Multi-Temporal High Resolution Aerial Image Registration Using Semantic Features

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Abstract. A new type of segmentation-based semantic feature (SegSF) for multi-temporal aerial image registration is proposed in this paper. These features encode information about temporally invariant objects such as roads which help deal with the issues such as changing foliage that classical handcrafted features are unable to address. These features are extracted from a semantic segmentation network and show good accuracy in registering aerial images across years and seasons.

Keywords: Image Registration · Semantic Features · Convolutional Neural Networks

1 Introduction

Image registration is widely used for aligning images of the same scene. These images can be from different times, sensors and viewpoints and hence have appearance differences due to the varying imaging conditions [23]. Registration is particularly useful in remote sensing for aligning multi-temporal and/or multi-spectral imagery for tasks such as multi-sensor data fusion and change detection [16]. It can also be used for UAV localisation by matching online UAV (query) images with the corresponding aerial (reference) images [3]. Image registration is also used in medical diagnosis for tumour monitoring or the analysis of treatment effectiveness [23].

Image registration methods can be broadly divided into two categories: area-based and feature-based methods [23]. Area-based methods try to match corresponding patches in images using similarity based metrics [21]. Feature-based methods, on the other hand, extract salient features from two images and then try to find corresponding features to estimate the transformation between the two images. Area-based methods are typically limited to images with a difference in translation and minor rotations but cannot deal with scale variation. They also do not perform any structural analysis, hence multiple smooth areas can lead to incorrect correlation. Feature-based methods match more distinctive
locations and are more robust. Hence, feature-based algorithms are more commonly used in registration, especially in remote sensing for matching areas with distinctive objects such as buildings and roads.

A number of popular feature-based methods are based on variants of scale-invariant feature transform (SIFT) descriptors [8,17,13]. SAR-SIFT was developed to register synthetic aperture radar (SAR) images [4]. Fast Sample Consensus with SIFT was proposed as an improvement to random sample consensus to improve the number of correct correspondences for image registration [20]. A coarse to fine registration strategy based on SIFT and mutual information was proposed that could achieve good outlier removal [9]. SIFT provides robust features in terms of translation and scale invariance. However, they can only take local appearance into account and lose global consistency.

Recently, deep learning is also being used to extract features from aerial imagery [22]. A method for combining SIFT features with Convolutional Neural Network (CNN) features has been developed for remote sensing image registration [19]. CNN features have also been used for registration of multi-temporal images [18]. However, these methods are trained for image classification and do not encode fine-grained information about objects, hence they do not work well in registering high resolution images with fine details.

In this paper, we focus on registering multi-temporal high resolution nadir aerial images which can have a large variation due to changing seasons, lighting conditions, etc. We propose to use semantic features extracted from a segmentation network for the purpose of aerial image registration. These segmentation-based semantic features (SegSF), as compared to handcrafted and classification-based CNN features, can be more finely localised than classification features and are more discriminative for multi-temporal registration.

2 Methodology

The proposed methodology comprises of two main steps, SegSF extraction and class-specific feature matching, which have been detailed further below.

2.1 Segmentation-Based Semantic Feature Extraction

A LinkNet34 [2] network trained for road segmentation with aerial images as the network input and binary road masks as the network output is used for SegSF extraction. The network structure is shown in Fig. 1. The network is trained with a pixel-wise loss function where the loss is given by the binary cross entropy between the predicted value and the ground truth road mask. This provides a probability mask as output which is converted to a binary road mask with a threshold of 0.5, so any pixels with a probability greater than 0.5 are assumed to be road pixels and vice versa.

The features from the output of the ‘Decoder3’ block shown in Fig. 1 are extracted as descriptors. Additionally, the keypoint locations on the image are
given by the center of the effective receptive field of the descriptors and can be calculated using Equations 1-3.

\[ j_l = j_{l-1} \times s_l \]  
\[ rf_l = rf_{l-1} + (k_l - 1) \times j_{l-1} \]  
\[ start_l = start_{l-1} + \left( \frac{k_l - 1}{2} - p_l \right) \times j_{l-1} \]

The subscripts \( l \) and \( l-1 \) give the layer index, \( s \) gives the stride, \( p \) gives the padding size and \( k \) gives the convolution kernel size. \( j \) gives the "jump" or the effective stride for each layer as compared to the input, so the jump for the first layer is the same as its stride. The effective receptive field has size of \( rf \) and \( start \) is the center coordinate of the receptive field of the first feature.

In practice, since the encoder is a ResNet34 \([6]\), the values of the padding, kernel and stride are chosen so that the effective jump only changes between two encoder blocks and the \( start \) value is always 0.5.

SegSF features are defined by three components: the class label, the descriptor and the keypoint location. Each descriptor-keypoint pair is assigned a class label based on the location of the keypoint on the segmentation output, hence adding semantic knowledge to the feature descriptor.

### 2.2 Feature Matching

All SegSF descriptors are L2-normalised individually and their dimensionality is reduced to 100 using class-specific PCA, again followed by L2 normalisation to obtain the final descriptor.
Matching class descriptors between the query and reference images are found using the nearest neighbour search in the per-class descriptor space where Euclidean distance is used as the distance metric. The correctness of the extracted correspondences is estimated using Lowe’s ratio test [8], where the match is assumed to be correct if the distance ratio between the first neighbour and the second neighbour is less than 0.7.

The keypoints of the feature matches are then used to estimate the homography matrix between the two images using random sample consensus [5]. This feature matching process has been given as Algorithm 1.

**Algorithm 1 SegSF matching**

**Inputs:** Query Image, Reference Image `query_image`, `ref_image`  
**Output:** Transformation Model `Transform_Model`

1: `all_ref_kp = []`  
2: `all_query_kp = []`  
3: for class in `num_classes` do  
4: `query_class_kp, query_class_des = GetClassFeatures(class, query_image)`  
5: `ref_class_kp, ref_class_des = GetClassFeatures(class, ref_image)`  
6: `query_class_des.NormalizePCANormalise`  
7: `ref_class_des.NormalizePCANormalise`  
8: `inlier_query_kp, inlier_query_des, inlier_ref_kp, inlier_ref_des = KNN(query_des, ref_des)`  
9: `all_ref_kp.append(inlier_ref_kp)`  
10: `all_query_kp.append(inlier_query_kp)`  
11: end for  
12: `Transform_Model = Affine TransformRansac(all_ref_kp, all_query_kp)`

### 3 Experimental setup

#### 3.1 Datasets

The segmentation network was trained on images from different seasons and years to learn temporally invariant features. Aerial imagery datasets provided by the Australian Capital Territory Government [1] for the years 2015-2018 were used for this purpose. The images in this dataset are georeferenced, orthorectified and have a ground sampling distance of 10 cm with an expected error less than 20 cm. An area of 27.5 km² around Canberra was extracted for the experiments, with 90% of the images from 2015, 2016 and 2017 being used for training and validation of the segmentation network. The remaining 10% images from 2017 and all images from 2018 were set aside for testing.

The annotations for training were extracted from the OpenStreetMap (OSM) [10] where all polylines marked as one of motorways, primary, residential, secondary, service, tertiary, trunk or their respective links were assumed to be roads. The
OSM roads were provided in vector format and were rasterised with a width of 2 m to obtain data suitable for training the segmentation network.

3.2 Training Details

The segmentation network was trained on image crops of $416 \times 416$ from the training dataset of 2600 images. It was trained for 200 epochs and the images were augmented by random horizontal and vertical flipping with a probability of 0.5. All image pixels were normalised between 0 and 1. The Adam optimiser [7] with a learning rate of 0.0001 was used for optimisation. Pytorch [11] was used for creating and training the neural networks.

3.3 Testing Scheme and Metrics

The test images from 2017 were rotated around their center point at angles of $1^\circ$, $2^\circ$, $3^\circ$, $4^\circ$, $5^\circ$, $10^\circ$, $15^\circ$, $20^\circ$, $30^\circ$ and $40^\circ$. Corresponding images from the 2018 dataset were extracted and the methods were tested on their accuracy in terms of registering these multi-temporal images. Samples of the test pairs can be seen in Fig. 2. Note that the network was not trained on any images from the 2018 dataset or on any images from the testing region.

Since the image transformation parameters were known, a per-pixel metric has been reported for the experiments. The root mean squared error (RMSE) between the pixel positions using the predicted transformation and the actual transformation was used as the error metric. The mean and the standard deviation of the errors over all the images for the different transformations has been reported in Section 4.

4 Results

We compared our results with CNN-Reg [18] which is based on extracting multi-scale CNN features for multi-temporal remote sensing image registration. They utilise features from a VGG-16 [14] network trained on the Imagenet dataset [12] for classification. We have also reported the t-values and p-values from Welch’s t-test [15] to obtain the significance of the results.

Table 1: Registration error of CNN-Reg and SegSF on multi-temporal aerial imagery dataset over different rotation parameters

| Method | RMSE | 1° | 2° | 3° | 4° | 5° | 10° | 15° | 20° | 30° | 40° |
|--------|------|----|----|----|----|----|-----|-----|-----|-----|-----|
| SegSF  | Mean | 37.03 | 37.33 | 41.93 | 46.43 | 61.51 | 70.08 | 90.63 | 131.91 | 184.06 | 372.39 |
|        | Std. | 49.58 | 39.75 | 65.32 | 61.37 | 62.72 | 59.17 | 66.85 | 118.5 | 135.98 | 269.84 |
| CNN-Reg| Mean | 88.05 | 143.51 | 213.18 | 242.806 | 267.13 | 423.63 | 522.5 | 596.35 | 715.13 | 777.54 |
|        | Std. | 50.22 | 80.81 | 90.19 | 102.59 | 108.44 | 128.11 | 115.21 | 104.41 | 74.75 | 38.88 |
| t-test | Mean | 5.11 | 8.38 | 10.87 | 11.62 | 12.41 | 17.82 | 22.92 | 26.79 | 24.21 | 10.37 |
|        | p-value | 1.53e-6 | 3.07e-12 | 8.31e-18 | 5.55e-19 | 9.99e-22 | 8.58e-28 | 5.68e-37 | 8.53 e-38 | 6.09e-38 | 6.09e-38 |
| Reference Image | Query Image | CNN-Reg | SegSF |
|-----------------|-------------|---------|-------|
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) |
| ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) |
| ![Image](image9.png) | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |

Fig. 2: Checkerboard results of registering multi-temporal images using CNN-Reg and SegSF
As can be seen from the results in Table 1, SegSF performs much better than CNN-Reg for all the transformation parameters. The p-values for the tests show that the results are extremely significant.

We believe the performance improvement can be explained by a couple of factors. Firstly, since CNN-Reg is based on Imagenet, they extract some universal patterns for feature matching. They do not train on any aerial datasets but we believe that finetuning on aerial datasets, as in the case of SegSF, provides more relevant features. However, their method cannot be finetuned with our dataset since they train for a classification based loss and our dataset does not contain any classes. Secondly, the addition of the semantic labels makes SegSF less sensitive to image variations. Note that both methods struggle when the rotation is increased beyond 20°.

Checkerboards of some of the images registered using both methods have been shown in Fig. 2. The query images are from 2017 and the reference images are from 2018 and the images have varied foliage. The quality of the registration can be estimated by how well the roads and buildings align on the checkerboard image. As can be seen from the figure, SegSF is able to achieve good registration results even with the foliage difference.

Fig. 3: Comparison of SegSF matching with SIFT matching. Left: Reference image from 2018 and query image from 2017 rotated by 15 degrees with colour and shadow variation due to different times of the day and year. Middle: All keypoints extracted by the two methods are shown in black circles with the correspondences estimated by RANSAC shown with blue lines. Right: Checkerboard of the registered images.

We have also compared SegSF with SIFT features in Fig. 3. As can be seen from the figure, SIFT features do not deal well with seasonal variations. Con-
versely, SegSF features match correctly even with a large seasonal variation. Only the road features have been used in this case for the SegSF to demonstrate the relevance of semantically meaningful features.

5 Conclusions

We have proposed a new semantic feature, SegSF, for multi-temporal aerial image registration which can deal with variations such as changing tree foliage caused due to changing seasons, changing shadows due to the time of day, and variations caused due to the difference in sensors. These features are extracted from a CNN trained for segmentation and are conditioned on the output class. We provide both quantitative and qualitative results and draw comparisons to previous work done in the area.

Our results show that the proposed features achieve better localisation precision due to the fine resolution allowed by the use of a segmentation network as compared to a classification CNN. These features are also able to deal with the temporal variations that classical features, such as SIFT, struggle with.

This work is limited in that it is only applicable to images with visible roads. However, this can be improved by increasing the number of classes for feature extraction. Further improvements in the registration accuracy can be achieved by extracting features from later layers in the network which have smaller receptive fields. Multi-scale features can also be used for dealing with scale differences.

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