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Research on obstacle climbing gait structure design and gait control of hexapod wall climbing robot based on STM32F103 core controller

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Abstract. The hexapod wall climbing robots have the advantages of traversing complex wall surfaces. To traverse complex environments autonomously, it must possess the capability to select gait parameters and paths appropriate for the wall surface. Path planning and gait optimization is a fundamental issue in the aspect of stable, energy efficient robot navigation in complex environments with static and dynamic obstacles. Traditional statistical models have been developed to get the optimal path and gait parameters but the result obtained was very poor. Metaheuristic algorithms are gaining importance in robotic gait planning. In this paper, we proposed robust two stage gait planning approach for predicting collision-free, distance-minimal, smooth navigation path and ensuring stable, energy efficient gait patterns for robots using hybrid metaheuristic algorithms. In the first stage, optimal climbing path for robot is predicted using Tri-objective Grey Wolf Path Optimization (TGWPO) based on obstacle and target detection. In the second stage, the gait parameters adaptive to the constructed climbing path are optimized using Adaptive multi-objective Particle swarm optimization (AMPSO). The hexapod wall climbing robot is designed with STM32F103 as core controller modeled with optimal path planner (using TDWPO) and gait optimizer module (using AMPSO). STM32F103 controller commands and controls the robot to climb on wall with optimized gait parameters according to the optimal path. We analyzed the efficacy of the proposed two stage gait planning approach using TDWPO-AMPSO for hexapod wall climbing robots with existing gait planning approaches in terms of path length, climbing time, gait stability, obstacle avoidance, and energy efficiency. The result analysis showed that the suggested gait planning approach is efficient over conventional strategies for climbing robots.

Keywords: Hexapod wall climbing robots / STM32F103 controller / obstacle avoidance
optimal navigation path / gait planning / gait stability

1 Introduction

It is very difficult for a human to do tasks directly in dangerous locations, but a robot may be a useful tool to perform such tasks there. Since their potential applications have quickly expanded to numerous tasks in hazardous environments, such as assisting high-rise building construction and wall cleaning, maintenance of pipes and storage tanks in power plants, surveillance of complicated structures like ships, planes, etc., there has been an increasing demand for mobile robots that can efficiently climb up vertical or inclined walls, steps or pipes [1]. The multilegged climbing robots have a clear advantage over wheeled robots in that they are very adaptable to new environments and rough walls. Hexapod climbing robots are among the multi-legged climbing robots that can make steady climbing motions in challenging terrain [2]. These six-legged robots have mechanisms for both basic manipulation and mobility. Figure 1 depicts the snapshot of a hexapod climbing robot. Due of the many circumstances in which humans are unable to command the robot, autonomous control of mobile robots through controllers has recently attracted a lot of attention and is a subject of intense study interest [3].

For hexapod climbing robots to be extensively employed autonomously in a variety of applications, there are still numerous obstacles to be solved. Solving issues with foot-wall contact, gait patterns, robot body balance or speed, climbing speed, obstacle avoidance, route planning, and other issues are some of the difficulties that must be overcome [4,5]. The adaptability of robots to different

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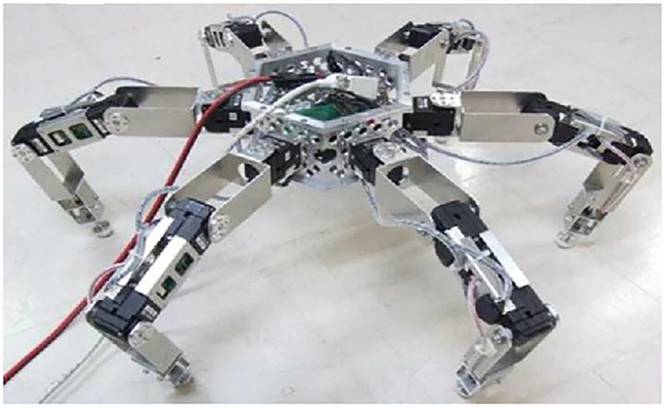

Fig. 1. Snapshot of hexapod climbing robot.

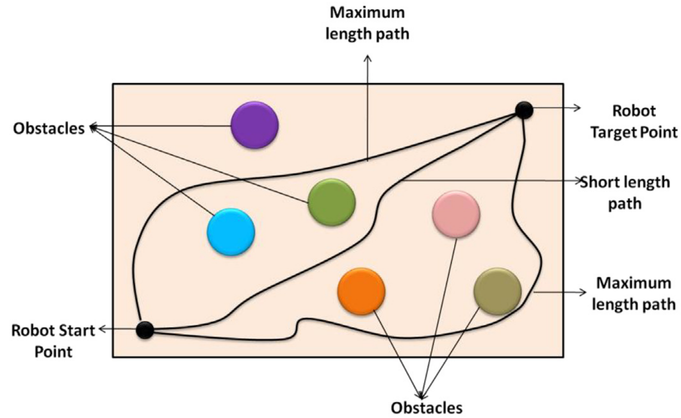

Fig. 2. Robot motion in climbing terrain with obstacles.

kinds of terrain and their energy efficiency are key components of their autonomy. For autonomous mobile robots, route or path planning entails creating a practicable trajectory that will allow every robot to go without colliding with obstacles on the way to the desired location. Figure 2 shows the motion of robot in terrain with obstacles. Finding the best start-to-target route while avoiding obstacles is the most frequent problem for a hexapod climbing robot. Creating an efficient route based on factors like distance, cost, energy, and time is one of the key challenges in robot navigation. An ideal route may be successfully found from one place to another and gets to its destination faster while avoiding all impediments. Several classic statistical approaches and metaheuristic algorithms may have been used to solve it [6]. However, these methods come at a great cost due to their computational complexity and expense.

Robot navigation challenges also include gait optimization for robots in addition to difficulties with route planning. Hexapod climbing robots' low velocity, instability, and high energy consumption are undoubtedly their limitations. Thus, addressing gait design of hexapod climbing robots becomes crucial [7,8]. Without an optimization index, the designer manually adjusts the settings, which results in inaccurate gaits. Conventional metaheuristic algorithms optimize typical and limited gait parameters like either step length or stability or energy consumption, which limit the efficiency of robot climbing [9]. Multi-objective metaheuristic algorithms considering several gait parameters must be developed for optimizing gait parameters for robots. Hence, in this paper, we addressed both the path planning and gait optimization issues in hexapod robot's climbing by hybrid metaheuristic approach. The contributions of the work are as follows.

– A robust two stage gait planning approach (TGWPO-AMPSO) was developed for fine-tuning STM32F103 controller in hexapod wall climbing robot.
– In the first stage, optimal climbing path for robot is predicted using TGWPO based on obstacle and target detection. In the second stage, the gait parameters adaptive to the constructed climbing path are optimized using AMPSO.

The following parts make up the rest of the article. Section 2 contains the related literature as well as the problem statement. Section 3 contains the methodologies involved in the planned work. The findings and discussions are included in Section 4. The conclusion of the proposed article is offered in Section 5.

2 Literature review

Biped robots' simple gait stability is a serious issue that has been covered in a number of literary works. To evaluate the walking stability, they performed "Zero Moment Point (ZMP)" analysis on the collected trajectory model. The "Whale Optimization Algorithm (WOA)" has drawn increased attention since it requires fewer control parameters and is simpler to implement. WOA, however, has poor accuracy and convergence speed. Simulation findings against five other well-known algorithms showed that the proposed "A-C parametric WOA" outperformed the others with a low STD and cost (DBM) value [10]. Gait stability is achieved by [11], the fine-tuning traditional PID controller utilizing the PSO approaches. The initial stabilization while movement approaching the barrier is provided by the traditional PID controller. In order to avoid colliding with the obstacles, the PSO approach has also been used to determine the ideal turning angle. The standard PID controller and the PSO-tuned PID controller operate separately during simulations and testing in the same environment. Utilizing statistical analysis, the output from the ACO and PSO tuned PID controllers has been investigated, and the findings show that the journey time and distance results are consistent with the output. The recommended WPG is taken into consideration with two objectives in mind: decreasing the distance between the ZMP and the foot centre over the course of a step cycle, and the difference between the estimated step length and the supplied step-length values. Then, this constrained optimization problem was separately treated using the "MO-NSGA-2, MO-PSO, and MO-JAYA" optimization algorithms to yield unique optimum Pareto fronts [12,13]. The actuators in the joints of the two legs of the bipedal

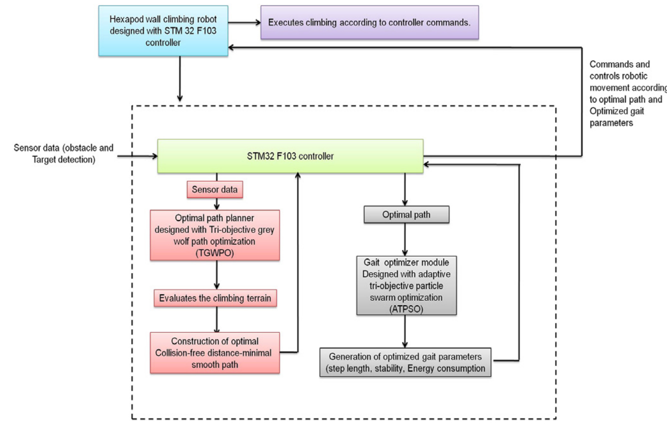

Fig. 3. Flow of the proposed gait planning approach.

body are estimated using inverse kinematics. The ideal solution for biped gait characteristics is then discovered using the CFO optimization method, with the aim of decreasing the ZMP distance between the centre of the supporting foot and the predetermined foot-lift value. The HUBOT-5 robot, a small biped, was subjected to the recommended approach, and the simulation and actual results demonstrate how well it succeeds in allowing the biped robot to walk stably with significantly less training time [14,15]. Anh and Huan [16] was measured the space between the ZMP and the foot centre during the step cycle and accurately quantifying the difference between the magnitude of the step length value and the step-length preset one, the biped walking gait trajectory that can steadily and naturally walk with preset step length magnitude has been obtained. The biped robot's gait characteristics were treated as variables, and we used the Jaya optimization technique to reduce them. By simulating the real-life biped robot HUBOT-4 on a computer, this novel idea has been shown to work. The suggested method may produce the biped gait trajectory in real-time since the optimization procedure is carried out for each period of time. Mandava and Vundavilli [17] noticed that compared to the PSO-trained NN, the MCIWO-tuned neural network-based PID controller produced more dynamically balanced gaits. The best gaits discovered by the MCIWO-NN algorithm were validated in our lab using a real two-legged robot. Proportional-integral-derivative (PID) controllers are mostly utilized in closed-loop control schemes to reduce the error between the intended set point and the actual measured value. It is important to remember that some kind of tuning technique is required to get the best values for the controller's gains in order to attain the desired set point. Eleven active links and ten active joints make up the biped's skeleton. Inverse kinematics is used to calculate the hip and foot location and speed of bipeds. The suggested MO-JAYA compares its performance against those of MO-PSO and MO-NSGA-2 in order to show its efficacy. The simulation results and experimental data on the real-world biped HUBOT-5 system show that the recommended MO-JAYA provides accurate step-length magnitude and efficient and reliable gait planning for bipedss [18,19]. The performance of biped robot walking is heavily influenced by gait generation. PSO and another genetic algorithm (GA) are used to compare the performance of the proposed MDE technique. A miniature humanoid robot prototype is used to implement and evaluate the suggested technique. The identification result shows that the newly developed neural AENM model is a successful technique for a precise and trustworthy production of biped gait [20]. The unique adaptive evolutionary neural model (AENM) generates a dynamic biped gait, which is more easily identified using the suggested modified differential evolution (MDE) optimization strategy. By comparing the suggested MDE technique's performance to that of genetic algorithms (GA) and PSO, its efficacy was shown. The suggested MDE algorithm and other algorithms are tested on the prototype small humanoid robot [21,22]. The robot arm's movement is modelled by inchworm locomotion, especially while moving from one wall to another, avoiding obstacles, and moving through uneven terrain. In comparison to earlier wall-climbing robots, the robot is more effective because of how easily the wheel and arm can be switched between. The suggested linked wheel and arm locomotion concept's kinematic and dynamic model has been developed. The wall-climbing robot's created prototype is used to test the concept of connected wheel and arm mobility under various wall-climbing conditions. The simulation and experimental results, which provide useful comparisons, support the wall-climbing robots' model-based design [23].

3 Proposed work

The main focus of this paper is to develop optimal path and generate optimized gait parameters to enhance the control mechanism of STM32F103 for robot climbing. To fine-tune the STM32F103 controller in the hexapod wall climbing robot, a reliable two stage gait planning technique (TGWPO-AMPSO) was proposed in this paper. Using TGWPO with target and obstacle recognition, the first stage predicts the robot's best climbing route. In the second stage, AMPSO is used to optimise the gait characteristics that are adaptable to the built-in climbing route. STM32F103 controller commands and controls the robot to climb on wall with optimized gait parameters according to the optimal path. Figure 3 shows the flow of the suggested stage gait planning technique.

3.1 Hexapod wall climbing robot with STM32F103 controller

In this study, a hexapod wall-climbing robot is created using the STM32F103 as the primary controller or the brain of the overall robotic control system. We chose STM32F103 as the robotic core because of its benefits of high computational capacity, quick speed, and affordable cost. STM32F103 controller is linked with wireless communication module (senses the climbing environment), power module (provides power for the robotic functioning), motor drive module (gathers wave signals with various robotic gait cycle, and forces the motor to operate the robot at various climbing speeds). To enhance the control mechanism of STM32F103, we linked STM32F103 controller with optimal path planner module (generates

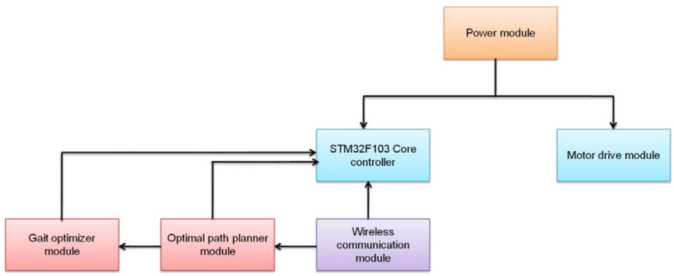

Fig. 4. Robotic control mechanism based on fine tuned STM32F103 controller.

collision-free, smooth, short length climbing path) and gait optimizer module (generates optimal gait parameters). Figure 4 shows the schematic diagram of robotic control mechanism based on fine tuned STM32F103 controller.

3.2 Optimal path planner module based on Tri-objective Grey Wolf Path Optimization (TGWPO)

The main purpose of optimal path planner module is to find an optimal path, with collision-free, smooth, and minimal path length. Sensory data such as the target and location of obstacles in the way to target are collected by the wireless communication module. This sensory data is sent as input to the STM32F103 controller. Then STM32F103 controller sends the location of obstacles and target to optimal path planner module. Conventional Grey wolf optimization is adopted for single objective optimization. Length of the path, degree of collision risk, and smoothness are all considered in the formulation of the objective function for the robotic path planning.

Assume the starting and target point as S and T for hexapod wall climbing robot. Let 'A' denote the number of intermediate points in the climbing route. The target point can also be denoted as $A+1$. The position of start point and target point is denoted by P_0 and P_{A+1} fined by $(x_0,\ y_0)$ and $(x_{A+1},\ y_{A+1})$. The path length for the climbing route can be defined by equation (1)

$$L_P = \sum_{j=0}^{A} ||P_{j+1} - P_j||, \tag{1}$$

where L_P means the length of the climbing path and $P_{j+1} - P_j$ || denotes the Euclidean distance between P_j and P_{j+1}.

The degree of path collision risk aims to determine the extent to which a path is impeded by barriers and it is taken into account while designing a route. The collision risk function is constructed using a Gaussian function for assessing the degree of collision risk. Equation (2) is used to predict the likelihood of a robot and obstacle colliding.

$$C(Y_{robot}, Y_{obstacle}) = \sum_{i=1}^{m} C_{robot,obstacle_i}\left(Y_{robot}, Y_{obstacle_i}\right), \tag{2}$$

where $C_{robot,obstacle_i}$ means the degree of collision risk exhibited between robot and obstacle i, m denotes the number of obstacles in the climbing path, Y_{robot} and $Y_{obstacle}$ define the position vector of mobile $robot$ and $obstacle_i$ correspondingly.

Equation (3) describes the probability of a robot and obstacle colliding

$$C\left(Y_{robot}, Y_{obstacle_i}\right) = \begin{cases} e^{-\frac{1}{2}\left(||Y_{robot} - Y_{obstacle_i}||^2\right)} & ||Y_{robot} - Y_{obstacle_i}|| \le C_i\,, \\ 0, & ||Y_{robot} - Y_{obstacle_i}|| \le C_i \end{cases} \tag{3}$$

where C_i means the maximum range influenced by the obstacle i.

The smoothness of the route is a measurement of how snaky the path is. Any three nearby points on the climbing path may be used to measure the smoothness of a route. Equation (4) may be used to determine the smoothness of a climbing route when three nearby locations are taken into account.

$$S_P = \sum_{j=1}^{A} \alpha_j = \sum_{j=1}^{A} arccos\left(\frac{\left(P_j - P_{j-1}\right).\left(P_{j+1} - P_j\right)}{|P_j - P_{j-1}| \times |P_{j+1} - P_j| \times 180}\right), \tag{4}$$

where α_j means the deflection angle at jth point for the climbing path, P_{j-1}, P_j, and P_{j+1} mean the three neighboring points in climbing path.

Equation (5) describes the weighted combination of route length, degree of path collision risk, and path smoothness as the overall goal function for optimizing mobile robot paths.

$$I(P, Y_{robot}, Y_{obstacle}) = v_1 \times L_P + v_2 \times C(Y_{robot}, Y_{obstacle}) + v_3 \times S_P, \tag{5}$$

where $I(P,\ Y_{robot},\ Y_{obstacle})$ means the objective function for optimal path planning, v_1, v_2, and v_3 are the weight coefficients ranging from 0 to 1.

In this way, the mobile robot route planning issue may be described as the following optimization problem of minimising the total objective function with constraints, which is given by equation (6)

$$\min I(P, Y_{robot}, Y_{obstacle}) \quad s.t. \quad P, Y_{robot} \notin S. \tag{6}$$

TGWPO (Tri-objective Grey wolf path optimization) is used to solve the challenge of minimizing the overall objective function for route planning. The TGWPO was designed to mimic the behaviour of a Grey wolf, which hunts and attacks its victims. Here the optimization work space is modeled with 'N' grey wolves and 'L' prey. Here grey wolf act as the robot and prey act as an obstacle. A grey wolf's alpha, beta, delta and omega were four distinct sorts of leaders. While Alpha, Beta, and Delta are regarded as the finest answers, Omega may be considered the remainder of the candidates. The position vector of grey wolf (robot) is mathematically defined by equation (7)

$$\vec{Y_W}(s+1) = \vec{Y_L}(s) - \vec{B}.\left|\vec{A}.\vec{Y_P}(s) - \vec{Y_W}(s)\right|, \tag{7}$$

where $\vec{Y_L}(s)$ and $\vec{Y_W}(s)$ mean the position vector of prey and grey wolf at time 's', and $\overline{\mathrm{A}}$ are the random vector parameters.

The location of a grey wolf (robot) may be updated based on the prey's position (obstacle). Other search agents (including omegas) are now required to adjust their locations in light of the best-performing search agents, since the first three most promising solutions have been discovered. The best solution for constructing optimal climbing path is defined by equation (8)

$$\vec{Y_W}(s+1) = \frac{\vec{Y_1} + \vec{Y_2} + \vec{Y_3}}{3}, \tag{8}$$

where $\vec{Y_1}$, $\vec{Y_2}$, and $\vec{Y_3}$ mean the top three ranked best solutions for optimization problem.

When the maximum iteration is reached, the grey wolf stops updating the position and provides the best fitness solution. The best fitness solution resulted by TGWPO is the optimal robot climbing path with collision-free, smooth, and short length. The optimal climbing path constructed by TGWPO is sent to STM32F103 controller and gait optimizer module.

3.3 Gait optimizer module based on adaptive multi-objective particle swarm optimization

The gait optimizer module is designed to optimize the gait parameters of hexapod climbing robot adaptive to the constructed optimal path. We transformed the gait optimization planning into multi-objective problem by considering the gait parameters like gait stability, energy consumption, climbing speed, torque, and time. The robot's dynamic balance or stability are assessed using the zero moment point concept (ZMP). When the ZMP is within the foot support polygon, the robot is considered to be dynamically balanced. To get the ZMP's location in relation to the ankle joint, equation (9) is used

$$y_{ZMP} = \frac{\sum_{6}^{j=1}\left(I_j\omega_j + m_j x_j\left(\ddot{y}_j g\right) m_j \ddot{x}_j y_j\right)}{\sum_{7}^{j=1} m_j\left(\ddot{y}_j g\right)}, \tag{9}$$

where I_j mean the moment of inertia at jth joint, ω_j means the angular acceleration, g denotes the acceleration due to gravity, m_j means the mass, (x_j, y_j) means the co-ordinates the robot position, $\ddot{y}j$, and $\ddot{x}j$ denotes the acceleration in y and x direction.

It is necessary to modify the robot's settings if the ZMP is found to be outside the foot support polygon. Equation (10) calculates DBM (dynamic balance margin) as the distance between the ZMP and the border of the support polygon.

$$DBM = \left(\frac{l}{2} - |y_{ZMP}|\right), \tag{10}$$

where l denotes the supporting foot length and y_{ZMP} denotes the distance of ZMP from the robot's ankle joint in the direction of climbing.

Motor torque and angular velocity may be used to compute the amount of power used by the jth joint. The average power consumption is calculated by equation (11)

$$P_j = \frac{1}{T}\sum_{j=1}^{l}\int_0^N\left(|\tau_j z_j| + G{\tau_j}^2\right)dt, \tag{11}$$

where P_j means the power consumed, τ_j means the torque, G means the constant, T means the climbing time, and Z_j means the angular velocity.

Equation (12) may characterize the multi-objective function for optimising the climbing gait as the weighted combination of power use, torque, stability, angular velocity, and time.

$$F = v_1 \times P + v_2 \times \frac{1}{DBM} + v_3 \times \frac{1}{\tau} + v_4 \times \frac{1}{Z} + v_5 \times T. \tag{12}$$

Equation (13) expresses the mobile robot's gait planning issue in terms of the following optimization problem as minimizing the total objective function with restrictions.

$$\text{Minimize } F(robot). \tag{13}$$

Particle swarm optimization (AMPSO) is used to solve the challenge of reducing the overall objective function for gait planning. 'N' particles make up the gait optimization workspace. Here, the robots are shown as particles. The AMPSO algorithm updates each particle using two values. The particle's "best personal experience" is stored as the first element in this array. The second number is the "best worldwide position," which refers to the highest position ever attained by particles. Each particle's location and speed are updated as soon as these two values are discovered. When the maximum iteration is reached, the particles stop updating the position and provide the best fitness solution. The best fitness solution resulted by AMPSO is the optimal energy-efficient, stable, gait parameters for robots. The optimal energy-efficient, stable, gait parameters generated by AMPSO is sent to STM32F103 controller. STM32F103 controller commands and controls the robot to climb on wall with optimized gait parameters according to the optimal path. Hexapod climbing robot executes the climbing process following the optimal path with optimized gait parameters.

4 Result and discussion

This section deals with the efficacy of the proposed two stage gait planning approach using TGWPO-AMPSO for fine-tuning the control mechanism of STM32F103 controller for hexapod climbing robots. The simulation model of hexapod climbing robot was built using SolidWorks [24] and imported into VREP software for scene simulation [25]. Figure 5 shows the snapshot of simulation results for

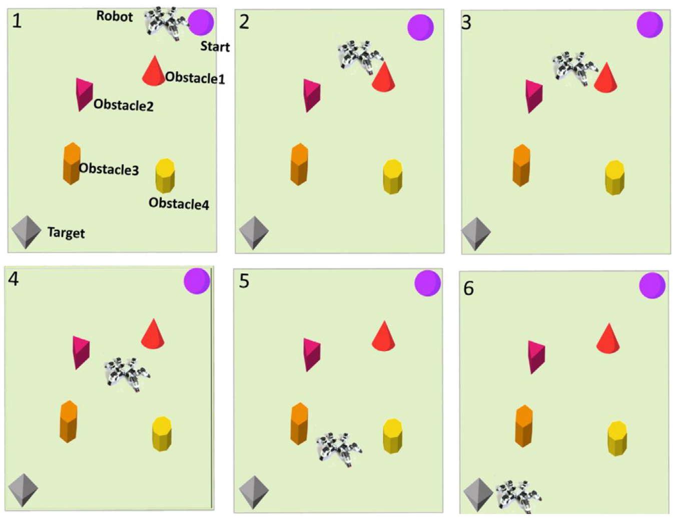

Fig. 5. Snapshot of simulation results for navigation of hexapod robots in complex wall.

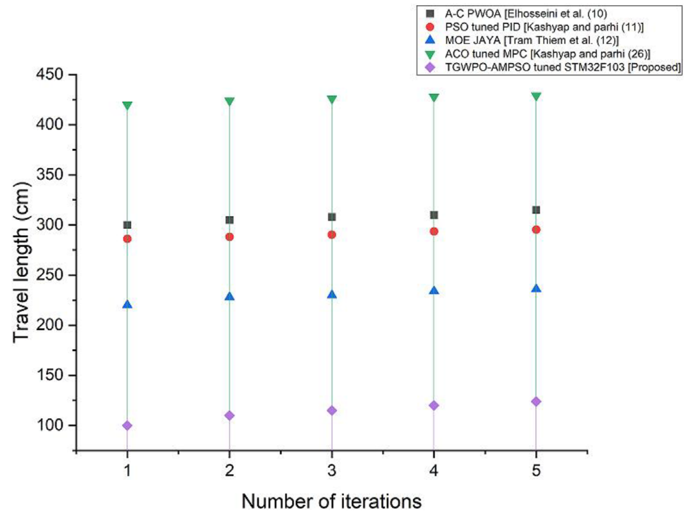

Fig. 6. Number of iterations versus travel length.

navigation of hexapod robots in complex wall. We simulated the climbing scene of hexapod climbing robots using VREP software with four obstacles to analyze the efficacy of TGWPO-AMPSO tuned STM32F103 controller in path planning and gait optimization. We evaluated the efficacy of TGWPO-AMPSO tuned STM32F103 with existing approaches like A-C parametric WOA, PSO tuned PID controller, multi-objective evolutionary JAYA, and ant colony optimization tuned MPC controller (ACO tuned MPC). The performance indicators used for evaluation are travel length, travel time, energy consumption, climbing speed, obstacle avoidance, path deviation, and gait stability.

Travel length means the distance covered by the robot while climbing from the starting point to destination point. Figure 6 shows the comparison of travel length of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The travel length of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was lesser than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. This ensured that TGWPO-AMPSO approach generated shortest path for wall climbing compared to existing approaches.

Travel time means the time taken by the robot to climb the wall following the optimal path constructed. Figure 7 shows the comparison of travel time of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The travel time of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was lesser than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. This ensured that hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 can reach the target point on wall in lesser time compared to existing approaches.

In this context, "energy consumption" refers to the amount of energy it takes for the robot to climb the wall using the route and gait patterns it has been programmed to follow. Figure 8 shows the comparison of energy consumption of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The energy consumption of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was lesser than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. This ensured that hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 can reach the target point on wall using minimum energy compared to existing approaches. Short path length and optimized torque constraints obtained using the proposed approach significantly reduced the energy consumption of climbing robots.

Climbing speed means the distance covered by the robot in unit time. Figure 9 shows the comparison of climbing speed of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The average climbing speed of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was lesser than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. Average climbing speed is efficiently optimized that contributes to minimal energy consumption. This ensured that hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 can reach the target point faster compared to existing approaches.

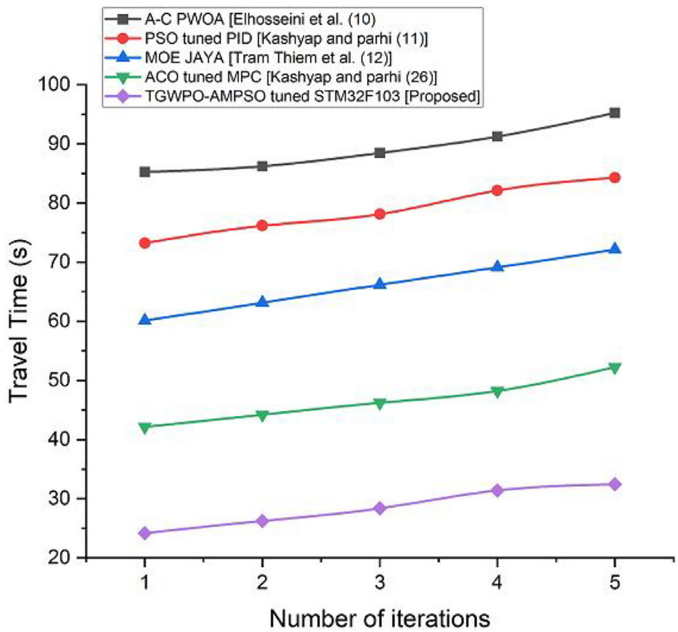

Fig. 7. Number of iterations versus travel time.

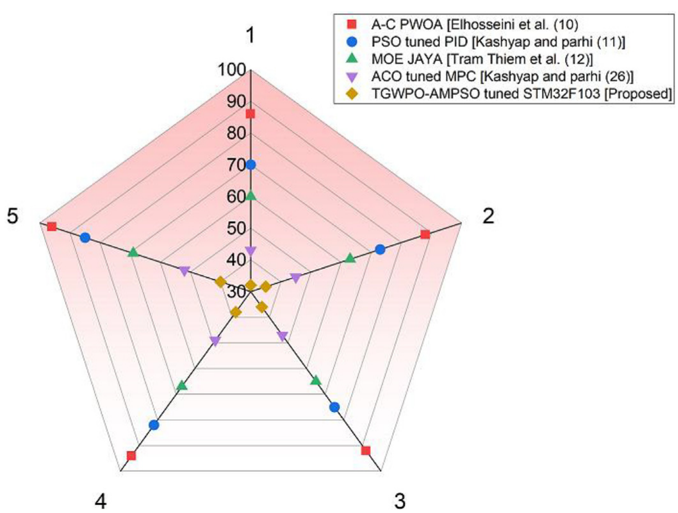

Fig. 8. Number of iterations versus energy consumption.

Obstacle avoidance efficiency means the efficiency of constructing climbing path with minimal obstacles. Figure 10 shows the comparison of obstacle avoidance efficiency of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The obstacle avoidance efficiency of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was higher than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. This shows that TGWPO-AMPSO approach constructs safe, collision-free path for wall climbing.

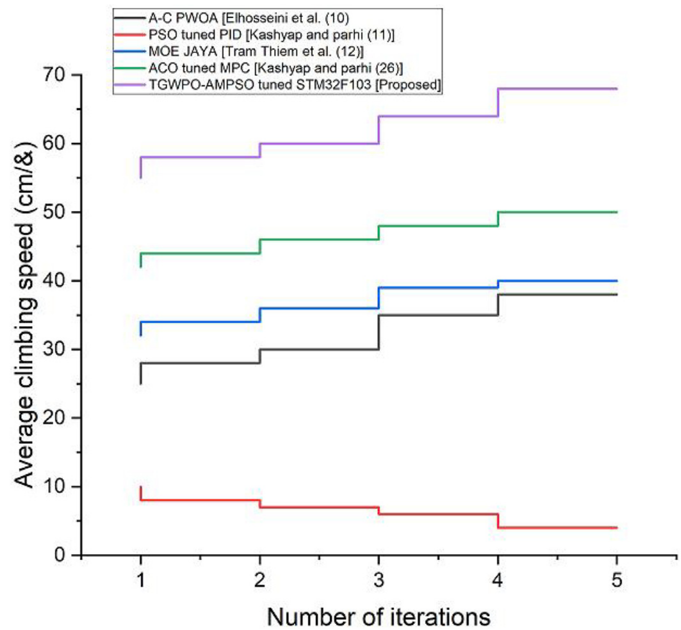

Fig. 9. Number of iterations versus average climbing speed.

Stable gait is defined as gait that does not lead to falls by controlling the position of the robot body relative to the base of wall. Figure 11 shows the comparison of climbing stability of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The climbing stability of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was higher than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. This shows that TGWPO-AMPSO approach efficiently controls the position of the robot body relative to the base of wall.

Path deviation is defined as the probability of robot being deviated from the climbing path. Figure 12 shows the comparison of path deviation of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 with that of other gait planning techniques. The path deviation of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was lesser than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller, MOEJAYA, and ACO tuned MPC controller. This shows that TGWPO-AMPSO approach efficiently controls the robot navigation.

Multi-legged walking robots have never been widely used because of their excessive energy consumption. We compared the efficiency of the proposed method with conventional techniques which have certain drawbacks. The Whale Optimization Algorithm (WOA) has drawn increased attention since it requires fewer control parameters and is simpler to implement. WOA, however, has poor accuracy and convergence speed. It is straightforward to enter a local optimum in high-dimensional space, and the PSO technique has a low rate of convergence throughout the iterative process.

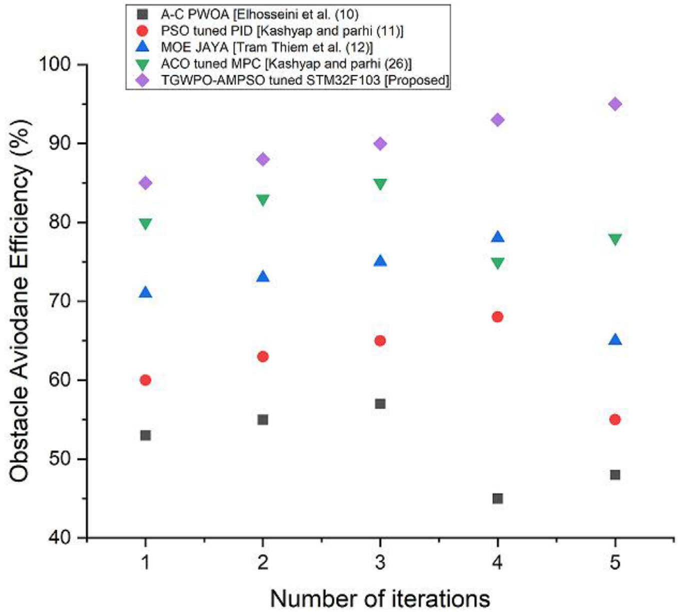

Fig. 10. Number of iterations versus obstacle avoidance efficiency.

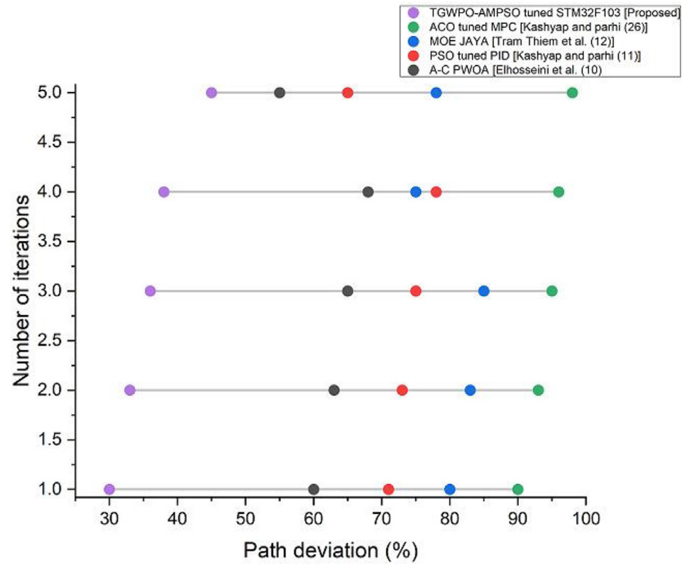

Fig. 12. Number of iterations versus path deviation.

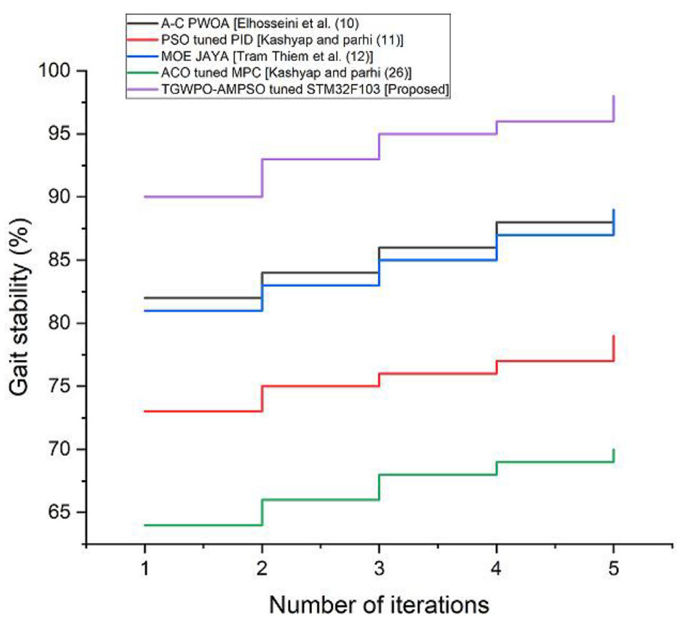

Fig. 11. Number of iterations versus gait stability.

The computation time of each tested approach, including TGWPO-AMPSO-tuned STM32F103, is an important aspect for evaluating their effectiveness in various applications. In comparison to existing approaches, such as A-C parametric WOA, PSO tuned PID controller, multi-objective evolutionary JAYA, and ant colony optimization tuned MPC controller (ACO tuned MPC), the TGWPO-AMPSO-tuned STM32F103 has shown promising results, and the use of the TGWPO-AMPSO tuning method enables efficient optimization of the control parameters, leading to reduced computation time. In addition, this approach delivers the optimal controller parameters and minimizes the error between the reference and output signals. The ACO-tuned MPC controller also shows good results in various applications, and is renowned for its robustness, ability to handle nonlinearities, and complex systems.

Furthermore, the multi-objective evolutionary JAYA provides a feasible solution within an acceptable computation time, whereas the PSO-PID controller is also effective in optimizing the PID controller parameters. However, the A-C parametric WOA approach has shown a comparatively higher computational time and requires significant expertise in system identification and tuning. TGWPO-AMPSO-tuned STM32F103, along with other existing approaches, offers a viable solution for improving the performance of various control systems with different computation times and complexity requirements. Further research is required to evaluate their effectiveness in different real-time applications.

The MO-NSGA-2, MO-PSO, and MO-JAYA optimization algorithms were used individually to solve this limited optimization issue and provide distinct optimal Pareto fronts. MPC does not provide the impression of being resilient when handling issues involving uncertainty, which leads to significant computing costs. The travel length, travel time, energy consumption, climbing speed, and path deviation of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was lesser than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller. The obstacle avoidance, and gait stability of hexapod climbing robot designed with TGWPO-AMPSO tuned STM32F103 was higher than that of robots trained by existing methods like A-C parametric WOA, PSO tuned PID controller. The suggested TGWPO-AMPSO method beat the other algorithms with a lesser amount of speed, energy, and reduces the unnecessary travel time length. Lower energy consumption observed for robots using the proposed technique reduced the cost of climbing.

Designing and controlling obstacle climbing robots can be a time-consuming process, but there are methods to help overcome these challenges. First, thorough research on the obstacle climbing gait structure design and gait control can provide valuable insights into the most efficient methods for designing and controlling hexapod wall-climbing robots. Next, utilizing a powerful core controller, such as STM32F103, can help streamline the process by providing high processing power and low power consumption. This controller offers real-time performance and sufficient memory to store important data, allowing for the smooth operation and efficient management of the robot's movements. In addition, using advanced algorithms and coding techniques can help optimize the performance of the robot and shorten the design and testing process. For example, utilizing algorithms such as motion planning and inverse kinematics can help a robot accurately navigate obstacles without wasting valuable time. Overall, by conducting thorough research, utilizing cutting-edge technology, and implementing advanced algorithms, it is possible to overcome the time-consuming hurdles when designing and controlling hexapod wall-climbing robots. Using these techniques, engineers can focus on optimizing their designs and achieving the best possible results.

5 Conclusion

Hexapods can scale intricate walls. To explore complicated surroundings independently, it must determine gait characteristics and wall routes. We present a two-stage gait planning technique for forecasting collision-free, distance-minimal, smooth navigation paths and assuring steady, energy-efficient walking patterns for robots utilizing hybrid met heuristic algorithms. First, the ideal climbing route is projected using TGWPO based on obstacle and target recognition. Second, AMPSO is used to optimize gait parameters for the created climbing route. The result analysis showed that TGWPO-AMPSO tuned STM32F103 controller is efficient for designing hexapod climbing robots. In the future, we'll explore the robot's dynamic properties utilizing distorted elastic legs. Combining claw shape legs and rapid jumping to conquer higher barriers, we'll also concentrate on the automated climbing control algorithm, which senses the position and height of barriers to switch gaits automatically.

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