

GRAPH SIGNAL PROCESSING AND GEOMETRIC DEEP LEARNING IN OPTICAL MESH NETWORKS

A THESIS

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of

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CERTIFICATE

This is to certify that the thesis titled **Graph signal processing and geometric deep learning in optical mesh networks**, submitted by **Anurag Prakash** (2015EEZ8275), to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy**, is a bona fide record of the research work done by him under our supervision.

The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

In any optical network with a generic topology, we can measure time-series data, such as optical power and Optical Signal to Noise Ratio (OSNR), which has a Euclidean structure¹ and a global co-ordinate system². In measured network data with such properties, deep learning models can be used to predict network problems such as node failure, congestion and OSNR estimation. We propose to apply these deep learning models, or *geometric* deep learning models, to non-Euclidean geometric³ data collected at different locations on an optical network. These *geometric* deep learning [1] models are based on Graph Signal Processing (GSP). In this dissertation, we develop and apply these novel geometric deep learning models to practical problems in optical mesh networks such as, fault assessment, fault localization and OSNR estimation.

In Chapter 3, first, we review the first of these classes of geometric learning problems, where we learn the structure of the data (domain), as a low-dimensional structural embedding. To do this, we use unsupervised clustering methods to provide low-rank parametric embeddings of network activity patterns. Since optical parameters exhibit spatial and temporal locality, this embedding is based on their time-series correlation coefficients. We use spectral and hierarchical clustering[2], [3] to create clusters (with a dendrogram representation) for different network activity patterns.

Secondly, in Chapter 4, we apply graph signal processing[4]–[6] to evaluate the *spread* or *impact* of optical network failures. We treat anomalies, congestion and network faults as discontinuities in graph signals, and the effect of these discontinuities defines a blast radius. The propagation of these discontinuities across the network is a measure of network degradation. A network in which a discontinuity

¹A Euclidean Structure in a real vector space is endowed by an inner product, which is symmetric bilinear form with the additional property that $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0$ with equality $\iff \mathbf{x} = 0$.

²A co-ordinate system with the same underlying domain.

³Geometric or spatial data is a set of data in n-dimensional space, simplest of it being on a 2-dimensional surface.

or failure does not propagate (in a domino effect) is *resilient*.

Next, in Chapter 4, we develop a sequential estimation algorithm to estimate the blast radius and post-discontinuity flow distribution in the network. We use graph transforms as a measure of congestion resulting from discontinuities. We use spectrograms[7], [8] to *locate* discontinuities. These spectrograms provide us a spectrum of graph frequencies varying over irregular⁴ graph domains, using which we can *measure* congestion.

The inverse of failure propagation is failure localization, which leads to causality. We use this to localize faults in optical networks. Optical networks are a typical testbed of choice since they are hard to debug. In optical networks, the network impairments are complex and include, inter alia, fiber losses, Non-Linear Impairments (NLI)[9] and Amplified Stimulated Emission (ASE). Optical networks pose a challenge to root cause silent failures in mesh deployments, when the impairments or losses do not exceed the thresholds to trigger alerts. The physical characteristics of an optical network are closely related to the underlying geometric structure; this prompts us to explore spectrograms and *graph wavelets*[10]–[12] for failure localization.

In Chapter 5, we propose a novel way of applying graph wavelets to localize faults. Graph wavelets and spectrograms enable multi-resolution analysis in mesh networks. Further, they allow us to analyze network patterns and localize the cause(s) of a discontinuity. We propose the use of spectrograms and wavelet coefficients to identify the irregularities in an otherwise smooth graph signal. To this end, we develop a novel Wavelet Coefficient Trail (WCT) algorithm based on graph wavelets to root-cause a client signal failure⁵ or OSNR degradation in a optical network.

In Chapter 6, we use the fact that the OSNR and received optical channel power are critical parameters to determine Quality of Transmission (QoT). These two critical parameters are influenced by network impairments such as fiber-loss, ASE noise and NLI. Extending the geometric learning techniques, we use geometric deep learning techniques such as Graph Convolution neural Network (GCN)

⁴Not having translation invariance or symmetry.

⁵A transceiver’s received optical signal Pre-Forward Error Correction Bit Error Rate (Pre-FECBER) exceeds its set threshold.

for OSNR and received channel power estimation. We note that environmental effects and Routing Modulation and Spectrum Assignment (RMSA) schemes influence the OSNR and, thus, the reach (measured in number of spans) of the optical channels. These impairments and their effects vary with the spectral occupancy and are hard to predict in a brownfield networks.

Several Deep Neural Network (DNN) based methods have been explored to estimate OSNR and non-linear noise[13]–[15]. However, these methods ignore network topology. We bridge this gap by leveraging supervised GCN [16]–[21], which operates directly on graphs to estimate OSNR and the received power in an optical mesh network. In addition, we develop and implement a novel Graph Windowed neural Network (GWinN) to reduce the over smoothing effects of GCN and, thus, to learn of localized limited-impact discontinuities like fiber cuts. For a reference OSNR ranging from 16–24 dB, our proposed method accurately estimates the OSNR with a mean prediction error of -0.02 dB and a standard deviation of 0.35 dB.

In summary, we propose the application of geometric learning to optical network problems, such as fault assessment, fault localization and OSNR estimation. We illustrate the use of our proposed methods to practical optical networks, using actual network data (with permission from Ciena Labs, in Ottawa, Canada).

ABSTRACT

जेनेरिक टोपोलॉजी वाले किसी भी ऑप्टिकल नेटवर्क में, हम समय-शृंखला डेटा को माप सकते हैं, जैसे कि ऑप्टिकल पावर और OSNR, जिसमें एक यूक्लिडियन संरचना है।⁶ और एक वैश्विक सह-ऑर्डिनेट सिस्टम⁷ है। ऐसे गुणों के साथ मापा नेटवर्क डेटा में, नोड विफलता, भीड़भाड़ और OSNR अनुमान जैसी नेटवर्क समस्याओं की भविष्यवाणी करने के लिए गहन शिक्षण मॉडल का उपयोग किया जा सकता है।

हम गैर-यूक्लिडियन ज्यामितीय (ज्यामितीय या स्थानिक डेटा एन-डायमेंशनल स्पेस में डेटा का एक सेट है, जो कि 2-डायमेंशनल सतह पर सबसे सरल है।) डेटा एकत्र करने के लिए इन डीप लर्निंग मॉडल, या जियोमेट्रिक डीप लर्निंग मॉडल को लागू करने का प्रस्ताव है। एक ऑप्टिकल नेटवर्क पर विभिन्न स्थानों पर। ये ज्यामितीय गहन शिक्षण [1] मॉडल ग्राफ़ सिग्नल प्रोसेसिंग पर आधारित हैं। इस शोध प्रबंध में, हम ऑप्टिकल जाल नेटवर्क जैसे गलती मूल्यांकन, गलती स्थानीयकरण और ओएसएनआर अनुमान में व्यावहारिक समस्याओं के लिए इन उपन्यास ज्यामितीय गहन शिक्षण मॉडल विकसित और लागू करते हैं।

अध्याय 3 में, सबसे पहले, हम ज्यामितीय सीखने की समस्याओं के इन वर्गों में से पहले की समीक्षा करते हैं, जहाँ हम निम्न-आयामी संरचनात्मक एम्बेडिंग के रूप में डेटा (डोमेन) की संरचना सीखते हैं। ऐसा करने के लिए, हम नेटवर्क गतिविधि पैटर्न के निम्न-श्रेणी के पैरामीट्रिक एम्बेडिंग प्रदान करने के लिए अनुपयोगी क्लस्टरिंग विधियों का उपयोग करते हैं। चूंकि ऑप्टिकल पैरामीटर स्थानिक और लौकिक इलाके को प्रदर्शित करते हैं, इसलिए यह एम्बेडिंग उनके समय-शृंखला सहसंबंध गुणांक पर आधारित है। हम विभिन्न नेटवर्क गतिविधि पैटर्न के लिए क्लस्टर (डेंड्रोग्राम प्रतिनिधित्व के साथ) बनाने के लिए स्पेक्ट्रल और पदानुक्रमित क्लस्टरिंग [2], [3] का उपयोग करते हैं।

दूसरे, अध्याय 4 में, हम ऑप्टिकल नेटवर्क विफलताओं के फैलाव या प्रभाव का मूल्यांकन करने के लिए ग्राफ़ सिग्नल प्रोसेसिंग [4]–[6] लागू करते हैं। हम विसंगतियों, संकुलन और नेटवर्क दोषों को ग्राफ़ संकेतों में विच्छिन्नता के रूप में मानते हैं, और इन विच्छिन्नताओं का प्रभाव एक विस्फोट त्रिज्या को परिभाषित करता है। पूरे नेटवर्क में इन विच्छिन्नताओं का प्रसार नेटवर्क अवक्रमण का एक उपाय है। एक नेटवर्क जिसमें एक विच्छिन्नता या विफलता फैलती नहीं है (एक डोमिनोज़

⁶एक वास्तविक वेक्टर स्पेस में एक यूक्लिडियन संरचना एक आंतरिक उत्पाद द्वारा संपन्न होती है, जो $\langle x, x \rangle \geq 0$ की अतिरिक्त संपत्ति $\iff x = 0$ के साथ सममित द्विवेखीय रूप है।

⁷समान अंतरिहित डोमेन के साथ एक समन्वय प्रणाली।

प्रभाव में) लचनशील है।

अगला, अध्याय 4 में, हम नेटवर्क में ब्लास्ट त्रिज्या और पश्च-विच्छिन्नता प्रवाह वितरण का अनुमान लगाने के लिए एक अनुक्रमिक अनुमान एल्गोरिथम विकसित करते हैं। हम ग्राफ रूपांतरणों का उपयोग विच्छिन्नताओं के परिणामस्वरूप होने वाले संकुलन के माप के रूप में करते हैं। हम स्पेक्ट्रोग्राम [7], [8] का उपयोग पता लगाने के लिए करते हैं। ये स्पेक्ट्रोग्राम हमें ग्राफ फ्रीक्वेंसी का एक स्पेक्टरम प्रदान करते हैं जो अनियमित ⁸ ग्राफ डोमेन पर भिन्न होते हैं, जिसका उपयोग करके हम माप कंजेशन कर सकते हैं।

विफलता प्रसार का व्युत्क्रम विफलता स्थानीयकरण है, जो कार्य-कारण की ओर ले जाता है। हम इसका उपयोग ऑप्टिकल नेटवर्क में दोषों को स्थानीयकृत करने के लिए करते हैं। ऑप्टिकल नेटवर्क पसंद का एक विशिष्ट परीक्षण है क्योंकि वे डिबग करना कठिन हैं। ऑप्टिकल नेटवर्क में, नेटवर्क हानि जटिल होती है और इसमें अन्य बातों के साथ-साथ फाइबर हानि, NLI[9] और ASE शामिल हैं। ऑप्टिकल नेटवर्क मेष परिनियोजन में मूक विफलताओं को जड़ से खत्म करने के लिए एक चुनौती पेश करता है, जब हानि या नुकसान अलर्ट ट्रिगर करने के लिए थ्रेशहोल्ड से अधिक नहीं होते हैं। एक ऑप्टिकल नेटवर्क की भौतिक विशेषताएं अंतरिहित ज्यामितीय संरचना से निकटता से संबंधित हैं; यह हमें विफलता स्थानीयकरण के लिए स्पेक्ट्रोग्राम और ग्राफ वेवलेट्स[10]–[12] का पता लगाने के लिए प्रेरित करता है।

अध्याय 5 में, हम दोषों को स्थानीयकृत करने के लिए ग्राफ वेवलेट लगाने का एक नया तरीका प्रस्तावित करते हैं। ग्राफ वेवलेट्स और स्पेक्ट्रोग्राम जाल नेटवर्क में बहु-रिजॉल्यूशन विश्लेषण संक्षम करते हैं। इसके अलावा, वे हमें नेटवर्क पैटर्न का विश्लेषण करने और एक असंतोष के कारण (ओं) को स्थानीयकृत करने की अनुमति देते हैं। अन्यथा चिकनी ग्राफ सिग्नल में अनियमितताओं की पहचान करने के लिए हम स्पेक्ट्रोग्राम और वेवलेट गुणांक के उपयोग का प्रस्ताव करते हैं। इसके लिए, हम क्लाइंट सिग्नल विफलता के मूल कारण के लिए ग्राफ वेवलेट्स पर आधारित एक उपन्यास WCI एल्गोरिदम विकसित करते हैं⁹ या एक ऑप्टिकल नेटवर्क में OSNR गिरावट।

अध्याय 6 में, हम इस तथ्य का उपयोग करते हैं कि QoI निर्धारित करने के लिए OSNR और प्राप्त ऑप्टिकल चैनल पावर महत्वपूर्ण पैरामीटर हैं। ये दो महत्वपूर्ण पैरामीटर नेटवर्क हानि जैसे फाइबर-लॉस, ASE शोर और NLI से प्रभावित होते हैं। ज्यामितीय सीखने की तकनीको का विस्तार करते हुए, हम GCN for OSNR जैसी ज्यामितीय गहरी सीखने की तकनीको का उपयोग करते हैं और चैनल शक्ति अनुमान प्राप्त करते हैं। हम ध्यान दें कि पर्यावरणीय प्रभाव और RMSA योजनाएं OSNR को प्रभावित करती हैं और इस प्रकार, ऑप्टिकल चैनलों की पहुंच (विस्तार की संख्या में मापा जाता है)। ये हानियाँ और उनके प्रभाव वर्णक्रमीय अधिभोग के साथ भिन्न होते हैं

⁸ट्रांसलेशन इनवेरिएंस या समरूपता नहीं है।

⁹एक ट्रांसीवर का प्राप्त ऑप्टिकल सिग्नल Pre-FECBER इसकी निर्धारित सीमा से अधिक है।

और ब्राउनफील्ड नेटवर्क में भविष्यवाणी करना कठिन होता है।

OSNR और NLI [13]–[15] का अनुमान लगाने के लिए कई DNN आधारित विधियों का पता लगाया गया है। हालाँकि, ये विधियाँ नेटवर्क टोपोलॉजी की उपेक्षा करती हैं। हम पर्यवेक्षित GCN [16]–[21] का लाभ उठाकर इस अंतर को पाटते हैं, जो OSNR और ऑप्टिकल मेश नेटवर्क में प्राप्त शक्ति का अनुमान लगाने के लिए सीधे ग्राफ़ पर काम करता है। इसके अलावा, हम GCN के ओवरस्मूथिंग प्रभावों को कम करने के लिए एक नया GWinN विकसित और कार्यान्वित करते हैं, और इस प्रकार, स्थानीयकृत सीमित-प्रभाव विच्छेदन जैसे फाइबर कटौती के बारे में सीखते हैं। एक संदर्भ OSNR के लिए 16–24 dB से लेकर, हमारी प्रस्तावित विधि -0.02 dB की औसत भविष्यवाणी त्रुटि और 0.35 dB के मानक विचलन के साथ OSNR का सटीक अनुमान लगाती है।

सारांश में, हम ऑप्टिकल नेटवर्क समस्याओं, जैसे गलती मूल्यांकन, गलती स्थानीयकरण और OSNR अनुमान के लिए ज्यामितीय सीखने के आवेदन का प्रस्ताव करते हैं। हम वास्तविक नेटवर्क डेटा (ओटावा, कनाडा में सिएना लैब्स से अनुमति के साथ) का उपयोग करके व्यावहारिक ऑप्टिकल नेटवर्क के लिए हमारे प्रस्तावित तरीके का उपयोग करते हैं।

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ABBREVIATIONS

API Application Programming Interface	130
AIS Alarm Indication Signal	99
AWGN Additive White Gaussian Noise	8
ASE Amplified Stimulated Emission	iv
BDI Backward Defect Indication	99
BER Bit Error Rate	90
BGP Border Gateway Protocol	7
BGP-LU Border Gateway Protocol Label-Unicast	2
CNN Convolution Neural Network	17
CKWT Graph Wavelet Transform of Crovella and Kolaczyk	36
COST266 European reference network topology	64
CUT Channel Under Test	128
CWT Continuous Wavelet Transform	37
DDoS Distributed Denial-of-Service	6
DWDM Dense Wavelength Division Multiplexing	12
DM Dispersion Managed	106
DNN Deep Neural Network	v
DSP Digital Signal Processing	41
DTW Dynamic Time Warping	52
EDFA Erbium-Doped Fiber Amplifiers	xvii
ES/SES Errored Seconds/Severely Errored Seconds	101
ES Errored Seconds	15
ESD Extreme Studentized Deviate	90
ESNR Effective Signal to Noise Ratio	131
EON Elastic Optical Networks	1
GN Gaussian Noise	107
GSP Graph Signal Processing	xvi
GFT Graph Fourier Transform	17
GWT Graph Wavelet Transform	36
GCN Graph Convolution neural Network	iv
GNN Graph Neural Network	7
GWinN Graph Windowed neural Network	v
gRPC grpc Remote Procedure Calls	59
KG Knowledge Graph	7
IP Internet Protocol	16
ILA In-Line Amplifier	xvi
IGP Interior Gateway Protocol	7
KDE Kernel Density Estimate	139
LOGON Local Optimization leads to Global Optimization	8
LOS Loss Of Signal	99
LP Light Path	xvi

LPF Low Pass Filter	64
LSTM Long Short-Term Memory	8
LVS Localized Vertex Spectrum	33
ML Machine Learning	5
MTTR Mean Time To Restore	10
MTTF Mean Time To Failure	60
MPLS Multi-Protocol Label Switching	2
MRA Multi-Resolution Analysis	x
MRA Multi-Resolution Analysis	x
MSE Mean Square Error	120
NLI Non-Linear Impairments	iv
NN Neural Network	8
NP Nondeterministic Polynomial-time	23
NMS Network Management System	xvii
OCh Optical Channel	16
OLF Optical Line Failure	99
ORL Optical Return Loss	99
ODU Optical Data Unit	2
ODU-j Optical channel Data Unit-j	88
ODU-k Optical channel Data Unit-k	88
OTU-k Optical channel Transport Unit-k	88
OTM Optical Transport Module	88
OTN Optical Transport Network	2
OM Operational Measurement	15
OPU Optical channel Payload Units	88
OLS Open Line System	9
ONSR Optical Noise to Signal Ratio	8
OSNR Optical Signal to Noise Ratio	iii
OSA Optical Spectrum Analyzer	7
OTN Optical Transport Network	2
PC Principal Components	xvi
PCA Principal Component Analysis	xvi
PM Performance Measurement	15
PM-QPSK Polarization-Multiplexed Quadrature Phase-Shift Keying . .	107
Pre-FECBER Pre-Forward Error Correction Bit Error Rate	iv
PSD Power Spectral Density	xvii
ReLU Rectified Linear activation	xxii
ROADM Re-configurable Optical Add-Drop Multiplexer	xvi
RMSA Routing Modulation and Spectrum Assignmment	v
RNN recurrent neural networks	38
QoT Quality of Transmission	iv
SES Severely Errored Seconds	15
SOP State Of Polarization	13
STFT Short Time Fourier Transform	32
SVM Support Vector Machine	8
SDN Software Defined Networking	xii
SLA Service Level Agreement	15
SNR Signal to Noise Ratio	131
SPF Shortest Path First	62
SR Segment Routing	2
SVM Support Vector Machines	8

TCA Threshold Crossing Alert	15
USNET US reference network topology	xv
WCT Wavelet Coefficient Trail	iv
WDM Wavelength Division Multiplexing	119
WL Weisfeiler-Lehman	117
XPM Cross Phase Modulation	107

NOTATION

$\mathcal{G} = (\mathcal{V}, \mathcal{E})$	Graph $\mathcal{G}$ with vertices in $\mathcal{V}$ and edges in $\mathcal{E}$
$\mathcal{C}_k$	k -clusters of vertices
d_i	Degree (weight) sum of vertex v_i
$Vol(\mathcal{U})$	Volume of subset $\mathcal{U}$
$d(A, B)$	Distance between vertex groups
$\rho_{X,Y}$	Pearson correlation coefficient for random variables X and Y
σ_X	Standard deviation for random variable X
μ_X	Mean for random variable X
$\mathcal{N}_i$	Neighborhood of node i
W	Graph adjacency matrix
D	Graph degree sum diagonal matrix
E	Graph Laplacian quadratic norm
L	Graph Laplacian for graph $\mathcal{G}$
u	Graph Laplacian eigenvector
U	Matrix with graph Laplacian eigenvector as columns
λ	Graph Laplacian eigenvalue
$T_k(x)$	Chebyshev polynomial approximations of order k
r_i	Rx power on span i
f_i	Network flow graph signal on node i
$\hat{r}(\lambda_l)$	GFT corresponding to λ_l
r	Network received power vector
$\mathbb{Z}_{\mathcal{G}}$	Number of zero-crossings
$\mathcal{S}_r(m, k)$	Graph window transform centered at vertex v_m
D	LVS (Local Vertex Spectrum) window width
$\mathcal{D}$	Dictionary of time-frequency atoms
$h_m(n)$	Windowing function
$\mathcal{N}_{\mathbf{D}}$	Neighbourhood window function at D hops
P_S	Energy density(spectrogram)
$\Phi(m)$	Wavelet function centered on vertex m
W_i	Wavelet coefficient
W'_i	Wavelet coefficient time differential
Rx_i	Received power on an optical span i
Tx_i	Transmit power on an optical span i
FL_i	Fiber Loss on an optical span i
$\sigma(\cdot)$	Sigmoid or Rectified Linear activation (ReLU) non-linear activation function
$\mu(\cdot)$	Pooling function