UniTac: Whole-Robot Touch Sensing Without Tactile Sensors

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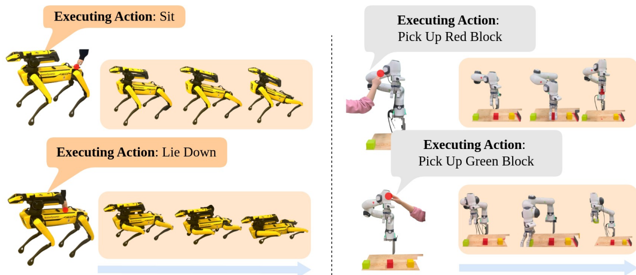

Fig. 1: **Interactions achieved using UniTac**. UniTac achieves whole-robot touch sensing without using any tactile sensors and empowers applications such as patting the quadruped for canine-inspired responses or touch-based instructions for manipulation.

I. Introduction

Commercial robots are becoming increasingly capable. We now have bipedal/quadrupedal robots that can walk or run in challenging environments [21, 20, 2], and robot arms that assemble products with precision [9]. Despite the impressive capabilities of these robots, they lack a critical aspect of animal behavior: physical interaction through touch (Fig. 1). Consider how a simple pat can convey trust or instruction when interacting with a person or an animal [8]. This limitation is largely due to the absence or difficulty in endowing robots with touch-sensing capabilities.

Touch sensing is essential for a variety of tasks, including perception of in-hand object states [13, 14, 16, 15] and provision of social support for the elderly [5]. These interactions have been supported by installing dedicated tactile sensors, including sensors on robot hands [11, 12], and full-body tactile skins [4, 23]. Despite their usefulness, rigid sensors tend to compromise the robot's dexterity, while soft sensors are prone to produce errors due to self-contact at joints [3]. Moreover, the integration of tactile sensors involves high costs and complex considerations such as calibration and communication infrastructure [22, 6].

In this paper, we propose **UniTac**, a unified method to enable **whole-robot touch sensing capabilities across different robots without tactile sensors**. Our approach is applicable to various robot platforms and leverages data from *only existing sensors*. Specifically, we use torque and position data from joint sensors, which are readily available on most commercial robots. Unlike model-based approaches [10, 18], which depend on physical models and demand extensive expert tuning for each robot platform, our technique is entirely data-driven. While prior data-driven methods [24, 17] depend on simulated data - necessitating the construction of bespoke simulations for each robot - we train a neural network on real-world joint sensor data to directly predict contact location in real time, thereby eliminating simulation designs and the sim-to-real gap. Notably, our efficient data collection process requires as little as 2.5 hours (for Spot), yet it is sufficient for robust real-world whole-robot touch sensing.

We demonstrate potential applications of UniTac in physical Human-Robot Interaction (pHRI) [7](Fig. 1). Our evaluation shows that the accuracy of UniTac is enough to support many useful sensing abilities and human-robot interactions (HRI).

In summary, our contributions are as follows:

- We present a data-driven model, UniTac, that leverages built-in joint torque sensors to achieve live whole-body touch sensing across various robot platforms, eliminating the need for dedicated tactile sensors.
- UniTac demonstrates generalizability across multiple robot instances with the same type, allowing a wider community to use it as an off-the-shelf interface directly.
- We demonstrate potential applications in touch-based human-robot interaction, including scenarios such as bio-inspired quadruped choreography.

II. Method

Our goal is to develop a method for localizing touch on the robot's surface using only proprioceptive feedback. We first randomly sample a preset number of n points on the surface of the robot mesh and define them as the ground truth contact locations. We collect joint data during contact at each point multiple times by varying joint configurations, and construct a dataset $\mathcal{D} = \{d_1, d_2, \ldots, d_k\}$ with k samples. A detailed process for contact collection will be explained in the next section. Each data tuple is $d_i = (p_i, q_i, \tau_i)$, where $p \in \mathbb{R}^3$ is the ground truth contact location. $q \in \mathbb{R}^{DoF}$ and $\tau \in \mathbb{R}^{DoF}$ are the joint positions and torques, respectively. We build a contact localization model that maps the proprioceptive signal - joint positions and torques (q and τ) - to the contact coordinate (p), defined in the robot frame, using a neural network, namely **UniTac-Net**. Contact localization can be treated as either a classification or a regression problem [19, 17], which differ in the output head of the neural network.

III. Experiments

We validate the effectiveness of UniTac on two platforms with distinct morphologies: the Spot quadruped from Boston Dynamics and the Franka Research 3 robotic arm from Franka Robotics.

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Method	Robot	Acc (%) ↑	L2 (cm) ↓
Classification	Franka	53.7	**14.8**
	Spot	54.9	**13.7**
Regression	Franka	83.5	**8.0**
	Spot	86.5	**7.2**

TABLE I: **Comparsion of model choices**. We compare the performance of our regression and classification models.

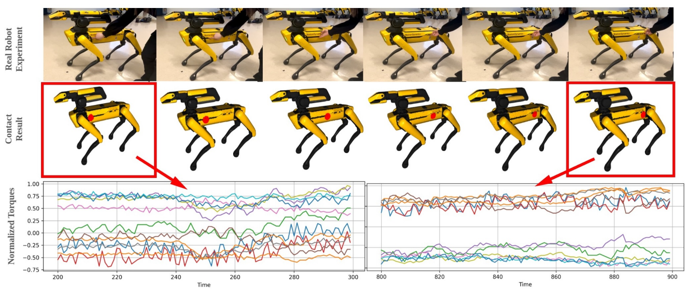

Fig. 2: **Live contact localization on Spots.** Top row: A human applies touch to the robot. Middle row: The system localizes the contact point on the robot's mesh. Bottom row: Normalized joint torque changes are displayed (different colors indicate distinct joint sensors).

Our data collection process starts with sampling 104 points on Spot and 10 points on Franka. Dense sampling on Spot covers the whole robot except for the legs, while the sparser sampling on Franka covers each link.

A. Quantitative Results

We use two metrics to evaluate the performance of our model: L2 norm and accuracy. L2 norm is defined as the Euclidean distance $||p - \hat{p}||_2$ between the predicted position $\hat{p}$ and ground truth contact position p. Accuracy (Acc) is calculated as the percentage of predictions whose Euclidean distance from the ground truth is within a threshold ϵ of 12 cm. We compare our regression model with the classification model (Tab. I). It suggests that avoiding discretization leads to more precise contact localization, especially in scenarios with noisy sensor readings.

B. Qualitative Results

On the Spot, we slide our touch horizontally along the left side of the body and visualize the live contact localization prediction results (Fig. 2). The results demonstrate that our model could accurately localize rapidly changing contacts in real time. Our real-time contact localization also generalizes to different instances of the same robot model without additional retraining.

IV. pHRI Applications

Using Spot, we program primitive actions using its Choreography SDK. Based on the predictions from UniTac-Net, we segment the robot's body into distinct regions, each triggering a specific action (Fig. 3). We divide Spot actions into three categories: 1) Motion actions; 2) Posture change; and 3) Body expression. All motion actions are inspired by human-equine interactions [1], while posture changes and body expression movements are derived from human-canine interactions.

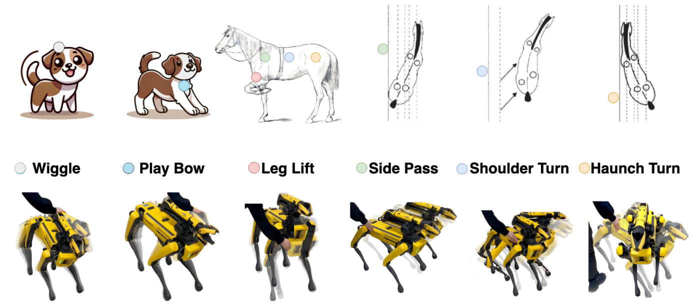

Fig. 3: **pHRI deployment on Spot.** The first row illustrates the inspiration from human-animal interactions, showcasing how dogs and horses respond to touch cues (colored dots). The second row depicts the corresponding robotic responses in deployment on Spot.

Motion Actions.

- *Turning on the Forehand* is triggered by touching the upper frontal section, prompting Spot to turn in the opposite direction by stepping with its front legs while its hind legs step in place.
- *Turning on the Haunches* occurs when the upper dorsal section is touched, making Spot step sideways while keeping its front legs stationary.
- *Shifting on Forehand/Haunches* results from touch on the lower frontal or dorsal sections, causing a weight shift in the opposite direction, mimicking a horse's response to abdominal pressure.

Posture Change.

- *Lying Down* is triggered by touching the middle section, causing Spot to fully lower itself.
- *Sitting* occurs when the rear section near the hip is touched, prompting Spot to lower its hindquarters, similar to a dog sitting when patted on the hip.

Body Expression.

- *Wiggle* occurs when the arm is touched, causing Spot to sway its body, similar to a puppy reacting to a pat on the neck.
- *Play Bow* is triggered by touch near the gripper, making Spot sway while opening its gripper, mimicking a dog playfully bowing to welcome a friendly pat.

V. Conclusion

We present UniTac, a whole-robot touch sensing method that uses only built-in joint sensors to localize contact in real time. Our pHRI demonstrations—such as quadruped choreography—highlight the practical benefits of our approach for natural human-robot interactions. UniTac offers a robust, easy-to-deploy alternative to dedicated tactile hardware, paving the way for more natural human-robot interactions. In our future work, we aim to scale up data collection to support more robust and multi-contact predictions.

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