Problem Statement: A common problem of Information Discovery in large archives of EO satellite images is content based image retrieval where the archive is scanned for images that show semantic similarity to a given query image. E.g., if a satellite records an image of burning forest, how can other regions in over the world be found that suffer from burning forest as well? Since EO image archives can contain petabytes of data, scanning the whole database would be very inefficient and therefore content based image indexing is required to enable efficient querying. This poster presents different techniques for building such indices.

Hash Indices for Images can be used to group images into a number of hash buckets that can be accessed efficiently. The goal is to assign similar images to the same bucket and dissimilar images to different buckets such that only one bucket needs to be considered when answering a query. Hashing can significantly reduce the time needed for processing a query while at the same time maintaining a high accuracy in comparison to an exhaustive search.

Similarity between images can be described by comparing content based descriptors of the images. The retrieved images can then be ranked by their similarity to the input.

Conventional Hashing Methods

Locality Sensitive Hashing (LSH)

This unsupervised method randomly creates n hyperplanes in the feature space that separate it into distinct hash-buckets. Similar images have a high probability to be contained in the same bucket and dissimilar images have a higher probability to be contained in different buckets.

Kernel Based LSH (KLSH)

This method uses a kernel to perform LSH and can therefore deal with data that is nonlinearly separable. It can be done in an unsupervised or supervised way.

Kernel Function

Before applying the hash function, images are transformed into a feature representation where images with similar features are represented by similar hash values. This hash function is then applied on these features.

Advantages

• Fast, scalable, data-independent

Disadvantages

• Data might not be linearly separable
• Bad accuracy

Deep Hashing

More recent approaches are aiming at learning a hash directly from an image using deep neural networks. This method is better capable of representing the contents of images in a hash because it does not require handcrafted features and instead learns what makes images similar on its own. The following picture shows the network architecture presented in [1].

Comparison to Supervised Kernel LSH

The following experimental results show that Deep Hashing achieves a much higher precision than Kernel LSH while being equally fast.

System Layout

Single-Code Hashing

Single Code Hashing uses exactly one hash per image that is used as an index in the hash table.

Multi-Code Hashing

Multi-Code Hashing describes different primitives in the image with different hash codes. A list of descriptors is retrieved from each image and then transformed into multiple hashes. This method is better capable of describing complex image contents than Single-Code Hashing. Therefore, it greatly improves the accuracy while maintaining high efficiency and scalability, but it comes at the cost of higher space complexity.

References