Laser Measurement System based maneuvering Target tracking formulated by Adaptive Competitive Neural Networks

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***Abstract*—To improve safety and security issues, maneuvering target detection and tracking are important facilities for navigation systems. Therefore, conventional navigation systems are equipped with Radar-based systems for the same purpose. However, Radar systems suffer some practical problems that are associated with the targets in close quarter navigation. Furthermore, Radar singles attenuate with distance, weather (ie. rain) and sea conditions, where the target tacking performances are degraded. Therefore, a Laser Measurement System (LMS) is proposed in this study to overcome the problems faced by the conventional Radar systems at close quarter navigation as well as bad weather and environmental conditions. Furthermore, capabilities of a LMS to measure accurate distance in close proximity as well as to observe the shape and size of the target are illustrated. In this study, each target is approximated by a cluster of data points rather than a single point target that is the main contribution in this paper. The adaptive Neural Network approach is proposed as a method of tracking maneuvering targets that are represented by clusters of data points. Successful simulation and experimental results of target detection and tracking that are tested on a experimental platform, SICK© LMS, are also presented in this paper.**

Keywords- Laser Measurement System, Competitive Neural Networks, Target tracking, Data Points Tracking

I. INTRODUCTION

Maneuvering target detection and tracking capabilities are important facilities for a navigation system to improve safety, security and survivability during its voyage. The conventional navigation systems are equipped with Radar-based systems to facilitate maneuvering targets and obstacles detection and tracking. However, Radar-based systems are suffered by practical problems especially with detection and tracking of targets in close quarter navigation. Furthermore, Radar singles attenuate with the distance, weather (ie. rain) and sea conditions, where the target tacking performances are degraded [1]. Therefore, under the distance, weather and environmental conditions, the frequent calibrations for Radar systems are required to improve its accuracy [2].

Furthermore, Radar-based systems are limited in evaluation of accurate range, bearing, shape and size of targets in long distance as well as close quarter navigation. The unsuccessful target detection and tracking in close quarter navigation could affect on inaccuracy of the distance

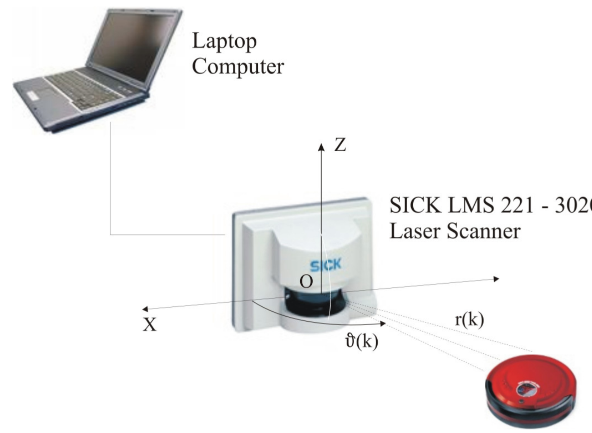

Figure 1. LMS Experimental Setup

measurements with respect to the targets and obstacles in the environment. Therefore, the errors in distance measurements can eventually affect on inaccurate collision risk evaluations and wrong navigational decisions.

This study proposes, a Laser Measurement System (LMS) that is integrated with an adaptive Neural Network algorithm for maneuvering target detection and tracking in close quarter navigation. Hence, these facilities can be formulated in navigation systems for accurate collision risk evaluations and better maneuvering decisions. The proposed LMS experimental platform in this study is presented in Figure 1. As presented in the figure, the experimental setup consists of a Laptop computer, where the adaptive Neural Network algorithm is implemented, SICK© LMS, which is the target detection sensor, and a moving target (ie. moving robot). Further details on this system are presented on Section V of this paper.

The work presented in this study is a part of ongoing effort to formulate an Intelligent Collision Avoidance System (ICAS) in ocean navigation as described in [3] and [4]. Therefore, two-dimensional target tracking formation with respect to ocean navigational conditions is considered in this study.

The organization of this paper as follows: An overview of recent developments in a LMS is presented in Section II. The proposed adaptive Neural Network approach is presented in Section III. The computational simulations are presented in Section IV. The experimental results generated by the LMS platform are presented in Section V. Finally, a brief conclusion is presented in Section VI of this paper.

II. Recent Developments in LMSs and Target Tracking

A. Laser Measurement System (LMS)

People and vessel/vehicles detection and tracking are popular experimental applications in recent LMSs. The people tracking system, based on Laser range data and using a multi-hypothesis Leg-Tracker, in-cooperated with the Kalman filter with a constant velocity based model, is proposed by [5].

Almost all research and commercial applications in the LMS area are 2D due to the limitations in current LMS sensor technology. However, 3D LMS applications are also been proposed in some studies by circulating the sensor in a third dimensional axis. The 2D Laser-based obstacle motion tracking and predicting in a dynamic unconstrained environment using the Kalman filter [6], and the Particle Filters and Probabilistic Data Association [7] are presented in respective studies. The implementation of a LMS for detection and classification of 3D moving objects is illustrated by [8] and [9]. Furthermore, an experimental evaluation of a LMS for tacking people by a mobile platform is presented by [10] and classifications of people by a mobile robot is presented by [11].

The integration of a LMS and a vision system can use for successful obstacle tracking and classification due to its capabilities of capturing the comprehensive details of the targets as well as the environment. The combined Laser and vision based approach for simultaneous detection and tracking of multiple pedestrians based on the Bayesian method is proposed by [12].

Furthermore, several industrial applications of LMSs can be observed in recent literature: As a navigational aid for a truck-trailer combination vehicle system [13], a collisions warning system for a transit bus [14], a safe driving aid system for a car driving in polluted environment [15], an obstacle avoidance system for a car navigation system [16] and an obstacle detection system for an off-road vehicle [17] are presented in respective studies.

However, the most model based LMS and other sensor based target-tacking algorithms could not facilitate the dimensional based target tracking and a target is approximated to a single data point. Therefore, in this study, this concept is further elaborated to formulate a target as a cluster of data points during its tracking process, which is the main contributions in this study.

B. Detection and Tracking of Moving Objects

Detection and Tracking of Moving Objects (DTMO) is one of the main research areas that was developed towards maneuvering target tracking. The main functionalities of the DTMO can be divided into three sections [18]: Scan unit, Target Classification unit and Target Tracking & Behavior Prediction unit.

The main objective of the Scan unit is to formulate geometrical clusters, where a cluster defined as a set of measured data points that could belong to a same object or multiple objects, of data points, lines and arcs with respect to targets and obstacles in the environment. However, this could be generated by the sensors (ie. Radar and LMSs) in the target tracking system.

The segmentation of data clusters by a geometrical method is proposed by [18]. Inscribed angle variations and recursive line-fitting methods for lines and arc/circles detection by LMS data are proposed by [19]. However, special considerations for the joints and break points should be considered during its segmentation of data clusters, in this method. Therefore, the proposed adaptive Neural Network approach can overcome the failures can occur in the segmentation process of data clusters due to varying geometrical constrains.

The main objective in the Target Classification unit is to formulate the Segment-Objects correspondence. The correspondence mainly classified into geometrical figures like circles or polygons. However, four classification methods are proposed by recent studies [20] for this prupose: Features to Features, Points to Features, Points to Points and Combinations. Furthermore, the identifications of geometrical figures and features are successful done by the Neural Network approach in recent studies [21].

Even though the proposed adaptive Neural Network approach is limited for detection and tracking of clusters of data points, this method can further develop for identification of geometrical figures and features of the targets. Finally, the Target Tracking and Behavior Prediction unit is proposed to estimate target current states and to predict future navigation trajectories. The EKF based system states estimation and maneuvering trajectory prediction for ocean vessel navigation is proposed in [22]. However, this area is beyond the scope of this paper.

III. Adaptive Neural Network based Detection & Tracking

A. LMS Scan & Data Collection

The LMS experimental platform is presented in Figure 1. The LMS sensor generates respective range $\mathbf{r}(k) \in \mathbb{R}^R$ and bearing $\theta(k) \in \mathbb{R}^R$ values in polar coordinates as presented in the figure. The accumulated data clusters of range and bearing values that represent complete environmental conditions, including the stationary and moving targets, at the k-th time instant in polar coordinates can be written as:

$$
\begin{aligned}
\mathbf{r}(k) &= \left[r_1(k)\ r_2(k) \ \ldots\ r_R(k) \right] \\
\vartheta(k) &= \left[\vartheta_1(k)\ \vartheta_2(k) \ \ldots\ \vartheta_R(k) \right]
\end{aligned} \tag{1}
$$

Then the range and bearing values in polar coordinates are converted into Cartesian position coordinates. The i-th position data point in Cartesian coordinates $[{}^R x_i(k)\ {}^R y_i(k)]$ can be formulated as:

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$$\begin{aligned} {}^{R}x_i(k) &= r_i(k)\cos\left(\vartheta_i(k)\right) \\ {}^{R}y_i(k) &= r_i(k)\sin\left(\vartheta_i(k)\right) \end{aligned} \tag{2}$$

Therefore, the i-th position data point of the data cluster at the k-th time instant can only have two coordinates of $[{}^{R}x_i(k)\ {}^{R}y_i(k)]$ that are measured by the sensor. However, these position data points should be normalized with respect to the maximum range of the sensor. The normalization requirements are further discussed in sub-section C of this main section. The normalization of the position coordinates can be written as:

$$\begin{aligned} x_i(k) &= \frac{{}^{R}x_i(k)}{R_{max}} \\ y_i(k) &= \frac{{}^{R}y_i(k)}{R_{max}} \end{aligned} \tag{3}$$

where R_{max} is the maximum range of the LMS sensor.

B. Artificial Neural Networks

The theoretical foundation of artificial neurons is derived from biological concepts and theories in the brain and nervous system. An artificial neuron has several inputs that correspond to the synapses of a biological neuron. An artificial neuron has one output that is corresponding to the axon of a biological neuron. Each input of a neuron is corresponding to a certain weight value that influences the corresponding signal over the neuron output. This concept can formulate into a transfer function in an artificial neuron.

The transfer function calculates sum of the net input with respect to the assigned weight values and compares that with a certain threshold level to generate the neuron output [23]. The connection of several neurons in a combination of series and/or parallel formations can recognize as a Neural Network.

C. Competitive Neural Network

The Competitive Neural Network (CNN) [24] integrated with an adaptive learning algorithm of the Instar Rule is proposed in this study for detection and tracking of maneuvering targets. The CNN is trained to track moving data clusters by competing its neurons, where a target is approximated for a cluster of data points. .

The structure of the CNN is presented in Figure 2. As presented in the figure, the CNN consists of four units: Scan unit (Data Points), Prototype vectors unit (**W**), Competition unit (**C**), and Feedback-loop (Instar Rule). The input to the CNN consists of a accumulated position vector $\mathbf{p}(k) \in \mathbb{R}^{Rx3}$. The prototypes vectors, $\mathbf{W}(k) \in \mathbb{R}^{Sx3}$, are stored as rows vectors in section **W,** that are target tracking neurons of the CNN. The net input $\mathbf{n}(k) \in \mathbb{R}^{R}$, is the input to the Competition unit, **C**, and $\mathbf{a}(k) \in \mathbb{R}^{S}$, is the output from the Competition unit, **C**, at the k-th time instant. Finally, the feedback loop, associated with the Instar Rule that is proposed to adjust the prototype neurons to continue tracking of maneuvering targets.

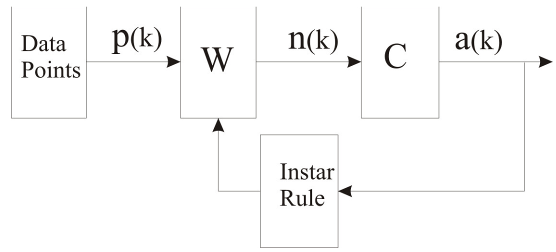

Figure 2. Competitive Neural Network

1) Competitive Layers

The Competition unit, **C,** consists of a transfer function that is used to generate competition among neurons. Hence, the proposed transfer function can be written as:

$$\begin{aligned} \mathbf{a}(k) &= \text{compet}\left(\mathbf{n}(k)\right) \\ &= \text{compet}\left(\mathbf{W}(k)\,\mathbf{p}(k)\right) \end{aligned} \tag{4}$$

where the competitive (compet) transfer function can be further elaborated as:

$$\text{compet}\left(\mathbf{n}(k)\right) = \begin{cases} 1 \text{ for neron with } \max\ \mathbf{n}(k) \\ 0 \quad\quad \text{all other nerons} \end{cases} \tag{5}$$

and the accumulated position vector $\mathbf{p}(k) = [\mathbf{p}_1(k)\ \mathbf{p}_2(k) \ldots \mathbf{p}_R(k)]$ is associated with the i-th position vector, $\mathbf{p}_i(k) = [x_i(k)\ y_i(k)\ z_i(k)]$ that represents the position of x, y and z coordinates of a data cluster as described previously. However, only normalized x and y position coordinates are calculated from equation (3). For a fair competition among neurons, each position vector, $\mathbf{p}_i(k) \in \mathbb{R}^3$, should have a unit magnitude condition. Hence, the position value of $z_i(k)$ can be derived considering a unit magnitude condition as proposed previously and can be formulated as:

$$|\,\mathbf{p}_i(k)\,| = \sqrt{x_i^{\,2}(k) + y_i^{\,2}(k) + z_i^{\,2}(k)} = 1 \tag{6}$$

Hence the coordinate $z_i(k)$ can be calculated considering equation (6) that gives a unit magnitude condition for each data point in the data culster. The coordinate $z_i(k)$ can be calculated as:

$$z_i(k) = \sqrt{1 - x_i^{\,2}(k) - y_i^{\,2}(k)} \tag{7}$$

One should note that this implementation can interpret as a transformation of 2D space position coordinates in the sensor range into 3D space position coordinates with a unit magnitude condition. Therefore, initially x and y coordinates are normalized considering the sensor maximum range (see equation (3)) that is an essential requirement of the neural competition.

Furthermore, the net input, $\mathbf{n}(k)$, can calculate from the scalar product between two vectors $\mathbf{W}(k)$ and $\mathbf{p}_i(k)$ as presented in equation (4). This scalar product between two position vectors related to the distance between position vector, $\mathbf{p}_i(k)$, and each prototype vectors $\mathbf{w}_j(k)$, where $\mathbf{W}(k) = [\mathbf{w}_1(k)\ \mathbf{w}_2(k)\ \dots\ \mathbf{w}_S(k)]$. A unit magnitude condition for each prototype vector, $\mathbf{w}_j(k)$, should also be considered for fair competition among neurons. Hence the j-th prototype vector, $\mathbf{w}_j(k)$, magnitude condition can be written as:

$$|\mathbf{w}_j(k)| = 1 \tag{8}$$

In the Competition unit, **C,** (see Figure 2), the distance between position vector, $\mathbf{p}_i(k)$ to each prototype vector $\mathbf{w}_j(k)$ is calculated. This concept can further be elaborated as:

$$\begin{aligned}\mathbf{n}_i(k) = \mathbf{W}(k)\mathbf{p}_i(k) &= \begin{bmatrix}\mathbf{w}_1^{\mathbf{T}}(k)\\ \mathbf{w}_2^{\mathbf{T}}(k)\\ \vdots\\ \mathbf{w}_S^{\mathbf{T}}(k)\end{bmatrix}\mathbf{p}_i(k)\\ &= \begin{bmatrix}\mathbf{w}_1^{\mathbf{T}}(k)\mathbf{p}_i(k)\\ \mathbf{w}_2^{\mathbf{T}}(k)\mathbf{p}_i(k)\\ \vdots\\ \mathbf{w}_S^{\mathbf{T}}(k)\mathbf{p}_i(k)\end{bmatrix} = \begin{bmatrix}\cos\theta_1(k)\\ \cos\theta_2(k)\\ \vdots\\ \cos\theta_S(k)\end{bmatrix}\end{aligned} \tag{9}$$

The i-th net input of scalar product between two vectors, $\mathbf{n}_i(k)$, is equal to $\cos(\theta_i(k))$, where $\theta_i(k)$ is the angle between a position vector, $\mathbf{p}_i(k)$, and a prototype vector, $\mathbf{w}_j(k)$. However, the scalar product between two vectors, $\mathbf{n}_i(k)$, is the input to the competitive transfer function. Therefore, the neuron, whose prototype vector is in the direction closest to the respective position vector, $\mathbf{p}_i(k)$, is assigned output of 1 and others are assigned 0 by the transfer function as formulated in equation (5).

This concept can further elaborate as a situation where the closet neuron gets excited by a data cluster and the excited neuron takes over all data points in the respective data cluster. However, after winning the data cluster, the prototype vector of the respective neuron should be improved (should move further closer to the data cluster).

This continues process consists of two different iteration loops. The first iteration loop formulates a continuous mechanism, where the wining neuron continuously gets closer to its respective data cluster. The second iteration loop formulates another continuous mechanism, where the dynamic data clusters that are observed by the sensor at different time instants are introduced into the CNN. Therefore, a capable learning rule should be formulated to facilitate proper update of the winning neurons with respect to different data cluster conditions.

2) *Competitive Learning*

Initially, the values of prototype vectors, $\mathbf{W}(k)$, in the CNN, are assumed to be unknown. Therefore, the learning rule is expected to calculate appropriate values for the prototype vectors. This concept is categorized as unsupervised learning. When a competitive layer excites a neuron that is closest to the data cluster, then the learning rule will use to modify the appropriate prototype vectors in the CNN to move close to the data cluster in this process. The Instar Rule is proposed in this study as an unsupervised learning mechanism to modify the appropriate prototype vectors in the CNN.

3) *Instar Rule*

The Instar Rule that is derived from the Hebb Rule is illustrated in [24] is briefly discussed in this section. The unsupervised Hebb Rule to update prototype vectors can be written as:

$$\mathbf{W}(k) = \mathbf{W}(k-1) + \alpha\mathbf{a}(k)\mathbf{p}^{\mathbf{T}}(k) \tag{10}$$

where α is a learning rate. However, a constant learning rate could be a disadvantage in the learning process of a neural network, where it could affect on the error convergence rate. Even though the beginning of a learning process a higher learning rate is an advantage to the neural network, with the error reduction it could be a disadvantage. Hence, to improve the Hebb Rule, a weight decaying term that is proportional to $\mathbf{a}_i(k)$ and $\mathbf{W}(k-1)$ is introduced. Equation (10) with a weight decaying term can be written as:

$$\mathbf{W}(k) = \mathbf{W}(k-1) + \alpha\mathbf{a}(k)\mathbf{p}^{\mathbf{T}}(k) - \gamma\mathbf{a}(k)\mathbf{W}(k-1) \tag{11}$$

where γ is the decay rate. Furthermore, assuming $\gamma = \alpha$, equation (11) can be written as:

$$\mathbf{W}(k) = \mathbf{W}(k-1) + \alpha\mathbf{a}(k)\left(\mathbf{p}^{\mathbf{T}}(k) - \mathbf{W}(k-1)\right) \tag{12}$$

Equation (12) is called as the Instar Rule that is proposed as an unsupervised learning rule for the CNN in this study.

IV. Computational Implementation and Simulations

The computational simulation of a multi-target tracking situation is presented in Figure 3. The simulation consists of two moving targets that are presented by two clusters of data points. Furthermore, two prototype vectors are also assigned in this simulation to tack both data clusters.

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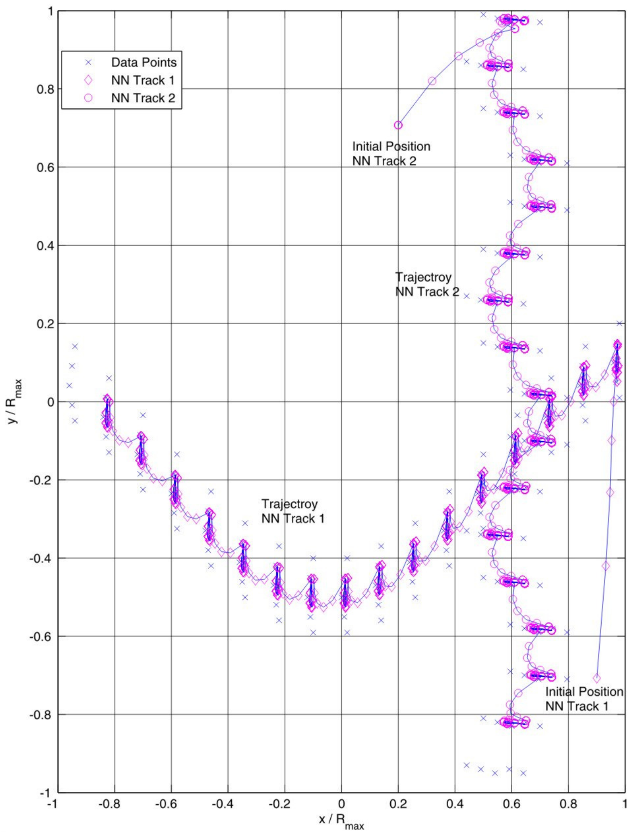

Figure 3. Computational Simulations : Multi-Target Tracking

The target tracking algorithm, simulated in this study, consists of two main loops: the LMS target scanning loop and the CNN target tracking loop. The main objective of the LMS target scanning loop is to scan the environment and to observe the stationary and moving targets as an accumulated data cluster. Then this information will transfer into the CNN target tacking loop. The main objective of the CNN target tacking loop is to adapt the CNN to track target maneuvers by updating its respective prototype vectors. This should be done by the proposed learning rule.

The two prototype vectors of the CNN are called as NN (Neural Network) Tracks 1 and 2. As presented in the figure, the NN Tacks 1 and 2 are presented by ◊ and ○ respectively. The initial prototype vector values of the NN Tracks 1 and 2 can be any arbitrary values as presented in the initial positions of the NN Tacks 1 and 2 (see Figure 3). Finally, both NN Tracks are adapted its prototype vectors to track moving targets that represented by two clusters of data points. The tracking trajectories of the neurons are presented by Trajectory NN Tracks 1 and 2 in the figure.

Furthermore, it is observed that NN Tracks 1 and 2 are finally converged into approximate mean values of the respective data clusters at each time instant. Therefore, the mean position values can be considered as measurement positions of the targets at each time instant and that can be used for further analysis of target state estimations and trajectory predictions [22].

V. EXPERIMENTAL PLATFORM AND SIMULATION RESULTS

A. *Laser Measurement System*

The experimental platform is presented in Figure 1. As presented in the figure, the hardware section mainly consists of SICK© Laser Measurement System (LMS). The SICK© LMS is an active position measurement unit that operates by measuring the time of flight of Laser light pulses, where Laser beam pulses are emitted by the sensor and reflected due to the objects in the environment [25]. However, the LMS is designed to scan 2D space and to collect range and bearing data of the targets that are located in the environment.

The SICK© LMS model of LMS221, that is designed for marine environment is used in this study. This sensor is capable of scanning bearing angle of 180^0 with 0.5^0 accuracy field views with 75 Hz scanning frequency. The operating range of 8 m with the minimum linear and angular resolution of 1 mm and 0.25^0 are initially programmed into the sensor. The SICK© LMS data communication is facilitated by RS-232 with the speed of 9.6 kBd.

Furthermore, the experimental platform consists of a Laptop computer with Windows© operating system and a power supply unit to power the LMS sensor. The Laptop computer is equipped with the RS-232 connection to communicate with the LMS sensor.

B. *Software Architecture*

The software architecture that is used in this study mainly consists of LABVIEW© Real-time platform. Further MATLAB© toolbox of neural networks is also integrated into the LABVIEW© Real-time platform for implementation of the CNN.

C. *Experimental Results*

The experimental result of a stationary and moving target tracking situation in Real-time environment is presented in Figure 4. The measurements are noted in mille-meters (mm) of SI units in the figure. The two targets, a stationary target and a moving target, are considered in this experiment. The stationary target is located in the middle of the figure and the moving target is circulating around the stationary target as presented in the figure. The moving target is presented by a moving cluster of data points. The CNN consists of two NN Tracks to track both targets as presented in the figure. Furthermore, the stationary target is monitored by the NN Track ○ and moving target is monitored by the NN Track ◊ are also presented in the figure.

However, the CNN tracking region is limited by upper, lower, left and right boundary values 9000 (mm), 10 (mm), -1200 (mm) and 1200 (mm), respectively. As presented in the figure, NN Track ◊ is following each point in the data cluster of the moving target alone its maneuvering trajectory. As a conclusion, the experimental results have shown that the NN Track ○ and Track ◊ are successfully tracking both stationary and moving targets as observed in the simulations.

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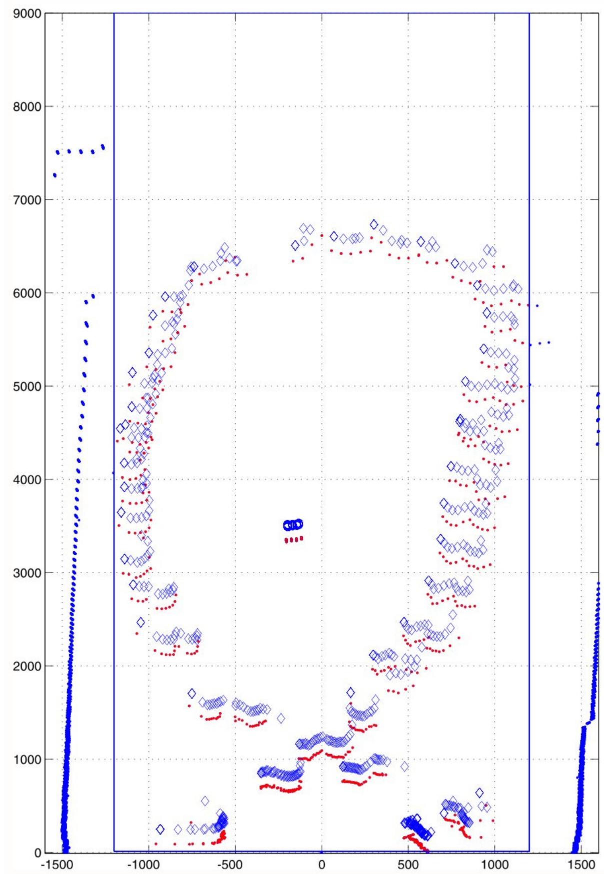

Figure 4. Experimental Results: Stationary and Moving Target Tracking

However, the data points beyond the limits of upper, lower, left and right boundary values are ignored in this analysis. These data points are located beyond the simulation limits, which represent other stationary and moving objects in the experimental environment.

VI. CONCLUSION

The dimension based target detection and tacking are main contributions in this study, where the most of target tracking methods are simulated for a data point or an approximated small data cluster based targets. Furthermore, one of the popular machine learning applications of an adaptive Neural Network associated with an unsupervised learning algorithm, the CNN, is implemented and successful simulation and experimental results are obtained in this study.

Even though the Neural Network applications are extensively used for recognition of stationary data patterns, moving data clusters can also be detected and tracked by the proposed method. Even though, the proposed CNN behave as an effective adaptive network for tracking targets, it also been affected by some inherited problems.

The first, the selection of a learning rate should be compromised with the target tracking speed. However, this compromise could affect on the stability of the prototype vectors.

The second, the stationary and moving target tracking under complex environmental conditions: several neurons can track different parts of the same target and one neuron can track several targets in close range navigation. This is another challenge that is faced in this CNN approach. However, this situation can be solved by selecting proper number of neurons with respect to the targets in the environment.

. Furthermore, the Laser-based CNN approach can further develop for identification and classification of maneuvering targets where the Neural Network approach is extensive implemented on statistical pattern recognition [26]. Furthermore, integration of image based (ie. Infra-red) facilities could improve the target detection and tracking process [27]. Hence, the integration of illustrated features (ie. identification and classification) into target detection and tracking are proposed as future work in this study.

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