared to other traditional approaches, our proposed foothold selection approach is implemented by using a convolutional neural network.

A. Training Dataset Collection

To train the CNN network we have collected the elevation submaps on the global elevation map. As the robot was walking over the terrain, the corresponding submaps under the four feet were collected shown in Fig. 5. We have simulated different types of terrains in the Gazebo simulation platform and the robot has collected as many as about 10,000 samples

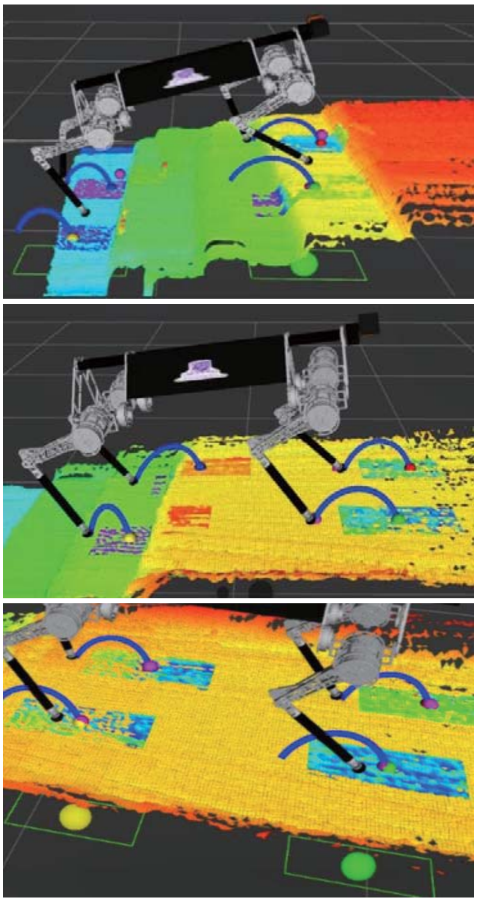

Figure 5. Sequence images showing that the robot is collecting elevation submaps (the small colour rectangle map) around the four feet locations as training data for CNN module.

for training. The size of submap is equal to the size of the foothold search region which is 8 × 32 with resolution of 1 cm per cell.

The training data are labeled automatically and the self-labeling procedure is described as below and depicted in Fig. 6. With the obtained four elevation submaps (Fig. 6a), first, we computed the traversability map (Fig. 6b). Similar to the method used in [23], our traversability score of the cell is computed from three terrain geometrical characteristics: the terrain roughness, slope angle and step height. The score describes the traversability for locomotion, i.e., a higher score stands for higher navigation traversablility. Second, we searched for the cell with the highest traversability score and nearest to the nominal foothold (Fig. 6c). The goal of this process is to find all the footholds (candidate foothold) that can

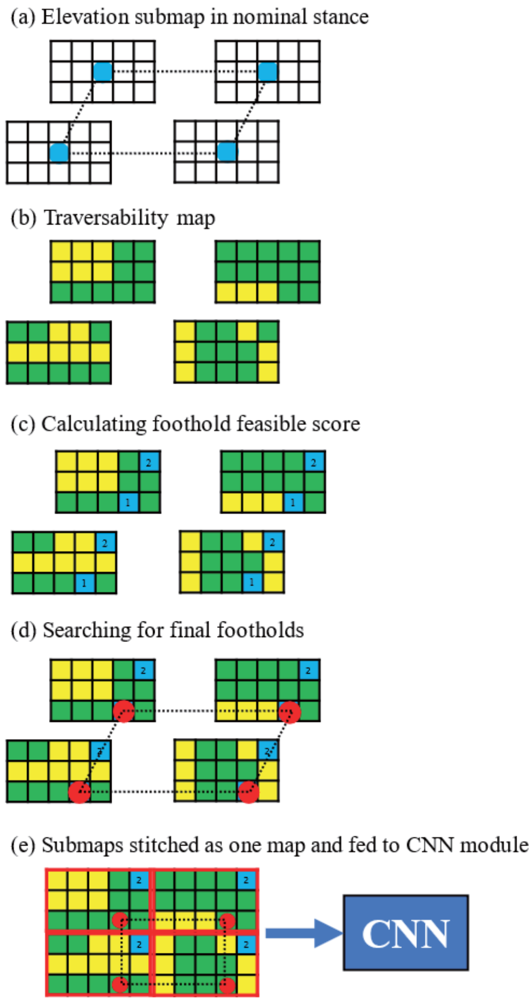

Figure 6. Auto labeling procedure. (a) Elevation submaps corresponds to the four feet placement. Blue spheres are nominal footholds. (b) Traversability map calculated based on terrain geometrical characteristics. Yellow cells are nonvalid and green cells are valid. (c) Foothold feasible score calculated based on the distance parameter. Blue cells are the candidate footholds that can form in nominal stance, and marked with a priority number (higher priority with higher foothold feasible score). (d) The cells with the highest foothold feasible score and can form in the optimized nominal stance are choosen as the final footholds (red spheres). (e) The four submaps are stitched as one map and fed to the CNN module.

form in the optimized nominal stance as described in Section III. And all those candidate footholds are marked with a priority number which corresponds to their feasible score. The search strategy is similar to ANYmal [13] which starts from the nominal foothold. However, a narrow rectangle search region is used instead of a circle because of the forward motion workspace more important than the lateral motion workspace while a quadrupedal robot walking forward. In this process, the foothold feasible score $F \in [0,1]$ of each cell is calculated depicted in (1).

$$F = 1 - \omega \frac{\mathrm{d}}{D} \tag{1}$$

where ω is the weight used for penalizing footholds which are far away from nominal foothold in forward movement direction. The value d is the Manhattan Distance to the nominal foothold. The ω is a constant value which is equal to half of the summation of the length and width of the foothold search region. Then, the candidate foothold with the highest priority number is labeled as the final foothold (Fig. 6d). As a result, all of the sample submaps can be labeled automatically. Lastly, the four labeled submaps are stitched as one map (Fig. 6e) that later will be used as the input of the CNN network. The labeled maps are converted to 8 by 30 matrices and saved in text files. Compared to grayscale images like [19], the matrices have the advantage in the efficiency loading into CNN network.

B. *CNN Architecture*

As described in Section IV, the CNN has one input image but with four classification outputs. Therefore, our foothold selection is a multi-label classification problem. We have designed a network that can deal with multi-label classification. A CNN architecture similar to [18] is used in this paper depicted in Fig. 7. The difference is that our network has four outputs that each stand for the final foothold of the RF leg, RH leg, LH leg and LF leg respectively. Because the input matrix size is 8 by 30, there are 240 potential footholds in each output one-hot vector. The structure of the network is simple but is accurate enough for our foothold selection.

With the labeled training data, our proposed CNN architecture can successfully learn the skill of how to find the footholds that are not only closest to the nominal foothold but also can form in the optimized energy-saving nominal stance.

C. *Online Foothold Classification*

In the first step, the robot gets elevation submaps from the built global map. The four submaps are stitched as one map and converted to matrix and fed the CNN network. In the next step, the network searches the final footholds that can form in the optimized nominal stance. For each final foothold, the search region is limited to the size of submap corresponding to its foot ID.

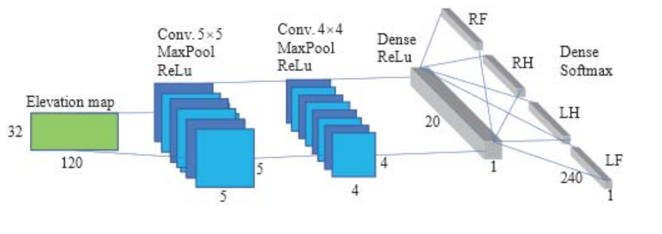

Figure 7. CNN architecture. The input is a 32×32 matrix of the stitched elevation map by the four submaps that corresponding to a foothold. There are two convolutional layers, 4 5 by 5 kernels and 8 4 by 4 kernels. Max Pooling is used in both layers to downsample the data. The output are the four one-hot vectors that each stands for one of the four legs.

Compared to similar CNN-based foothold selection method like [18] and [19], our CNN model can plan any user specified number of footholds (for example 4 footholds, 8 footholds, or 12 footholds, etc.) at one time of calculation.

V. Experiments

We have validated our approach on a real quadrupedal robot platform Pegasus. The optimized gait parameter settings for energy-efficient locomotion used in our experiments are summarized in Section IV. The gait cycle is 15 s.

By using our proposed navigation framework, the robot can automatically climb a set of standardized stairs with a run of 30 cm and a rise of 8 cm as depicted in Fig. 1 and Fig. 8a. The robot starts from the same starting position and stops until the last foot touched on the top of stairs, i.e., the robot travels approximately the same distance in these two comparative experiments.

The robot locomotion COT can be generated by the energy consumption divided by the product of velocity and weight [5]. We calculated each gait cycle's average COT and the averaged COT of the entire locomotion. First, the power consumption is calculated according to the equations in Ref [1]. The total power consumption during locomotion includes the joule heating $JouleHeating = \sum_{12motors} I_{motor}^2 \times R$ and the mechanical power $MechanicalPower = \sum_{12motors} K_t \times I_{motor} \times \omega$, where K_t is the torque constant and R is the winding resistance. For Pegasus, the torque constant $K_t = 0.217$ Nm/A, the winding resistance R = 2.28 Ω. Second, for each gait cycle, the energy is calculated by the power times gait cycle. Then, with the traveled distance of each gait cycle, the COT can be calculated.

The COT of each gait cycle during the entire climbing

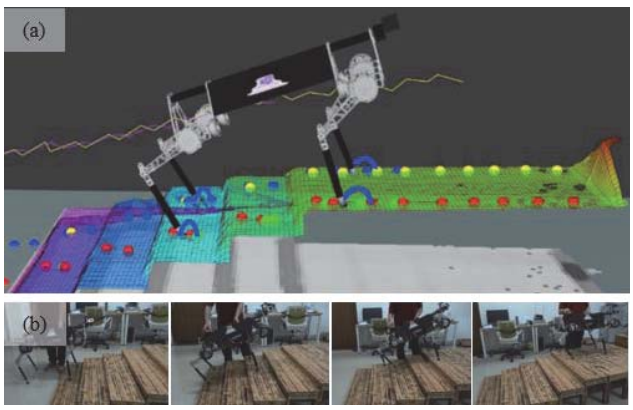

Figure 8. Pegasus is climing stairs. (a) The Rviz shows the planned global COG trajectory (yellow line) , the swing-leg trajectory (blue line) and the selected global footholds (color spheres, red-RF,green-RH, blue-LH, yellow-LF) as well as the elevation map and the traversability map (the grayscale image). (b) Sequence of snapshots shows the process of climing stairs.

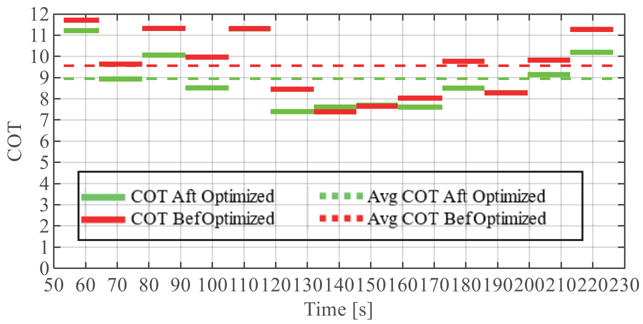

Figure 9. The COT of the quadrupedal robot Pegasus shows the results of climing stairs locomotion.

stairs process is depicted in Fig. 9. Compared to non-optimized method, by using our optimized locomotion strategy, the robot can achieve a lower COT at each gait cycle stage. Additionally, the average COT of the entire climbing stairs locomotion is calculated and shown as the dashed lines in Fig. 9. The average COT of our optimized locomotion and the non-optimized one is 8.947 and 9.561 respectively. The optimized average COT has approximately 6.42% reduction to the non-optimized one. The experimental results have demonstrated the effectiveness of our proposed strategy.

Our robot Pegasus has achieved a lower averaged COT value of 8.947 when compared to other legged robots including Hexapod Robot Weaver and BigDog whose COT is 36.43 and 15 respectively.

VI. Conclusion

The experimental results have successfully demonstrated that a quadrupedal robot can achieve high energy efficiency locomotion when walking on challenging terrains by using the CNN-based classifier presented in this paper. In addition, our method is general enough that can be applied to other legged robots to achieve more efficient locomotion in similar way.

In future work, we will focus on improving the feasibility of the energy-efficient locomotion strategy to dynamic gaits such as trot.

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