Errors Detection based on SDWT and BNN Applied for Position, Velocity and Acceleration signals of a wheeled Mobile Robot

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Abstract:

Errors in robot systems leads to many problems in work. Error's detection in one or more wheels in a mobile robot is important because it can be as a sign of mechanical or electrical failure in wheel of the mobile robot. The Symlet discrete wavelet transform has to be applied for the purpose of detection. The Bayesian neural network has to be used then for the classification purpose of error to specify the wheels at which it had been happened. Straight line and circular paths with two different path's time's durations were tested in the presence of errors on single wheel or both wheels. The simulation's results showed that acceleration's signal for a straight-line path gave high accuracy with a smaller number of iterations (15 and 23) in comparison to the results from velocity and displacement for 4- and 2-seconds durations; respectively. While; for a circular path displacement's signal gave high accuracy with a smaller number of iteration (17 and 13) in comparison to the results from acceleration and velocity for 4- and 2-seconds durations; respectively. The Bayesian neural network extracted the error's features even when the duration time of motion had been reduced to 2 seconds.

Keywords: Error, Detection, Mobile robot, SDWT, BNN, Signals.

1. Introduction

Most of errors can occur in robot systems, hence leading to many problems in work. Errors are happened in robots with all their types: robot arms and mobile robots. There are three main types of errors which are mechanical, electrical (Hard), and computational (Soft). Both soft and hard components may cause errors. Some of errors may be happened because of one or more of the three main mentioned components 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 more sensible and intelligent [1–3]. The Errors detection and diagnosis is generally based on the software types components and the program environment used to scan the defective errors behaviors, while the prognosis is primarily based on the residual standards of the device [4, 5]. In [6, 7], an error detecting and isolating model is proposed. The errors in actuators are detected and removed from a specific transmission model inside a special mobile robot. Every wheel of this mobile robot is moved by a DC motor blended with a 25:1 gearbox. With this gearbox, for the purpose of decision pulse increment, an incremental encoder will be introduced. The vehicles are controlled by using a dual-mode controller, velocity, and role. While the controller gets a function command, it is going to be switched to the position mode, and while it gets the rate command, it is going to be switched to the rate mode. Kinds of effects are done, faulty, and ordinary.

In [8], a study of errors-tolerant control is proposed for a special mobile robot for the purpose of detecting and controlling the errors those mostly happen in the actuators those connected to the wheels, beside the unknown robot's parameters. These errors lead to a special path which is considered untrue (wrong trajectory), this because of the friction factors beside the driving gain in the used two-independent wheeled mobile vehicle. In other works, the authors proposed a system of a feedback control based on the theory of Lyapunov stability, which is used for solving the errors inside the mobile robot trajectory. The mentioned study can be applied for other motion control systems' types in robotic systems, also can be used in aircraft, ships, and others [9, 10].

The extraordinary mobile robots (special type of robots) in the field, have typically taken place through experimental feedback and mission sequence analysis, there is a significant lack of dependability when logical or physical problems occur [11], [12], [13], [14]. Unfortunately, this restriction serves as a significant roadblock for the creation of actual public-oriented robots, which must effectively address issues related to availability, dependability, safety, and maintainability. It is crucial to think about and incorporate dependability principles as early as possible into the robot's design life cycle in order to meet this goal [15].

In this paper, a simulation study focuses on the detection of errors on one or more wheels in a mobile robot. These detected errors can be signs of mechanical or electrical failure in the wheel of the mobile robot; this idea can be applied to cars in the same manner. 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 (2 and approximately 4. A comparison study about error detection and classification in a wheeled mobile robot will be done depending on the signals of position, velocity, and acceleration. The SDWT has to be applied for the purpose of detection. The BNN has to be used then for the classification purposes of signals.

2. Kinematic equations of motion

The two wheels mobile robot is shown on Figure (1). Global coordinate frame is $\{X_G, O_G, Y_G\}$, while $\{ x_l, c, y_l \}$ are 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. This angle is measured from global X_G to x_l. ω_L and ω_R are angular velocities of left and right-side wheels of the robot; respectively, and represent control inputs [16]. The angular velocity around center of mass is $\dot{\phi}$. v_c is center of mass linear velocity. Let v_L and v_R are linear velocities of the left and right-side wheels centers; respectively. The kinematics relations are given by:

$$v_L = \omega_L \; r$$

$$v_D = \omega_D \; r \qquad (1)$$

$$v_c = \frac{1}{2}(v_L + v_R)$$

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

$$2b\dot{\phi} = v_R - v_L \qquad (2)$$

Combining equations (1 & 2) leads to:

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

$$\dot{\phi} = \frac{r}{2b}(\omega_L + w_R) \qquad (4)$$

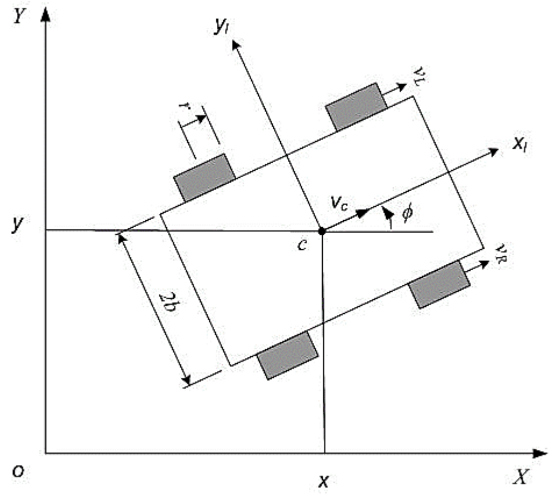


Fig.1: Schematic model of mobile robot

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 onto in global coordinates can be written as:

$$\dot{x} = v_c \; \cos\phi$$

$$\dot{y} = v_c \; \sin\phi \; (5)$$

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

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

Equations (6) is the kinematic equation for two-wheeled differential drive mobile robot.

3. 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 [17]. 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 [18] to give a more salient and thorough time-frequency distributed representation, the discrete wavelet transformation is 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 [19-21]. Mostly the Daubechies type of discrete wavelet transform is depended and used: In compared with the Daubechies, the Symlets is approximately considered as a symmetrical wavelet that modify the db. family. The two wavelet families have comparable characteristics. These families considered as entertaining wavelets. In this paper, the Symlet discrete wavelet transform (SDWT) is presented, as those of Daubechies, many types of Symlets were prepared. In [18], Daubechies type 5-levels db4 is depended, in this work, the approximately Symlet type 5 levels sym4 is proposed as shown in Figure (2).

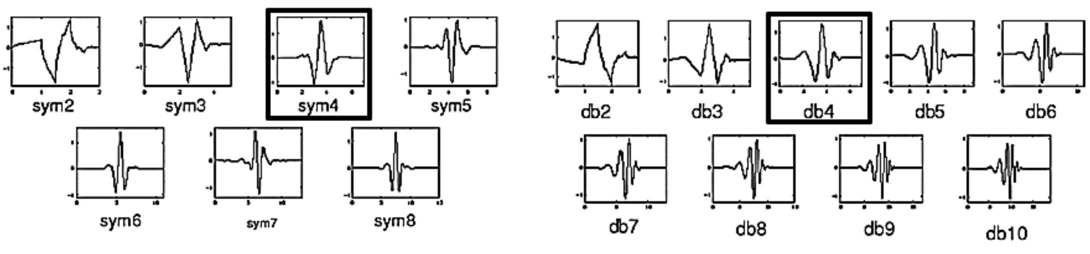


Fig.2:Symlet and Daubechies Families [18]

4. Bayesian Neural Network

In recent works, the neural network is used hugely in the most of the fields, the errors and the errors detection is considered as critical cases which requires immediate solution. Thus, the neural network has been proposed hundreds of times in this field [22-25]. The perceptron and the multi-layer neural networks were used many times for the purpose of classification and errors or errors diagnosis [26-29]. One of the mostly preferred types of neural network and considered new relatively is the Bayesian neural network (BNN). Many researchers applied it in their works for the purpose of classification and detection [30-32]. In order to avoid over fitting, BNN can be applied to solve problems in fields where data is limited. The BNN approach applies probability distribution which is statistical technique so as to provide all the details, including model parameters (weights and biases in neural networks) as shown in Figure (3).With BNNs, data of unknown targets can be recognized so as to automatically compute the error related to the predictions [33]. In this work, the BNN is suggested and used for the purpose of signals classification.

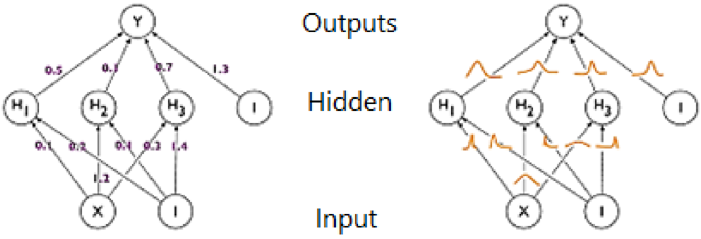


Fig.3:Bayesian Neural Network

5. Proposed Methods

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 [34]. 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. 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, Figure (4).For each of the signals (position, velocity and acceleration), two types of paths are considered, straight and circular. Also, for each path, two cases are enrolled according to the running time of simulation (2 and approximately 4 (exactly 3.9728) seconds) [35], the number of recorded signals were 2003 and 3973; respectively. 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 [36-38]. The SDWT with 5-level, referred to that 10 inputs have to be used as features (inputs for the BNN), that because the presented mobile robot can translate in two directions which are x and y as mentioned before in section 2.

According to the suggested scenarios, four cases have to be expected to be happened. Thus ten (10) inputs and 4 outputs have to be used for the BNN. The error is considered to be happen in each one or both the mobile robot' wheels. Thus, in addition to the healthy case, four sub-cases are presented for each of the two main paths cases. In this paper, three kinematics' vales (position, velocity, and acceleration) are proposed with their detailsas shown in Figure (5).

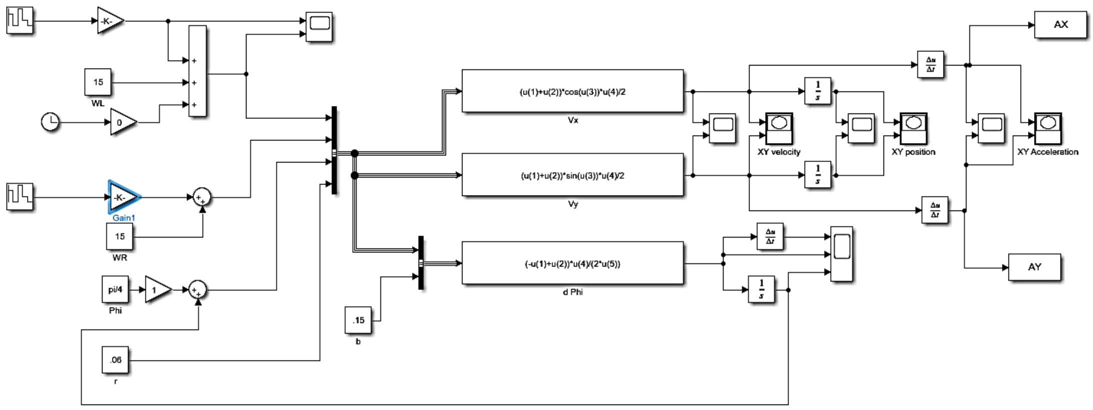


Fig. 4: Mobile Robot Designed Simulation

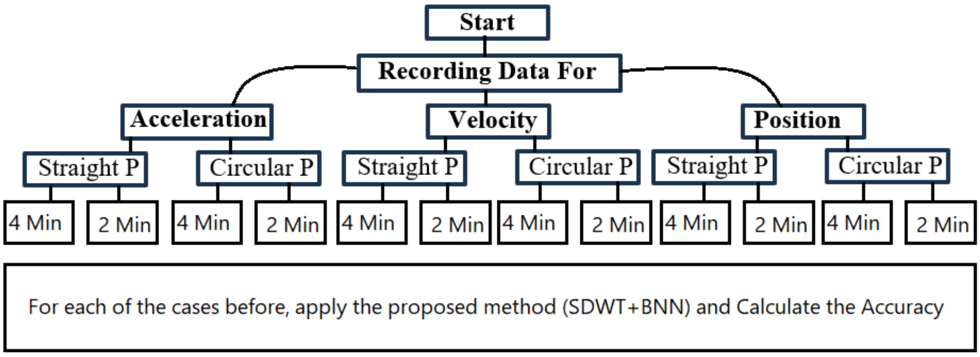
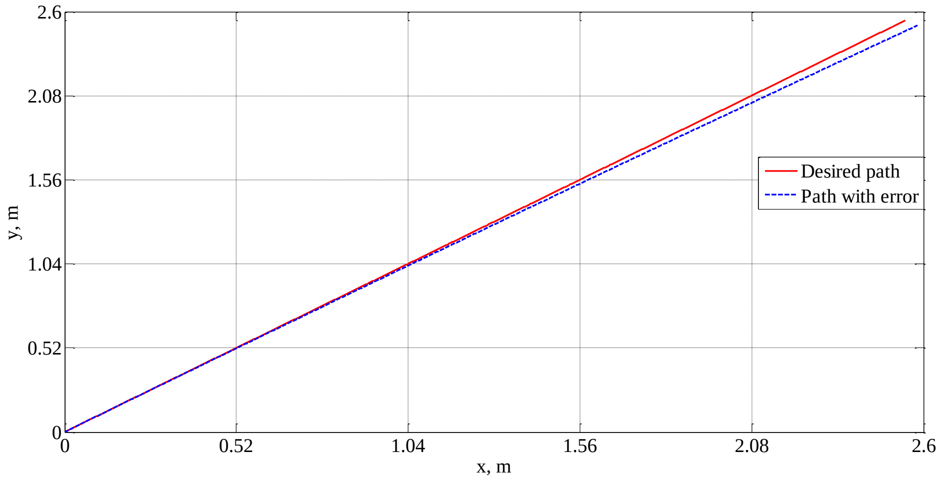


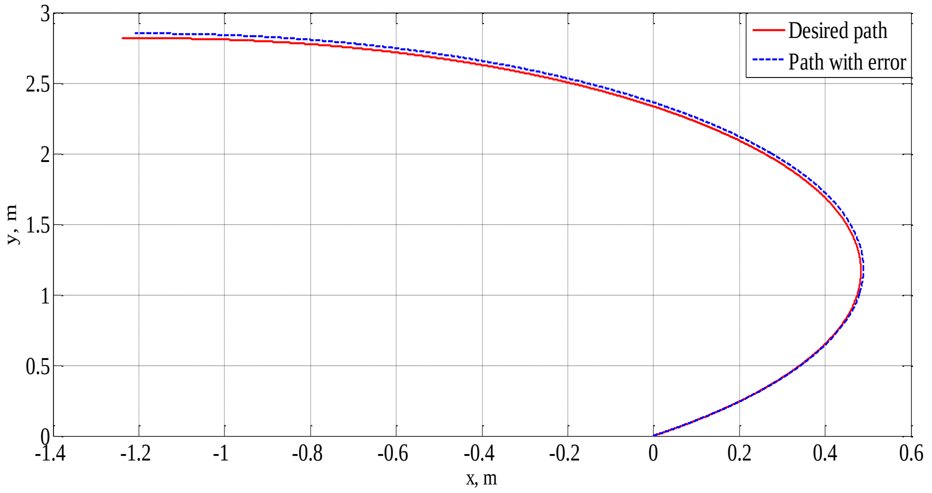
Fig. 5: Work Plan Diagram

6. Simulation results

Two – wheels robot mobile is used in this simulation. It translates in two directions due to its two wheels. The wheel radius (r) equals to 0.06 m. The width (b) equals to 0.15 m. The wheels have angular speed of 15 rad/sec for straight line path. In the circular path, the right wheel is given an angular speed of 18 rad / sec. The mobile robot has plane motion with two components (x and y) of kinematics values for position, velocity, and acceleration. The components are constant for straight line path, while are chancing for circular path. Figure 5 shows the desired path and the path with error from left wheel for straight line and curved paths; respectively.



a- Straight line path



b- Circular path

Fig. 6: Desired path and the path with error from left wheel

According to the experiments done as shown in table(1), eighteen (18) neurons with one hidden layer has been selected for all the cases. The used BNN is shown in Figures (7). The training and processing times are presented in Figures (8) and (9).

Table (1): Training time in the position, velocity and acceleration signals

No of Neuron in H. Layer	**1**	**3**	**5**	**10**	**15**	**17**	**18**	**20**	**25**
Position T.T	**121.5526**	**11.54423**	**11.61124**	**17.29985**	**16.68842**	**13.37854**	**8.6347593**	**36.98957**	**36.99958**
Acceleration T.T	**115.5526**	**7.466357**	**7.532956**	**15.29212**	**8.222537**	**11.32852**	**6.4484413**	**36.80844**	**36.89845**
Velocity T.T	**166.0689**	**150.6952**	**129.0951**	**125.1751**	**109.0851**	**35.05838**	**16.848319**	**75.05838**	**85.55838**

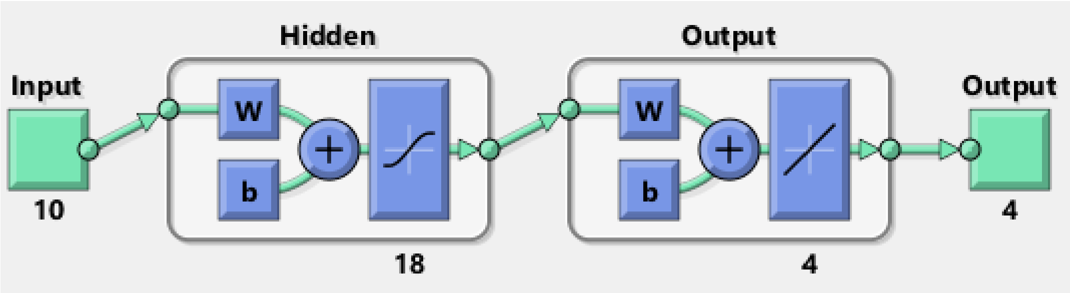


Fig. 7: The Bayesian neural network

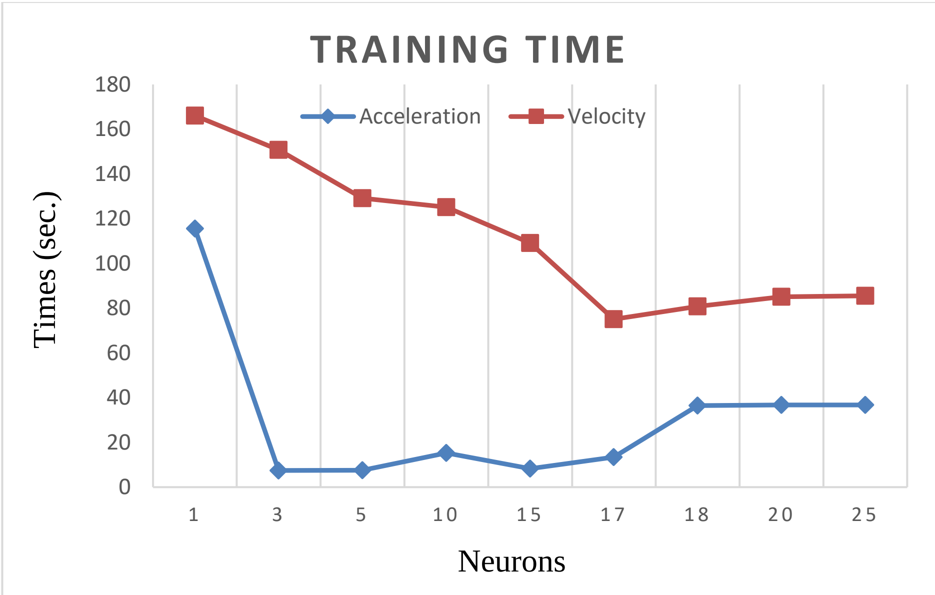


Fig. 8: Training time foracceleration and velocity signals

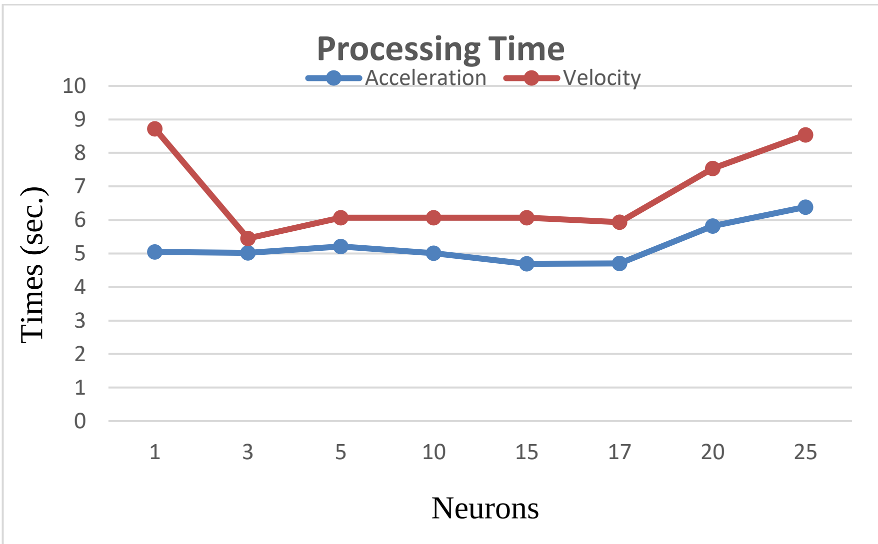


Fig. 9: Processing time foracceleration and velocity signals

6.1 Positional Signals

In this case the signal of position is recorded for the straight and circular paths (achieved by increasing the second wheel speed gain which is selected to be equal to 18, incompare with the first wheel speed gain that equal to 15), 2 and 4 minuts of duration time, applying the SDWT- 5 Level, and collect the results and use them as inputs to the BNN, and calculate the accuracy, performance (Mean Squar Error (MSE)), Processing Time (P. Time), Training Time. The results for these cases are listed in table (2). The accuracy reached 100% for both straight and cirular paths with a very slight increasing in procesing, training time and the number of itterations and epoches. This can be an indication of the complexity of the circular path case in compare with the straight path. The BNN had shown the capability of extructing error's feature even when the duration time of motion is reduced to 2 seconds. This makes it possible to implement this proceduer of error detection in real time.

Table(2): Positional Diagnosis' Signal results

<table>
<tr><th colspan="8">Position</th></tr>
<tr><th colspan="4">Straight Path</th><th colspan="4">Circular Path</th></tr>
<tr><th colspan="4">Wheels Speed = 15rad/s for both wheels</th><th colspan="4">Wheels speed : W_L= 15rad/sec,W_R=18 rad/s</th></tr>
<tr><th colspan="4">Motion's Time (sec.)</th><th colspan="4">Motion's Time (sec.)</th></tr>
<tr><th colspan="2">Duration time = 4 sec.</th><th colspan="2">Duration time = 2 sec.</th><th colspan="2">Duration time = 4 sec.</th><th colspan="2">Duration time = 2 sec.</th></tr>
<tr><td>P. time</td><td>4.706970</td><td>P. time</td><td>4.968172</td><td>P. time</td><td>4.794702</td><td>P. time</td><td>5.282325</td></tr>
<tr><td>Train time</td><td>9.064185</td><td>Train time</td><td>16.124553</td><td>Train time</td><td>10.862482</td><td>Train time</td><td>8.634759</td></tr>
<tr><td>Accuracy</td><td>100%</td><td>Accuracy</td><td>100%</td><td>Accuracy</td><td>100%</td><td>Accuracy</td><td>100%</td></tr>
<tr><td>MSE</td><td>4.75×10^{-17}</td><td>MSE</td><td>1.20×10^{-15}</td><td>MSE</td><td>8.86×10^{-16}</td><td>MSE</td><td>3.76×10^{-18}</td></tr>
<tr><td>Iterations</td><td>10</td><td>Iterations</td><td>72</td><td>Iterations</td><td>17</td><td>Iterations</td><td>13</td></tr>
<tr><td>Epochs</td><td>10</td><td>Epochs</td><td>72</td><td>Epochs</td><td>17</td><td>Epochs</td><td>13</td></tr>
</table>

6.2 Velocity Signals

The same work'steps are repeated for the volocity recorded signals in the wheeled mobile robot. The results for both straight and circular cases are listed in table (3). According to the result, the accuracy bacomes smaller in comparision to that of the poitional signal. The proceing time becomes more than twice, while the raining time is more thanten times in comparision to that from the positional signals. The feature extruction of error is improved when the time duration of motion is reduced from 4 seconds to 2 seconds.

Table(3): Velocity Diagnosis' Signal results

Velocity							
Straight Path				Circular Path			
Wheels Speed = 15rad/s for both wheels				Wheels speed : W_L= 15rad/sec,W_R=18 rad/s			
Motion's Time (sec.)				Motion's Time (sec.)			
Duration time = 4 sec.		Duration time = 2 sec.		Duration time = 4 sec.		Duration time = 2 sec.	
P. time	8.535635	P. time	4.713347	P. time	6.431829	P. time	4.624014
Train time	55.058380	Train time	11.128758	Train time	187.857184	Train time	16.848319
Accuracy	75%	Accuracy	85%	Accuracy	75%	Accuracy	90%
MSE	0.1240	MSE	1.14×10^{-14}	MSE	1.71×10^{-5}	MSE	1.11×10^{-17}
Iterations	143	Iterations	29	Iterations	578	Iterations	67
Epochs	30	Epochs	29	Epochs	90	Epochs	67

6.3 Acceleration Signals

The same work'steps are repeated for the acceleration recorded signals of the wheeled mobile robot, the results are listed in table (4). The feature extruction of error from the acceleration signal requires shourter training time in comparsion to that of position and velocith. The accuracy equals 100% for both stright line and circular paths.

Table(4): Accelerational Diagnosis' Signal results

Acceleration							
Straight Path				Circular Path			
Wheels Speed = 15rad/s for both wheels				Wheels speed : W_L= 15rad/sec,W_R=18 rad/s			
Motion's Time (sec.)				Motion's Time (sec.)			
Duration time = 4 sec.		Duration time = 2 sec.		Duration time = 4 sec.		Duration time = 2 sec.	
P. time	6.366393	P. time	4.590458	P. time	4.814348	P. time	5.973453
Train time	7.553691	Train time	6.508332	Train time	8.506232	Train time	6.924454
Accuracy	100%	Accuracy	100%	Accuracy	100%	Accuracy	100%
MSE	3.05×10^{-23}	MSE	9.81×10^{-17}	MSE	7.06×10^{-15}	MSE	3.01×10^{-15}
Iterations	15	Iterations	23	Iterations	46	Iterations	95
Epochs	15	Epochs	26	Epochs	46	Epochs	95

7. Conclosion

According to the processsing time, training time, performance, results show that the more suitable signals to be used for error diagnosis in mobile robot is the positional signal while the wrost one is the volocity signal. The Accelerational signals given 100% accuracy for both the straight line and circular paths, the performance (MSE) in the accelerational signal is better than the position and the velocity signals. The processing time of applying the methods for the accelerational signals is smaller than that of the velocity and positional signals in circular paths, while the processing time for the positional signals is smaller than that of accelerational signals. The results shown that the acceleration is better to be used, then the position, and finaly the wrost case is the velocity dependent signals.For all the tested cases, the BNN had secceded to extruct the error features with less training time when the duration time of motion is reduced from 4 seconds to 2 seconds.

8. Future Work

As shown in results the acceleration is suggested as better type of signals can be examined, then the position and finally the velocity signal, which considered as the worst one. As a future work, suggested to apply all of the studied and examined methods in an real mobile robot or a car.

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