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Applications and Datasets for Superpixel Techniques: A Survey

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Abstract—The use of superpixels instead of pixels can significantly improve the speed of the current pixel-based algorithms, and can even produce better results in many applications such as robotics, remote sensing, industrial inspection, and medical diagnosis. Two main tasks related to vision could benefit from superpixels, named object class segmentation and medical image segmentation. In both cases, superpixels can increase performance significantly and also reduce the computational cost. In addition to superpixel applications, various datasets were employed for the evaluation of the superpixel algorithms. This work aims to survey the recent applications and the most common datasets that can be used based on superpixel techniques.

Index Terms— Digital image processing, image superpixels, industrial inspection, medical diagnosis.

I Introduction

The use of superpixels instead of pixels can improve significantly the speed of the current pixel-based algorithms, and can even produce better results in some cases [1]. For example, particular graph-based algorithms can achieve a 3-times speed increase using superpixels [2, 3]. There is a definite need for the superpixel generation itself to improve the speed of the algorithms to be fast enough for them to be practical [4, 5]. Two tasks related to vision that could benefit from superpixels are object class segmentation and medical image segmentation [6, 7].

In different cases, superpixels can increase the performance significantly and at the same time reduce the computational cost [8, 9, 10, 11]. On the other side, many datasets were employed recently for superpixel algorithms evaluation [12, 13, 14], and biometric-based applications [15, 16, 17, 18]. The most commonly used datasets are introduced in this work. The main contributions of this survey are as follow:

1. Discuss the most common applications of the superpixel techniques.
2. Discuss the superpixels machine learning applications.
3. Discuss the superpixels medical diagnosis applications.
4. Discuss the common datasets that can be employed in the application of superpixels.

The following sections are organized as follows. Section II shows the common machine learning application of the superpixel technique. The applications of medical image segmentation based on superpixel is discussed in Section III. Section IV introduces the common datasets that have been employed using the superpixels. Finally, the conclusion is shown in Section V.

II Machine Learning Applications

There are various machine learning techniques that can be applied on different types of applications. These applications ca be in the fields of robotics, remote sensing, industrial inspection [19, 20], data classification [21, 22, 23], cloud computing [24, 25, 26, 27], grid computing [28], foot orthoses [29], picture archiving [30], resources allocation [31], Leaf identification [32] and medical diagnosis [33, 34]. This section list some of the common application in the track of superpixels.

A general method, called learning to Agglomerate Superpixel Hierarchies (LASH), to segment images by clustering superpixels was introduced [35]. An agglomerative clustering algorithm combines clusters according to how similar they are at every iteration. The evaluation function for similarity is usually designed manually, although it was proposed supervised or semi-supervised settings in which ground-truth clustered data is available for training. The researcher showed how to train a similarity function by considering it as an action-value function of a reinforcement learning problem.

In [36], the authors proposed an active learning procedure for performing hierarchical agglomerative segmentation from superpixels. Their method integrated a few features at different scales of the agglomerative process, working on data with an arbitrary number of dimensions while scaling up to very large datasets. They have utilized the use of information variation to measure segmentation accuracy, especially in 3D neural tissues electron microscopy (EM) images, and used that metric to demonstrate an improvement over other algorithms in EM and natural images.

In [37], a classification model for grouping images into one of two classes. In a prepossessing stage, an image is over-segmented into superpixels. The researchers defined a variety of features derived from the classical Gestalt cues, including texture, contour, brightness, and good continuation. The information-theoretic analysis is applied to evaluate the power of these grouping cues. They have trained a linear classifier on how to combine these features.

In [38], an approach was proposed for segmenting and localizing objects that used the image superpixels. The researchers used superpixels as the basic unit of a class segmentation. they constructed a classifier on the local features of the histogram found in each superpixel.

In [39], an approach for a fast online segmentation was proposed to be applied to moving objects in video using learning and classification based superpixels. It showed the algorithm as a discriminative online learning task, where supervising labels are autonomously generated by a motion segmentation algorithm.

III Medical Image Segmentation Applications

In the work done in [40], the MSFCM algorithm was introduced to segment brain MRI images that consist of both the superpixel method and the FCM algorithm. In the beginning, the image needs to be parsed into several superpixels, then deep segmentation is to be done for the areas with bigger gray variance than a predefined threshold. In order to get the fuzzy membership of each superpixel, the FCM algorithm is used to cluster the superpixels and not the pixels, while the membership is used to determine the classification for these superpixels. Finally, the segmented brain MRI image is done by integrating the superpixels with the FCM classification.

In [41], a method based on the superpixel technique was presented to classify each superpixel. That was achieved using a number of image features including Gabor textons, intensity-based, curvatures, and fractal analysis were calculated from each superpixel contained the whole brain area in the MRI to ensure the classification robustness. Finally, to classify every superpixel into non-tumor and tumor tissues, randomized trees (ERT) classifier was compared with a support vector machine (SVM).

Paper [42] proposed an approach for segmenting the prostate from MRI images. A superpixel-based 3D graph cut algorithm was introduced to get the prostate surface. In that approach, superpixels were used to construct a 3D superpixel-based graph. The superpixels were labeled to be either prostate or background by minimizing an energy function using graph-cut based on the 3D superpixel-based graph.

Authors in [43] introduced an effective slice by slice liver segmentation method by combining shape constraints according to previously slice segmentation that has been proposed based on graph cut. they apply a clustering algorithm to firstly group slice pixels into superpixels as nodes for constructing a graph, which not only greatly reduces the graph scale but also significantly speeds up the optimization procedure of the graph. Furthermore, we restrict the regions near the organ boundary as shape constraints, which can further reduce computational time.

In [44], the researchers presented an automatic segmentation based on superpixelization and illumination invariant methods. They developed an automatic superpixel generation method using automatically modified quick-shift parameters based on invariant images. The proposed approach segments a color image into homogeneous regions using a quick-shift method with initial parameters, followed by the calculation of the best similarity between the output image and the invariant image by changing the quick-shift parameter values to get the final segmented image [45, 46, 1].

In [47], the researchers proposed hyper-spectral imaging technology and classification method using principal component analysis (PCA), superpixels, and support vector machine (SVM) to differentiate between regions of tumor from healthy tissue. The classification method uses 2 main components derived from hyperspectral images and achieves an average specificity of 85% and an average sensitivity of 93% for 11 mice.

In [48], a semi-supervised organ segmentation approach for CT images. In the first step, an Eikonal-based algorithm creates a dense over-segmentation of the image. The presented superpixel algorithm outperformed many modern algorithms on classical metrics. In a second step, the semi-supervised segmentation is performed on the underlying Region Adjacency Graph created using over-segmentation.

A semi-supervised superpixel-by-superpixel classification method for glaucoma screening was proposed [49]. The method consists of three main steps: The first step is to prepare the labeled and unlabeled data, and to apply the superpixel method then to bring an expert for the superpixels labeling. In the second step, knowledge a priori is incorporated to the optic disc and cup by including spatial and color information. In the final step, semi-supervised learning by the Co-forest classifier is trained with a number of labeled superpixels and a large number of unlabeled superpixels to produce a robust classifier.

IV Common Datasets for Superpixels

Many datasets were used for superpixel algorithms applications and performance evaluation. The following are the most commonly used datasets.

BSDS500 [50]. The Berkeley Segmentation Dataset 500 (BSDS500) was the first to be used for superpixel algorithm evaluation. It contains 500 images and provides at least 5 high-quality ground truth segmentation per image. The images represent simple outdoor scenes, showing landscape, buildings, animals, and humans, where foreground and background are usually easily identified. Nevertheless, natural scenes where segment boundaries are not clearly identifiable, contribute to the difficulty of the dataset.

SBD [51]. The Stanford Background Dataset (SBD) combines 715 images from several datasets. As result, the dataset contains images of varying sizes, quality, and scenes. The images show outdoor scenes such as landscapes, animals, or street scenes. In contrast to the BSDS500 dataset, the scenes tend to be more complex, often containing multiple foreground objects or scenes without clearly identifiable foreground.

NYUV2 [52]. The NYU Depth Dataset V2 (NYUV2) contains 1449 images including pre-processed depth. The provided ground truth is of lower quality compared to the BSDS500 dataset. The images show varying indoor scenes of private apartments and commercial accommodations which are often cluttered and badly lit.

SUNRGBD [53]. The Sun RGB-D dataset (SUNRGBD) contains 10335 images including pre-processed depth. The dataset combines images from the NYUV2 dataset and other datasets with newly acquired images. The images show cluttered indoor scenes with bad lighting taken from private apartments as well as commercial accommodations.

Fash [48]. The Fashionista dataset (Fash) contains 685 images that have previously been used for clothes parsing. The images show the full body of fashion bloggers in front of various backgrounds.

Berk [54]. Berkeley Image Segmentation Dataset is used by most of the superpixel evaluation algorithms. It consists of 500 natural images of size 482×321 and divided into 200 training, 100 validation as well as 200 test images. The given segmentation, from which at least five per image, reflect the difficulty associated with image segmentation.

V Conclusion

This work aims to survey the recent applications and the most common datasets that can be used based on superpixel techniques. The use of superpixels instead of pixels can significantly improve the speed of the current pixel-based algorithms. This can produce better results in many applications such as robotics, remote sensing, industrial inspection, and medical diagnosis. Superpixels can increase performance significantly and also reduce the computational cost. In addition to superpixel applications, various datasets were employed for the evaluation of the superpixel algorithms.

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