Feature extraction of clouds from GOES satellite data for integrated model measurement visualization*

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ABSTRACT

We process multispectral satellite imagery to load into our environmental database on the UCSC/ NPS/MBARI–REINAS project.[1] We have developed methods for segmenting GOES (Geostationary Operational Environmental Satellite) images that take advantage of the multispectral data available. Our algorithm performs classification of different types of clouds, as well as characterization of the cloud elevations. The resulting information is used to incorporate the texture mapped satellite imagery into a combined model/measurement visualization. The approximate cloud elevations, types, and opacities are used to develop a three-dimensional model of the cloud for use in visualization. Discrete Karhunen-Loeve transformations, or Hotelling transformations, are used to calculate the principle components from the multispectral data. The accurate segmentation and feature extraction of the clouds assists in validation and evaluation of atmospheric prediction models with true remotely sensed data. We demonstrate the integrated measurement model visualization with an Open GL application using texture mapping. The spectral data is also used to control the free parameters in the texture mapping of the modelled clouds. We are working on further improvements to develop novel compression techniques utilizing the KLT with segmentation and feature extraction, and also hope to develop algorithms that visualize the compressed imagery directly.
*Keywords:*Multispectral imaging, KLT, texture mapping, morphology, feature extraction, visualization

1 INTRODUCTION

Clouds are a commonly encountered phenomena that are difficult to simulate because they are complex in shape and interact with light in a complex fashion. In addition, failures in simulation are easy to detect, as

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everyone knows what clouds look like. They are also an important phenomena in weather, and therefore important for meteorological nowcasting, forecasting, and understanding. There is a wealth of information available from the visible clouds, and satellite remote sensing makes gillions of bytes of data available. This paper overviews the challenges in interpreting satellite cloud images for use in evaluating environmental atmospheric forecasting models. Our research goal is data fusion, which includes combining model (forecaster's numerical weather models) and measurement data (satellite remote sensed images and information from weather sensors.)

Data fusion and data assimilation are not only necessary to validate forecaster's numerical models, but they are also necessary to start or initialize model runs. We focus on the image processing and graphics visualization necessary for this fusion. We break the analysis into a five step pipeline: satellite and model collection, cloud segmentation/extraction, cloud classification, cloud modelling, and finally rendering satellite and model data, Figure 1. Satellite data are downloaded to ground stations where they are disseminated to analysts. Model data are computed at regular intervals at regional supercomputing facilities. Once the satellite data are available, image processing techniques are used to separate the clouds from the background, and to separate the various cloud types. Once the images have been suitably segmented, the cloud regions are classified to find cloud types, elevations, and thicknesses. This information is used to create three dimensional cloud models depending on cloud type. The modelled clouds should reflect the reality of the remotely sensed data as closely as possible, while extrapolating to three–dimensional cloud objects from the two–dimensional satellite images. This problem is very similar to tomographic back projection with the difficulties of only a single projection, but there is a wealth of domain knowledge available. Using the three–dimensional cloud models, a combined visualization of the cloud model and forecast model can be rendered. Many features are available within the forecast data including temperature fronts, humidity regions, wind shears, and comparison to remotely sensed clouds may be used for validation, hypothesis testing, and context.

We have built a system which uses the GOES-8 (Geostationary Orbital Earth Satellite) satellite multispectral data to create 3D cloud models. We have tried extensive use of discrete Karhunen–Loeve transform techniques for segmentation and compression. (See our paper on compression.[2]) We have also tried various classification approaches and cloud modelling techniques. In this paper we illustrate a functioning system, discuss implementation tradeoffs, prior work, and future planned enhancements.

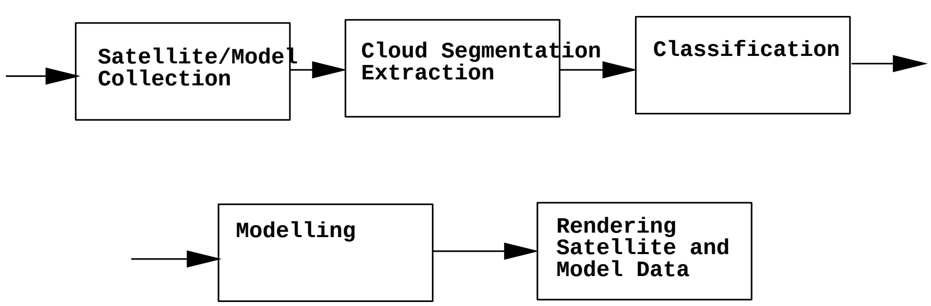

Figure 1: Five Stages for Multispectral Cloud Processing to 3D Visualization Fusion

1.1 EXISTING METHODS

As this is an important area of research, there are numerous published examples of cloud rendering, modelling, segmentation, and remote sensing. Approaches can be grouped into graphics and image processing and rendering systems. Our goal has been to fuse these areas.

Graphics work such as Blinn's demonstrates early modelling of planetary rings,[3] using transparency equations to model the complex effects of dust particles. He stated that the 3D light and particle modelling problem was the next important step. Kajiya and Von Herzen used simple models of clouds and complex 3D shading and radiation transfer calculations.[4] The modelled clouds and lighting calculations took many hours to compute on available hardware (1984). Gardner[5] developed models of clouds using a 3D volume texture function. He stressed a simplification over the earlier models to generate good results using planar and simple curved surface models with variable surface shading and transparency. Recent work using 3D textures includes Ghazantarour et al..[6] Max et al.[7] in order to animate clouds created simple models of clouds, and in Max[8] they also extended the earlier light models, and showed some simple clouds. In Max, Crawfis, and Williams[9] they created clouds using an isosurface threshold from a computed climate model, and texture mapping on surfaces. Computing clouds from a model is much more difficult than using satellite remotely sensed data to create clouds. Max et al. also experimented with computing haze.

Image processing systems such as those developed at NRL demonstrate development of segmentation and classification software in order to automate at sea use of satellite images. The work is surveyed in Peak et al.,[10] and subsequent work on larger software packages such as TESS3 and ExperCAT have incorporated these results. Other efforts similar to ours include the use of sounder data for determining cloud elevations as done in Brubaker et al.[11] Earth Watch Communications Inc. has developed GOES-8 segmentation, classification, and modelling of clouds for various areas of the globe. They also use Silicon graphics workstations to render their cloud models, which are viewable from the world wide web.[12] Local TV News stations, in San Jose California use a similar visualization, which may be Earth Watch Communication's product to present fly throughs during their weather forecasts. The clouds are clearly texture mapped–large polygons, and the main visual impact is a result of rendering the underlying complex San Francisco and Monterey Bay areas.

Hardware systems such as those used in flight simulators have also required modelled and rendered clouds. Cloud modelling is essential for photorealistic flight simulation, and also needs to be highly efficient for the necessary real-time rendering rates. Some simple approaches to ellipsoidal clouds are shown in flight simulators in the survey book by Schachter page 161 to 164.[13] Simulators also compute haze and fog which is related to the modelling work of Blinn, with the added advantage of specialized hardware for real-time rendering. Modern flight simulators including cloud effects include our Boeing B1-B CIG[14] and the McDonnell Douglas trainers. In video games there is a need for simplistic effective models to heighten the reality of flight simulation or other 3D rendered games. Video games optimize on the visual impact versus cost, and the use of clouds has therefore been more surrealistic than photorealistic. Video games incorporating 3D models of clouds include BlackOps-Entertainment's Agile Warrior F-11X for the Sony Playstation and Graphic Simulation's FA-18 Hornet for the Macintosh.[15]

1.2 SATELLITES, RADARS, SENSORS, AND MODELS

As part of the ONR-REINAS project, the University of California Santa Cruz is spearheading the collection of many modalities of data in real–time to support meteorologists and oceanographers. We are ingesting satellite, radar, in situ sensors, and model data into an information system. One of the goals of the project is to make progress towards combined model measurement visualization. In this section we briefly cover the data sources that this study makes use of. The satellite sources we have focused on are the collection of GOES (Geostationary Observational Environmental Satellite)[16] satellites. Most of the data used is from the current GOES-East satellite, which has an AVHRR sensor for high resolution capture, on GOES-8. We are eagerly awaiting the switch over of the GOES-West satellite from GOES-7 to GOES-9, so we will have the same resolutions and spectral data as for GOES-East. Our current data feed is the National Weather Service, and NASA Goddard.[17] The data are available in resolution spacings of 1 km, 4km, and 24km. We are using 8 bit images of 5 bands, with 600 vertical by 1400 horizontal resolution.

We also have data available from Radars and sensors, such as three Codar (TM) (Coastal Ocean Dynamic Radars) ocean current sensing radars, NOAA and Varian wind profilers, and a network of anemometers–wind, humidity, temperature, and pressure sensors. Currently the real–time network has a sampling about the size of the Monterey Bay (50 miles), but the GOES-W satellite resolution is poor for this coverage (5 pixels). Further details on sensors can be obtained through our technical report.[18]

The model data that are computed more closely match the available scale of satellite data. We currently use the NORAPS data,[19] a regional forecast model. The footprint of the NORAPS data can be seen with the combined GOES-West/NORAPS visualization in Figure 2. Our satellite processing techniques use the GOES-East satellite until the GOES-9 becomes fully operational.

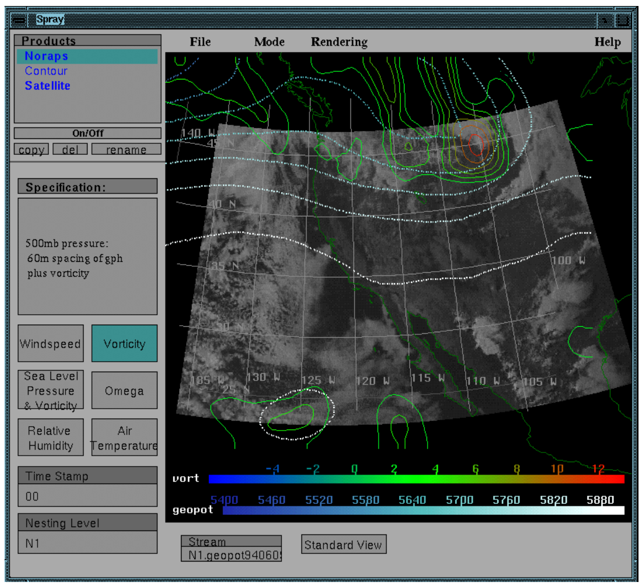

Figure 2: Simultaneous GOES satellite images rendered with NORAPS data in the Spray visualization system

2 CLOUD SEGMENTATION/EXTRACTION

2.1 Overview

Figure 5.a shows a cloud visible band image. The clouds are easily apparent in these visible band images, but there are a few complications to segmentation. Large masses of clouds, varying illumination, underlying snow cover, and irregular shapes make cloud segmentation more of a challenge. Cloud detection methods can be divided into several classes. The simplest is the so-called "radiance" threshold method where all pixels over a fixed value of illumination are considered to be cloud. These methods imply the choice of an arbitrary threshold value. From this simple approach more complex methods have been developed by meteorologists. As reviewed by Rosbow,[20] they can be divided depending on the use of radiance, variance in space, time or wavelength. The most common is the spatial variation cloud detection method,[21] having some drawbacks when used in some land ares and polar

regions. The time variation based methods[22] fail when the clouds exhibit very small time variations as tropical marine boundary layer. Finally, the spectral variance methods take into account the spectral signature of clouds and identify specific cloud types.[23] These spectral methods use information from given selected channels and detect clouds by cluster identification in a typically 2-D scatter plot.

In our approach, all the available wavelengths are used to detect the clouds. The main different spectral signatures present in the scene are first extracted (principal components) and a 4-D clustering algorithm is used to extract the regions belonging to each main component, clouds being one of them.

2.2 Multispectral Cloud Extraction

Multispectral information provides more effective segmentation for cloud extraction. The use of multispectral bands for feature extraction can be a precious source of information but it poses a number of problems. Having several spectral bands makes the analysis algorithms more complex and inefficient, thus it is important to choose the most representative bands. One means for band selection is to apply a decorrelating transformation to the spectral images. We have chosen to use the discrete Karhunen-Loève Transformation (KLT) (more properly known as the Hotelling transform), because it optimally extracts and sorts the spectral components of the scene by order of importance. By using this transformation, the analysis algorithm may use fewer components in their order of importance. The KLT has been widely used in remote sensing for multispectral imagery, and is also known as principal component analysis. It has been shown to be more efficient than analysis of the original spectral bands.[24] These components usually contain the most relevant information of the scene. For our application the components are mainly clouds, sea, land, and snow.

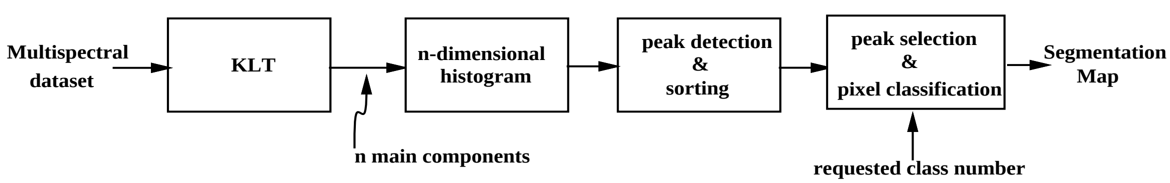

Figure 3: Block diagram of the multispectral cloud extraction

Figure 3 shows the cloud extraction algorithm. The principal components are obtained, and the first n are selected. The choice of n is a trade-off between low analysis complexity and accurate representation. Experimental results have shown that $n = 3$ is a good value. The three main components are then mapped into a 3-D histogram.[25] Figure 4 shows a multidimensional histogram. The choice of a multidimensional histogram avoids the recursive computation used in classical clusterings. The 3-D histogram defines a hypersurface (a 4-D surface). This *surface* presents a set of well defined maxima that are extracted by morphological opening operators after smoothing. The maximal peaks are extracted and sorted in order of importance. Given a number of classes (typically small) the same number of peaks are selected, and all the pixels are classified following a criterion of maximum correlation.

The algorithm yields a segmentation map with different classes. Since the requested number of classes is small (typically three) all types of clouds are segmented into the same class. The procedure of selecting the class belonging to the clouds is based on the analysis of the mean of the spectral signature of all the pixels belonging to the segment. In this way the class of clouds is easily detectable (the one that presents higher pixel values in the visible and lower in the infrared band). Figure 5 shows the cloud extraction results.

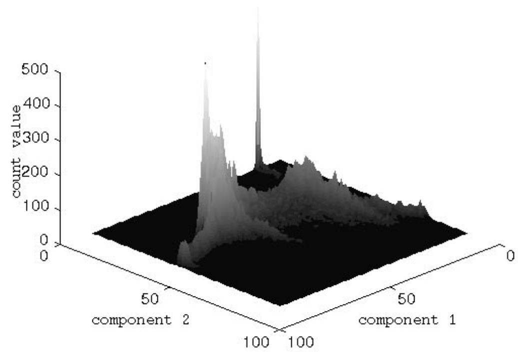

Figure 4: Multidimensional Histogram for Cluster Detection and Segmentation (example showing only 2 components)

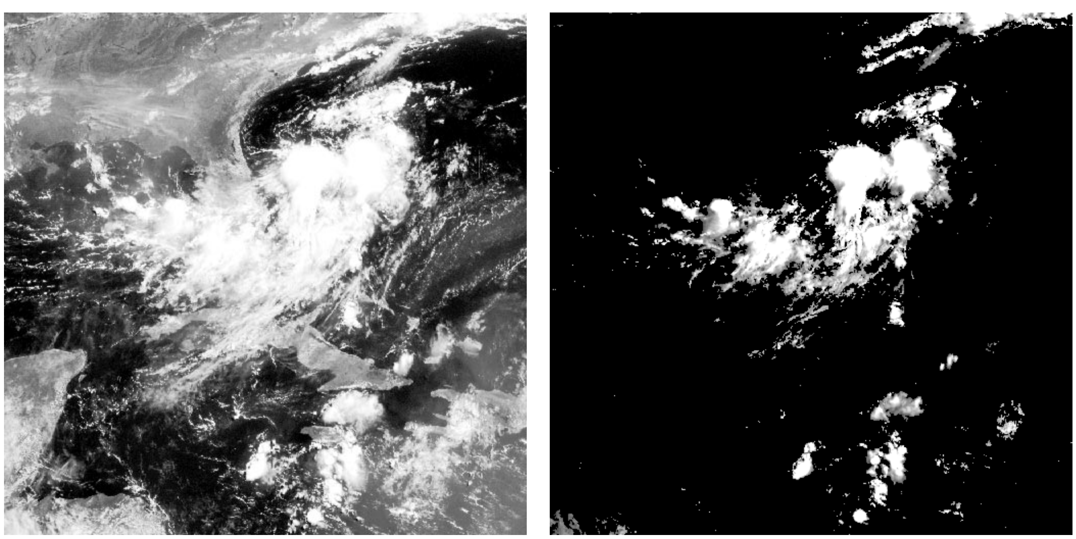

Figure 5: a. Visible GOES8 band. b. Extracted cloud by multispectral segmentation.

3 CLOUD CLASSIFICATION

In the previous section we presented a cloud extraction method. The cloud can be further segmented into different classes depending on their spectral signatures. The same clustering algorithm can be applied again inside the cloud classified image areas. Different types of clouds can then be obtained. There are three principal cloud forms: Cirrus, Stratus, and Cumulus. These forms have been refined into 10 basic types.[26] See Table 1. There are many ways to classify clouds given the satellite remotely sensed data. Clouds are classified by shape, temperature/elevation, elevation from sounder data, elevation from aircraft, spectral clustering analysis, and training of rule based systems or neural networks. The temperature-to-elevation-mapping and type of cloud dependence changes in different latitudes, and through different seasons so the classification is highly time dependent. True classification of the clouds requires climatology and meteorology expertise, and some systems have worked on codifying that expertise.[10] Once the remotely sensed clouds are classified, they can be more easily modelled, making assumptions about their shape, size, characteristics, and thickness. We have developed various ideas for cloud classification such as using a temperature to elevation mapping, which then maps elevations to cloud types. Other more sophisticated table based schemes can also be used, for example by building a multidimensional table with size and temperature as independent variables, and the lookup value would be the cloud type. The GOES data users's guide even provides classification tables for image regions, seasons, and wavelengths to aid in interpretation. These tables should be used as part of the classification process.

Table 1: 10 basic cloud types and classification information

cloud type	description	elevations (feet)
Cirrus	fibrous like or silky sheen	26,000-35,000
Cirrocumulus	thin white patch	26,000-31,000
Cirrostratus	transparent clouds that make halos of sun or moon	20,000-26,000
Altocumulus	bumpy rounded masses, like wool	12,000-20,000
Altostratus	transparent blue/gray clouds with no halo	7,000-15,000
Nimbostratus	storm cloud, dark, covers sun	0-6,000
Stratocumulus	gray or whitish layer with dark parts	5,000-10,000
Stratus	low clouds with drizzle or snow, no halo	0-5,000
Cumulus	Rising mounds of cauliflower white	2,000-10,000
Cumulonimbus	Huge towers, storm clouds, hail, lightning	2,000-26,000

We use cloud thickness as a key modelling parameter. Extraction of cloud properties has been studied by meteorologists.[23,27] The determination of cloud thickness from multispectral infrared channels is somewhat difficult and dependent on the satellite features.[28] In this paper the determination of the numerical cloud thickness is estimated by using the third infrared channel of GOES8 to be proportional to the cloud thickness. This channel, although not giving a true thickness cloud value, can be considered as representative of the thickness. More sophisticated models using additional remotely sensed data can be substituted to improve the thickness estimate. We believe that more sophisticated multispectral processing techniques shall greatly improve the cloud modelling process.

4 CLOUD MODELLING

The simplest cloud model is a plane or polygon. The result depends upon the rendering angle. The planar cloud is ideal when rendering from a large distance at nearly a perpendicular angle. If rendering from the side the texturing cannot compensate for the lack of thickness. We have developed a simple polygonal modelling approach.

It consists of two symmetric regular grids each one modeling one side of the cloud as shown in Figure 6. The distance between symmetric grid points, or thickness, is proportional to the infrared channel number three of the GOES satellite. In order to avoid cloud artifacts due to noise, the infrared image is smoothed slightly. Although, typically, clouds are not symmetric the polygonal approach leads to a very realistic rendering, and we have found it suitable for most instances.

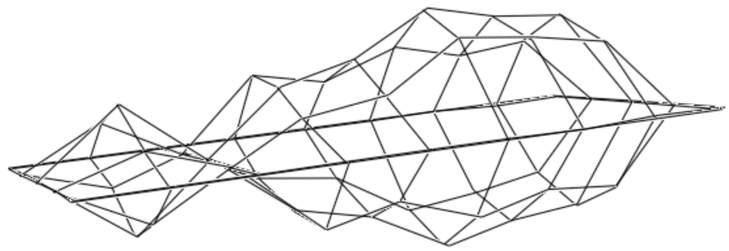

Figure 6: Polygonal cloud modeling

The second factor that our cloud model takes into account is the transparency. Infrared information is used again to model the transparency of the cloud. Infrared satellite images detect the thermal information radiating from the earth. This energy is modulated by the cloud. Therefore, the infrared can be contrast enhanced to serve as a transparency value for the texture map. The visible cloud images, after segmentation from sea, ground, and snow, are used to texture map the polygons in the final rendering.

5 RENDERING SATELLITE AND MODEL DATA

The polygonal cloud model is used as a prop for the cloud image. This is done by texture mapping also known as rubber sheeting or warping. The visible cloud image is used as a texture for both polygonal grids. Texture mapping is a method of choosing the scan converted polygonal color by back projecting into a texture. Two dimensional (2D) and three dimensional (3D) textures have been used to render photo realistic scenes, and for scientific visualization. We apply 2D texture mapping. The first step is to define the texture map coordinates and their correspondence to the 3D world polygon coordinates. The registration process is done by geometrically warping the satellite images to the same map space in which the data fusion is occurring. GOES satellite data support routines for satellite navigation, or the geometric correction, are available from the University of Wisconsin in a package called wiscnav. The wiscnav package can compute the coordinate conversions for a variety of satellite images which have been converted to that format. Using wiscnav we warp the satellite image from satellite camera coordinates. The next step is to warp the image to the appropriate map coordinates. We have experimented with using Lambertian Conformal Conic because our collaborators at the Naval Postgraduate School compute their 3D models in this map projection. A collection of routines available in both C and Fortran from the USGS allows conversion between the many available commonly used map projections for environmental data. We use these routines to compute the inverse transformations to warp the satellite image from latitude, longitude coordinates into Lambertian conformal conic. The General Cartographic Transformation Package (GCTP) is available via ftp.[29]

We have implemented the texture mapping using OpenGL on Silicon Graphics workstations. An example image of the final rendering is shown in Figure 7. Here clouds are shown rendered over the Caribbean Ocean and the Gulf of Mexico. An artificial pseudocolored map is used as a background to provide a clear demarcation of the underlying terrain for Florida, Cuba, Jamaica, etc. Using an Indigo^2 Extreme provides interactive performance in viewing these 3D cloud models, as there is hardware support for the texture mapping. We have also run the rendering program on an SGI Reality Engine^2 for even better performance.

Figure 7 shows the final 3-D cloud rendering. Given a polygonal model in world space, the visible texture map, and the transparency texture map, our remotely sensed clouds may be rendered in many data fusion contexts such as Spray.[30] We plan to incorporate the multispectral code into our new visualization program SlugViz, where the cloud tool will assist meteorologists by placing realistic clouds computed from remotely sensed data in the visualization of their 3D meteorological models.

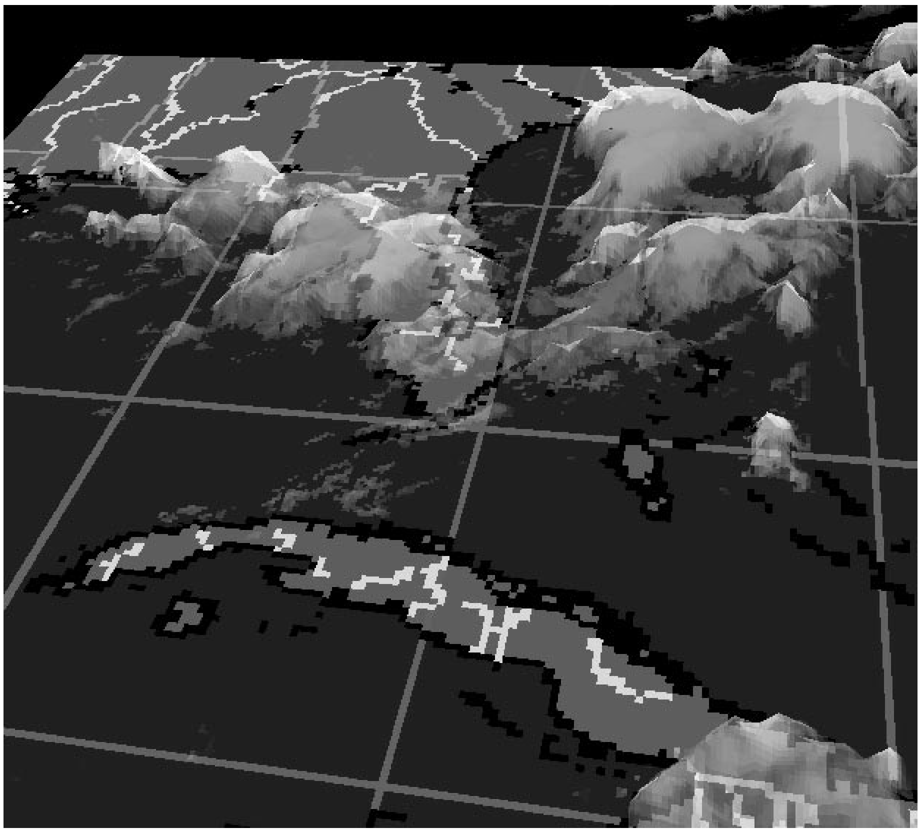

Figure 7: Final 3D cloud rendering

6 SUMMARY AND CONCLUSIONS

In this paper we have presented a method for segmenting GOES images that takes advantage of the multispectral data available. The five step process was overviewed: satellite and model collection, cloud segmentation/extraction, cloud classification, cloud modelling, and texture mapped 3D rendering. We described our primary data feed for remotely sensed cloud imagery, the GOES-8 (GOES-East) data. Once the GOES-9 (GOES-West) is available, we will have co-located 3D clouds (this paper) and 3D atmospheric models (NPS computed NORAPS data) for effective truthing of model runs. We described our KLT processing to compute the principle components, and our choice of three out of five bands for segmentation. A morphologically processed 3D histogram has its primary peaks extracted, which we use for clusters in the segmentation. We also described cloud classification, and possible approaches using GOES calibration data, lookup tables, and rule based systems. In our implementation we use the infrared channel to estimate the thickness through a linear scaling. We also modelled the clouds' transparency with an infrared channel. Our 3D polygonal cloud models are quite realistic, and provide many parameters, such as thickness, elevation, and transparency that may be improved by meteorologists. The KLT processing in combination with the classification, modelling, and rendering provide an efficient and straightforward means for 3D data/model fusion and visualization.

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