IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 8, Issue 8, August 2020

DOI 10.17148/IJIREEICE.2020.8804

Preservation of Gradient Histogram for Texture Enhancement, Pedestrian Detection and Image Matching based on SURF

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Abstract: Blurring is a particular type of optimal bandwidth reduction due to inaccurate image-forming process that reduces crucial texture and therefore results in less visual efficiency of the image. To remove the blur, many image deblurring techniques aim to reverse the distorted image to recover the natural image and concentrate on creating appropriate regularizations to prevent the image from being restored. The prior image, including the non-local prior pixel intensity, plays an important role among all methods available. Just like prior picture enhances the reduction of noise and ringing artifacts, fine detail is often enhanced. Thus, GHP based de - noising method is associated with a non-local sparse prior that is able to produce rich textures. With a reconstructed image gradient variation creates a large residual image and the texture characteristics of the reconstructed images can be restored excellently, making them appear more natural. Detection of features is restrained to pedestrian detection, which operates well on grayscale gradients between adjacent pixels. HOG is a feature descriptor based on gradients which normalises and classifies the extracted feature using linear SVM. SURF algorithm, which has high performance and accuracy, is used to detect excellent points which are symmetric to adjacent points. There may also be a mismatch effect when conducting matching of feature points. SURF methodology is merged with RANSAC algorithm that eliminates the false points. Simulation observations from our studies indicate that these techniques are making at least as well as other methods available.

Keywords: Gradient Histogram Preservation (GHP), NCSR (Non-locally Centralized Sparse Prior), human detection, Histogram Oriented Gradients (HOG), linear Support Vector Machines classifier (SVM), feature matching, Speeded-Up Robust Features (SURF).

I. INTRODUCTION

Digital image processing is an image analysis approach in which the source is a picture and hence the output will be either a picture or a set of image-related properties. Sometimes even the image can get corrupted and these disruptions can be due to either motion blur or noise or camera misfocus. So, image deblurring came up with these ideas in which the original image from the corrupted images can be recovered. Image deblurring is among the most critical issues which need to be resolved in certain scenarios, for example in monitoring systems, medical image processing, satellite images and robot navigation. Different image deblurring techniques focus on developing improving the way of regularization to restrict the reconstructed image. Such terms of regularization are based on natural priors of the image and are designed to describe the quality of real images in relevant environments. Many more existing image deblurring techniques modify such regularizations and eliminate artifacts from multi-frequency bands while decreasing ringing effect and noise in a deblurred image.

Most denoising methods tend to smooth image textures of a high degree while eliminating noise and degrading the visual quality of the image. Some of the most challenging problems in photographs is how to maintain a fine-scale pattern structure when eliminating noise. Specific priors of the natural picture are used to minimize noise. Nevertheless, it is hard to eliminate noise while maintaining texture at the same time and this has been one of the most complicated issues in denoising real picture. Since the texture areas in the image are uniform, they are usually composed of pattern-like statistical descriptors, such as histograms, that are much more precise to depict. Likewise, image gradients convey nearly all of the training data in an image, and are essential to processing the quality images through human vision. These all factors influenced us to have a gradient-based image histogram to create a new image denoising model called GHP in which the gradient of any well-reconstructed image will be less than that of the input images. Integrating the GHP model with an NCSR deblurring algorithm, we create a texture-enhanced image deblurring process, and the texture features of the resulting image are improved well. Features descriptors includes not only textures but also corners, edges & ROI [9]. Descriptors of features define, evaluate, explain and classify a particular application that is observable and capable of capturing relevant object information. Feature extraction is a critical computing mechanism as well as the most important

Vol. 8, Issue 8, August 2020
DOI 10.17148/IJIREEICE.2020.8804

stage in object tracking implementation, and is generally restricted to human detection. HOG is one of the algorithms common for detection of features. This approach portrays the entire human body with local points of interest and clearly illustrates the images' edge details and decreases the effect of the illumination. Pedestrian identification is a challenging task as it has several postures, may occur in different road scene with different color combinations of their clothing, walking in complex background has various shades and lighting are some of the challenging processing problems. A window slides through a test image and the HOG detector determines for each slot if it is pedestrian or not [10]. We use SVM as a classifier in the pedestrian recognition process, and extract the HOG functions. HOG feature descriptor achieves higher decision levels but also has a high dimensionality drawback. As a result, the SVM classification criterion for measuring costs and storage is much smaller. The strength of the HOG component is that it can be based on the distribution of the histogram gradient direction, because it can determine the contours of the body and not be susceptible to fluctuations in light. Another popular algorithm for detecting features is SURF. As a standard method in image matching operations, this algorithm acts as feature point extraction and then analyzes the entire image. Matching approach uses the image gray value directly to evaluate the transformation of the space geometry between the images. The window size is set in the matching step of the function, and the calculation of the entire matching image is adopted. The mismatched point is removed by RANSAC algorithm in the process of matching feature point. Thus, the resulting matched points will approximate the geometric transformation specifications between two images, and the process of matching features is completed.

II. RELATED WORKS

Rudin et al., [1] suggested a model of Total Variation (TV) for image denoising, where the gradient histogram is used as Laplacian distribution. Davis et al., [2] Proposed the retrieval for feature classification of features such as contrast, homogeneity and identification of clusters from the grey level competition matrix. Cho et al., [3,4] Used a gradient framework with high energy-Laplacianto and predicted image denoising by applying different method boundary conditions and even different gradient production image domains earlier. Through following the gradient histogram distribution, the deblurred images have both fine textures and improved visual quality. Dalal and Triggs [5] suggested HOG, a gradient-based detection approach that operates on grey histogram cell values and efficient block normalization to prevent lighting effects. It has strong edge and gradient-based descriptors of local features to define representation of the object. It is easily controllable, invariant to translation and rotation, and results in accurate detection. In addition, we train an SVM [6] classifier to distinguish between target and non-target, using a broad range of positive and negative examples. Herbert Bay created the SURF algorithm [7] that can be used to determine the specific features of images. It was partially motivated by the SIFT descriptor but the SURF key point detector is a good algorithm compared to SIFT in its speed. The SURF scheme is robust at rotation of images and other color transformations of images. Scale Invariant Feature Transform (SIFT) algorithm [8] is an extraction of features algorithm which was first developed in 1991 by David Lowe to trace and describe local features in an image. It describes the behaviour that have properties, and helps to recognize the object. Such defining features invariant to various image transformations.

III. GRADIENT HISTOGRAM PRESERVATION (GHP)

A. *Algorithm*

Gradient Histogram Preservation (GHP) model with non-locally centralised sparse regularization for image denoising to overcome the suggested Texture Improved Denoising Image model.

1. Initialize k=0, $x^{(k)} = y$
2. Iterate on k=0,1, 2…. J
3. Update g:

g = $F(\nabla x)$

4. Update x:

$$x^{(k+1)/2} = x^{(k)} + \delta \left[\frac{1}{2\sigma^2}\left(y - x^{(k)}\right) + \mu\nabla^T\left(g - \nabla x^{(k)}\right)\right]$$

5. Upgrade correlation computation for each slot.

$$\alpha_i^{(\frac{k+1}{2})} = D^T R_i x^{(k+\frac{1}{2})}$$

6. Upgrade variable code non-local mean.

$$\beta_i = \sum_q w_i^q \alpha_i^q$$

7. Update α.

$$\alpha_i^{(k+1)} = S_{\lambda/_d}\left(\alpha_i^{\left(k+\frac{1}{2}\right)} - \beta_i\right) + \beta_i$$

8. Update x. $x^{(k+1)} = D \cdot \alpha^{(k+1)}$

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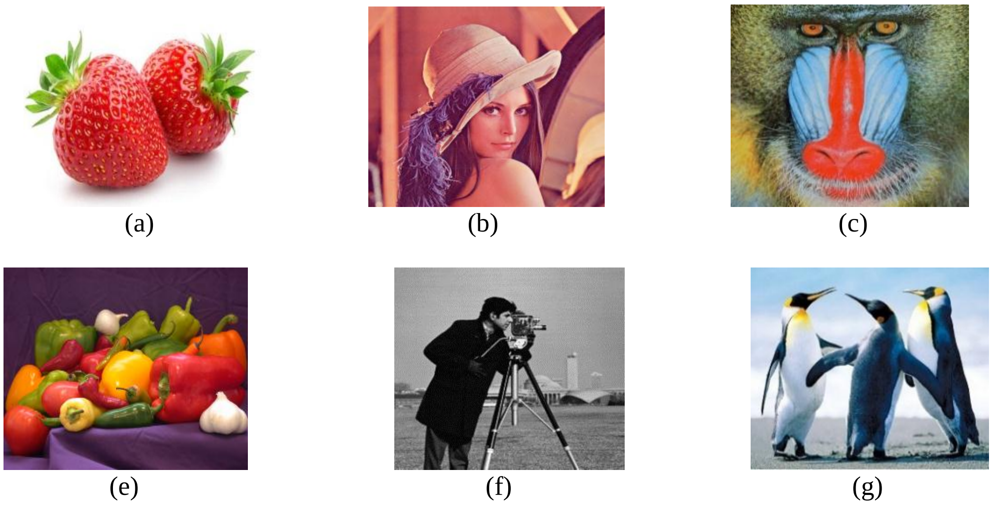
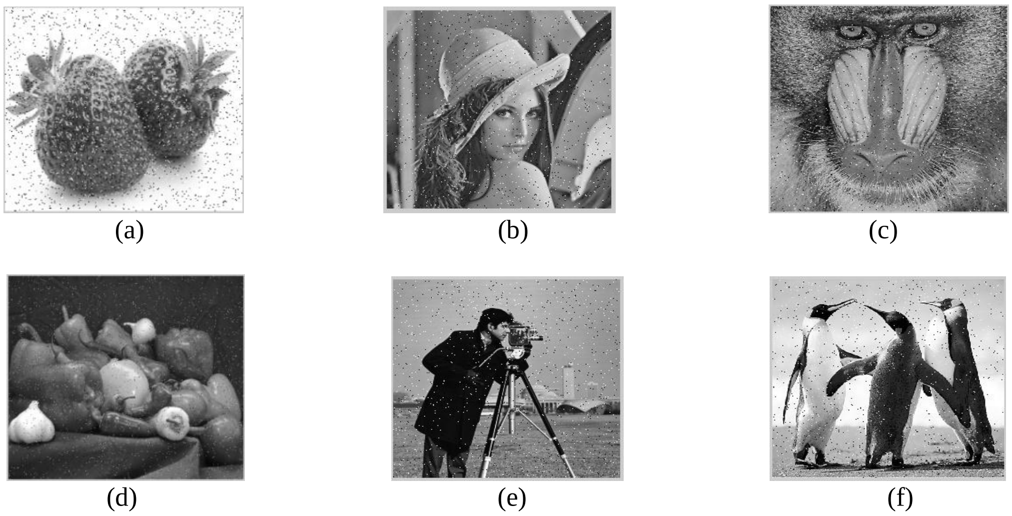
9. $k \leftarrow -k + 1$
10. $x = x^{(k)} + \delta[\mu \nabla^T (g - \nabla x^{(k)})]$

B. *Experimental Results*



(a) (b) (c) (e) (f) (g)

Fig.1 Input datasets



(a) (b) (c) (d) (e) (f)

Fig.2 Noisy images

(a) (b) (c) (d) (e) (f)

Fig.3 Denoised natural images

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Table I Comparison of performance parameters for different datasets.

Sl No.	Different Datasets	Performance Parameters		
		SNR	PSNR	SSIM
1.	Strawberry	19.14	21.34	0.772
2.	Lena	16.67	22.36	0.837
3.	Mandril	16.66	22.56	0.420
4.	Pepper	13.24	21.83	0.937
5.	Cameraman	16.59	22.17	0.775
6.	Penguin	18.07	21.25	0.732

We tested GHP computational efficiency on many other different data training sets including deblurring processes. To authenticate the robustness of the proposed GHP-based image denoising process, we apply it to multiple datasets, generated by different texture processes. Table I lists the result of the analysis values SNR, PSNR, and SSIM.

IV. HISTOGRAM ORIENTED GRADIENT(HOG)

A. *HOG Feature Descriptors*

HOG tests the representation of the target image by gradient. Dalal and Triggs[5] tested the images with excellent results for human detection. To represent a detection window, it is measured over 16-pixel blocks. It has been shown that this representation is accurate to incorporate SVM classifier to classify people. In particular, each detection window is segmented into 8x8 pixel cells, each group of 2x2 cells is combined into a sliding block so that the blocks overlap then each cell is a 9-bin centred approach HOG.

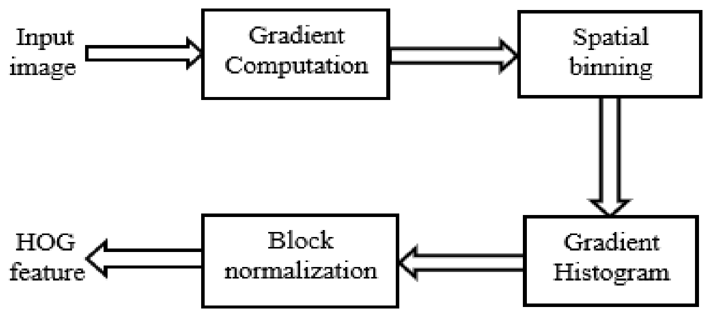

Fig.4 HOG Features Extracting Flow Chart

B. *Gradient operation*

Initially, the gradient value of each pixel is calculated. Considering image, I, perpendicular and lateral gradients are computed for pixel by pixel (x, y), as shown below:

$$Gx(x,y) = [-1\ 0\ 1]\,.\,I(x,y) \tag{1}$$

$$Gy(x,y) = [-1\ 0\ 1]\,.I(x,y) \tag{2}$$

The value of the gradients is shown in equation 3 and the gradient direction is shown in equation 4.

$$G(x,y) = \sqrt{G_x(x,y)^2} + \sqrt{G_y(x,y)^2} \tag{3}$$

$$\theta(x,y) = arctan[\frac{G_y(x,y)}{G_x(x,y)} \tag{4}$$

C. *Block and Cell*

Each source image is shown in 7 × 15 blocks. Dalal and Triggs [5] resized an input sliding window to 64×128. Each input image is divided by an average of 8×16 cells. Locally normalized cells must be grouped into greater and more sparsely related units. Normally, these blocks overlap which means that each cell contributes multiple times to the overall modifier.

D. *Spatial Binning*

Our second method of calculation include to set the histograms for cells only. The weighted orientation of each pixel is, depending on the centred gradient element orientation. They divide the orientation (0-180 degree) into 9 histogram channels: [0-20], [20-40 ......, [160-180]. The appropriate orientation weight [0, 20) of pixel (x, y) is 1 if the value is in [0-20], only certain orientation weight is 0.

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E. *Block Normalisation*

To adjust the intensity and brightness of the pixels it is important to normalize the intensity of the gradients to blocks. Hence, we use the techniques described now as equation (5):

$$f = \frac{v}{\sqrt{v^2 + e^2}} \tag{5}$$

Where v is the denormalized vector in a given block containing all histograms, and e is a constant.

F. *Linear SVM Classifier*

Through SVM classifier throughout the detection system, we may identify specific properties belonging to almost the same class in order to recognize the class of an unknown new sample afterwards. The SVM classificatory is a binary classification algorithm [6]. This technique constructs an effective hyper-plane to distinguish image characteristics in a high-dimensional space with two different categories. Considering the following set: {Xk, Yk}: Xk is HOG vectors which are given by the decision function:

$$f(x) = w * \phi(x) + b$$

(6)

Using the following equation, f(x) significantly increases the separation between the nearest $\sigma(x)$ and the hyperplane:

$$\min_{\omega} \xi \ \frac{1}{2} \parallel w \parallel^2 + c \sum_{k=1}^{m} \xi_k \tag{7}$$

G. *Experimental Results*

(a) (b) (c) (d)

Fig.5 Some examples of our experimental results.

HOG has assessed overall performance for various situations. The characteristics were positive size of training dataset, negative size of training dataset and method of classification. In tests two different output styles are assessed. Positive Quality Analysis is performed using real pedestrians 70 x134.

V. SPEEDED-UP ROBUST FEATURE(SURF)

SURF is a feature extraction descriptor initially presented by Herbert Bay in 2006 that can be used for applications such as object detection or video processing. SURF is better and flexible against different image transformations than SIFT. It is based 2D Haar Wavelet responses and makes good use of the integral images. It used the a real - valued approximation to the Hessian blob detector significant factor that can also be calculated swiftly using an integral image. Image Matching is obtained by analysing multiple kinds of descriptors obtained from the various kinds of images.

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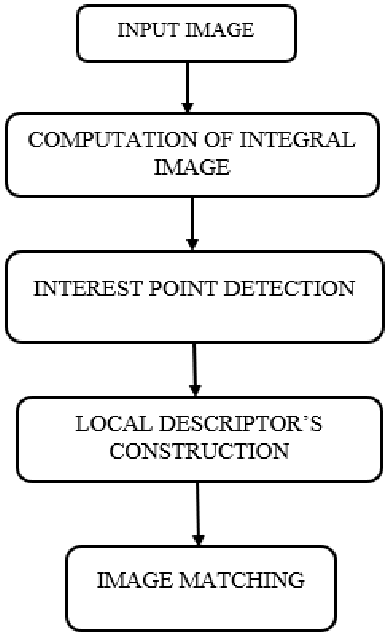

Fig.6 Flowchart of SURF algorithm

Let $P(x,\sigma)$ be a point and $H(x,\sigma)$ Hessian matrix of an image of the scale value σ is:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \tag{8}$$

$L_{xx}(x,\sigma)$, $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$ are the convolutions of the second-order partial derivatives $\frac{\partial^2 g(\sigma)}{\partial x^2}$, $\frac{\partial^2 g(\sigma)}{\partial x \partial y}$ and $\frac{\partial^2 g(\sigma)}{\partial y^2}$.
The determinant values of the Hessian matrix are:

$$Det(H) = L_{xx}\, L_{xy} - L_{xy}\, L_{xx} \tag{9}$$

The SURF algorithm simulates variable second-order functions of Gaussian functions using a box filter. The L_{xx} and L_{yy} reflect the vertical horizontal edge from the composition of the filter, and L_{xy} represents the diagonal edge. In the given algorithm, the histogram scale is constant but the size of the box filter increases as the image size increases. The image and the box filter are twisted together to produce multi-size response graph image of an additive noise [11].
Weight coefficient, expressed as:

$$\omega = \frac{\|L_{xy}\,(1{,}2)\|_F\ \|L_{xx}(9)\|_F}{\|\,L_{xx}(1{,}2)\|_F\ \|L_{xy}\ (9)\|_F} \tag{10}$$

Therefore:

$$Det(H) = D_{xx}\, D_{yy} - (\omega D_{xy}) \tag{11}$$

A. *Feature point vector generation*

It is essential to generate function variables when making the decision with respect to the direction of the feature points. The feature point definition vector represents the change in gradient in the grey value around the feature point. Gradient values are drastically different near the pixel intensities, while gradient values do not change in the smoother regions.

1) A quadrilateral section of size is based on the point of interest $20\sigma * 20\sigma$ is created for which the region's horizontal x-axis is moved to the main direction, where σ is the scale of the pixel.

2) The square region is divided into specific regions of size 4X4, then the Haar wavelet transform is measured in horizontal and vertical directions in each sub-area within the range of 5X5.

3) Through sub-region 's four-dimensional features are measured and summarized which ultimately results in a sixty-four-dimensional vector descriptor for 16 sub-regions.

B. *Feature point vector matching*

Hessian matrix was obtained in the preceding definition of feature points, a positive result is in one category and a negative point is in another category. If the two feature points have same result, the Euclidean distances of the two vectors in the description can be determined. If the Euclidean distance between the points are equal a pair of matching points is resulted

$$D_{ij} = \left[\sum_{k=0}^{k=n}\left(X_{iK} - X_{jK}\right)^2\right]^2 \tag{12}$$

X_{iK} is the kth element of the ith feature point descriptor in the original image; and X_{jK} is the kth element of the jth feature point descriptor in the matched image.

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C. *RANSAC ALGORITHM*

RANSAC is a commonly used algorithm for extracting mismatched points. Until the matching points are sorted by the RANSAC algorithm, the initial optimal inner spots Si must be set. The Algorithm for RANSAC is as follows:

1) In the RANSAC sampling algorithm, only a certain number of N need to be chosen and the correct samples has to be collected.

$$N = \frac{log^{(1-p)}}{log^{(1-\omega^{n})}} \tag{13}$$

2) For matching points, 4 matching point pairs are chosen randomly, and the matched pairs are not collinear to determine the Hessian matrix.

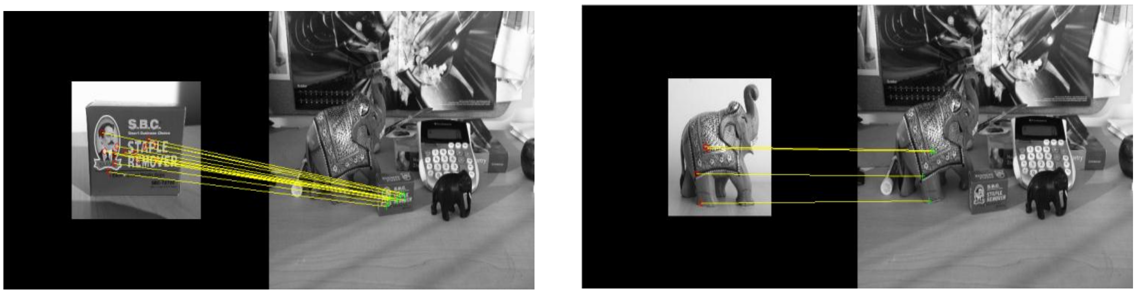
3) According to the Hessian matrix, the Euclidean distance from each matching point to the alternating matching point is calculated.

4) Establish a T threshold and set the corresponding point that meets d conditions to keep the number of inbuilt points essentially the same.

5) Evaluate the obtained internal points with Si. If the internal point is more than Si, then the resulted matrix is the new matrix H, and then the Si value is modified.

6) After multiple random sampling, the number of iterations N exceeds the maximum number of iterations and we shall note that the number of internal points remains essentially the same.

Experimental Results



(a) (b)

Fig.7 Matched points for different image.

Fig.8 Matched points for cropped image

Fig.9 Matched points for rotated features of image.

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After using both the primary and the altered SURF algorithm, the matching image witnessed a rotational shift, grey-scale shift resulted in image matching and prototype image matching with a major difference [7].

VI. CONCLUSION

In this paper, we have provided GHP model for texture enhanced denoised image and achieves promising results when eliminating random noise in improving the texture structure. GHP contributes denoising process using PSNR parameter. GHP also limits that it cannot be extended explicitly to the removal of non-additive noise. The experimental results achieve natural image along with rich texture features. The feature points can also be extracted for detection computation in which we have used pedestrian detection as an application using HOG algorithm. HOG function depicts the image's edge features and reduces the impact of illumination. The combination of HOG-SVM makes algorithm efficient and simple. It even detects target objects in visual difficulties and SVM is used for classification of pixels. The extracted features can also be used for image matching purpose in which we have used SURF-based approach for improving the output detection and matching. It incorporates color invariant transformation, entropy of information to significantly preserve color information and to detect more feature points. Based on the actual algorithm, the extension is made of RANSAC method which eliminates inconsistency. The experimental results demonstrated that the proposed SURF approach can significantly reduce discrepancies, and increase the matching accuracy of the result effectively.

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