A Target Classification Architectural Scheme for Secure Decision Making in Network Centric Environment with MPLS-VPN Architecture

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Abstract

We present a new approach for military decision-making in a network centric environment in perspective of warfare information received from sensors of several networks geographically dispersed. Sensors used across various networks are different types, which generate data that need to be classified for target identification in real time. We also describe the network architecture and secure data communication using Multi Protocol Level Switching (MPLS)-Virtual Private Network (VPN) techniques that enables interoperability, convergence in diverse communication structures across land, air and sea to protect war assets and go offensive when required, which depends on effective communication, information assurance and information security across a challenging terrain and various theatres of battlefield arena. Our proposed network architecture and classification framework ensures packet level authentication that enables the network to restructure itself after a large scale or dedicated attack. It ensures scalability of the system as a whole. It is resilient to data corrupted by enemy's countermeasures and can perform even if a sensor is jammed. Also, the diversity in the classifiers of our ensemble system allows different decision boundaries to be generated by using slightly different training parameters, such as different training datasets. The classification approach primarily applies to a single target or multiple targets that are separated sufficiently in space and/or time.

Keywords: Network Centric Warfare, MPLS-VPN, Belief Functions, Decision Support System, Datafusion, Bayesian Theory, Dempster-Shafer Theory

1. Introduction

The development of society and warfare goes hand in hand. With the proliferation of modern information technology, in particular communication technology, concepts such as information warfare and Network-Centric Warfare [1] have emerged. Information is one of the core elements in military decision-making, where the purpose is to gain information superiority over the adversaries. Network-centricity comes from the fact that communication networks are used to enable information warfare in a theatre of war thereby supporting the decision-making process. Target classification [2] and tracking [3] form one of the key battlefield tactical applications necessary for effective decision-making for the success of military operations. Decision-making in command and control today is characterized by asymmetric threats and international operations. This is essential for any type of weapon deployment or defence system. The Decision Support System [4] (DSS) in the NCW environment needs to provide meaningful and timely concept information and predict the target class that enhances the process of human judgement while making critical battlefield decision. This is particularly required in the modern battle management multi-sensor NCW scenario, which demands faster reaction and quick commander response. Data received from

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sensors across various networks at the nation's centrally located DSS need to be analyzed and classified in real-time for proper decision making so as to allocate suitable weapons to neutralize threats in order to protect the nation's defended assets. The DSS under consideration forms an integral part of the development of the NCW's high-performance information grid called the Central Information Grid (CIG) for the nation that meets the demands of the challenging and highly dynamic battlefield conditions. The CIG is a centralized C4ISR system. The NCW scenario consists of several C2I networks interacting with each other through the CIG, a centralized controlling grid.

A. Background and Perspective

The CIG-DSS in the NCW uses multiple types of sensors placed at different locations, like radars, sonars, infrared (IIR) detectors to mention a few, to increase the accuracy with which a quantity can be observed and characterised. Each sensor of a multi-sensor system is only a contributor to a composite decision process. Information level fusion applications especially in military domains are often characterized as a high degree of complexity due to three challenges: (1) sensory information obtained from multiple perspectives of sensors is often corrupted, (2) decisions must be made quickly and (3) the world situations as well as sensory observations evolve over time. A reliable classification architectural scheme for the CIG-DSS for a collaborative multi-sensor, multi-network [5] approach in a NCW environment is required in which multiple sensors operate together in a non-interference limited manner in distributed sensor networks, and where decision algorithms and also fusion algorithms are applied to generate an optimised classification result. Sensors could be both ground based and airborne. The approach is an ensemble of different classifier architectures [6]. It employs data fusion which uses a combination of geographically distributed sensors of several types and multiple intelligent sources to collect information from these sensors from multiple perspectives and to develop the best possible perception of the military situation which would ultimately aid in good decision-making in a combat scenario.

2. Architecture Methodology and Design

The scheme we propose in this paper addresses the problem of building classifiers for the NCW-CIG-DSS based on uncertain data from Radar sensors addressing the challenges posed due to incomplete evidence and information using belief function techniques. The classification approach primarily applies to a single target or multiple targets that are separated sufficiently in space and/or time.

A. Classification

Target localization and classification problem is to make the best estimates with regard to the location and type of the observed targets by rationally combining information collected by relevant sensor nodes. Results from the target identifier help disambiguate observations to track associations, and provide input for higher-level situational assessment.

B. Fusion

Classifiers combine information in two ways: data fusion and decision fusion [7]. The main objective of employing fusion is to produce a fused result that provides the most detailed and reliable information possible. Fusing multiple information sources together also produces a more efficient representation of the data. Multi-sensor data can be (1) Multi-temporal data, (2) Multi-resolution data or (3) Multi-parameter data. Data fusion can be from one sensor (time series), redundant sensors, redundant variables, variables and systems. Algorithm fusion techniques fuse the decision results from multiple algorithms to yield a more accurate decision. Adequate literature is available on the concepts, features and benefits of data fusion (feature fusion) and decision fusion and hence we will not deliberate further on these subjects.

Choice of Fusion Classifier: We assessed the advantages and disadvantages of both, the data fusion and also the decision fusion classifiers. While data fusion is needed in general for best performance if different measurements yield correlated information, it is best to combine the decisions of the component classifiers (for different measurements) to make the final decision if the different measurements are statistically independent. It was seen that data fusion performed the best, with decision fusion in-between single node and data fusion. However, the decision fusion classifier performs nearly as well, but with significantly lower communication and computational burden, as a result of which it is preferable and also requires less data for training. This is particularly important when limited training data are available as it enables more accurate estimation of classifier parameters [8] (covariance matrices). Decision fusion performs overall better than data (feature) fusion as far as apriori data can be trusted. In contrast to data (feature) fusion, decision fusion may be based on different classification methods, eg, neural network for IR and correlation for radar, whereas feature fusion normally uses only one classifier.

Types of Classifiers: Classification algorithms can be categorized into four groups: (1) supervised parametric classifier, (2) unsupervised parametric classifier, (3) supervised non-parametric classifier and (4) unsupervised non-parametric classifier. All the information of the class probability distribution comes from the analysis of the training samples.

C. Design Methodology for NCW-CIG-DSS classifier

We propose three main ways of classifying sensor data

- Receive data from all sensors, fuse kinematic parameters of all sensors and then classify the targets using the fused kinematic data at the NCW-CIG-DSS (data fusion)
- Receive target classification information from every sensor independently, then fuse the classification parameter received from all sensors at the NCW-CIG-DSS (decision fusion)
- Receive data from all sensors, classify targets based on kinematic parameters for every sensor independently at NCW-CIG-DSS and then fuse the result of classification from all the sensors at the NCW-CIG-DSS (independent classification and decision fusion)

Whatever be the type of kinematic parameters available from a sensor, data of these parameters are used to classify a target for that particular sensor at the NCW-CIG-DSS. This feature provides the flexibility of using different types of sensors including thermal imaging sensors across all networks in the NCW environment. However, it is observed that different classification schemes need to be adopted at the NCW-CIG-DSS, particularly for thermal imaging sensors. We present here, the third approach in combination with the first approach that fits well into the NCW environment and provides robustness to the classification approach of the NCW-CIG-DSS. Our approach is a multiple classifier system, which combines an ensemble of generally weak and/or diverse classifiers. Figure 1 shows the architecture of the NCW-CIG-DSS classification scheme. While kinematic parameters received from different sensors are classified independently (channel#1), they are also subjected to a unified data fusion and passed through a suitable classifier (channel#2). Data Fusion uses a common feature vector built of the features extracted from the individual sensor data, associated with the target. With decision fusion, each sensor identifies targets individually and the extracted features complement each other since they reflect different physics of the target. The design is a mix of both, data fusion and decision fusion. The outputs (decisions) of all the individual classifiers of channel#1 are fused with the classifier result of channel#2 to achieve a sound decision-making approach.

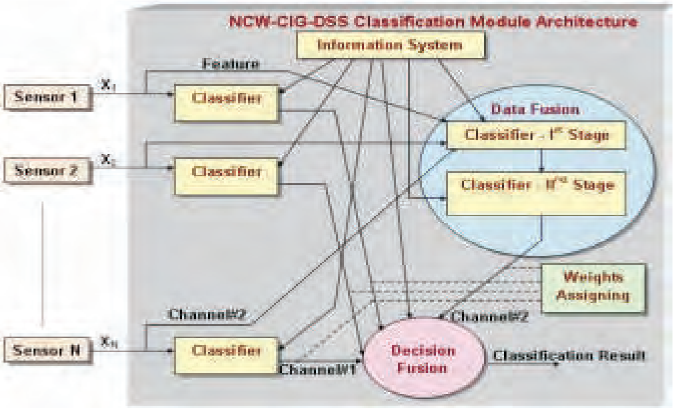

Fig. 1: Architecture of the
NCW-CIG-DSS Classification Architecture

For simplicity, only Radars as sensors have been considered in this paper. Sensor parameters that are typically used as input information for classification are: altitude, speed, vertical velocity, vertical acceleration, specific energy, perigee distance, RCS (Radar Cross Section) and positional co-ordinates of a target. The output from a sensor tracker provides target state estimates. For reliable identification, we must measure the positions of the prominent and hence resolvable, target features. This is particularly important for aircraft; many in number being similar in size and shape. ESM data and direction of arrival information (as seen from the sensor), classification of target as friend, foe or neutral, or any other attribute of the target could also be used.

Since we have several sensors on a platform to collect/receive data about the targets and generate 'information' by local processing of data, some of the information will turn out to be complimentary and some amount of the data will be redundant. Hence even if the quality of data received by some of the sensors is affected either due to propagation effects or due to wilful enemy action like employing electronic countermeasures, the target detection, classification and tracking does not get effected significantly. Thus by 'fusing' the location information and attributes of each target available from the data processors associated with each of the sensors at a node, a fairly accurate threat assessment applicable to that node can be made. In analyzing high dimensional data in large volumes, processing time becomes an important factor. To address this problem, we have adopted a two-stage classifier process approach for classification of fused tracks of all sensors. The first stage is a coarse classifier called the 1st stage classification followed by a selected classifier that would reduce the ambiguity in classification. Since it is found that the results of the 1st stage approach are fuzzy/ambiguous, it becomes necessary to go for a second stage classification. The second stage classification is a sub-classification. By using this approach to represent and combine data, each sensor is allowed to contribute information at its own level of detail. The two-stage classification approach reduces the computational load and also the processing time substantially by eliminating unlikely classes from further consideration at each stage of the NCW-CIG-DSS classification architecture to be able to achieve real-time performance. Feature selection is done to reduce the dimensionality of the feature space by selecting only the salient features necessary so that classification is done on a vastly reduced feature space. Feature vectors of the sensors are selected in a manner that avoids unnecessary or unproductive sensor actions and computations.

As the battlefield scenario become more complex with increasing numbers of sensors and weapon systems, the challenge is to use already available information effectively to enhance sensor performance. Knowledge-based processing, which could be heuristic or statistical, addresses this need and helps meet the challenge. The statistical knowledge-based approach provides a systematic framework for incorporating prior knowledge about the different target classes within the observational models. With statistical models, it is possible to obtain an optimal solution to the classification problem by application of basic principles of statistical inference. Besides, applying classification algorithm supplemented with domain knowledge provides good performance. Also, combining a classification algorithm with heuristic knowledge turns out to be an effective solution. The knowledge base aids in the process of classification and sub-classification of the data of channel#2 of figure 1. Both, 2nd stage classifier and knowledge-based approach are used to reduce ambiguity in classification, more so, for aircraft and cruise missile discrimination, which is rather difficult. A knowledge-based approach is needed for automatic processing of sensor data that has become essential in order to cope with the volume of evidence available in real-time and to support higher-level decision-making.

The most extensive support function required to support data fusion processing is database management. The fusion process is facilitated with the incorporation of an Information System, containing relevant databases, knowledgebase, data mining and libraries. The data fusion part of the architecture though being computational intensive carries the advantage of developing a global view of the object from the original data.

D. Criteria for Selection of Classifier

We have set several criteria for selection of classifiers for the NCW-CIG-DSS. In classifier fusion, it is desirable to use classifiers that, besides offering reasonable performance, have a mutual low correlation; least redundancy is maintained and is cost effective with reduced computational load. The performance of each individual classifier has to be optimized prior to using it within any fusion schemes by selecting appropriate kinematic parameters so as to improve the overall classification result relative to the performance of the individual classifiers. Diversity as a measure is to be used for selecting ensembles in design of multiple classifier systems.

The choice of a classifier [9] is data dependent since the performances of different classifiers on the same data set may differ significantly and also, if one classifier performs well on one data set, it can perform rather badly on another. Besides, the nature of the data and domain of application determines which classification algorithm will provide the best solution to the given problem. The algorithm can differ with respect to accuracy, time to completion, and transparency. Furthermore, the best information varies with time as the situation changes even if the goal remains unchanged. We need to choose a classifier based on factors like data characteristics, measurement scale, resolution and dimensionality, algorithm complexity, form of knowledge and procedure for classification and also that maximizes profit.

Several classification algorithms and architectures exist, there is a rich set of algorithms for choice, but we need suitable means of representation and manipulation of uncertainty of information and knowledge, which is a feature of our application domain. Our application demands the handling of the dual nature of uncertainty; both stochastic and subjective types. This is a challenge, which has to be met, for computerized decision-making based on imperfect input. Inputs to the classification algorithm from all sensors are stochastic, i.e., the kinematics of all sensor inputs are non deterministic. Also missing data issue needs to be taken care.

E. Classifier Architectural Schemes Explored

We chose to restrict our study for consideration for selection of classifier algorithms based on supervised non-parametric approach. We explored the following options: (1) Bayesian Inference Method (2) Dempster-Shafer (D-S) theory of evidence, (3) Decision Tree, (4) k-Nearest Neighbor (k-NN), (5) Support Vector Machine, (6) Transferable Belief Model and (7) Belief formulation from Confusion Matrices. Extensive literature is found to contain a detailed explanation of each of these classifiers.

Two prevalent classification architectural schemes that handle uncertainty/indeterministic inputs using the theory of evidence or degree of belief are the Bayesian inference method and the Dempster-Shafer (D-S) theory of evidence [10]. These are the commonly used algorithms for multisensor information fusion in military applications. It was found that management of uncertainty could not be handled by simple rule based systems. Our method is based on the belief decision tree method. The decision tree learning method is widely used for classification purposes. Belief functions are used to compute an uncertainty measure that will replace the concept of entropy used in ordinary decision tree learning methods. The method of decision tree learning does not in itself address the problems of uncertain class labels in training data. It is our belief that the introduction of belief functions [11] would enable us to train the classifier on data with the kind of uncertainty we would encounter.

The theory of belief functions provides a non-Bayesian way of using mathematical probability to quantify subjective judgments. Whereas a Bayesian assesses probabilities [12] directly for the answer to a question of interest, a belief-function user assesses probabilities for related questions and then considers the implications of these probabilities for the question of interest.

There are three major discriminating criterion to choose an appropriate scheme; (1) if there exists a probability measure with known values, use the Bayesian model, (2) if there exists a probability measure with some unknown values, use the ULP (Upper and Lower Probabilities) model and (3) if the existence of a probability measure is not known, use the Transferable Belief Model (TBM). Our application falls well within schemes (1) & (2). We therefore restrict ourselves to considerations of the first two schemes only.

F. Comparison of Probabilistic Inference Mechanisms

The Bayes and Dempster-Shafer (D-S) approaches are both based on the concept of attaching weightings to the postulated states of the system being measured. The major difference between these two theories is that Bayes works with probabilities, while the D-S theory considers a space of elements that each reflect not what nature chooses, but rather the state of our knowledge after making a measurement. The D-S Theory of Evidence, also called the theory of belief functions, is a generalization of the Bayesian theory of subjective probability. It is developed to overcome inability of Bayesian method to represent incomplete or uncertain evidence. The Bayes approach is found to be a better performing method for combining statistical information from multiple sensors. Tables I compares the two approaches. Extensive literature is available on these theories.

G. NCW-CIG-DSS Classifier

Classification of sensor data into various categories is an important element of the NCW-CIG-DSS architecture. The effectiveness and efficiency of the classification approach adopted acts as an important deciding parameter on the efficiency and effectiveness of performance of the real-time NCW-CIG-DSS. All classifiers have their own set of advantages and limitations. The combination of several different fusion schemes is found to be a useful strategy, which could achieve better quality of results. We have focused on minimizing computational cost by optimizing the use of number of classifiers. To fuse different features, including target state estimates and High Range Resolution (HRR) signatures, a target identifier is needed. Target identification at radar wavelengths must be approached very differently from target identification at optical wavelengths. However, for simplicity we assume that all sensors use the same classifier for individual classification (channel#1) for which we choose to apply the D-S classifier. Appropriate weights are assigned dynamically to each of the individual sensor classifiers based on the kinematic parameters of the sensor and its performance is optimized prior to using it within any fusion schemes. For the NCW-CIS-DSS data fusion channel#2, we chose to apply the belief decision tree for coarse classification as the first stage of classification of channel#2 followed by the Bayesian approach for refined classification as the data fusion schemes.

The decision tree technique is proposed to be a part of the NCW-CIG-DSS classifier architecture to function in an uncertain environment where the uncertainty is represented by belief functions as interpreted in the TBM. One of the fundamental parameters in a decision tree (and consequently in a belief decision tree) is the attribute selection measure. This measure is used in order to choose "the best" test attribute at each decision node of the tree. This classification result is then fused with the individual classifier results of channel#1 to generate the final decision fusion output. When multiple models constructed on the same domain are available, which consists of a combination of Bayesian models and D-S models, a framework for combining the knowledge that does not require experts to reassess one model or another using a different numerical or graphical representation is needed. Additionally, when knowledge is non-causal, building a D-S belief network and solving the network by translating it to a corresponding Bayesian network will be computationally less expensive than solving the D-S belief network directly. Figure 2 shows the classifiers used for the NCW-CIG-DSS classification module while figure 3 shows the flow chart of the NCW-CIG-DSS classification architectural scheme.

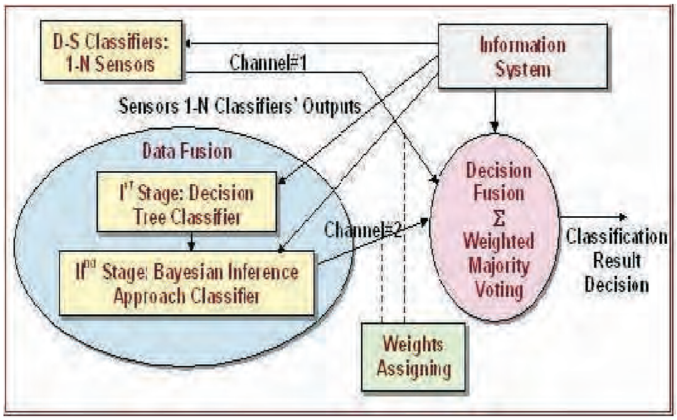

Fig. 2: Classifiers for the
NCW-CIG-DSS Classification Architecture

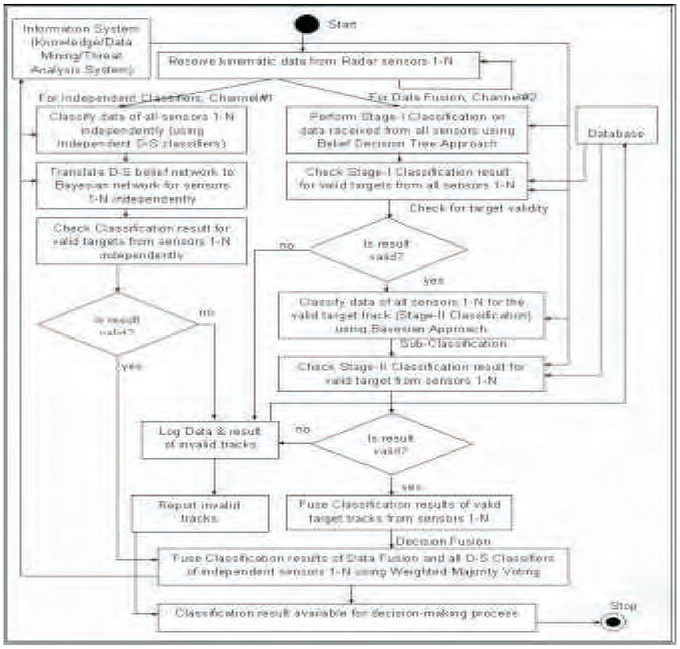

Fig. 3: Flow chart of the
NCW-CIG-DSS Classification Architecture

3. Experimental Procedure and Result

Multiprotocol label switching (MPLS)[13] is a versatile solution to address the problems faced by present-day military networks speed, scalability, quality-of-service (QoS) management, and traffic engineering. We have simulated the MPLS based VPN[14] network for point to point networking separated in space and IP satisfying the bandwidth-management and service requirements for next-generation Internet protocol (IP) based backbone networks. MPLS addresses issues related to scalability and routing (based on QoS and service quality metrics) and can exist over existing asynchronous transfer mode (ATM) and frame-relay networks.

A. Multiprotocol Label Switching (MPLS)

In MPLS, data transmission occurs on label-switched paths (LSPs), LSPs are a sequence of labels at each and every node along the path from the source to the destination. LSPs are established either prior to data transmission (control-driven) or upon detection of a certain flow of data (data-driven). The labels, which are underlying protocol-specific identifiers, are distributed using label distribution protocol (LDP) or RSVP or piggybacked on routing protocols like border gateway protocol (BGP) and OSPF. Each data packet encapsulates and carries the labels during their journey from source to destination.

B. Labels and Label Bindings

A label, in its simplest form, identifies the path a packet should traverse. A label is carried or encapsulated in a Layer-2 header along with the packet. The receiving router examines the packet for its label content to determine the next hop. Once a packet has been labelled, the rest of the journey of the packet through the backbone is based on label switching. The label values are of local significance only, meaning that they pertain only to hops between LSRs. Once a packet has been classified as a new or existing FEC, a label is assigned to the packet. The label values are derived from the underlying data link layer. For data link layers (such as frame relay or ATM). Layer-2 identifiers, such as data link connection identifiers (DLCIs) in the case of frame-relay networks or virtual path identifiers (VPIs)/virtual channel identifiers (VCIs) in case of ATM networks can be used directly as labels. The packets are then forwarded based on their label value. Labels are bound to an FEC as a result of some event or policy that indicates a need for such binding. These events can be either data-driven bindings or control-driven bindings. The latter is preferable because of its advanced scaling properties that can be used in MPLS. A summary of the various schemes for exchange of labels are LDP (maps unicast IP destinations into labels), RSVP, CR-LDP(used for traffic engineering and resource reservation), Protocol-Independent Multicast (used for multicast states label mapping) and BGP (external labels VPN).

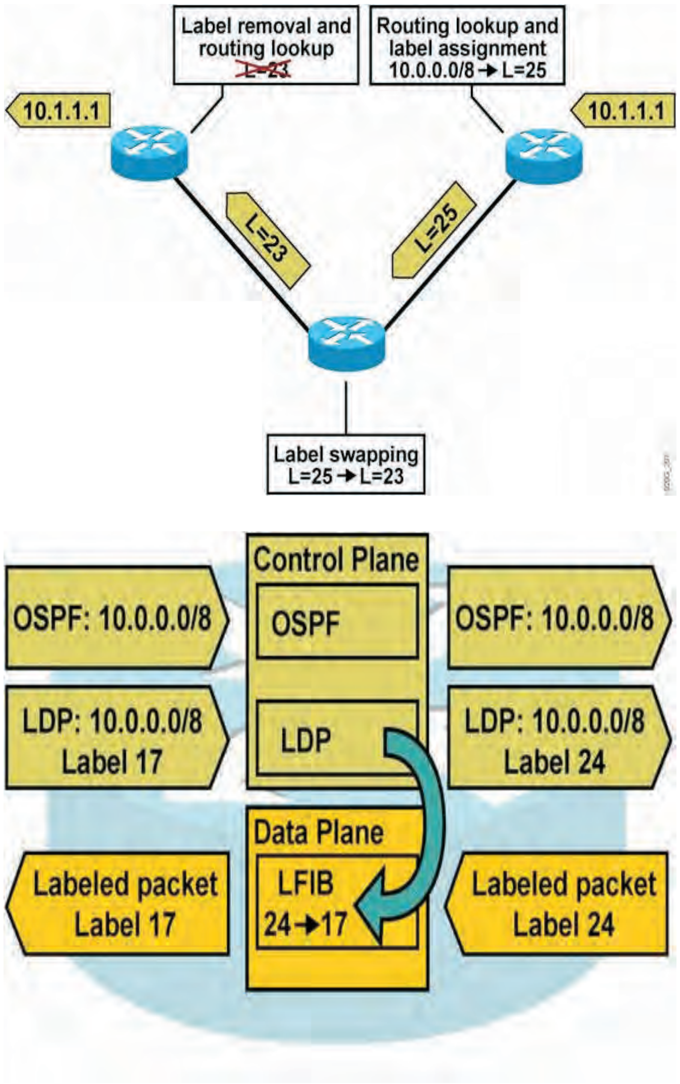

Fig. 4: Basic MPLS architecture

C. Basic topology for MPLS Configuration

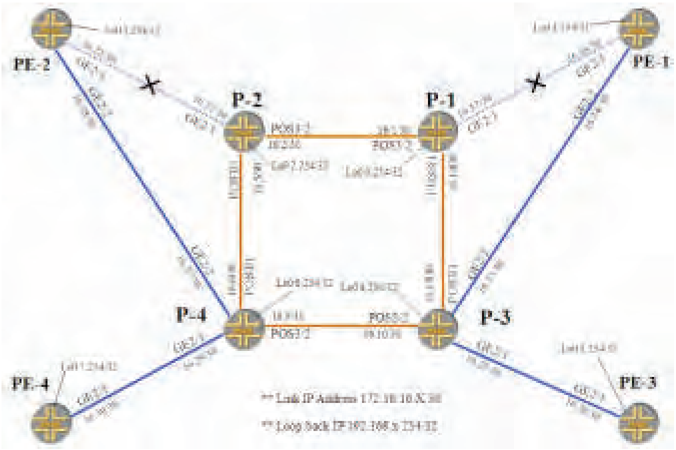

Fig. 5: Basic Topology design for NCSDSS simulation

```
P-1 Preliminary configuration
User Access Verification
Password:xxxxx
P-1>en
Password:xxxxx
P-1# conf t
P-1(config)#interface Loopback0
P-1(config-if)# description ** P-1's Loopback 0 Interface **
P-1(config-if)# ip address 192.168.0.254 255.255.255.255
P-1(config-if)# no shutdown
P-1(config-if)# exit
P-1(config)#interface GigabitEthernet2/1
P-1(config-if)# description ** P-1-PE-1 GigE link **
P-1(config-if)# ip address 172.16.16.17 255.255.255.252
P-1(config-if)# no shutdown
P-1(config-if)# exit
P-1(config)#interface POS3/1
P-1(config-if)# description ** P-1-P-3 STM-1 link **
P-1(config-if)# ip address 172.16.16.14 255.255.255.252
P-1(config-if)# encapsulation ppp
P-1(config-if)# clock source internal
P-1(config-if)# no shutdown
P-1(config-if)# exit
P-1(config)#interface POS3/2
P-1(config-if)# description ** P-1-P-2 STM-1 link **
P-1(config-if)# ip address 172.16.16.1 255.255.255.252
P-1(config-if)# encapsulation ppp
P-1(config-if)# no shutdown
P-1(config-if)#end
P-1#write memory
Building configuration...
[OK]
P-1#
```

D. MPLS architecture and traffic Engineering

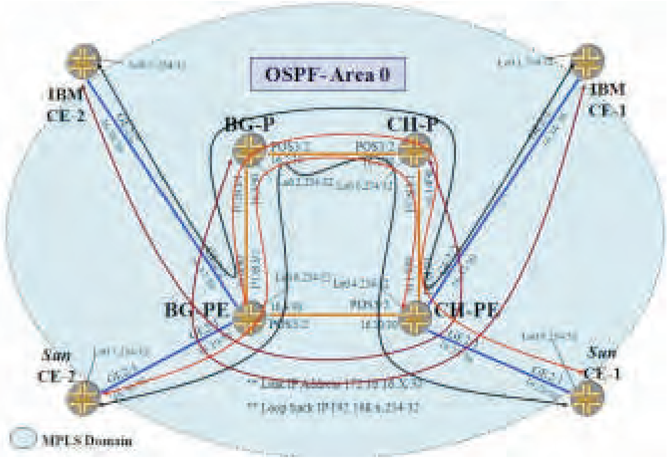

Fig. 6: Traffic engineering for NCWDSS information transmission

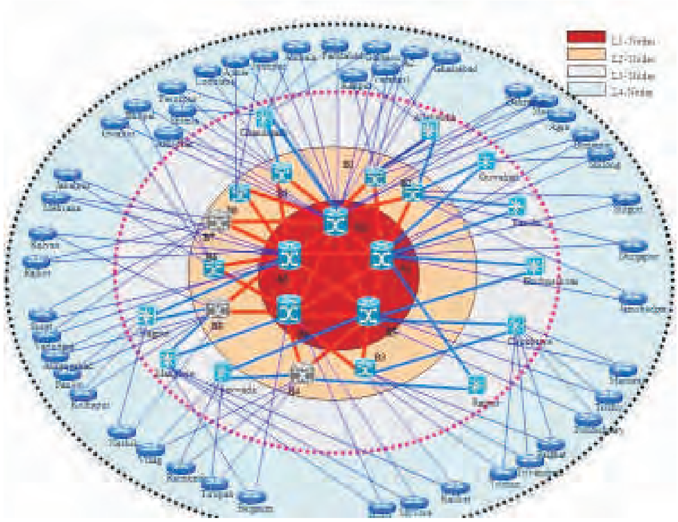

Fig. 7: Proposed MPLS VPN based network for NCWDSS information transmission

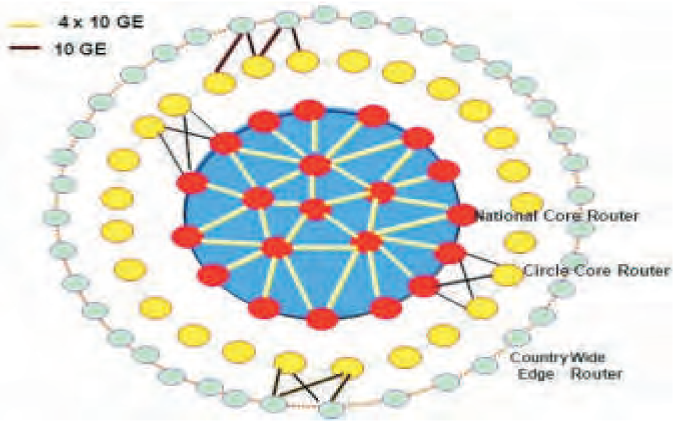

Fig. 8: Unified MPLS based IP core network

E. MPLS based L3 VPN using MP-BGP/ OSPF

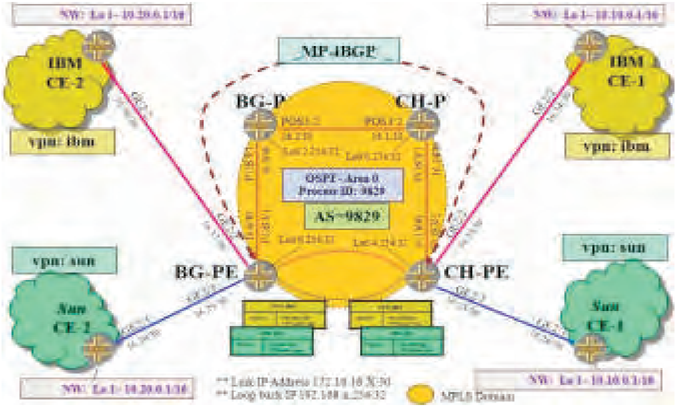

Fig. 9: MPLS based L3 VPN using MP-BGP/OSPF

```
CONFIGURING OSPF 1200
BG-PE# conf t
Enter configuration commands, one per line.  End with CNTL/Z.
BG-PE(config)#router ospf 1200 vrf ibm
BG-PE(config-router)#auto-cost reference-bandwidth 1000
BG-PE(config-router)#network 172.16.16.36 0.0.0.3 area 0
BG-PE(config-router)#redistribute bgp 9829 subnets
BG-PE(config-router)#exit
BG-PE(config)#
CONFIGURING OSPF 2100
BG-PE(config)#router ospf 2200 vrf sun
BG-PE(config-router)#auto-cost reference-bandwidth 1000
BG-PE(config-router)#network 172.16.16.28 0.0.0.3 area 0
BG-PE(config-router)#redistribute bgp 9829 subnets
BG-PE(config-router)#exit
BG-PE(config)#
MODIFYING THE MP-BGP CONFIGURATION
BG-PE#conf t
Enter configuration commands, one per line.  End with CNTL/Z.
BG-PE(config)#router bgp 9829
BG-PE(config-router)#address-family ipv4 vrf ibm
BG-PE(config-router-af)#no neighbor 172.16.16.38 remote-as 1200
BG-PE(config-router-af)#no neighbor 172.16.16.38 activate
BG-PE(config-router-af)#no neighbor 172.16.16.38 next-hop-self
BG-PE(config-router-af)#redistribute ospf 1200 match internal ext1 ext 2
BG-PE(config-router-af)#exit-address-family
BG-PE(config-router)#address-family ipv4 vrf sun
BG-PE(config-router-af)#no neighbor 172.16.16.30 remote-as 2200
BG-PE(config-router-af)#no neighbor 172.16.16.30 activate
BG-PE(config-router-af)#no neighbor 172.16.16.30 next-hop-self
BG-PE(config-router-af)#redistribute ospf 2200 match internal ext 1 ext 2
BG-PE(config-router-af)#exit-address-family
BG-PE(config-router)#end
BG-PE#wr
04:49:30: %SYS-5-CONFIG_I: Configured from console by console
Building configuration...
[OK]
BG-PE#
IBM-CE-1 : OSPF CONFIGURATION
REMOVING BGP 1100 AND CONFIGURING OSPF 1100:-
IBM-CE-1# conf t
Enter configuration commands, one per line.  End with CNTL/Z.
IBM-CE-1(config)#no router bgp 1100
IBM-CE-1(config)#router ospf 1100
IBM-CE-1(config-router)#auto-cost reference-bandwidth 1000
IBM-CE-1(config-router)#network 172.16.16.32 0.0.0.3 area 0
IBM-CE-1(config-router)#network 10.10.0.0 0.0.255.255 area 0
IBM-CE-1(config-router)#passive-interface loopback 1
IBM-CE-1(config-router)#end
IBM-CE-1#write memory
Building configuration...
[OK]
IBM-CE-1#clear ip ospf 1100 process
Reset OSPF process? [no]: y
IBM-CE-1#
03:47:36: %OSPF-5-ADJCHG: Process 1100, Nbr 172.16.16.33 on GigabitEthernet2/2 from FULL to DOWN, Neighbor Down: Interface down or detached
```

```
IBM-CE-1#
03:47:40: %OSPF-5-ADJCHG: Process 1100, Nbr 172.16.16.33 on GigabitEthernet2/2 from LOADING to FULL, Loading Done
IBM-CE-1#

IBM-CE-2 : OSPF CONFIGURATION
REMOVING BGP 1200 AND CONFIGURING OSPF 1200:-
IBM-CE-2# conf t
Enter configuration commands, one per line.  End with CNTL/Z.
IBM-CE-2(config)#no router bgp 1200
IBM-CE-2(config)#router ospf 1200
IBM-CE-2(config-router)#auto-cost reference-bandwidth 1000
IBM-CE-2(config-router)#network 172.16.16.36 0.0.0.3 area 0
IBM-CE-2(config-router)#network 10.20.0.0 0.0.255.255 area 0
IBM-CE-2(config-router)#passive-interface loopback 1
IBM-CE-2(config-router)#end
IBM-CE-2#write memory
Building configuration...
[OK]
IBM-CE-2#clear ip ospf 1200 process
Reset OSPF process? [no]: y
VERIFICATION COMMANDS
Eg. For CH-PE router
CH-PE#show ip vrf
CH-PE#show ip vrf detail
CH-PE#show ip vrf interfaces
CH-PE#show ip protocols vrf ibm
CH-PE#show ip route vrf ibm
CH-PE#show ip bgp vpnv4 vrf ibm
CH-PE#show ip bgp vpnv4 vrf ibm neighbors
CH-PE#show ip bgp vpnv4 all summary
CH-PE#show ip bgp neighbors
CH-PE#show mpls forwarding vrf ibm
CH-PE#show ip cef vrf ibm
CH-PE#ping vrf ibm 10.20.0.1
CH-PE#trace vrf ibm 10.20.0.1
CH-PE#telnet 10.20.0.1 /vrf ibm
```

4. Conclusions

The approach presented has several positive features. At the foremost, the approach ensures scalability of the system as a whole. It fits well in distributed multisensory NCW environment [15] and is real-time compliant [16]. It is robust, reliable and is resilient to data corrupted by enemy's countermeasures and can perform even if a sensor is jammed. The ensemble of classifiers used helps to achieve better quality of results and thus excels in superiority over single classifier systems. Also, the diversity in the classifiers of our ensemble system allows different decision boundaries to be generated by using slightly different training parameters, such as different training datasets. The intuition is that each expert will make a different error, and strategically combining these classifiers can reduce total error. This approach excels in superiority over single classifier systems. The approach contains the ability to combine the outputs of the different classifier architectures outputs for (i) a stronger overall classifier, (ii) a classifier capable of incremental learning, and (iii) a classifier capable of data fusion. The evaluation of our proposed classifier design using test results will be reported in a forthcoming paper. As an extension to this work, different classifiers like the SVM could be adopted for the NCW-CIG-DSS classification architecture. Our proposed VPN mechanisms are needed which work over existing deployed backbones, and which can also be migrated to new backbones like MPLS (Multi-Protocol Label Switching). MPLS is the latest step in the evolution of multi-layer switching in the Internet. In this paper, we simulate how MPLS can be applied to creating VPNs. For this, we researched an architectural model for building VPNs in an MPLS domain. The proposed model takes advantage of both network layer peering and packet switching, and link-layer circuit and per-stream switching. It comes with a design scheme and an implementation procedure for VPN services in MPLS systems for efficient and cost-effective use for future.

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