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Retraction

Retracted: Uncovering Resilient Actions of Robotic Technology with Data Interpretation Trajectories Using Knowledge Representation Procedures

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Teekaraman, I. Kirpichnikova, H. Manoharan, R. Kuppusamy, and A. Radhakrishnan, "Uncovering Resilient Actions of Robotic Technology with Data Interpretation Trajectories Using Knowledge Representation Procedures," *Security and Communication Networks*, vol. 2023, Article ID 7419259, 8 pages, 2023.

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Research Article

Uncovering Resilient Actions of Robotic Technology with Data Interpretation Trajectories Using Knowledge Representation Procedures

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This article highlights the importance of learning models which prevent the resilient attack of robotic technology with a subset of trajectories. Many complement models are introduced in the field of path planning robots without any knowledge of representation procedures, so robotic data are subject to different attacks from several users. During such attacks, the data will be misplaced and commands specified to robots will be disorganized so a new training data set has to be incorporated which is a difficult task. Therefore, to prevent probability of data failure time-dependent binary probability prototypes are introduced with low training data. Furthermore, a regularized boosting procedure (RBP) has been applied with different weights to switch multiple robots with discrete knowledge representation. Then a high space block is incorporated for maximizing coverage areas during loss functions and this is implicit as an innovative technique as compared with existing procedures. To validate the effectiveness of proposed learning techniques in robots, four scenarios are considered which include accuracy and success rate of detection. Subsequently, the outcomes prove that the robotic path with learning models are highly effective for an average percentile of 86% as compared to conventional techniques.

1. Conventional Models

In this section, some basic approaches that are related to the secure processing of data in robotic systems are analyzed where more difficult tasks are handled. Even the basic approaches that are present in industrial processes will be processed with the help of secured data processing techniques, and conventional techniques using real time test bed approaches are also observed for further developments. In [1] an adversarial sample of test bed data is established for processing the images towards destination, and this technique detects the malware's functions within a short period of time. But the same method fails to examine the effect of resilient actions if video metaphors are processed even in the presence of a deep learning technique. Thus, a scalable system has been developed to provide a multistate control on moving objects which are recorded using video samples [2]. This category of multiple processing techniques involves time-dependent networks where more generalization formulations are needed for developments which are considered a major drawback. To reduce generalization problems a path planning algorithm is developed to avoid collision [3] between parallel networks thus finding local optimal solutions. However for multiple networks fast solutions will not guarantee any resilient actions which provide zero percent actions against monitored networks.

In the case of resilient failure in robots, a probable method is formed where coverage of individual networks is maximized and this development can be applied at the same time in all multiple robotic systems [4]. This form of improvement process provides maximum coverage for utilizing submodular ranges which are present within a range of 100 meters. In addition to coverage maximization high agile aerial robots can also be implemented for avoiding all resilient actions by improving the crash percentage rate above 80 [5]. This aerial mode of operation can be carried out in two different modes and even it can be combined as hybrid operating cases. But in hybrid operation only soft rigid robots can be controlled under high risk conditions. Furthermore, to develop operations in hybrid mode, a physical activity context is enabled where all actions are processed only with finger print records [6] of robots. In the case of physical activities, it is observed that the percentage of improvement is much higher than other methods with a low latency level. In path planning systems, a trajectory curve is obtained within a period of 250 seconds as compared to methods without curve points [7]. The abovementioned curve points can be applied to all industrial processes and sports activities for tracking the movement of individuals.

Moreover, in robotic systems, it is possible to establish secured communication without any prior knowledge of network models [8] where all resilient actions can be detected and corrected. These categories of insignificant information on network models are tested using real-time simulation setup and validation of the same system model, which proves to be more effective and flexible as compared to knowledge representation systems. But every time in robotic systems, it is not possible to establish and train robots without any preprocessing techniques as the ability to react mode is always needed in real-world implementation inscriptions. Suppose in lack of understanding, a nonlinear mathematical model can be established to prevent all ferocity in robotic movement at unrestricted places [9]. Besides the irregular activities of robotic systems, a collaborative model can be established, thus sustaining demand for features with high potential influence. At the same time, demand can never be satisfied for any robots as training models are much difficult in the presence of cognitive representations. To have more information on cognitive models, a control system with physical representation architectures are characterized, thus preventing high resilient values [10]. If physical models are rationalized, then central activities can be monitored without any noise in the system. Nevertheless, nonexistence of the noisy system can be assured in all situations with high recovery capabilities.

It is also essential to quintessence on cost functions of implementing robots which is termed as coordination function determination using dt mathematical functions [11]. The model of matching systems is based on the rule of center point functions which have large capabilities of detecting multiple robots in neighboring boundaries. Still, cost functionalities will be much higher if neighboring nodes are integrated using aggregation rules, so at high risk times it can be avoided. Additional to dt functions a multiagent determination technique is integrated for finding multiple paths across same networks and the same agent model can be easily solved using routing techniques [12]. In the abovementioned routing agent cases many new strategies are determined for the same network model, thus increasing the cost of implementation. If robotic process is moving towards a resilient environment then physical characteristics of robustness and automation practices can be compensated with several engineering designs [13]. Still many engineering problems cannot arrange a robotic system in sequence order for carrying out distinct work features. Even authors [14] have distinct views on adversarial attacks which can be solved using linear approaches with input parameters that are provided in the percentage routine. Though it is much harder because percentage techniques that are implemented at the input side can add only a few parameters, to examine the input parametric implementation a fruit classification technique has been incorporated with robotic technology using deep neural networks, and percentage improvements are also obtained as robots are prevented from all resilient actions [15]. Besides the classification technique, the data is not corrupted at the end systems as a separate pattern is followed at the training set. From all determined models, exact dataset is not obtained, and the classification mechanism is not appropriately assimilated, thus providing conducts on the resilient actions of robots. To prevent unambiguous behavior of robots, several drawbacks are observed from the conventional systems, and they are solved using a discrete model as discussed in Section 2.

1.1. Research Gap and Motivation. Many existing methods [1–15] that are used for describing the resilient actions with knowledge representation procedures are applied in real time without any task classification mechanisms. Thus the best state of tasks are not performed. However, the design is capable of performing only a single task, and once the task period is completed then the next task is undertaken. The abovementioned procedure is observed as a major gap in designing of the robotic technology but to overcome the gap, a knowledge representation procedure is developed where the robot performs multitasks by applying the inputs.

Moreover, the projected method functions with the underlying principle using the learning method which is applied using the bosting procedure. Sometimes there is a high possibility that the designed task is open to all users, in that way, the robots cannot be functioned in an effective way. Thus, to prevent different attacks from users; a resilient procedure is developed where the methods of handling resilient data are provided. Thus, in this way, the projected method is developed and applied in industrial applications with predefined input tasks.

1.2. Contributions. The knowledge representation procedures for solving the resilient attack are based on the multiobjective model that solves the following:

(i) Classifies the input data at a correct task periods with the prevention of resilient data

(ii) Maximizes the accuracy of detecting input data units at varying time periods

(iii) Incorporate learning models for testing processes with boosting algorithms in order to apply them in industrial applications.

2. Resilient Design Model

In military applications, there is a high chance of external attacks by users, and they are divided into different types such as white and black hole attacks which can be processed in either direct or indirect modes. Thus, to prevent different attacks, a design model is established with discrete test sample times during the training period of past data. In case if any error occurs during training model then it can be solved using the following equation:

$$E_i = \sum_{i=1}^{n} |t - \hat{t}|^2, \tag{1}$$

where t indicates the received information for training, $\hat{t}$ represents the deceived information in the training set of robots.

The difference in the changed information set will provide error values which are subject to the following conditions:

$$\hat{t} = \begin{cases} 0, & \text{if } t = \hat{t}, \\ 1, & \text{if } t \neq \hat{t}. \end{cases} \tag{2}$$

The constraint represented in equation (2) specifies a binary value for maximum collaborative sets that are explicable by error characteristics. If a robot succeeded and addresses the error characteristics after the training set by displaying the value as 1 then the attack model can be defined using a trajectory function, and in this case, multiple robots are considered.

$$A(i) = \sum_{i=1}^{n} f\left(\frac{\alpha_i}{x \epsilon y}\right), \tag{3}$$

where α_i denotes coverage behavior of multiple robots, x, y represents a subset of trajectories that are involved in the training model.

The problem of resilience can be avoided by maximizing the monitoring coverage of robots using defined subsets x and y. The coverage maximization depends on the number of robots and it can be mathematically represented using equation (4) as follows:

$$\max \alpha_i = \sum_{i=1}^{n} f\left(\frac{1}{R_i}\right), \tag{4}$$

where R_i denotes number of robots that are present in trajectory subsets.

In the abovementioned steps, only trajectory subsets are represented, but the original attack on robots is based on replay actions using residual functions which are represented using the sum of current values as denoted in the following equation:

$$\max \Delta_i = \sum_{i=1}^{n} \frac{|I_{in}(t)|}{N_i}, \tag{5}$$

where $I_{\text{in}}(t)$ represents the value of current in terms of varying time period, N_i denotes number of sample for multiple robots.

Equation (5) which is represented in terms of current can be converted to residual time period. In the design model ten multiple robots are represented as a subset thus giving rise to delta = 9 time periods. Thus the raising alarm limits can be defined as follows:

$$rt(i) = \sum_{i=1}^{n} rt(i-1) - 9\delta, \tag{6}$$

where, $rt(i-1)$ denotes the previous residual samples according to training data set.

The alarm will be raised at central station if values of external attack are greater than 9δ thus preventing incorrect commands from entering the robot destination. In several conditions the robots are designed using voltage take off values which is mathematically represented as follows:

$$V\delta_{\text{input}} = \sum_{i=1}^{n} \text{TO}_{\text{volts}} + \vartheta_{\text{volts}}\left(\frac{\text{lift}_{\text{vin}}}{f_{\text{in}}}\right), \tag{7}$$

where TO_{volts} represents the robot take off voltage period and ϑ_{volts} denotes scaling period of robots.

Equation (7) represents the importance of take off time in the path planning of multiple robots where the quality factor of take off time period can be determined using equation (8) as follows:

$$\rho_i = \sum_{i=1}^{n} (is_n, is_{n+1})(\tau_i, \tau_{i+1}), \tag{8}$$

where is_n, is_{n+1} represents the initial paths followed by a robot in desired directions and τ_i, τ_{i+1} indicates the change in path due to external attacks.

The prevention of external attacks can be completely avoided by changing the robotic path as represented in equation (8), and this changing model will be integrated with the learning algorithm for choosing appropriate decisions.

3. Learning Models: Algorithmic Interpretation

In the proposed model to prevent the external attack of robots a learning model is integrated, and the design model that is implemented in the foregoing section will be applied in the development steps which are discussed under this section. The major advantage of choosing the learning algorithm is that a regularized boosting procedure (RBP) [16–20] can be applied directly in robots thus paving a way for preventing all external attacks. Furthermore, the drawbacks of different weights in unclassified mechanisms that are present in tree-based decisions can be solved using RBP with a parallel optimization technique. In this category of parallel processing technique, multiple robots can be prevented at the same time before being attacked by classes of attacks. Moreover, the major objective in the proposed work which is indicated by development speed can be resolved by the step-by-step approach of RBP where ten times the normal speed can be easily achieved within a short duration. Therefore, if any robot changes its behavior it will be immediately reported to the central server, and the corresponding subset of robots will be removed from the group and presented in Figure 1.

The data handling mechanism of RBP is quite different from other learning algorithms as the data is transferred in the form of blocks. These blocks are compressed, thus providing high space for saving memory in robots, and even blocks can be subdivided for distinct robotic groups which can also be stored in primary memory. This memory group will provide a way for scalable reading with low-cost operation. The mathematical model of RBP can be defined using classification and regression models as follows:

$$\partial_{i\text{class}} = \sum_{i=1}^{n} st_i - \text{class}_i, \tag{9}$$

$$\partial_{i\text{reg}} = \sum_{i=1}^{n} l_i - \text{reg}_i, \tag{10}$$

where st_i and l_i denotes the subtrees and linear trees for classification and regression models.

Based on the type of attack either equation (9) or (10) can be chosen with arbitrary indicators using robotic dart classifications. Using the indicators the gain of prevention can be mathematically formulated using equation (11) as follows:

$$g(i) = \sum_{i=1}^{n} A_i^s - B_i^s, \tag{11}$$

where A_i^s and B_i^s represent the set of classifications obtained before and after excruciating of robots.

After coloration gain of robots a new predicted value should be obtained to check whether the robots are free from attacks. This can be determined using the following equation as follows:

$$P_n(i) = \sum_{i=1}^{n} O_n(i) + \varepsilon_i * z_i, \tag{12}$$

where O_n and ε_i denotes the node predicted values and corresponding knowledge representation of robots, and z_i indicates the output representation of robots.

4. Simulation Results

This section provides an insight about the validation of the proposed method where all resilient actions are controlled in the robotic technology. The simulation results are carried out to provide immune systems in robots that are present in learning models without any interpretation. In the projected model, raw data is implemented directly in the robotic toolbox which is present in MATLAB. Thus, after assimilating necessary hardware components many input

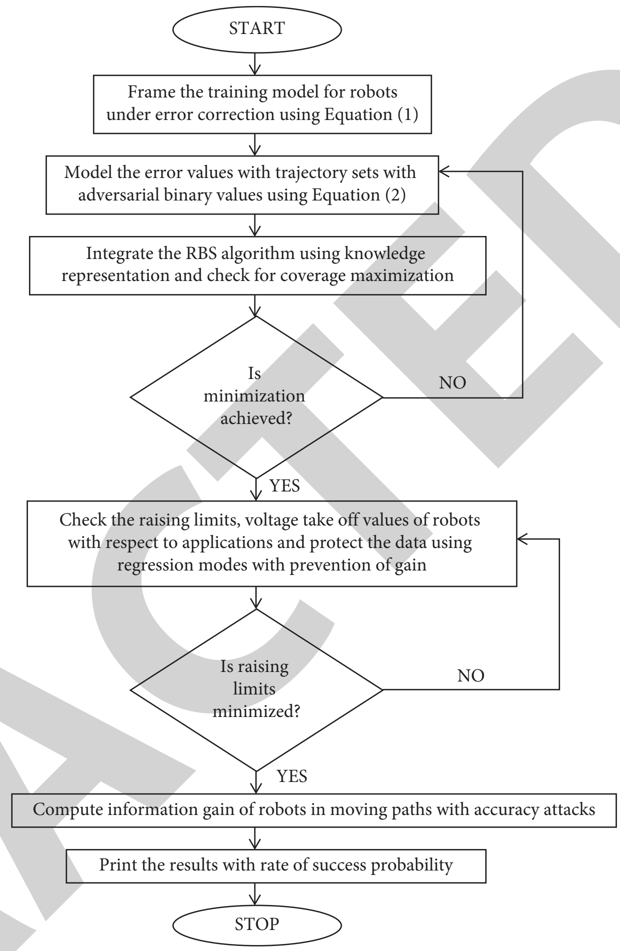

Figure 1: Proposed flow for avoiding resilient actions.

parameters are processed in the presence of knowledge representation that makes the proposed model to function under four different scenarios as follows:

Scenario 1. Loss of physical activity

Scenario 2. Speed of classification

Scenario 3. Proportions of attack vs accuracy

Scenario 4. Success rate of resilient actions.

All the scenarios that are listed above are carried out in real time using the learning approximate technique where at stage 1 algorithmic parametric values are evaluated with gain values. If gain values are lesser then the process will be stopped immediately without any further delay as resilient actions will have high impact on decrease in gain values. To increase the value of gain, a three-dimensional model is chosen for avoiding all obstacle detection, and the path of robots are chosen in the precise mode of operation. Furthermore details about individual scenarios are provided separately in the subsequent section.

4.1. Scenario 1. In this scenario, physical activities of multiple robots are monitored and if any loss of activities in the entire list is present it will be monitored and informed to the central station within a short span of time. The movement list process will be created to improve the performance measurement within specified video frames which is carried out at 100 ∗ 150 frames per second. All the gesture activities will be developed and executed one time per frame; no repetition period can be found in the proposed method using learning models. Since the repetition period is lesser, the loss values are reduced, and it is indicated as the minimum with a high improvement in gain values. This prevention of loss value further maximizes the coverage regions as represented in equation (4) with trajectory subsets. Furthermore, a communication segment without any error is carried out in a single room where many users are treated as unauthenticated persons, and in this case, the robot avoids such users as anonymous activities are found. In this case, only authenticated users are found and allowed to interact within the physical environment, and the simulated loss activities are plotted in Figure 2.

From Figure 2, it can be observed that a number of epochs are carried out for two periods of time where corresponding loss activities are monitored within stipulated regions. This category of loss activities is much higher for the existing method [1], as it extends up to 0.973 percentage of time, whereas for the projected system the loss activities are minimized with maximization of coverage values. This can be clearly detected during the epoch period of 14 as the number of loss activities are 0.783 without knowledge representation technique and 0.063 in presence of learning models. Furthermore, for all epochs learning models in robots provide the best representation in terms of loss and coverage as one representation is considered. In addition, the simulation results are checked for multiple robots with different representations, and in this case, the loss activities are nearly the same for both existing and conventional models. However, in the proposed model, a single objective case study is proposed, so subsequent case studies are performed for lossy regions.

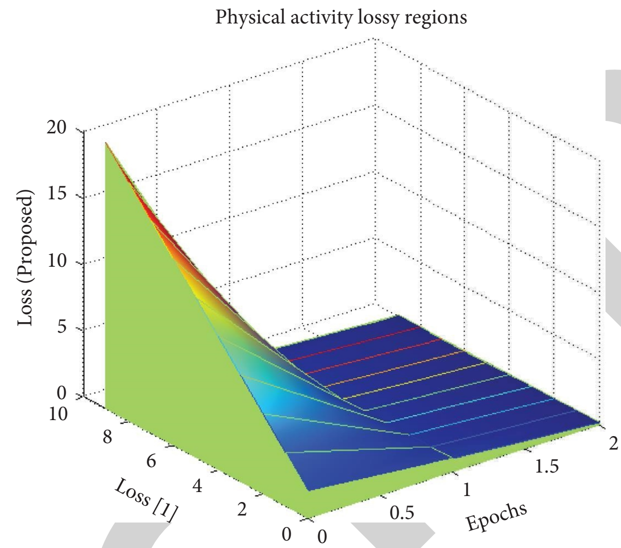

FIGURE 2: Maximization of coverage in lossy regions.

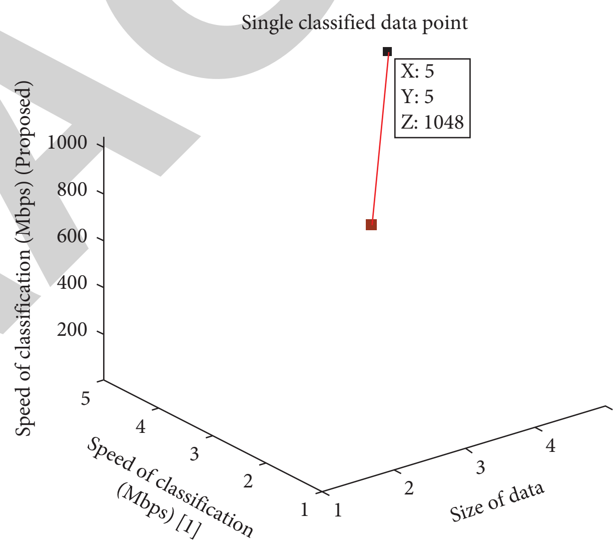

FIGURE 3: Speed of classification.

4.2. Scenario 2. Once loss activities are measured then the speed of robots are classified with respect to the size of data implementation. In the learning models, size of the data is varied with respect to image classification with disparity of 64, 128, 256, 512, and 1048 bits per second. In this scenario, two distinct functions are carried out where the power source is measured over multiple differentiated topographies. In this case, the power source of robots is reserved as secondary source in case of failure detection but in existing methods a secondary backup is not formed which is sensed as major contribution of learning representation models. Also, the initial power representation in this case study is found to be 5 kilo watts as robots move within the allocated frame in the cell. The classified data will be merged at data the representation stage to prevent loss of data which can be better understood by humans and is simulated in Figure 3.

Figure 3 shows the early and culmination speeds of classification with respect to data points in x-axis regions. It can be clearly detected that as the size of the data increased the classification speed is maximized with coverage points. However using the same setup both the conventional and proposed method are compared, where the speed of classification is much higher for learning robotic techniques. This can be clearly implicit with large data set at 1048 bits per second where speed of classified frames will be 2.4 in the case of the existing method [1] and 1.4 with the knowledge representation technique. The same classification can be observed for the insignificant size of data which starts at 64 bits per second as video frames are considered. This in turn provides a clear view of information visualization technique with different data patterns, as a high advantage is provided only for proposed implementations.

4.3. Scenario 3. The major importance of implementing learning models is that accuracy against a number of attacks can be measured in a precise manner. This type of representations usually starts with low training data at 0.05 as more number of representations at initial stage will have high misperception during movement formation. Even the difference between learning and nonlearning techniques can be implicit using replay actions, as represented in equation (5). Furthermore, for the proposed model accuracy is increased due to the periodic delta time which is considered to be 9. However, the same process can be processed in manual form using human interaction, but accuracy of 1 micron can never be obtained in this case. Thus, the automatic accuracy using contour simulation is deliberated in Figure 4.

From Figure 4, it can be detected that as low training data is increased from 0.05 to 0.5 bits per second, accuracy against resilient attacks are also maximized with a high shield of data protection. This can be evidently proved using training data of 0.3 where the existing method [1] delivers an accuracy of 25 percentage which is much lesser as expected values. But with 0.3 training data of the robot with single case knowledge representation, the projected method can achieve 76 percentage of accurate values against diverse attack periods. The contour plot is executed using two dimensional with t period of 200 variations with different color bars where indicated red color marks prove that learning technique offers low attack with less than 70. The target functions are indicated in blue color with a set of trajectory values which extend between 10 and 40.

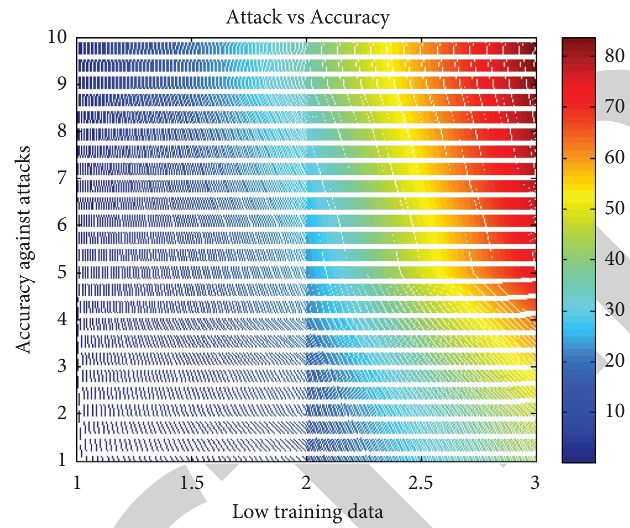

Figure 4: Accuracy against attack.

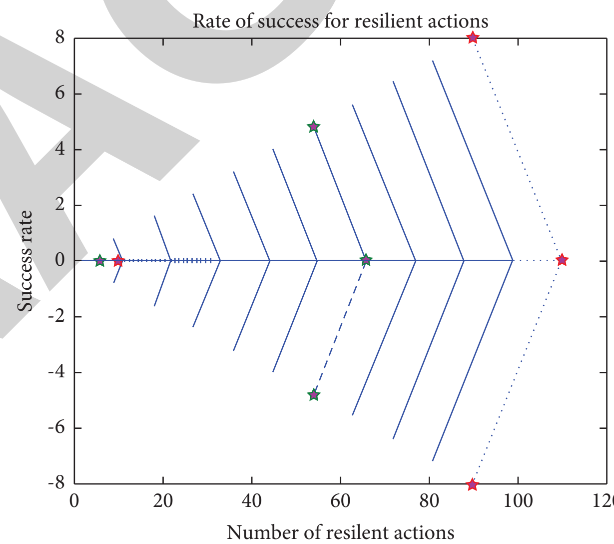

Figure 5: Rate of success with the learning model.

4.4. Scenario 4. In this case, the comparison persistence has been made by determining the success rate which provides a difference with respect to accuracy. This scenario computes attack against different fields of interoperation as number of attacks is varied up between 10 and 100. In addition for trajectory subsets the motion of robots is tracked which is considered as an additional setup that is added with existing methods. Thus again a feather determination are made and is reflected in Figure 5 with high increase in success values for both learning and nonlearning models. Even the same method can be executed with different step periods but corresponding periods will have less impact on resilient actions. Therefore, in the direct case variations are performed with 100 feather point with t period as zero.

From Figure 5, it is obvious that a continuous success rate is achieved after 40 resiliency periods for the proposed method whereas existing methods can able to achieve the same at 80. Thus, in terms of resilient attacks more accurate rate of success can be observed, and it is indicated with space markers. The first space marker extends to an action period between 10 and 15, and further, it is carried out for the same five periods whereas the last period is extended to 80 as constant marks are achieved. After certain observations, it can be determined that an average rate of 0.87 can be achieved with knowledge representation cases, whereas existing methods in case of absence of nonlearning techniques are able to achieve 0.62 percent of success rate which is much lesser than expected techniques.

4.5. Scenario 5. In this scenario, the application of knowledge representation in robotic technology in addition to resilient design has been projected. The knowledge representation procedures used for describing robotic technology is highly helpful in all applications as once the inputs are given then at the next moment the tasks are immediately performed by robots. In this way, all the application-oriented actions are monitored by implementing a common path that is followed by robots. For identifying the paths, certain applications usually prefer a black mark points as the robots have high knowledge on the described operational cases. Moreover, with this knowledge representation application, all tasks are integrated in industrial applications where the robot performs data gathering, rotation, and packing of different products. Even in large-scale industries using these knowledge representation applications, a robot can perform modelling tasks within a stipulated time period. Thus, the tested knowledge representation for industrial applications is simulated in Figure 6.

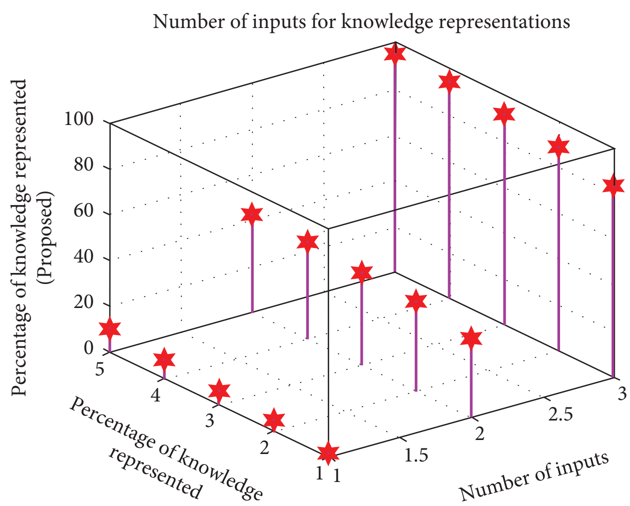

FIGURE 6: Percentage of knowledge representation applications.

From Figure 6, it can be observed that the percentage of knowledge that is represented for industrial applications is measured by giving a few numbers of inputs to perform specific task functions. Also, the same task-functioning inputs are given to the existing method without incorporating the learning procedures. Since the rate of learning is much reduced in the existing method the percentage of knowledge representation is much lesser. However, in the proposed method, learning rates are provided so the robot performs the given input task where the percentage of knowledge representation is highly increased. This can be proved for five different task inputs 2,4,6,8, and 10 where in all the abovementioned number of tasks percentage of knowledge that is represented for the proposed method is 34,39,40,42, and 43, respectively, in case of the existing method. Whereas the same number of inputs percentage of knowledge that is represented for proposed method is 83, 89, 92, 94, and 95, respectively. This proves that for any application oriented mechanisms knowledge representation is much essential and using the proposed method can be incorporated in the real-time robotic systems.

4.6. Performance Measurements. The effectiveness of the integrated boosting algorithm can be proved by simulating the performance of the proposed method and comparing it with existing models using the best optimal results with a low error rate in industrial applications. The best optimal results are tested with the number of epoch which is varied from 10 to 100 and the same is compared with existing methods. The optimal results are plotted in Figure 7 where even after a larger number of tests the proposed method proves to be achieving optimal results as compared to the existing models. For this number of iteration variations best optimal results are minimized which indicate that only low energy is spent for performing a particular task in the proposed method. Whereas with the same iteration period the optimal solutions for existing method are randomly varied, which indicates that the energy is maximized for certain tasks. This performance measurement proves that the proposed method is highly beneficial for implementing robots at a reduced energy rate.

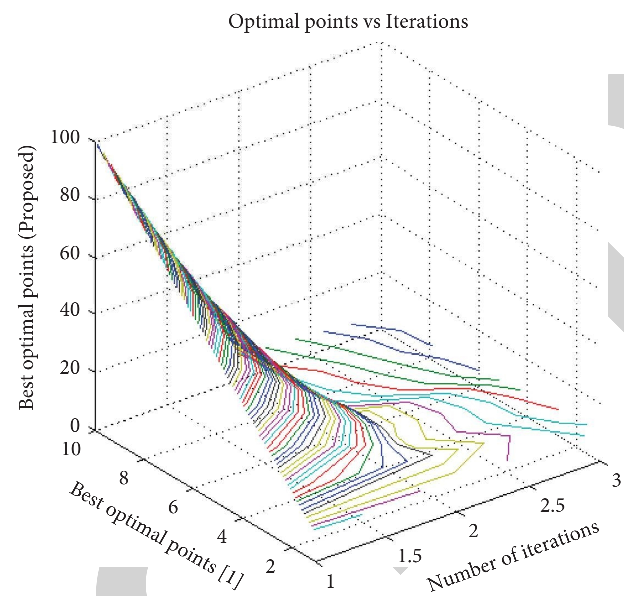

FIGURE 7: Best performance measurements.

5. Conclusions

Many conventional techniques have been implemented in robotic technology for handling various applications to tackle real world problems. However, all application processes grieve from the major drawback of external attacks from different users as data handling techniques will result in slow development stage. Even there is a high probability that during the data transmission phase data will be lost due to the failure movement detection of robots. Thus, this article provides great advantage on analyzing the impact of adversarial attacks with diverse set of trajectories. In the proposed method, a training model is incorporated with a training set using binary values where pathway for robots can be planned using subset of routes. This process differs from the standard protocol technique as an automated process of coverage maximization is added in the case of lossy data in corresponding regions. In addition, a raising alarm limit has been arranged with nine distinct standard delta values for input voltage take off values, and power limitation has been provided with secondary backup. Moreover, quality factor of robots has been determined with initial take off values which differs from the path planning algorithms thus paving a way for knowledge representation process. Furthermore, the learning models are tested using different scenarios which include success rate with feather simulation models, and it is observed that an improvement has been achieved for multiple robot scenarios under multiobjective case studies. In the future, the same procedure can be applied with multiple trajectory sets where speed of classification can be improved with different training dataset.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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