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Errors Detection Based on SDWT and BNN Applied for Position, Velocity and Acceleration Signals of a Wheeled Mobile Robot

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***Abstract*—Accurate error detection in mobile robots is crucial for reliable operation and prevention of mechanical or electrical failures. Mechanical defects on the wheels of mobile robot make real path deviate from the desired path and trajectory. From the kinematics equations, error in the angular velocity of wheel affects the position, velocity, and acceleration. Each of these signals is fed to the Symelet discrete wavelet transform (SDWT) for the purpose of error's feature detection and extraction. The SDWT with 5-level for each component of the signal produce 10 inputs for the Bayesian Neural network (BNN). The BNN with single layer of 18 neurons classifies the inputs either no error case or specify the wheel(s) at which error had been happened. Straight line and circular paths were tested in the presence of errors in single wheel or both wheels. Two different path's time durations are tested to investigate robustness of the proposed methodology. The simulation's results of two wheels mobile robot showed that acceleration's signal for a straight-line path has accuracy of 100%, MSE 3.05×10^{-23} and 9.81×10^{-17}, training iterations are 15 and 23 for 4- and 2-seconds durations; respectively. While for a circular path, displacement's signal gave high accuracy 100%, MSE $8.86\cdot10^{-16}$ and 3.76×10^{-18}, training iteration 17 and 13 for 4- and 2-seconds durations; respectively. Acceleration signal can be used for detecting errors in real time by using accelerometer. Limitations such as amount of data besides to the sensor noise affects the proposed methodology.**

Keywords*—*Error; Detection; Mobile Robot; SDWT; BNN; Signals.

I. INTRODUCTION

In robotic systems, particularly mobile robots, the occurrence of mechanical, electrical, and computational errors can significantly impair functionality and efficiency. There are three main types of errors which are mechanical, electrical (Hard), and computational (Soft). Generally, the mechanical errors due to bearing, gears, shaft bending are the mostly happened in robotics systems. These errors produce mechanical vibrations. When the current flowing is interrupted due to equipment, environment, human error, abnormal condition is happened. Also, the high torque, applied energy, and system power which are related to the electrical components make the same symptoms and errors. These mentioned errors are considered as types of hard errors[1]. The third type is related to the computer programs and control when the software directs mobile robot to untrue trajectory due to crash or data loss. This type is the more difficult one to be diagnosed. Some of errors may be happened due to one or more of the three main mentioned types simultaneously. Several concentrations have been paid to the self-sufficient navigation of mobile robotic systems. Many issues have to be solved recently, this can make the mobile robot very sensible and intelligent [2]. The robots can be in different and changed environments [3], that can lead to many problems in their components and functions. Many types of robots which are considered very important like ground and underwater robots are suspectable to be infected with errors [4].

In [5], the error diagnosis was dependent on the residual principle for the purpose of identifying the error from software or hardware. The mechanism of recovery is generally dependent on the principles of modality to adapt the control loop of the robot due to the main purposes processed for the robot. The errors in actuators were removed and detected from a specific transmission model in a special mobile robot [6]. Every wheel of this mobile robot is moved by a DC motor blended with a 25:1 gearbox and incremental encoder. It was controlled by using a dual-mode controller to remove the error in position and velocity. These systems are mostly called as dynamic system which are mostly important to be diagnosed and studied when researchers are looking to faults and error detections field [7].

In [8], a study of errors-tolerant control was proposed for the purpose of computationally tractable error detection and diagnosis process of a special mobile robot with six-wheels. The probabilistic state-estimation theory of was used for the purpose of estimating the general state (non-Gaussian, non-linear) dynamic systems in real-time. Two complementary algorithms are depended and used: the decision-theoretic particle filter (DTPF) which is used to reduce the number of particles which is required to states of unlikely track, and the variable resolution particle filter (VRPF) which was used to reduce the number of required particles. In other works, the authors proposed a system of a feedback control based on the theory of Lyapunov stability, which was used for solving the errors inside the mobile robot trajectory [9]. The mentioned study can be applied for other motion control systems' types in robotic systems such as aircraft, ships, and others [10]. The detection and diagnosis of faults tolerance and error become more important in the field of automatic control [11]. It is considered as the first step of any abnormal management events in complicated system [12][13]. In the industrial field, many extraordinary mobile robots (special type robots) have typically taken place through experimental feedback and mission sequence analysis. It is important to say that there is a significant lack of dependability when logical or physical problems occur [14]. Any manufactured products such robots contain defects and errors to a certain acceptable limit. After cycles of operation these defects and errors become effective leading to malfunction. Thus detection and diagnosis of error is important to increase life time and assure correct operation.

In [15], a study of faults and errors on sensors and actuators was presented. It was model-base method facing the challenge of detecting and distinguishing wheel sensor from wheel actuator's additive faults. Many researchers proposed studies about the error detections and diagnosis in mobile robots [16][17][18], the discrete wavelet transform in different types, the neural network in different types including the Bayesian type [19][9]. In [20], a faults detection method was used to detect the problems happened in engine vibrations using vibration, noise, air sensors and reading their data by using Message Queuing Telemetry Transport (MQTT) protocol, which is a messaging standard protocol in internet of things (IoT). The important thing of using the error or fault diagnosis methods is to make a check for the machine or the system without stopping it [21][22][23]. The errors and faults those can be happened in the mobile robot make it not safe to be used [24][25]. It is mostly considered more risky and sensitive systems [26][27][28].

Mobile robot has three degrees of freedom and moves in plane motion. Defects or faults in its components make error in position, velocity, and acceleration. Thus untrue trajectory is resulted. The path is straight line or circular depending on wheels' angular velocity. The recent studies and works in the field of error detection and diagnosis were not focused on the effective of trajectories or paths of the mobile robot, also no comparisons' studies were done for the position, velocity and accelerations simultaneously. In this paper, a simulation study focuses on the detection of errors on one or more wheels of a mobile robot. These detected errors can be signs of mechanical or electrical failure in the wheel of the mobile robot. Two types of paths are considered, straight line and circular. Also, for each path, two cases are enrolled according to the running time of simulation (approximately 4 sec. and 2 sec.). A comparison study of error detection and classification in a wheeled mobile robot will be done depending on the signals of position, velocity, and acceleration. Each signal is firstly modified by the SDWT filter producing 5 outputs for each component. As the mobile robot has plane motion (x and y coordinates), 10 inputs are fed to BNN for 4 classes of classification (no error, and 3 errors). This paper is organized as follows: after the introduction section, a kinematics equations of motion (x and y) are presented in Section 2. The Symlet - discrete wavelet transform and Bayesian neural network are presented in Sections 3 and 4; respectively. The proposed methods are presented in Section 5. Section 6 is devoted to results and discussion. Finally, conclusions are given in Section 7.

II. Kinematic Equations of Motion

The two wheels mobile robot is shown on Fig. 1. Global coordinate frame is $\{X_G, O_G, Y_G\}$, while $\{x_l, c, y_l\}$ is local coordinate frame at the robot centre of mass (c). This mobile robot has three degrees of freedom which are x, y, and angle ϕ (rad). This angle is measured from global X_G to x_l. ω_L and ω_R are angular velocities (rad/s) of left and right-side wheels of the robot; respectively. Angular velocity represents control input [9]. v_c is center of mass linear velocity(m/s) [29]. Let v_L and v_R are linear velocities (m/s) of the left and right-side wheels centers; respectively. Also r is the wheel's radius (m). The linear velocities are given by[30]:

$$\begin{aligned} v_L &= \omega_L\ r \\ v_R &= \omega_R\ r \\ v_c &= \frac{1}{2}\ (v_L + v_R) \end{aligned} \tag{1}$$

According to Fig. (1), the relative linear velocity between both sides of mobile robot gives:

$$2b\dot{\varphi} = v_R - v_L \tag{2}$$

Where ($2\cdot b$) is the distance (m) between two wheels, and $\dot{\varphi}$ is the angular velocity around center of mass. Using and combining equations (1) and (2) lead to:

$$v_c = \frac{r}{2}(\omega_L + w_R) \tag{3}$$

$$\dot{\varphi} = \frac{r}{2b}(\omega_R - w_L) \tag{4}$$

The above kinematics equations are on local coordinates. The velocity components can be transferred to global coordinates by using the angle ϕ. The components of v_c in global coordinates can be written as:

$$\begin{aligned} \dot{x} &= v_c\ cos\ \varphi \\ \dot{y} &= v_c\ sin\ \varphi \end{aligned} \tag{5}$$

Finally combining equations (3)-(5), the kinematic model of mobile robot is obtained [31]:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} \frac{r}{2} cos\ \varphi & \frac{r}{2} cos\ \varphi \\ \frac{r}{2} sin\ \varphi & \frac{r}{2} sin\ \varphi \\ -\frac{r}{2b} & \frac{r}{2b} \end{bmatrix} \begin{bmatrix} \omega_L \\ \omega_R \end{bmatrix} \tag{6}$$

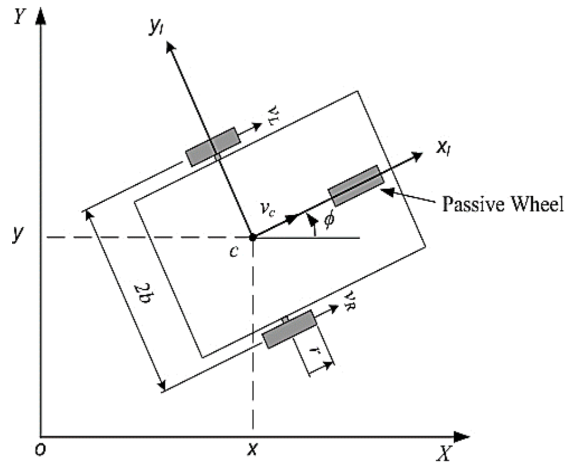


Fig. 1. Schematic model of mobile robot

Equation (6) is the kinematic equation for two-wheeled differential drive mobile robot. From Eq. (6), the Cartesian components of velocity and other kinematics values are function of the angular velocities of wheels.

III. Symlet-Discrete Wavelet Transform

Although the most features of time and frequency domains cannot provide good representations of the nonstationary signals that are commonly happen in machine errors, the wavelet transform is used in many applications to solve this problem [32]. Discrete wavelet transforms, recently developed time-frequency techniques, are more suited to analyze non-stationary signals and are frequently used to capture significant error characteristics in the field of error diagnosis. Wavelet transform with their both two types (continues and discrete) are used many times for the purpose of error (faults) detections. In [33] to give a more salient and thorough time-frequency distributed representation, the discrete wavelet transformation was applied. A highly potent and effective method for removing in-band disturbances that taint all signals like sounds which produced by vibrations is the wavelet transform [34]. Mostly the Daubechies type of discrete wavelet transform was depended and used [35]: In comparison with the Daubechies, the Symlets is approximately considered as a symmetrical wavelet that modify the db. family. The two wavelet families have comparable characteristics [36]. The Symlet discrete wavelet transform has an advantage of that both the low and high pass decomposed filters' components have closed to a mirror image of each other. The ability of behave with both the frequency and time make it suitable to be used for diagnosing, feature extraction in different type of signal processing tasks [37].

In [35], the DWT type Daubechies with 5-levels is depended. In this paper, the Symlet discrete wavelet transform (SDWT) is presented as those of Daubechies, Fig. 2 includes the Daubechies and the Symlet filter types with their families. These families are considered as almost identical wavelets. As shown, there are eight filters for Symlet and ten for the Daubechies. It is clear that each one of the Symlet filter type is can be considered as a mirror image to that of the Daubechies (sym2: db2, sym3: db3, sym4: db4, and etc.). The recorded signals from the designed simulation in this paper are firstly modified with the SDWT filter. The process is repeated five times for each component. Thus, five outputs will be obtained for each signal. These outputs are then used as inputs to the neural network for classification.

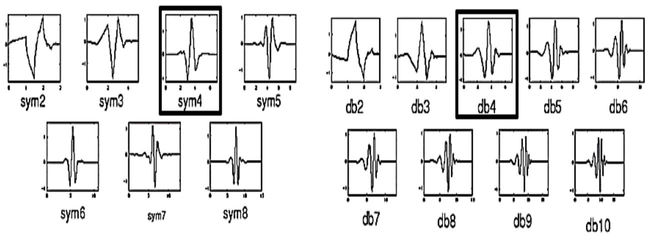


Fig. 2. Symlet and Daubechies Families [35]

IV. Bayesian Neural Network

In recent works, the neural network is used hugely in the most of the fields [38]. The error's detection was considered as critical cases which requires immediate solution [39]. Thus, the neural network has been proposed hundreds of times in this field [40]. The perceptron and the multi-layer neural networks were used many times for the purpose of classification and errors' diagnosis [41][42]. The artificial neural network may predict values outside the trained dataset, this due to the problems of over fitting and under fitting. One of the mostly preferred types of neural network and considered new relatively is the Bayesian neural network (BNN)[43][44]. Many researchers applied it in their works for the purpose of classification and detection [45][46]. In order to avoid over fitting, BNN can be applied to solve problems in fields where data is limited [47][48]. The BNN approach applies probability distribution which is statistical technique so as to provide all the details, including model parameters (weights and biases) as shown in Fig. 3. With BNNs, data of unknown targets can be recognized so as to automatically compute the error related to the predictions [49]. Bayesian regularization is used to modify the objective function by incorporating the mean of the sum of squares of network connection weights. The BRNN prevent the overfitting by maximizing weights of the training data and reducing the weights of the testing data. The training iterations stopped as soon as the square error validations reaches to the minimum [50]. For this reason the BRNN is robust than ANN [51]. The following equation represents the early halting for the ANN (ED):

$$E_d(D|w, M) = \sum_{i=1}^{n}(t_i - \overline{t_i})^2 \tag{7}$$

where $\overline{t_i}$ is the i-th goal, w is the weight, M is the ANN structure, n is the training data size, and t_i is the output. In ANNs, premature convergence leads to over fitting of the model. Through the Bayesian regularization of ANN, the prior values of the ANN parameters are used to optimize the ANN parameters. Because of this, the BRNN's objective function has an extra term (E_w) that looks like this:

$$E_d(D|w, M) = \sum_{i=1}^{n}(t_i - \overline{t_i})^2 + E_w \tag{8}$$

where the unreal weights are penalized using E_w to enhance generalization and progressive conversion. An optimization method based on gradients is used to minimize the function:

$$F = \beta E_D(D|w, M) + \alpha E_w(w|M) \tag{9}$$

where β and α stand for the hyper parameters that need to be optimized, and $E_w(w|M)$ is the sum of the squares of the ANN architecture's errors. BRNN is considered a powerful predictive model because it can make theoretically intricate input-output relationships visible [52][53][54]. Bayesian Regularization is an ANN technique that can work well by using mathematical science to train multiplayer networks based on created network architecture models. The training function of the Bayesian Regularization approach can train the network by optimizing the Levenberg-Marquardt and updating its weights and bias.

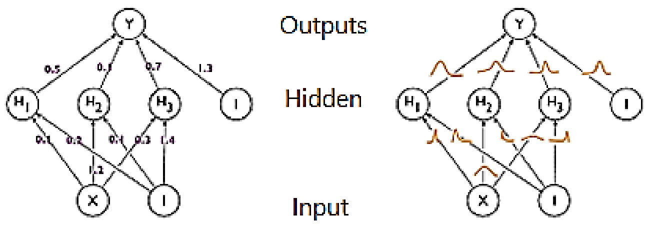


Fig. 3. Bayesian Neural Network

V. PROPOSED METHODS

Tracking the desired path by robots is important so as to avoid obstacles in the environment and reach the goal. Error in the angular velocity magnitude of wheel affects the position, velocity, and acceleration according to the kinematics relations (Eq. (6)). Monitoring these kinematics values is important because it can be as a sign of mechanical or electrical failure in wheel of the mobile robot. A lot of new sciences and technologies have been added to the device's parts like motor bearing for detection technology of defects in recent years, making it a comprehensive technology [55]. These devices have to be monitored and observed continuously.

During investigation, workers can locate, isolate, and recognize errors with the use of error diagnostics. The neural network type BNN can handle and classify a variety of uncertainty issues well according to its good properties as mentioned in section 4. Thus, it has been used in this paper in the second part of the diagnosis process (classification). To identify the network, the number of hidden layer and the number of neurons in hidden layer have to be justified correctly [56].

The Symlet type sym4 discrete wavelet transform is depended as a feature extraction method in part one. These two parts were applied for three types of signals (position, velocity, and acceleration), which are recorded from a mobile robot simulation designed especially for this work using Matlab, Fig. 4. For each of the signals (position, velocity and acceleration), two types of paths are considered: straight and circular. Also, for each path, two path's time durations of motion are enrolled in simulation (approximately 4sec. and 2 sec). The number of recorded data for 4 sec. and 2 sec. are 3973 and 2003; respectively.

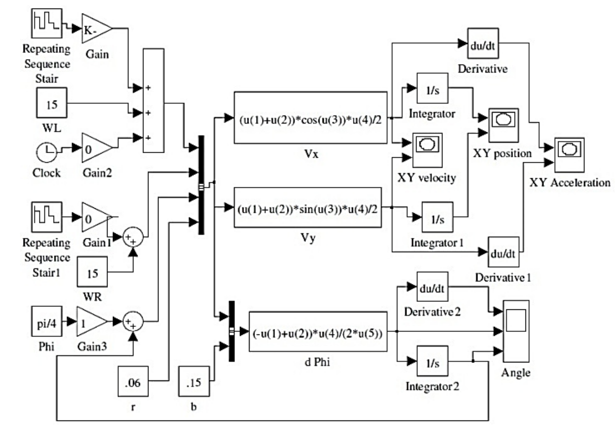


Fig. 4. Mobile robot designed simulation

All the mentioned cases are done under the same environments. Many types of features extraction methods can be used in the field of errors diagnosis [57][58][59].The SDWT with 5-level produces 10 inputs as features to be used by the BNN. That because the presented mobile robot can translate in two directions which are x and y as mentioned before in section 2. The error is considered to be happen in each one or both of mobile robot's wheels. Four cases have to be expected which are no error, error on left wheel, error on right wheel, and error on both wheels. Thus ten (10) inputs and 4 outputs have to be used for the BNN. In this paper, three kinematics' vales (position, velocity, and acceleration) are proposed with their details as shown in Fig. 5.

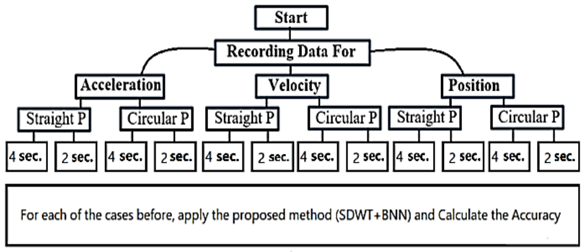


Fig. 5. Work plan diagram

The steps for proposed method are presented below to provide logic sequence for error classification:

Step 1: Use straight line path.
Step 2: Analysis for position.
Step 3: No error in wheels.
Step4: Obtain five level values for each x and y components using SDWT to produce ten inputs for BNN.
Step 5: Store the ten inputs.
Step 6: Repeat steps 4 to 5 for error in left wheel.
Step 7: Repeat steps 4 to 5 for error in Right wheel.
Step 8: Repeat steps 4 to 5 for error in left and right wheels.
Step 9: Train BNN for classification of errors.
Step 10: Repeat steps 3 to 9 for velocity.
Step 11: Repeat steps 3 to 9 for acceleration.
Step 12: Repeat steps 2 to 11 for curved path.
Step 13: Repeat steps 1 to 12 for reduced duration's time.

A. *Validation of proposed method*

The proposed method is tested for defect classification on a ball bearing in order to validate it. Defects in ball bearing may occur in outer race, inner race, cage, or rolling element. Resonances appear when the rolling elements strike a local defect. The envelope spectrum analysis and spectral kurtosis were used to identify different types of defects from acceleration signal [60]. The outer race defects are slightly noticeable. Thus, enhancing the signal-to-noise ratio was necessary by using keratogram for a selected band. Also, only single defect can be detected. More details are presented in MathWorks.com under the title " Rolling element bearing fault diagnosis". In the present proposed method, SDWT produces five inputs for BNN to perform classification for three classes (normal, outer race defect, inner race defect). The results are presented in Table I. The accuracy is 100% and MSE is 7.8×10^{-17}.

TABLE I. VALIDATION TEST RESULTS

Training Time	No. of Iterations	Accuracy
13.09 sec.	12	100%
Processing Time	No. of epoch.	MSE
5.85sec.	12	7.78×10^{-17}

VI. RESULTS AND DISCUSSION

The simulation is based on the kinematics equation (Eq. (6)). A repeated sequence stair block is used to generate error on angular velocity of the wheel. The linear velocity is function of angular velocity of wheels and robot's dimensions. The error bound is (0.060 - 0.015) rad/s. The linear velocity components are differentiated and integrated to obtain acceleration and position; respectively. The two wheels mobile robot has plane motion into x and y coordinates. The initial value of _ is 45o so as to produce x and y components of position, velocity, and acceleration. The wheel radius (r) equals to 0.06 m. The half width (b) equals to 0.15 m. The wheels have angular velocity of 15 rad/sec for straight line path. In the circular path, the right wheel is given an angular velocity of 18 rad/sec. These angular velocity values are for normal application [61][62].

According to the obtained results, eighteen (18) neurons with one hidden layer has been selected for all the cases because it has smallest time. One output layer has four neurons (one for each class). The linear activation function is used for the output layer, while the Bayesian activation function is used in the hidden layer. The output is [1 0 0 0] for no error; while it is [0 0 0 1] for error on both wheels. The data is divided according to that 70% for the training, 15% for the validation and 15% for the testing process. The training time of classification from acceleration signal for straight line with path's duration 4 sec. is presented in Table II. The used BNN is shown in Fig. 6. The suggested neural network is used with 0.05 learning rate, one hidden layer, with 18 neurons, and sigmoid activation function. The training time is presented in Fig. 7. These results depend on complexity of data set and hardware of the used computer. Fig. 8 shows the desired path and the path with error on left wheel for straight line and circular paths; respectively. The two components are equal for straight line path, while are different for circular path.

TABLE II. TRAINING TIME IN THE POSITION, VELOCITY AND ACCELERATION SIGNALS

No of Neuron in hidden Layer	5	10	15	17	18	20	25
Position sec.	11.6	17.3	16.7	13.4	8.6	37.0	37.0
Acceleration sec.	7.5	15.3	8.2	11.3	6.4	36.8	36.9
Velocity sec.	129.1	125.2	109.1	35.1	16.8	75.1	85.6

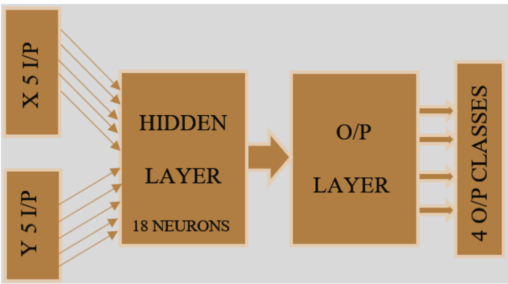


Fig. 6. The used Bayesian Neural Network's structure

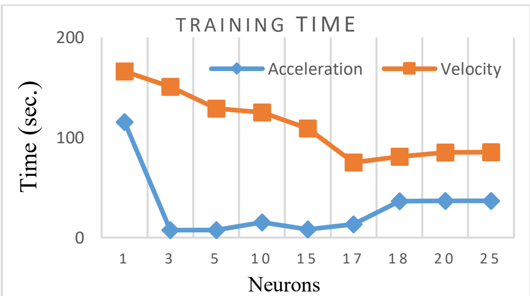
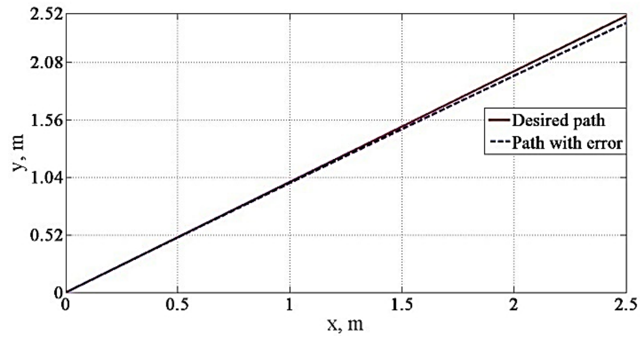
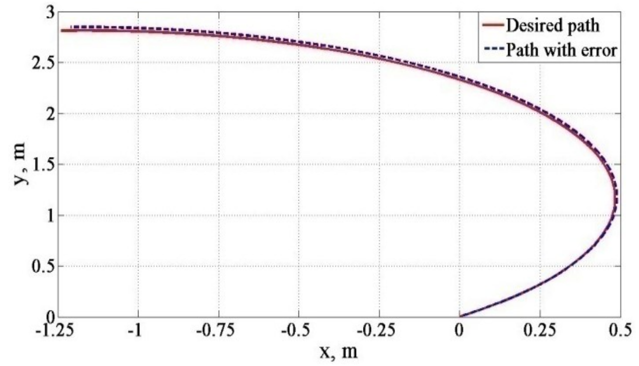


Fig. 7. Training time for acceleration and velocity signals



(a) Straight line path



(b) Circular path

Fig. 8. Desired path and the path with error from left wheel

A. *Positional Signal*

In this case the signal of position is recorded for the straight line and circular paths with 4 and 2 sec. of time duration. The features of position's values are extracted by applying the SDWT- 5 Level and used as inputs to BNN for classification of error. The results for these cases are listed in Table III. The accuracy reached 100% for both straight line and circular paths, with a very slight increase in training time due to the complexity of the circular path case in comparison to the straight-line path. Accuracy of 100% is indication on the performance of BNN. It is the percentage of number of correctly classified cases to the total amount of data. While; the MSE is the square difference between the predicted and true output. The ratio of wheel's radius to mobile's width affects the position value. The error is magnified for position because of dimensions of mobile robot as can be noticed from Eq. (6). The BNN had shown the capability of extracting error's feature even when the duration time of motion is reduced to 2 seconds.

TABLE III. POSITIONAL DIAGNOSIS' SIGNAL RESULTS

Position				
	Straight Path		Circular Path	
	Wheels Speed = 15rad/s for both wheels		Wheels speed: WL= 15rad/sec, WR=18 rad/s	
Duration time	4 sec.	2 sec.	4 sec.	2 sec.
Processing time	4.71	4.97	4.79	5.28
Train time	9.06	16.12	10.86	8.63
Accuracy	100%	100%	100%	100%
MSE	4.75×10^{-17}	1.20×10^{-15}	8.86×10^{-16}	3.76×10^{-18}
Iterations	10	72	17	13
Epochs	10	72	17	13

B. Velocity Signals

The same steps are repeated for the velocity recorded signals. The results for both straight and circular cases are listed in Table IV. According to the result, the accuracy becomes smaller in comparison to that of the positional signal. As small percentage of error is added to the angular velocity (0.1 %), the SDWT and network capability of classification are decreased to 75%. The processing time becomes more than twice, while the training time is more than ten times in comparison to that from the positional signal. The processing time is the time of SDWT processing of data, which depends on the hardware specifications of the used computer. The training time depends on the network size, structure, and complexity of training set. As the number of batches of one epoch increases, the training time increases. Also, big data requires more memory for processing. The accuracy is improved when the time duration of motion is reduced from 4 sec. to 2 sec. because the BNN can work when the data is limited.

TABLE IV. VELOCITY DIAGNOSIS' SIGNAL RESULTS

Velocity				
Straight Path			**Circular Path**	
Wheels Speed = 15rad/s for both wheels			Wheels speed: WL= 15rad/sec, WR=18 rad/s	
Duration time	**4 sec.**	**2 sec.**	**4 sec.**	**2 sec.**
Processing time	8.54	4.71	6.43	4.62
Train time	55.06	11.13	187.86	16.85
Accuracy	75%	85%	75%	90%
MSE	0.12	1.14×10^{-14}	1.71×10^{-5}	1.11×10^{-17}
Iterations	143	29	578	67
Epochs	30	29	90	67

C. Acceleration Signals

The same steps are repeated for the acceleration recorded signals. The results are listed in Table V. The features extruction of error from the acceleration signal require shourter training time in comparsion to that of position and velocity. The accuracy equals 100% for both stright line and circular paths. As the acceleration is the differentiation of velocity, the error effect becomes noticeable in the signal. Thus SDWT levels produced distinguishable features to be used by BNN for classification.

TABLE V. ACCELERATION DIAGNOSIS' SIGNAL RESULTS

Acceleration				
Straight Path			**Circular Path**	
Wheels Speed = 15rad/s for both wheels			Wheels speed: WL= 15rad/sec, WR=18 rad/s	
Motion's Time (sec.)			Motion's Time (sec.)	
Duration time	**4 sec.**	**2 sec.**	**4 sec.**	**2 sec.**
Processing time	6.37	4.59	4.81	5.97
Train time	7.55	6.51	8.51	6.92
Accuracy	100%	100%	100%	100%
MSE	3.05×10^{-23}	9.81×10^{-17}	7.06×10^{-15}	3.01×10^{-15}
Iterations	15	23	46	95
Epochs	15	26	46	95

A comparison between the simulation's results shows 100% accuracy from position and acceleration; while it is 75% from velocity. Also the MSE from position and acceleration signals is very small than that from velocity. A comparison between position and acceleration showes that the MSE of acceleration signal for straight line path is less than that from position; while it is higher for circular path. Accelerometer can be used in practical application for error detection. The collected data should be sent to computer so as to be processed by SDWT and BNN for error detection and classification; respectively.

VII. CONCLUSION

A repeated sequence of error is added to the angular velocity of the wheel. The position and acceleration signals are obtained by integrating and differentiating the velocity signal; respectively. The error of position signal is accumulated by integration; while it is exaggerated by differentiation. Signals of both position and acceleration produced 100% accuracy for calcification of error. When the time duration is reduced, the data set for training decreases. The BNN is succeeded in classifying the error from the features of the signals obtained by SDWT. For acceleration signal, the training time decreases from 7.553 sec. to 6.505 sec. for straight line path; while it decreases from 8.506 sec. to 6.924 sec. for circular path. Also, for circular path and 2 sec. time duration, the MSE of position and acceleration is 8.86×10^{-16} and 7.06×10^{-15}; respectively. This makes it possible to implement this procedure of error's classification in real time.

According to the results of simulation, the more suitable signals to be used for error diagnosis in mobile robot is the acceleration signal while the worst one is the velocity signal. The SDWT and BNN can be used for error diagnosis in other mobile robots because the method depends on signals nature. In practical application, the accelerometer should be inclined to the heading angle of mobile robot so as to produce readings for two components of acceleration. Then signals have to be sent to computer without noise. The training time is not priority in real-time application since training is achieved off-line. The hardware and number of readings decide the processing time of SWDT and BNN. Improvement for velocity signal processing may be achieved by increasing the levels of SDWT and complexity of BNN model. Using signal fusion strategies require more sensors in practical application besides increasing the data set. Combining multiple signal types for hybrid approach to error diagnosis will double the number of inputs, resulting on increasing network size and complexity of training set.

VIII. FUTURE WORK

As a future work, non-repeating sequence error type can be considered. Also, it is suggested to apply proposed method in a real mobile robot or a car so as to investigate more errors. Accelerometer can be used in practical application for error detection. The collected data should be sent to computer so as to be processed by SDWT and BNN for error detection and classification.

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