Stereo Vision Based Navigation of Four-Legged Robot Through Unknown Terrain

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This research aims to develop a stereo vision-based navigation system for a quadruped robot, enabling it to move autonomously through rough, unfamiliar terrain and detect blockages in sewer pipelines. The robot uses a stereo camera to capture images, which are then processed to create disparity maps and 3D point clouds. These tools help the robot identify and avoid obstacles. Image rectification and 3D mapping are performed using OpenCV, which generates an occupancy grid to distinguish between free and occupied spaces. Based on this grid, the A* algorithm is used to plan the robot's path. To ensure smooth movement, inverse kinematics calculates the required motor angles and applies predefined Bezier curves for stable locomotion.

Keywords: Quadruped Robot; Disparity Map; Stereo Vision; Depth Map; 3D Point Cloud; Inverse Kinematics; Bezier Curve.

Introduction:

The sewerage pipeline system plays a crucial role in collecting and transporting wastewater from residential, commercial, and industrial areas to treatment plants. Since these pipelines are usually located underground, regular inspection and maintenance become challenging. Traditionally, inspections are carried out manually by human operators who enter the pipelines or by using cameras mounted on cables. However, these conventional methods are time-consuming and pose serious health risks to workers. In addition to these challenges, human operators often encounter various obstacles, navigate bends, and endure the harsh conditions inside the pipelines.

Advancements in robotics over the years have led to the development of autonomous robots for pipeline inspection. These robots can collect diverse types of data, including videos, images, and sensor readings, providing a comprehensive analysis of the pipeline's condition.

With the increasing demand for infrastructure maintenance and pipeline inspection, robotics has emerged as a promising solution to address the challenges of limited accessibility, hazardous environments, and labor-intensive inspection processes. Sewerage pipelines, in particular, pose significant challenges due to narrow spaces, bends, and potential blockages that make traditional inspection methods inefficient and unsafe for human operators. While wheeled robots and sensor-based systems have been developed for pipeline inspection, these methods often struggle with navigating uneven terrains, negotiating tight curves, and accurately detecting obstructions. This has led to the growing interest in legged robots, which offer enhanced mobility, adaptability, and stability in rough and unstructured environments. Legged robots can overcome obstacles, traverse dynamic terrains, and access confined spaces that would otherwise be inaccessible to wheeled or tracked robots.

Among various sensing technologies, stereo vision has gained attention due to its ability to provide detailed depth perception and 3D mapping, enabling robots to better understand their surroundings. Unlike ultrasound sensors or monocular cameras, stereo vision captures disparity maps and 3D point clouds, which improve the robot's ability to detect obstacles, calculate distances, and plan optimal paths. Integrating stereo vision with advanced path planning algorithms, such as the A* algorithm, allows for real-time obstacle avoidance and efficient navigation in dynamic environments. Additionally, the use of inverse kinematics for gait control enhances the robot's movement precision, ensuring smooth locomotion even on uneven terrain. This study aims to leverage the strengths of stereo vision, path planning, and inverse kinematics to develop a fully autonomous quadruped robot capable of navigating unknown terrains and inspecting sewerage pipelines with enhanced efficiency, accuracy, and stability.

The main goal of this study is to develop a fully autonomous quadruped robot capable of walking independently, avoiding obstacles, and efficiently reaching its destination. This requires creating real-time algorithms for obstacle detection, path planning, and locomotion. Unlike traditional methods, such as ultrasound sensors [1], which often produce inconsistent results due to weak signal reflection, our approach enhances navigation reliability. While Deep Q-Network (DQN)-based navigation [2] is effective, it has limitations, including high sensitivity to environmental changes and the need for extensive datasets and hyperparameter tuning.

To overcome these challenges, we incorporated stereo vision-based navigation, which enhances adaptability and enables the robot to navigate in dynamic environments. The key objectives of this study include designing an autonomous quadruped robot model, developing a stereo vision algorithm for obstacle avoidance and path planning, and improving the robot's locomotion. Additionally, this research represents a significant advancement in autonomous robot navigation, as discussed in [2], [1].

Objectives of the Study:

The main objectives of this study are:

- To develop a fully autonomous quadruped robot capable of navigating unknown terrains and inspecting sewerage pipelines.
- To implement a stereo vision-based navigation system for real-time obstacle detection, depth mapping, and 3D point cloud generation.
- To design and optimize path planning algorithms, specifically the A* algorithm, for efficient and collision-free navigation.

Related Work:

Model-based predictive controllers (MBPCs) using Neural Networks and ultrasonic sensors create mathematical models that perform effectively in static environments [3]. Dynamic Artificial Neural Networks (DANNs) are employed for motion planning and robot pathfinding but are primarily suited for flat surfaces with static and dynamic obstacles. The model's efficiency increases in dynamic environments by relying on past behavior and sensor inputs [4]. A Sprint-bot prototype, capable of smooth movement and turns, was developed for pipeline navigation. Initially designed for dry pipes, it requires precise sensor node positioning to detect leakage. A novel SLAM algorithm was implemented to create 3D pipeline maps from 2D data, enhancing performance with geographical pipeline information. Graph optimization techniques improve the robot's localization [5]. Building on previous work involving reactive controllers with balancing control, this research focuses on dynamic locomotion using active impedance and IMU feedback [6]. The IMU provides essential data, such as acceleration, deceleration, and tilting, helping the robot counter external forces. Using camera images, the robot can walk toward targets, with an advanced CAM shift algorithm enabling target tracking through a color probability map. This process generates a map and pinpoints the target's location [6].

A defect detection system for pressure pipelines uses the Phased Array Ultrasonic Technique (PAUT) to identify cracks and corrosion. This wheeled robot features a camera to capture pipeline interiors and an ultrasonic phased array system for hidden defect detection [7]. A Vibro-impact capsule robot, designed for the oil industry, moves through pipelines using rectilinear motion, independently navigating harsh conditions without an external driving mechanism [7]. Another robot was developed for navigating vertical, curved, and inclined pipelines, incorporating kinematic and dynamic analysis to optimize its trajectory and motion [8]. MAKRO, a pipe-inspection robot, can operate inside 30 cm diameter vertical pipelines. It captures images, live streams video, detects cracks, and determines their exact location using online image processing [9]. A multi-link articulated robot with omni- and hemi-spherical wheels was also designed to adapt to winding pipes, operating in both horizontal and vertical pipelines and transmitting data via a wireless camera [10]. Research on a self-propelled capsule system optimized its design for stability and reliability under extreme conditions [11]. Another semi-automatic robotic system, equipped with a CCD camera, steering mechanism, and sensors, was proposed to monitor pipelines. Real-time pipeline data is gathered through image processing, and gyro sensors and encoders generate pipeline maps and localize the robot's position [12].

Simultaneous Localization and Mapping (SLAM) is a key technique for robotic navigation and mapping. A modified CAO algorithm was introduced to resolve local minima issues, helping the robot escape deadlocks [13]. To improve navigation, IMU-based sensors were combined with stereo vision. Since inertial sensors accumulate errors over time, stereo vision corrects these inaccuracies, reducing long-term navigation errors. Two coupling methods—MSF and MSCKF—were tested, with MSCKF showing higher efficiency [14]. Deep reinforcement learning (RL) allows robots to learn tasks independently but faces challenges such as reward-setting, sensor inaccuracies, and unpredictable behavior. This study proposed guided constrained policy optimization (GCPO), which improves RL by enforcing specific rules during training. RL models typically require large datasets and are trained using physics simulators. This method was tested on a quadruped robot, leading to faster learning and enhanced performance without precise reward adjustments [15].

A deep learning model (LSTM-DL) for pipeline defect detection achieved 98.31% accuracy in identifying blockages and leaks by analyzing pressure and flow sensor data [16]. SQuRo, a compact legged robot, was designed for confined spaces. With a slim body (aspect ratio of 3.42), it offers flexibility, superior mobility, and the ability to carry small loads up to 200 grams [17]. The self-propelled capsule system provides a novel pipeline inspection approach by detecting abnormalities using onboard sensors [18]. Another robot with a single tracked drive and rotational capability about a perpendicular axis enhances navigation in narrow, winding pipelines [19]. Real-time image processing improves defect detection, while offline processing supports deeper analysis and maintenance planning, ultimately enhancing pipeline inspection and safety [20]. The Tarantula robot, equipped with cameras and sensors, monitors drainage systems for blockages and defects, minimizing human exposure to hazardous environments [21]. Navigating sewer-bots in harsh conditions remains challenging, requiring precise control to handle tight spaces and obstacles [22]. Cameras provide internal views, ultrasonic sensors detect cracks and leaks, and magnetic sensors identify metallic objects left behind during construction or maintenance [23]. These autonomous robots transmit real-time data via routers acting as alternative servers, streamlining pipeline monitoring [24].

Methodology:

This section discusses the key operations and algorithms involved in the navigation of a quadruped robot. The research methodology is outlined in Figure 1, which highlights the essential components and methods used in developing autonomous quadruped robot operations.

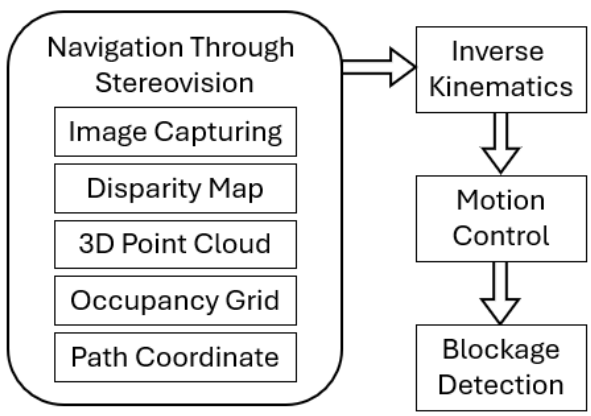

Figure 1. Operational block diagram of autonomous quadruped robot

A. Image Capturing

The first step in navigation involves capturing images with a stereo vision camera module. This camera, mounted on a Raspberry Pi 4, captures images that are essential for detecting obstacles, planning paths, and identifying blockages.

B. Image Rectification

Image rectification is a key step in 3D reconstruction that reduces geometric distortions and restores images to their proper alignment. This step is crucial for creating a 3D model used in navigation. The process involves comparing two images taken from slightly different angles and matching corresponding pixels to align them correctly. This alignment is achieved using pre-calculated camera calibration parameters.

C. Disparity Map

A disparity map is a two-dimensional image that shows the difference in pixel intensity between the left and right stereo images. In this map, higher values indicate objects closer to the camera, while lower values indicate objects farther away. The two images are compared pixel by pixel in their respective positions to generate the disparity map, which shows the horizontal shift of pixels. From these shifts, information about the distance of objects from the camera is obtained. To improve accuracy, the Semi-Global Block Matching (SGBM) algorithm is used to calculate disparities by analyzing pixel intensity differences in multiple directions, striking a balance between accuracy and efficiency. Additionally, the Weighted Least Squares (WLS) filter is applied to reduce noise and remove speckles from the disparity map, further refining the result.

D. 3D Point Cloud

Once the disparity map is computed, a 3D point cloud is generated using the OpenCV library. This point cloud stores image data in x, y, and z coordinates, providing detailed information about the surroundings. It allows the system to detect obstacles and understand the environment for autonomous navigation. The projection matrix (Q), obtained during image rectification, converts disparity values into 3D coordinates. Any points with y-coordinate values exceeding a set threshold are identified as obstacles, as they are considered part of the floor. The reprojection equation is used to achieve this transformation.

E. Path Planner

For path planning, the A* algorithm is employed to determine the shortest path between two points while avoiding obstacles. The occupancy grid, generated from stereo vision data, helps map out the path from the current position to the destination by identifying clear routes.

F. Inverse Kinematics

Inverse kinematics is used to precisely control the movement of quadruped robots by calculating the joint angles needed to achieve a specific end-effector position and orientation. To simplify these calculations, the coordinates are transformed, focusing on the z-direction.

$$y = -\sqrt{(z+L)^2 + y^2} \quad (1)$$

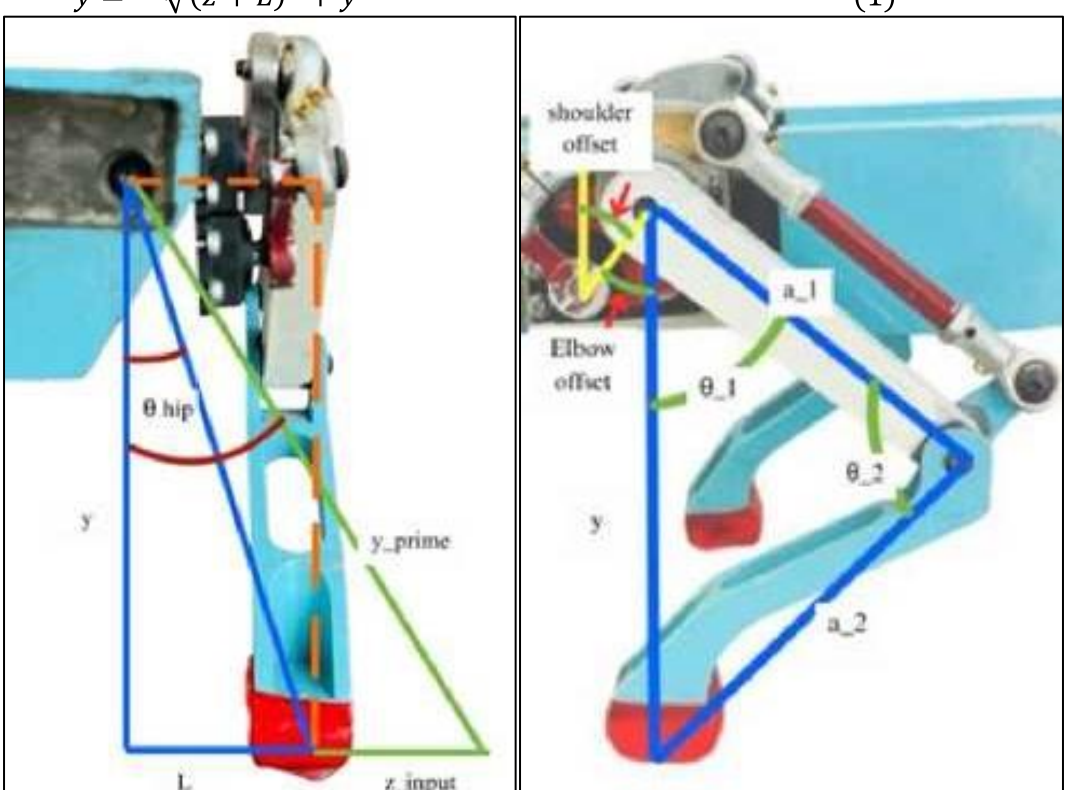

Figure 2. Robotic Leg (a) Y-Z side view (b) X-Y side view

Calculated y coordinate is used to calculate the angle theta z for the hip joint:

$$\theta_z = tan^{-1}\left(\frac{z+L}{|y|}\right) - tan^{-1}\left(\frac{L}{|y|}\right) \quad (2)$$

Segments *a,* and *a₂* represent the upper and lower leg, respectively. The angles at the shoulder (θ_1) and elbow (θ_1) are computed using the laws of sines and cosines. To find the cosine of an angle, the law of cosines is applied. This formula is derived from the triangle formed by the upper leg, lower leg, and the line connecting the shoulder and foot.

$$\cos(\theta_2) = \frac{x^2 + y^2 - a_1^2 - a_2^2}{2a_1a_2} \quad (3)$$

$$Sin(\theta_2) = \sqrt{1 - cos^2(\theta_2)} \quad (4)$$

Calculating the inverse tangent of sin over cosine to get the elbow angle.

$$\theta_2 = tan^{-1}\left(\frac{\sin(\theta_2)}{\cos(\theta_2)}\right) \quad (5)$$

Similarly, calculate the sine and cosine of $\theta 1$ using the law of cosines. Then, compute the angle $\theta 1$ as:

$$\cos(\theta_1) = \frac{x\,(a_1 + a_2\cos(\theta_2)) + y\,(a_2\sin(\theta_2))}{x^2 + y^2} \quad (6)$$

$$\sin(\theta_1) = \frac{y(a_1 + a_2C_2) - x(a_2s_s)}{x^2 + y^2} \quad (7)$$

$$\theta_1 = tan^{-1}\left(\frac{\sin(\theta_2)}{\cos(\theta_2)}\right) \quad (8)$$

Results:

Image Rectification:

The camera calibration parameters are used to rectify the stereo images. These parameters include camera metrics, distortion matrices, rotation, and projection metrics, which help align the left and right images correctly. The rectified images are then compared, as shown in Figure 3. After rectification, OpenCV converts the images to grayscale, a necessary step for generating the disparity map.

Figure 3. Left and right images before and after rectification

Disparity Map:

The grayscale images are then processed using the Semi-Global Block Matching (SGBM) algorithm to compute the disparity map. In this map, each pixel represents the disparity between corresponding points in the stereo images. The resulting disparity map is shown in Figure 4.

Figure 4. Disparity map without WLS filter

To smooth the disparity map and reduce noise, the Weighted Least Squares (WLS) filter is applied to enhance depth information. The filter's parameters are adjusted to control regularization and color influence. The disparity map after applying the WLS filter (7) is shown in Figure 5.

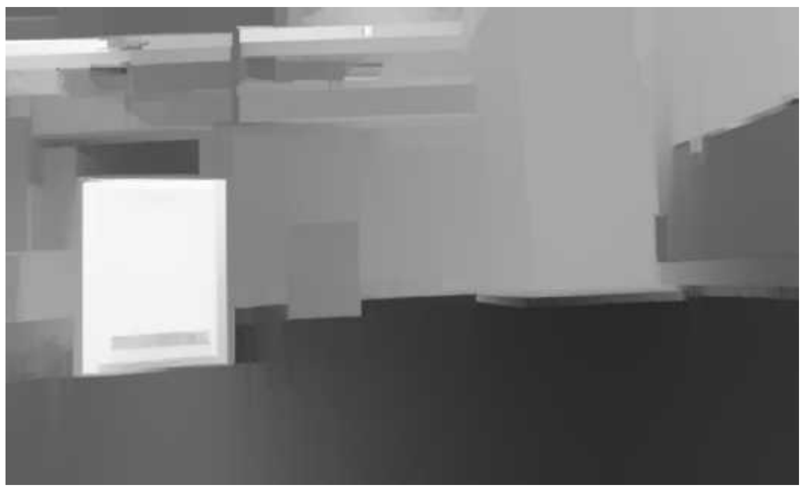

Figure 5. Disparity map after WLS filter

Point Cloud:

The projection matrix (Q), derived from intrinsic and extrinsic parameters, is used to convert disparity values into 3D coordinates. The resulting point cloud contains data on width, height, and the three spatial coordinates: x, y, and z. The point cloud generated from the disparity map is shown in Figure 6 below.

Figure 6. 3D point cloud image of environment

Occupancy grid:

The algorithm then iterates through the generated 3D point cloud and updates the occupancy grid by marking free space with a value of 0 and occupied space with a value of 1. It subsequently checks the minimum Z-value for each grid cell to identify the nearest and farthest obstacles within that cell. The calculated occupancy grid is shown in Figure 7.

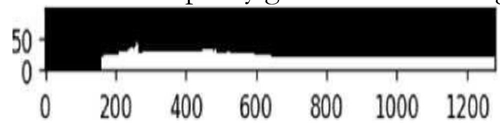

Figure 7. Occupancy grid of environment in 2D

Path Planning:

The starting point is set at the center of the current location, while the endpoint corresponds to the farthest obstacle recorded in the occupancy grid. This setup allows the A* algorithm to determine the shortest obstacle-free path to the endpoint. Figure 8 illustrates the planned path between the farthest obstacle and the current location.

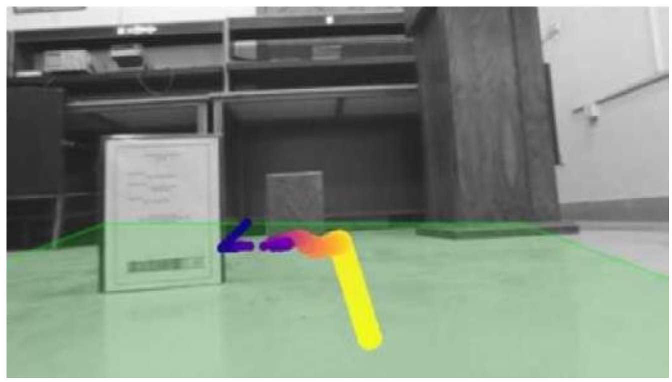

Figure 8. Planned Path

Gait Pattern:

Once the planned path is obtained, the robot performs locomotion using inverse kinematics. Cubic Bézier curve control points are defined for both linear and cubic paths to ensure smooth leg movement. These points are then used in inverse kinematics calculations to determine the motor angles. The defined Bézier curve points are as follows:$cubic\ Bexier\ Curve = \begin{bmatrix} -1.0 & -1.0 & -1.0 & -1.0 \\ -1.0 & -1.0 & -1.0 & -1.0 \\ -15 & -10 & -10 & -15 \end{bmatrix}$

Discussion:

This study focuses on the development of a fully autonomous quadruped robot designed for obstacle avoidance, path planning, and sewerage pipeline inspection. Traditional sewerage inspection robots typically use wheeled designs and various sensor-based techniques for navigation and environmental perception. While technologies such as ultrasound sensors, convolutional neural networks (CNNs), region-based convolutional networks (RCNNs), and monocular cameras have shown success in object detection, each has limitations that affect robot performance in dynamic environments like pipelines. A key innovation in our approach is the use of stereovision cameras to calculate depth maps and generate 3D point clouds. Unlike ultrasound sensors, which rely on sound waves and may be influenced by environmental factors, stereovision cameras provide a more robust alternative by using disparity mapping to calculate depth. This enhances the robot's ability to interpret complex environments, which is particularly beneficial in sewerage systems where visibility and accurate object recognition are critical.

While CNN and RCNN-based methods achieve high object detection accuracy, they require extensive training datasets and significant computational power. In contrast, our stereovision-based approach is less computationally intensive and more power-efficient. Deep learning models can also face challenges like overfitting to specific environments, whereas our stereovision technique, combined with real-time path planning algorithms, improves adaptability without relying on pre-trained models. Overall, this study contributes to the field of autonomous robotic navigation by presenting a novel application of stereovision-based obstacle detection and path planning. The findings demonstrate the potential of stereovision as an alternative to LiDAR and traditional sensor-based systems, offering a balance between computational efficiency and reliable environmental perception. This study demonstrates the significant advantages of integrating stereo vision-based navigation, path planning, and inverse kinematics for enhancing the mobility and adaptability of quadruped robots in challenging environments such as sewerage pipelines. Unlike traditional wheeled or tracked robots, which often encounter limitations in maneuvering through uneven terrains and navigating sharp bends, the proposed quadruped robot leverages real-time depth mapping and 3D point cloud generation to gain a comprehensive understanding of its surroundings. This enhanced environmental perception, combined with the A* path planning algorithm, enables the robot to efficiently detect obstacles, calculate optimal routes, and avoid collisions. Furthermore, the implementation of inverse kinematics and Bezier curves for gait control ensures smooth and precise locomotion, improving the robot's stability during traversal. These innovations contribute to a more robust and scalable framework for autonomous navigation, with potential applications in industrial pipeline inspection, hazardous environment exploration, and disaster response scenarios. Future work could focus on optimizing computational efficiency, integrating additional sensors for multi-modal perception, and enhancing the robot's performance in real-time dynamic environments.

Conclusion:

In this paper, the autonomous navigation algorithm for the robot involved several key processes, including stereo image rectification, disparity map calculation, 3D point cloud generation, and occupancy grid creation. The A* path planning algorithm was used to plan and generate the navigation path. Based on the planned path coordinates, inverse kinematics was applied to calculate the joint angles, enabling the robot's legs to respond and follow the predicted path. To achieve smooth trajectory control, a cubic Bezier curve was generated for forward and backward steps, while a linear Bezier curve was used for sliding (left and right) movements. These features enhanced the robot's ability to navigate through rough and unfamiliar terrain. The robot demonstrated excellent performance on planned navigation paths and maintained smooth trajectories, as shown in the results.

The proposed stereovision-based navigation approach significantly improved the autonomous navigation capabilities of quadruped robots. By integrating stereovision cameras for disparity mapping, obstacle avoidance, and path planning with the robot's inverse kinematics for gait control, the robot could detect blockages inside sewerage lines and identify objects obstructing sewage flow. This integration enhanced the robot's ability to walk efficiently and stably, increasing both accuracy and efficiency when navigating rough terrain.

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Conflict of interest. The authors have no conflict of interest for publishing this manuscript in IJIST.

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