AUTOMATIC CONTRAIL DETECTION AND SEGMENTATION IN POLAR-ORBITER SATELLITE IMAGES

A Thesis in
Electrical Engineering

by

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ABSTRACT

Contrails are important in local to regional scale climate change. Various studies to date have found circumstantial evidence linking contrails with modifications in surface temperature (e.g., in the eastern U.S. and parts of Europe). It is clearly important to understand what a contrail is and where and when contrails occur to more definitively relate their occurrence to surface climate. The use of surface observations for developing contrail climatology is problematic, owing to the occurrence of intervening cloud layers.

Accordingly, satellite images have been used to identify and map contrails, mostly from manual (subjective) interpretation of images, although some automated (quantitative) approaches have been developed but whose success is variable and dependent on a number of factors (Cirrus clouds, curved contrails, complexity of algorithm, etc.) Detecting contrails, therefore, is critical in understanding the atmospheric effects of aviation.

This research involves the automatic detection of jet contrails in Advanced Very High Resolution Radiometer (AVHRR) imagery with a high degree of confidence and its segmentation written in MATLAB programming language. Contrails are characterized as thin, nearly straight linear features of higher intensity than the background. Contrails possess another highly characteristic feature; they tend to create straight lines in satellite images. Due to the large volume of satellite imagery, selecting contrail images for study by hand is impractical and highly subject to human error. It is far better to have a system in place that will automatically evaluate an image to determine whether it contains contrails and where. This research develops and tests two new and easier quantitative approaches to find contrails in satellite image data, for a variety of atmospheric and cloud conditions (e.g., clear-skies, partly cloudy skies; cloudy skies).
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Chapter 1

Introduction

Contrails are important in local to regional scale climate change. Various studies to date have found circumstantial evidence linking contrails with modifications in surface temperature (e.g., in the eastern U.S. and parts of Europe). It is clearly important to understand what a contrail is and where and when contrails occur to more definitively relate their occurrence to surface climate. The use of surface observations for developing contrail climatology is problematic, owing to the occurrence of intervening cloud layers. Accordingly, satellite images have been used to identify and map contrails, mostly from manual (subjective) interpretation of images, although some automated (quantitative) approaches have been developed but whose success is variable and dependent on a number of factors (cirrus clouds, non-linear contrails, complexity of algorithm, etc). Detecting contrails, therefore, is critical in understanding the atmospheric effects of aviation. This research develops and tests two new and easier quantitative approaches to find contrails in satellite image data, for a variety of atmospheric and cloud conditions (e.g., clear-skies, partly cloudy skies; cloudy skies). This is the research problem undertaken in this thesis.

1.1 What is a Contrail?

Contrails are thin line-shaped ice clouds that can develop in the wake of an aircraft’s engines. These artificial clouds are the visible sublimate of water vapor around combustion products, primarily soot (Figure 1-1, 1-2). Contrails were first observed during high-altitude flights in the 1920s, and the national air forces developed interest in not causing them because they enhanced the visibility of their planes. The formation of contrails underlies many physical processes, such as chemical reactions in the aircraft plume, aircraft wake dynamics, ice
microphysics, the state of the atmosphere within the flight corridors, atmospheric dispersion rates and engine technology.

Figure 1-1. Ground based photograph of contrails of different ages. (NASA-The Contrail Education Project; http://science-edu.larc.nasa.gov/contrail-edu/contrails-mixed.php)

Figure 1-2. Ground based photograph of contrail cirrus cloud
1.2 Why scientifically study Contrails?

Contrails can add a significant amount of high-level thin cloudiness over high-traffic areas (Seaver and Lee, 1987), and this additional cirrostratus may lead to higher surface temperatures on a diurnally-averaged basis (Liou, 1986) as the overnight minimum temperature is raised higher than the daytime maximum temperature is reduced (i.e., the diurnal temperature range—DTR-- is suppressed). Thus, contrails may influence recent climate change in regions characterized by considerable jet air traffic.

Depending on the ambient atmospheric conditions, contrails can either evaporate shortly after formation, or persist for time periods of up to several hours. These persisting contrails spread laterally and thin vertically, enhancing their potential effects on surface climate. On average, the backscattering of terrestrial radiation by the contrail’s ice crystals is more effective than the reflection of solar radiation, creating a net positive radiative forcing. First concerns regarding air-traffic effects on the climate were made by Appleman (1953). The announced introduction of a large fleet of supersonic transport aircraft in the 1970s, which never eventuated, initiated first studies of the effect of air-traffic on cirrus formation and clouds. Later, this topic was picked up by Changnon (1981). This author concluded that an increase in cloudiness and decrease in sunshine duration for the Midwest U.S.A. provided circumstantial evidence for a jet-induced cirrus influence.

The potential effects of contrails on the climate subsequently were discussed by Schumann and Wendling (1990), who identified that the infrared heating or cooling rate magnitude within the cirrus clouds was typically a factor of two larger than that induced by water vapor in a 5 km thick layer near the tropopause.
The emissions from subsonic aircraft, which fly at an altitude between 8 and 13 km, and include NOx, CO2, CO, HC, soot, and water vapor, lead to contrail and aerosol formation. Pitchford et al. (1991) argue that if the upper tropospheric and lower stratospheric (UT/LS) buildup of exhaust emissions continues to increase, photochemical reactions and surface changes of these particles could enhance the cloud condensation nuclei (CCN) formation. This would lead to enhanced opacity of cirrus clouds formed from such conditions. However, Pitchford et al. do not go as far in their statements regarding the contrails’ potential to lead to increased precipitation.

Sausen et al. (1998) presented first estimates regarding global contrail coverage (the global potential contrail coverage was calculated to be 16%). and these estimates were included in an Intergovernmental Panel on Climate Change (IPCC) special report on aviation impacts on the atmosphere. They concluded that the global and annual mean potential contrail coverage was 16% for the layer between 100 and 500hPa. The maximum cover was about 5% over Eastern USA, with the annual global mean value being 0.09%. Since then, a relatively large number of studies have been performed to understand formation mechanisms of contrails and their potential impact on the global climate (Penner et al., 1999).
Following the tragic events of 11 September 2001, the airspace over the USA was closed to commercial and personal air-traffic for about 72 hours, resulting in the absence of contrails over the USA. Although contrails likely have a heating effect on the atmosphere on a global scale, as noted earlier they lower near-surface temperatures during daytime and raise nighttime temperatures (Ponater et al., 2002), thereby reducing the average DTR. Travis et al. (2002) determined the U.S.-average DTR for the periods 8-11, 11-14 and 14-17 September 2001, and calculated its departure from the climatological values for 1971-2000 (Figure 1-3) The increase in the average departure of DTR during 11-14 September 2001 is larger than at any comparable time in the previous 30 years, and suggested the influence of contrails. Subsequently, Travis et al.
(2004) determined the regional dependence of the DTR anomalies for the 11-14 September 2001 aviation grounding, and showed that these were greatest in areas typically seeing high frequencies of contrails. Model simulations were carried out by Minnis et al. (2003) to explain the temperature anomaly caused by coverage of linear contrails and also taking into account their lateral spreading. The surface-based cloud data consist of quality-controlled surface synoptic weather reports from land stations and ships. Minnis suggested to improve the calculation for more accurate results. Better measurements of UTH, cloud distributions, and contrail properties, and more precise specification of flight paths and improved parameterizations of cirrus and contrail formation in GCMs were needed to more rigorously determine the contrail climate impacts. Minnis’ study indicated that contrails already have substantial regional effects where air traffic is heavy. As air travel continues growing in other areas, the impact may become globally significant.

Results of general circulation model simulations suggest that the annually and globally averaged total contrail cover and the associated radiative forcing should approximately quadruple during the next six decades due to the increased air-traffic, especially in Asia (Marquart et al., 2002). If these predictions are realized, contrail impacts on climate will increase from being a largely regional to hemispheric-scale phenomenon.

The radiation and energy budgets of the earth-atmosphere system are in balance between the incoming solar energy (insolation) and the outgoing longwave radiation. The insolation is attenuated by clouds, aerosols, and other particles in the atmosphere, and the outgoing longwave radiation is absorbed and reemitted by gases and these particulates. With increasing trace gas emissions from anthropogenic sources, especially CO2 and CH4, there is a growing concern about greenhouse warming and possible climate change implications. As contrails become a larger-scale phenomenon in the coming decades, their influence is likely to exacerbate the warming due to greenhouse gases.
Lee et al (2009) show that the radiative forcing of surface temperature is about 30 times more sensitive to aircraft emissions of nitrous oxides than to surface emissions alone. As an important subset of thin cirrus clouds, jet contrails are considered to enhance the greenhouse effect due to their semitransparent nature.

It is clear that the study of jet contrails is of major importance to a wide range of disciplines, from military planners to climate researchers. Contrails act as tracers that may serve as potential intelligence to military planners. In terms of atmospheric effects, climate researchers are interested in contrail radiative effects and their role in trends of cloud cover (Carleton et al. 2013) and near-surface temperature.

Contrails are clearly a very important phenomenon. It is critical that their occurrence (when and where) be known and determined accurately. Space-based (i.e., satellite) detection of contrails is considered more reliable than surface-based observations, owing to the spatially inhomogeneous observing network of the latter, and the impact of intervening layers of cloud that biases contrail detection towards partly cloudy or clear skies.
Chapter 2

Background

2.1 Detection and Analysis of Contrails

In addition to their climatic significance, contrails may mask important landscape information in a satellite image. The optically thin character of persisting contrails complicates their detection, yet they may still influence the satellite-based retrieval of upwelling longwave radiation, thereby biasing determination of surface temperature. Also, it is difficult to detect a single contrail in a satellite image because it is thin and the associated grey-scale pixel values are similar to the background. Moreover, as a contrail ages, the change in shape due to the influences of wind and atmospheric dissipation, further complicates its detection in satellite data.

Early work on contrail detection mostly involved their visual identification from pattern recognition of line-shaped, cold cloud signatures in satellite thermal infrared (TIR) images. For example, DeGrand et al. (1991) applied hardcopy images of high-resolution Defense Meteorological Satellite Program (DMSP) data to identify contrails. Their study built upon that of Carleton and Lamb (1986), which utilized DMSP-OLS with a spatial resolution of 600 x 600 m, to detect contrails manually. Bakan (1994) used a similar visual inspection method for AVHRR images to map contrail coverage over Europe and the North Atlantic. Degrand et al. (2000) applied the manually-interpreted contrails on 3-years’ (1977-79) DMSP TIR satellite images over the United States to develop a spatial climatology of contrail occurrence. Travis (1996) determined statistics on the width and length of contrails using visual interpretation. He determined an average width of 2.9 km and an average length of 137km. These satellite-image manual inspection methods for contrails, while superior to surface-based observations, are
subjective, time consuming, and mostly consider contrails in partly cloudy or otherwise clear-sky conditions.

To overcome the limitations of manual detection methods for contrails, researchers attempted to develop automatic (computer-based) algorithms to detect contrails in satellite image data. Lee’s (1989) method, applied to AVHRR images, used the TIR brightness temperature difference in channels 4 and 5. Building upon this radiance differencing method, Engelstad et al (1992) developed pattern recognition algorithms to detect linear (i.e., relatively young) contrails. The algorithms made use of ridge detection and Hough transform. Ridge detection differentiates ridge pixel of the contrail from background pixels, and Hough transform is applied to detect straight lines among these ridge pixels. The Engelstad et al. algorithms gave some inaccurate results because of the spurious contrail detection arising from linear streaks of natural cirrus which are also often associated. Forkert et al. (1993) used a similar approach, but their method could sometimes misinterpret linear features such as coastlines, valleys and cloud edges as contrails. Weiss (1998) improved the ridge detection and Hough transform algorithms with the help of width-related searches, to create contrail-enhanced images that aid in the detection process. When contrails are young, they are also quite narrow, thus the Weiss (1998) searching method proved to be efficient and largely overcame the false detection problems. The author, however, did not attempt the method on aged and wider contrails.

More recently, neural networks have been applied to contrail detection by Meinert et al. (1994, 1997). In information technology, a neural network is a system of programs and data structures that approximates the operation of the human brain. A neural network usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access to data in its local memory. Typically, a neural network is initially "trained" or fed large amounts of data and rules about data. A program can then tell the network how to behave in response to an external stimulus or can initiate activity on its own (within the limits of its access
to the external world). In making determinations, neural networks use several principles, including gradient-based training, fuzzy logic, genetic algorithms, and Bayesian methods. Meinert et al. (1994) trained a neural network to classify contrails by use of the AVHRR thermal split-window channels. However, the application of this method was too time and effort intensive to acquire suitable samples and involved substantial amounts of data. Moreover, the neural network model required a large computational time for acceptable detection results. To obtain good results a huge set of well-chosen, pixel-precise training samples was needed. These had to represent the full variability of contrail occurrences in AVHRR data to be operational. Furthermore, good contrail detection needs a large number of input neurons resulting in long training cycles. Finally, the amount of the needed training was estimated to be beyond the limits of feasibility (Meinert et al. 1997).

Mannstein et al. (1999) introduced a contrail detection method to detect linear (i.e., young) contrail features by using scene-invariant threshold and binary masks. Fixed thresholds could be used, because the images were normalized. Their algorithm was capable of the fast operational detection of persistent and roughly linearly-shaped contrails from the AVHRR channels 4 and 5. The scheme was relatively robust to misdetections of other linear structures in thermal images such as coastlines, mountain ridges and valleys, or sensor line failures. However, a drawback of this method was that the masks were sometimes insufficient to remove all non-contrail edge features, leading to underestimation of contrail occurrence. Recent studies have incorporated Mannstein et al.’s automated algorithm to detect contrails and develop regional short-period climatology of contrails. For example, Palikonda et al. (2001) identified contrails over various regions of the United States in AVHRR and MODIS images using this approach indicating a maximum value of 2.0% over southeastern states, New Mexico, west Texas, and Alberta, Canada with minima or 0.2% over western Colorado and the Atlantic Ocean.
Meyer et al. (2007) detected contrails over Thailand and Japan using 400 NOAA-14 satellite scenes from four months of the year 1998. Hetzheim (2007) proposed a complex approach to detect contrails using mathematical methods of texture or contrail stochastic behaviors. The solutions obtained were given as sequential procedures using grey values of neighboring pixels, though it was very time consuming. Although these mathematical methods may better distinguish contrails from the surface and lower cloud background of the satellite images, they are very time consuming with respect to the creation of samples to “train” the algorithm and the time it takes to run them on a computer. More recently, Zhang et al (2012) proposed an object-based classification method, which tries to overcome the limitations of the pixel-based methods by combining both spatial and spectral information into the classification process. The method takes advantage of using other supplemental information besides spectral brightness to differentiate contrail pixels from non-contrail pixels. However, the classifier used in this paper is a fuzzy nearest neighbor classifier, which looks like a “black-box”. Given the number of the dimensions in the feature space, though the feature space could be optimized, users do not know the mechanism that differentiates an object into a certain class; one cannot control the classification process. In addition, the choices of the training samples usually have to be repeated many times to be decided. This restricts the automation of contrail detection using the object-based method. It is also difficult to prevent overfitting. Overfitting occurs when a statistical model describes random error or noise instead of the underlying relationship. Overfitting generally occurs when a model is excessively complex, such as having too many parameters relative to the number of observations. A model which has been overfit will generally have poor predictive performance, as it can exaggerate minor fluctuations in the data.
2.2 Thesis Overview

Accordingly, in this research I develop and test two pixel-based methods to detect contrails from satellite images. The advantage of these methods is that they offer simple, quick and efficient ways to detect contrails, to obtain their coordinates in latitude-longitude format, and identify characteristics of the contrail, including but not restricted to its width, length, and age.

The first method makes use of phase congruency to detect edges and Hough transform to detect straight line contrails. Curved-contrails can be detected, on shorter (less than 10 pixels) contrails. This is an improvement over previous Hough transform based methods. The second method makes use of spatial derivatives along both x and y axes to identify possible contrail candidates and then use binary morphological operations to detect contrails. Using spatial derivatives eliminates most cirrus clouds and non-contrail background details.
Chapter 3

Data Type and Format

3.1 Data Type and Format: NOAA Advanced Very High Resolution Radiometer (AVHRR) images

The AVHRR is a multi-spectral radiation-detection imager that can be used for remotely determining cloud cover and the surface temperature. The term surface can mean the surface of the Earth, the upper surfaces of clouds, or the surface of a body of water. This scanning radiometer uses 6 detectors that collect bands of radiation wavelengths ranging from the visible to the thermal infrared, as shown below (Table 3-1).

Table 3-1. AVHRR/3 Channel Characteristics NOAA Satellite Information System Website (http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html)

<table>
<thead>
<tr>
<th>Channel Number</th>
<th>Resolution at Nadir</th>
<th>Wavelength (um)</th>
<th>Typical Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.09 km</td>
<td>0.58 - 0.68</td>
<td>Daytime cloud and surface mapping</td>
</tr>
<tr>
<td>2</td>
<td>1.09 km</td>
<td>0.725 - 1.00</td>
<td>Land-water boundaries</td>
</tr>
<tr>
<td>3A</td>
<td>1.09 km</td>
<td>1.58 - 1.64</td>
<td>Snow and ice detection</td>
</tr>
<tr>
<td>3B</td>
<td>1.09 km</td>
<td>3.55 - 3.93</td>
<td>Night cloud mapping, sea surface temperature</td>
</tr>
<tr>
<td>4</td>
<td>1.09 km</td>
<td>10.30 - 11.30</td>
<td>Night cloud mapping, sea surface temperature</td>
</tr>
<tr>
<td>5</td>
<td>1.09 km</td>
<td>11.50 - 12.50</td>
<td>Sea surface temperature</td>
</tr>
</tbody>
</table>
Although AVHRR/3 is a six channel radiometer, only five channels are transmitted to the ground at any given time. AVHRR images have 1.1km nadir point pixel resolution, and are the primary input used for contrail detection in this study. I obtained the data from the online Comprehensive Large Array-Data Stewardship System (CLASS) of the National Oceanic and Atmospheric Administration (NOAA) (www.nsof.class.noaa.gov). To ensure maximum resolution, only the High Resolution Picture Transmission (HRPT) data were obtained from within the broader AVHRR archive.

3.2 Image Pre-processing

The AVHRR/3 provides three solar channels; in the visible and near infrared region; and three thermal infrared channels. Jet contrails are the most difficult to detect in band 3 of the thermal infrared band). Due to smaller crystal sizes, especially young contrails (Gayet et al. 1996) tend to show higher transmissivity in the AVHRR-channel 4 (10.3± 11.3 mm) than in channel 5 (11.5± 12.5 mm), compared to natural cirrus (Betancor-Gothe and Grassl 1993). This often causes contrails to appear brighter on channel 4 - channel 5 temperature difference images. The contrail features become indistinct in the visible red band (band one) and near-infrared band (band two), having similar radiance characteristics to the background in these two bands. Contrails exhibit the most difference in radiance characteristics from the background in thermal infrared bands four and five.

In the AVHRR/3 an instantaneous field of view (1.3 milliradians by 1.3 milliradians) is scanned across the earth from one horizon to the other by continuous 360 degree rotation of a flat scanning mirror. The scan lines are perpendicular to the spacecraft orbit track (i.e., image swath), and the speed of rotation of the scan mirror is selected so that adjacent scan lines are contiguous at the subsatellite (nadir) position. Complete strip maps of the earth from pole to pole are thus
obtained as the spacecraft travels at an altitude of approximately 833 km (450 n. miles). A total of 2048 samples are obtained per channel per Earth scan, each of which spans an angle of ±55.4 degrees from the nadir (subpoint view). The six spectral channels of the AVHRR/3 are registered so that they all measure energy simultaneously (i.e., from the same spot on the earth at the same time). All six channels are calibrated so that the signal amplitude in each channel is a measure of the scene radiance.

3.3 AVHRR images and subsamples used

AVHRR images from April and October 2007 have been used. The list of images is shown in Table 3-2. The date/time details and the extent of each image in longitude-latitude format is also shown in the Table. Each of these images are sampled into smaller sub-images. These sub-images are chosen such that they contain visible contrails, ranging from one to multiple contrails in each sample. (Source: NOAA KLM User's Guide. (http://www.ncdc.noaa.gov/oa/podguide/ncdc/docs/klm/html/c3/sec3-1.htm))
Table 3-2. List of the AVHRR images

<table>
<thead>
<tr>
<th>ID</th>
<th>Date and Time</th>
<th>Extent</th>
<th>Scenario Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>8484</td>
<td>04/01/2007 S: 23 hours 20 mins E: 23 hours 10 mins</td>
<td>53° 52’ N - 120° 7’ W to 21° 41’ N - 90° 34’ W</td>
<td>3 subsamples, each with one long contrail</td>
</tr>
<tr>
<td>4040</td>
<td>04/05/2007 S: 16 hours 07 mins E: 16 hours 19 mins</td>
<td>55° 30’ N - 110° 3’ W to 21° 44’ N - 76° 40’ W</td>
<td>6 subsamples, all containing many short contrails</td>
</tr>
<tr>
<td>8585</td>
<td>04/14/2007 S: 09 hours 20 mins E: 09 hours 30 mins</td>
<td>56° 32’ N - 135° 41’ W to 21° 04’ N - 103° 45’ W</td>
<td>1 subsample, interconnected contrail</td>
</tr>
<tr>
<td>3939</td>
<td>04/19/2007 S: 15 hours 45 mins E: 15 hours 56 mins</td>
<td>51° 29’ N - 98° 21’ W to 21° 13’ N - 70° 54’ W</td>
<td>3 subsamples</td>
</tr>
<tr>
<td>5454</td>
<td>04/20/2007 S: 17 hours 00 mins E: 17 hours 11 mins</td>
<td>56° 52’ N - 119° 40’ W to 24° 52’ N - 89° 05’ W</td>
<td>2 subsamples, each with many contrails</td>
</tr>
<tr>
<td>8282</td>
<td>10/15/2007 S: 12 hours 03 mins E: 12 hours 13 mins</td>
<td>53° 32’ N - 118° 16’ W to 25° 49’ N - 89° 13’ W</td>
<td>4 subsamples, each with many contrails</td>
</tr>
<tr>
<td>2424</td>
<td>10/18/2007 S: 10 hours 50 mins E: 11 hours 04 mins</td>
<td>50° 35’ N - 103° 26’ W to 14° 42’ N - 74° 45’ W</td>
<td>4 subsamples, each with many contrails (partly cloudy)</td>
</tr>
<tr>
<td>4444</td>
<td>10/26/2007 S: 17 hours 39 mins E: 17 hours 51 mins</td>
<td>53° 00’ N - 132° 21’ W to 15° 03’ N - 103° 18’ W</td>
<td>4 subsamples, each with many contrails</td>
</tr>
</tbody>
</table>

S – Start Time, E – End Time

These samples were initially used to test the different cases (e.g., clear-skies, partly cloudy skies; cloudy skies) and various contrail frequencies (no contrail, one contrail, multiple contrails). Various parameters and thresholds were set based on the outputs from these test cases.

The final algorithm was later tested on all 30 samples, one sample per day for the month of April 2007. Each image of size roughly 3500 x 2000 pixels were divided into 3360- 256x256 and 840- 512x512 size images and were tested for different cases (Section 6.3)
The samples used in the thesis cover most parts of North America, mostly USA. The longitude-latitude details shown (Figure 3-1) indicate the areas covered by each sample.
Chapter 4

Phase – Hough Method

First Method of contrail identification and classification: Phase congruency and Hough transform

This chapter discusses the first method I used for contrail detection. In Section 4.1 the phase congruency method to detect edges is discussed. Section 4.2 discusses binary morphological operations used to clean out the image. This includes removing noise, small non-linear clouds, etc. Next, Section 4.3 discusses the Hough transform which is used to detect the linear contrails. Last, Section 4.4 explains the method to identify the endpoint of each contrail and retrieve its coordinates in latitude-longitude format, as well as ways to detect contrail length and width.

Section 4.1: Phase Congruency edge detection

Phase congruency is an illumination and contrast invariant measure of feature significance. Unlike gradient-based feature detectors, which can only detect step features having a phase angle of 0 or 180 degrees, phase congruency correctly detects features over all phase angles. Phase congruency reflects the behavior of the image in the frequency domain. Phase congruency is a dimensionless quantity that is invariant to changes in image brightness or contrast; hence, it provides an absolute measure of the significance of feature points, thus allowing the use of universal threshold values that can be applied over wide classes of images. It has been noted that edge-like features have many of their frequency components in the same phase (Kovesi 1991, 1999). Hence its significance in satellite images, as it can be used to detect edges irrespective of the background.
Phase congruency provides a way of identifying features within images. By combining phase congruency information over multiple orientations into a covariance matrix, and calculating the minimum and maximum moments a highly localized operator that can be used to identify both edges and corners in a contrast invariant way is produced (Kovesi 1999). The contrast invariance facilitates the tracking of features over extended image sequences under varying lighting conditions. An additional advantage of the operator is that the phase congruency corner map is a strict subset of the phase congruency edge map. This simplifies the integration of data computed from edge and corner information.

Phase congruency is derived by frequency domain considerations operating on the considerations of phase (i.e. time). It is illustrated detecting some 1D features in Figure 4-1, where the features are the solid lines: a (noisy) step function in Figure 4-1(a), and a peak (or impulse) in Figure 4-1 (b). By Fourier transform analysis, any function is made up from the controlled addition of sine waves of differing frequencies. For the step function to occur (the solid line in Figure 4-1 a), the constituent frequencies (the dotted lines in Figure 4-1 a) must all change at the same time, so they add up to give the edge. This means that to find the feature in which we are interested, we can determine points where events happen at the same time: this is phase congruency. By way of generalization, a triangle wave is made of peaks and troughs: phase congruency implies that the peaks and troughs of the constituent signals should coincide.
The constituent sine waves plotted in Figure 4-1 (a) were derived by taking the Fourier transform of a step and then determining the sine waves according to their magnitude and phase. The Fourier transform in Equation 2.15 delivers the complex Fourier components $F_p$. These can be used to show the constituent signals $x_c$ by

$$x_c (t) = |F_p_u| e^{j\left(\frac{2\pi}{N}ut + \phi(F_p_u)\right)}$$ (4.1)

where $F_{p_u}$ is again the magnitude of the $u^{th}$ Fourier component and $F_{p_u}$ is the argument.

The (dotted) frequencies displayed in Figure 4-1 are the first four odd components (the even components for this function are zero). The addition of these components is indeed the inverse Fourier transform which reconstructs the step feature. The advantages are that detection of congruency is invariant with local contrast: the sine waves still add up so the changes are still in the same place, even if the magnitude of the step edge is much smaller. In images, this implies that we can change the contrast and still detect edges.
Essentially, we seek to determine features by detection of points at which Fourier components are maximally in phase. By extension of the Fourier reconstruction functions in Equation 4.1, Morrone and Owens (1987) defined a measure of phase congruency $PC$ as

$$PC(x) = \max_{\phi(x) \in 0.2\pi} \left( \frac{\sum_u |Fp_u| \cos(\phi_u(x) - \phi(x))}{\sum_u |Fp_u|} \right)$$

(4.2)

where $\phi_u(x)$ represents the local phase of the component $Fp_u$ at position $x$.

Essentially, this computes the ratio of the sum of projections onto a vector (the sum in the numerator) to the total vector length (the sum in the denominator). The value of $\phi_u(x)$ that maximizes this equation is the amplitude weighted mean local phase angle of all the Fourier terms at the point being considered. In Figure 4-2 the resulting vector is made up of four components, illustrating the projection of the second onto the resulting vector. Clearly, the value of $PC$ ranges from 0 to 1, the maximum occurring when all elements point along the resulting vector. As such, the resulting phase congruency is a *dimensionless normalized measure* which is thresholded for image analysis.

Figure 4-2. Summation in phase congruency
In this way, we have calculated the phase congruency for the step function in Figure 4-3(a), which is shown in Figure 4-3(b). Here, the position of the step is at time step 40; this is the position of the peak in phase congruency, as required. Note that the noise can be seen to affect the result, although the phase congruency is largest at the right place.

![Figure 4-3. One-dimensional phase congruency](image)

One interpretation of the measure is that since for small angles, \( \cos \theta = 1 - \theta^2 \), then Equation 4.2 expresses the ratio of the magnitudes weighted by the variance of the difference to the summed magnitude of the components. There is certainly difficulty with this measure, apart from difficulty in implementation: it is sensitive to noise, as is any phase measure; it is not conditioned by the magnitude of a response (small responses are not discounted); and it is not well localized (the measure varies with the cosine of the difference in phase, not with the difference itself, although it does avoid discontinuity problems with direct use of angles). In effect, the phase congruency is directly proportional to the local energy (Venkatesh and Owens, 1989).
For these reasons, Kovesi developed a wavelet-based measure which improved performance, while accommodating noise. In basic form, phase congruency can be determined by convolving a set of wavelet filters with an image, and calculating the difference between the average filter response and the individual filter responses. The response of a (1D) signal $I$ to a set of wavelets at scale $n$ is derived from the convolution of the cosine and sine wavelets denoted $M_n^e$ and $M_n^o$ respectively

$$(e_n(x), o_n(x)) = (I(x) * M_n^e, I(x) * M_n^o)$$

(4.3)

to deliver the even and odd components at the $n$th scale $e_n(x)$ and $o_n(x)$, respectively. The amplitude of the transform result at this scale is the local energy

$$A_n(x) = \sqrt{e_n(x)^2 + o_n(x)^2}$$

(4.4)

At each point $x$ we will have an array of vectors which correspond to each scale of the filter. Given that we are only interested in phase congruency that occurs over a wide range of frequencies (rather than just at a couple of scales), the set of wavelet filters needs to be designed so that adjacent components overlap. By summing the even and odd components we obtain

$$F(x) = \sum_n e_n(x)$$

$$H(x) = \sum_n o_n(x)$$

(4.5)

and a measure of the total energy $A$ as

$$\sum_n A_n(x) \approx \sum_n \sqrt{e_n(x)^2 + o_n(x)^2}$$

(4.6)

Then a measure of phase congruency is

$$PC(x) = \frac{\sqrt{F(x)^2 + H(x)^2}}{\sum_n A_n(x) + \varepsilon}$$

(4.7)

where the addition of a small factor $\varepsilon$ in the denominator avoids division by zero and any potential result when values of the numerator are very small.
This gives a measure of phase congruency, which is essentially a measure of the local energy. Kovesi (1999) improved on this, improving on the response to noise, developing a measure which reflects the confidence that the signal is significant relative to the noise. Further, he considers in detail the frequency domain considerations, and its extension to two dimensions (Kovesi, 1999). For 2D (image) analysis, phase congruency can be determined by convolving a set of wavelet filters with an image, and calculating the difference between the average filter response and the individual filter responses. The filters are constructed in the frequency domain by using complementary spreading functions; the filters must be constructed in the Fourier domain because the log-Gabor function has a singularity at \( \omega = 0 \). To construct a filter with appropriate properties, a filter is constructed in a manner similar to the Gabor wavelet, but here in the frequency domain and using different functions. Following Kovesi’s implementation, the first filter is a low-pass filter, here a Gaussian filter \( g \) with \( L \) different orientations

\[
g(\theta, \theta_l) = \frac{1}{\sqrt{2\pi}\sigma_s} e^{-\frac{(\theta-\theta_l)^2}{2\sigma_s^2}}
\]  

(4.8)

where \( \theta \) is the orientation, \( \sigma_s \) controls the spread about that orientation and \( \theta_l \) is the angle is local orientation focus.

The other spreading function is a band-pass filter, here a log-Gabor filter \( lg \) with \( M \) different scales.

\[
lg(\omega, \omega_m) = \begin{cases} 0 & \omega = 0 \\ \frac{1}{\sqrt{2\pi}\sigma_\beta} e^{-\frac{(\log(\frac{\omega}{\omega_m}))^2}{2(\log(\beta))^2}} & \omega \neq 0 \end{cases}
\]  

(4.9)

where \( \omega \) is the scale, \( \beta \) controls bandwidth at that scale and \( \omega_m \) is the centre frequency at that scale. The combination of these functions provides a 2D filter \( l2Dg \) which can act at different scales and orientations.
\[ l2Dg (\omega, \omega_m, \theta_l) = g (\theta, \theta_l) \times lg (\omega, \omega_m) \]  

(4.10)

One measure of phase congruency based on the convolution of this filter with the image \( P \) is derived by inverse Fourier transformation of the filter \( l2Dg \) (to yield a spatial domain operator) which is convolved as

\[ S(m)_{x,y} = F^{-1} (l2Dg (\omega, \omega_m, \theta, \theta_l))_{x,y} \ast P_{x,y} \]  

(4.11)

to deliver the convolution result \( S \) at the \( m \)th scale. The measure of phase congruency over the \( M \) scales is then

\[ PC_{x,y} = \frac{\sum_{m=1}^{M} S(m)_{x,y}}{\sum_{m=1}^{M} |S(m)_{x,y}| + \varepsilon} \]  

(4.12)

where the addition of a small factor \( \varepsilon \) numerator again avoids division by zero and any potential result when values of \( S \) are very small. This gives a measure of phase congruency. As described above, local frequency information is calculated by convolving the image with banks of quadrature pairs of log-Gabor wavelets. Local frequency information is obtained by applying quadrature pairs of log-Gabor filters typically over six orientations and 3-4 scales. For each point in the signal the responses from the quadrature pairs of filters at different scales will form response vectors that encode phase and amplitude. Phase Congruency values are hence calculated for every orientation.

At each point in the image compute the Phase Congruency covariance matrix:

\[
G = \begin{bmatrix}
\sum PC_x^2 & \sum PC_xPC_y \\
\sum PC_xPC_y & \sum PC_y^2
\end{bmatrix}
\]  

(4.13)

where \( PC_x \) and \( PC_y \) are the \( x \) and \( y \) components of Phase Congruency for each orientation. The minimum and maximum singular values correspond to the minimum and maximum moments of Phase Congruency. The magnitude of the maximum moment, \( M \), gives an indication of the significance of the feature. A large maximum moment, \( m \), indicates that the feature has a strong
2D component and can be classified as an edge. The principal axis, about which the moment is minimized, provides information about the orientation of the feature. This Phase congruency method is accomplished using the phasecong.m, a Matlab function available on Kovesi’s Research website. (http://www.csse.uwa.edu.au/~pk/Research/research.html)

The above mentioned Matlab function produces an edge image, as shown in Figure 4-4.

![Phase Congruency output.](image)

Channel 4-5 difference image (top). Phase congruency edge image (bottom)
Figure 4-4 shows part of a channel 4 – channel 5 difference image on the top. The image on the bottom shows the possible contrail candidates, after applying the phase congruency edge detection algorithm. The possible candidates are shown in a brighter color while the background is black.

Section 4.2: Binary morphological operations

The edge image shown above contains possible contrails but also non-linear cirrus clouds and other non-contrails. When natural cirrus is present, these wispy features often contaminate the ridge image; the artificially produced contrails are much more likely to form straight lines. Contrails are defined by their linearity, i.e., the contrails being straight lines. Therefore, this method detects straight lines in the edge image. The computationally efficient Hough transform (Hough 1962) is used for this purpose.

Prior to using Hough transform, binary morphological operations (bridge, spur and skeletonization - see below) are used to clean up the image. This means making use of these operations to remove noisy pixels, regions of small size (less than 10 pixels), and deformations, which could be falsely identified as contrail candidates by the phase congruency method. This can aid in eliminating false positives (i.e. cold linear features that are not contrails, such as small cirrus clouds). Because contrails are longer than about 10-15 pixels (each pixel in the image is 1.1km²), we use this criterion to find the “major axis length” of the candidates. The major axis length is a scalar specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region (Figure 4-5).
Figure 4-5. Major axis length

(Source: Matlab documentation)

All potential contrail candidates with an axis length greater than the specified threshold are retained. Next, binary morphological operations to de-noise the image are used. The ‘bridge’ operator is used first. This operator bridges unconnected pixels; that is, it sets 0-valued pixels to 1 if they have two nonzero neighbors that are not connected. This operator connects candidates which are closely spaced, but have been separated due to errors in the image. This can include sensor problems, transmission issues in obtaining the AVHRR image, to errors in calculating phase congruency. For example:

\[
\begin{array}{ccc}
1 & 0 & 0 \\
1 & 0 & 1 \\
0 & 0 & 1 \\
\end{array}
\]

Figure 4-6. Bridge Operator

(Source: Matlab documentation)

The next operation removes the spurious pixels (i.e., removes small irregularities). For example:
Next, the image skeleton is extracted. The operation removes pixels on the boundaries of objects but does not allow objects to break apart. The remaining pixels make up the image skeleton. The skeleton (or topological skeleton) of a shape is a thin version of that shape that is equidistant to its boundaries. The skeleton usually emphasizes geometrical and topological properties of the shape, such as its connectivity, topology, length, direction and width. Together with the distance of its points to the shape boundary, the skeleton can also serve as a representation of the shape (i.e., they contain all the information necessary to reconstruct the shape). For example (Figure 4-8), the thin red line represents the skeleton of the white ‘PENN STATE’.

Figure 4-7. Spurious pixel removal
(Source: Matlab documentation)

Figure 4-8. Example of skeletonization
Section 4.3: Line detection using Hough transform

The simplest case of Hough transform for detecting straight lines is the linear transform for detecting straight lines. In the image space, the straight line can be described as \( y = mx + b \) where the parameter \( m \) is the slope of the line, and \( b \) is the intercept (y-intercept). This is called the slope-intercept model of a straight line. The Hough transform considers the characteristics of the straight line not as discrete image points \((x_1, y_1)\), \((x_2, y_2)\), etc., but in terms of its parameters according to the slope-intercept model; i.e., the slope parameter \( m \) and the intercept parameter \( b \). In general, the straight line \( y = mx + b \) can be represented as a point \((b, m)\) in the parameter space. However, vertical lines pose a problem. They are more naturally described as \( x = a \) and would give rise to unbounded values of the slope parameter \( m \). Thus, for computational reasons, Duda and Hart (1971) proposed the use of a different pair of parameters, denoted \( \Upsilon \) and \( \theta \) (theta), for the lines in the Hough transform. These two values, taken in conjunction, define a polar coordinate.

![Figure 4-9. \( \Upsilon \) - \( \theta \) line parametrization](image)

The parameter \( \Upsilon \) represents the algebraic distance between the line and the origin, while \( \theta \) is the angle of the vector from the origin to this closest point. Using this parameterization, the equation of the line can be written as
\[ y = \left( \frac{\cos \theta}{\sin \theta} \right) x + \left( \frac{r}{\sin \theta} \right) \]  
(4.14)

which can be rearranged to \( Y = x \cos \theta + y \sin \theta \) (Shapiro and Stockman, 2001).

The range of theta is \(-90^\circ < \theta < 90^\circ\). It is therefore possible to associate with each line of the image a pair \((Y, \theta)\).

The linear Hough transform algorithm uses a two-dimensional array, called an accumulator, to detect the existence of a line described by \( Y = x \cos \theta + y \sin \theta \). The dimension of the accumulator equals the number of unknown parameters, i.e., two, considering quantized values of \( Y \) and \( \theta \) in the pair \((Y, \theta)\). For each pixel at \((x,y)\) and its neighborhood, the Hough transform algorithm determines if there is enough evidence of a straight line at that pixel. If so, it will calculate the parameters \((Y, \theta)\) of that line, and then look for the accumulator's bin into which the parameters fall, and increment the value of that bin. By finding the bins with the highest values, typically by looking for local maxima in the accumulator space, the most likely lines can be extracted, and their geometric definitions approximated. (Shapiro and Stockman, 2001) The simplest way of finding these peaks is by applying some form of threshold, but other techniques may yield better results in different circumstances: determining which lines are found as well as how many. Because the lines returned do not contain any length information, it is often necessary (next step) to find which parts of the image match up with which lines.

The final result of the linear Hough transform is a two-dimensional array (matrix) similar to the accumulator; one dimension of this matrix is the quantized angle \( \theta \) and the other dimension is the quantized distance \( r \). Each element of the matrix has a value equal to the number of points or pixels that are positioned on the line represented by quantized parameters \((Y, \theta)\). Thus, the element with the highest value indicates the straight line that is most represented in the input image.
Running the algorithm results in each \((x_i, y_i)\) being transformed into a discretized \((Y, \theta)\) curve, and the accumulator cells which lie along this curve are incremented. Resulting peaks in the accumulator array represent strong evidence that a corresponding straight line exists in the image.

The advantage of the Hough transform technique is that it is unaffected by gaps in the line and relatively robust in the presence of noise. The in-built Matlab functions to detect the Hough transform and the lines are used. (Table 4-1)

Table 4-1. In-built Matlab functions used to detect Hough transform and lines
(Source: Matlab Documentation, Matlab 2012a)

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>hough</strong></td>
<td>The hough function implements the Standard Hough Transform (SHT). The Hough transform is designed to detect lines, using the parametric representation of a line: [ \rho = x\cos(\theta) + y\sin(\theta) ] The variable (\rho) is the distance from the origin to the line along a vector perpendicular to the line. (\theta) is the angle between the x-axis and this vector. The hough function generates a parameter space matrix whose rows and columns correspond to these (\rho) and (\theta) values, respectively.</td>
</tr>
<tr>
<td><strong>houghpeaks</strong></td>
<td>After you compute the Hough transform, you can use the houghpeaks function to find peak values in the parameter space. These peaks represent potential lines in the input image.</td>
</tr>
<tr>
<td><strong>houghlines</strong></td>
<td>After you identify the peaks in the Hough transform, you can use the houghlines function to find the endpoints of the line segments corresponding to peaks in the Hough transform. This function automatically fills in small gaps in the line segments.</td>
</tr>
</tbody>
</table>

Peaks in the accumulator array are chosen such that their values are 0.05 to 0.20 times the maximum value (based on trials I conducted optimum outputs). Lines within a 5 to 10 pixel...
distance are automatically connected by the algorithm and lines less than a certain pixel length are deleted (20 to 30 pixels based on trials).

**Section 4.4: Identifying contrail endpoints and their coordinates in latitude-longitude format.**

The latitude-longitude (lat-long) details of the top-left and the bottom-right corner of the AVHRR image are also input into the algorithm to identify the (lat-long) details of each detected contrail. These values are first converted into longitude-per-x-pixel and latitude-per-y-pixel values, which are calculated by dividing the total longitude value by the number of y-axis pixels, and by dividing the total latitude value by the number of x-axis pixels.

The Matlab function ‘houghlines’ (Table 4-1) identifies the lines and their endpoints. Each (x,y) coordinate extracted from this function is multiplied with the longitude-per-x-pixel and latitude-per-y-pixel values, to yield longitude-latitude details of the endpoints of each detected contrail in degrees, minutes format. The function also assigns each line with a rho, theta value pair. Each such pair is compared to find if the detected contrails are part of the same longer contrail.
Chapter 5

Derivative Method

Second Method of contrail identification and classification: Using Derivatives and binary morphological processes

This chapter discusses the second method of contrail detection. In section 5.1 the derivative of the image and the search mask used are discussed. Section 5.2 explains the different binary morphological operations used to remove the unwanted components of the image and clear the results. This includes removing noise, small non-linear clouds, etc. Section 5.3 explains the method to identify the endpoint of each contrail and to retrieve its coordinates in latitude-longitude format, and ways to determine its length and width.

Section 5.1: Spatial Derivative

The first step in this method is to calculate differences between adjacent rows (Derivative along x-direction). In the thermal channel 4- channel 5 difference image, contrails have a higher pixel value than the background (Earth’s surface) producing a zero crossing. The top edge of the contrail produces a negative change. This is adjacent to or within very close proximity (1 or 2 pixels), followed by the bottom edge of the contrail which produces a positive change (Figure 5-1).
The negative change is darker than the background and the positive change is brighter than the background. This image is further thresholded to remove small changes in the pixel brightness. (The value of threshold varies from 800 to 1000). These small changes are assigned a value of zero.

In the next step, all positive changes are assigned 1 and all negative changes are assigned -1, to facilitate creating a mask and searching for the contrail (Figure 5-2). The mask (Figure 5-3) is run across the entire image, centered on -1 and searches for a +1. The mask returns assigns the center pixel a value of +1 (+1 being TRUE and 0 being False in a binary logical image), if any of the shown positions contains a +1.

Figure 5-1. Representation of a zero-crossing
Figure 5-2. Zero crossings in the image

Figure 5-3. Mask along y-direction

This mask produces a BW (Black and White) image, with potential contrail candidates shown in white (Figure 5-4).
This mask, however, fails to detect vertical or close to vertical contrails, (ie, contrails oriented north-south on an image). To overcome this short-coming, the derivative along columns (x - direction) is taken and the following mask is used to detect potential contrail candidates.

```
  x  x  x  +1  +1
  x  x  x  +1  +1
  x  x  y  +1  +1
  x  x  x  +1  +1
  x  x  x  +1  +1
```

Figure 5-6 shows a Channel 4-5 difference image, and the potential contrail candidates after using mask along x-direction and along y-direction. The image shows why the use of both masks is necessary in detecting all potential candidates.
Figure 5-6. Spatial derivatives in x and y directions.
(Clockwise from top – Channel 4-5 difference image ; after using mask along x-direction ; after using mask along y-direction)

Section 5.2: Binary Morphological operations and contrail detection

As in the previous section, binary operations are used to clean up the image and remove small (fewer than 5) unwanted pixels. These operations—bridge, spur and skeletonization—remove most non-contrail pixels from the candidate image. Next, all the connected components pixels are labeled (each with a different integer value) and the length (Major-axis length) of each
such region is calculated. Small regions (fewer than 5-10 pixels) are discarded iteratively, increasing the threshold size from 10 to 30 pixels. This procedure is done for both the x-direction and y-direction masked image, and the results are combined to give the final output.

**Section 5.3: Identifying contrail endpoints and their coordinates in latitude-longitude format.**

The latitude-longitude (lat-long) details of the detected contrails are calculated as explained before (Section 4.4). The endpoints of each detected contrail are calculated using an in-built Matlab function (bwmorph) and each (x,y) coordinate is multiplied with the longitude-per-x-pixel and latitude-per-y-pixel values, to yield longitude-latitude details of the endpoints of each detected contrail in degrees, minutes format. Their slopes are then calculated and compared to identify same but disconnected contrails.
Chapter 6

Results

The previous sections described the two methods used to identify contrails, viz. the first method, consisting of the Phase congruency and Hough transform (Phase-Hough), and the second consisting of spatial derivatives. This section describes the results of applying these methods on various test images. Both methods were tested on images with a variety of atmospheric and cloud conditions (e.g., clear-skies, partly cloudy skies; cloudy skies) and different contrail types (no contrail, single contrail, multiple contrails). Both methods were tested on a total of 27 images. Section 6.1 discusses the results of contrail detection using method A, and Section 6.2 discusses the results when using Method B. Section 6.3 discusses the performance and compares the two methods based on these test results.

Section 6.1: Phase Congruency and Hough transform method:

In this section the first method consisting of applying phase congruency edge detection and following this by a Hough transform based line detection algorithm, is applied to various test case satellite images. The algorithm detects contrails and calculates the endpoints on each detected contrail. It shows the longitude-latitude coordinates of the detected contrails.
6.1.1 Image containing no contrail

Figure 6-1. No contrail using Phase-Hough

(Clockwise from top-left) The original image (channel 4), Channel 4-5 difference image, Final output, intermediate image showing phase congruency.

The test image is partly cloudy, but contains no contrails. The initial phase congruency test reveals many edges, including very faint ones that are not easily visible. However, these
edges are not very bright (pixel value < 200). These false positive edges are later deleted by the algorithm, and the final output image shows no contrails, as expected.

6.1.2 Image containing one contrail (partly cloudy)

![Image of contrail using Phase-Hough](image)

Figure 6-2. One contrail using Phase-Hough
Top image shows the partly cloudy channel 4 image. Bottom image shows the detected contrail (in blue). The yellow and red points are the start and end points of the contrail.

The test image is partly cloudy and contains a single contrail. The contrail is disjoint, and has a few gaps in between. The algorithm not only detects the contrail but also classifies the disjoint segments as the same contrail and displays the end points. Thus the occurrence of natural clouds does not affect the detection and classification of the contrail. The coordinates of the contrail are also calculated in degrees and minutes, as shown in table 6-1.

Table 6-1. Contrail coordinates for image with one contrail using Phase-Hough

<table>
<thead>
<tr>
<th></th>
<th>Longitude</th>
<th>Latitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start</td>
<td>135° 28′</td>
<td>56° 26′</td>
</tr>
<tr>
<td>End</td>
<td>133° 27′</td>
<td>55° 41′</td>
</tr>
</tbody>
</table>
6.1.3 Image containing more than one contrail (cloudy)

Figure 6-3. More than one contrail using Phase-Hough
The first image in Figure 6-3 shows the original channel 4 image. The second image shows the detected contrails superimposed on the channel 4-5 difference image, and the last image shows the detected contrails on the original image (channel 4).

This test image has two contrails. A major part of both the contrails is hidden by clouds. All contrails, including the hidden ones are detected. The algorithm also differentiates between different contrails as shown by assigning the different color used in displaying them. Figure 6-3 shows the two contrails (green and blue contrails). Some regions of the contrails which fade away are not detected. However, the discontinuous contrail (blue) is detected as the same contrail and the correct endpoints are detected, and as such, do not cause an error or problem in the detection and classification. Table 6-2 shows the coordinates (degrees° minutes’).

Table 6-2. Contrail coordinates for image containing more than one contrail using Phase-Hough

<table>
<thead>
<tr>
<th></th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Longitude</td>
<td>Latitude</td>
</tr>
<tr>
<td>Green Contrail</td>
<td>110°01´</td>
<td>54°54´</td>
</tr>
<tr>
<td>Blue Contrail</td>
<td>109°39´</td>
<td>53°57´</td>
</tr>
</tbody>
</table>
6.1.4 Image containing an intersecting contrail (partly cloudy)

![Contrail Image]

Figure 6-4. Intersecting Contrail using Phase-Hough

Top image shows the original channel 4 image. Bottom image shows the detected contrails.
This test image has two intersecting contrails. The algorithm detects both contrails. It also detects a hidden third one. It correctly classifies each of the contrails as a distinct feature. The fact that two contrails intersect does not affect the behavior of the algorithm. It succeeds in classifying them as different contrails. The blue contrail is seen to start spreading laterally in the original image. The algorithm detects it nonetheless. Some of these contrails are shown as a collection of lines rather than just one. This helps in detecting curved contrails as well. Minor curvature is depicted using short lines. Table 6-3 shows the coordinates of the contrails.

Table 6-3. Contrail coordinates for image containing intersecting contrails using Phase-Hough

<table>
<thead>
<tr>
<th></th>
<th>Start Longitude</th>
<th>Start Latitude</th>
<th>End Longitude</th>
<th>End Latitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green Contrail</td>
<td>135°2’</td>
<td>56°18’</td>
<td>135°38’</td>
<td>55°36’</td>
</tr>
<tr>
<td>Blue Contrail</td>
<td>134°29’</td>
<td>56°30’</td>
<td>134°53’</td>
<td>55°42’</td>
</tr>
<tr>
<td>Red Contrail</td>
<td>134°32’</td>
<td>55°47’</td>
<td>134°47’</td>
<td>55°35’</td>
</tr>
</tbody>
</table>
6.1.5 Image containing multiple contrails (cloudy)

Figure 6-5 a. Original channel 4 image, multiple contrails
Figure 6-5 b. Multiple Contrails using Phase-Hough

Top image shows the original channel 4 image. Bottom image shows the detected contrails.

This test image has multiple contrails, some of them are embedded within clouds. The contrails vary in size and orientation (vertical and horizontal). The algorithm performs well in this case also. As seen in Figure 6-5, various contrails are detected and classified as the same contrail. The presence of clouds does not affect the output, except in making the contrails disconnected. In spite of the fact that some of the contrails are disconnected due to the presence of clouds, the algorithm correctly identifies parts of a contrail as the same contrail, as shown by the color coding. The black ellipse in the image shows regions not classified as contrails.
Section 6.2: Spatial Derivatives Method:

In this section, the second method: applying bi-directional spatial derivatives is used to detect the contrails. The same four test images as the previous section are used. All resulting images and the contrail coordinates that are output are shown below.

6.2.1 Image containing no contrail

Figure 6-6. No Contrail using Derivative Method
(Clockwise from top-left) The original image (channel 4), Channel 4-5 difference image, Final output, intermediate image showing no contrail candidates.
The test image is partly cloudy, but contains no contrails. The initial spatial derivative and contrail search method, shows a blank output. No contrail candidates exist and the final output image also shows no existence of contrails, as expected.

6.2.2 Image containing one contrail (partly cloudy)
Figure 6-7. One contrail using derivative method

Top image shows the partly cloudy channel 4 image. The center image shows the detected contrail (in blue). The red points are the end points of the contrail. The bottom image shows a zoomed in part of the detected contrail.

This test image is partly cloudy and contains a single contrail. The contrail is disjoint, and has a few gaps in between. The algorithm detects the contrail and also classifies the disjoint contrail as the same contrail and displays the end points. The coordinates of the contrail are also calculated in degrees and minutes, as shown in Table 6-4. Figure 6-7 also shows a zoomed in view of a part of the output image. It is seen that this method does not produce straight lines and follows the exact path of the contrail.
Table 6-4. Contrail coordinates for image containing one contrail using Derivative method

<table>
<thead>
<tr>
<th></th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Longitude</td>
<td>Latitude</td>
</tr>
<tr>
<td>Green Contrail</td>
<td>135°34′</td>
<td>56°54′</td>
</tr>
<tr>
<td></td>
<td>134°6′</td>
<td>55°27′</td>
</tr>
</tbody>
</table>

6.2.3 Image containing more than one contrail (cloudy)

Figure 6-8. More than one contrail using derivative method

Top image shows the original channel 4 image. The bottom image shows the detected contrails superimposed on the channel 4-5 difference image
This test image has a major part of the contrails hidden by clouds. All contrails, even the hidden ones are detected. The algorithm detects two (or both the) contrails and classifies them as two different contrails. Parts of the contrail which fade away are not detected. However, the endpoints are detected correctly, and as such, should not cause an error in the detection. Table 6-5 shows the coordinates (degrees° minutes´).

Table 6-5. Contrail coordinates for image containing more than one contrail using Derivative method

<table>
<thead>
<tr>
<th></th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Longitude</td>
<td>Latitude</td>
</tr>
<tr>
<td>Green Contrail</td>
<td>109°47´</td>
<td>54°58´</td>
</tr>
<tr>
<td>Blue Contrail</td>
<td>109°57´</td>
<td>53°49´</td>
</tr>
</tbody>
</table>
6.2.4 Image containing an intersecting contrail (partly cloudy)

Figure 6-9. Intersecting contrails using derivative method

Top image shows the original channel 4 image. Bottom image shows the detected contrails
This test image has two intersecting contrails. The algorithm detects both the contrails and a hidden third one and classifies them accordingly. The intersection does not affect the algorithm. It succeeds in classifying them as different contrails. Table 6-6 shows the coordinates of the contrails.

Table 6-6. Contrail coordinates for image containing intersecting contrail using Derivative method

<table>
<thead>
<tr>
<th></th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Longitude</td>
<td>Latitude</td>
</tr>
<tr>
<td>Green Contrail</td>
<td>135°2´</td>
<td>56°18´</td>
</tr>
<tr>
<td>Blue Contrail</td>
<td>134°29´</td>
<td>56°30´</td>
</tr>
<tr>
<td>Orange Contrail</td>
<td>134°32´</td>
<td>55°47´</td>
</tr>
</tbody>
</table>
6.2.5 Image containing multiple contrails (cloudy)

Figure 6-10 a. Original Channel 4 image, multiple contrails.
Figure 6-11 b. Multiple contrails using derivative method.

Top image shows the original channel 4 image. Bottom image shows the detected contrails. This test image has multiple contrails, some of them covered by clouds. The contrails vary in size and orientation (vertical and horizontal). The algorithm performs well in this case also. As seen in Figure 6-10, vertical as well as horizontal contrails are detected making use of the bi-directional spatial derivative. The presence of clouds does not affect the output greatly, except
in making the contrails disconnected. However, there are a few false positives, especially in regions which contain thin cirrus clouds which can confuse the algorithm. It also fails to detect certain thin contrails. The black ellipse shows contrails which have not been detected. The red circle shows false positives.

Section 6.3 Accuracy Assessment Result

Table 6-7. Contrail coordinates for image containing intersecting contrails using Phase-Hough

<table>
<thead>
<tr>
<th></th>
<th>256 x 256 pixels</th>
<th>512 x 512 pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase-Hough</td>
<td>Derivative</td>
</tr>
<tr>
<td>No Contrail</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Number of contrails &lt;=4</td>
<td>97.27%</td>
<td>97.27%</td>
</tr>
<tr>
<td>Number of contrails &gt;4 and &lt;=10</td>
<td>94.36%</td>
<td>91.56%</td>
</tr>
<tr>
<td>Number of contrails &gt;10</td>
<td>87.67%</td>
<td>86.13%</td>
</tr>
</tbody>
</table>

To get a better idea of the algorithms’ performance, it is necessary to test them on a larger sample size of images. In order to achieve this, and eliminate the bias associated with me testing all samples, each 3500 x 2000 pixel image was sampled into smaller 256 x 256 and 512 x 512 size images and distributed amongst 4 other individuals. They were trained to recognize contrail. A total of 3360 images of size 256 x 256 and 840 images of size 512 x 512 were used for the testing purpose.

The above table (Table 6-7) describes the percentage accuracy of the two algorithms. It is calculated by dividing the number of contrails detected by each method and the number of contrails manually detected, as described above. It can be seen that as the number of contrails increase, the accuracy of detection of contrails decreases. The accuracy also decreases as the
sample size increases. This reduction in accuracy is mainly due to a fixed threshold being used to
determine the presence or absence of contrails in the scene. However for larger sample sizes, the
derivative method performs better than the Phase-Hough, because the threshold used during the
phase congruency step largely affects the contrail candidates detected and because a smaller
sample size has less variance of pixel intensities. Where the sample contains no contrails, the
algorithm concurs every time, except for the 512x512 size samples while using the Phase-Hough
method. The Phase congruency detects a few faint edges which are classified as contrails by the
algorithm.

**Section 6.4 Comparison of the two methods**

Based on the results discussed above, we can say that both methods work well in
detecting and classifying the contrails for simple test cases when there are few contrails.
However, the Hough transform method is faster and more efficient in classifying the contrails as
compared to the derivative method. However, the derivative method is better when it comes to
classifying curved contrails and detects the contrails up to their very edge. (refer test cases 6.2.2-
6.2.4) The contrails detected by the Hough transform method fade away at the edges. (refer test
cases 6.1.2- 6.1.4)

In the Hough transform method, the initial step of phase congruency tends to detect even
the faintest of edges, which may cause many false positives in the output (case 6.1.4). Cirrus
cloud edges may be incorrectly classified as a contrail. Hence, to rule out false positives, rigorous
and strict binary morphology methods and cleaning up may be needed when using this method.
Moreover, the derivative method displays the contrails as a set of points and is hence not a straight line. The output is an irregular jagged line, because of which the exact path of the contrail is detected. The Hough transform method strictly displays the contrails as straight lines. This causes the contrail to be broken into smaller lines, and sometimes may cause the classifier to classify the same contrail as different contrails. Strict thresholding conditions and checks may be needed to avoid this.

Both algorithms have similar performances. For the simple cases (case 1-3), they both perform equally well in detecting and classifying the contrails. However for case 4, where there are multiple contrails, the phase-Hough method fails to detect some contrails and contains a few false positives. This is because of the phase congruency method being very sensitive to less bright edges. However, the derivative method has no false positives. The derivative and the mask makes sure of this. From table 6-7 we can also see that for larger size images the derivative method performs better.

Detecting endpoints and classifying the contrails as the same is easier in the Phase-Hough method. This is mainly because; the Hough transform not only calculates the end points for each detected line but also a rho, theta pair (Section 4.3) for each line. These rho, theta pairs for each line can be compared and similar pairs are classified as the same line. However, classification using the derivative method is a bit difficult. Although the endpoints can be calculated easily, using a slope-y coordinate method to classify the lines is difficult and can cause errors since lines close to each other with a similar slope get classified as the same contrail, while disjoint contrails with a minor change in slope get classified as different ones. Also it becomes increasingly difficult as the number of lines goes up. This is because of only one universal threshold being used.
Chapter 7

Conclusion and Future Work

7.1 Conclusion

Contrails are important for understanding how humans contribute to contemporary climate change by adding new elements into the atmosphere. The ice crystal trails could affect climate in the long run. Identifying contrails is the first and preliminary step in their overall study. This thesis proposes two pixel based methods for contrail detection using AVHRR images.

The phase congruency and Hough transform method do well as compared to previous Hough transform based methods in detecting curved contrails. These curved contrails are detected as a collection of smaller straight contrails especially at the region where it curves. Both methods successfully detect contrails under various atmospheric and cloud conditions (e.g., clear-skies, partly cloudy skies; cloudy skies).

However, for cases where the image contains multiple contrails, the performance of both the algorithms decreases. It detects most contrails. However, less bright contrails are not detected. This can be improved by increasing the threshold, but at the cost of increasing false positives. A comparison shows that both methods perform almost equally well. The Phase-Hough method detects curved contrails, an improvement over previous Hough transform based approaches. It however fails to detect trailing edges which tend to fade away. The derivative method detects contrails as a collection of points rather than lines and hence follows the contrail path more closely.

Finally, the object-based method cannot effectively detect atypical contrails such as fully spread ones (i.e. ones that become contrail cirrus), which are hard to distinguish from natural cirrus. The detection of contrails from cirrus clouds is difficult because the cirrus clouds usually
have a homogeneous appearance and similar brightness values to contrails. These clouds and contrails usually are so extensive that they are virtually indistinguishable from one another and the individual line shapes of contrails disappear.

We conclude that while the algorithm is robust in the detection of most contrails, it is less effective when features are weak or extremely diffused. Especially difficult are highly cluttered scenes with many cirrus streaks. Increased contrail detection may be achieved but only at the cost of increasing false alarms, while decreasing the number of false alarms necessarily eliminates some faint contrails.

7.2 Future Work

We need to further improve the results of both the above mentioned approaches to obtain even better results. An improvement on the Phase congruency method is would ensure a better thresholding method, such that even the faintest of contrails are detected without getting false positives. Using the Hough transform to detect curved contrails can be used instead of the aforementioned line detection [Fernandes et al, 2012]. One can use the fact that the contrail cross-sections have a characteristic profile that resembles a Gaussian curve to improve results.

Also a combination of both the above methods could be used to better identify contrails; the derivative method to detect possible candidates, and the Hough method to identify their linearity. This dual approach combined with a dynamic, neighborhood dependent threshold could give even better results. This would mean applying iteratively and area specific thresholds, to improve results. As shown in this thesis, it is difficult to identify contrails from cirrus clouds using the normal object features--brightness, shape index, and width; that problem remains. However, some possible object characteristics to distinguish contrails from cirrus clouds should be studied in future work.
References


