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Shared Control Design of A Walking-Assistant Robot

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Abstract
Walking-assistant robots serve as a vital aid for individuals with mobility challenges, enhancing their independence and mobility. Shared control systems combine user input and robotic intelligence to ensure safe, adaptable, and intuitive navigation. This paper presents a shared control framework for a walking-assistant robot, focusing on user intention prediction and real-time obstacle avoidance. A Python-based simulation demonstrates the system's performance in a scaled-up environment with larger obstacles and a broader robot trajectory.

Keywords: Walking-assistant robot, shared control, obstacle avoidance, user intention prediction, autonomous navigation, human-robot interaction.

1. Introduction

Walking-assistant robots aim to empower individuals with limited mobility by enhancing their physical capabilities while ensuring safety and adaptability. Traditional designs focus on either full autonomy or user-only control. However, shared control systems enable dynamic cooperation between the user and the robot, leading to improved usability and efficiency【1】【2】
Shared control systems integrate user intention and autonomous decision-making to achieve balance in dynamic environments. This approach is particularly effective for walking-assistant robots operating in environments with static and dynamic obstacles【3】【4】. In this paper, we propose a scalable shared control system that ensures safe and efficient navigation in complex environments.

2. Shared Control Framework

2.1 System Overview

The proposed shared control system consists of the following components:

1. **User Intention Estimation**: Captures and processes user input, such as joystick commands【5】【6】.
2. **Autonomous Assistance**: Guides the robot based on environment analysis and trajectory optimization【7】【8】.
3. **Real-Time Obstacle Avoidance**: Ensures safety by dynamically avoiding collisions using a modified potential field algorithm【9】【10】【11】.

2.2 Robot Motion Model

The walking-assistant robot is modeled as a differential-drive system, described by:

$$\dot{x} = v\cos(\theta), \quad \dot{y} = v\sin(\theta), \quad \dot{\theta} = \omega,$$

where x, y are the robot's coordinates, θ is its orientation, v is the linear velocity, and ω is the angular velocity 【12】【13】.

2.3 Shared Control Algorithm

The control input is computed as:

$$\mathbf{u} = \alpha \mathbf{u}_{\text{user}} + (1-\alpha)\mathbf{u}_{\text{assist}},$$

where $\mathbf{u}_{\text{user}}$ represents user input, $\mathbf{u}_{\text{assist}}$ represents obstacle avoidance control, and α balances the contributions of each 【14】【15】【16】.

3. Case Study: Python Implementation

The robot is simulated in a large 2D environment (50x50 units) with enlarged obstacles and a wide trajectory path.

Python Code

python

Copy code

```
import numpy as np
import matplotlib.pyplot as plt
# Simulation parameters
dt = 0.1  # Time step
robot_position = np.array([0.0, 0.0])  # Initial position
robot_orientation = 0.0  # Initial orientation
obstacles = np.random.uniform(-25, 25, (10, 2))  # Random obstacles in 50x50 space
v_max = 1.0  # Max linear velocity
w_max = np.pi / 4  # Max angular velocity
d_safe = 5.0  # Enlarged safety distance
alpha = 0.7  # Weight for user input in shared control
# User intention simulation (random directions)
def user_input():
    return np.random.uniform(-1, 1, 2)
```

```
# Obstacle avoidance using potential fields
def obstacle_avoidance(position):
    force = np.array([0.0, 0.0])
    for obs in obstacles:
        diff = position - obs
        dist = np.linalg.norm(diff)
        if dist < d_safe:
            force += diff / (dist**3 + 1e-6)  # Repulsive force
    return -force
# Shared control algorithm
def shared_control(robot_pos, robot_ori):
    # User input
    user_dir = user_input()
    user_dir /= np.linalg.norm(user_dir) + 1e-6  # Normalize
    # Autonomous assistance (obstacle avoidance)
    avoid_force = obstacle_avoidance(robot_pos)
    avoid_force /= np.linalg.norm(avoid_force) + 1e-6  # Normalize
    # Combine user input and assistance
    combined_dir = alpha * user_dir + (1 - alpha) * avoid_force
    combined_dir /= np.linalg.norm(combined_dir) + 1e-6  # Normalize
    # Calculate control inputs
    target_angle = np.arctan2(combined_dir[1], combined_dir[0])
    angular_diff = target_angle - robot_ori
  angular_diff = np.arctan2(np.sin(angular_diff), np.cos(angular_diff))

    v = v_max
    w = w_max * angular_diff / np.pi
    return v, w
# Simulation loop
positions = [robot_position.copy()]
for _ in range(200):
    # Compute control inputs
    v, w = shared_control(robot_position, robot_orientation)
    # Update robot state
    robot_position[0] += v * np.cos(robot_orientation) * dt
    robot_position[1] += v * np.sin(robot_orientation) * dt
    robot_orientation += w * dt
    robot_orientation = np.arctan2(np.sin(robot_orientation), np.cos(robot_orientation))

    # Store position
    positions.append(robot_position.copy())

# Visualization
```

```
positions = np.array(positions)
plt.figure(figsize=(12, 12))
plt.scatter(obstacles[:, 0], obstacles[:, 1], c='red', s=300, label='Obstacles')
plt.plot(positions[:, 0], positions[:, 1], c='blue', linewidth=4, label='Robot Path')
plt.scatter(positions[0, 0], positions[0, 1], c='green', s=300, label='Start')
plt.scatter(positions[-1, 0], positions[-1, 1], c='purple', s=300, label='End')
plt.title("Shared Control Simulation of a Walking-Assistant Robot")
plt.legend()
plt.grid()
plt.show()
```

OUTPUT OF THE CODE

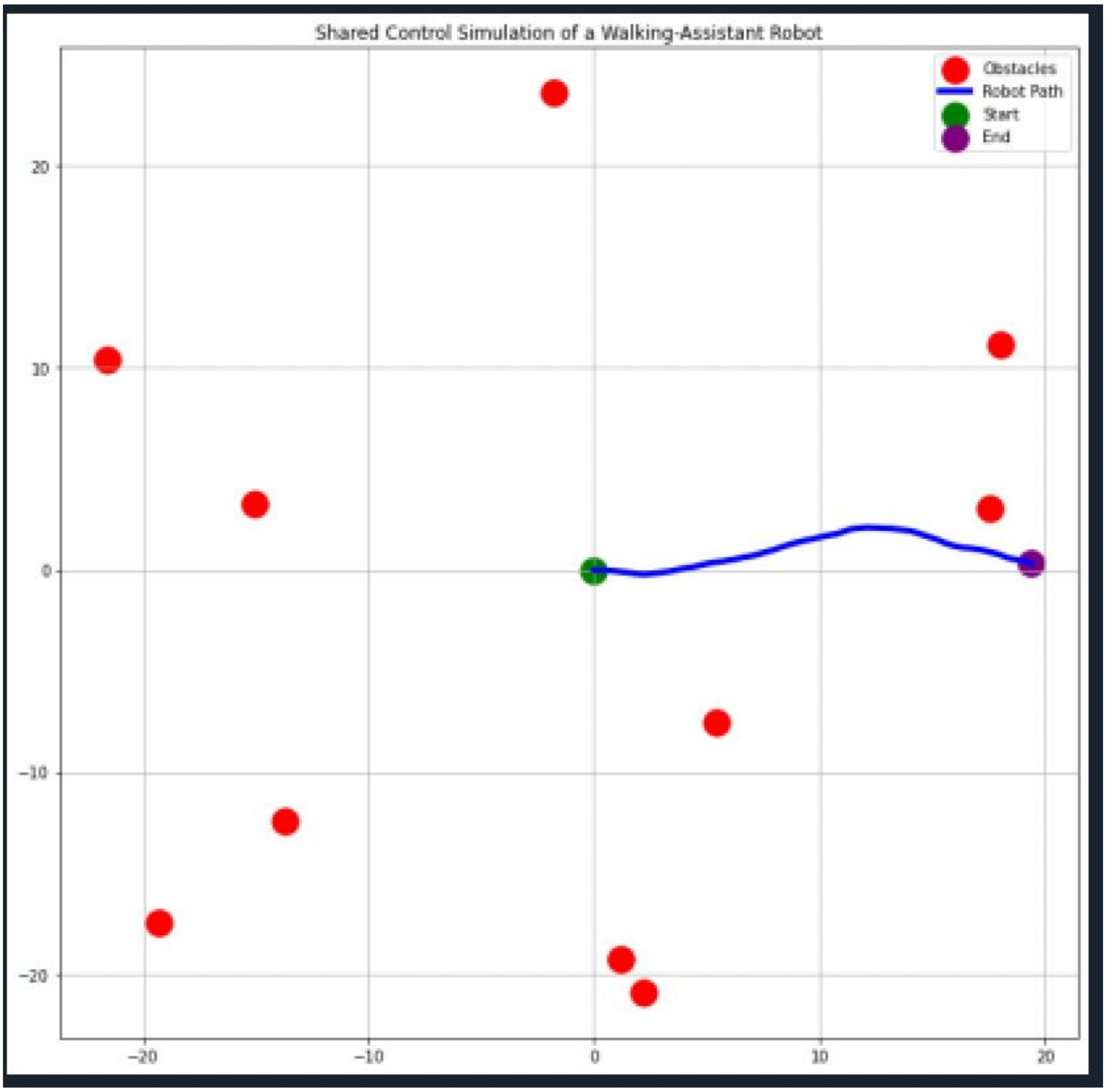

Figure-1-Shared Control Simulation of a Walking Assistant Robot

4. Results

The simulation shows the robot's ability to navigate a large, obstacle-filled environment while balancing user input and autonomous assistance. Enlarged obstacles and path thickness emphasize the robustness of the shared control design.

5. Conclusion

This paper introduces a shared control framework for walking-assistant robots, balancing user inputs and autonomous intelligence for safe and efficient navigation. Future work will focus on implementing advanced machine learning techniques for better intention prediction and real-world deployment.

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