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Dynamic Reconfiguration of Communication Hubs during Offensive Military Operations

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***Abstract**:*

In offensive military operations, the communication hubs move swiftly to provide multi-media communications to the fighting forces. As the fighting formations move forward with the progress of operations, the communication hubs also move forward. Existing dynamic routing algorithms update the configuration tables, but cannot converge quickly. In this paper, we present a dynamic and adaptive reconfiguration routing algorithm which would make the communication system transparent to the movement of fighting formations and improve the success rate of packet delivery.

Keywords

Dynamic reconfiguration, communication hubs, military operations.

1. Introduction

In battlefield, the armed forces conduct offensive operations to win over the enemy and occupy the ground. During offensive military operations, the forces move forward swiftly. The commanders at various levels communicate with one another to coordinate the movement of troops. Therefore communications take vital place in the offensive operations. In conventional warfare scenario, communication equipment was integral part of the formations and commanders at various formation headquarters were provided with radio sets to communicate with formations / troops under their command. The radio sets provided basic voice communication only. As the formation moves forward, the communication equipment which is integral to that formation also moves along with it.

Mobile Radio Engineering Network Communication Centers (MRENCC) were developed during 1980s to provide networked communication support to the troops on move to provide audio and data communications. It is based on the Radio Relay links networked using electronic switches and routers. The routing algorithms implemented on these routers were primitive.

1.1. Topology of the MRENCC

The MREN Communication Center (MRENCC) consists of MREN network terminals which are based on vehicles. A model of MREN terminal is shown in figure 1.1. These terminals are equipped with the radio relay links, switching / routing equipment. A formation hooks on to the communication center using the mobile communication terminals which are integral part of that formation. The MREN Communication centers are inter-linked with one another in mesh topology forming a grid which covers certain area of operations. As the formations move forward, they hook on to the nearest MREN center. As the operations progress and formations move forward, a new MREN center is moved ahead and established to extend the grid in the direction of offensive operations. Therefore, the formations are provided with communications continuously while on move.

Figure 1.1: Mobile Radio Engineered Network Terminal

1.2. Tactical Communication System (TCS)

As the technology changed, the conventional warfare has given way to modern warfare. Besides the three dimensions of war that is, land, water and air, two more dimensions are added. The additional two dimensions are electronic warfare and information warfare. These two dimensions of war are playing vital role in winning the battles. The commander needs data, video and information besides voice communications. Modern command and control systems like Battlefield Management System (BMS), Battlefield Surveillance Systems (BSS), Command, Information and Decision Support Systems (CIDSS) and tactical Command, Control, Communication and Information systems (C3I) are introduced to support fire power, night fighting, surveillance systems and night vision devices [1].

To support the above command and control system, Tactical Communication Systems (TCS) are developed.

The TCS systems provide high bandwidth networked communication providing voice, data and video services. However, when-ever there is a change in the network topology, the network performance goes down as the routing algorithms are not suitable for the mobile operations.

In this paper, we presented an adaptation model which dynamically reconfigures the communications hubs and optimizes the performance of the network as and when there is a change in the network. The algorithm is pre-emptive to the changes and adaptive to the traffic load generated by the formation nodes.

This paper is organized into six sections. The next section reviews the related work in the routing algorithms and the adaptive techniques used in the network management. Section 3 deals with the theoretical background to the new modified algorithms. Proposed adaptation model is covered in Section 4. Section 5 deals with experimentation details, analysis of the output data. Section 6 gives the conclusions and future enhancements are discussed in section 7.

2. Related Work

Nachum Shacham et al. of US Army Research Center studied the dynamic network topologies in military communications. They focused their study on command, control, communication and information related network resources and suggested ways to optimize the performance of the networked communications [2].

The routing protocols used in most of today's computer networks are based on shortest path algorithms that can be classified as distance-vector or link-state algorithms [3, 4]. The existing dynamic routing algorithms have the disadvantage that they take a lot of time to converge. In fast dynamic topological network, like in offensive military operations, the network routing tables do not stabilize and therefore the packet losses will be unacceptably high.

Brian Panneton and James Adametz analyzed that the military data communication networks and made useful recommendation regarding tactical communication networks for high performance in computing [5].

3. Theoretical Background

Theoretical background for the research work is given below.

3.1. Machine Learning Techniques

Supervised learning differs from unsupervised learning in availability of class information of data samples. The data samples are used for parameter estimation. For example, the data sample is denoted by a pair (y, c). Here, y is the observed data and it belongs to class c. The pair (y, c) is jointly distributed random variables. For example, y is a segment of speech and it belongs to a class of phonemes c. It means that the speech data segment and its transcription into phoneme sequence are available. Such data samples where both data and its class are given, are termed as complete data or labeled data. Labeled data is given in supervised learning. The data is unlabeled or class information is missing in unsupervised learning [6].

3.1.1. Supervised Learning. Supervised learning has class information for the data. Only the probabilistic structure needs to be learned. It is termed as parameter estimation.

The MLE algorithm aims at maximizing the probability of producing the training data from the data which is observed. In the same way, MAP estimation algorithm estimates the parametric vectors when the prior distribution is known. In general, MLE is used for estimating parameters from scratch without any prior knowledge and MAP estimation is used for parameter adaptation where the behavior of prior distribution is known and only a small amount of adaptation data is available. When the amount of adaptation data increases, MAP estimation converges to MLE.

3.1.2. Unsupervised Learning. In unsupervised learning, the class information *c* of the data y is missing. The observed data is incomplete since class information *c* of the data is not available. Vector Quantization (VQ) and the Expectation Maximization (EM) algorithm are two unsupervised learning techniques.

3.2. Vector Quantization (VQ)

The VQ technique is one of the conventional pattern recognition techniques. It is popularly used in network design, data compression and speech recognition [7].

A codebook defines the VQ model. It contains prototype vectors called code-words. Each code-word in the VQ model is mapped to an index. The model uses some distortion measure to compare the input vector with the code-words. The index corresponding to the code-word with the smallest distortion is output as the class information of the input vector. The VQ process comprises of firstly, a distortion method and secondly, an enrolment of code-words in the codebook.

Let x be the vector in the 2-dimensional space and is mapped to an index vector z, then

$$z = q(x) \qquad (3.1)$$

where $q()$ is the quantization operator and z is a vector from a finite set $Z = zj$, $\{1 \le j \le M\}$, where zj is also a 2-dimensional vector.

The set Z is the codebook with size M code-words. zj is the jth code word. The size M of the codebook is also called the number of partitions in the codebook. The codebook is designed as follows:

- The vector space of the original random vector x is partitioned into M cells Cj, $\{1 \le j \le M\}$, and each cell Cj is associated with a code-word vector zj.
- VQ quantizes the input vector x to code-word zj if x lies in Cj. That is,

$q(x) = zj$, if $x \in Cj$ (3.2)

- The code word zj is known as the centroid of the cell Cj.

Since the code-words are replaced with the index of the code-words in the VQ process, there is invariably some distortion between the input and output of the VQ model. Distance measures like Dynamic Time Warping (DTW), Mahalanobis distance and Euclidean distance are some examples of distortion measures.

A quantization error results when x is quantized as z. A distortion measure $d(x, z)$ is defined as the distance between x and z. The above equation can be reformulated as follows:

$q(x) = zj$, if and only if $j = \text{argmin}_k\, d(x, z_k)$ (3.3)

3.3. Modified Vector Quantization (MVQ)

In this dissertation, MVQ is used for enrolment and storage of network configurations (NWConfigs). The MVQ is described by a codebook with the NWConfigs as the code-words. The MVQ uses the load distance as the distortion measure d(x, z) to compare the input configuration x with code-word configuration z. Each load array is mapped to the corresponding configuration. All loads are mapped to a configuration are classified as one configuration-class. In MVQ, the input load is compared with the entire list of loads in the codebook. The configuration class corresponding to the load with minimum load distance is output as the configuration corresponding to the input load. In the past, the phonetic distance between two sound signals was used as the distortion measure in VQ-based speech coding applications [8, 9, 10].

4. Proposed Solution

An adaptation model designed to address the problem of dynamic reconfiguration of the network hubs is given in figure 4.1. The adaption model has the following modules.

4.1. Dynamic Load Warping (DLW) Module

DLW measures the load distance between two the sequences of loads. The selection Dmin is based on the minimum load distance. The mapped network configuration (NC) is passed taken as NC hypothesis and is given to the Resolution Module

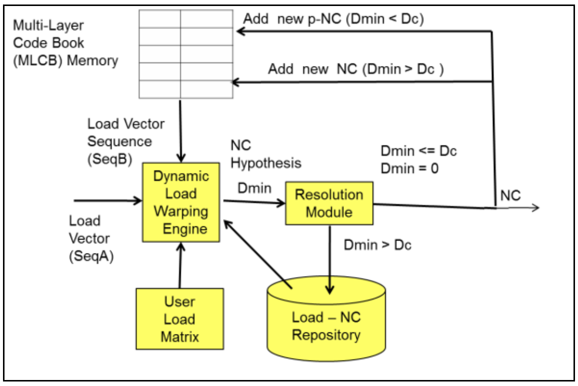

Figure 4.1: Adaptation model

4.2. Resolution Module

The resolution module adds the NC to memory in case the Dmin is less than critical distance. If the Dmin is equal to zero, the NC is given out the NC output. In case the Dmin is more than the critical distance, then the cycle is repeated after considering the data from NC repository.

4.3. User Load Matrix

It gives the list of formations and its load on the network.

4.4. Resolution Module

It resolves whether the input load vector on the network is same as one of the loads in the MLCB memory, close to one of the loads or is it different load from the existing loads. The decision whether the load vector is close to the existing load vector or otherwise, is decided by the critical distance parameter.

4.5. MLCB Module

This is a code book. It holds various load vector code words indexed to their NCs. It has four levels. All 'Most Frequently Used' and 'Most Recently Used' code words are kept in first level. 'Most Frequently Used' words are kept in second level and the 'Most Recently Used' code words kept in third level. Remaining code words are kept in fourth level. To keep the size of the code book to a manageable level, a time stamp is maintained for each code word. The code words are moved to the repository beyond a predefined 'Time to Live' period.

5. Experimentation

Two experiments have been conducted. First experiment is conducted for purpose of estimating the critical distance and the second experiment is for the purpose of evaluating the proposed adaptation model.

5.1. Experiment No. 1

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The first experiment is carried out to estimate the critical distance (Dc) which classifies the load vectors into a variation of existing NC in the MLCB or the load vector corresponds to a new NC.

5.1.1 Experimental Setup. The experimental set up is given in figure 5.1.

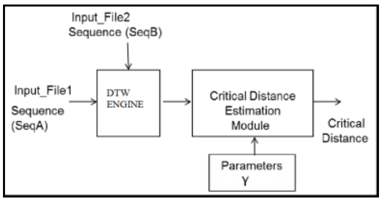

Figure 5.1: Experimental setup for estimation of Dc

5.1.2. Datasets. The data sets used for the experiment No1 are the NCs and their load vectors (LVs). Ten load vectors are chosen for each NC. The data set consists of different number of ten to fifty thousand NCs.

5.1.3. Procedure. The NCs and their LVs are kept in two input files named Input_File1 and Input_File2. A LV from Input_File1 is compared with itself and its variations and also with LVs of different NCs. Based on the distance between a pair of LVs; it is classified as a variation of its NC or LV of different NC. The value of parameter gamma is varied between 0 to 1 in steps of 0.5. The errors are counted in each experiment. The results are given in Table 5.1. and graphically shown in figure 5.2.

5.1.4. Result Analysis. The results show that the errors in classification are the lowest at gamma equal to 0.5. The curves B, C, D and E correspond to different datasets with varying number of comparisons. The Dc is re-estimated after every updation of MLCB memory.

Table 5.1: Results of classification

	Data Set			
γ	B	C	D	E
0.20	1.66	1.35	1.46	1.25
0.25	0.94	0.83	1.04	1.04
0.30	0.73	0.62	0.94	0.62
0.35	0.62	0.52	0.94	0.52
0.40	0.73	0.52	0.83	0.31
0.45	0.73	0.52	0.83	0.31
0.50	0.42	0.31	0.62	0.10
0.55	0.62	0.52	0.73	0.21
0.60	1.46	0.83	0.73	0.21
0.65	1.87	1.14	1.35	0.31
0.70	2	1.77	1.70	0.73
0.75	2.1	1.77	2.00	1.35
0.80	8.95	7.80	10.61	3.64

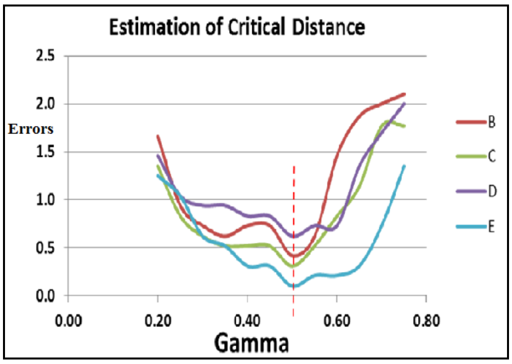

Figure 5.2: Graphical view of the results

5.2. Experiment No.2

The second experiment is conducted to evaluate the adaptation model. The Dc estimated in the first experiment is used in the adaption model. The adaptation model given in figure 4.1 is used for experimental setup.

5.2.1. Datasets: The load vectors for different divisions are taken as the datasets. The network consists of seventeen communication centers and the formations hooked to the communication centers are taken as loads. The actual data during two different military exercises is used for inclusion in the datasets.

5.2.2. Procedure: The MLCB memory is kept empty at the beginning of the experiment. The first dataset consists of 25 load vectors. All the 25 load vectors are added to the memory. The NCs for these load vectors are taken from the LV-NC repository. Fifteen experiments are conducted with increasing number of load vectors. The number of variation of loads and new NCs are recorded. The network performance is measured as percentage of packet losses in the network.

5.2.3. Results and Analysis: The results are shown in figure 5.3. The performance of the system with adaption model is better than the performance of the network using non-adaptive dynamic algorithms like distance vector routing and link state routing.

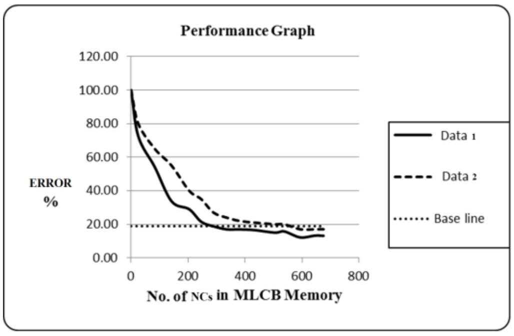

Figure 5.3: System performance testing

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6. Conclusions

TCS is a networked communications system with dynamic network topology and dynamic changing load on the network. The existing dynamic routing algorithm cannot converge in offensive military operations due to rapid movement of military formations. An adaptation model is presented in this paper. The experimental results showed that the performance of the network with adaptation model is better than the network performance with existing routing algorithms.

7. Future Enhancements

The adaptive routing model is generic and can be used in any dynamically changing networks like road traffic control systems etc.

8. Acknowledgements

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