УДК 004

VIRTUAL NETWORK EMBEDDING FRAMEWORK IN FIBER-WIRELESS ACCESS NETWORK

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Abstract. *This paper focuses on the virtual network embedding problem in fiber-wireless access network, and formulates it as an Integer Linear Programming (ILP). Simulation results verify the effectiveness of proposed framework.*

1. Introduction

Fiber-Wireless (FiWi) access network [1] is a large-capacity, long-distance and low-cost solution for "last mile", which is now facing the challenge of resource optimization of varieties of new applications. Network virtualization [2] that supports networks with diverse natures over a common Substrate Network (SN) is supposed to be a promising solution, where Service Provider (SP) creates Virtual Networks (VNs) according to demands of end users, and Infrastructure Provider (InP) manages physical resources and leases them to SPs. The process of leasing the specified resources to SPs is called Virtual Network Embedding (VNE), in which InP will obtain profit, as shown in Fig. 1. This paper emphasizes on the VNE problem in FiWi to set a benchmark for further research.

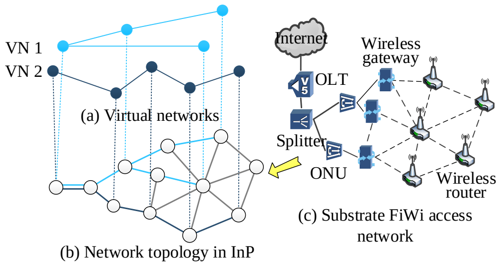

Figure 1 – Illustration of virtualized FiWi access network

Table 1 – Simulation settings of network resources

	parameter		value
SN	Node CPU capacity (uniform distribution)	OLT & ONU	[200,500]
		wireless router	[50,100]
	Link bandwidth capacity (Mbps)	feeder fiber	1000
		cable	54
		wireless link	54
VN	Node CPU demand (uniform distribution)		[10,30]
	Link bandwidth demand (Mbps)		[5,10]
	Duration time (exponential distribution)		50 time units

2. Network Models

The FiWi access network can be represented by $G^S = (N^S, L^S)$. The nth physical nodes in N^S that located at LCT_n has a node type $TYPE_n \in \{OLT, ONU, WR\}$ where OLT, ONU and WR indicate Optical Line Terminal (OLT), Optical Network Unit (ONU) and Wireless Router (WR) respectively. The resources in G^S cover the CPU capacity CAP_n^{CPU} of node n and the bandwidth capacity CAP_l^{BNDW} of link l. For VN sets G^V, in the kth VN $G_k^V = (V_k^V, E_k^V)$, the ith virtual node $v_{(k,i)}$ has demands of node type $REQ_{(k,i)}^{TYPE} \in \{A, T\}$ where A indicates "Access" representing OLT and T implies "Transmit" indicating ONUs and WRs, CPU demand $REQ_{(k,i)}^{CPU}$, preferred location $REQ_{(k,i)}^{LCT}$ and embedding location offset $\Delta LCT_{(k,i)}$. Besides, the jth virtual link in G_k^V, i.e., $e_{(k,j)}$, is associated with a bandwidth demand $REQ_{(k,j)}^{BNDW}$ and a path length constraint $REQ_{(k,j)}^{LEN}$. The InP profit obtained from embedding G_k^V is formulated as (1) where InP revenue and resource cost are considered. α, β stand for the revenue and cost of each unit of resource, and ρ^V and ρ^E elaborate the weights between CPU and bandwidth.

$$Profit(G_k^V) = \alpha\left[\rho^V \sum_{\forall i} REQ_{(k,i)}^{CPU} + \rho^E \sum_{\forall j} REQ_{(k,j)}^{BNDW}\right] \\ -\beta\left[\rho^V \sum_{\forall i} REQ_{(k,i)}^{CPU} + \rho^E \sum_{\forall j} (REQ_{(k,j)}^{BNDW} \cdot LEN_{(k,j)})\right] \tag{1}$$

3. Integer Linear Programming (ILP) of VNE in FiWi

Firstly, we introduce following notations. 1) ξ_k: a binary variable indicating if G_k^V has been embedded successfully; 2) $\chi_{k,i}^n / \eta_{k,j}^l$: a binary variable implying if $v_{(k,i)} / e_{(k,j)}$ has been embedded on substrate node n / link l. And $\psi_{k,i}^n / \varphi_{k,j}^l$ denotes the volume of resource that n / l provides to $v_{(k,i)} / e_{(k,j)}$; 3) $DIS(n, v_{k,i})$: distance between n and $v_{(k,i)}$; 5) $SRC_{k,j}$ and $DET_{k,j}$: source and destination nodes of $v_{(k,i)}$; 6) I_n and O_n: sets of instream and outstream links of node n.

Objective:

$$\text{Maximize:} \sum_{k \in G^V} Profit(G_k^V) \cdot \xi_k \tag{2}$$

Node embedding constraints:

$$\chi_{k,i}^n = 0, \text{if } DIS(n, v_{(k,i)}) > \Delta LCT_{(k,i)}, \forall k, i, n \tag{3}$$

$$\chi_{k,i}^n = \xi_k, \text{if } REQ_{(k,i)}^{TYPE} = A \,\&\, TYPE_n = OLT, \quad \forall k, i, n \tag{4}$$

$$\sum_{n \in N^S} \chi_{k,i}^n = \xi_k, \forall k, i \tag{5}$$

$$\sum_{i \in N_k^V} \chi_{k,i}^n \le \xi_k, \forall k, n \tag{6}$$

$$\sum_{n \in N^S} \psi_{k,i}^n = \xi_k \cdot REQ_{(k,i)}^{CPU}, \forall k, i \tag{7}$$

$$\sum_{k \in G^V} \sum_{i \in N_k^V} \psi_{k,i}^n \le CAP_n^{CPU}, \forall n \tag{8}$$

$$\chi_{k,i}^n = \psi_{k,i}^n / REQ_{(k,i)}^{CPU}, \forall k, i, n \tag{9}$$

Link embedding constraints:

$$\sum_{l \in I_n} \varphi_{k,j}^l - \sum_{l \in O_n} \varphi_{k,j}^l = REQ_{(k,j)}^{BNDW} \cdot (-\chi_{k,SRC_{k,j}}^n + \chi_{k,DET_{k,j}}^n), \forall k, j, n \tag{10}$$

$$\sum_{l \in I_n} \eta_{k,j}^l \le \xi_k, \forall k, j, n \tag{11}$$

$$\sum_{l \in O_n} \eta_{k,j}^l \le \xi_k, \forall k, j, n \tag{12}$$

$$\sum_{k \in G^V} \sum_{j \in L_k^V} \varphi_{k,j}^l \le CAP_l^{BNDW}, \forall l \tag{13}$$

$$\sum_{l \in L^S} \eta_{k,j}^l \le REQ_{(k,j)}^{LEN}, \forall k, j \tag{14}$$

$$\eta_{k,j}^l = \varphi_{k,j}^l / REQ_{(k,j)}^{BNDW}, \forall k, j, l \tag{15}$$

The objective in (2) targets to maximize the total profits of VNs. For virtual nodes, (3) and (4) make sure the location and type constraints are satisfied. (5) and (6) imply that each virtual node should be embedded onto only one substrate node and different nodes from the same VN are confined to be embedded onto different substrate nodes, respectively. (7) and (8) formulate the CPU demand constraint and the capacity limitation, and (9) restricts the relationship between variables. In addition, for each virtual link, the flow conservation (10), path disjointness (11) – (12), bandwidth capacity (13), path length (14) and the definition between variables (15) are defined.

4. Performance Evaluation

A simulator is developed for the virtualized FiWi access network utilizing the IBM CPLEX studio software where one OLT, 2 ONUs and 12 wireless routers are randomly deployed. The resources capacity of SN and the resources demand of VNs are listed in Table 1. Figs. 3-4 demonstrate the InP profit and VN acceptance ratio under different number of VNs respectively. Because of sufficient physical resources, the VN acceptance ratio hits 100% when the number of VNs is lower than 6 before it decreases with the increase of VN number. However, the InP profit keeps growing up when the VN number increases on account that the number of the increased accepted VNs.

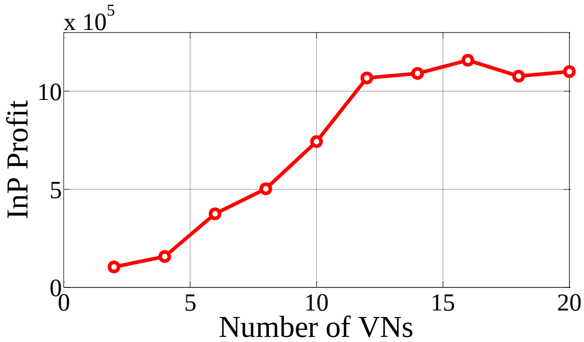

Figure 2 – InP profit

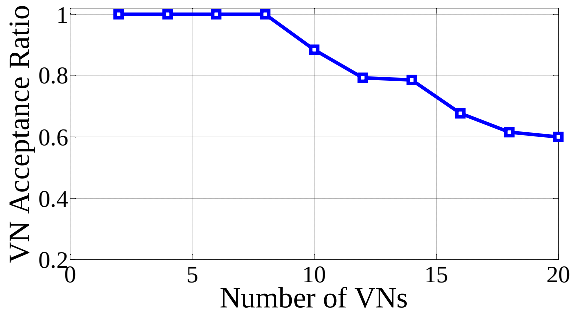

Figure 3 – VN acceptance ratio

5. Conclusion

In this paper, we formulate the VNE problem in FiWi access network to be an ILP where more comprehensive constraints are taken into account to achieve the optimal solution. Future works will highlight the network performance improvement including Quality of Service (QoS) satisfying, energy-saving and survivability guaranteeing.

References

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УДК 004

COMPUTER-AIDED DIAGNOSIS FOR PATHOLOGY IMAGE

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Abstract. *Accurate analysis for pathology image is of great importance in medical diagnosis and treatment. Specifically, nucleus detection is considered as an important prerequisite for this purpose. With the rapid development of computer-aided diagnosis, several computer-aided diagnosis (CAD) models using machine learning and deep learning have been developed fo accurate automatic nucleus detection. In this paper, we propose a nucleus detection method using two layers' sparse autoencoder (SAE) and transfer learning. First, 26832 image patches of breast cancer are utilized to train the SAE in an unsupervised learning method, which could be regarded as the feature extraction process. Then, the softmax classifier are used to classify that whether an image patch contains a complete nucleus or not. Finally, following transfer learning and sliding window techniques, we use the trained SAE and softmax models for nucleus detection on liver cancer pathology image. Experiments demonstrate that our proposed method could achieve the satisfactory detection results.*

1. Introduction

Diagnosis from pathological images remains the "gold standard" in diagnosing a number of diseases including most cancers 1. Nucleus detection is a critical step and it provides location information of each cell nuclei for further treatment. The automated detection method has become a research focus due to the fact that manual detection is time-consuming and operator subjective.

Recently, computerized nucleus detection approaches have been developed over the years with the aim to provide efficient image interpretation automatically. For example, Wang *et al.* 2