＜寄稿＞

APPLICATION OF REMOTELY SENSED ENVIRONMENTAL DATA FOR CONTROL AND AUTOMATION

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1 Introduction

Remote sensing is frequently used in for scientific observation for a variety of purposes including discovery and characterizing long-term trends. It has rarely been used for real-time control and automation. The reasons for not using remotely sensed data for control is more related to the nature of problems being managed and controlled than the applicability of the data. As environmental problems become more complex, more global and our needs for solutions increase, remotely sensed data and automation and control will be used together more frequently to solve these problems. It is the objective of this paper to review several sources for remotely sensed, environmental data and to show its emerging applications for automation and control.

1.1 Background

Remote sensing is the acquisition of information about some property of an object by a device that is not in physical contact with that object. In a technological setting, remote sensing is usually related to data gained by sensors and instruments which measure emitted or reflected electromagnetic energy. The data can be formatted in a digital arrangement which can be evaluated later with a computer to give valuable information (Sanchez and Canton, 1999). Indeed, many scientists in diverse disciplines have taken advantage of this technology to automate the acquisition of important parameters required for their modeling efforts. For example, environmental engineers can detect impervious surfaces from satellite images to use as inputs to their stormwater models. Usually, impervious surface is delineated from aerial photographs and field surveys, which is a long and tedious process. Remotely sensed environmental data can also be applied for controlling a system. For instance, a satellite image can show eroded areas or potential erosion sites. After efforts have been done to mitigate this situation, a satellite data of the same area with a more recent date can be assessed to determine if the land has been restored to a better state.

Satellite remote sensing has been a viable technology for more than 30 years. The technology is continuing to be vigorously developed. At first, only a few countries, like the United States and the Soviet Union, were able to launch satellites into space. Recently, however, many other countries, for example, Korea and India, have begun their own space programs. Coarse resolution images were the first to be developed (e.g., Landsat MSS at 80 meter resolution). But now, with higher resolution data (e.g., IKONOS with 4 meter resolution), more objects of different composition can be identified on the earth's surface. Spectral resolution has also improved. In the past, only the visible bands (blue, green, red) were available, but now, the longer infrared bands can also be utilized. In addition, the range of the bands is narrower. This means that the sensor has more capability to distinguish an object. The overall advances in this technology have led to more applications in many different disciplines.

This paper will present how remotely sensed environmental data can be used for control and automation in several environmental applications. First, the concepts of remote sensing are reviewed. We introduce briefly how natural and man-made features interact with electromagnetic radiation and how the emitted or reflected

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radiation is captured by a remote sensing system. Then, we present several applications in the environmental field. The application of remotely sensed data in stormwater management is discussed in more detail.

1.2 Energy Interactions With Earth Surface Features

When incident electromagnetic radiation or energy from the sun strikes an object on the surface of the earth, some of the radiation is absorbed, some is transmitted, and the rest reflected. This incident radiation is of different types, depending on their position in the electromagnetic spectrum. Only some of these radiation types are used in remote sensing because some are scattered and/or absorbed by the particles in the atmosphere. Hence, only those in the atmospheric windows, namely the blue (0.4-0.5 μm), green (0.5-0.6 μm), red (0.6-0.7 μm), near infrared (NIR) (0.7-1.3 μm), middle infrared (MIR) (1.3-3 μm), thermal infrared (TIR) (beyond 3 μm), and the microwave energy (1 mm to 1 m) are utilized for remote sensing. For a particular surface feature, different types of incident energy will result in different amounts of absorbed, transmitted, and reflected energy. Water, for example, reflects little blue, green, and red energy, and completely absorbs NIR. If the reflected energy in per cent is graphed against the wavelength of the energy, the result is called a spectral signature. The distinctive shapes of the spectral signatures of earth surface materials provide the basis for the identification of their characteristics or properties (e.g., land cover, moisture content, biomass) (Lillesand and Kiefer, 1994).

1.3 Sensor And Platform Characteristics

The sensor and the platform together constitute a remote sensing system. A passive remote sensing system utilizes the sun's electromagnetic radiation, while an active remote sensing system supplies its own source of energy to illuminate earth surface features. Aboard a satellite, remote sensing devices electronically code radiation in numeric format to produce a digital image. The most common sensing devices are the multi-spectral scanners and the microwave sensors (Harrison and Jupp, 1989).

The multi-spectral scanners utilize the visible, near infrared, middle infrared, and thermal infrared parts of the electromagnetic spectrum to obtain data. One wavelength range (e.g., 0.4 - 0.5 μm) corresponds to one band or channel (e.g., blue band). Multi-spectral scanners, which depend on natural illumination from the sun (passive system), operate in various ways. There are three types that are categorized according to the mechanism used by the sensor to view each pixel. Electromechanical scanners have a sensor which oscillates from side to side to form the image. In a linear array scanner, there is an array of detectors that sense the pixel values along a line simultaneously. While in a central perspective scanner, the sensing device does not move during data acquisition. Hence, the sensor views all pixels from the same central position. In this aspect, this sensor is similar to a photographic camera (Harrison and Jupp, 1989).

The microwave sensors function between the wavelengths of about 1-1,000 mm. These devices are employed in both active and passive systems. In active systems, like radar, the device not only supplies the energy but also detects the response from the features of interest. In the passive system, the earth sends out natural radio emission that the microwave devices can sense (Harrison and Jupp, 1989).

Platforms carry the sensors that gather data. The most common platforms are aircraft and spacecraft. Some of the multi-spectral scanners aboard an aircraft are the Airborne Thematic Mapper (ATM) which operates in 11 wavelength bands or channels, the Thermal Infrared Multi-Spectral Scanner (TIMS) which utilizes six channels, and the Airborne Imaging Spectrometer (AIS), which uses 128 channels. Spacecraft can be manned or unmanned (Harrison and Jupp, 1989). Mercury, Gemini, Apollo (launched in the 1960s), Skylab (1970s), and the Space Shuttle (1980s) are some of the manned spacecraft operated by the United States which took numerous images of the earth (Sanchez and Canton, 1999).

Unmanned spacecraft may be categorized into two general groups: polar orbiting earth observation satellites and geostationary meteorological satellites. Geostationary satellites orbit at an altitude of about 36,000 km above the equator. They always view the same point on the earth's surface. This is caused by the satellite's circling around the earth with the same angular velocity as the earth's rotation. Hence, the satellite views images of the same part of the earth at regular intervals (Harrison and Jupp, 1989). Some of the satellites that monitor the atmosphere covering the entire globe include Meteosat-2, INSAT 1B, GMS-3, GOES-6 (West), and GOES-7 (East) (Griersmith and Kingwell,1988).

Polar-orbiting satellites invariably pass a specific latitude at the same solar time. They cover regions between the latitudes 82° north and 82° south of the equator. Hence, they are called polar, sun-synchronous satellites. Their orbits in space can vary from 700 km to 1,500 km from the surface of the earth. Because of the orbital characteristics of these satellites, the near global imaging of the earth's surface can be done on a routine and predictable basis. The Landsat series of satellites have been the best-known satellites of this nature. Imagery that they acquire is also the most commonly utilized. But there are many other polar orbiters in space. One of these is the SPOT satellite which carries the multi-spectral (MSS) and panchromatic sensors. The MSS operates in three channels; the panchromatic, in one channel. Another example is the NOAA satellite which contains the AVHRR (four channels) and the AVHRR/2 (five channels). Another satellite, MOS-1, has three sensors, the MESSR (four channels), the VTIR (four channels), and the MSR (two channels) (Harrison and Jupp, 1989).

2 Current Applications

Because of the variety of sensors and platforms, remotely sensed data are regularly employed in many disciplines, including hydrology and water resources. For example, the snow water equivalent (SWE) of snow packs is important to estimate because snowmelt contributes to runoff, sometimes significantly. Bernier and Fortin (1998) used the C-band of synthetic aperture radar (SAR) to calculate the SWE of snowpacks in a watershed in the Appalachian Mountains in Canada. They developed a model associating the scattering coefficient to the physical characteristics of snow (e.g., depth, density, temperature) and underlying soil parameters (e.g., temperature, moisture). Because remote sensing can cover extensive areas, another parameter that can be efficiently calculated is soil moisture. Margulis *et al.* (2002) used the Electronically Scanned Thinned Array Radiometer (ESTAR) aboard the P3B aircraft to estimate surface soil moisture in central and eastern Oklahoma. To do this, they merged the satellite observations with data from ground stations (e.g., soil texture, vegetation type), and applied models with an ensemble Kalman filter. Drought and flooding have also been continually monitored by means of remote sensing data. For example, Birkett (2000) consulted satellite radar altimetry to determine changing water levels of Lake Chad in the Sahel region of Central Africa and its tributaries. NOAA AVHRR data also provided additional information. Data showed that the lake is subject to both drought and flooding.

Another field that significantly benefits from remote sensing technology is ecology. For example, habitat mapping is a task which is suitable with satellite data because it is closely associated with land cover mapping. The life requirements and reproductive success of species are generally dependent on land cover. In addition, habitat maps cover large areas. Mumby and Edwards (2002) used different types of imageries to determine the most cost-effective data that can map various habitats in clear, shallow water (e.g., coral, algae, seagrass). Because of its high resolution, textural information from the IKONOS image improved the classification. For coarse-level habitat mapping, however, Landsat TM yielded higher accuracies. Satellite remote sensing has also been extensively applied in coral reef management. Spencer *et al.* (2000) studied the relationship between coral bleaching in the southern Seychelles and sea surface temperatures measured by the NOAA AVHRR during a warming event of the Indian Ocean in 1997-1998. They observed that the amounts of bleaching are different in various locations, in different environments at the within-reef scale, and in various coral growth types.

When news of global warming circulated, scientists in many fields began to gather proof of this phenomenon. Most of the investigations involving satellite data look at the evidences of global warming in terms of, for example, rise in sea-level, or faster melting of snow packs. Masek (2001) predicted that boreal forest stands in two regions in northern Canada would extend because of a rise in temperatures. He worked on Landsat observations spanning 25 years. He concluded, however, that boreal forest has not shown this expansion. He suspected a lag between forest stand reaction and global warming. It is also possible that the surrounding vegetation out competed the forest stands.

Table 1 lists the papers just discussed and the highlights of their investigations.

3 Stormwater Management

The objectives of stormwater management are to regulate runoff and optimize water quality. The tool that engineers and planners use to attain these goals is a stormwater model. A stormwater model requires a lot of parameters such as elevation, land use, and imperviousness. These parameters are usually obtained from field surveys, aerial photographs, and other available analogue maps. However, these techniques are tedious and time-consuming. Remote sensing technology offers an efficient alternative to acquire some stormwater model input parameters. Below are some studies that extracted these critical parameters. Because of the large amount of data that has to be processed with satellite data, a geographic information system (GIS) is usually employed to store, retrieve, and analyze the data.

The following studies are based on investigations conducted on the same study area, which is a highly urbanized are in Los Angeles, the Marina del Rey area. Landsat ETM+ images were used in the studies. The resolution of 30 meters is sufficient for the particular application. It also has a high spectral resolution of seven bands. Hence, combination of bands can be chosen to suit a particular purpose. It is also available to the public.

3.1 Land Use

Land use is a critical input parameter in stormwater modeling. The type of land use is associated with the generation of specific pollutants. For instance, oil and grease concentrations were larger in stormwater runoff in commercial areas and parking lots than in residential properties (Stenstrom *et al.,* 1984). Land use is also indirectly associated with runoff rates and volumes. Certain types of land use have more impervious areas than others. For example, light industrial areas have much impervious surfaces like roofs and concrete. On the other hand, single-family residential areas have less impervious surfaces because of the presence of lawns.

Application	Parameter Extracted	Resolution	Platform	Sensor	Reference
Snowmelt runoff estimation	Snow water equivalent	6 m	Convair-580 Aircraft	SAR	Bernier and Fortin (1998)
Soil moisture estimation	Soil moisture	800 m	P3B Aircraft	ESTAR	Margulis *et al.* (2002)
Drought/Flooding	Water level	1.1 km at nadir	NOAA	AVHRR	Birkett (2000)
Habitat mapping	Land cover	4 m 80 m 30 m 20 m 10 m 1 m	IKONOS Landsat Landsat SPOT SPOT Aircraft	Multispectral MSS TM HRV (XS) HRV (Pan) CASI	Mumby and Edwards (2002)
Coral reef management	Sea surface temperature	1.1 km at nadir	NOAA	AVHRR	Spencer *et al.* (2000)
Global warming	Land cover	80 m 30 m	Landsat Landsat	MSS ETM+	Masek (2001)

Table 1: Some Applications of Environmental Remotely Sensed Data

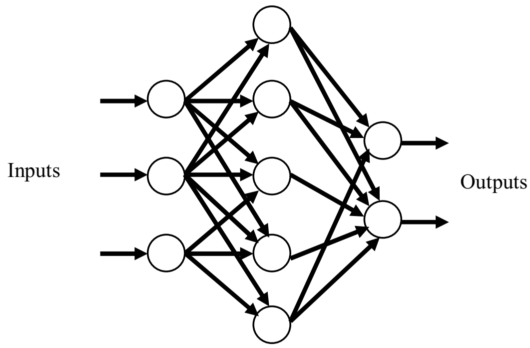

Fig. 1: A Neural Network

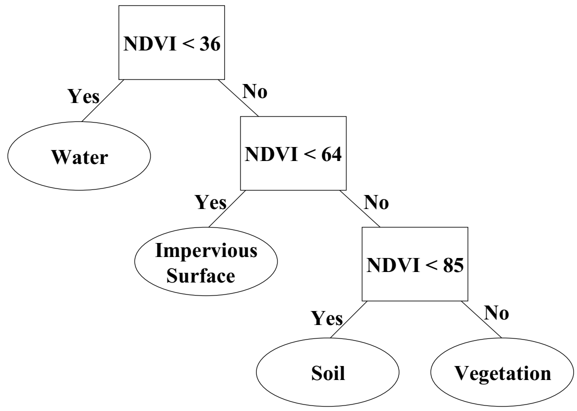

Fig. 2: Knowledge-based Classification

Lee (2003) used various versions of neural networksto classify land use relevant to stormwater modeling. A neural network is a system of interconnected neurons (Awad, 1996). In Fig. 1, neurons calculate the sum of the inputs with their associated weights. This value is compared to a threshold. If larger than the threshold, the neurons fire or produce an output. No signal is produced otherwise. This system is capable of learning. This happens when the neural network changes the weights and hence its course of action based on the inputs. Here, the inputs are the digital numbers (DNs) of each pixel. The DN is the digital equivalent of the analogue reflected energy that the sensor captured for each pixel. The outputs are the land use classes of the pixels. Lee initially worked on the spectral information of the image, but later found that with the addition of ancillary data, that are also inputs to the network, such as elevation and centroids of each pixel, the overall classification accuracy improved.

3.2 Impervious Surface

Impervious surface is another critical parameter in stormwater modeling. The amount of impervious surface areas in a watershed increases the stormwater runoff. Large volumes of runoff can result to flooding, erosion, and habitat destruction. Therefore it is important to know the overall imperviousness of a particular watershed. Knowing this, and knowing where these impervious surfaces are located, planners will be able to know which best management practices are applicable at particular points in the watershed.

Abellera and Stenstrom (2005, in press) applied knowledge based systems to locate impervious surfaces in the study area. In a knowledge-based classification (Fig. 2), land-cover classes are depicted as leaves of bi- or multinary trees, with rules employed at every node to end or continue on a course of action (Jackson, 1999). Initial classifications were applied on a transformed image called the normalized difference vegetation index (NDVI = (NIR band – red band) / (NIR band + red band)). Further rules were created using the six raw bands. In the first stage of the classification, rules were based only on spectral information alone, (i.e., raw DNs and NDVI values.) With these, there were gross misclassifications of impervious surface areas inland to beach. Therefore, in the second stage of the classification, ancillary data was added, in the form of a buffer zone from the Pacific Ocean. This increased the classification accuracy. With the addition of ancillary data, such as neighborhood information, the overall imperviousness approached the overall impervious surface area calculated from public records.

3.3 Pollutant Loadings

Stormwater modeling aims to estimate the amount of pollutants received by a water body. To do this, one must know the event mean concentrations of particular pollutants, rainfall, and areas of specific land uses. Usually, pollutant loadings are indirectly calculated

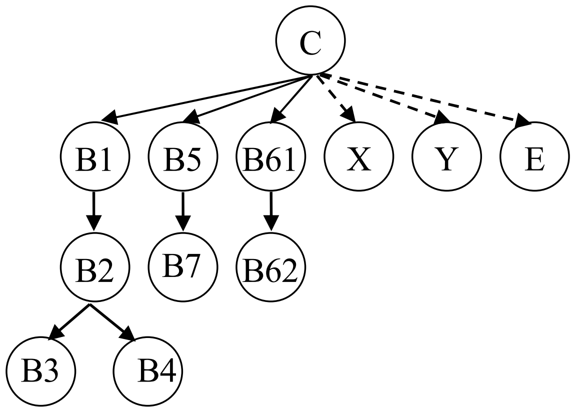

Fig. 3: Bayesian Networks

from these parameters. However, Park and Stenstrom (2004) skipped on the land use part, and instead directly estimated the qualitative characteristics of pollutant loadings to the Santa Monica Bay by applying Bayesian Networks. In this technique (Fig. 3), each node represents a variable. The arrows depict their dependence relationship to each other. The relationships between the nodes can be measured and shown using a conditional probability table (Pearl, 1988). The main inputs to the model are the spectral information (e.g., B1 represents the DN value of the pixel in band 1, the blue band). However, pixel locations (X and Y) were also incorporated in the model. Although the locational ancillary data improved the classification, the addition of elevation (E) was not significant probably because the study area was relatively flat. The results of the classification indicated that the transportation class must be prioritized first because it has high emissions of COD (chemical oxygen demand), BOD_5 (biochemical oxygen demand), TKN (total Kjeldahl nitrogen), and TP (total phosphorus). Alternatively, the open land use category shows the fewest pollution problems having only low emissions of COD, BOD_5, TKN, $NO_{2\&3}$ (nitrite and nitrate), TP, and SP (soluble phosphorus).

4 Conclusions

Tools used early by control engineers are now finding their way into earth science areas and environmental areas that rely heavily on remotely sensed data. The combination of knowledge-based tools, control theory and remote sensing is a powerful tool to address many traditional and emerging environmental problems. Detecting the impacts of climate change and habitat loss are two obvious examples. Managing non-point source pollution is another.

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APPLICATION OF REMOTELY SENSED ENVIRONMENTAL DATA FOR CONTROL AND AUTOMATION

リモートセンシング環境データの制御・自動化への適用

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要 約

30 年来活用されてきた観測衛星に代表されるリモートセンシング（遠隔監視，遠隔測定）技術は，ある現象の持つ長期的な傾向を見つけ出し，その特徴を明らかにするなどを主な目的とする科学的な観測手法として多用されている。しかし，今日までのところ，リモートセンシング技術はリアルタイム制御や自動化にはほとんど利用されていなかった。リモートセンシングデータが制御にあまり利用されなかった理由は，観測データの有用性に問題があるのではなく，むしろ管理や制御される対象の性質によるものであった。今後，環境問題がより複雑に，そして，より地球的な規模に拡大していくにつれ，また解決に向けた私たちの要求がより高度になるにつれ，これらの問題解決のためにリモートセンシングデータと制御・自動化技術が連携して用いられる機会が増えていくものと考えられる。本論文では，地球温暖化監視や生態系監視に利用されているリモートセンシング環境データの情報源について概説すると共に，雨水（洪水）監理など，今日，普及しはじめたこれらの情報の制御・自動化への適用例について述べる。

キーワード： リモートセンシング，制御・自動化，環境データ，雨水管理

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