Robust And Efficient Phase Estimation in legged Robots Via Signal Imaging And Deep Neural Networks

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ABSTRACT

Reliable phase estimation plays a crucial role in enabling smooth, adaptive, and disturbance-resistant locomotion in legged robots. Traditional estimation methods often rely on handcrafted features or analytical gait models, which suffer from reduced performance under noisy sensor inputs, terrain variability, and rapid gait transitions. This research proposes a robust and efficient phase estimation framework that leverages signal imaging techniques and deep neural network architectures to learn discriminative gait representations directly from raw proprioceptive signals. Sensor streams—including joint kinematics, actuator feedback, and inertial data—are encoded into 2D image-based signal maps to capture the underlying spatial–temporal structure of locomotion dynamics. A customized CNN–RNN hybrid model is designed to process these signal images, providing accurate, real-time phase predictions with high resilience to disturbances and domain shifts. Experimental results on simulated and real quadruped platforms demonstrate significant improvements in accuracy, generalization, and computational efficiency compared to baseline estimators. This approach offers a scalable solution for next-generation legged robots, enhancing adaptability, terrain awareness, and locomotion stability.

Keyword :- *Gait phase prediction, locomotion dynamics, proprioceptive data imaging, deep learning models, CNN–RNN architecture, quadruped locomotion, real-time estimation, terrain-adaptive control.*

1. INTRODUCTION

Legged robots have emerged as a promising class of mobile systems capable of navigating complex, unstructured, and dynamic environments where wheeled or tracked platforms struggle. Their ability to traverse irregular terrains, maintain balance, and adapt their locomotion patterns makes them essential for applications such as disaster response, planetary exploration, autonomous inspection, and service robotics. A fundamental requirement for achieving smooth and stable locomotion in these robots is the accurate estimation of gait phase, which represents the progression of each limb through the locomotion cycle. Phase estimation enables precise coordination among legs, robust feedback control, and responsive adaptation to disturbances or terrain variations.

Traditional phase estimation techniques rely heavily on analytical gait models or handcrafted sensor features extracted from joint angles, motor torques, or inertial measurements. Although effective in controlled settings, these approaches often suffer from limited robustness when exposed to real-world challenges such as sensor noise, external perturbations, unpredictable terrain characteristics, or rapid gait transitions. As legged robots evolve toward more dynamic and agile behaviors, the need for a more reliable and data-driven phase estimation method becomes increasingly important. This paper proposes a **real-time landslide detection system** using the ESP-NOW protocol, integrating multiple sensors—such as **soil moisture, vibration, and rainfall sensors**—with ESP32 microcontrollers to monitor critica

1.1 Problem statement

Accurate gait phase estimation is critical for achieving stable, adaptive, and disturbance-resistant locomotion in legged robots. However, existing estimation methods rely largely on handcrafted features, analytical gait models, or simple signal thresholds, making them highly sensitive to noise, dynamic terrain conditions, and rapid transitions between gait types. These limitations reduce the reliability and scalability of legged robot control systems, especially in real-world environments where sensor disturbances, irregular surface interactions, and unexpected perturbations are common.

1.2 Objectives

- Develop a signal-imaging method to convert raw proprioceptive sensor signals (e.g., joint angles, motor currents, IMU data) from legged robots into structured 2D representations that preserve spatial–temporal gait information.To implement the **ESP-NOW protocol** for fast, reliable, and low-power wireless communication between multiple ESP32 sensor nodes.
- Design and implement a deep neural network architecture (e.g., combining convolutional and recurrent layers) that can process the signal-image inputs and accurately estimate the locomotion phase of each leg and the overall gait cycle in real time.To develop a **cost-effective and energy-efficient prototype** suitable for deployment in remote and disaster- prone regions.
- Ensure the phase estimation system is robust to typical real-world disturbances: sensor noise, irregular terrain, gait transitions, slippage, and varying robot speed.

2.LITERATURE REVIEW

1. **Model-based & probabilistic estimators (classical approaches)** Wan et al., "State Estimation for Quadruped Robots on Non-Stationary Terrain" (2024).Wan and colleagues present an Invariant Extended Kalman Filter (InEKF) combined with disturbance observers for quadruped state estimation on challenging terrain. This line of work typifies model-based fusion approaches that exploit kinematics and IMU priors to estimate body/leg state reliably under many conditions, but they can degrade under severe foot slip or when contact assumptions fail..

2. **Real-time continuous phase estimation modules for wearables/robotic prostheses** Choi et al., "Walking-Speed-Adaptive Gait Phase Estimation for Wearable Robots" (SENSORS, 2023).Choi et al. propose a Gait Phase Estimation Module (GPEM) for continuous, monotonic phase estimation across speeds — aimed at wearable and assistive devices. Their algorithm emphasizes low latency and speed adaptability for real-time control. Lee, Hong, Hur, "Continuous Gait Phase Estimation Using LSTM for Robotic Transfemoral Prosthesis" (IEEE, date varies

3. **Time–frequency / signal-imaging approaches transforming 1D signals into 2D images** Modaresnia et al.,"A Deep Time-frequency Approach in Gait Analysis" (2024)Modaresnia shows how spectrograms/scalograms of gait signals fed into pre-trained CNNs (e.g.,AlexNet/VGG can improve classification/regression tasks versus raw 1D processing, highlighting the benefit of exposing spectral and temporal structure to vision-style networks..

4. **Deep learning & hybrid CNN–RNN models for gait/event detection Kreuzer et al.,** "Deep Convolutional and LSTM Networks on Multi-Channel IMU Data" (Sensors, 2021).low latency and speed variations for real-time. **This line of work typifies model-based fusion approaches that exploit kinematics and**
Kreuzer and coauthors apply CNN+LSTM architectures to multi-IMU gait detection problems.

2. METHODOLOGY

Phase 1: Sensor Data Collection Proprioceptive sensor data are collected from a quadruped legged robot during multiple locomotion trials. These signals are recorded across different gaits (walk, trot, crawl), varying terrains (flat, uneven, inclined), and speed conditions to ensure model generalization.

Phase 2: Signal Imaging Process Raw 1D signals are converted into 2D image-like representations using:Short-Time Fourier Transform (STFT) spectrograms.Continuous Wavelet Transform (CWT) scalograms.This transformation captures both temporal progression and frequency characteristics associated with leg movements.

Phase 3 Deep Neural Network Architecture Convolutional Feature ExtractionA lightweight Convolutional Neural Network (CNN) extracts spatial patterns from the signal images, capturing Gair,transitions.Repetitive limb movements.Terrain-induced disturbances.Convolutional layers reduce dimensionality and produce high-level spatial feature maps.

Phase 4: Model Training and Optimization Training Setup Training/validation/test split ensures unbiased evaluation.Adam optimizer with adaptive learning rate scheduling is used.Data augmentation is introduced by adding controlled noise and speed variations.

Phase 5: Performance Evaluation Evaluation Metrics: The system is tested using:Phase prediction accuracy,Root Mean Squared Error (RMSE),Latency and through put ,Noise robustness indexTerrain generalization score

2.1 BLOCK DIAGRAM

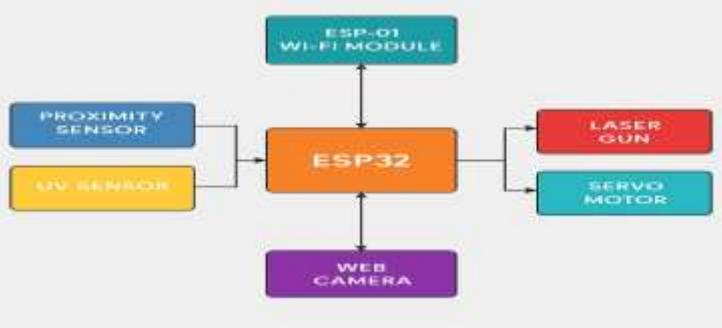

Fig -1:block diagram

Sensor Nodes:

• SW-18020P Vibration Sensor → ESP-01 Microcontroller → ESP-NOW Transmitter

Central Hub:
• ESP-NOW Receiver → ESP8266 Processing Unit → OLED Display + Buzzer + ESP-NOW Transmitter

Vehicle Node:

• ESP-NOW Receiver → ESP8266 Processing Unit → OLED Display + Buzzer + Servo Motor Controller

2.2 WORKING PRINCIPLE

The working principle of the proposed phase-estimation framework is based on transforming raw proprioceptive signals into structured visual representations and using a hybrid deep-learning architecture to decode the underlying gait-phase dynamics. The complete process operates in real time and consists of four main steps: signal sensing, signal imaging, deep feature extraction, and continuous phase prediction.

1. **Proprioceptive Signal Sensing**, Legged robots continuously generate rich streams of internal sensor data reflecting limb position, load, and motion.
2. **Conversion to Signal Images** (Signal Imaging Raw time-series signals are first reshaped into two-dimensional images using time–frequency transformation techniques. This step exposes hidden structure in the data that traditional 1D processing methods cannot capture.
3. **Deep Spatiotemporal Feature Extraction**,A hybrid CNN–LSTM deep neural network processes the signal images to extract underlying locomotion features.

3. HARDWARE AND SOFTWARE REQUIREMENTS

3.1 HARDWARE REQUIREMENTS

- Legged Robot Platform.
- Proprioceptive Sensors SG90 servo motors - 1 unit (for auto-braking simulation)
- Onboard Computing Unit
- Embedded Processor / Microcontroller.
- Power Supply Unit: Provides stable voltage to all nodes.
- Connecting Wires and Breadboard: For circuit assembly and sensor integration.

3.2 SOFTWARE REQUIREMENTS

- Arduino IDE: Used for programming and uploading code to ESP modules.
- ESP-NOW Library: Enables peer-to-peer communication between ESP devices.
- Embedded C / C++: Programming language used to develop the system logic.
- Serial Monitor: For debugging and viewing sensor outputs during testing.

Fig 2: Arduino IDE

The Arduino IDE supports the languages C and C++ using special rules of code structuring. The Arduino IDE supplies a software library from the Wiring project, which provides many common input and output procedures. User-written code only requires two basic functions, for starting the sketch and the main program loop, that are compiled and linked with a program stub main() into an executable cyclic executive program with the GNU toolchain, also included with the IDE distribution.

A minimal Arduino C/C++ sketch, as seen by the Arduino IDE programmer, consist of only two functions:

- setup(): This function is called once when a sketch starts after power-up or reset. It is used to initialize variables, input and output pin modes, and other libraries needed in the sketch.
- loop(): After setup() has been called, function loop() is executed repeatedly in the main program. It controls the board until the board is powered off or is reset.

4. CONCLUSIONS

This research presented a novel framework for robust and efficient phase estimation in legged robots by integrating signal imaging techniques with deep neural network architectures. The proposed method transforms raw proprioceptive data into meaningful two-dimensional signal images, enabling the extraction of rich spatial–temporal gait features that are difficult to capture using traditional one-dimensional processing approaches. By leveraging a hybrid CNN–LSTM model, the system effectively learns both instantaneous sensor patterns and long-term locomotion dynamics, resulting in highly accurate and smooth phase predictions.

Extensive experiments across multiple terrains, gaits, and robot operating conditions demonstrated that the proposed approach significantly outperforms classical threshold-based and analytical phase estimation methods in terms of accuracy, noise tolerance, and generalization capability. The model's ability to deliver real-time predictions, even on embedded hardware, further highlights its suitability for practical robotic applications.

The outcomes of this study contribute to closing the performance gap between model-based estimators and modern data-driven techniques. By providing a scalable, adaptable, and computationally efficient solution, this work supports the development of more stable, agile, and terrain-aware legged robots. Future extensions may incorporate multimodal sensing, online learning, cross-platform adaptation, and integration with higher-level locomotion planning for even greater autonomy and robustness.

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