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A Hybrid Approach to Cognition in Radars

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ABSTRACT

In many engineering domains, cognition is emerging to play vital role. Cognition will play crucial role in radar engineering as well for the development of next generation radars. In this paper, a cognitive architecture for radars is introduced, based on hybrid cognitive architectures. The paper proposes deep learning applications for integrated target classification based on high-resolution radar range profile measurements and target revisit time calculation as case studies. The proposed architecture is based on the artificial cognitive systems concepts and provides a basis for addressing cognition in radars, which is inadequately explored for radar systems. Initial experimental studies on the applicability of deep learning techniques under this approach provided promising results.

Keywords: Cognitive radar; Cognitive architecture; Artificial cognitive system; Convolutional neural network; Long short-term memory - recurrent neural network

1. INTRODUCTION

Artificial intelligence (AI) applications to engineering domains can potentially take defence equipment to the next level. The concept of cognitive radar was introduced by Haykin[1]. The early initiatives in radars were based on first generation AI techniques such as knowledge based systems and expert systems. Subsequently knowledge based fully adaptive radar (FAR) schemes started to evolve. Further there were misperceptions between cognitive radar and fully adaptive radar terminologies. The distinctions between these types of radars were clearly brought out by Haykin[2], *et al.* Any programmable fully adaptive radar cannot be called as a cognitive radar. A cognitive system should have the ability to perceive the environment, learn from experiences, anticipate outcome of events and act to pursue goals.

2. TRADITIONAL RADARS AND COGNITIVE RADARS

Radars are classified[2] into traditional active radar (TAR), fore-active radar or fully adaptive radar (FAR) and cognitive radar (CR). The traditional active radars operate in feed forward manner. TAR could implement adaptive algorithms for radar operations. The FAR has feedback loop, which could get information feedback from the environment. The paper defines cognitive radar which will have capabilities of TAR, FAR and ability to learn from experience using Fuster's paradigm of cognition[2]. The Fuster's paradigm of cognition has four elements viz., perception-action cycle, memory, attention and intelligence. The whole radar system constitutes a dynamic closed feedback loop encompassing transmitter environment and receiver. To proceed further for realisation of cognitive radars, it is important to study advances in artificial cognitive systems (ACS), their models, and architectures.

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3. ARTIFICIAL COGNITIVE SYSTEMS

Cognition is defined[5] as the process by which an autonomous system perceives its environment, learns from experiences, anticipates the outcome of events, acts to pursue goals and adapts to changing circumstances. The artificial cognitive systems attempt to capture attributes of natural cognitive systems. Artificial cognitive systems are typically abstracted in three categories viz., Cognitivist systems, emergent systems, and hybrid systems[5].

In cognitivists system, the world knowledge is represented as symbols and symbolic manipulations. Emergent systems evolve continuously based on self-organisation through outside interactions. Emergent systems[5] are further categorised into connectionist, dynamic and enactive systems. The connectionist approaches are based on activation and interconnection of multiple processing elements. Typical connectionists systems are various types of artificial neural networks. The dynamical systems[5] represent the system as set of differential equations and temporal changes of state variables. The enactive systems[5] make sense of outside world through interactions. Many implemented cognitive systems use cognitivist and emergent approaches. Both cognitivist and emergent system have both their advantages and disadvantages. Though the cognitivists systems are good at reasoning, they have difficulties in dynamically changing situations. Emergent systems have the ability to evolve for dynamic situations, and they have difficulties in logical reasoning. The hybrid approaches offer combination of cognitivist symbolic approaches with emergent systems approaches.

Cognitive systems operate on memories. Memories play important role for recalling past, predict future, and orient towards the current scenario. The three major types of memories are long term memory (LM), short term memory (SM), and working memory (WM)[5-7]. The long term memory maintains learned scenarios, semantic knowledge and experiences. The short term memory (SM) holds current scenario and environment information. The LM is of three types; semantic, procedural, and episodic. The semantic memory is a declarative type of memory that stores all the global knowledge about the environment that is known. The episodic memory is a temporal knowledge in which experiences are stored. The procedural memory is an implicit type of memory that learns how to do actions. Procedural memories are acquired progressively. The working memory is a small short term memory that holds information to aid current task execution. There could be memories for probabilistic reasoning and sub-symbolic processing.

4. COGNITIVE ARCHITECTURES FOR RADARS

Research on cognitive radar is very limited whereas in other intelligent systems, the research is well advanced. It is possible to draw analogies from these architectures and make cognitive architectures for radars.

From the perspective of artificial cognitive architecture, all types of architectures, i.e., cognitivist symbolic, emergent and hybrid type of architectures may be applied. This paper proposes hybrid approach due to the flexibilities it offers. This approach complies with cognitive radar approach proposed[2]. The hybrid approach proposed here is similar to cognitive architectures in[6,7].

The hybrid approach provides incremental path to cognition which is widely accepted approach in cognitive research. It is an accepted fact that cognition capabilities have to be built over a period of time, capability by capability. This also opens up opportunities for limited cognification of already developed radars. The architectures for cognition should define the memories as well. However the memories for cognition are not well studied in cognitive radars, though Haykin[2] provides scope for memories. This paper also introduces memories for the cognitive radar architecture elaborated.

It is to be noted that generally the radar as a sensor, forms an element of sensory component of any bigger cognitive systems. For example a radar may be a sensory component of a smart unmanned aerial vehicle (UAV). Though the radar may be a sensory component for some higher architecture, the radar itself could be built as a cognitive architecture. This recursive nature can help to build cognitive radar networks. The top level hybrid architecture (Fig. 1) for radar is similar to the one defined for intelligent soft arm control (ISAC)[7].

5. A HYBRID COGNITIVE ARCHITECTURE FOR RADARS

Hybrid architecture and the associated memories for digital array radars are suggested here. The architecture is defined as interacting software agents for various functionalities of typical digital array radars.

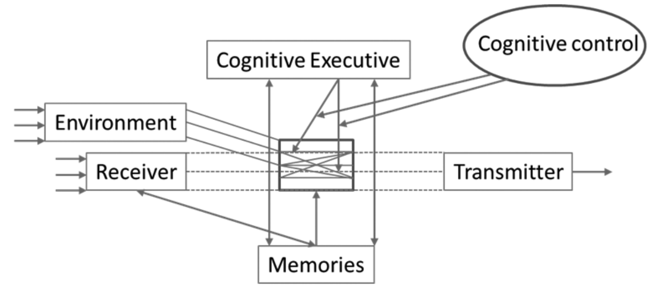

Figure 1. Top level cognitive radar architecture.

The cognitive architecture has two agents and an executive cognitive controller. The receive path agent has signal processor, multi-target tracker and target recognition components. The transmit path agent consists of resource allocator and waveform generator components. All of these components interact with each other and share feedback as well as with transmit path agent components.

The executive cognitive controller is responsible for perceiving the environment, situation assessment, planning, and directing towards goals. The executive controller works with memories of receive agent and transmit agent as well as long term memory. The executive controller also has interactions with human operator for long term learning as well as instantaneous decisions. Learning across the missions improves radar capabilities over a period of time. For example initially a maritime surveillance radar may have radar classification models which were trained using simulated models, which could be refined using real measurements during day-to-day operation with the assistance of the operator.

In this architecture the memories are defined with radar application perspective. Short term Memories (SM) typically deal with current radar scan/time frame information pertaining to signal detections, target tracks' states, geographical information system (GIS) information, and change detections, if any. The SM has memories for symbolic and sub-symbolic reasoning.

The Working Memory (WM) deals with current optimised waveforms for transmission, perception from the signal detection, perception from GIS systems, and adjusts learning parameters and utilises long term memory for actions and knowledge, if any.

The radar long term memory (LM) typically deals with information pertaining to multi-scan, multi-mission events, radar parameters, and General handling procedures for typical radar events.

The LM has semantic, procedural and episodic memories. It also has memories for sub-symbolic information for probabilistic reasoning. The semantic memory holds radar parameters and other declarative nature of information. The procedural memory stores action part pertaining to general radar event handling actions. The typical event handling actions are handling of missed targets, cued acquisition of targets, calibration, etc. The episodic memory handles long-term temporally ordered information such as multi-scan/multi-radar time frame information, which could be

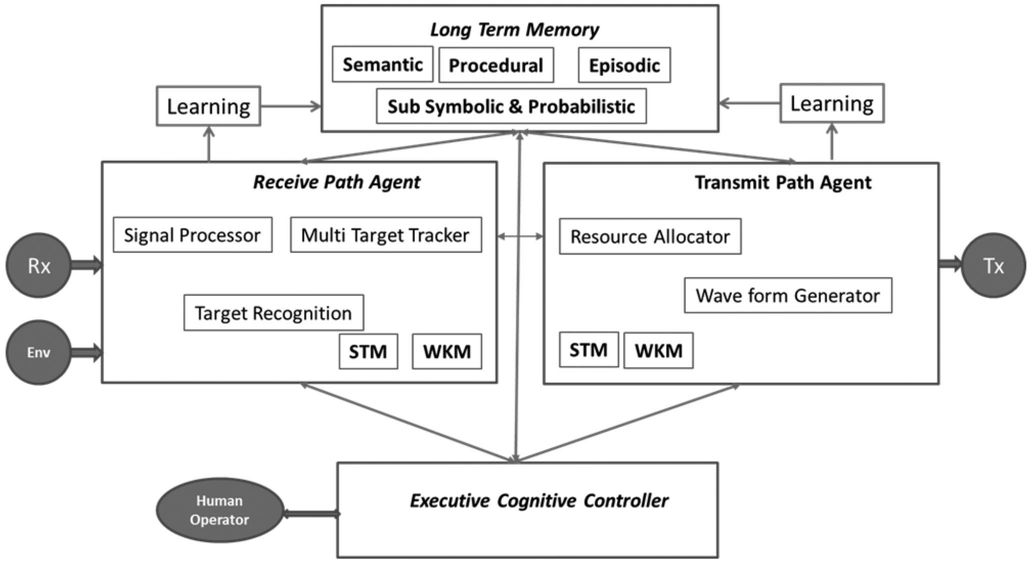

Figure 2. Hybrid cognitive radar architecture.

used by the Cognitive executive controller for situation assessment. The LM is continuously built by WM and SM activities.

Each of the components in the receive and transmit agents need to employ variety of cognitive techniques based on symbolic, emergent and enactive models of cognition. The choice of cognition techniques are tabulated for different components.

Table 1. Available cognitive approaches

Component	Cognitive approaches
Signal processor	Symbolic (knowledge based), probabilistic
Multi-target tracker (filtering and data association)	Symbolic, probabilistic, connectionist, dynamic and enactive
Target recognition	Symbolic, probabilistic and connectionist
Resource allocator	Symbolic, probabilistic and connectionist[10]

Though many of the solutions for components of receive path agents and transmit path agents are available and studied extensively, the cognitive architectures integrates them with human cognition approaches through feedbacks and memories, which will be a way for future cognitive radars.

Under the hybrid architecture, this paper presents, deep learning approaches for high-resolution radar range profile (HRRP) based target recognition and sampling time interval selection in target tracking for phased array radars, in the case studies section.

6. CASE STUDIES

6.1 Radar Target Classification Based on High-Resolution Radar Range Profiles

High-resolution radar range profile (HRRP) represents a one dimensional range projection of a target's return onto the radar line of sight. The range profiles of a target are aspect dependent in the sense they vary with look angle. Classification of radar targets based on their HRRP has been studied[12-20]. A recent study using long short-term memory - recurrent neural network (LSTM-RNN) may be found in Sagayaraj[19], *et al*. Application of convolutional neural network (CNN) in radar target classification problems based on SAR images and micro doppler signatures have also been studied[23-25]. This paper extends the applicability of CNN and LSTM to HRRP. In many radar applications availability of SAR and micro doppler signatures is not guaranteed, whereas HRRP measurements could be made available in all radars. Therefore HRRP based classification is an important aspect for cognition in radars.

6.1.1 HRRP Data Simulation

To generate the radar range profile data an asymptotic electromagnetic solver was used. Three different target models (perfect electric conductor) were used in this simulation. It included scaled versions of two missile models and one aircraft model. Incident plane wave (1 GHz - 2 GHz) from the front was considered in the simulation.

For each target, simulations were carried out for 128 equidistant time samples and 91 aspect angles. Each profile covers the entire range of 128 cells and is for one aspect angle. These data files were then converted to *'csv'* format, labelled with OneHot encoding and then combined together to a single csv file using pre-processing. Each row in the profile shows the HRRP for one aspect angle (of one target). The dataset thus contained 273 range profiles (91 profiles per target). Additive Gaussian noise with signal to noise ratio (SNR) varying from 0 dB to 20 dB were added to the data set to generate 21 different datasets to study the effect of random noise.

Three classification algorithms were tried out in the initial study: Back-propagation network (BPN), CNN, and LSTM-RNN.

6.1.2 Computational Complexity

All the algorithms used here are of polynomial time complexity. The computational requirements of these algorithms are not significant in the real-time usage phase. The training phase was done in offline mode in this study. However, online learning also will not impose any computational constraints. The time complexity of the standard back-propagation neural network algorithm is of $O(w^3)$; where w is the count of weights in the network. The LSTM network's computational requirement per weight and time step is essentially that of back-propagation network (BPN)[26], but has far more weights than BPN. In CNN, the convolution layer has a computational workload of $O(r \times q \times m \times n \times k \times l)$; but for the down-sampling layer the complexity is $O(q \times m \times n)$, where q is the number of input feature maps, r is the number of output feature maps, the feature map size is $m \times n$ and the convolution kernel[27] size is $k \times l$.

6.1.3 Implementation

All the neural networks use 128 nodes in their input layer and 3 nodes in their output layer. The BPN implementation has 90 nodes in the hidden layer. The learning rate was taken as 0.25 and the network uses Softmax with gradient descent optimiser. The training was performed for 500 epochs.

Our LSTM - RNN implementation has one hidden layer with 32 nodes and uses Adam Optimiser. The learning rate is 0.001. The training was performed for 200 epochs.

Our CNN model has 3 feature map (convolutional) layers and one fully connected layer. The number of nodes n the feature map layers are 16, 32, and 64, respectively and the fully connected layer has 256 nodes. The feature map layers use filters of width 4×1, max pooling with width 2 and stride 2. The keep probability for dropout in the convolutional layers is 0.8 and that for the fully connected layer is 0.5. The network has a learning rate of 0.001 and it uses RMS optimiser with decay 0.9. The training was performed for 200 epochs.

In each dataset, of the 273 range profiles, 200 (randomly picked, but the same across the datasets) profiles were used for training the networks and the rest were used in testing.

6.1.4 Results and Discussion

The results are summarised in Table 2. The last row of the table shows the classification accuracy of the three Neural Network (NN) algorithms when there was no noise present in the profiles. The remaining rows summarise the accuracy when SNR ranges from 0 dB to 20 dB.

From the table it is evident that LSTM provided 100 per cent accuracy in predicting the target in all cases. CNN provided above 97 per cent accuracy in all cases and the accuracy is 100 per cent when SNR is above 3 dB. Conventional back propagation technique also gave reasonably good results and above 9 dB SNR, it predicted the targets with 100 per cent accuracy. CNN has the inherent advantage of automatic feature extraction unlike traditional NNs and LSTM. LSTM has the advantage of temporal learning.

Table 2. Classification accuracy of NNs

SNR (dB)	Classification accuracy (%)		
	BPN	CNN	LSTM
0	88.88	97.22	100.0
1	90.27	98.61	100.0
2	93.05	98.61	100.0
3	93.05	98.61	100.0
4	94.44	100.0	100.0
5	94.44	100.0	100.0
6	97.22	100.0	100.0
7	97.22	100.0	100.0
8	98.61	100.0	100.0
9	98.61	100.0	100.0
10	100.0	100.0	100.0
11	100.0	100.0	100.0
12	100.0	100.0	100.0
13	100.0	100.0	100.0
14	100.0	100.0	100.0
15	100.0	100.0	100.0
16	100.0	100.0	100.0
17	100.0	100.0	100.0
18	100.0	100.0	100.0
19	100.0	100.0	100.0
20	100.0	100.0	100.0
No Noise	100.0	100.0	100.0

6.2 Track Update Rate Prediction

Depending on the behaviour of the radar target, the update interval for the target under track can be varied. A high update rate may be used when the target begins a manoeuvre and a relatively low update rate is sufficient for benign targets. Thus by dynamically changing the update rate based on target dynamics, we can use radar resources in an economic manner.

Feed-forward networks have no notion of order in time, and the only input they consider is the current data value they have been exposed to. They have no memory in the sense 'they won't remember their recent past'. Recurrent networks, on the other hand, use information in the input sequence to perform tasks that feed-forward networks can't. They also take what they perceived one step back in time. So recurrent networks have two sources of input, the present and the recent past, which combine to determine how they respond to new data. It is often said that recurrent networks have memory, but they lack long-term memory. LSTMs can remember information for long time periods and help preserve the error that can be back-propagated through time and layers.

6.2.1 Implementation

In order to study the effectiveness of deep learning in predicting track update rate for a phased array radar, a simulation study was carried out. In this study, an LSTM-RNN was used in predicting the update rates. First, we trained the network with simulated update rate data and then tested it with a synthetic scenario.

In the synthetic scenario here, the target initially travels with constant velocity for 60 s; takes a 2 g turn followed by 3 g, 3 g, and 2 g turns to the left; travels with constant velocity for 30 s; 6 g, 7 g, 7 g, and 6 g turns to the right; 6 g, 7 g, 7 g, and 6 g turns to the left; an accelerated travel for 30 s; accelerated

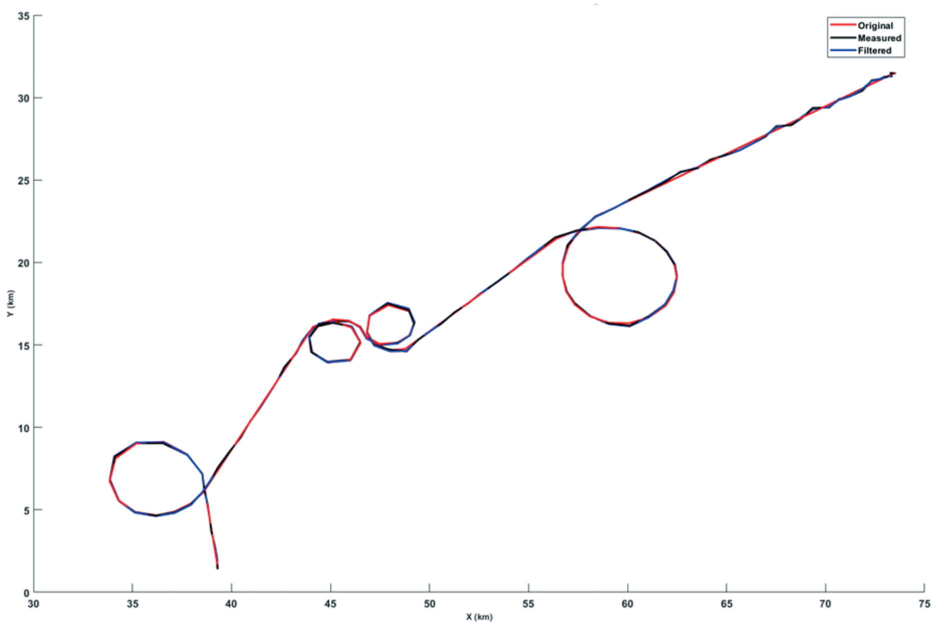

Figure 3. True, measured and predicted tracks.

4 g, 6 g, 6 g, and 4 g turns to the right and finally travels with acceleration for 15 s.

The scenario is shown in red continuous path in Fig. 3. Gaussian noise was then added to this scenario to generate the measurements (shown in black).

The LSTM- RNN prediction model has one input node, one output node and has 5 hidden RNN layers. In the training stage, the learning rate is 0.01 and the number of epochs is 20,000. The network was trained with 233 data values and asked to predict the next 113 values (which includes the last maneuvering of accelerated 4 g, 6 g, 6 g, and 4 g turns in Fig. 3). The update rates were then used in an IMM-Kalman Filter based tracker to perform tracking.

6.2.2 *Results and Discussion*

The filtered track is shown in blue lines in Fig. 3. The distance measurements in X and Y axes are in km. The co-variance in range, Azimuth and elevation are shown in Fig. 4.

From Figs. 3 and 4, it evident that the with the predicted update rates the tracker could keep the co-variances minimal and track the target with very good accuracy. Another advantage was the reduction in the computation time compared to conventional approach described in[22].

The approach was then successfully applied to the six benchmarking problems for radar allocation and tracking described in[21,23]. Training the model with more complicated maneuvering scenarios will further improve the performance.

This new approach is computationally efficient and it completely eliminates the iterative revisit time computation used in[21-23] as it predicts the revisit times in single step for each target. Once the neural network is trained it can be used for all targets.

7. CONCLUSIONS

This paper introduced a Hybrid Cognitive Architecture for radars with concept of memories associated with it. The

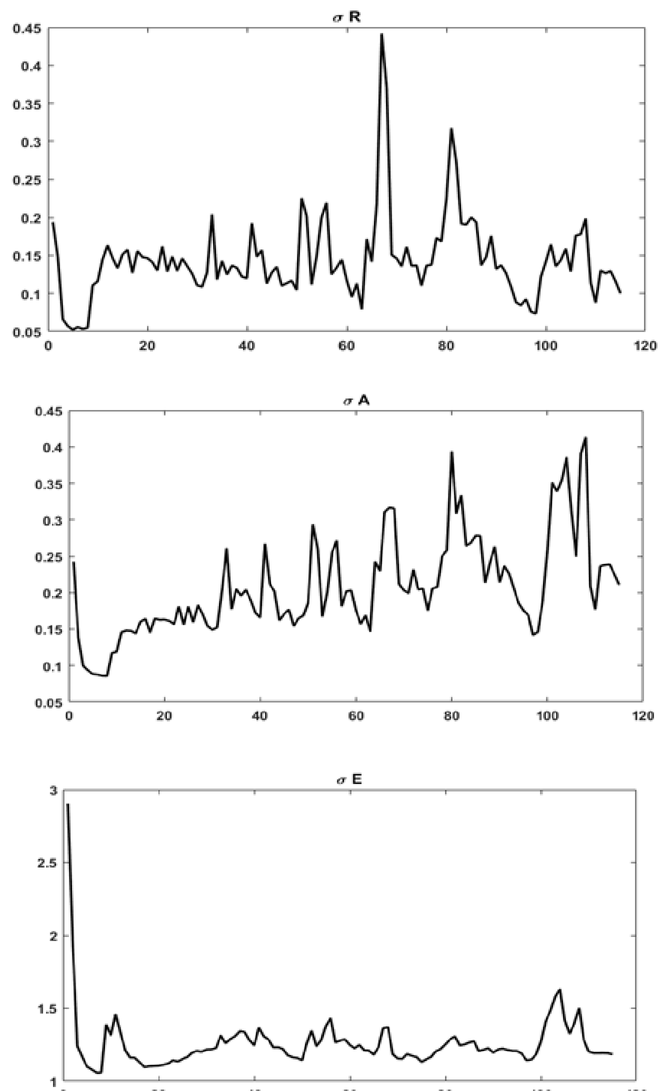

Figure 4. Range, Azimuth and elevation covariances.

proposed architecture is based on the ACS concepts and provides a basis for addressing cognition in radars, which is inadequately explored for radar systems. This paper also presented deep learning examples for radar applications under this architecture. Initial experimental studies on the applicability of deep learning techniques under this approach provided promising results.

As the cognitive radar research is still in primitive stage, radar domain has lot of potential to benefit from advanced researches in ACS. Further studies will be carried out to arrive at memory configuration and applications of cognitivist/ emergent/enactive algorithms under the proposed architecture.

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Mr V. Jithesh obtained his MSc and MPhil (Mathematics) from the University of Kerala and MTech (Computer Science) from Cochin University of Science and Technology, in 2001. Presently working as a scientist in DRDO-Electronics and Radar Development Establishment, Bengaluru. His areas of interest include : High performance computing, machine learning, radar target classification, signal and data processing algorithms, and computational electromagnetics.
Contributions to the current study, he has performed the studies and implementation of deep learning based target classification and track update rate prediction. He has also generated and pre-processed the HRRP data.

Mr Jang Bahadur Singh did his BE(Computer Science and Engineering) from Kumaum Engineering College, Dwarahat, in 1996. Presently working as a scientist in DRDO-Electronics and Radar Development Establishment, Bengaluru. He has worked for the development of radar data processors and is currently working in the area of radar simulators and IV and V of radar software.
Contributions to the current study, he implemented the IMM-Kalman Filter in the track update rate prediction study and helped in incorporating deep learning technique in prediction.

Ms Dange Roshani did her BE (Computer Technology) from Kavikulguru Institute of Technology and Science (KITS), Ramtek and MTech (CSE) from Vishveshwarya National Institute of Technology (VNIT), Nagpur, in 2014. She is working as a Junior Research Fellow at Electronics and Radar Development Establishment, Bengaluru. Her areas of interests include : Machine learning techniques, Advanced DB techniques and IOT.
Contributions to the current study, she helped in generating the HRRP data, optimised the deep learning techniques used in this study and performed all results comparison and analysis for target classification.

Dr K.G. Srinivasa obtained BE (Information Science and Engineering) and ME and PhD(Computer Science and Engineering) from Bangalore University, in 2000, 2003, and 2007, respectively. Currently working as an associate professor at CBP Govt. Engineering College, Jaffarpur, New Delhi. He has published 2 books, and more than 100 technical papers in Journals and Conferences. His research interests include : Cloud computing, data mining, soft computing, bioinformatics, FOSS and machine learning.
Contributions to the current study, he provided the overall guidance and support in the preparation of this manuscript.