STATE OF THE ART

REMOTE SENSING APPLICATIONS – NEW VISTAS FOR MEASUREMENT AND CONTROL

Invited paper

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Abstract:

The field of remote sensing is an area of science and technology that has undergone rapid development in recent years. This paper focuses primarily on how to exploit the capabilities made available by remote sensing and how to put them to use by combining them with a systemic approach to design and analysis in various measurement and control applications. The emphasis is placed on high-resolution satellite and Lidar sensors – the most prevalent remote sensing technologies. Following the presentation of some general issues related to low- and high-level processing of remote sensing data, such as data dimensionality reduction, data fusion, and change detection, the paper provides examples of control-related applications of remote sensing technologies. It is argued that successful exploitation of new generations of remote sensing technologies will require extensive development of new algorithms based on a variety of approaches, such as machine vision, statistical learning, and artificial intelligence.

Keywords: *remote sensing, satellite imagery, Lidar, image processing, data fusion, distributed control, modeling and simulation.*

1. Introduction

The field of control has traditionally, since its origins in the eighteenth century with Watt's governor, combined the development of coherent foundations for systems theory with simultaneous engagement in the solution of practical problems in a broad spectrum of diversified application areas. Research has probed such issues as stability and estimation, robustness and adaptation, optimality, information structures and decentralization. Important results have been obtained around the core problem of closed-loop design for linear and non-linear systems. Those results as well as the systemic, formal approach based on rigorous modeling of the underlying physical phenomena governing the behaviors of the system subject to control have been instrumental in expanding the scope of applications of control systems. Areas where control theory has made a major contribution include robotics, manufacturing, power systems, signal processing, operations research, transportation, agriculture, telecommunication networks and economics. The breadth of the applications of automatic control shows that the development of the control field closely follows the development of technology, and benefits from paying attention to technological trends. By understanding the details of a technology, the control specialist is able on the one hand to identify the technological bottlenecks and crucial problems that hinder the full development of the technology, and on the other hand to introduce systemic methodology based on a rigorous approach to analysis and design that advances the particular field.

The field of remote sensing is one area of science and technology that has experienced rapid development in recent decades. Remote sensing can be defined as the use of sensors installed on satellites or aircraft in order to detect electromagnetic energy scattered from or emitted by the Earth's surface. Specific wavebands are chosen according to the characteristics of the intended target. The driving force behind the use of space-borne remote sensors installed on satellites has been the expansion of space technology, since the launch of the first satellites in the sixties, into many aspects of everyday life. Telecommunications and weather forecasting are just a few examples of how space technology has become embedded in the contemporary technological landscape. Sensors operating in the optical electromagnetic spectrum are complemented by instruments operating in the microwave band, such as radars. Another major technological development has been the introduction of Global Positioning Systems (GPS), which have opened the way for the wide use of precise optical altimetry (Lidar systems).

We can define the relationships between remote sensing technologies and control systems as being of two kinds. The first type of relationship is *intrinsic* and relates to the use of the principles of control systems science and engineering in remote sensing devices and systems. Control technologies, such as those found in satellite control, are an integral part of remote sensing systems themselves. Attitude control or the control of navigation and communication systems are un essential requirement for the very deployment of satellites. The other type of relationship is *extrinsic*. It relates to the issue of how one can exploit the capabilities made available by remote sensing technologies to construct next-generation control systems in a wide range of applications.

This paper focuses primarily on the extrinsic function of remote sensing. It reviews the areas where remote sensing technologies find novel applications, and the challenges associated with their implementation to address selected technical problems. The first part of the paper briefly introduces the most prevalent remote sensing technologies, with the emphasis on high-resolution satellites (an example of passive sensors) and Lidar sensors (an example of active sensors). This is followed by the presentation of some general issues related to low- and high-level processing of remote sensing data, such as data dimensionality reduction, data fusion, and change detection. The final part of the paper provides examples of control-related applications of remote sensing technologies.

2. Remote sensing technologies

2.1. Satellites

Satellite sensors are characterized by their spatial, spectral, radiometric, and temporal resolution [15]. Spatial resolution refers to the size of the smallest possible feature that can be detected and depends primarily on the Instantaneous Field of View (IFOV). Spectral resolution describes the ability of a sensor to define fine wavelength intervals. Radiometric resolution describes sensor's ability to discriminate slight differences in the magnitude of the electromagnetic energy, determining its sensitivity to small differences in reflected or emitted energy. The absolute temporal resolution of a satellite corresponds to the revisit period of the same area at the same viewing angle. Because of some degree of overlap in the imaging swaths of adjacent orbits, the actual temporal resolution of a sensor depends on a variety of factors.

The spatial resolution of a satellite sensor is often different for panchromatic images and for images in particular spectral bands. The most widely used satellite optical instruments, such as Landsat ETM+ or SPOT, feature 4-7 spectral bands. Hyperspectral sensors offer the acquisition of several hundreds of bands. NASA's AVIRIS acquires data in 224 bands in the range 0.35-1.5 μm with a bandwidth of 10 nm. The large number of spectral bands has a significant impact on the subsequent stage of data processing and pattern recognition. Since the launch of IKONOS in September 1999, we have witnessed the emergence of sensors with high (< 1m) spatial resolution. Table 1 presents a list of recent high-resolution satellites.

One issue that has to be considered when planning work with satellite data is the availability of data. Only Landsat 7 is programmed to collect and archive 4 sets of global land images every year. Furthermore, this is the only program that makes all of its data available to all for the cost of reproduction. Another consideration is that acquisition of imagery from space can be hindered by weather conditions.

2.2. Lidar

Lidar (Light Detection And Ranging) is one of the most widely used ranging techniques, which also include supersonic wave ranging, infrared system ranging and satellite navigation ranging.

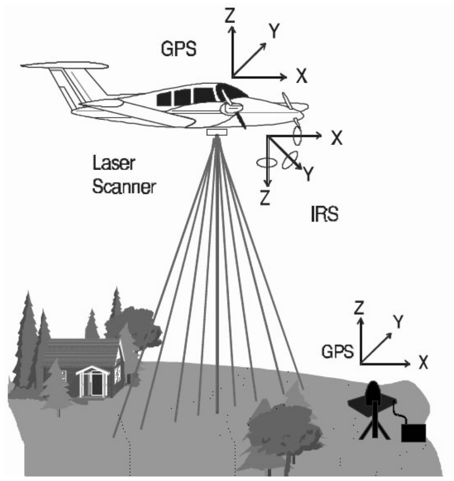


Fig. 1. Components of an airborne Lidar system (©Terrapoint).

A Lidar system (Fig. 1) consists of the following concurrently operating components: a laser range finder, a Global Positioning System (GPS) receiver and an Inertial Navigation System (INS). Laser, GPS and INS data are stored on a logging computer and processed off-line.

The return signal can be recorded in the form of a multiple-return signal or a continuous signal. Interpretation of the return signal is schematically depicted in Fig. 2.

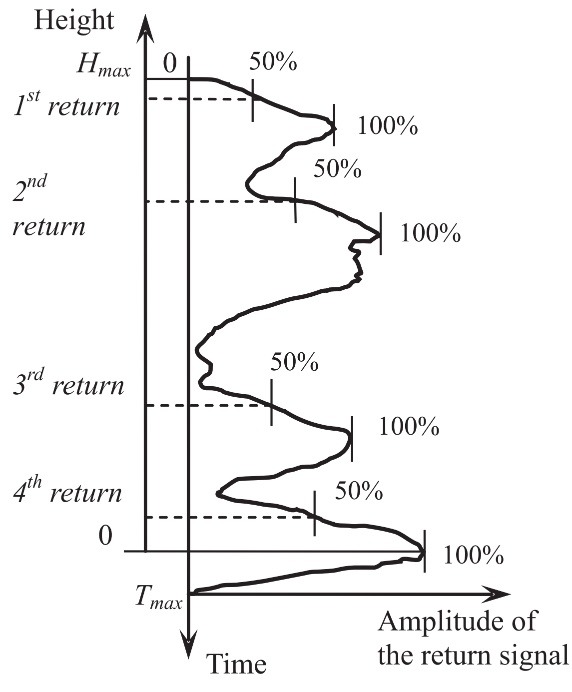


Fig. 2. Lidar multiple return signal.

Table 1. High-resolution satellites.

Satellite	Country	Launch	Panchromatic resolution [m]	Multi-spectral resolution [m]	Swath [km]
QuickBird-2	US	Oct. 2001	0.6	2.4	16
Resurs DK-1	Russia	June 2006	1	3	28
GeoEye-1	US	March 2007	0.41	1.64	15
WorldView-2	US	2008	0.5	1.8	16
Pleiades-1	France	Late 2008	0.7	2.8	20
Eros C	Israel	2009	0.7	2.5	16

Depending on the wavelength and signal reception techniques, Lidar systems can operate for different types of measurements. The depth of coastal waters is measured by bathymeters that use two laser wavelengths. The water depth is calculated as a function of the time difference between two signals: an infrared one reflected by the water surface, and a co-aligned blue-green signal which penetrates the water surface. The concentration of aerosols in the atmosphere is measured by Differential Absorption Lidars (DIALs). They exploit the difference in the absorption level of light at different wavelengths by the gas, the concentration of which is measured. An increasing number of Lidar systems come in the form of integrated packages with digital image capture tools, targeting the commercial survey, civil engineering, mining and industrial markets.

2.3. Radar

Radars belong to the class of remote sensing devices operating in microwave regions. Synthetic Aperture Radar (SAR) is a space-borne or airborne electromagnetic imaging sensor widely used in remote sensing applications due to its independence from weather conditions. There are three main differences between SAR and an optical sensor.

Fig. 3. RADARSAT-2 image.

- The two techniques use different frequencies or wavelengths. SAR uses microwave wavelengths (in the range of 1 cm to 1 m), while optical sensors use wavelengths near that of visible light, or 1 micron. This means that SAR can see through clouds and storms.
- SAR sensors do not rely upon the sun's illumination or thermal radiation; they carry their own illumination source, in the form of radio waves transmitted by an antenna. Therefore, SAR can be used with equal effectiveness at any time of day or night.
- SAR is a side-looking sensor (optical sensors mainly look straight down).

Table 2 summarizes the characteristics of recently announced SAR systems.

A RADARSAT-2 image of Iqaluit, Nunavut in Canada acquired January 7, 2008 is shown in Fig. 3 (courtesy of McDonald, Dettwiler and Associates Ltd.). The resolution of the three radar data channel (HH, VV, HV) image is 8 m.

3. General problems

3.1. Complexity of the information system involved in the processing of remote sensing data.

Data complexity

A defining feature of a large class of remote sensing systems, particularly those with multi-spectral sensors, is high measurement complexity [4]. In the case of multispectral imagery, the measure of the complexity of the image depends exponentially on the number of bits per band (dynamic range), and the number of spectral bands. The measurement complexity influences the performance of the accuracy of a classification task that uses the data. The number of training samples needed to adequately discriminate between the classes grows rapidly with the measurement complexity. The relationship between the expected classification accuracy and the number of training samples and the measurement complexity was initially investigated in [13]. The results show that for a fixed number of training samples there is an optimal measurement complexity. Consequently, one can expect to increase classification accuracy by using more bands and a higher dynamic range N, but to achieve the increased accuracy, more training samples are needed. This becomes an increasingly important practical consideration as we start to incorporate hyperspectral data in pattern recognition and classification tasks.

Dimensionality reduction

A closely related problem is the issue of high dimensionality of data, regarded in more general terms as the

Table 2. SAR space sensors.

SAR system	Country	Launch	Spatial resolution [m]	Swath [km]
Cosmo-SkyMed-1	Italy	June 2006	<1 100	10 200
RADARSAT-2	Canada	December 2007	3 100	20 500
Surveyor	China	2007	10, 25	100, 250
TerraSAR-X	Germany	June 2007	1 16	10 100
RISAT	India	2008	3 50	30 240

Table 3. Feature extraction methods for dimensionality reduction.

Method	Principle	Type of reduction	Optimization criterion	Limitations/Notes
Principal Component Analysis (PCA)[8]	2^{nd}-order statistics	Linear decomposition to covariance eigenvectors.	Axes maximize the variance of orthogonal projections.	Not efficient when the data are poorly correlated.
Self-Organizing Maps (SOM) [16]	Neural network (non-supervised learning)	Projection of data on a map (usually 2D or 3D).	Maximum number of iterations.	Dimensions of the map selected *a priori*.
ISOMAP [31]	Geodesic distances incorporated with metric multidimensional scaling	Projection on nonlinear hyperplanes.	Minimum geodesic distance on a neighborhood graph.	Dimensionality results from the algorithm.
Locally Linear Embedding (LLE) [25]	Maintains local linearity.	Computation of neighborhood-preserving embeddings of high-dimensional inputs	Minimum reconstruction error.	Inputs mapped into a single global coordinate system. Dimensions selected *a priori*.

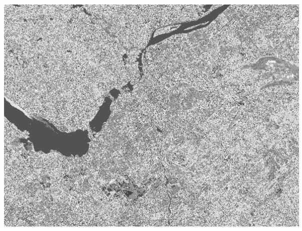
dimensionality of the feature space. The analysis process applied in low-dimensional spaces is in most cases not appropriate in spaces with higher dimensionality. Several approaches and methods have been developed to reduce the dimensionality of the data. The dimensionality reduction methods can be broadly categorized as feature extraction and feature selection methods.

Feature extraction implies the search for m features that are functions of n initial dimensions, where $m \ll n$. However, the physical sense of the dimensions can be lost. In the methods based on feature selection, the most pertinent dimensions are retained. Table 3 compares typical dimensionality reduction methods that apply to the feature extraction approach.

The use of Self-Organizing Maps related to the analysis at different levels of dimensionality can be intuitively assessed using an example [36] illustrated in Fig. 4. The scene captured by a Landsat-7 ETM+ sensor (Fig. 4a) is segmented using SOM with a different number of neurons (Fig. 4b, c, d). With the number of segments equal to 5 the urban areas can be much easier distinguished than with higher numbers of segments. On the other hand, finer features on the image, such as shallow water in the left part of Fig. 4b, can be detected only when the number of neurons becomes sufficiently high.

a)

b)



c)

d)

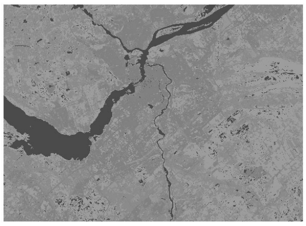


Fig. 4. SOM-based segmentation of Landsat-7 ETM+ image. a) Original image, b) 100-cluster SOM, c) 11-cluster SOM, d) 5-cluster SOM.

Another example demonstrates the utility of the LLE method. Sixty directly taken 16x16 pixel 4-band QuickBird images of tree crowns belonging to three coniferous tree species are plotted (Fig. 5) in a 2D space. The dimensionality is therefore reduced from 1024 (16·16·4) to 2. Figure 5 shows the resulting distribution of the images. The circled points indicate the positions of images of crowns of three different tree types. The images are shown in the bottom part of Fig. 5. It is clear from Fig. 5 that the discrimination of the crown tree types is greatly enhanced when using LLE-generated representations of a reduced dimensionality.

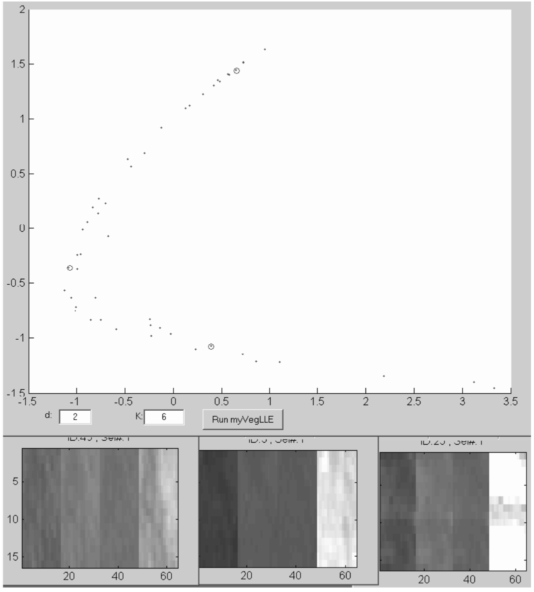


Fig. 5. Reduction of dimensionality of 16x16 QuickBird images using the LLE method.

A variety of methods have been developed for the selection of pertinent features from high-dimensional data. Approaches such as genetic algorithms [11], fractal dimension [33], rough set theory and Support Vector Machines have been reported.

Spatial sparseness

Another problem encountered with processing some remote sensing data is spatial sparseness of the data. There are several sources of the sparseness. The data may be acquired in the form of a sparse image due to the discrepancy between the spatial resolution of the sensor and the size and distribution of the objects of interest. The results of unsupervised classification of image pixels often produce salt-and-pepper-like effects. The output of a change-detection algorithm where decisions are made independently at each pixel is often in the form of sparse, noisy data.

The simplest techniques dealing with the spatial sparseness problem use standard binary image processing operations, such as median filters, or morphological operations. More complex solutions are needed to better adapt the operations to the application requirements. Scale independence can be achieved, for example, by the use of wavelets. The Multi-Scale Isotropic Matched Filtering (MIMF) operator (Eq. 1) takes into account four features of the sparse image [23]: contrast, local non-homogeneity of the scene, radial symmetry, and size.

$$M\{f(i,j)\} = \left(\frac{1}{|O|} \sum_{(m,n)\in O(i,j)} f(m,n) - \frac{1}{|B|} \sum_{(m,n)\in B(i,j)} f(m,n) \right)^2 - \gamma \cdot \left(a - \frac{1}{|O|} \sum_{(m,n)\in O(i,j)} f(m,n) \right)^2 \quad (1)$$

Fig. 6 depicts the calculation of the operator components in the case of raster images.

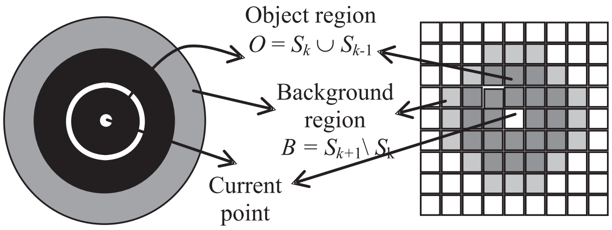


Fig. 6. MIMF calculation in the discrete domain.

Equation 1 can be extended by additional terms that take into account other image characteristics that are of interest for the user. Also, the analysis of successive maxima of the surface obtained by performing MIMF filtering on an input image permits to extract shape parameters of the objects of interest located on the image.

3.2. Sensor fusion

The purpose of sensor fusion is to obtain more reliable and accurate information through the synergistic combination of sensory data from multiple sensors. Moreover, by fusing complementary information from multiple sensors, we can perceive additional features, impossible to perceive using just the information from each individual sensor.

The development of smart sensors and integrated multi-sensor systems requires an interdisciplinary approach that involves the application of concepts from control theory, signal processing, statistics, artificial intelligence, and other disciplines. The following methods are used in sensor fusion algorithms [19]:

- estimation,
- classification,
- inference, and
- Artificial Intelligence methods.

Estimation methods can be divided into simple non-recursive methods, which take a weighted average of information provided by individual sensors and use this as the fused value, and recursive approaches that apply Kalman filtering. The Kalman filter determines the output estimates using the statistical characteristics of the measurement model. Extended Kalman filters (EKF) can be used where the model is nonlinear. The divergence due to modeling errors is critical in Kalman filter application. A fuzzy logic adaptive system was used in [27] to adjust the exponential weighting of a weighted EKF and prevent the Kalman filter from divergence. Classification methods apply cluster analysis in order to partition the multidimensional feature space into distinct regions defined by geometrical or statistical boundaries each representing an object class. Inference methods combine sensor information according to the rules of probability theory. DempsterShafter evidential reasoning extends the Bayesian approach by dealing with any lack of information on the hypothesis probability. Artificial intelligence methods rely on the application of rule-based systems and computational intelligence techniques.

In the realm of remote sensing, a typical problem is the fusion of Lidar data with the spectral information about the environment. Fig. 7 illustrates the form of input data we deal with in such a data fusion by showing a cloud of Lidar points superimposed on a QuickBird image of a rural terrain in central Alberta.

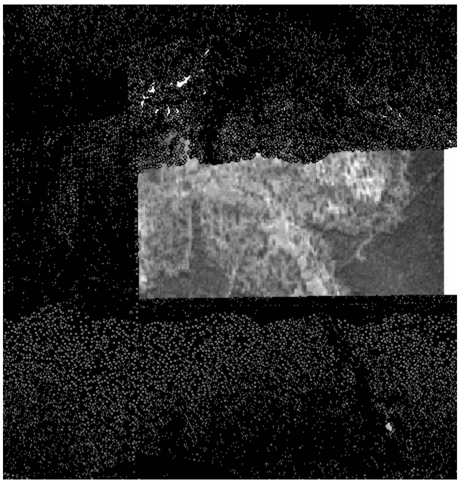


Fig. 7. Lidar data superimposed on a QuickBird satellite image.

Examples of sensor fusion architectures include the combination of video and multi-beam Lidar [32], pan-sharpening schemes [35], and the integration of the AVIRIS (Airborne Visible Infrared Imaging Spectrometer) hyperspectral data with the surface texture information derived from the TOPSAR (Topographic Synthetic Aperture Radar) radar data [5]. A combination of SAR and IRS (Indian Remote Sensing) optical data was used in the application of automatic procedures for earthquake damage classification.

In real world situations, information about the sensed environment is subject to the presence of various forms of uncertainty, and the sensors are not always perfectly functional. A challenging task is, therefore, the design of robust fusion algorithms.

3.2. Change detection

The generic problem of detecting changes in process parameters has been widely studied [29]. These changes may be due to a shift in the mean values of process parameters or to a variation in signal dynamics. The abrupt change detection methods typically find their application in preventive maintenance and quality control. Three different change detection methods – the difference method, the possibilistic approach, and the model-based approach – were tested in [26] in the context of monitoring a sequential manufacturing process.

In the analysis of multi-temporal and multi-spectral remote sensing data, various automatic and unsupervised change-detection methods have been developed [7], [12], [2]. Typically, a test metric is computed from two adjacent images and a decision is made by thresholding the metric. A few examples of the metrics are given below [37]: chi-square (Eq. 2), absolute value of histogram differences (Eq. 3), likelihood ratio (Eq. 4), and Snedecor's F-test (Eq. 5).

$$\chi^2 = \sum_{i=1}^{M} \frac{\{h_j(i) - h_k(i)\}^2}{\{h_j(i) + h_k(i)\}} \tag{2}$$

$$\delta = \frac{\sum_{i=1}^{M} \left| h_j(i) - h_k(i) \right|}{\sum_{i=1}^{M} \{h_j(i) + h_k(i)\}} \tag{3}$$

$$\lambda = \frac{\left[\frac{\sigma_j + \sigma_k}{2} + \left(\frac{\mu_j - \mu_k}{2} \right)^2 \right]^2}{\sigma_i \sigma_k} \tag{4}$$

$$F = \frac{\sigma_j^2}{\sigma_k^2} \tag{5}$$

where: $I\,(x, y; j)$ - intensity of point (x, y) of the jth image; (j, k) - indices of two sequential images; $h_j(0)$ - histogram of image j ; μ - intensity mean; σ - intensity standard deviation.

In template-based metrics, such as template matching Δ or based on normalized $(\mu = 0; \sigma = 1)$ inner product γ as given in Equations (6) and (7), the structures of the images are compared.

$$\Delta = \sum_x \sum_y \left| I(x, y; j) - I(x, y; k) \right| \tag{6}$$

$$\gamma = 1 - \frac{I_j \bullet I_k}{\|I_j\| \|I_k\|} \tag{7}$$

In the problem of change detection in an image sequence, the temporal consistency of pixels in the same location at different times is exploited. Pixel intensities over time have frequently been modeled as an autoregressive (AR) process [14]. However, linear models perform poorly in more demanding conditions. As suggested in [3], a nonlinear dependence to model the relationship between two images in a sequence and under the no-change hypothesis. An adaptive neural network was used in [6] to identify small-scale changes from a sequence of multispectral images. Pixels for which the non-linear neural predictor performs poorly are classified as changed.

The employment of Lidar rather than spectral information as primary data in updating is of particular interest in such applications as reliable damage assessment in earthquake-prone and dynamically changing urban areas [34]. Synthetic aperture radars have been exploited less extensively than optical sensors in the context of change detection, mainly due to the fact that SAR images suffer from the presence of the speckle noise. An unsupervised change-detection approach specifically oriented to the analysis of single-channel single-polarization multi-temporal SAR images was presented in [1]. The proposed approach is based on a closed-loop process made up of a controlled adaptive iterative filtering, and a comparison between multi-temporal images carried out according to a standard log-ratio operator.

3.4. Quality of Service

Independent of the type of service, the precision of the remote sensing data itself is an important consideration. The number and the variety of errors sources in remote sensing technologies are particularly large. As an example, the major components of the error budget in Lidar systems are the following:

A) Laser
- Timing precision;
- Scan method (oscillating, elliptical, ...);
- Beam divergence;
- Angular precision.

B) GPS
- Aircraft GPS installation;
- Base station location;
- Clock and ephemeris errors;
- Site interference and obstructions;
- Satellite configuration;
- Ionosphere errors;
- Troposphere errors.

C) IMU (Inertial Measurement Unit)
- IMU to Laser and GPS antenna offsets;
- Pitch, roll, heading accuracy;
- Alignment.

4. Control related applications

Remote sensing techniques have proven to be a valuable monitoring tool, providing data that can be used for modeling and control of processes with important spatial dimensions, particularly those involving natural phenomena. The considerations that go beyond process modeling, such as decision making and the interactions between complex system components and the networking of individual agents, extend the applicability of remote sensing techniques to the domain of control systems. Some representative types of applications are discussed below.

A. SLAM

Sonar and laser range sensors, and to a lesser extent vision systems, can be used in mobile robotics to build maps of the unknown surrounding area when no GPS data is available. The process of building a map of the environment while simultaneously using this map to deduce robot localization information is called Simultaneous Localization and Mapping (SLAM). In SLAM, both the trajectory of the moving platform and the location of all landmarks are estimated online without the need for any *a priori* knowledge of location, and in spite of errors caused by readings from sensors and the motion control system.

In probabilistic form, the SLAM problem requires that the probability distribution (Eq. 8) describing the estimates of the landmark locations and vehicle state be computed for all times k

$$P(x_k, m \mid Z_{0;k}, U_{0;k}, x_0) \qquad (8)$$

where:

x_k – state vector describing the location and orientation of the mobile platform;
u_k – control vector;
m_i – time invariant location of the *i*th landmark;
Z_{ik} – observation (taken from the vehicle) of the location of the *i*th landmark at time *k*.

It can be shown that the precision of these estimates increases monotonically and that the vehicle location estimate becomes bounded [10]. In order to solve the SLAM problem, optimal state estimators such as the Kalman filter (KF) and the extended Kalman filter (EKF) have been used. Although this approach produces good results, it suffers from two limitations: quadratic complexity and sensitivity to failures in data association [21]. Alternative algorithms, such as those based on the expectation maximization (EM) algorithm, fastSLAM, and dense-SLAM [22] have been investigated. Nonethe-less, multi-robot mapping remains a challenging area, with a large number of issues still to be investigated.

While optimal robot motion can be well specified in fully known environments, exploring robots have to cope with partial and incomplete models. Any viable exploration strategy has to be able to accommodate contingencies that might arise during map acquisition. Hence, exploration is a challenging planning problem, which is often solved sub-optimally *via* simple heuristics. In future, the SLAM algorithms and strategies will increasingly relate to a broader range of perceptual problems, such as sensor-based manipulation and interaction with human operators.

B. Navigation

Navigation for mobile robots and autonomous vehicles using vision has been widely investigated [9]. Recently, the number of applications of laser scanners has greatly expanded, ranging from driver assistance systems, through collision avoidance and map building, to driverless transport in factory yards.

An example of modular architecture of the navigation system is presented in [30]. The architecture, shown in Fig. 8, contains an inner and an outer control loop. The outer control loop is used during the initial phase, when the laser scanner delivers sensor data for the target classification and path planning modules. The inner control loop manages the complete approach process. The laser scanner and odometer provide the required sensor data.

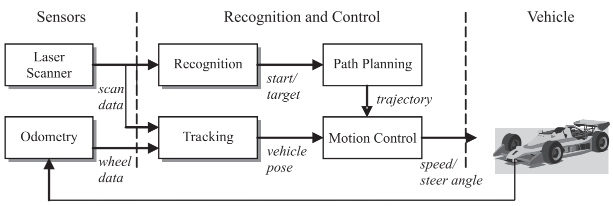


Fig. 8. Automated navigation system.

An interesting problem of navigation, i.e., gate recognition, and gate crossing for a real-size outdoor mobile robot, was presented in [28]. The vehicle's general navigation is based on information from Global Positioning System (GPS) and Inertial Navigation System (INS). When the robot is near the gate, the laser scanner sensor gives information about the exact location of gate, its shape, and attitude of the vehicle with respect to the gate. The gate-crossing problem differs from range-based, wall-following problems, since it requires a transition from the open-field (essentially GPS or sensor fusion-based) navigation to range-based navigation.

Advantages of laser scanners over other types of sensors include their high precision and independence of prevailing ambient conditions. This is especially impressive when operating at night, where no additional illumination is needed.

C. Automated Highway Systems

Automated Highway Systems (AHSs) have recently been the focus of extensive research effort. This particular area of navigation systems is driven by the continuous development of the auto industry. In an AHS, each vehicle must be under computer control in both longitudinal and lateral directions. Lateral vehicle control schemes can be generally categorized into roadfollowing control and vehicle-following control.

An essential component of an AHS is an automatic ranging system (Fig. 9) equipped with risk estimation and decision making capabilities. Lidar sensors have been studied for this purpose, for instance, in the California PATH vehicle guidance project [17].

Fig. 9. Lidar-equipped experimental vehicle (IEEE).

The experimental study has also revealed an interesting relation between Lidar outputs and magnetometer measurements, showing that the Lidar output may be roughly approximated by the look-ahead scheme using the outputs from two sets of magnetometers. This demonstrates that Lidar may be reasonably considered as a look-ahead sensor, which can provide a considerable amount of phase lead. Consequently, new lateral control systems can be developed with Lidar as the only sensor.

A real-time feature-level sensor fusion system incorporating spatio-temporal aligned vision and multi-beam Lidar measurements for robust vehicle detection and tracking has been developed [20]. The detection process does not rely on target motion, hence the system can be used in traffic jam and stop-and-go applications. Tracking multiple targets is achieved by fusing asynchronous heterogeneous sensor data, with multi-instance Kalman filters for the targets and a single Kalman filter for the ego-motion estimation.

D. Modeling

Understanding processes requires models, and often the use of AI approaches. In this context, satellite and airborne remote sensing sensors have proved particularly useful in extracting meaningful information, especially for modeling applications related to environmental monitoring, agriculture, urban studies, and forest management. Next-generation commercial radar satellites offer advancements that will enhance marine surveillance, ice monitoring, disaster management, resource management and mapping in zones around the world where access is difficult or impossible.

A well-developed area of application of Lidar sensors is urban modeling. Models of urban zones can further be used for municipal planning or disaster studies. They allow the quick detection of damage and building collapses due to natural disasters, such as flooding or earthquakes. Various spatial dynamic models, especially those based on cellular automata (CA) and geographical information system (GIS), have been constructed. The selection of dynamic models is influenced by the results of the application analysis.

Remote sensing is used to estimate biological, physical and chemical properties over a range of temporal and spatial scales, ranging from local and rapid through to large and slow. Spatial scale is a concept that is closely connected with measurement and sampling. Therefore, it is important to distinguish between scales of measurement, which relate to the sample, and scales of the spatial variation of data.

5. Conclusions

The operation and use of high resolution satellites and many other remote sensing technologies are no longer restricted to a few countries with advanced technology. Over twenty countries have already direct access to satellite technologies and space-borne data. Deployment of fleets of small satellites and HALE (High-Altitude Long-Endurance) UAVs will significantly reduce the high cost of large systems, which currently hampers the commercial use of these technologies.

Remote sensing technologies are particularly useful for acquiring environmental data. They play a major role in studies of climate change, forestry, and security issues. One of the most important applications of remote sensing is the detection of changes occurring on the earth's surface. This stems from the fact that knowledge of the dynamics of either natural resources or man-made structures is a valuable source of information to support decision making by governments as well as by public and private institutions. We expect future change-detection algorithm developments to be fueled by increasingly integrated approaches combining elaborate models of change, robust statistics, and global optimization methods. Further system improvement is expected, particularly from heterogeneous sensor data fusion strategies.

The successful exploitation of new generations of very high resolution imagery from space, Lidar sensors and other remote sensing technologies will require extensive development of new algorithms based on a variety of approaches, such as machine vision, statistical learning, and artificial intelligence. The construction of useful automatic measurement and control systems incorporating information extracted from remote sensing sources must follow the guiding principles of systems science.

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