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# HIERARCHICAL HYBRID-HEXAPOD LOCOMOTION CONTROL MODEL INTEGRATING HIGH-LEVEL LOCOMOTION MODE SWITCHING WITH LOW-LEVEL LEG CONTROL

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**Abstract**. This paper describes the development of a hierarchical control model for hybrid wheel-leg hexapods that integrates high-level decision-making for locomotion mode switching with low-level decentralized leg controllers based on a switching policy that is guided by visual environment classification according to terrain roughness for autonomous gait selection. The method utilizes Digital Elevation Models (DEM) of terrain over which the hexapod travels, to determine which high-level locomotion mode to engage in controlling the low-level leg-joint variables to effectively travel along the terrain. The model was simulated and validated in MATLAB/Simulink in which the Stateflow Application was used to model the switching decision making logic, while a Medium Gaussian Support Vector Machine (SVM) algorithm was developed to model the terrain identification and classification function. The model of the decision-making logic was simulated without errors and its response graph indicated complete (100%) accuracy in switching locomotion modes to fit different types of terrain, while the Medium Gaussian SVM model demonstrated an accuracy of 98.9% in identifying and classifying different types of terrain.
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**Keywords**: DEM (Digital Elevation Model), Hexapod, Locomotion, Mode-Switching, Terrain.

## 1. Introduction

The idea of developing robotic versions of animals is an old one that has persisted till current times [1]. This is not surprising considering the admiration that is often evoked by animals over their beauty, efficiency, effectiveness and graceful bearing [2]. Likewise, the use of animals as a means of conveyance has a very long history [3]. So, it is not surprising that ideas on using robotic versions of animals as a means of conveyance have a long history as well [4]. Amongst animal-mimicking robots, hexapods in particular have attracted an appreciable amount of interest because of certain associative, design and operational reasons [5].

Hexapods are commonly associated with walking insects [6]- including ants which are well known for their remarkably agile and graceful gaits, even when bearing burdens that are heavier than their own weight [7]. The design of hexapods is considerably simplified by the relative abundance of research information on insects upon which hexapod designs can be developed [8]. From an operations point of view, although hexapods possess six legs, they have greater intrinsic

mechanical stability than two-legged and four-legged robots [9] – as they can be viewed as a stable tripod that is complementarily stabilized by its mirror image tripod. Also, they do not have so many legs as to make the power consumed by moving the legs impractical [10].
Amongst the wide variety of hexapods that have been developed so far, hybrid wheel-leg hexapods have a special niche due to the fact that they not only possess the ability to locomote by wheeled motion when the terrain permits, but also have the ability to walk when the terrain is too rough for wheeled motion [11]. This ability makes hybrid wheel-leg hexapods more energy efficient in wheel-permitting terrain than walking-only hexapods, while endowing them to travel in rough terrain that is beyond the capability of wheeled vehicles [12].
The fact that they possess more than one locomotion mode necessitates a switching mechanism to effectively switch between modes when certain conditions prevail [13]. Within each of these high-level locomotion modes, are lower-level locomotion methods consisting of several timed combinations of wheel and leg-joint motion to make for effective travel over terrain. Effectively combining high-level locomotion mode switching with low-level decentralized leg control presents some challenges which are often surmounted by using complex solutions which ultimately translate to an increase in cost of the hexapod along with greater difficulty in solving problems or implementing improvements on the system.
This paper presents the development of a simple but effective form of such a hierarchical control model for hybrid wheel-leg hexapods that integrates high-level decision-making for locomotion mode switching with low-level decentralized leg controllers based on a switching policy that is guided by visual environment classification according to terrain roughness for autonomous gait selection. The developed system was modelled and simulated in the MATLAB/Simulink ® 2024 modelling environment with results that indicate they are viable solutions. The MATLAB Stateflow application was used to model the decision logic of the locomotion switching system, while the MATLAB Classification Learner application was used to develop the machine-learning (ML) terrain classification model. The MATLAB Stateflow application has been successfully used to model the switching logic of various dynamic systems [14], while the MATLAB Classification Learner application has been successfully used to develop machine learning classification algorithms for visual pattern identification and classification [15], [16].
Details of the methodology utilized in developing the models is presented in section 2. The results obtained from simulating the models are discussed in section 3, and the conclusion drawn from the research is provided in Section 4.

## 2. Materials and Method

This section presents the method used in modelling and simulating the high-level mode switching control system, along with the terrain identification/classification system it works with. Section 2.1 and 2.2 describe the creation of the MATLAB Stateflow model for the high-level switching logic that switches locomotion modes in accordance with how the terrain is classified based on its visual terrain features, while Section 2.3 describes the steps involved in using the MATLAB Classification application to model the algorithm that detects and classifies the terrain based on its visual features.

### *2.1 Operating Philosophy of the High-Level Mode-Switching Control System*

The system was modelled based on an operating philosophy for a semi-autonomous hybrid wheel-leg hexapod system. The steps required to operate the system are as follows:

i. The hexapod is powered on by the user.
ii. The hexapod's operating system initializes (checks that all instrument/control, electrical and mechanical subsystems are functional) and when complete, displays the area covered

by its surveillance cameras on a touch-sensitive human-machine interface (HMI), with a prompt to the user to select a destination and a travel route to get there.

iii. The user touches a destination on the surrounding area displayed on the HMI and traces a travel route to get there.

iv. The hybrid hexapod mobility platform (HHMP) receives the user-selected destination and travel route inputs, then the terrain data of the most proximate section of the route is analyzed to extract its topographical features which is then used to select locomotion modes.

v. If the terrain of the section is classified to be relatively smooth, the high-level locomotion switching controller switches on the lower-level locomotion controller specifically trained for Wheeled Locomotion mode of travel. The lower-level algorithms in this mode then generate (or predict) a velocity of travel, the angles of the leg joints for stability and the joint compliance levels for safe and comfortable wheeled travel over the terrain.

vi. If the terrain is classified to be too rough for wheeled travel, but has regular/periodic (predictable) features, the high-level locomotion switching controller switches to Rhythmic Walking Locomotion mode of travel. The lower-level locomotion controllers in this mode then generate (or predict) rhythmic walking locomotion parameters such as the velocities, accelerations and angles travelled by each of the leg joints, along with their joint compliance levels and timing signals.

vii. If the terrain is classified as too rough and unstructured for both wheeled travel and rhythmic walking modes, the high-level locomotion switching controller switches to the Non-Rhythmic Walking Locomotion mode of travel. The lower-level locomotion controllers in this mode then generate the non-rhythmic walking locomotion parameters such as the velocities, accelerations and angles travelled by each of the leg joints along with the joint compliance levels and timing signals.

viii. If during the swing phase of a walking-step, a leg gets stuck on an unmovable obstacle, this 'stuck' condition will be sensed as an abnormally high reaction force (by reaction-force sensors) and will trigger the locomotion mode switching controller to switch to the 'Elevator Reflex' mode in which the stuck leg performs arching elevation movements of increasing height and range until the leg is freed from the obstacle.

ix. If at the end of its swing phase while walking, a leg does not come in contact with a firm surface as expected, this state will be sensed as an abnormally low ground reaction force, which will trigger the locomotion mode switching controller to switch to the 'Rhythmic Searching' mode in which the leg performs up and down motions in a sweeping search pattern in the area around the point initially designated as a ground target position.

This operating philosophy is illustrated in the flowchart of Fig. 1. Following from it, the attributes in Table 1 were identified for use in modelling and simulating the high-level locomotion mode switching functions in the MATLAB/Simulink Stateflow modelling environment.

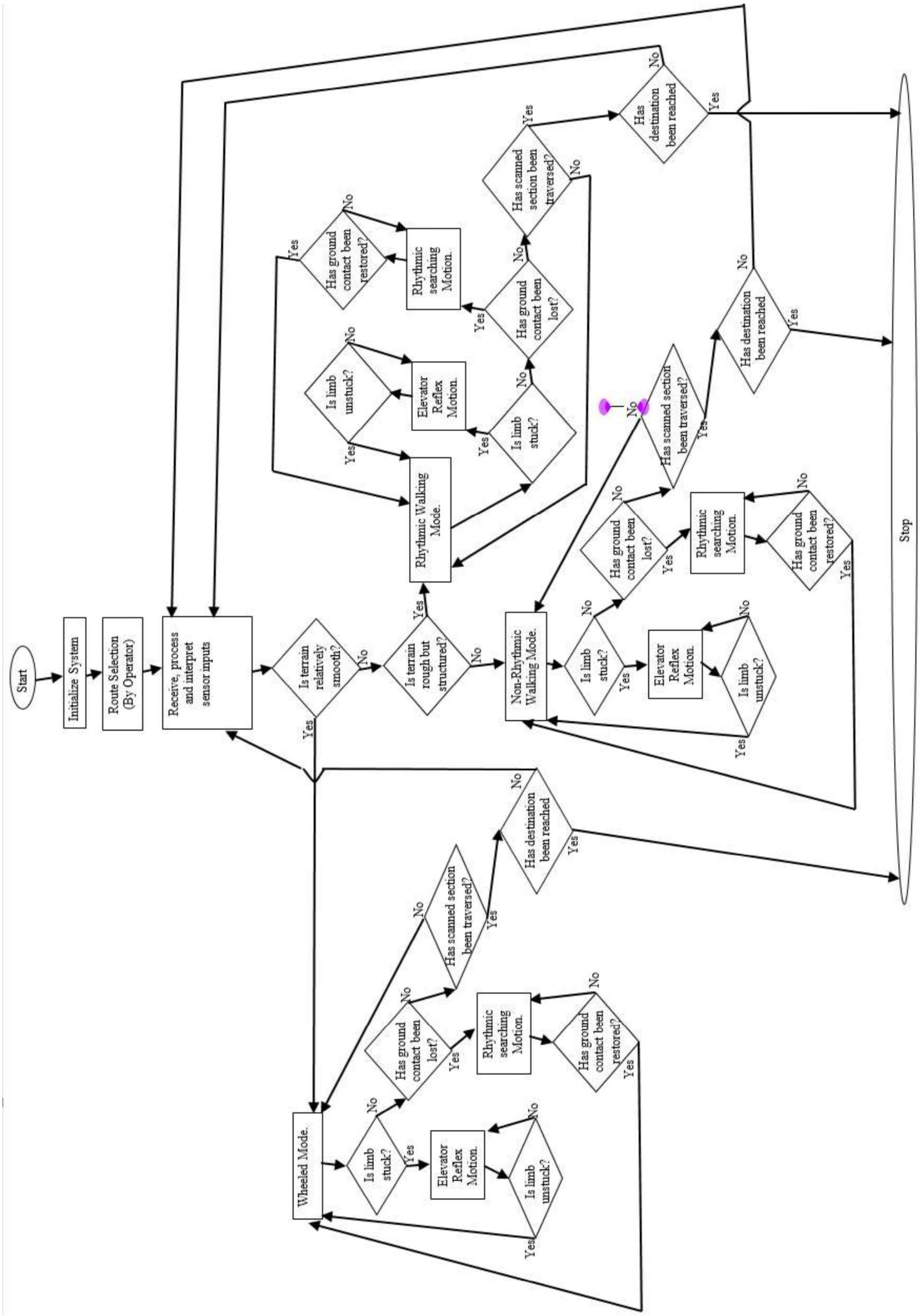


Figure 1: Flowchart Illustrating the Operation of the Locomotion Switching System

Table 1: Attributes of the High-Level Locomotion Mode Switching Control System

| Attribute | Characteristic |
|---|---|
| Operating modes | i. System initialization, to perform sub-system checks before beginning the locomotion process.<br>ii. Sensor signal reception/processing mode, to receive inputs from sensors on which locomotion decisions will be made.<br>iii. Wheeled mode, which is the locomotion mode on relatively smooth terrain suitable for wheeled movement.<br>iv. Rhythmic walking mode, which is the locomotion mode in rough but predictably structured terrain.<br>v. Non-rhythmic walking mode, which is the locomotion mode in rough and unstructured terrain.<br>vi. Elevator reflex mode, which is the fail-safe mode when one or some legs are stuck against an immovable obstruction.<br>vii. Rhythmic searching mode, which is the fail-safe mode when ground contact is lost by one or some of the legs during wheeled travel or at the end of a leg step. |
| Transitions | i. System initialization to sensor signal reception/processing mode<br>ii. Sensor signal reception/processing mode to Wheeled mode<br>iii. Sensor signal reception/processing mode to Rhythmic walking mode<br>iv. Sensor signal reception/processing mode to Non-rhythmic walking mode<br>v. Wheeled mode to Elevator reflex mode<br>vi. Wheeled mode to Rhythmic searching mode<br>vii. Rhythmic walking mode to Elevator reflex mode<br>viii. Rhythmic walking mode to Rhythmic searching mode<br>ix. Non-rhythmic walking mode to Elevator reflex mode<br>x. Non-rhythmic walking mode to Rhythmic searching mode.<br>xi. Elevator reflex mode to Wheeled mode<br>xii. Rhythmic searching mode to Wheeled mode<br>xiii. Elevator reflex mode to Rhythmic walking mode<br>xiv. Rhythmic searching mode to Rhythmic walking mode<br>xv. Elevator reflex mode to Non-rhythmic walking mode<br>xvi. Rhythmic searching mode to Non-rhythmic walking mode<br>xvii. Wheeled mode to Sensor signal reception/processing mode (after a partitioned section of route has been travelled).<br>xviii. Rhythmic walking mode to Sensor signal reception/processing mode (after a partitioned section of route has been travelled).<br>xix. Non-rhythmic walking mode to Sensor signal reception/processing mode (after a partitioned section of route has been travelled). |
| Parallel Modes | None. Only one mode can be active at any given time. |
| Default Mode | Sensor signal reception/processing mode |
| Inputs | i. Touch sensor signal from user indicating destination and preferred travel route.<br>ii. Terrain sensor signal<br>iii. Reaction force signal indicating: (i) Normal ground reaction force - 1 (ii) Abnormal loss of ground contact - 0 (ii) Stuck condition of legs – 2 |
| Outputs | Locomotion mode appropriate to the terrain. |

*2.2. Modelling of the High-Level Mode-Switching Control System*

The high-level operation of the Locomotion Controller of the HHMP was modelled as an event-driven system in the MATLAB/Simulink Stateflow modelling application. Signal source blocks, a chart block and a scope block for output signal display were utilized to build the model as shown in Fig. 2.

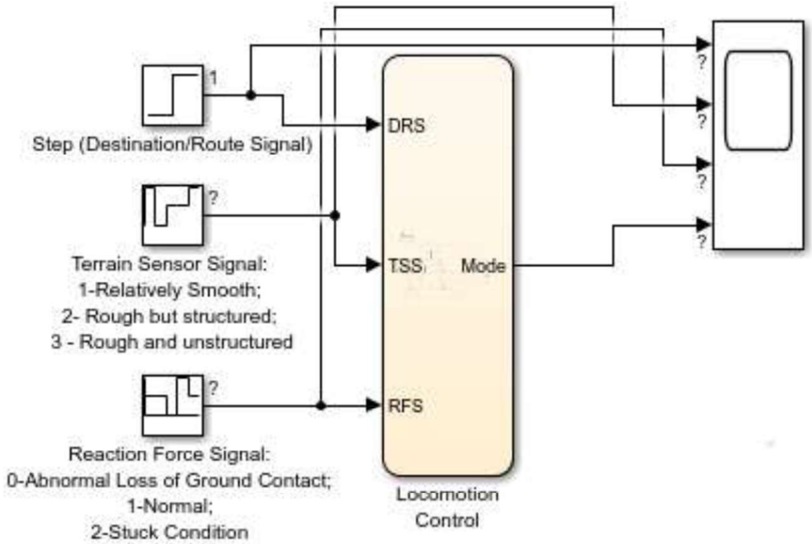


Figure 2: Model of the High-Level Locomotion Mode-Switching Control System

Within the chart block, seven state blocks were added and their entry actions defined to represent operating modes as shown in Fig. 3.

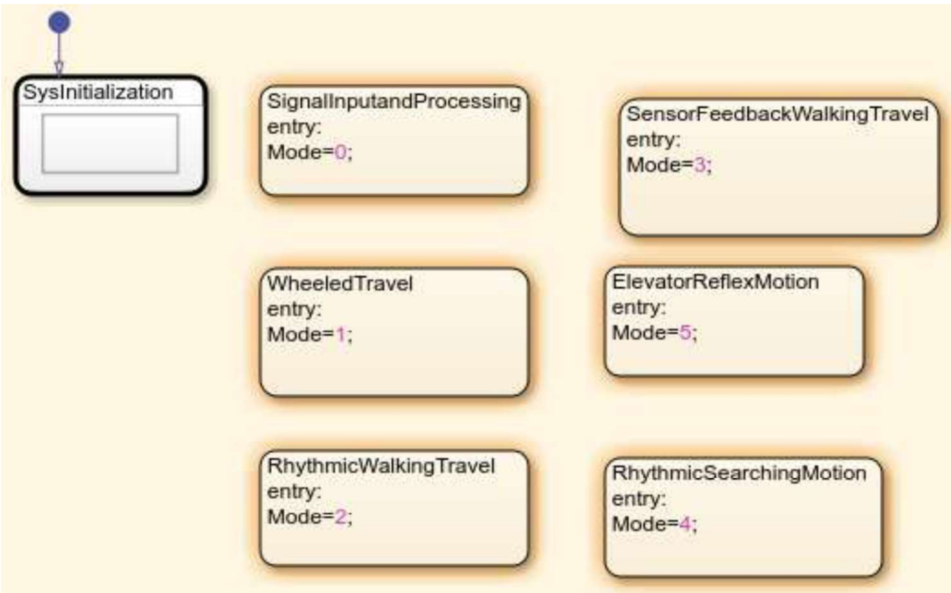


Figure 3: State Blocks within the Stateflow Chart Block Representing Operating Modes

Thereafter, transitions were drawn between the seven states, and their transition conditions were defined according to the operating philosophy of the controller outlined earlier in section 2.1. This is depicted in Fig.4. In Fig. 4, DRS means Destination/Route Signal which is inputted by the user.

A condition of DRS==1 indicates that the user has inputted a destination and a route to the destination. TSS means Terrain Sensor Signal with numerical values having meanings indicated by the tag on the Terrain Sensor Block shown in Fig 2. RFS mean Reaction Force Signal and the meaning of the numerical values of this signal are specified in the Reaction Force Signal Block tag shown in Fig. 2.

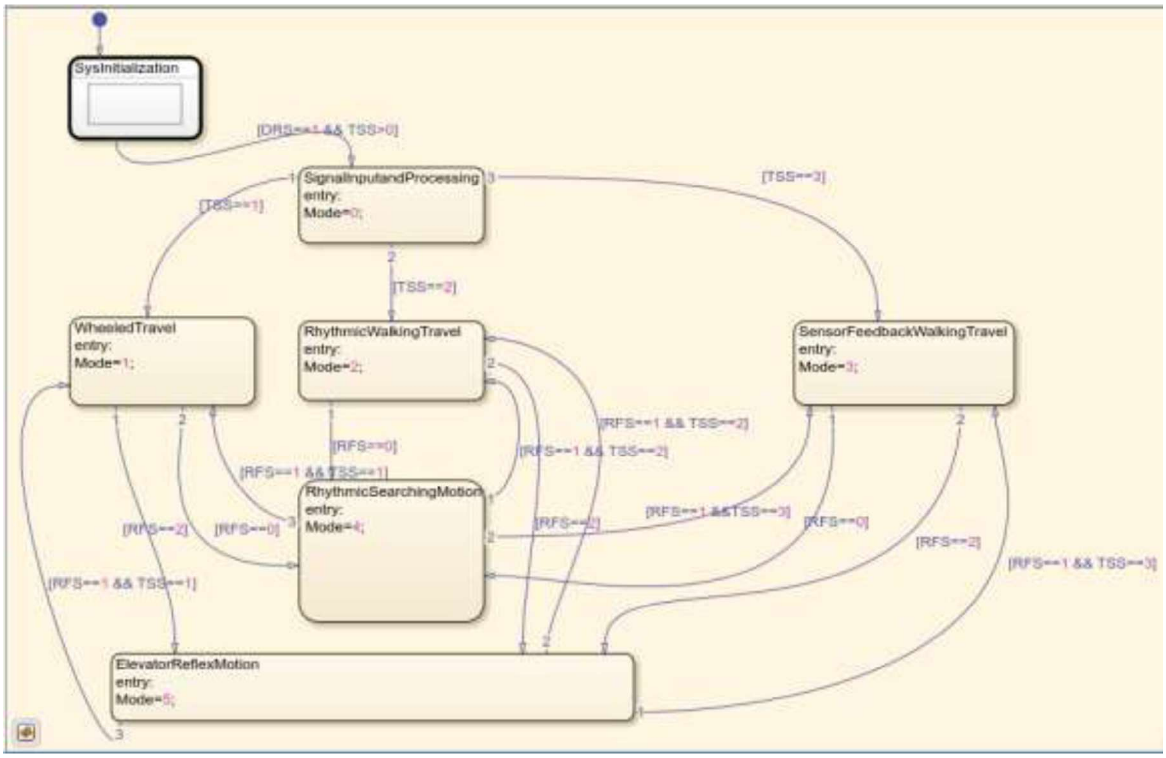


Figure 4: Transitions between States and their Conditions

The model was simulated, debugged, and modified to ensure its response consistently reflects its operating philosophy accurately. The modification involved adding transitions to the chart-block logic model shown in Fig 4. These new transitions are shown in Fig. 5 and Fig 6.

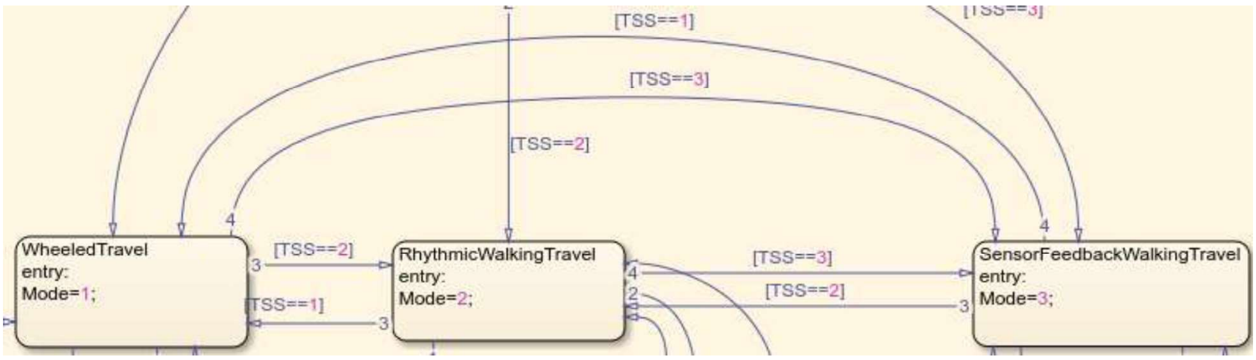


Figure 5: New Transitions Made Between Modes 1, 2 and 3

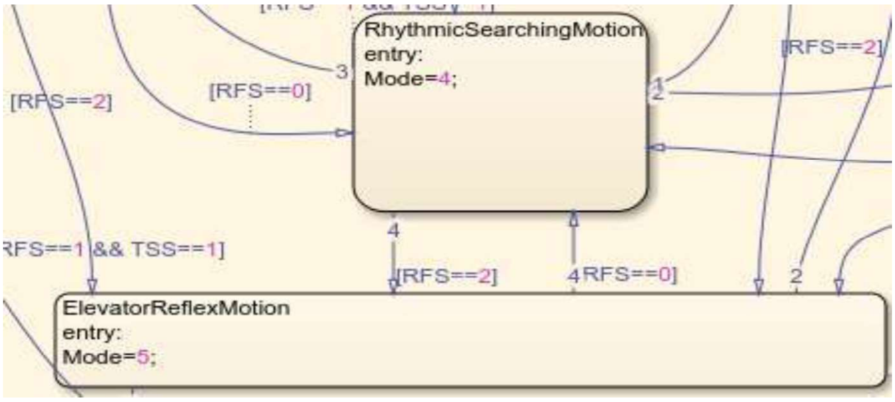


Figure 6: New Transitions Made Between Modes 4 and 5

### *2.3. Modelling the Terrain Identification and Classification System*

The model for terrain identification and classification was developed using the Classification Learning Process in MATLAB/Simulink's Supervised Learner Toolbox [14]. The process for developing the model is as described:

i. Acquisition of the training/validation data
ii. Structuring the training/validation data
iii. Fitting (training) and validating models.

Next each of these steps was implemented.

#### *2.3.1 Acquisition of the Training/Validation Data*

The digital elevation model (DEM) data of terrain was modelled using the Random Number Generation Tool of MATLAB's Machine Learning and Deep Learning toolbox. The settings entered into the tool's interface to generate the data are shown in Fig. 7. One hundred and one (101) terrain scans were generated in this way.

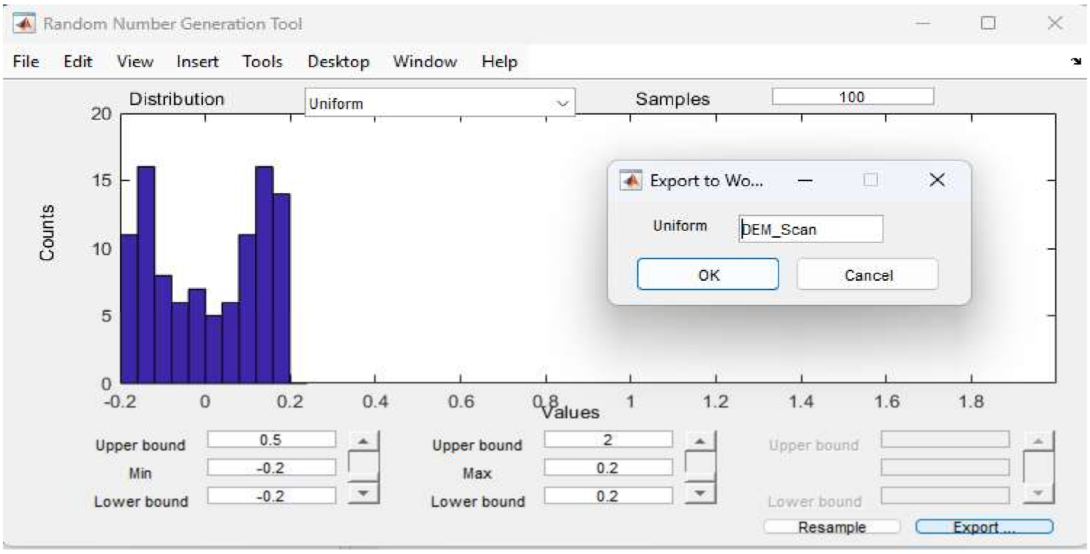


Figure 7: Settings Entered into the Random Number Generation Tool to Model DEM Data

#### *2.3.2 Structuring the Training/Validation Data*

Each of the 100-element column vectors (generated by the Random Number Generation tool) was transposed to represent a serial row of DEM of a scanned terrain area. 101 of such rows were generated to represent the DEM scans of 101 different types of terrain.

To modify the DEM rows to represent either 'Smooth', 'Rough with regularity', or 'Rough' terrain, thirty (30) of the 101 rows were modified to represent smooth terrain by multiplying their elements by 0.05, thereby smoothening the terrain elevation values. Another thirty (30) terrain scans were modified to represent rough but regular terrain (like stairs or level terrain with regularly spaced bumps), by dividing their elements by 0.05 (to pre-smoothen them), then adding or subtracting a constant value (between 0.1 meters and 0.2 meters) to all the elements in regularly spaced rows to elevate or depress them. The DEM elements of the last 41 rows were unmodified to represent rough terrain.

The modified data with a single descriptor header-row was then copied to a Microsoft Excel sheet, and pasted as values. The Excel sheet was then saved in the .csv (comma separated or delimited values) format which MATLAB can import into its workspace as a table to be used for supervised training of ML models.

#### *2.3.2 Fitting (Training) and Validating the Models*

The structured data was loaded into the MATLAB workspace from where it was imported into MATLAB's Classification Learner application in a new training/validation session with a cross-validation scheme having 5 folds and a reserved validation dataset of 10 as shown in Fig 8. All 33 models in the application were trained/validated on the data from which the best performing was selected.

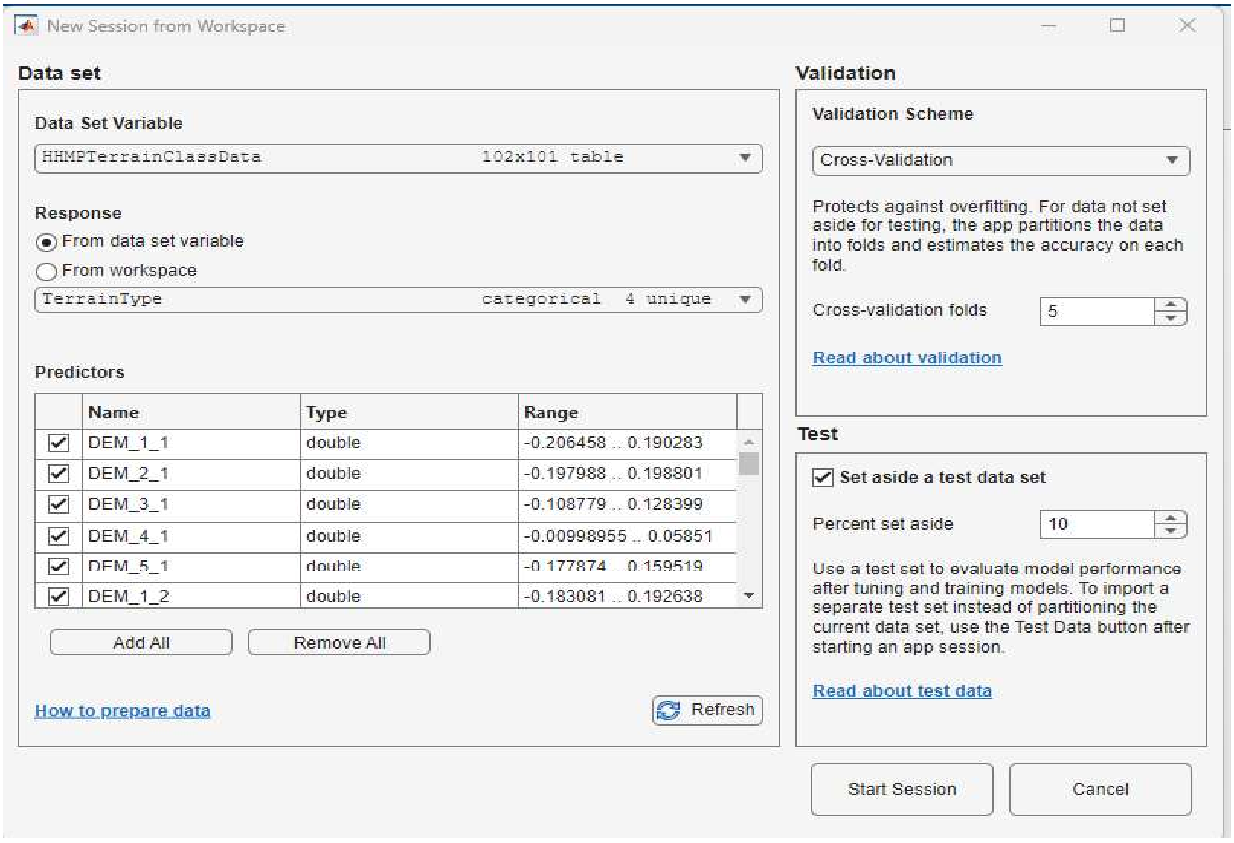


Figure 8: Settings Utilized in the Training/Validation Session

## 3. Results and Discussion

The Stateflow model depicting the decision logic of the high-level locomotion-mode switching system was simulated successfully in the MATLAB Stateflow modelling environment and it produced an accurate output response graphically in the model's scope in response to different terrain types and sensor signals. This is shown in Fig. 9. It can be seen in Fig. 9 that when a user inputs a destination/route signal (indicated by a signal level of 1 in the topmost graph) in terrain detected as rough and unstructured (indicated by a signal level of 3 in the second graph from the top), if the legs of the hexapod in a normal state, meaning that they are neither stuck nor in loss of ground-contact (indicated by a signal level of 1 in the third graph from top ), the hexapod switches its locomotion mode to 'Non-Rhythmic Walking' mode (indicated by a signal level of 3 in the bottom-most graph of Fig. 9). Hence using the four graphs of Fig 9, the response of the locomotion mode switching system to varying signal levels from a user, terrain sensors, and ground-reaction force sensors were examined and found to accurately represent the original switching logic captured in the system's operating philosophy.

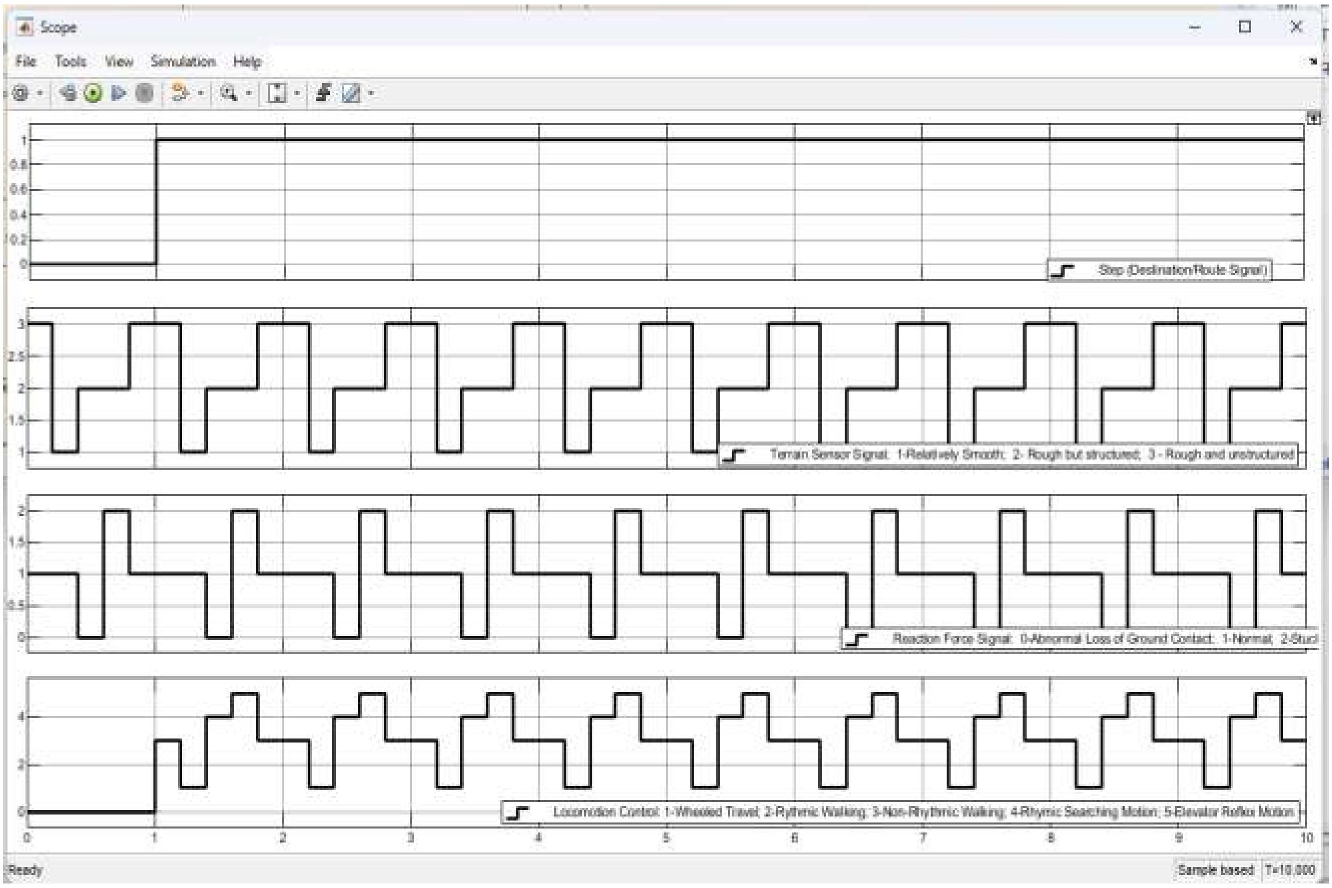


Figure 9: Graph Showing Response to Different Terrain Types and Sensor Signals

The ML model trained (using supervised learning) to receive the DEM of different terrain and classify them as smooth, rough with predictable features (structured) or rough and unstructured was successfully modelled and validated by simultaneously training and validating 33 different models from which the Medium Gaussian SVM (Support Vector Machine) model was determined to be the best ML model developed, based on its classification accuracy of 98.90% and training speed of 19.189 seconds.

Figure 10 shows the MATLAB generated graphs of accuracy of all 33 models developed.

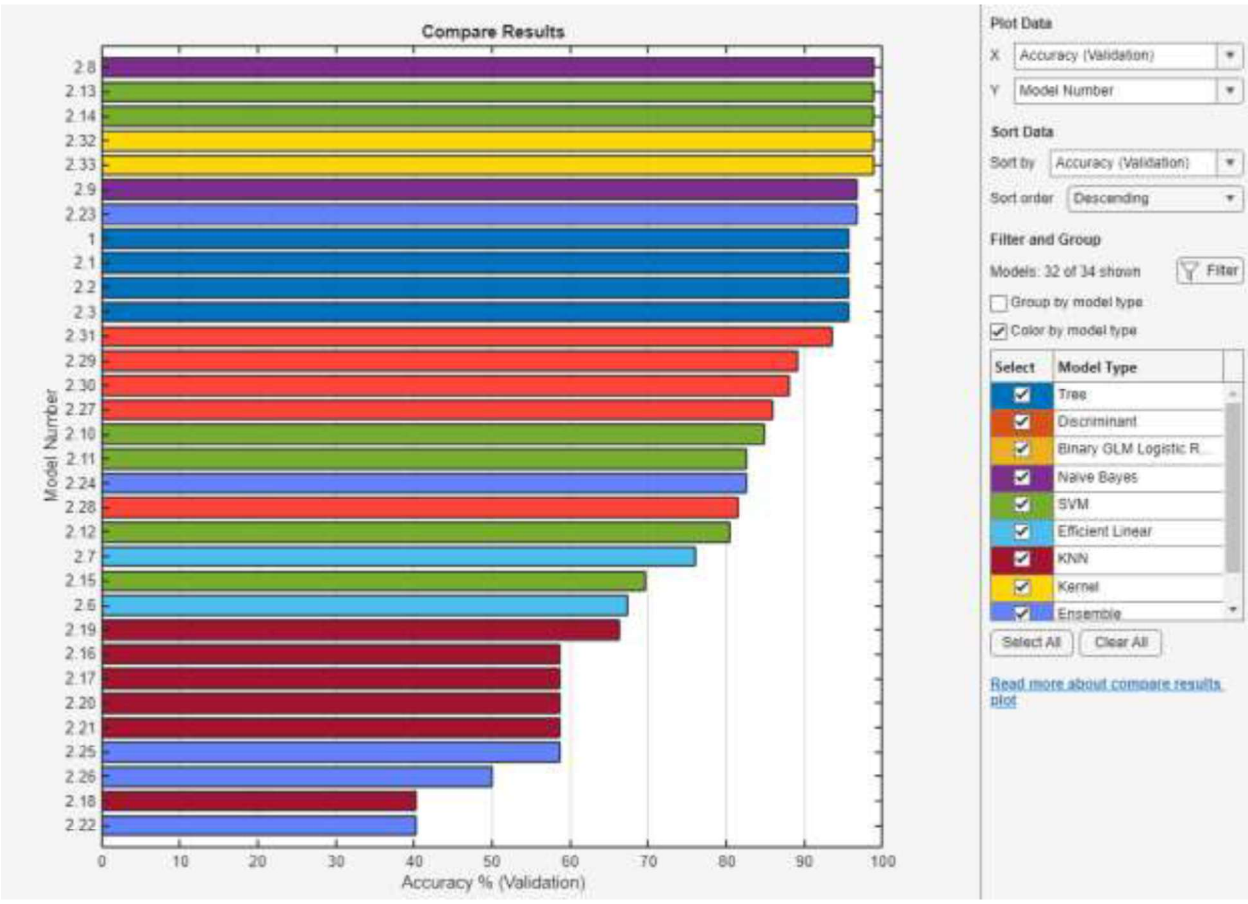


Figure 10: MATLAB-Generated Graph Showing Accuracy of the 33 Models Trained

## 4. Conclusion

The results of this research indicate that the hierarchical control model developed is a viable one for hybrid wheel-leg hexapods that have a need to integrate high-level decision-making for locomotion mode switching with low-level decentralized leg controllers. The model adequately demonstrated its operation based on a switching policy that is guided by visual environment classification according to terrain roughness for autonomous gait selection.

## References

1. Truitt, E. R., 2015. *Medieval Robots: Mechanism, Magic, Nature, and Art.* 1st ed. Philadelphia: University of Pennysylvania Press.
2. Bekey, G. A., 2005. *Autonomous Robots: From Biological Inspiration to Implementation and Control.* 1st ed. Cambridge: MIT Press.
3. Diamond, J., 1997. *Guns, Germs, and Steel: The Fates of Human Societies.* 1st ed. New York: W. W. Norton & Company.
4. Silva, M. F. and Machado, J. T., 2012. A literature review of the optimization of legged robots. *Journal of Vibration and Control, 18(12)*, pp. 1753-1767.
5. Tedeschi, F. and Carbone, G., 2014. *Design issues for hexapod walking robots.* 1st ed. New York: Nova Science Publishers.
6. Chen, C., Lin, J., You, B., Li, J. and Gao, B., 2025. "Hexapod robot motion planning investigation under the influence of multi-dimensional terrain features," *Frontiers in Neurorobotics, 19(1)*.

7. Dupeyroux, J., Passault, G., Ruffier, F., Violet, S. and Serres, J., 2017. Hexapod: a small 3D-printed six-legged walking robot designed for desert ant-like navigation tasks. Toulouse, *IFAC World Congress 2017*.
8. Manoonpong, P., Pasemann, F. and Worgotter, F., 2013. "Biologically-inspired adaptive obstacle negotiation behavior of hexapod robots". *Frontiers in Neurorobotics*, 7(3).
9. Tejado, I., Torres, D., Perez, E. and Vinagre, B., 2021. C-Legged Hexapod Robot Design Guidelines Based on Energy Analysis. *Applied Sciences*, *11(6)*, p. 2513.
10. Cservenak, A., and Budai, C., 2022. Mechanical Design and a Novel Structural Optimization Approach for Hexapod Walking Robots. *Machines*, *10(6)*, p. 409.
11. Han, L., Li, E., Jinag, S., Xu, K., Wang, X., Ding, X., and Zhang, C., 2025. "Research on a Hexapod Hybrid Robot with Wheel-Legged Locomotion and Bio-Inspired Jumping for Lunar Extreme-Terrain Exploration," *Biomimetics, 10(4)*.
12. Poramate, M., Luca, P., Xiaofeng, X., and Ilya, B., 2021. "Insect-Inspired Robots: Bridging Biological and Artificial Systems," *Sensors,* pp. 5-6.
13. Iyekekpolo, E. N., and Orukpe, P. E., 2025. "Conceptual Design and Modelling of a Hybrid Hexapod Mobility Platform," *Journal of Engineering for Development, 17 (Special Issue: University of Benin, Faculty of Engineering First International Conference June 18 to 19, 2025),* pp. 77-86.
14. Wu, R., Du, Y., and Li, M., 2025. "A model transformation method based on Simulink/Stateflow for validation of UML statechart diagrams," *Mathematics, 13(5)*, p. 724.
15. Khan, S., Ahmad, M., Rehman, A. and Alharbi, A., 2025. "Context aware machine learning techniques for brain tumor classification using MRI and histopathology imaging: A comprehensive review.," *Heliyon, 11(3).*
16. The MathWorks, Inc., 2026. "Classification Learner," 29 May 2026. [Online]. Available: https://www.mathworks.com/help/stats/classificationlearner-app.html. [Accessed 29 May 2026].
17. The MathWorks Inc., 2026. "Statistics and Machine Learning Toolbox," The MathWorks Inc., 10 May 2026. [Online]. Available: https://www.mathworks.com. [Accessed 23 August 2025].
18. Suzuki, S., Kano, T., Ijspeert, A., and Ishiguro, A., 2021. "Simple analytical model reveals the functional role of embodied sensorimotor interaction in hexapod gaits," *PLOS Computational Biology, 17(3)*, p.2.
19. Liu, Y., Fan, X., Ding, L., Wang, J., Liu, T., and Gao, H., 2022. "Adaptive Gait Generation for Hexapod Robots Based on Reinforcement Learning and Hierarchical Framework," *Machines*, *10(6)*, p.417.