InSAR Image Coherence using Super Pixel and Graph Networks

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***Abstract*—Interferometric Synthetic Aperture Radar (InSAR) is a satellite-based imaging technique which has been used to learn about earth's surface and sub-surface movements. It can measure earths displacements by comparing phase information from the SAR images taken at different points in time. But, due to high level of noises, the wrapped phases are distorted, because of which, it cannot be used for its intended purposes. Understanding the coherence of the images becomes rather important in this situation to denoise the image and extract useful information from it.**

In our project, we focus on applying Super Pixeling using both traditional Computer Vision methods as well as Graph Neural Networks to understand how better we can estimate image coherence between two SAR images. By applying Super pixeling in two stages, using specific clustering techniques, we would be able to expose non-local similarities and measure the coherence from a non-local perspective.

***Index Terms*—Image Coherence, Super Pixels, Graph Neural Networks, SAR Interferometry, InSAR**

I. Introduction

The advent of satellite imaging has empowered the researchers to capture the ground images from a bird-eye view and interpret the details using computer vision techniques for nuances difficult to discern just with human eyes. Enumerating the different types of images which modern satellites can capture, Synthetic Aperture Radar (SAR), or SAR, is a coherent mostly airborne or space-borne side-looking radar system which utilizes the flight path of the platform to simulate an extremely large antenna or aperture electronically, and that generates high-resolution remote sensing imagery.

The data is captured and stored electronically with every transmission/ receive cycle of the radar. To be specific, the elements of variable aperture reflect the signal in their own characteristic ways and the Time of Flight (ToF), phase and amplitude of every pulse are processed using image processing techniques to create a high-resolution image of the target terrain.

The SAR interferometry technique uses two SAR images of the same area acquired at different times and "interferes" (differences) them, resulting in maps called interferograms. Interpolating the coherence between multiple captured interferograms can help the scientists understand ground-surface displacement (range change) between the two time periods.

II. Problem Statement

Albeit the interferogram coherence has multiple applications ranging from ground-displacement measure to volcanic surface deformation, the underlying processing techniques suffer a major hurdle of denoising the employed SAR images that are used to develop interferogram. This noise can occur due to doppler effects, [2] baseline measurement errors, and even the surface reflectance properties of target terrain that can induce aberrant signals. Henceforth, the research community condenses its focus towards articulating the fine-tuned coherence estimation methods and algorithms that can be utilized for constructive applications.

III. Objectives

The project focuses on novel methods of estimating the coherence between SAR image pairs as close as possible to the actual image coherence (ground truth). Once the coherence is calculated, it can be used to study the multivariate information available in the SAR pixels and separate them into individual components viz-a-viz motion of scatterer, the altitude of scatterer, atmospheric pressure, temperature and much more.

IV. Proposed Method

Since the estimation of coherence from the interferograms involves understanding the minuscule correlation between the constituent pixels of the images and comprehend the information out of it, investigating the concept of super-pixel is preferable. The two folded attempt to investigate the problem using the methods of computer vision and recently proclaimed graph driven networks. To surmise, a study to discriminate the performance of both the employed approaches by measuring the errors between estimated coherence and actual coherence will gauge the performance and novelty.

A. Approach 1- "Superpixeling"

In this approach, computer vision techniques can be employed for image coherence estimation. Initially, the constituent pixels of each of the SAR images pair will be cluster into superpixels which would group the pixels based on their distance and similarity. This approach is used as opposed to blocking matching technique in BMINSAR [1] , as it generates the clusters which are not dependent on the window size of the

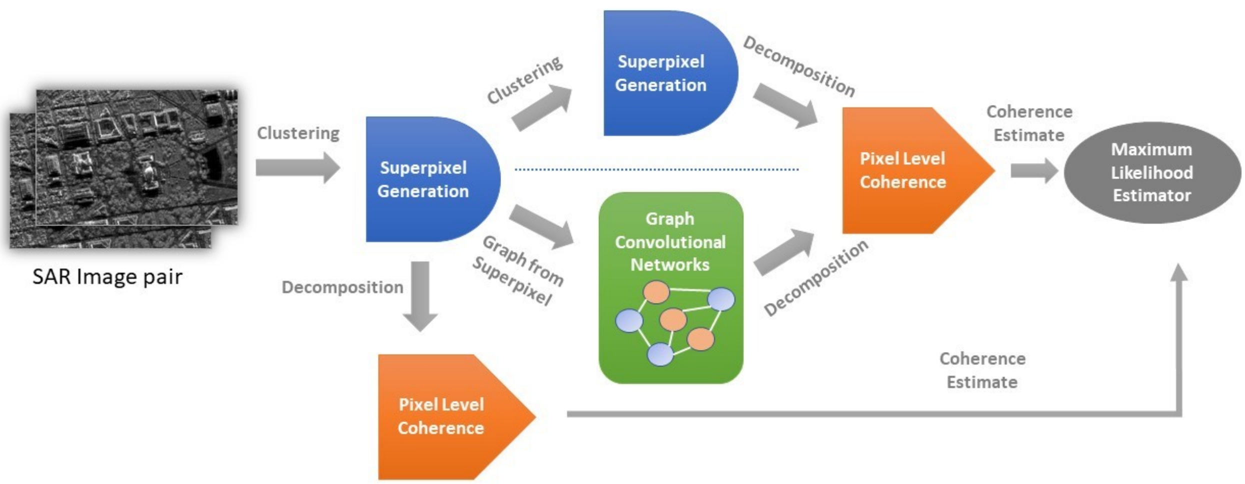

Fig. 1. The complete pipeline of the proposed approach

block but rather based on the location and similarity of pixels. Superpixels [3] would also preserve the relative dependence of the pixels.

In contrast to the traditional clustering techniques, the caveat in this application is that the generation of superpixels are complex as the values represented by pixels are complex numbers. Hence, the features used to cluster the pixels are different from that of digital images, which would ideally use color channels or pixel intensities. In the case of SAR images, different feature vectors namely,

1) Cosine difference of real and imaginary components,
2) Euclidean distance between two points on an XY plane with the real and imaginary components as the axes, and
3) the absolute value of the exponential of the phase difference between two SAR images to cluster the pixels can be employed.

After the initial superpixel(cluster) generation, the intra-cluster pixels are closely correlated, but there will be inter-cluster pixels which can also be closely correlated to each other. This would potentially limit our next steps in estimating the image coherence as it would suffer from not capturing the non-local coherence. Hence, addition of a second level of clustering the superpixels generated from the first stage that results in highway superpixels, which would essentially capture non-local coherence must be considered.

At the end of each stage of clustering, the coherence estimates will be decomposed to the pixel level in order to identify the difference between estimated and actual coherence using the Maximum likelihood estimator of the coherence magnitude over an estimation window of given pixels. It is calculated by the given formula:

$$\delta_L = \frac{\sum_{i=1}^{L} z_1^{(i)} z_2^{*(i)}}{\sqrt{\sum_{i=1}^{L} \left|z_1^{(i)}\right|^2 \left|z_2^{(i)}\right|^2}} \tag{1}$$

where z_1 and z_2 are the two zero-mean circular Gaussian variables representing the SAR image pair. For this approach,an assumption is made that the observations of the smaller regions will be stationery.

B. *Approach 2- "Graph Networks"*

In this approach, recent development of neural networks called Graph Convolutional Network, which generalizes the concept of neurons driven learning to the graph domain. GCN [4] is unique on its own as it can capture the spatial relationship between the nodes.

The initial stage of the superpixel generation will be common to both approaches. Once the superpixels are generated, they will be assigned a node inside the graph. This graph will serve as an input for the GCN that will learn the spatial relationship between the nodes of the graph. The output of GCN would be the coherence estimate on a superpixel level, which should then be decomposed into pixel level to calculate the difference from the actual image coherence.

C. *Dataset*

The dataset is the simulated SAR image pairs from the Multimedia Research Centre at the University of Alberta. For the first approach, a single SAR image pair will be elected to estimate the coherence. For the second approach, a rather large column of data will be required that can acquired from this archive.

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