An Effective Robotic End-Effector Engagement Approach for Automated Grapevine Pruning on a Quadrupedal Manipulator

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***Abstract*—This paper presents an approach to engage the end-effector of a quadrupedal manipulator successfully on a grapevine cane during automated pruning. We employ a momentum observer to estimate contact forces between the plant and the robot's shears. Experimental results demonstrate that the observer has the necessary accuracy for safe interaction between the plant and the manipulator. Moreover, the solution ensures precise and gentle execution of pruning tasks without causing any harm to the plant. To the best of the authors' knowledge, this is the first time a disturbance observer has been applied to a legged manipulator for pruning operations.**

***Index Terms*—Precision Agriculture, Momentum Observer, Loco-Manipulation.**

I. Introduction

Pruning grapevines is a crucial horticultural practice involving precise cuts on dormant grapevines. The primary objective is to remove a portion of the previous season's growth while strategically retaining specific dormant shoots, such as canes and spurs [1]. These retained spurs are essential for the upcoming harvest season as they will grow into new canes, serving as the foundation for grape growth. The careful pruning process is pivotal in determining the vine's final yield. By selecting and nurturing suitable canes and spurs, viticulturists can ensure optimal fruit production and maintain the health and vitality of the grapevines. A well-executed pruning strategy can lead to improved grape quality and yield, impacting the overall success of grapevine cultivation. Vinum[1] is a project that focuses on developing an automatic grapevine winter pruning system utilizing legged robots. The main objectives involve: (i) machine learning techniques to accurately identify the cutting points on the grapevine; (ii) manipulation capabilities to ensure precise and effective pruning actions; (iii) robust robot locomotion control to navigate challenging terrains and execute pruning tasks precisely. Tasks of this kind are effectively accomplished using a mobile manipulator, offering an extension of the manipulability and operational space compared to stationary manipulators [2]. In practice, some vineyards exhibit challenging scenarios for wheeled systems with uneven terrains, steep hills, and terraces containing rocks and fallen branches. A legged system can locomote environments of this kind and adjust its torso orientation and height, increasing the workspace of onboard tools, such as a robotic arm [3]. Then, a manipulator equipped with cameras and a tool can recognize the pruning points and execute automatically the pruning task.

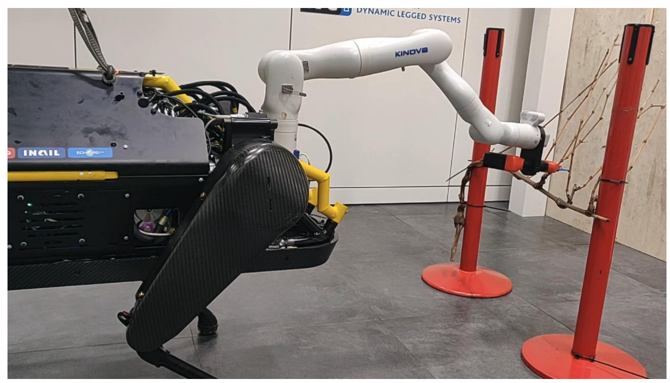

Fig. 1. Legged Manipulator interacting with a vine.

In automated grapevine pruning, cameras are crucial in localizing the pruning point and gathering information from the plant [4], [5]. [6] employed a computer vision algorithm to detect grapevine buds; [7], [8] used a deep neural network

[1] https://vinum-robot.eu/

to identify five different plant organs and consecutively detect the pruning points of mature spur-pruned grapevines. However, obtaining an exact measurement of the pruning point becomes indispensable to achieving precise and damage-free interaction between the robotic manipulator and the grapevine [9]. Such accuracy is vital in preventing potential plant harm during the pruning process. Despite the numerous benefits of automatic pruning, it also brings challenges in complexity and computational power. Implementing an automated pruning system that ensures precise positioning and avoids damage can be computationally intensive and may require sophisticated vision sensors. These complexities can escalate costs and resource requirements, making adopting fully automated pruning systems a potentially costly endeavor.

To circumvent such undesirable consequences, rapidly detecting collisions between the shear center and the trim point becomes essential, enabling the robot to avoid unnecessary vine pushing. One solution involves mounting a force sensor on the manipulator's end-effector, but this approach can be expensive and invasive requiring modifications to the robot's structure. An alternative, non-invasive approach to collision detection involves using observers, such as the momentum-based observer [10], [11], which prevents the need for deploying exteroceptive sensors. By leveraging such observer-based techniques, the robot can estimate and react to contact forces during pruning without the added costs and modifications associated with sensor installations. This approach can streamline the automation of grapevine pruning, striking a balance between precision, efficiency, and cost-effectiveness.

The main contribution of this paper is the utilization of the momentum-based observer on a mobile-manipulator platform comprising a quadruped robot and a manipulator (Fig. 1). The application aims to detect interaction forces between the shear and the canes, facilitating the automation of grapevines' winter pruning. To the best of the authors' knowledge, this is the first time a disturbance observer has been applied to a legged manipulator for pruning operations.

II. TASK SPACE TORQUE CONTROL

This section explains the controller used to drive the manipulator to the pruning point. The following dynamic equation governs the robotic arm of n DoF.

$$H(q)\,\ddot{q} + C(q,\dot{q})\,\dot{q} + g(q) = \tau + J(q)^\top f_{ext} \tag{1}$$

where $H(q) \in \mathbb{R}^{n\times n}$ is the joint-space inertia matrix, $q, \dot{q}, \ddot{q} \in \mathbb{R}^n$ denote the joints positions, velocities and accelerations, $C(q,\dot{q}) \in \mathbb{R}^{n\times n}$ denotes the Coriolis and centrifugal forces matrix, $g(q) \in \mathbb{R}^n$ is the gravity term, $\tau \in \mathbb{R}^n$ denotes the torque applied to the system, $J(q) \in \mathbb{R}^{6\times n}$ is the geometric Jacobian and $f_{ext} \in \mathbb{R}^6$ represents the interaction forces between the robotic arm and the plant. To ensure simplicity, the computation of the dynamic terms is limited to the robotic arm, assuming that the quadruped robot remains stationary while the end-effector interacts with the plant.

To control the position and orientation of the arm's manipulator on the task space, the following PD controller law is introduced:

$$u_x := K_p \begin{bmatrix} x_d - x \\ e_o \end{bmatrix} - K_d\,J(q)\,\dot{q} \tag{2}$$

Here $K_p, K_d \in \mathbb{R}^{6\times 6}$ are positive definite matrices, $x, x_d \in \mathbb{R}^3$ denote the actual and desired end-effector position relative to the base and $e_o \in \mathbb{R}^3$ is calculated using unit quaternions.

Let $Q_d = \{\eta_d, \epsilon_d\}$ and $Q_e = \{\eta_e, \epsilon_e\}$ represent the quaternions associated with the desired R_d and current R_e orientations of the end-effector to the base obtained using direct kinematics [12]. In this representation, there are two ways to represent a 3D rotation, and we address the negative representation by introducing the following artificial discontinuity

$$e_o = \begin{cases} -(\eta_e\,\epsilon_d - \eta_d\,\epsilon_e - \epsilon_d \times \epsilon_e) & \delta,\eta < 0, \\ \eta_e\,\epsilon_d - \eta_d\,\epsilon_e - \epsilon_d \times \epsilon_e & \delta,\eta >= 0 \end{cases} \tag{3}$$

to guarantee the system's stability. The quaternion's scalar part $\Delta\,\eta$ is obtained from $\Delta\,Q = Q_d\,Q_e^{-1}$.

Consequently, in cases where the robotic arm to be controlled is a redundant manipulator, infinite joint configurations exist for a specific pose in the task space. Thus, a null-space controller is added to obtain the solution closest to the initial joint configuration q_0.

$$u_n := K_n\,(I - J(q)^\dagger J(q))\,(q_0 - q) \tag{4}$$

Finally, the torque sent to the robot is obtained by

$$\tau = J(q)^\dagger\,u_x + u_n + g(q) \tag{5}$$

III. MOMENTUM OBSERVER

This section briefly introduces the algorithm to estimate the interaction forces between the plant and the end-effector; a more detailed explanation can be found in [13], [14].

The generalized momentum in the system is defined by $p = H(q)\,\dot{q}$ and its derivative is given by $\dot{p} = \tau + C(q,\dot{q})^\top\,\dot{q} - g(q)$. The momentum observer is defined in Algorithm 1, where $\rho, \gamma \in \mathbb{R}^{n\times N}$ are auxiliary vector arrays, whose dimensions vary according to the observer's order N, $K_i \in \mathbb{R}^{n\times n\times N}$ is an array of positive definite gain matrices. The subscript $_i$ denotes the element's index in each iteration of the for loop.

Algorithm 1 The *N-th* order momentum observer.

$\dot{\rho}_1 = C(q,\dot{q})^\top\,\dot{q} - g(q) + \tau + J(q)^\top\,\hat{f}_{ext}$
$\gamma_1 = K_1(H(q)\,\dot{q} - \rho_1)$
if $N > 1$ **then**
  for $i \in \{2,\dots,N\}$ **do**
    $\dot{\rho}_i = \gamma_{i-1} - J(q)^\top\,\hat{f}_{ext}$
    $\gamma_i = K_i\rho_i$
  end for
end if
$\hat{f}_{ext} = (J(q)^\dagger)^\top \gamma_N$

Fig. 2. Picture of commercial pruning blades with the definition of the Shears center.

IV. Experimental Results

This section explains the experimental setup and the successful results. To begin, we conducted a comparative experiment, comparing the observer's response against the measurement from an external force sensor fixed on the environment. Subsequently, we mounted the robotic arm on a quadruped robot to assess the efficiency and practical viability of the control system for detecting contact with the plant.

We used the Kinova Gen3 robotic arm with modified commercial shears (Fig. 2) as the end-effector. The arm's control was implemented using the C++ API on a Dell G5 laptop, with communication via an ethernet cable at a rate of 500 Hz. Both the controller and observer operated in a separate thread at 100 Hz.

We utilized the Pinocchio library [15] to compute the system dynamics terms required for the controller and observer algorithms (1). The gains were set as follows: $K_p = 80\,I$, $K_d = 1.6\sqrt{80}\,I$, and $K_n = 2\,I$. The observer used in the experiment was a second-order observer with $N_1 = 2.5\,I$ and $N_2 = 1.58\,I$. I represents an identity matrix with the appropriate dimensions.

We initiated the experiments using the external force/torque sensor Bota SensONE ECAT to heuristically measure the average force (experienced-based) that could be applied to the plant while pruning, resulting in approximately 15 Newtons (N). Next, we evaluated the precision of the Momentum observer, as described in Algorithm 1. To achieve this, we mounted the sensor in a fixed position in the environment, aligned it with the end effector, and drove it towards the sensor to measure its response.

Figure 3 illustrates the observer's response compared to the sensor. Before and after the contact, an offset of -2.3 N at the observer is evident. The robot started approaching the sensor at 4.8 seconds; at 7.4 seconds, the external sensor detected the collision. During the contact, we saw a delayed response of the observer of approximately 0.6 seconds compared to the sensor's measurement and an offset of 1 N, possibly due to minor inaccuracies in the robot model and sensor measurements.

Then, we implemented an engagement detection method to avoid applying more force than required to execute the motion, which consists of triggering a flag when a contact force is

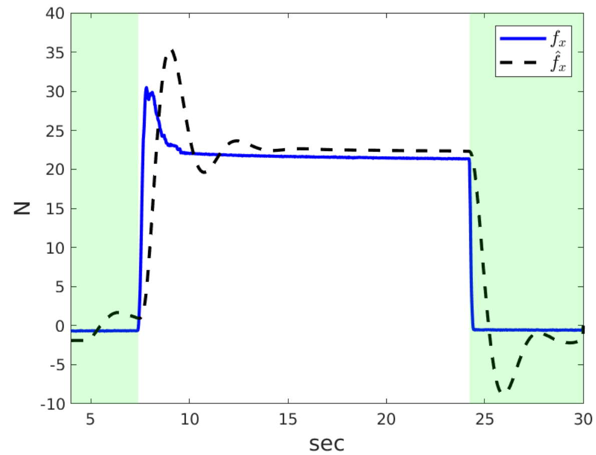

Fig. 3. Force response before and after the contact between the robot's end-effector and the external sensor, depicted in blue and black, respectively. The green areas highlight the phases when the end-effector moved towards and away from the external sensor.

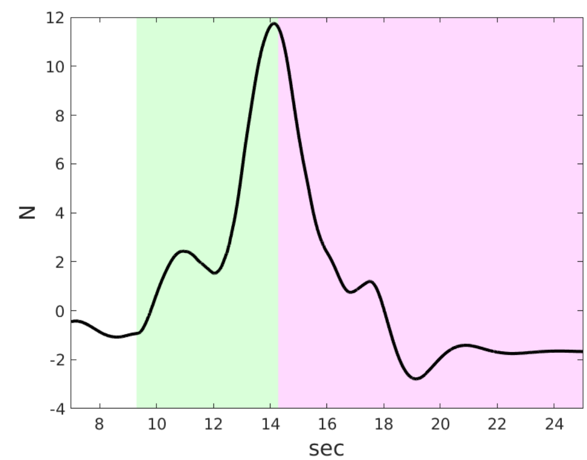

Fig. 4. Estimated force $\hat{f}_x$ response before and after the contact between the robot's end-effector and the plant's cane. The green area highlights the phase when the end-effector moved towards the cane and the magenta area shows the phase where the end-effector stops pushing and adjusts its orientation to execute the cut.

higher than 8 N for one second. The experiment starts by moving the arm from its folded configuration to the deployed configuration. The plant's cane is aligned to the arm's end-effector, similar to the previous experiment but replacing the external sensor with the plant's cane.

Next, we mounted the robotic manipulator on a 140 kg quadruped robot, HyQReal, and conducted several experiments, as shown in the accompanying video.

Figure 4 shows the observer's response during the experiment execution. At 9.3 seconds, the command is triggered to engage the cane. At 14.28 seconds, the engagement detection mechanism activates, prompting the arm to stop pushing and adjust the end-effector orientation to reduce the interaction force while keeping the cane at the center of the shear, ensuring a safe cut without subjecting the plant to high contact forces.

V. Conclusion

In conclusion, the experiments demonstrate the successful application of the momentum-based observer on a quadrupedal-manipulator platform for detecting the correct engagement of the plant's cane for automating grapevine winter pruning. The approach ensures precise and safe pruning actions, overcoming the limitations of visual measurements. Integrating the observer with the robotic arm enables accurate engagement detection, reducing the risk of damage to delicate grapevine canes without using an extra force sensor.

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