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Research paper

Improved speeded up robust features for low contrast images

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Abstract

The proposed work aims at improving the feature detection in Speeded up Robust Feature (SURF) Algorithm. It has been observed that the SURF feature detector shows low feature detection in low contrast images which is caused due to the application of weighted gaussian at multiple scales before feature point detection. To overcome this problem an effective pre-processing technique is proposed which increases the image contrast to an optimum level enabling detection of more features by SURF Algorithm. The paper also introduces an effective optimization which clusters the feature points describing the same region proposal and concatenating these feature points into a single feature point with a new region proposal which holds minimal region in common with other feature points to reduce the redundant feature points generated due to the application of pre-processing. Finally, to obtain the feature vector of the new region proposal of the feature point, the feature vectors of the feature points belonging to the same cluster are concatenated to form an arbitrary dimensional feature vector.

Keywords: *Speeded Up Robust Features; Low Contrast Images; Clustering, Contrast Limited Adaptive Histogram Equalization; Object Recognition; Contrast Enhancement; Feature Point Detection; Feature Descriptor Formation; Entropy.*

1. Introduction

Computer Vision has been expanding with several applications in our day to day lives. One of the main applications of Computer Vision is object recognition. Object recognition is extensively used in several tasks like self-driving cars, face detection, tumor detection and video surveillance etc. Object recognition is the process of identifying objects inside an image or video which can be performed either on the basis of appearance or features.

Appearance based object recognition relies on the visual characteristics of the objects in the image which involves edge, gradients and histogram-based recognition. In appearance based object recognition the appearance of the object is captured using multiple views of object. The appearance based methods can be divided based on local and global descriptors. The local descriptors are the intensity, entropy and contrast of the region of interest. The global descriptors describes the appearance of the complete image these descriptors includes methods like Principal component analysis (PCA) [2], Independent component analysis (ICA) [3] and Non - negative matrix factorization (NMF) [4].

The feature based object recognition refers to the calculation of features of the objects in an image. There are several methods involved in feature based object recognition which includes deep neural network models [5] and computer vision algorithms like Speeded Up Robust Feature, Scalar Invariant Feature Transformation [6] etc., each of these have their own set of advantages and disadvantages.

The feature-based object recognition can also be categorized into local feature-based methods as well as global feature-based methods. The local feature based methods are Scalar Invariant Feature Transformation (SIFT), Speeded Up Robust Feature (SURF) and the global feature methods are Histogram of oriented gradients (HOG) [7] etc. The SIFT is a feature detector and descriptor used to extract local features in an image and the SURF is an improvement over the SIFT in terms of speed. The BRISK [8], BRIEF [9] and FREAK [10] are other alternatives to these algorithms which further decreases time complexity of feature matching by converting the features into a binary form.

It has been observed that the SURF algorithm is not invariant to contrast changes of the image due to application of the multiple sized weighted gaussians applied before feature point detection. The requirement for such invariance to contrast is important since several real time systems are only capable of capturing low contrast images, which includes underwater image acquisition, images captured inside human or animal body, images captured at night or when faulty tools have been used to capture the image.

Section 2 of the paper discusses the related work that has been done in the similar context. Section 3 describes the proposed Feature descriptor generation technique in detail. Section 4 deals with the Experimental Result Analysis section which shows the analysis of proposed work on brain tumor [17] and hand metric [18] datasets. Section 5 is about the Conclusion which is arrived based on Section 4. The Acknowledgment and References are provided in Section 6 and 7 respectively.

2. Related work

The Speeded up Robust Feature (SURF) algorithm was proposed by Bay et al [1] in 2006. The SURF is one of the most commonly used feature detection and descriptor algorithm in the field of computer vision and machine learning. The reason for its extensive use is its scalar invariance, rotational invariance, low computational complexity and it gives local features. The SURF algorithm has been severely used in both industrial and research appli-

cations. The SURF algorithm is commonly used in applications like object recognition, object detection, gesture recognition, motion tracking, image alignment etc.
Some of the recent works on SURF algorithms shows the usage of SURF in low contrast settings such as the one where Suneel et al [11] has discussed about classifying the skin images into normal skin, burn, bloody, cancer and allergic skin by using the SURF features. The authors start their work by enhancing the image through a series pre-processing techniques like morphological operation, histogram equalization, noise removal and median blurring which is applied to the image. Later the SURF features are detected for this image which is used by the classifier for classifying of the image.
Nivedha et al [12] had proposed an effective dehazing method with conceptual regularization using SURF for haze images. In this work the authors first recover the radiance of the image by using global air light estimation method and further they enhance the contrast of the image by increasing the luminance Factor L based on hue (H) and saturation (S). The authors have made a new optimization for dehazing metric based on weighted L1-norm with the contextual regularization and the boundary constraints.
Surya et al [13] used a series of image enhancement techniques starting from Histogram Equalization, NLMeans normalization and steerable Gaussian filtering to create an illumination and pose invariant efficient ear recognition technique. The features are extracted for this image using SURF and then these features are used for classification by a fusion of 3 different nearest neighbor classifier.
Hatem et al [14] has devised a method for choosing the most important features for point matching. The method used binary classifier to extract important feature points in the image and results have been compared with other classifiers and feature detectors.
Adithya et al [19] has proposed an improved version of SIFT which is robust to low contrast images. This has been achieved by adding the Sobel output of the input image to the input image until the entropy of the resultant image is high to make sure that high contrast exists in the images. This entropy based optimization lead to over-amplification of visual cues and in-order to reduce this effect, affinity propagation clustering is performed to cluster similar feature descriptors.
A key point to be noted from these related works is that each of these works suffered from the issue of abruptness in the contrast of levels of the input image. Hence, this shows the importance of solving such a ubiquitous problem.

3. Proposed work

The proposed work improves the SURF algorithm by enhancing the contrast of the input image using Contrast Limited Adaptive Histogram Equalization (CLAHE) [15] with optimal parameter settings. It is observed that the count of feature points gets increased by a considerable amount when the SURF features are calculated for this CLAHE enhanced image. But this gives rise to some features which appear due to the artefacts induced by CLAHE. Hence, these artefacts tend to describe redundant region proposals. This problem is handled by performing feature point optimization. A novel feature point optimization approach is introduced to reduce the number of feature points by finding the shared region between the feature points along with its Hessian and Laplacian values. The clustering approach followed here is based on the region proposal decided during the formation of feature descriptor. Once the clusters are recognized, all the feature descriptors for the points inside the newly formed cluster are concatenated based on the region of overlap.
The proposed work consists of the 3 modules:

- Contrast enhancement using Contrast Limited Adaptive Histogram Equalization.
- Feature point detection using Speeded Up Robust Features on contrast enhanced image
- Optimization of feature points based on the shared regions.

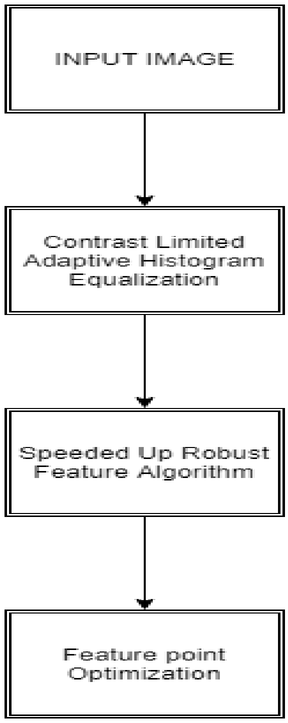
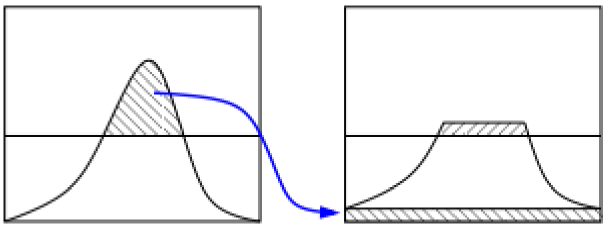


Fig. 1: Modules of the Proposed Work.

3.1. Contrast enhancement using contrast limited adaptive histogram equalization

SURF algorithm identifies feature points in image by using approximate box filters. It is observed that the SURF algorithm identifies lower number of feature points due to application of Approximate Box Filters at multiple scales. As the scale is increased, the contrast of the image at that particular scale is decreased. Thus any object lying in the low contrast region of the image will not be detected.
Solution to this problem is to increase the contrast of the image to an optimum level such that it nullifies the smoothening effect of the weighted Box Filter. This can be done by CLAHE.
Contrast Limited Adaptive Histogram (CLAHE) is a computer vision technique suitable for improving the local contrast and augmenting the definition of edges of the given input image. CLAHE was proposed by Pizer et al. [15] and it builds upon the principles of Adaptive Histogram Equalization (AHE) technique. It improves traditional histogram equalization by computing several histograms of distinct regions in the image and then using them to equally distribute intensity values of the image. While applying Adaptive Histogram Equalization (AHE) if the image region under consideration has a relatively small intensity range then the noise in that region gets more amplified leading to the appearance of undesired artefacts in those regions. CLAHE solves the problem of over amplifying noise by limiting the contrast enhancement of AHE by setting a clip limit which limits the slope at that point.
The amount of contrast enhancement to be done on the image is directly proportional to the slope of the neighborhood Cumulative Distribution Function (CDF). CLAHE limits the amplification by clipping the histogram at a predefined value, as shown in Figure 2, before computing the CDF. The resulting neighboring regions are then put back together using bilinear interpolation. To achieve optimal enhancement from CLAHE on the input image, the parameters grid size and the clip limit of the CLAHE are chosen from the location of the maximum curvature in the entropy curve [16].
Proposed technique does the contrast enhancement as a preprocessing step before feature points detection. Although the contrast of the image is improved, the SURF feature detector detects redundant feature points due to the artefacts created by CLAHE.



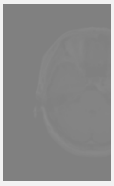
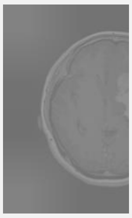
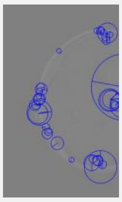
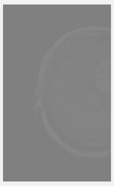
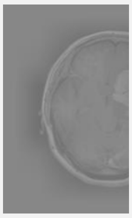
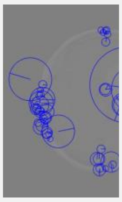
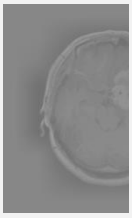
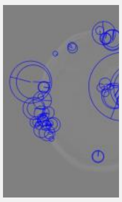
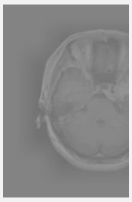
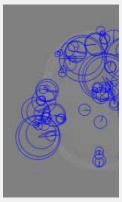
(a) (b)

Fig. 2: CLAHE Clip Limit and Grid Size (Source of the Image: Wikipedia).

3.2. Feature point detection using speeded up robust feature

The feature points are detected using SURF algorithm on the brain tumor dataset [17] images. Table 1 shows the comparative results of the feature point detection using SURF with the low and high contrast brain images.

Table 1: Feature Point Detection after Contrast Enhancement

Low contrast Image	Feature points detected using SURF for the input image without contrast enhancement	Number of feature points detected using SURF for the input image without contrast enhancement	High Contrast Image	Feature points detected using SURF for the input image with contrast enhancement	Number of feature points detected using SURF for the input image with contrast enhance ment
		0			55
		0			72
		0			78
		0			111

As seen in the Table 1, it is clearly observed that the number of feature points in the image has increased drastically compared to the low contrast image and it is also observed that several feature points detected cover the same region proposals.

3.3 Novel Feature point optimization and variable length feature vector formation

The CLAHE contrast optimization causes artefacts in the image which leads to the formation of extraneous features which describes redundant regions in the image. This problem is solved by employing a novel feature point optimization technique which exploits the shared region between region proposals as shown in Figure 3. This optimization technique works as an unsupervised learning-based clustering approach.

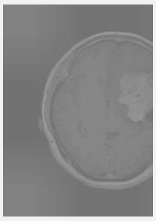
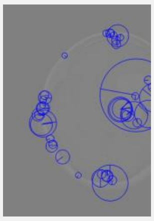
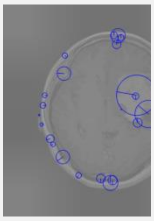
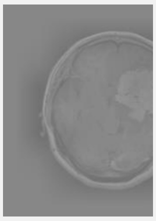
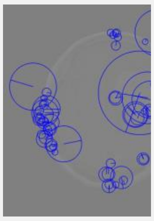
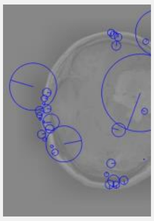
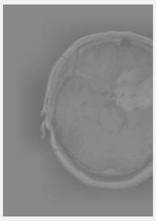
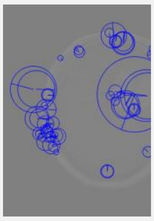
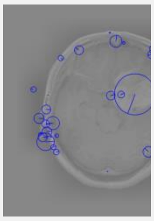
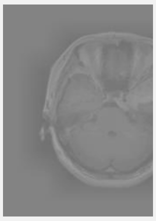
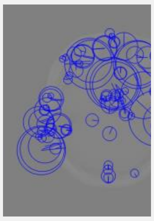
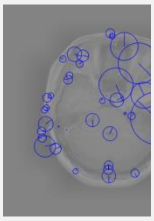
This clustering technique first estimates the strength of the feature points based on its Hessian value in the image and sorts them in descending order. For every point a search is made into its 20σ neighbourhood and checks if any feature points are found in this neighbourhood having strength lower than the point itself and whether its sign of Laplacian (-1,1) is same as that of itself. The reason for choosing the same sign of Laplacian is that we are looking into neighbourhood of the point and there is a possibility that the point lying in the vicinity is of the same object but there could also be a possibility that the nearby region is not of the same object, so we use sign of the Laplacian which gives the contrast information of the feature point. If the feature points to be clustered are in the same object region then they'll have same sign of Laplacian. The sign of the Laplacian is calculated using the formula in Equation (1). If all these conditions are satisfied then the point is added into the cluster with the strongest point as the cluster centre. This process is continued until all the points are clustered.

$$\nabla^2 L = tr(H) = L_{xx}(x,\sigma) + L_{yy}(x,\sigma)$$
(1)

Now starting from least strong cluster center and its associated cluster, the common region between this point and the points inside the cluster is approximated and the Haar wavelet response for that particular region is concatenated into feature vector of the cluster centre. This is done sequentially for all the points with increasing value of the feature point strength.

Table 2: Feature Points after Optimization

Contrast enhanced image	Feature points detected using SURF for the input image with contrast enhancement	Number of feature points detected using SURF for the input image with contrast enhancement	Clustered feature points detected using SURF for the input image with contrast enhancement and after clustering	Number of feature points detected using SURF for the input image with enhancement and optimization

		55		28
		72		42
		78		38
		111		54

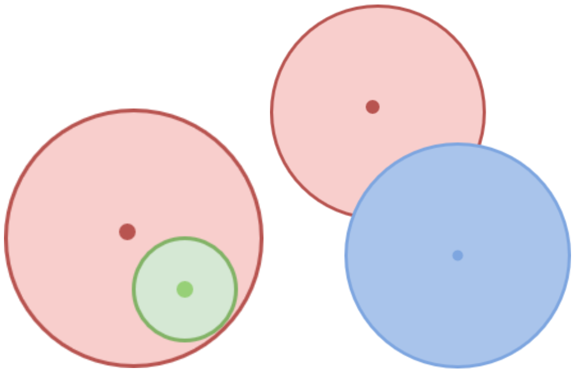


Fig. 3: Intersecting Region Proposals.

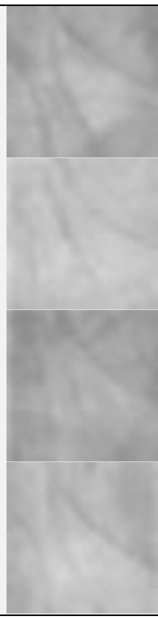
The advantage of this process lies not only in reducing the number of feature points in the image but also compressing the information of multiple regions of an image into a single feature vector. The results of the clustering based feature vector can be viewed in the Table 2.

4. Experimental results

The modified speeded up robust features for low contrast region of the images has been tested with Brain dataset [17] and Hand Metric dataset [18]. After a series of experiments on the Brain dataset [17] and Hand Metric dataset [18], it is observed that the CLAHE acts as a good pre-processing technique and increases the contrast level sufficiently enough to enhance the contrast to the optimum level.

In the experimental setup, we use images from Hand Metric Dataset as these images display very low contrast information. The Table 3 shows the set of Input Images:

Table 3: Input Image

Input Image


The Table 4 shows that the set of resultant images that are obtained after CLAHE enhancement, we can observe that optimal contrast enhancement is achieved as discussed in section 3.1 apart from the contrast enhancement we can also discern the artefacts that are being created in the image.

Table 4: Contrast Enhanced Images.

Resultant Image from the Application of CLAHE


The Table 5 shows the feature points obtained after using the SURF where the left part shows the features which we were supposed to obtain without enhancing the image and the right part shows the set of features obtained by using enhanced image:

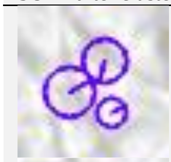
Table 5: Feature Point Detection

Feature points detected using SURF for the input image without contrast	Number of feature points detected using SURF for the input image	Feature points detected using SURF for the input image with contrast en-	Number of feature points detected using SURF for the input image

enhancement	without contrast enhancement	hancement	with contrast enhancement
	1		4
	1		3
	2		2
	2		3

The proposed clustering has been applied on the feature points detected and the resultant features can be seen in Table 6.

Table 6: Optimized Feature Points

Feature points Detected using SURF after clustering	Number of feature points detected using SURF after clustering
	3
	3
	1
	3

5. Conclusion and future enhancements

The proposed work improves the SURF algorithm by making it robust to low contrast images and by reducing the number of features points by clustering them into a single feature point. The future work relies on the fact that although the feature points are clustered together there still exists few feature points which are still sharing a common region proposal with other feature points, so future research of this work will be focusing on the improvement of clustering.

Acknowledgment

We would like to thank the authors of Brain dataset [17] and Hand Metric dataset [18] as these datasets have helped us to perform empirical analysis and prove the effectiveness of our research.

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