Operational detection of contrails from NOAA-AVHRR-data

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Abstract. This paper describes a fully automated scheme that allows for the detection of contrails using the infrared channels of the Advanced Very High Resolution Radiometer (AVHRR). The presented algorithm is adjusted to have a low rate of misdetection in spite of the low contrail detection efficiency resulting from this tuning. A time-series and regional patterns of contrail cloudiness over Central and Western Europe are derived. Daily analysis of noon scenes in 1996 indicates that the average of daytime contrail coverage over Central Europe was 0.5% ± 0.25 with regional maxima of 1.2%. Comparing noon and midnight scenes shows that night-time contrail coverage, which is especially effective in greenhouse forcing, is approximately one-third of that of daytime.

1. Introduction

Whether there is a significant climatic impact of contrails is still an open question. High and optically thin cirrus clouds and also aged contrails may increase the net radiation at the surface. They reduce terrestrial upward radiation flux at the top of the atmosphere, while albedo is only slightly enhanced. Thus an increase of high thin ice clouds may lead to warmer surface temperatures, while all other cloud types lead to surface cooling (Stephens and Webster 1981, Liou 1986).

The global mean areal coverage by contrails is not known. Bakan et al. (1994) derived from visual inspection of Advanced Very High Resolution Radiometer (AVHRR) data a contrail coverage of the Eastern North Atlantic region and Northwestern Europe. They found averages around 1%. This must be related to an average coverage of natural thin cirrus clouds which reaches almost 20% in northern midlatitudes (Wang et al. 1996).

Because of the rapid growth of high-flying jet air traffic, its possible effects need further study. In spite of development of more effective engines, fuel consumption is increasing by about 3% per year (Schumann 1994).

Theory on the formation of contrails was recently reviewed by Schumann (Schumann 1996) and adapted to the high engine propulsion efficiency of modern jet engines. Detailed knowledge of formation processes combined with meteorological model data and flight activities can be used to estimate contrail formation (Ponater et al. 1996a and b). But there are still some open questions concerning contrail persistence and spreading that lead to uncertainties in the contrail coverage. For
example, the dependency on airmass lifting and wind shear is still not well understood. To test the theory and understand the effect of synoptic conditions on persistence of contrails, it is necessary to identify the corresponding air masses. In areas with plenty of traffic they may be recognized by clusters of many individual contrails.

Passive remote sensing methods can be used to recognize ice clouds, mainly by their low brightness temperatures in the thermal infrared. 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 \( \mu \text{m} \)) than in channel 5 (11.5–12.5 \( \mu \text{m} \)) compared to natural cirrus (Betancor-Gothe and Grassl 1993). This often causes contrails to appear brighter on channel 4 – channel 5 temperature difference images. Unfortunately, this feature of anthropogenic ice clouds slowly changes as the cloud ages and is more like natural cirrus after a while. In-situ measured size spectra of old widespread contrails were found to approach those of cirrus clouds (Strauss et al. 1997). Therefore, from the limited spectral information of present meteorological satellites in space, contrails may not be clearly distinguished from natural cirrus. In AVHRR images the edges of clouds and even some features on land can also show similar thermal signatures.

Contrails can be distinguished in satellite images by their shape: this is what enables the human eye to detect them. When atmospheric conditions are favourable, contrails form shortly behind the aircraft, starting with a width of around 100 m. Freudenthaler et al. (1995) observed spreading rates for contrail width of 18–140 m min\(^{-1}\) by ground based LIDAR measurements. This agrees with numerical simulations of Gierens (1996) giving rates of 26–58 m min\(^{-1}\). Thus widths of 1 km are reached after about 20 min. In airmasses where conditions for persistence are good, contrail length is mainly limited by the size of these regions.

Ponater et al. (1996a, 1996b) showed that only persistent contrails can be of climatic impact. Thus, the AVHRR instrument (nadir resolution 1 km) should be suitable to detect most of the climatically relevant contrails. Data of higher spatial resolution was used by Joseph et al. (1975) (Landsat-MSS (Multi-Spectral Scanner) with 80 m resolution) and by Carleton and Lamb (1986) (DMSP-OLS (Defense Met. Sat. Program Operational Line Scanner) with 600 m resolution). Unfortunately these sensors do not provide at least a daily repetition which is needed for climatologic studies. National Oceanic and Atmospheric Administration (NOAA) platforms guarantee at least four scenes a day for the regions of interest. AVHRR/2 instruments equipped with channels 4 and 5, which were used in the present study, have been operated since the launch of NOAA-7 in 1981. Thus, developing an algorithm for these instruments gives an opportunity to analyse trends in contrail cloudiness.

Up to now, only a few studies on regional contrail coverage have been performed. Because of the great variability of the phenomena a long series of observations has to be made. Schumann and Wendling (1990) mention the first value for areal contrail coverage derived from satellite data. From 99 AVHRR scenes they estimate an average contrail coverage of 1.5% for Southern Germany and the Alps. For the same region Strauss et al. (1994) observe an average contrail coverage of about 0.5% from AVHRR data. They evaluated the digital images by hand and by an early version (Forkert et al. 1993) of the pattern recognition scheme presented here.

The largest satellite data set analysed so far is reported by Bakan et al. (1994). Through visual inspection of daily AVHRR hardcopies from 52 months, an average contrail coverage of 1% over Central Europe and 2% over the eastern part of the North Atlantic was obtained.
Worldwide data on contrail coverage are strongly needed to estimate the overall effect of contrails on today’s and the future climate. Due to the huge size and unavailability of a global remote sensing dataset with high spatial resolution, only estimates exist. Ponater et al. (1996 a) parameterized contrail coverage for a Global Circulation Model (GCM). They applied the thermodynamic theory of contrail formation (Schumann 1996) to the atmospheric parameters, folded the results with a global dataset of air traffic fuel consumption and adjusted the resulting index with the results of Bakan et al. (1994). Thereafter, the global mean contrail coverage might be 0.04% with an uncertainty of one order of magnitude.

Regional studies are very important input into GCMs. They assist in understanding contrail formation in distinct weather situations and support airborne small-scale microphysical contrail investigations.

Unfortunately, the manual interpretations are very subjective and time-consuming. They are not feasible either to obtain a longtime climatology for trend analysis of contrail cloudiness or for inspection of large areas with accurate positioning. Therefore, some attempts have been made to solve the problem by various image processing algorithms. Most algorithms use an idea of Lee (1989), who showed that contrails appear very bright in images of brightness temperature difference (channel 4 – channel 5). Both Engelstad et al. (1992) and Forkert et al. (1993) enhance ridge structures in the temperature difference images and detect linear structures by the Hough transformation (Pratt 1991). The algorithm of Engelstad et al. (1992) worked well on some scenes, but had the tendency to misinterpret linear streaks of natural cirrus as contrails. Forkert et al. (1993) claim that their algorithm underestimates contrail cover in situations with wide contrails and suffers from misclassifications of coastlines, valleys and cloud edges. Both procedures were prototypes that had to be manually adapted to each situation.

An attempt was made by Meinert (1994) who trained a neural network to classify contrails by use of the AVHRR thermal split window channels. To get good results a huge set of well-chosen, pixel-precise training samples is needed. These must 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).

A new algorithm that is, as far as the authors know, the first that is able to work operationally is described below. Some results of the operational contrail detection are presented. Finally, the differences in recognizing contrails by man and machine and the limits of contrail detection efficiency are discussed.

2. **Contrail detection algorithm**

The scheme presented here is the latest stage of an algorithm development aiming to detect contrails in AVHRR data. Earlier work has been described in Forkert et al. (1993) and Mannstein (1996).

Different tests are combined to avoid misdetections. Independence from the properties of a single scene is achieved by normalizing the data on a regional scale and avoiding scene-dependent operators like the Hough transform (Pratt 1991).

The logical structure of the data flow is drawn in figure 1. Figure 2 shows an extreme case of contrail occurrence over Denmark, southern Sweden, northern Germany and the western part of Poland. This small part of an AVHRR scene is used in the following to illustrate the major steps of the contrail detection algorithm.
The chosen scene contains many coastlines, which make this pattern recognition task much harder than over open sea.

2.1. Description of algorithm

Contrails are best visible for human observers in a display of the brightness temperature difference between channels 4 and 5 ($T_D$, figure 3). But, also, cloud edges and surface features appear as bright lines. This does not happen in the temperature images (figure 2). Because of better contrasts, the equivalent blackbody temperature derived from channel 5 ($T_5$) was used additionally to the temperature difference ($T_D$) as input data for the detection algorithm. To avoid interference with artifacts produced by remapping, the data remains in the original satellite projection.

As the temperature of contrails is lower than that of the surrounding region, the brightness temperatures were inverted, resulting in $T_5i$. This permits treatment of the temperature image and the temperature-difference image with the same procedures.
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To have comparable contrasts and use constant thresholds for the whole year, it was decided to normalize the data. Both datasets ($T_5i$ and $TD$) were first smoothed with a rotationally symmetric Gaussian $5 \times 5$ pixel lowpass kernel resulting in the images $T5$ and $TD$. Filtering the square of the differences between the original and the smoothed images again with the same kernel derived a local standard deviation defined over the region given by the Gauss-kernel: $SDT5 = \sqrt{(T5i - T5i)^2}$ (figure 4) and $SDTD = \sqrt{(TD - TD)^2}$. The difference between the original and the smoothed image was normalized with the local standard deviation resulting in the normalized images $N5$ (figure 5) and $ND$:

\[
N5 = \frac{(T5i - T5i)}{(SDT5 + 0.1 K)}
\]

\[
ND = \frac{(TD - TD)}{(SDTD + 0.1 K)}
\]

The addition of 0.1 K to the local standard deviation avoided occasional division by zero and limits the sensitivity over very homogeneous areas like the open sea. Without this, horizontal lines produced by changes in the inflight calibration of the AVHRR-temperature channels from one image-line to the next were sometimes

![Figure 3. NOAA-12 temperature difference ($TD$), 4 May 1995, 07:43 UT.](image)

![Figure 4. Regional standard deviation ($SDT5$) of $T5$.](image)
detected as contrails. To avoid outliers, both normalized images were limited to the range \(-2\) to \(+2\). Within these normalized images the contrast is evenly distributed and independent from size and content of the actual scene. Therefore, it was possible to use global thresholds without losing much sensitivity. This normalization process, which acts as an adaptive highpass filter, has the negative side effect of transforming strong edges into lines. Without any further considerations they could be interpreted as contrails.

In the next step, the sum of the normalized images \(N = N5 + ND\) was used to avoid the interpretation of boundary layer cloud streets as contrails. These opaque clouds are usually colder than the surrounding, while the interstitial, often semi-transparent, regions then show higher values of \(TD\). Adding the normalized images cancels these effects.

\(N\) is then convolved with a line filter of \(19 \times 19\) pixels in 16 different directions (similar to Hou and Bamberger 1994). Some filter-kernels are displayed in figure 6, and their profile is shown in figure 7. The result of the line filtering for an angle of \(45^\circ\) is shown in figure 8.
Figure 8. Sum of normalized images $N$ convolved with line detection kernel for $45^\circ$.

Because of the normalization of the input data, a single threshold then is sufficient to isolate connected regions. As contrails are often very thin, we use the eight-connection criterion, which states that if one of the eight neighbour pixels of a marked pixel is also marked then both belong to the same region, was used. These regions were now treated as separate objects which might be contrails.

Each of these objects was now checked against a binary mask (check) shown in figure 9 which combines the following criteria:

$$N > 1.5$$  \hspace{1cm} (3)
$$TD > 0.2 \text{ deg K}$$  \hspace{1cm} (4)
$$G_5 < 2 \times SDT_5 + 1 \text{ K}$$  \hspace{1cm} (5)

The threshold of 1.5 in condition (3) depends on the type of normalization. It selects pixels which are brighter than the surrounding. $G_5$ is the large-scale maximum gradient for $T_5$ calculated in a $15 \times 15$ pixel vicinity shown in figure 10. Cloud edges and sometimes also shorelines show a high $TD$ signal. Due to the highpass properties of the normalization filter they also show up as lines in $N_5$. Condition (5) applies an upper limit to the large-scale gradient of the temperature image depending on the regional standard deviation to eliminate such lines before further processing. Contrary to earlier contrail algorithms, a very low threshold of $0.2 \text{ deg K}$ was selected.

Figure 9. First guess mask for detection of contrails at full resolution (no wide objects).
for the temperature difference in condition (4). Because of the difference in emissivity of transparent ice clouds in channels 4 and 5, $T_D$ usually reaches values from 1 to 10 K (see Betancor-Gothe and Grassl 1993), but this contrast will be reduced when contrails above lower opaque clouds are observed. Afterwards, elongated structures disrupted by this check are recombined using morphological functions.

To be regarded as contrails, the resulting objects have to fulfill the following criteria:

- number of pixels $> 10$  
- length $> 15$ pixels  
- correlation of the pixel coordinates to a straight line $> 0.975$

Requirements (6) and (7) reject short line elements and artifacts produced by the line filter. Condition (8) checks if the coordinates of the found linear structure closely correlates with the actual-filter direction. It determines whether the object under consideration represents a line which is straight enough to be regarded as a contrail. Very diffuse and bent structures like cirrus streaks are neglected by this condition. Figure 9 displays the mask after applying conditions (6), (7) and (8) to the 45° filter direction.

The filtering and testing procedures were repeated for all 16 directions and the results (e.g. figure 11) were added to a binary contrail array. The proposed scheme mainly marks contrails of a width of 1 or 2 pixels. To detect wider contrails, the whole algorithm was then applied to images reduced by a factor of 2 using neighborhood averaging. The results of this step were again added to the final binary contrail mask (figure 12).

Tuning of the parameters in the requirements (3) – (8) was supported by an evolutionary algorithm which maximized the correlation of the resulting mask with the visual analysis of some test cases.

2.2. Testing by Visual Interpretations

Sixty satellite images ($T_5$ and $T_D$) from different days were carefully interpreted and the results compared with the algorithm’s output. Knowledge of the meteorological situations enables one to distinguish better between artificial and natural cirrus.
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Figure 11. Contrails derived from direction 45° at full resolution.

Figure 12. Result of the contrail detection scheme (contrail clusters grey).

Crossed linear cirrus clouds, especially, are clearly recognized as contrails by visual interpretation. Additional geographical knowledge helps to reject surface features.

Actually, most detected contrails are certainly contrails. The most frequent false alarms are misdetections of elongated cirrus streaks close to frontal systems and cumulus streets. Due to the \(N\)-threshold (3) and the gradient requirement (5), misdetections of cloud borders, coastlines, mountain ridges and valleys are rare. In some images, misdetections of the Elbe river in Northern Germany and Lake Balaton in Hungary were recognized. The skillful setting of parameters also avoids misinterpretation of sensor line failure and line-to-line calibration differences.

Errors are greatest at the off-nadir scene borders due to the reduced horizontal pixel resolution there. To diminish this effect only a scan-angle of \(\pm 50^\circ\) is used, which means that the outer 100 pixels on both sides of the satellite overpass are neglected.

Accurate visual inspection by zooming and optimizing the contrast confirms the assumption that many actual contrails are still undiscovered by the algorithm. In spite of the normalization the automatic scheme with its fixed parameters is inferior to the human eye in adapting to the specific contrasts in parts of the image. Thus, the observer is able to recognize many more mostly weak contrails.

Contrail coverage from AVHRR images derived by various trained observers differed by a factor of 2, which shows that visual inspection is highly subjective.
With the presented algorithm we reached a detection efficiency defined as the ratio of correct contrail detections to the amount of all visually recognized contrails of 30–50% was reached, keeping the false alarm rate in the order of 0.1%. The setting of the parameters in requirements (3) and (5) is a very sensitive method to choose between a low false alarm rate and weak detection efficiency or a high false alarm rates at improved detection efficiency.

Detected contrail width seems to be reasonable in cases of small contrails. The width of aged contrails is often underestimated by the algorithm. This further reinforces the assumption that the derived contrail coverage is too small.

3. Results

3.1. Actual AVHRR-detected contrail coverage

The contrail detection algorithm is applied to AVHRR-data preprocessed with the APOLLO system (Kriebel et al. 1989, Gesell et al. 1993) for 1440×2048 pixel images covering Central Europe (figure 13). The actual detection for a scene of this size presently takes less than 30 min processing time on an Ultra Sparc 2 machine. Since January 1996 it has been run daily for the noon overpass of NOAA-14.

In figure 13 all derived noon (12:30 UT±45 min) contrail masks for 1996 are mapped to a equidistant cylindrical projection with a resolution of 1 km per pixel and superimposed. It can be seen that the observed contrails accumulate mainly close to and in the direction of the major flight routes. It is assumed that the observed persistent contrails are about 30 min old. Suggesting a wind-component perpendicular to their direction of 20 m s⁻¹, their position usually moved 36 km against their position of formation. This smoothes the expected image.

Figure 13. Stacked contrail masks of 1996 indicate frequency and predominant bearing of air traffic (derived from 357 AVHRR noon-passages).
Figure 13 indicates that the algorithm is robust against misdetections of surface features. Counts of more than 10 are obtained for only 25 pixels in the whole image. As all found contrail pixels are defined as fully covered, this corresponds to a yearly averaged local contrail coverage (contrail frequency/number of measurements at pixel location) of 3% in the very limited area of 25 km$^2$. The absolute maximum of 12 (of 357 possible) counts, equivalent to 4% local coverage, is found right above Lake Balaton, Hungary. This single pixel together with few other outliers forms a structure along this elongated flat lake. As air traffic in the Balaton region is high, at least some of the detected features might be real contrails. All other outliers cannot be related to stationary surface features. Therefore, misdetections of static surface features can be neglected for regional contrail cloud coverage.

To calculate the regional AVHRR-derived contrail coverage (cc) we divide the counts of the superimposed contrail masks (figure 13) are divided by the number of possible detections and the data are filtered with a circular gauss-kernel of 50 pixels (approx. 50 km) FWHM (full width half mean). This radius was chosen to represent the visibility range of a ground-based observer.

Comparing the frequency of AVHRR-derived cc (figure 14) with the pattern of the standard deviation of temperatures in channel 5 for a $5 \times 5$ pixel kernel $SDT_5$ (figure 15) we recognize a strong relationship. $SDT_D$ (not shown) is very similar to $SDT_5$. Above sea we mostly detect higher cc-values than above land. A correlation coefficient of $-0.55$ between cc and $SDT_5$ shows that thermal heterogeneity caused by ground features and clouds influences the contrail detection efficiency. This strong dependence of detection efficiency on $SDT_5$ is caused by normalizing the temperature data for the detection scheme using (1) and (2). Looking at cc above the Alps, it is recognized that obviously above a certain value of $SDT_5$ hardly any contrails are
detected. As this effect cannot be avoided, all pixels where $SDT5$ exceeds 0.85 K (figure 16) are excluded from further considerations. Assuming that air traffic and atmospheric conditions which allow formation of persistent contrails are not correlated to $SDT5$, $cc$ is corrected for variations of $SDT5$ as follows. Applying a linear regression we raise all values of regional $cc$ according to

$$
ccc = \frac{1}{1 - 0.397/0.489 \times SDT5} \times cc(SDT5 < 0.85 K)
$$

(9)
to the heterogeneity-corrected AVHRR-derived regional contrail coverage (ccc) where $SDT_5$ is Gauss-filtered like cc. This widely removes the influence of $SDT_5$ ($SDT_5$ to cc correlation coefficient: $-0.01$) as can be seen in figure 17 but strongly enhances the average contrail cloudiness by extrapolation to a fictitious value of $SDT_5 = 0\, \text{K}$ where the algorithm would work best. This correction results in an average ccc of 0.5% for the observed area, which approximately doubles cc. If an observed $SDT_5$ value of 0.4 K is applied, a more conservative correction by an average factor of 1.4 will be obtained. As actual detection efficiency would require correction factors of 2 to 3, the adaptation to $SDT_5 = 0\, \text{K}$ was preferred. Thereby, it has to be accepted that the derived absolute ccc after heterogeneity-correction have an RMS-error of 50%, but their relative spatial variations now are highly significant.

The average for the corrected daytime ccc in the whole dataset (figure 17) amounts to $(0.5 \pm 0.25)\%$ for the year 1996. The spatial pattern of the algorithm-derived cc agrees with the contrail observations of Bakan et al. (1994). They also obtained the maxima in the North Atlantic flight corridor with declining contrail cloudiness to the eastern and southern parts of Europe. Table 1 gives explicit averages for sub-regions from both datasets. A lower ratio between Bakan and the present observations for the two southern boxes can be explained by the fact that Bakan did not take into account the differing visibleness of contrails against the background, which influences his results in the same way as the present detection efficiency. Obviously, the absolute value for contrail cloudiness observed by Bakan is on the average 1.6 times higher than the annual mean of ccc derived here. This may be an effect of analysing different years, but it is also assumed, that the deviations of absolute values may arise from the applications of two different methods. Visual interpretation of

Figure 17. Annual AVHRR-derived heterogeneity-corrected contrail coverage (ccc) at noon for 1996.
Table 1. Comparison (%) of annual averaged AVHRR-derived heterogeneity-corrected contrail coverage (ccc) with the previous results (ccb) with the Bakan et al. (1994).

<table>
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<tbody>
<tr>
<td>0–10° E 45–50° N</td>
<td>0.5%</td>
<td>0.8%</td>
<td>1.5</td>
</tr>
<tr>
<td>0–10° E 50–55° N</td>
<td>0.6%</td>
<td>1.1%</td>
<td>1.9</td>
</tr>
<tr>
<td>10–20° E 45–50° N</td>
<td>0.4%</td>
<td>0.5%</td>
<td>1.1</td>
</tr>
<tr>
<td>10–20° E 50–55° N</td>
<td>0.4%</td>
<td>0.7%</td>
<td>1.6</td>
</tr>
<tr>
<td>Total area: 0–20° E 45–55° N</td>
<td>0.5%</td>
<td>0.8%</td>
<td>1.6</td>
</tr>
</tbody>
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Hardcopies often lead to overestimation of contrail width, because granulation can enlarge these very narrow features. Again, this comparison indicates that trained human observers are more effective in contrail detection.

An advantage over the analysis of Bakan et al. (1994) is the higher spatial resolution. Some heavily flown air traffic routes can still be recognized in figure 17. Maxima of contrail coverage of 1.0% and higher are found over Wales, the Channel and in the Balaton region. But the latter is, as mentioned before, partly caused by some misdetections occurring over Lake Balaton. The criterion $SDT_5 < 0.85$ K did not prevent this misdetection.

Comparing the derived contrail frequencies to the fuel consumption at altitudes from 8 to 12 km, where contrails generally appear, produces a similar pattern (figure 18, Gardner et al. 1997). A good agreement is found for the region leading

Figure 18. Annual air traffic fuel consumption in the heights 8–12km (ANCAT/EC2- data, derived from mid-1991 to mid-1992, Gardner et al. 1997).
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1655 to the North Atlantic flight corridor, the high air traffic over Belgium and the Netherlands, and in both datasets the strong air traffic heading from mid-Europe southeast is recognizable. The minimum in contrail cloudiness over former Yugoslavia is not as pronounced in the ANCAT/EC dataset as it is in the derived contrail cloudiness. The reason might be the different period of time observed. The ANCAT/EC data were collected from mid-1991 to mid-1992. Due to the political crisis, air traffic over former Yugoslavia could have been less in 1996. The high observed contrail cloudiness over Poland which does not correspond to the fuel consumption rate and the results of Bakan et al. (1994) may also be explained by the impact of political changes in Eastern Europe on the air traffic, but higher ccc values then suggested by fuel consumption are found also over the Biskaya and the North Sea.

Figure 19 shows the daily variation of the average cc in the area between 0° E and 20° E, 48° N and 55° N. To derive values comparable to figure 17, the heterogeneity-correction was applied using the annual average of $SDT_5$ for this box. Thereafter, the daily ccc varied from 0.0 up to 5.7% with a standard deviation of 0.6%. Because contrails themselves lead to enhanced heterogeneity in the temperature images, the actual $SDT_5$ of the analysed scene for heterogeneity-correction were not taken into account. But, avoiding this positive feedback on ccc, reduced detection efficiency caused by other image features was not neglected. For the absolute values of daily ccc, an error in the order of a factor of 2 is estimated.

As the 30d-floating average in figure 19 suggests, there are remarkable annual variations with a ccc-minimum below 0.2% during summer and a ccc-maximum close to 0.9% during winter and spring. But temporal variations of detection efficiency might have influenced the results, e.g. higher surface temperature contrasts in summer may have led to reduced ccc. In winter a higher fog-frequency leading to smoothed temperature contrasts may increase the number of AVHRR-detected contrails in certain regions.

Figure 19. Average AVHRR-derived corrected contrail coverage for the box 0° E to 20° E, 48° N to 55° N. Asterisks are noon-passages, diamonds night-passages. The solid line shows the 30d-floating average, the dotted line marks the annual average for daytime. (Plotted are all values where data coverage was higher than 70%. The absolute maximum of 5.6% at 14 January is not shown.)
For January and April 1996, night-passes of NOAA 14 (01:45 UT ± 50 min) were additionally processed. With regard to the higher detection efficiency during night, the corresponding SDT5-images for the heterogeneity correction were used. A mean night-time ccc of 0.24% was found, while ccc for the same period on daytime was 0.70% (figure 19). Thus, ccc at night is about one-third of the daytime noon coverage.

3.2. Some characteristics of contrail cloudiness

The lengths of the automatically detected contrail streaks varied from 2.4 to 600 km, with an average of 20 km. In spite of the 15-pixel-length-criterion, very short contrail streaks were detected. This is caused by additional application of conditions (3), (5) and (4) (check, figure 9).

Travis (1996) reported much longer contrails (137 km) from visual interpretation. As the present visual inspection showed, automatic contrail classification detects many more short streaks, which by observers often are connected to long non-interrupted structures or are totally neglected. This hardly influences the areal coverage of contrails, because usually a shorter typical contrail length will be compensated by higher number of contrail streaks.

Figure 20 displays the annual mean temperatures that are found in contrails and their direct surrounding as a function of the distance from the contrail boundary. It is seen that the average temperature contrast in AVHRR channel 5 offers slightly better possibilities for contrail detection than the contrast in channel 4. As most of the contrails in the analysis are narrow, pixels with margin distances of -2.5 are rare. Weighting temperature averages by pixel frequency produces a typical temperature contrast of 2.5 K for T5 and 3.3 K for T5.

Temperature reduction against the background directly shows the influence of contrails on the reduction of the upward radiation flux in the thermal infrared atmospheric window.

![Figure 20. Mean observed temperatures (T4, T5) in contrails and surrounding pixels.](image)
Contrail width is calculated from the number of pixels in one connected streak of contrail divided by its length. It ranges from 0.9 to 15 km, with a mean width of 1.9±0.8 km. Defining contrail width as the distance where half of the temperature contrast is reached (figure 20) would produce 0.9 pixels wider contrails on average. This would result in an average AVHRR-detected contrail width of 2.8 km, which fits very well to the observations of Travis (1996), who determined an average width of 2.9 km.

3.3. Evaluation of airmasses for potential contrails

It was found that contrails usually appeared in clusters. The typical length scale of these clusters is in the order of several hundred kilometres. Their shape is often elongated. It is concluded that these clusters mark regions where the state of the atmosphere at the cruising levels of jet aircraft is suitable for the formation of persistent contrails.

In regions where air traffic is very high and where detection efficiency of the algorithm is sufficient, it can be assumed that some persistent contrails are detected as soon as atmospheric conditions are suitable in at least one of the flight levels. To estimate the areal extent of airmasses for potential persistent contrails, compact regions with contrails were determined. This is achieved by applying the morphological image processing operator ‘dilate’ (Pratt 1991) to extend the contrails with a circular template of 49 pixel radius and shrink by ‘erode’ to the ends of the detected contrails. The result is shown in grey in figure 12. Regions where the algorithm detected contrails are connected, while regions without contrails within a distance of 25 pixels are left blank.

High air traffic (ccc>0.5%) and high detection efficiency ($SDT > 0.5$ K) are found in some areas over the Channel and the Biskaya. Here, contrail clusters at 7–14% of all days of 1996 were observed. Under unchanged atmospheric conditions, this sets an upper limit to cc in case of increased air traffic.

3.4. Limitations of the scheme

If air traffic is intensive in an area and at an altitude which is suitable for the formation of persistent contrails, many contrails appear which spread and merge. This rare but relevant situation where a considerable proportion of the sky is completely covered by contrails cannot be recognized by the present pattern recognition scheme that is adapted to elongated structures. Therefore, in regions with very dense traffic the cc might be underestimated.

Also, widespread fuzzy patches of old contrails which no longer show their typical shape are not recognized. Minnis and Young (1997) observed cirrus clouds developing out of contrails, which lasted for 5–19h. The observations indicate that in some critical situations, air traffic triggers cirrus formation by adding condensation nuclei. More generally, the regular addition of condensation nuclei by aircraft emissions favours cirrus formation and persistence (Schumann 1994). Wang et al. (1996) showed that the occurrence of high sub-visible clouds in northern midlatitudes is almost a factor of 2 higher than that in southern midlatitudes. The tendency for an increase in cirrus coverage will require analysis using a cirrus cloud climatology.

Also, single contrails smaller than half a pixel in width are very unlikely to be recognized, especially if they are also optically thin. On the other hand, such contrails will have a low impact on the net radiation.

As noted in section 3.1, misdetection of other linear structures does not seem to
be a problem, but decreased detection efficiency over extremely heterogeneous surfaces like the Alps are significant. Knowledge about actual aircraft movements and atmospheric conditions will help to interpret these situations.

The detection efficiency of contrails over mid-level and high-level clouds may also be less than over warmer low clouds due to a lower temperature contrast against the background. However, the higher these natural clouds are, the less will be the temperature contrast and the less will contrails affect the radiation budget. Therefore, the bias in the results from this limitation in the contrail detection scheme will not be as significant as an underestimate of occurrence over uncovered land or sea.

4. Conclusions

The algorithm presented here is capable of the fast operational detection of persistent and roughly linearly-shaped contrails from the AVHRR channels 4 and 5. The pattern recognition approach makes it easy to adapt to other sensor types and to compare results. The scheme is relatively robust to misdetections of other linear structures in thermal images such as coastlines, mountain ridges and valleys or sensor line failures. The parameter settings derived are a conservative adjustment resulting in a low false alarm rate but also a low detection efficiency.

Sensitivity of the algorithm depends on the thermal homogeneity of the background. Intense temperature contrasts as can be found in high mountains strongly affect detection efficiency. When deriving a climatological parameter such as regional contrail coverage, it is advisable to omit those regions. To level differences in detection efficiency, the derived contrail coverage is adapted by the annual average of the temperature deviation in channel 5.

The annual mean of the heterogeneity-corrected AVHRR-derived contrail coverage reached $0.5 \pm 0.25\%$ in 1996. The authors recognize strong temporal and spatial variations in contrail coverage which match those derived by Bakan et al. (1994). Absolute values derived here are smaller by a factor of 1.6, which is of low significance due to analysis of different time-periods. Large differences of the two investigations can also be explained by an overestimation of the visual interpretations, but also by the poor detection efficiency of the automated scheme. The present authors showed that detection efficiency suffers from underestimation of contrail width (1.9 km) and recognized that the algorithm cannot detect very weak contrail structures which can still be seen by the human eye.

For January and April 1996, a night-time contrail coverage of 0.2% was derived, compared to 0.7% for the same period from AVHRR noon-passages. The observed annual cycle has its maxima during winter and spring, but it might still be influenced by a differing detection efficiency.

Beyond this the scheme is not able to detect atypical contrails such as very wide spread and fuzzy ones, which are hard to distinguish from natural cirrus. The approach also cannot recognize cases where contrails cover a large proportion of the sky, destroying their individual line pattern.

Validation by synchronous high resolution satellite or sky-camera data is strongly recommended to confirm detection efficiency. Furthermore, this would enable a better definition of which types of contrails are recognized. It should be possible to adjust contrail cloudiness by more realistic corrections of the algorithm derived values as well as helping in further development of the algorithm.

The temporal variability of contrail cloudiness is known to be strong. The results
of analysis of 1 year’s data have been presented here. Work is going on to analyse a longer time-series for more robust statements on seasonal averages and trends.

Influence of cloudiness on net radiation depends also on sun zenith. Therefore, the daily cycle of contrail coverage should be further investigated.

In contrast to visual analysis, automated contrail recognition gives the opportunity to derive local cloud coverage by contrails. Pixel-precise detection enables investigation of contrails’ optical properties and cloud forcing.

The scheme can be used as a valuable check of whether AVHRR data for land or sea surface investigations are free of contrails. If unrecognized, contrails can lead to drastic interpretation errors caused by lower transmission of the reflected sunlight and shadowing.

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