COMBINING STRONG FEATURES FOR REGISTRATION OF HYPERSPECTRAL AND LIDAR DATA FROM FIELD-BASED PLATFORMS

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ABSTRACT

This paper presents an approach to automatically register hyperspectral images with lidar point clouds using a combination of SIFT and SURF feature descriptors. The aim is to generate 3D terrain maps of the environment combining spectral and geometrical information. The datasets are acquired from field-based platforms which, due to the lack of georeferencing, cannot be simply fused and require a registration processing step. In addition, some applications, such as in mining, cannot rely on reliable GPS signal. The proposed method is validated using experimental data acquired from vertical mine walls.

Index Terms— Hyperspectral imaging, terrain mapping, sensor fusion, image registration, feature extraction

1. INTRODUCTION

The mining industry has great demand for remote sensing and surveying techniques due to the large areas and high cost associated with mineral exploration and mapping. Hyperspectral imaging data has long been used to determine the composition and distribution of mineral ores in outcrops, since each material has a characteristic spectral signature which can be analysed to identify and quantify its abundance. Laser scanners, also known as light detection and ranging (lidar) sensors, provide the terrain's geometric information as digital elevation maps. Combining these different sensing modalities has many potential applications. For example, the 3D volumetric information can be used to estimate the amount of each mineral present in the scene, and detailed knowledge of the geometry could assist in the calibration and analysis of hyperspectral images.

Data fusion provides methods to combine measurements from different sensors, which is a very challenging task in general. The choice of approaches for data fusion will depend on the nature of the application and sensing modalities involved [1]. In traditional remote sensing products, data acquired from satellite or airplanes is calibrated and georeferenced, which renders data registration trivial. Therefore, most remote sensing research has focused in fusing data with diverse spatial, temporal and spectral resolutions. However, for some environments and sensors GPS data is unavailable or unreliable, for example in mine pits. Data acquired from imaging sensors have the additional challenge of different camera pose and resolution. We focus on image registration, also called image alignment, where the data is transformed from one sensor to align with the other. Most research in this area has arguably been conducted for medical applications, typically combining different modalities such as MRI and PET scans. There are numerous methods to register either 2D or 3D images. In computer vision, image alignment methods are able to produce large panoramas from multiple photos [2].

In this paper, we present experiments using portable, field-based sensors which can be mounted in tripods or on top of light vehicles. This brings new challenges for the registration of the different sensing modalities. Traditional methods for combining hyperspectral and lidar data rely either on

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geo-referenced data or manually selected control points [3]. In our experiments, while the lidar data is geo-referenced using high-accuracy GPS, the hyperspectral data is not. We present a method to automatically register hyperspectral and lidar data using a combination of strong feature descriptors. The result is a high-resolution, geo-referenced 3D map of the local environment.

2. REGISTRATION OF HYPERSPECTRAL AND LIDAR DATA

Hyperspectral sensors collect data in hundreds of bands. Typically, spectra are measured across a spatial line in the image, and the sensor "scans" the scene, either by moving the sensor or the scene, in other to build the other spatial dimension. The hyperspectral data can be represented by a hyper cube in which an image slice represents each wavelength. There are several methods for hyperspectral analysis for different applications, resulting in a map representing the distribution of materials in the scene [4]. For registration, it is necessary to represent the hyperspectral data by a single image. This can be performed using either raw data (single bands) or final thematic maps. The desirable characteristic is that the representation has as much similar, matching features with the other sensor modality as possible. In this paper, we transform the hyperspectral data using principal component analysis (PCA) followed by the spectral angle mapper (SAM) to produce a land cover map.

Laser range finders are sensors which measure the time-of-flight of a laser beam to determine the distances to a scene. The 3D view of the environment is generated by scanning the scene using a set of rotating mirrors which spin at high speed to obtain readings from all angles. Different data representations are then possible, from raw point-cloud data to parameterised models [5]. In this paper, we relied on RGB color available at each 3D point, which was acquired from a digital SLR camera positioned on top of the laser scanner. The RGB camera was pre-calibrated with the laser scanner using proprietary software provided by the manufacturer. Alternatively, images for registration can be generated by some visualization calculated from the 3D point-cloud, e.g. depth maps, surface normals, simulated lighting, etc.

We developed a method to automatically register and overlay a hyperspectral image to a 3D point cloud [6]. We

Fig. 1. Hyperspectral camera and lidar scanner mounted on the roof of a vehicle.

first transform the 3D point cloud into a 2D image plane by projecting each 3D point onto a cylinder, similar to the panoramic model described in [7]. The 2D image can then be registered with hyperspectral images using control points followed by a transformation. In this paper, we use both, a piecewise linear and a polynomial transformation. Instead of manually picking control points, we use a combination of strong feature descriptors, specifically, Scale Invariant Feature Transform (SIFT) [8] and Speeded Up Robust Features (SURF) [9]. Other feature descriptors were considered, but SIFT and SURF combined were sufficient to produce the best results.

Registration follows using an approach similar to stichting panoramas, as in [10]. Control points are matched by searching for the two closest features from each image. Two points are matched if the ratio of the sum-of-square-distance is less than a certain threshold compared to the second closest point. Mismatched points are removed by using RANSAC filters, which enforce viewpoint consistency constraints. Once the transformation that registers the images is calculated, hyperspectral data can be projected back onto 3D laser data by means of the cylindrical projection model. Each 3D point now has a corresponding hyperspectral signature overlayed. This hyperspectral 3D point cloud corresponds to a 3D geological map of the environment and can be visualized from different poses.

3. EXPERIMENTAL RESULTS

For the experiments, we used two hyperspectral cameras co-located adjacent to each other, one capturing the visible and

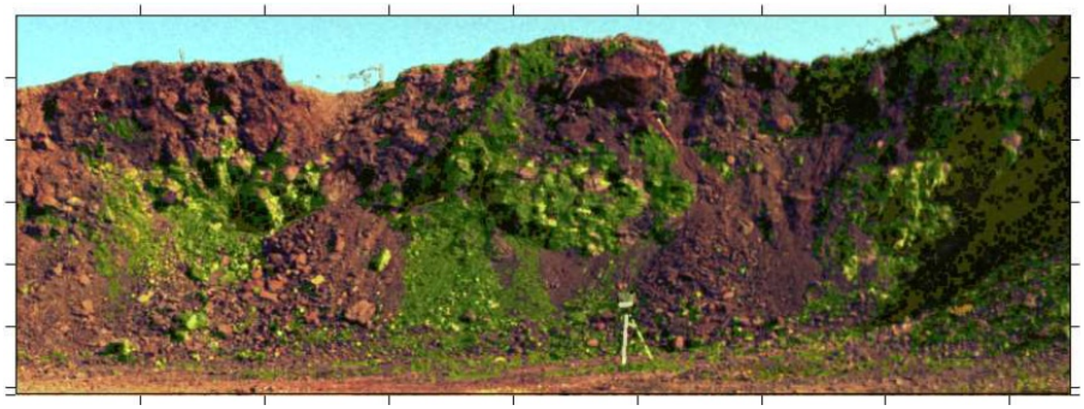

Fig. 2. Registered image using SIFT and SURF features.

near-infrared (VNIR) and, the other, the short-wave infrared (SWIR) spectrum. Lidar data was collected using a high-resolution 3D laser scanner. The experimental setup is shown in Fig. 1. Experimental data was collected from an open pit mine. Further experiments using data from an urban environment are currently under way.

An example of registration result combining the control points obtained from SIFT and SURF is presented in Fig. 2. Due to the increased and better coverage of feature pairs, the misalignment problem is greatly reduced when compared with SURF or SIFT alone. However, the extra accuracy comes at a significant computational cost since extracting and matching the higher number of features more than doubles the processing time required compared with a single feature descriptor.

4. CONCLUSIONS

We demonstrated a method to register hyperspectral image data to 3D lidar data by using strong feature descriptors. The registration can be performed using control points automatically extracted from natural features in the scene, in contrast with competing approaches that rely on highly-reflective artificial targets [11]. One limitation of this approach is that featureless regions, such as green fields or large walls, can be largely misaligned. Combining various feature descriptors minimizes this effect, which justified the added computational load. Research is under way to remove some of the assumptions of our method, e.g. the reliance on RGB data in the point-cloud, and to exploit the geometrical information for hyperspectral analysis, e.g. to compensate the reflectance for changes in surface orientation.

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