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Original Research Article

Design, Optimization and Fabrication of a Climbing Six Articulated-Wheeled Robot using Artificial Evolution and 3D Printing

ABSTRACT

Over the last decade, various mobile robots have been developed and widely used in myriad sectors. However, the vast majority of mobile robots are manually designed where the designers must have the preliminary knowledge of the interaction between the robots with the environment. Additionally, the high complexity involved in the design of the kinematics and controllers of a mobile robot has always been the biggest challenge for the researchers and practitioners alike. Thus, the task of designing a robot can be considered very demanding and extremely challenging. In this research, an artificial evolution approach utilizing Single-Objective Evolutionary Algorithm (SOEA) and Multi-Objective Evolutionary Algorithm (MOEA) respectively are investigated in the automatic design and optimization of the morphology of a Six Articulated-Wheeled Robot (SAWR) with climbing ability. Results show that SOEA is able to produce optimized SAWR with climbing ability while MOEA is able to produce a set of Pareto optimal solutions which provide users with a choice of solutions for trade-off between the objectives of morphology size and climbing performance. The Pareto optimal set of solutions are the smallest SAWR with least climbing ability to biggest SAWR with the best climbing motion. The research continues by transferring the evolved solutions from simulation to the real world using 3D printing. The body, legs and wheels of the evolved robots are printed by a 3D printer and assembled with sensors, servos and motors for real world testing. Results show that the fabricated real world SAWRs are able to perform the climbing motion with the average accuracy of 85.8% in comparing to the performance in simulation.

Keywords: [Articulated-Wheeled Robot, Evolutionary Robotics, 3D Printed Robots, Climbing Robots, Hybrid Mobile Robots]

1. INTRODUCTION

Since the first implementation of mobile robots in World War II, mobile robotics has become an extremely popular research topic. Mobile robotics can be utilized in a wide range of applications. For example, service industry, military deployments, manufacturing, cleaning, entertainment and remote exploration, especially in search and rescue operations where human lives can be endangered. Mobile robot can be traditionally categorized into two categories which are wheeled and legged mobile robots. Wheeled robots have the characteristic that they can traverse a longer distance with a faster speed with their wheels than legged robots. Besides that, wheeled robots are more powerful in terms of load/weight ratio [1]. However, wheeled robots generally having difficulties when traversing over a rough terrain i.e. with obstacles, steps, discontinuous contact surface, among others. On the other hand, legged robots provide a flexible adaptive mobility in unstructured environment and a better performance while traversing over rough terrain. In terms of travelling speed and power efficiency, legged robots are still falling behind of wheeled robots achievement.

30 A hybrid platform with the combination of leg and wheel has excellent maneuverability on flat
31 ground and uneven terrain. Therefore, a hybrid platform is highly recommended for general
32 indoor and outdoor environment operations as it is the trend for “future” mobile platforms [2].
33 In recent years, hybrid mobile robots have been designed for various functionality and
34 purposes. For example, hybrid mobile robots designed for stairs climbing purposes,
35 performing jumping behavior, in-situ reconfiguring robots posture and adapting to uneven
36 terrain, among others. In general, hybrid mobile robots can carry out their mission better in
37 rough terrain compared to traditional wheeled or legged mobile robots. Hybrid mobile robots
38 utilize the advantages of both wheeled and legged mechanisms while compensating the
39 downside of each other.

40
41 There are many successful examples of hybrid mobile robots which are built and designed
42 for wide range of operations. A group of researchers from a few universities in Japan had
43 developed a hybrid wheeled-legged platform through a retracting mechanism inspired by the
44 armadillo [3]. The idea of a retractable wheeled-legged module is that the specially-designed
45 wheels can be transformed into a legs-like mechanism. Smith, Sharf and Trentini from McGill
46 University proposed PAW, a four legs robot with wheels equipped at the end of each leg [4].
47 PAW is the first to combine wheeled mode locomotion with dynamically stable legged
48 locomotion.

49
50 There are numerous of hybrid mobile robots have been proposed and developed. However,
51 as far as we aware, most of the hybrid mobile robots are manually designed where the
52 designers must have the preliminary knowledge of the interaction between the robots with
53 the environment. Besides that, the extremely complexity in the kinematic and controller
54 designing of a hybrid mobile robot has always been the biggest challenge for the
55 researchers. Planning is an important aspect of the effort to design robots that perform their
56 task with some degree of flexibility and responsiveness to the environment [5]. According to
57 Akerka, planning is a difficult problem for a number of reasons, not the least of which is the
58 size of the space of possible sequences of moves [5]. Even a simple robot which can only
59 move forward, backward, right or left has so many different ways that the robot can possibly
60 move around in an environment. On the other hand, manually morphology designed on trial-
61 and-error basis is not guaranteed to be optimal from the large design space [6]. Thus, the
62 task of designing a robot can be considered demanding [7], especially in designing a hybrid
63 mobile robot. Here raises the research question on the ability of obtaining an optimized
64 morphology of a climbing SAWR with evolution approach.

65
66 The use of artificial evolution for the automatic generation and synthesis of controllers and/or
67 morphologies for robots is one of the more recent methods in developing robots [8]. By
68 implementing evolutionary algorithms in designing a robot, an optimized controller and/or
69 morphologies can be obtained where at times, these evolved solutions might be beyond the
70 designers' design capability.

71
72 Successful examples of designing robots with artificial evolutionary approach, walking robots
73 designed with evolutionary computation in optimizing the morphology and controller [9] and
74 swarm robotics with their controllers designed by evolutionary algorithms with artificial neural
75 networks [10].

76
77 In this research, an artificial evolution method with single-objective and multi-objective
78 evolution algorithm is proposed to design and optimize the morphology of a six articulated-
79 wheeled robot (SAWR) with climbing ability. Instead of stopping the research after obtaining
80 results from simulation, evolved solutions from simulation are transferred into real world
81 SAWRs and their performance in real world environment are investigated.

82

2. METHODOLOGY

In this research, a Six Articulated-Wheeled Robot (SAWR) has been designed and served as test bed. The locomotion mechanism of the SAWR allows a traditional leg robot to overcome their complex and slow walking mechanism by attaching wheels at the end of each leg. On the other hand, articulated-wheel mechanism allowed a traditional wheeled robot to traverse through rough terrain and further enhance the robot with climbing capability. Thus, the SAWR in this research is designed to have the capability to perform climbing motion.

2.1 SAWR and the Climbing Motion

The SAWR has six legs with 180 degree of one degree-of-freedom (DOF) motion. An active wheel is attached to each leg of the SAWR. The main traversing method of the SAWR is based on wheel locomotion. While with the support of legs, the robot can reconfigure itself to perform climbing motion in order to overcome obstacles. The SAWR is actuated with twelve independent actuators where six for the legs and six for the wheels. There are two sensors integrated to drive the SAWR autonomously especially in obstacle negotiation ability.

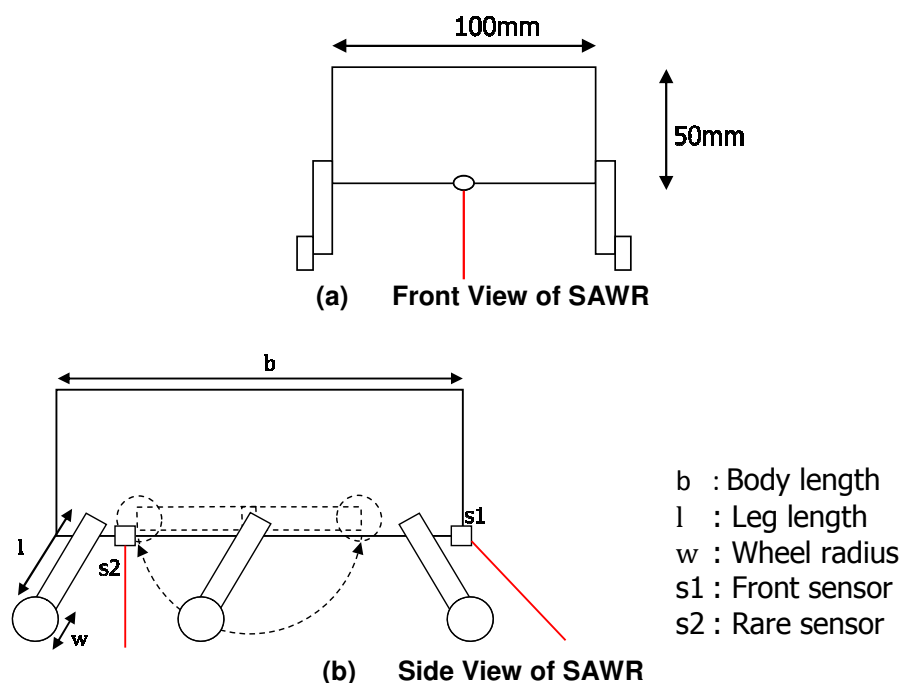
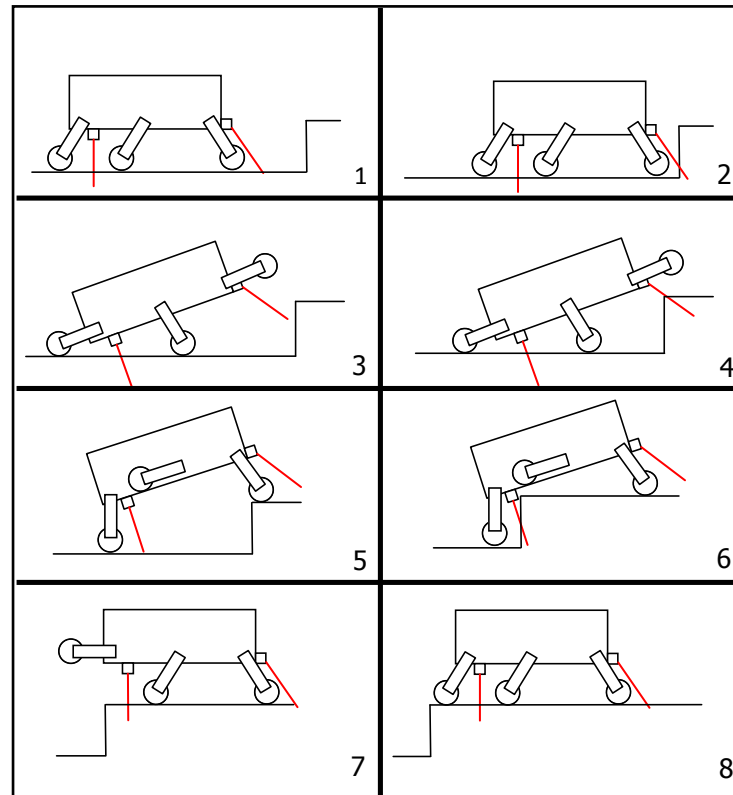


Fig. 1. Morphology Design of the SAWR.

Fig. 1. shows the front view and side of the SAWR. In the figure, s1 is representing the front sensor and s2 is representing the rare sensor. While b, l and w are the evolving parameters which are to be optimized in the evolution process in this research. The SAWR is designed to have the capability of climbing obstacles and steps in order to operate in a more complex environment. With two sensors and six active wheels where each are attached on one DOF legs, the SAWR can perform a sequence of reconfiguration motions to climb up and down from obstacles.

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The original idea of the reconfiguration method for climbing upward and downward steps is obtained from Lu and Bu on their paper "Study on the Mobile Robot Reconfiguration Control Methods" [11]. They had proposed a series of reconfiguration method of a six legged-wheeled robot for ridges and channels negotiation. However, the reconfiguration method is enhanced in this research to sensors-based reconfiguration method. The robot with our proposed reconfiguration method can perform climbing motion autonomously based on the changes of values from the sensors onboard.



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Fig. 2. Reconfiguration Method of Climbing Upward Step.

The series of reconfiguration method of climbing upward step is shown in Fig. 2. Fig 2.1 shows the original marching position where the SAWR is moving forward. When the SAWR is approaching to obstacles, value from front sensor, s1 will be changed when the obstacle is detected by the sensor as shown in Fig. 2.2. The climbing reconfiguration method will be activated when obstacle is detected by sensor s1. Firstly, the SAWR will reconfigure itself as in Fig. 2.3 and continue move forward until the s1 sensor value is changed again as in Fig. 2.4. Then the SAWR is now ready to place both of the front legs down on the obstacle which can be seen in Fig. 2.5. After that, the SAWR will continue moving forward until the value of s2 sensor is changed as shown in Fig. 2.6. Then the SAWR will reconfigure itself by placing down the middle wheels on the obstacle as seen in Fig. 2.7. The SAWR will continue moving forward for a short duration and finally reconfigure itself back to the original marching position as shown in Fig. 2.8.

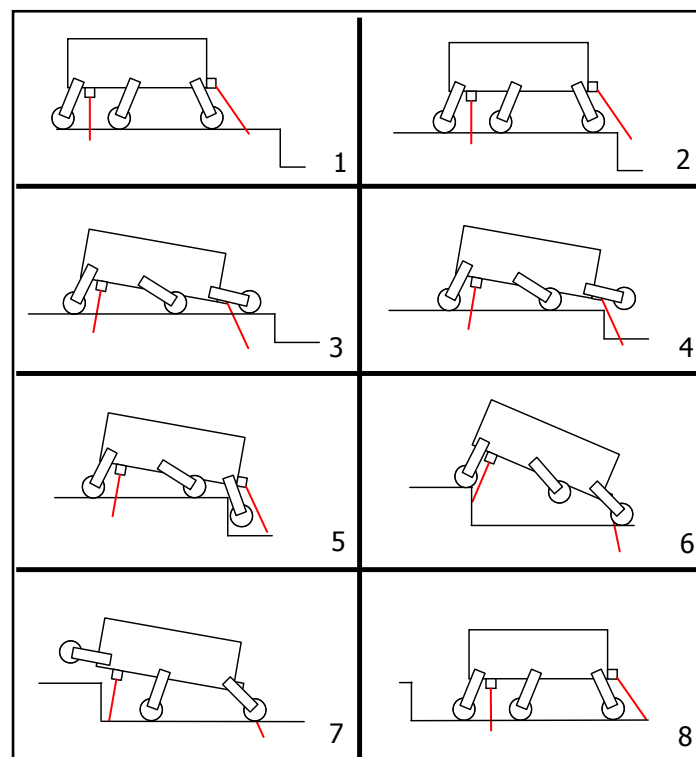


Fig. 3. Reconfiguration Method of Climbing Downward Step.

Fig. 3.1 shows the original marching position where the SAWR is moving forward. By referring to the value changes of sensor s1, SAWR can determine a downward step is approaching as shown in Fig. 3.2. Firstly, the SAWR will reconfigure itself as in Fig. 3.3 and continue moving forward. The SAWR will move forward until the front wheels goes off from the step for a certain distance, this can be determined by referring to the value changes of s1 sensor as shown in Fig. 3.4. After that, the angle of the front leg will be adjusted as in Fig. 3.5 and the robot will continue moving forward. By inspecting the value changes of s2 as shown in Fig. 3.6, the SAWR can determine whether the middle wheels are going off from the step and ready to reconfigure itself as in Fig. 3.7. Lastly, the SAWR will put down the rear wheels onto the ground after moving forward for a short period and the robot is recovered to the original marching reconfiguration as shown in Fig. 3.8.

2.2 Evolutionary Algorithms

In this research, two evolutionary algorithms had been proposed which is the evolution method with the integration of Single-Objective Evolutionary Algorithm (SOEA) and Multi-Objective Evolutionary Algorithm (MOEA). SOEA is able to produce fittest climbing SAWRs with optimized/minimized morphology while MOEA is able to produce Pareto-sets of optimal solutions which are different sizes of SAWRs with different degree of goodness in performing climbing motion in the task environment. This can provide users a choice of solutions for trade-off between the two objectives which are the size of the SAWR and the ability in performing climbing motion.

2.2.1 Single-Objective Evolutionary Algorithm (SOEA)

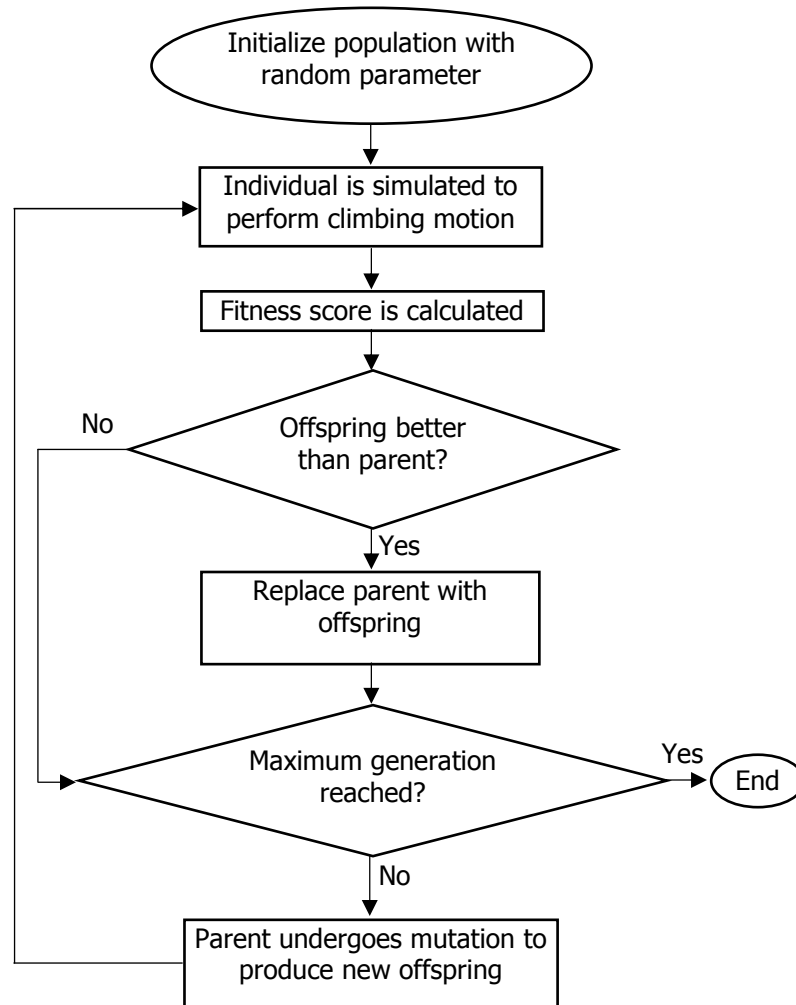


Fig. 4. Flowchart of the SOEA.

Fig. 4. shows the flowchart of the SOEA. The SOEA starts with initializing population with random parameters for the SAWR body length, leg length, and wheel radius. Then the individual will be simulated in simulation to perform climbing motion and the performance of the individual will be evaluated. A fitness score will be calculated based on a fitness function which will be described later. The fitness score will be compared with the parent's fitness score. The parent will be abandoned and replace with the individual if the individual has better score than the parent. After that, parent will undergo mutation operation to produce offspring for next generation if the maximum number of generation is not reached. New offspring will then be started again with the simulation to perform climbing motion and the process will repeat until the maximum number of generation is reached.

Fitness function of the SOEA is shown in equation 1. The fitness function is designed as in the way that the lesser is the fitness score, the better it is. The first part of the fitness function is a direct addition of the SAWR body length with the SAWR leg length and the SAWR wheel radius to reflect the main objective of this research which is to obtain a smallest possible climbing SAWR.

$$\text{Fitness} = (b + l + w) \times (1 + d \times 10) + (c \div mc) \quad (1)$$

186 b = robot body length;
 187 l = robot leg length;
 188 w = robot wheel radius;
 189 d = robot final destination from target destination;
 190 c = number of collision occurs during simulation;
 191 mc = maximum number of collisions possible to occur during one simulation.

192
 193 Besides that, the capability of the SAWR to perform climbing motion is also an important
 194 criterion in determining the fitness of a robot as a small SAWR without the capability of
 195 climbing obstacle is not a desired solution. Thus, the second part of the fitness function is to
 196 ensure individuals with the capability to perform climbing motion must be credited with better
 197 score in comparing to smaller individuals without the climbing capability. This can be
 198 achieved by taking the distance of the individual final position from the goal destination to
 199 multiply with ten in order to increase the weight. Then the value will be added by one before
 200 multiplying with the first part of the fitness function which is the size of the SAWR.

201
 202 The last part of the fitness function is to penalize individuals that have collision with the
 203 obstacles during the simulation. The total number of collisions occurs during the simulation is
 204 divided by the maximum number of collision that is possible to occur in a single run of
 205 simulation in order to scale the penalize score with the fitness function.

206
 207 Mutation is carried out after parent selection. The selected parent will undergo mutation
 208 operation in order to produce new offspring for next generation. In this research, a fixed,
 209 non-adaptive mutation operation is implemented. Mutation operation is an addition operation
 210 of the parent evolving parameters with Gaussian numbers (random numbers with mean of
 211 zero and standard deviation of one). Mutation operation will be done to the parent body
 212 length, parent leg length and parent wheel radius which are shown in Equation 2, 3 and 4.

$$\begin{aligned} 213 & \\ 214 & \text{Offspring Wheel Radius} = PR + (G/3) \times (R_{\max} - R_{\min}) \quad (2) \\ 215 & \text{Offspring Leg Length} = PL + (G/3) \times (L_{\max} - L_{\min}) \quad (3) \\ 216 & \text{Offspring Body Length} = PB + (G/3) \times (B_{\max} - B_{\min}) \quad (4) \end{aligned}$$

217
 218 G = Random Gaussian number;
 219 PR = Parent wheel radius;
 220 Rmax = Maximum value of wheel radius;
 221 Rmin = Minimum value of wheel radius;
 222 PL = Parent Leg length;
 223 Lmax = Maximum value of leg length;
 224 Lmin = Minimum value of leg length;
 225 PB = Parent body length;
 226 Bmax = Maximum value of body size;
 227 Bmin = Minimum value of body size.

228 229 **2.2.2 Multi-Objective Evolutionary Algorithm (MOEA)**

230
 231 Multi-objective evolutionary algorithm (MOEA) is used to solve problems that involve
 232 optimizing multiple objective functions simultaneously. In this experiment, MOEA is
 233 implemented in attempting to produce a set of Pareto optimal solutions in a single run. In our
 234 case, the Pareto set optimal solutions are different sizes of SAWR with different degree of
 235 goodness in performing climbing motion in the task environment. This can provide users a
 236 choice of solutions for trade-off between the two objectives which are the size of the SAWR
 237 and the ability in performing climbing motion.

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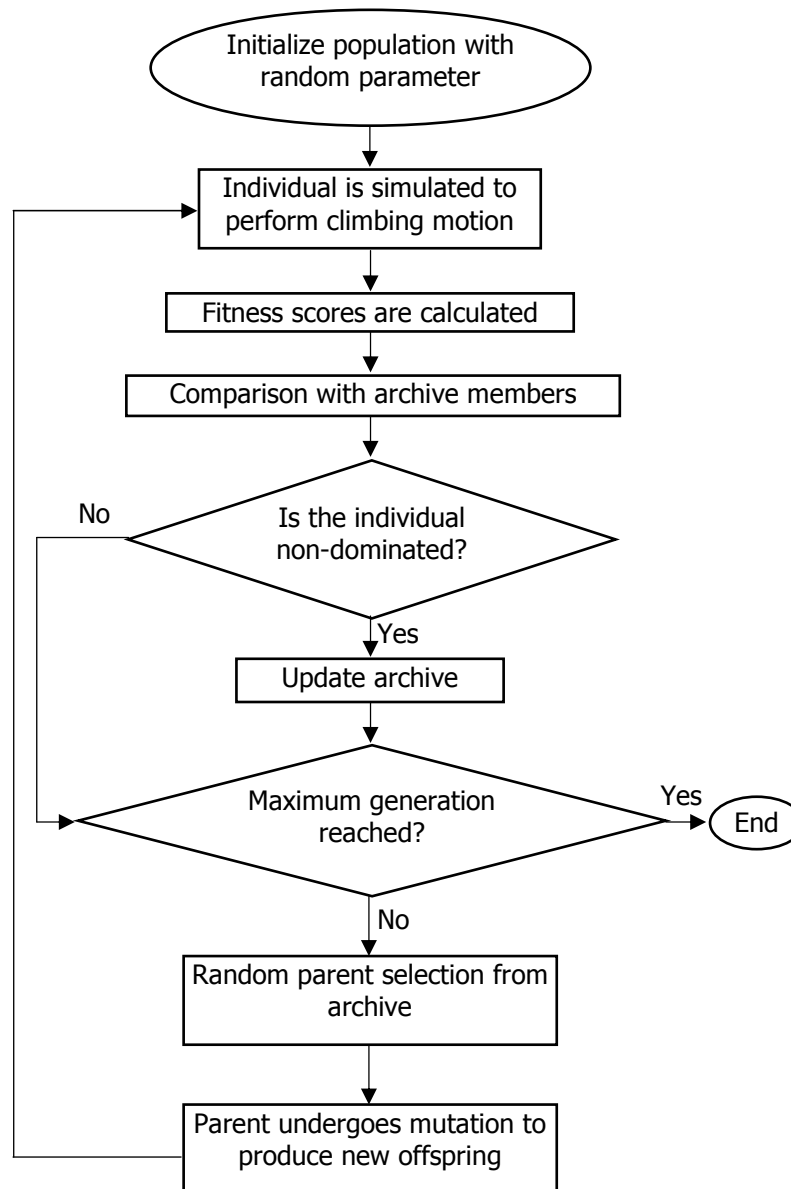


Fig. 5. Flowchart of the MOEA.

The MOEA starts with initializing population with random parameters for the SAWR body length, leg length, and wheel radius. Then the individual will be simulated in Webots to perform climbing motion and the performance of the individual will be evaluated. There are two fitness functions in the MOEA which are the size fitness and performance fitness. Performance fitness will be scored by evaluating the performance of the individual in climbing obstacle while the size fitness will be scored based on the size of the morphology. After both of the fitness scores have been credited, the individual will be compared to each member from the archive. If the individual is non-dominated where either one of the fitness score is better, the archive will be updated by adding the individual as a new member and also removing all the other dominated solutions. A parent will be randomly selected from the archive if the maximum number of generation is not reached. Selected parent will undergo mutation operation to produce new offspring for next generation. New offspring will then be

254 started again with the simulation to perform climbing motion and the process will repeat until
255 the maximum number of generation is reached.

256 In MOEA, distinct from SOEA, there are more than one fitness functions which are the
257 objectives to be optimized simultaneously. In this research, there are two fitness functions in
258 the MOEA which are the size fitness and performance fitness. Both of the fitness functions
259 are designed as in the smallest is the value, the better is the score.

$$260 \text{Size Fitness} = b + l + w \quad (5)$$

261
262
263 b = robot body length;
264 l = robot leg length;
265 w = robot wheel radius.

$$266 \text{Performance Fitness} = d^2 + (c \div mc) \quad (6)$$

267
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269 d = robot final destination from target destination;
270 c = number of collision occurs during simulation;
271 mc = maximum number of collisions possible to occur during one simulation.

272
273 Equation 5 shows the first fitness function, size fitness. Size fitness is built up with the
274 summation of three parameters which are the body length of SAWR, leg length of SAWR
275 and wheel radius of SAWR. Thus, SAWR with bigger morphology will have higher value of
276 fitness score which is poorer. On the other hand, smaller SAWR will be credited better
277 fitness score which is score with lower value.

278
279 While for the second fitness function, the fitness score of the performance of the robot during
280 the simulation will be evaluated. The main factor of the performance fitness is the evaluation
281 of the travelled distance of each individual from the origin to the goal destination. The final
282 distance of the individual from the goal destination is squared in order to increase the weight
283 in the fitness function. Thus, the individual with shorter travelled distance will be severely
284 penalized while successful individual that reaches goal will be greatly rewarded. The second
285 part of the performance fitness is to penalize individuals that have collision with the
286 obstacles during the simulation. The total number of collisions occurs during the simulation is
287 divided by the maximum number of collision that is possible to occur in a single run of
288 simulation in order to scale the penalize score with the fitness function. The mutation
289 operation of the MOEA is similar with mutation operation of SOEA which has been described
290 earlier.

291 292 **2.3 Fabrication Methodology**

293
294 One of the critical issue in evolutionary robotics is to transfer the simulation results into real
295 world. High cost and long turnaround time of fabricating the robot parts are hindering
296 researchers in transferring the simulation results into real world. In this research, a recent
297 technology is accessed in fabricating the robot parts, which is by 3D printing technology.
298 Fabrication cost of fabricating robots is considered high as the cost of manufacturing robots
299 has to be absorbed in mass production [12]. Fabrication cost can be reduced with 3D
300 printing as parts of the selected results to be fabricated with different sizes can be easily
301 obtained by 3D printing.

302 303 **2.3.1 3D Printing Technology**

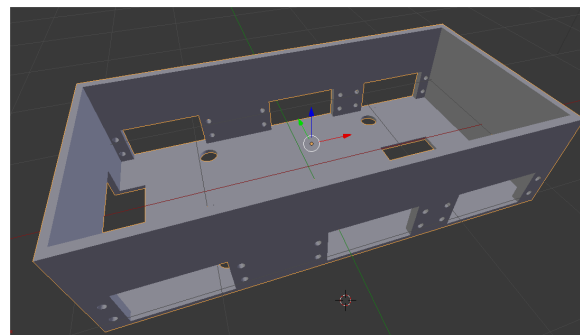
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305 3D printing is a process of making three dimensional solid objects from a digital file. 3D
306 printing may referred as Additive Manufacturing (AM). The creation of a 3D printed object is
307 achieved using additive processes. In an additive process an object is created by laying
308 down successive layers of material until the entire object is created. Each of these layers
309 can be seen as a thinly sliced horizontal cross-section of the eventual object [13].

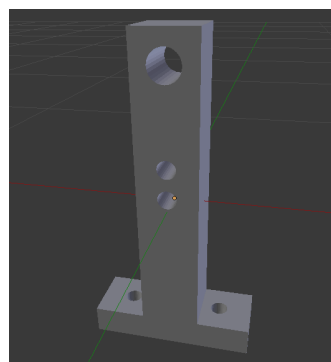
310 Difference from traditional ink-printing technology, 3D printing is capable to be done with a
311 variety of materials. For example: plastics, glass, metal, polymers, wax, edible food, human
312 tissue, sand & glue mixes, etc. 3D printing technology has been widely used in a lot of
313 applications such as: design visualization, prototyping/computer-aided-design (CAD),
314 architecture, metal casting, manufacturing, healthcare, entertainment and etc.

315 **2.3.2 STL File Generation for Robot Parts**

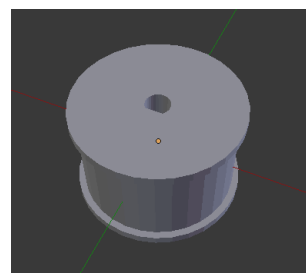
316
317 Most of the available 3D printers required 3D model file in STL format to perform printing.
318 Thus, robot parts that are needed to be fabricated have to be modeled and saved in STL file.
319 There are three main parts of the robots that are needed to be fabricated by 3D printers
320 which are the body, legs and wheels. A program has been designed in order to generate the
321 STL file for 3D model of robot parts automatically.
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326 **(a) Robot Body.**



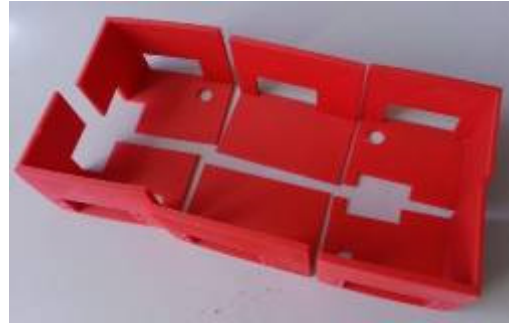
327
328 **(b) Robot Leg**



329 **(c) Robot Wheel Rim**

330 **Fig. 6. 3D Models Generated for Robot Parts.**

331 Fig. 6 shows the examples of printable 3D models generated for robot parts. The 3D models
332 generated are according to the defined input parameters with sockets which are ready to
333 assemble with servos and sensors. Fig. 7 shows the printed robot parts.



(a) Printed Robot Body



(b) Printed Robot Legs



(c) Printed Robot Wheels

Fig. 7. Printed Robot Parts.

3. EXPERIMENT SETUP AND RESULTS

3.1 Task Environment and Simulation Parameters Setup

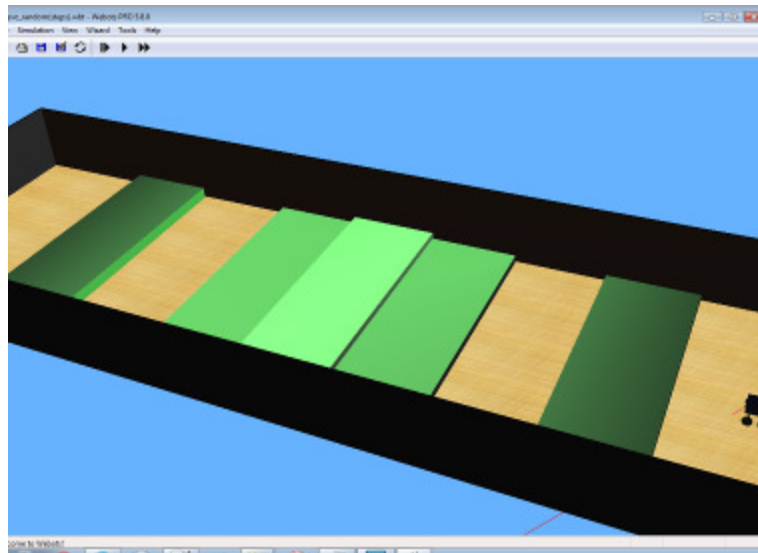


Fig. 8. Multi-Steps Task Environment.

As can be seen from Fig.8, the task environment designed in this research is a multi-step environment. The first step is 50mm in height, the stairs-like step is 55mm in height and the last step is 80mm in height. The task for the robot in the environment is to travel from origin to goal by climbing over all the obstacles.

Table 1. Summary of Simulation Parameters Setup

Parameter	Values
Runs	5
Simulation Time (seconds)	60
Maximum Number of Generation	500
Population Size	1

Each experiment is conducted with five runs in order to determine the efficiency of the algorithm in obtaining the optimized morphology of a climbing SAWR. Individuals are given 60 seconds to simulate for the simulation in multi-steps environment where the amount of time is obtained from preliminary experiments. The maximum number of generation for all experiments are 500 as preliminary experiments showed that optimized solutions are able to be obtained within 500 generations. Last but not least, the population size for each generation is one where one parent will produce one offspring for next generation. The summary of the simulation parameters setup are shown in Table 1.

Table 2. Evolving Objects Parameter Setup

Object	Wheel Radius	Leg Length	Body Length
Minimum (mm)	15	35	200
Maximum (mm)	40	100	350

Besides the setup for the simulation parameters, the parameter of the evolving objects has to be set too which is the maximum value and minimum value for each evolving object. The evolving objects parameter setup is presented in Table 2. The minimum value set for wheel radius is 15mm, leg length is 35mm and body length is 200mm. All these values are chosen as these are the minimum values for the parts to be fabricated with 3D printer later. While the maximum value for wheel radius is 40mm, leg length is 100mm and body length is 350mm. The maximum values are chosen with the consideration of measurement for the highest step in the task environment.

3.2 Simulation Results

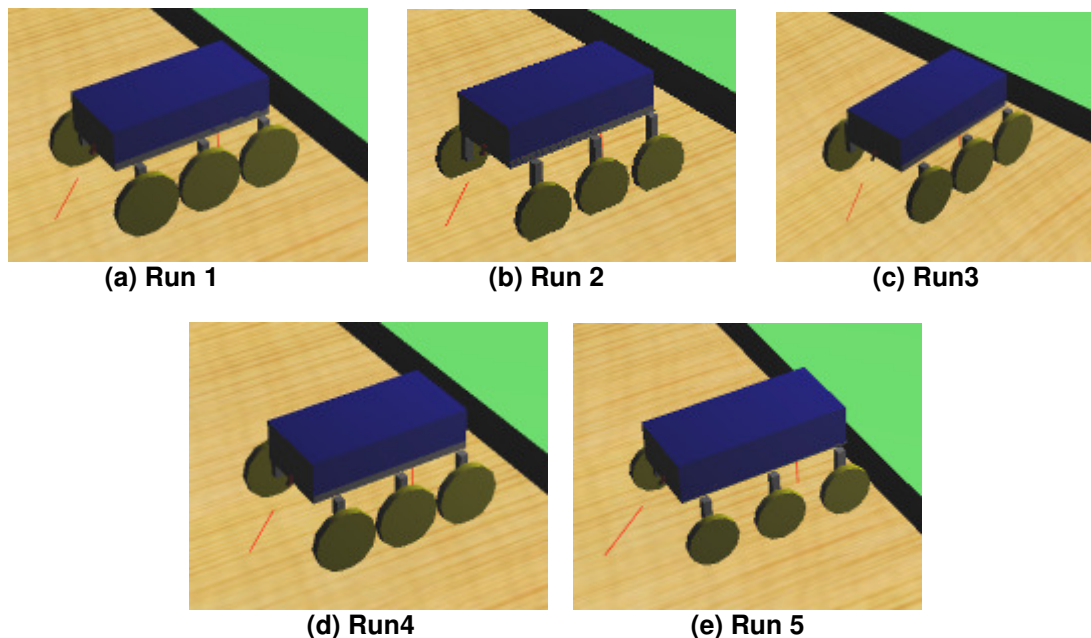
3.2.1 SOEA Results

The results for the five runs of experiments with SOEA are shown in Table3. From the results, each run of the experiment with SOEA is able to produce a climbing SAWR with optimized morphology. As can be seen from Table 3, solutions from the five runs of SOEA are approaching to optimum solutions as the fitness scores of the optimized solutions are closed to each other. Fig. 9 shows the optimized solutions which are climbing SAWRs with optimized morphology in simulation software. Fig. 10 shows the fitness score of fittest individual over generations for five runs of SOEA experiments.

Table 3. Optimized Solutions for Five Runs of SOEA.

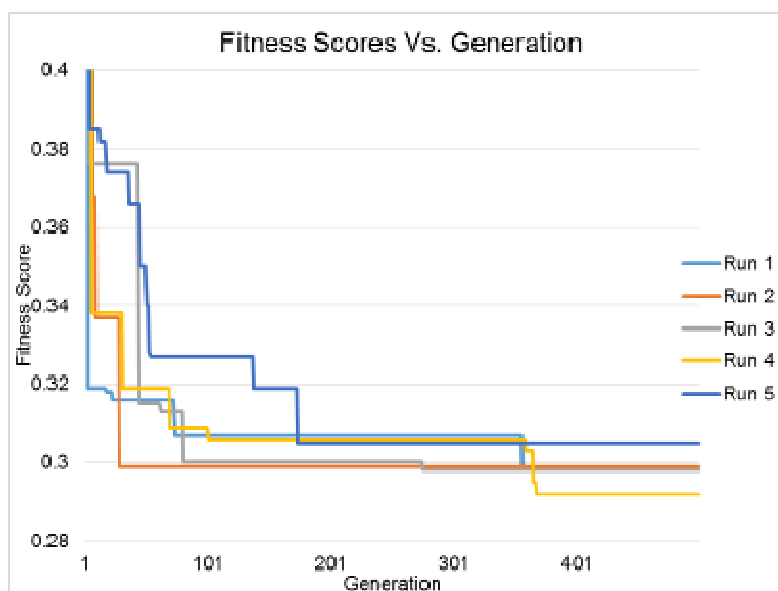
	Run 1	Run 2	Run 3	Run 4	Run 5
Fitness Score	0.298	0.299	0.298	0.292	0.305
Body Length (mm)	206	200	209	200	216
Leg Length (mm)	52	64	49	54	57
Wheel Radius (mm)	40	35	40	38	32
Distance from Goal	0	0	0	0	0
Collisions	0	0	0	0	0

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Fig. 9. Optimized Solutions for Each Run in Simulation Software.



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Fig. 10. Fitness Scores Vs. Generation for Five Runs.

3.2.2 MOEA Results

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From the experiments, each run of MOEA is able to produce a set of Pareto optimal solutions. In this paper, the result presentation is only presented for one run of MOEA experiment. The graph of the Pareto-set optimal solutions is presented in Fig. 11. The graph of Pareto-set optimal solutions is divided into few regions based on the achievement of the individual SAWR. For example, solutions in region one have the worst performance where they are not able to perform any climbing motion while solutions in region four are the best in performance fitness where they can complete the task environment by climbing all the steps. One solution from each region is selected for presentation. Detailed descriptions for each selected optimal solution are presented in Table 4.

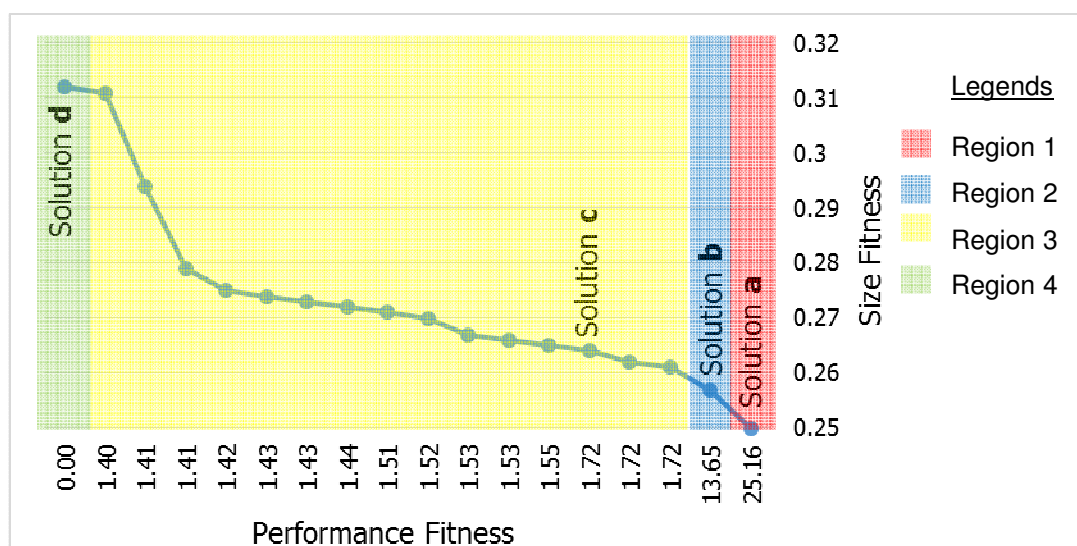
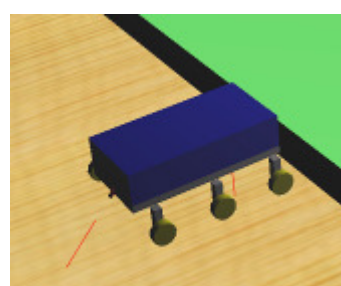


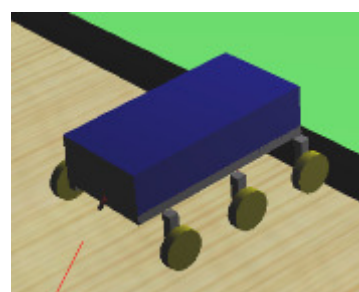
Fig. 11 Pareto-Set Optimal Solutions.

Table 4. Detailed Description of Selected Solutions from Pareto-Set Optimal Solutions.

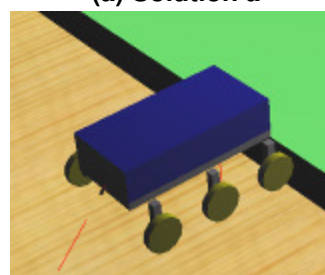
	Solution a	Solution b	Solution c	Solution d
Size Fitness	0.25	0.257	0.264	0.312
Body Length (mm)	200	200	200	215
Leg Length (mm)	35	37	41	65
Wheel Radius (mm)	15	20	23	32
Performance Fitness	25.16	13.65	1.72	0
Distance From Goal	5.015912	3.693954	1.310031	0
Collisions	0	0	0	0



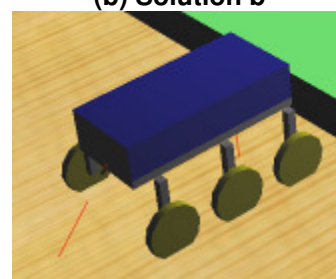
(a) Solution a



(b) Solution b



(c) Solution c

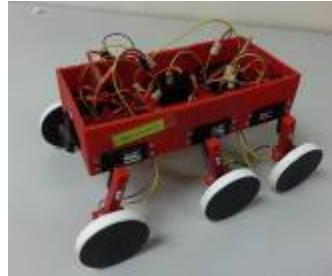


(d) Solution d

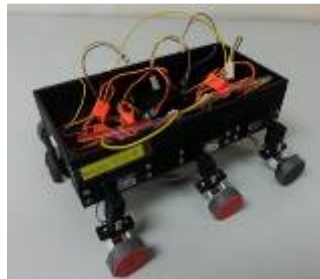
Fig. 12. Selected Solutions of Pareto-Set Optimal Solutions in Simulation Software.

3.3 Fabricated Real World SAWRs

For the fabrication, an optimized solution from SOEA experiment and selected solutions from a Pareto-set optimal solution of MOEA experiment are chosen. In this research, optimized solution from Run 5 of SOEA and selected solutions from Pareto-set optimal solutions of MOEA which are Solution **a**, Solution **b**, Solution **c** and Solution **d** that are presented in previous section are selected to be fabricated. Fig. 13 shows the fabricated real world SAWRs based on the selected optimal solutions from SOEA and MOEA.



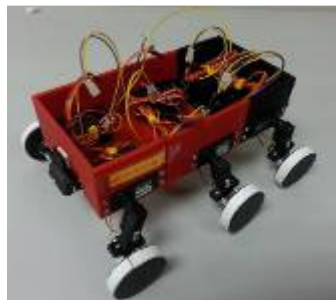
(a) SOEA Run 5.



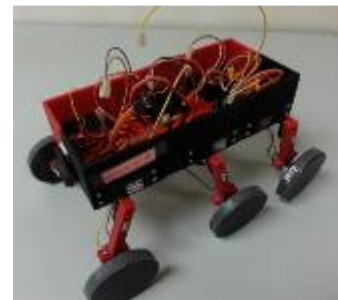
(b) MOEA Solution a



(c) MOEA Solution b



(d) MOEA Solution c



(e) MOEA Solution d

Fig. 13. Fabricated Real World SAWRs.

3.4 Real World Testing of Fabricated SAWRs

The accuracy of the fabricated real world SAWRs in comparing to the SAWRs in simulation are rated based on the performance of the fabricated real world SAWRs in performing climbing motion in real world environment. The accuracy is evaluated based on formula shown in equation 7. Since the main objective of this research is to obtain an optimized SAWR with climbing ability, thus higher percentage which is 70% of the accuracy is credited based on the climbing ability. While the remaining 30% is credited based on the overall performance evaluation of the fabricated real world SAWRs in performing the climbing motion and interacting with the environment.

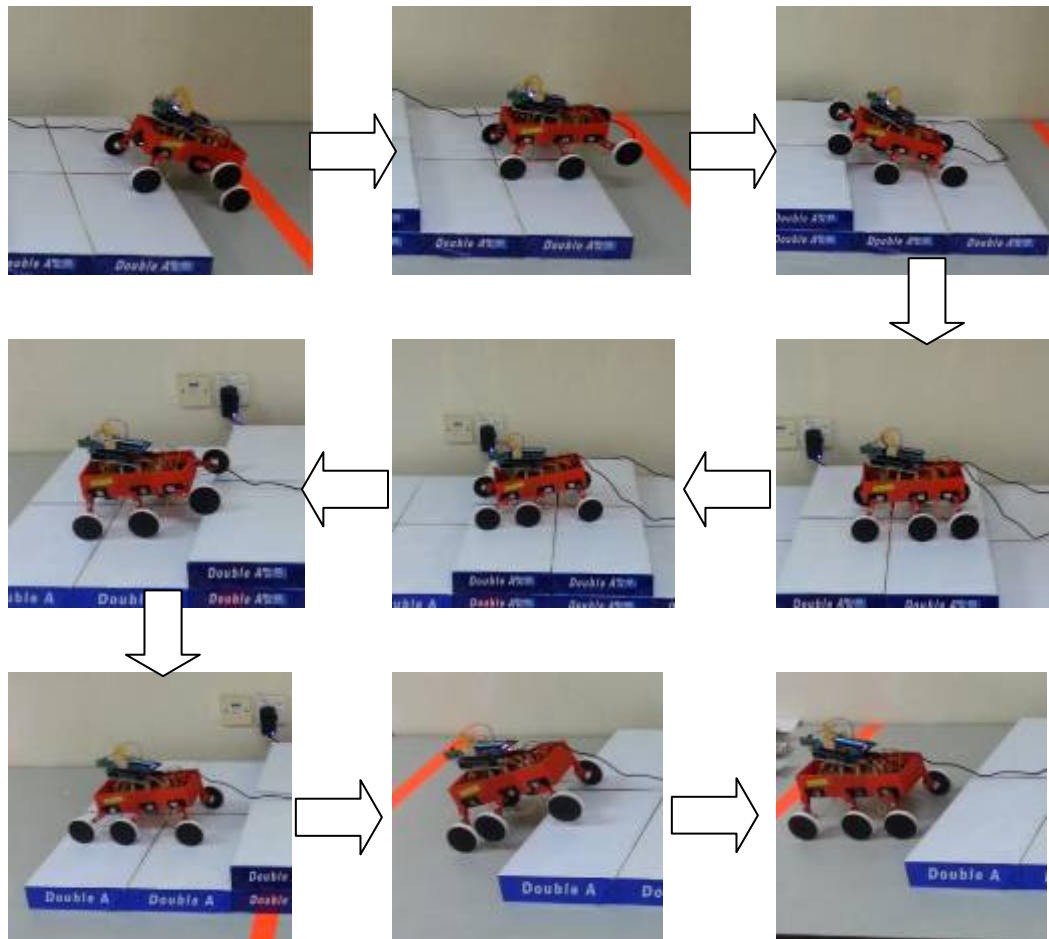
441 Accuracy = Climbing Ability (70%) + Overall Performance (30%) (7)

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452 **Fig. 14. Fabricated Real World SAWR Performing Climbing Motion.**

453 Fig. 14 shows the example of fabricated real world SAWR (SOEA Run 5) performs climbing
454 motion over stair-like steps. From the figure, fabricated real world SAWR is able to perform
455 climbing motion over stair-like steps as how the SAWR performs climbing motion in
456 simulation.

457 **Table 5. Accuracy of Fabricated Real World SAWRs Compared to SAWRs in**
458 **Simulation**

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SAWR	Climbing Ability (70%)	Overall Performance (30%)	Accuracy (100%)
SOEA Run 5	70%	20%	90%
MOEA Solution a	70%	25%	95%
MOEA Solution b	70%	20%	90%
MOEA Solution c	70%	15%	85%
MOEA Solution d	70%	10%	80%

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Table 5 shows the accuracy of all the fabricated real world SAWRs compared to SAWRs in simulation. The accuracy calculation is based on Equation 7 which has been explained previously. From the results, each fabricated real world SAWR is able to climb over the

obstacles that it is managed to climb over in the simulation. All the obstacles designed in the real world task environment are exactly the same in height with all the obstacles in the simulation task environment. Therefore, the climbing ability for all the fabricated real world SAWRs are credited with full score. For the overall performance, each fabricated real world SAWR is credited based on the degree of defect during the climbing performance. In general, defects of the climbing performance are caused by the distortion of direction of the fabricated real world SAWRs during the operation in real world environment. In the simulation, all the SAWRs are able to march forward in a straight line after performing climbing motion. The defection is speculated as the servos of fabricated real world SAWRs are not turning synchronously as in simulation.

4. CONCLUSION

In this research, an artificial evolution method in designing and optimizing the morphology of a climbing SAWR has been proposed. Results show that the proposed evolution with SOEA in this research is able to produce climbing SAWRs with optimized which is smallest possible morphology. On the other hand, the proposed evolution with MOEA is able to produce a Pareto-set of optimal solutions which are different sizes of SAWR with different degree of goodness in performing climbing motion. The optimal solutions obtained from the evolution are then transferred into real world SAWRs with 3D printing technology. Fabricated SAWRs are then assembled with servos and sensors and the ability of each fabricated real world SAWR in performing climbing motion is evaluated. Results show that overall accuracy of the fabricated real world SAWRs in comparing to the evolved solutions in simulation is rated at 85.8%. All the fabricated real world SAWRs are able to complete the task environment which are the climbing motion that is designed in the simulation.

With the results finding from this research, future work should be focusing on looking for more opportunity to apply artificial evolution method in designing robots. Results from this research are again proven that artificial evolution method is able to help human designers in designing and optimizing morphology of robots. The artificial evolution method is not only limited in designing and optimizing the morphology of robots, future work can be done in co-evolving the morphology as well as the controller of the robots for a comprehensive evolution process. Besides that, investigation can be done on releasing the constraints of current research by evolving more objects. In this research, the evolution is only done on three objects which are the length of robot body, length of robot legs and radius of robot wheels. Suggested objects that can be involved in the evolution of future work are the coordinate of sensors and legs placement. The placement of sensors and legs in current research are fixed. Evolving the placement of sensors and legs is foreseen to produce different and might be better optimized solutions. On the other hand, the task environment for the evolution process can be further improved to a more challenging environment in the future work; which may include uneven terrain and steps. Last but not least, realization of real world robots from evolved solutions using 3D printing has been proven workable. In this research, selected evolved solutions are successfully fabricated into real world SAWRs by 3D printing technology with minimum fabrication cost and turnaround time. Therefore, the methodology of robot fabrication with 3D printing technology can be used or referred in the future.

REFERENCES

1. Ong CH, Shamsudin, HM, Amin. A Biologically Inspired Hybrid Three Legged Mobile Robot. Student Conference on Research and Development. 2002: 181-183.

- 516 2. Shen S, Li C, Cheng C, Lu J, Wang S, Lin P. Design of a Leg-Wheel Hybrid Mobile
517 Platform. IEEE International Conference on Intelligent Robots and Systems. 2009: 4682-
518 4687.
- 519
- 520 3. Tadakuma K, Tadakuma R, Maruyama A, Rohmer E, Nagatani K, Yoshida K, Ming A,
521 Makoto S, Higashimori M, Kaneko M. Armadillo-Inspired Wheel-Leg Retractable Module.
522 IEEE International Conference on Robotics and Biomimetics. 2009: 610-615.
- 523
- 524 4. Smith J, Sharf I, Terntini M. PAW: A Hybrid Wheeled-Leg Robot. Proceedings of the IEEE
525 International Conference on Robotics and Automation. 2006: 4043-4048. Orlando, Florida.
- 526
- 527 5. Akerka, R. Introduction to Artificial Intelligence. PHI Learning Pvt. Ltd; 2005.
- 528
- 529 6. Endo K, Yamasaki F, Maeno T, Kitano H. Co-evolution of Morphology and Controller for
530 Biped Humanoid Robot. In Kaminka, A. Gal, Lima, U. Pedro, & R. Rojas, RoboCup 2002:
531 Robot Soccer World Cup VI. Springer; 2003.
- 532
- 533 7. Lee W. An Evolutionary System for Automatic Robot Design. IEEE International
534 Conference on Systems, Man, and Cybernetics. 1998: (4) 3477-3482.
- 535
- 536 8. Wang L, Tan K, Chew C. Evolutionary Robotics: From Algorithms to Implementations.
537 World Scientific Publishing; 2006.
- 538
- 539 9. Rommerman M, Kuhn D, Kirchner F. Robot Design for Space Missions Using Evolutionary
540 Computation. IEEE Congress on Evolutionary Computation (CEC). 2009: 2098-2015.
- 541
- 542 10. Kadota T, Yasuda T, Matsumara Y, Ohkura K. An Incremental Approach to an
543 Evolutionary Robotic Swarm. IEEE/SICE International Symposium on System Integration
544 (SII). 2012: 458-463.
- 545
- 546 11. Lu J, Bu C. Study on the Mobile Robot Reconfiguration Control Methods. IEEE
547 International Conference on Automation and Logistics. 2009: 2045-2049.
- 548
- 549 12. Lipson H, & Pollack JB. Automatic Design and Manufacture of Robotic Lifeforms. Nature.
550 2000: 974-978.
- 551
- 552 13. Anonymous. What is 3D printing? 2015. Accessed 13 January 2015.
553 Available: <http://3dprinting.com/what-is-3d-printing>.
- 554
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DEFINITIONS, ACRONYMS, ABBREVIATIONS

Here is the Definitions section. This is an optional section.

DOF: Degree of freedom

MOEA: Multi-Objective Evolutionary Algorithm

SAWR: Six Articulated-Wheeled Robot

SOEA: Single-Objective Evolutionary Algorithm