Histogram of Structure Tensors: Application to Pattern Clustering

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ABSTRACT

Pattern clustering is an important data analysis process useful in a wide spectrum of computer vision applications. In addition to choosing the appropriate clustering methods, particular attention should be paid to the choice of the features describing patterns in order to improve the clustering performance. This paper presents a novel feature descriptor, referred as Histogram of Structure Tensors (HoST), allowing to capture the local information of an image. The basic idea is that a local pattern could be described by the distribution of the structure tensors orientations and shapes. The proposed HoST descriptor has two major advantages. On the first hand, it captures the dominant orientations in a local spatial region taking into account of the local shape of the edges structure. In fact, it is based on the structure tensor that represents a very interesting concept for characterizing the local shape. On the other hand, the use of the histogram concept makes the proposed descriptor so effective and useful when a reduced feature representation is required.

In this paper, the proposed HoST descriptor is addressed to the pattern clustering task. An extensive experimental validation demonstrates its performance when compared to other existing feature descriptors such as Local Binary Patterns and Histogram of Oriented Gradients. In addition, the proposed descriptor succeeds in improving the performance of clustering based resolution enhancement approaches.

Keywords

Local feature descriptor, Histogram of structure tensors, Pattern clustering, Orientation and shape information.

1 INTRODUCTION

Pattern clustering is an unsupervised data analysis process whose goal is to partition a given unlabeled database into groups of similar patterns, called clusters. It has been widely involved in various applications including machine learning, pattern recognition, object detection and recognition, image analysis and image retrieval. Specifically, pattern clustering represents an integral step in a variety of research works on textual image analysis and interpretation such as resolution enhancement [Wal13a,Wal13b], handwritten character recognition [Con01,Vuo02] and writer identification and verification [Dah10a,Dah10b,Sid07,Bul05].

Feature extraction aims to describe an image by a set of features. The local description of an image is still critical in many computer vision applications. In addition to the choice of the appropriate clustering technique and its parameters setting, it is very important to involve effective features that allow patterns to be well discriminated and thus improve the clustering performance. The emergence of pattern clustering in various works on textual images introduces the need for efficient features that focus on the writing specificities. In fact, there is a regularity of fine patterns that distinguishes textual images from natural ones. Moreover, textual images are composed by several structural primitives (e.g. edges, corners, line segments, and curvatures) constituting complex structures. That's why, we study in this work the feature extraction issue for the clustering of writing patterns. We propose a new local feature descriptor, referred as Histogram of Structure Tensors (HoST). It is based on the structure tensor which represents a very interesting concept in differential geometry because it can provide substantial information in a local neighborhood. The proposed descriptor provides better pattern clustering performance than the other existing descriptors including pixel intensities based descriptor, gradients based descriptor, Local Binary Patterns based descriptor and Histogram of Oriented Gradients based descriptor which becomes increasingly popular in computer vision and pattern recognition applications.

Moreover, we demonstrate the usefulness of the HoST descriptor for an example of clustering based magnification approach [Wal13b] that is recently proposed to up-scale low-resolution textual images.

The rest of this paper is structured as follows. Section 2 briefly presents related works on feature extraction. Section 3 details the proposed local feature descriptor. Experimental evaluations and comparative studies on pattern clustering and magnification tasks are provided in section 4. The main conclusions and some perspectives are given in section 5.

2 RELATED WORKS

The local description of an image is still critical to applications performance. Therefore, it is important to choose effective local feature descriptor to represent an image. The intensity values of pixels are directly employed as a feature descriptor in a variety of works [Wal12,Wal13a,Wal13b]. First order and Second order of gradients based features are also widely used in the literature to locally describe writing patterns [Loc12,Agg12]. Ojala *et al.* [Oja96] introduced the Local Binary Patterns (LBP) as a local feature descriptor. Its principle is to label each pixel by thresholding the neighborhood pixels and considering the result as a binary number. The LBP descriptor has been recently used to describe writing patterns for writer identification and verification task [Ber13] and also for character recognition of vehicle license plate [Liu10]. Anthimopoulos *et al.* [Ant10] have used descriptors based on the LBP concept for text detection.

Dalal and Triggs [Dal05] introduced the Histogram of Oriented Gradients (HOG) as a local texture descriptor. It is based on the gradient information as a local feature and counts occurrences of edge orientations in a local neighborhood. The HOG descriptor has attracted a great deal of attention and it becomes one of the most widely used local feature descriptor. This is due to its performance achieved in many computer vision and pattern recognition applications [Den11]. The HOG descriptor has been successfully applied for text analysis and recognition [New11,Min13].

The structure tensor provides rich information about the local shape based on a local gradient vector field. Such concept has been used for estimating the curvature in oriented patterns, detecting complex symmetries [Wei01], restoring document images by diffusion [Wei99,Dri12,Dri09] and detecting local features such as the Harris corner detector [Kot03].

3 HISTOGRAM OF STRUCTURE TENSORS: NEW LOCAL FEATURE DESCRIPTOR

This paper presents a novel feature descriptor to capture the local information of an image. It is based on the structure tensor which is a very interesting concept in differential geometry because it represents the local structure of an image based on a local gradient vector field. We refer to the proposed descriptor as Histogram of Structure Tensors (HoST). The basic idea is that a local pattern could be described by the distribution of the structure tensor orientation and shape. In the following, we briefly present the structure tensor principle and then we detail the proposed local feature descriptor.

3.1 Structure Tensor: Brief Review

Given an image I, the first order derivative structure tensor at a certain pixel is defined by the product of gradients (Equation (1)) [Diz86].

$$T = \nabla I \times \nabla I^t \tag{1}$$

where ∇ is the first order derivative in the gradient field:

$$\nabla I = \begin{pmatrix} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{pmatrix} \tag{2}$$

In practice, gradients need to be calculated on a slightly smoothed image to avoid the singular points of the input image [Alv92]. Therefore, a Gaussian convolution kernel G_σ is applied on the image I. In addition, Weickert [Wei99] proposed to use a second Gaussian convolution kernel G_ρ in order to enhance the local consistency of neighboring tensors. This leads to the generation of the smoothed structure tensor T_σ^ρ :

$$T_\sigma^\rho = G_\rho \otimes \Big(\nabla(G_\sigma \otimes I)\nabla(G_\sigma \otimes I)^t\Big) \tag{3}$$

In differential geometry, the structure tensor T_σ^ρ is defined as a 2×2 symmetric matrix:

$$T_\sigma^\rho = \begin{pmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{pmatrix} \tag{4}$$

where $J_{12} = J_{21}$. The structure tensor T_σ^ρ could be decomposed in an orthonormal basis formed by two orthogonal eigenvectors Θ_+ and Θ_- associated respectively with two positive eigenvalues λ_+ and λ_- (Equation (5)). The eigenvectors Θ_+ and Θ_- indicate the local orientations of the variations in the image, while the eigenvalues λ_+ and λ_- that are formally given by Equation (6) measure the associated derivative energy (i.e. the magnitude of these variations).

$$T_\sigma^\rho = \lambda_- \times \Theta_-\Theta_-^t + \lambda_+ \times \Theta_+\Theta_+^t \tag{5}$$

$$\lambda_{+/-} = \frac{1}{2}\Big(J_{11} + J_{22} \pm \sqrt{(J_{11}-J_{22})^2 + 4J_{12}^2}\Big) \tag{6}$$

Geometrically, the structure tensor T_σ^ρ represents an ellipse whose radii are λ_+ and λ_- and its principal axis Θ_+ forms an angle θ with the horizontal axis. The formula for calculating the angle θ is written in Equation (7). The eigenvalue analysis determines the shape of the structure tensor (isotropic or anisotropic) in the principal directions. The geometric interpretation of the structure tensor T_σ^ρ is depicted in Fig. 1.

$$\theta = \frac{1}{2}\arctan\left(\frac{2J_{12}}{J_{11}-J_{22}}\right) \tag{7}$$

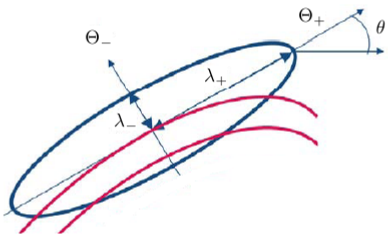


Figure 1: Geometric interpretation of the first order derivative structure tensor.

3.2 The Proposed Histogram of Structure Tensors

The structure tensor at each pixel is characterized by two useful parameters : Θ_+ and λ_+. In fact, the direction of Θ_+ indicates the most prominent orientation in a local neighborhood. Furthermore, The eigenvalue λ_+ represents the local derivative energy in such direction. From now, we use $(\Theta_+)_i$, $(\lambda_+)_i$ and $(\theta)_i$ as references to respectively the principle axis, the largest eigenvalue and the angle with the horizontal axis of the structure tensor $(T_\sigma^\rho)_i$ at a given pixel i.

The orientation field is a very useful appearance information because it describes the changing direction within a spatial region. To take advantage of this information, we propose to gather the structure tensor orientations of the pixels in a spatial region via an histogram representation. In order to incorporate the derivative energy in the most prominent orientation, we propose also to calculate for each structure tensor orientation $(\theta)_i$ a weighted vote that involves the largest eigenvalue $(\lambda_+)_i$ (Equation (8)). This allows us to capture the dominant orientations in a local region taking into account of the local structure shape.

Similarly to [Dal05], votes are weighted by using bilinear interpolation to reduce aliasing effect. More precisely, for each structure tensor orientation $(\theta)_i$, the two nearest orientation bin centers $c_{j\in\{1,2\}}$ are involved by weighting the vote by coefficients $w_{i,j}$ inversely proportional to the distance between the given orientation $(\theta)_i$ and its neighboring bin centers $c_{j\in\{1,2\}}$. So, each structure tensor orientation $(\theta)_i$ of a given pixel i contributes a weighted vote that will be accumulated into the corresponding orientation bins b_j of the histogram $HoST$ (Equation (8)).

$$HoST[b_j] = \sum_i w_{i,j} \times (\lambda_+)_i \quad s.t. \quad (\theta)_i \in b_j \tag{8}$$

The implementation of the proposed histogram of structure tensors descriptor are summarized by the following steps:

Step 1: Compute the matrix of the structure tensor $(T_\sigma^\rho)_i$ for each pixel of a given spatial region (Equation 3).

Step 2: Estimate the eigenvector $(\Theta_+)_i$ and the eigenvalue $(\lambda_+)_i$ of each $(T_\sigma^\rho)_i$ (Equation 5 and 6).

Step 3: Calculate the angle $(\theta)_i$ corresponding to the most prominent direction of $(T_\sigma^\rho)_i$ (Equation 7).

Step 4: Compute the weights $w_{i,j}$ based on the distance between the orientation $(\theta)_i$ and the nearest orientation bin centers $c_{j\in\{1,2\}}$ of the histogram $HoST$.

Step 5: Accumulate the weighted vote into the corresponding orientation bins b_j of the histogram $HoST$ (Equation (8)).

In practice, the proposed local feature descriptor is applied by dividing the input image into small spatial regions, called patches. Each patch is described by an histogram $HoST$. The combined histograms form the representation of the input image. Such a descriptor is very useful when a reduced feature representation is needed to describe an input image whose size is large. In this paper, the proposed HoST descriptor is addressed to the pattern clustering task.

4 EXPERIMENTS AND RESULTS

Before introducing the implementation details and reporting the performance of the proposed HoST descriptor, we present the database considered in our experimental study.

4.1 Database

In this work, all experiments are run on a large database used in recent research works on resolution enhancement of textual images [Wal12,Wal13a,Wal13b]. It contains 124,000 image patches collected from high quality character images which are automatically generated by using an efficient font engine called FreeType[1]. Such character images cover a large variety of sizes, styles (italic, non-italic) and fonts (serif, sans-serif) currently used in textual documents, signs, labels, bills, etc. The image patches sampled from these character images are of size 7×7 and localized along the edges of characters (Fig. 2). This leads to the collection of a generic image patch database including numerous writing patterns which are very different due to their shapes, sizes, orientations and positions in the image patches. Fig. 3 shows some samples of the database.

[1] www.freetype.org

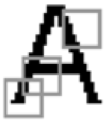


Figure 2: Illustration of selecting patches from a character image.

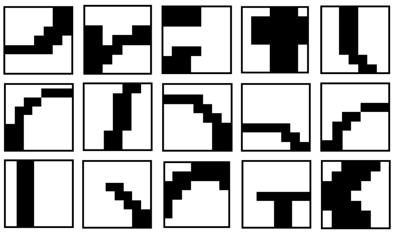


Figure 3: Writing pattern samples from the database.

4.2 Application to Pattern Clustering

In this section, we perform an evaluation of the proposed HoST descriptor for the clustering of writing patterns. In fact, each image patch of the database presented above is described by a HoST representation. After that, an intelligent version of the Kmeans method, referred as iK-means [Mir05], is applied to gather similar patterns in the same cluster. Such unsupervised technique automatically determines the number of clusters and initial centroids for the K-Means method using the so-called Anomalous Pattern (AP) algorithm. In this work, the iK-means method is used in all experiments. In the following, we describe the cluster validity indices used in this study for evaluating the clustering results. After that, we perform a comparative study between different local feature descriptors.

4.2.1 *Evaluation Metrics*

When the ground-truth data partition is available, it is possible to compare it with the partition proposed by the clustering method based on many indices such as Adjusted Rand and Jaccard [Bat95]. But, when the ground-truth data partition is not available, another kind of indices is used to estimate the quality of clustering by measuring the cohesion (intra-variance) and separation (inter-variance) of the clusters [Ber97]. We focus on the second kind of indices because the correct partition of the database used in this work is not available.

Calinski and Harabasz [Cal74] proposed a clustering validity index, referred as Calinski-Harabasz (CH) index. It estimates the cohesion based on the distances from an element in a cluster to its centroid and the separation based on the distance from the centroids to the global centroid. The larger the CH index value, the better the clustering solution. Davies and Bouldin [Dav79] proposed another clustering validity index, referred as Davies-Bouldin (DB) index, which estimates the cohesion based on the distance from an element in a cluster to its centroid. The separation is based on the distance between centroids. In contrast to the CH index, the minimal value of DB index indicates the best clustering solution. The silhouette is another popular cluster validity index [Rou87]. The silhouette measure is defined for each observation in a dataset. It gives information of how well each observation lies within its cluster. Thus, the average of silhouette measures over the entire dataset provides an indicator of how appropriately the data has been clustered. The silhouette measure ranges from -1 to +1. A good clustering solution results in a measure close to 1. In this paper, the silhouette based clustering validity index will be used for the final comparison between different local feature descriptors.

In [Arb13], the authors demonstrate that CH, DB and silhouette indices are within the group of indices that shows a better behavior for clustering validation than other indices.

4.2.2 *Pattern Clustering Results*

HoST is designed to be non-oriented in contrast to the HOG descriptor. So, the orientation bins of the histogram are spaced over $[0° - 180°]$. Table 1 summarizes the effect of varying the number of orientation bins on pattern clustering performance. Results are investigated in terms of DB and CH indices. In order to enhance the local consistency of neighboring tensors and avoid singular points in a spatial region, we use the Gaussian convolution kernels mentioned previously with $\sigma = 0.7$ and $\rho = 1.5$. According to Table 1, we can see that sampling the structure tensor orientations into 4 bins achieves the lower DB result, the higher CH result and thus the best clustering accuracy. The number of clusters determined by the AP algorithm is 12 when using 4 orientation bins. Increasing the number of orientation bins yields to decrease the pattern clustering performance.

As HOG descriptor become increasingly popular in computer vision and pattern recognition applications, we compare the proposed HoST descriptor with it. Before that, we study the effect of varying the number of orientation bins in the case of HOG descriptor. Tests are performed for the same sizes of orientation bins as in the previous experiment, but these bins are spaced over $[0° - 360°]$. Indeed, HOG descriptor is designed to be oriented and the gradient directions have an effect in the case of writing patterns [Min13]. For instance, an histogram of 4 orientation bins spaced over $[0° - 180°]$ in the case of HoST descriptor corresponds to an histogram of 8 orientation bins spaced over $[0° - 360°]$ in the case of HOG descriptor. In order to make a fair comparison, the same clustering method described above is used in all experiments. According to Table 2, the best clustering accuracy is achieved when using 8 orientation bins in HOG descriptor. This proves again that 45° is the appropriate orientation bin size to cluster the writing patterns as shown in the above experiment.

Number of Bins	Number of Clusters	Cluster Validity Index	
		DB index	***CH index***
3	12	1.0018	5.1936 e+04
4	**12**	**0.8229**	**7.4998 e+04**
5	13	0.9379	6.4887 e+04
6	11	0.9036	6.0035 e+04

Table 1: Evaluation of HoST descriptor for pattern clustering with different orientation bins spaced over $[0° - 180°]$.

In the following experiments, we use the optimal number of orientation bins in the case of HOG descriptor and HoST descriptor.

To examine the effectiveness of the proposed HoST descriptor, we compare it with HOG descriptor and other existing local feature descriptors on the pattern clustering task. Such features include pixel intensity, first order of gradients, first order and second order of gradients and LBP based descriptors. Evaluation results of this comparative study are listed in Table 3. Fig. 4 compares also our descriptor with those cited above in terms of silhouette measures. At the same testing settings, Table 3 shows that the clustering performance is significantly improved when our proposed feature descriptor is applied to represent image patches of the database. Indeed, pattern clustering by using the HoST descriptor achieves the best results in terms of mean of silhouette and DB index. In addition, it greatly outperforms the tests applying the other feature descriptors involved in this study in terms of CH index.
Furthermore, results of clustering plotted in Fig. 4 via graphic representations of silhouette measures illustrate again that the use of our proposed feature descriptor improves the pattern clustering performance. In fact, the silhouette measure is negative when the average distance of an element to the others in the same group is larger than the average distance to elements in other groups. Such undesirable characteristic is clearly observed in Fig.4(a-e) where the silhouette measures are plotted for pattern clustering using respectively pixel intensity, first order and second order of gradients, LBP and HOG based descriptors. Fig. 4(f) that represents the results of clustering using the proposed HoST descriptor includes the lowest number of silhouette measures that are negative.

4.3 Application to Resolution Enhancement of Textual Images

This experiment concerns the application of the proposed HoST descriptor to the magnification of low-resolution textual images. In fact, recent research works on the resolution enhancement of textual images, such as [Wal13b], are based on incorporating a pattern clustering step in order to learn multiple dictionaries from a clustered database. This clustering step is very important in this approach because it is responsible for improving the quality of resolution enhancement results. The authors of [Wal13b] have simply used the intensity values of pixels as feature descriptors to represent writing patterns included in the training database. Such a database is used in this paper and described in section 4.1. Rather than using intensity based descriptors, we propose to incorporate our HoST descriptor in such a magnification approach in order to improve the writing pattern clustering performance. Experimental results of section 4.2.2 illustrate such improvements in terms of different clustering validity indices. In this experiment, we study the effect of using our descriptor on the quality of the learned dictionaries and even on the resolution enhancement results.
In [Wal13b], a coupled high-resolution/low-resolution dictionaries are learned from each cluster. Fig. 5(a) plots some of these high-resolution dictionaries determined by using the intensity based descriptor. On the other hand, Fig. 5(b) displays some high-resolution dictionaries generated by using the proposed HoST descriptor. We can notice that more appropriate dictionaries are found by the application of our descriptor which allows gathering patterns with similar dominant orientations in the same cluster.
In order to evaluate quantitatively the effect of using the proposed HoST descriptor in the resolution enhancement approach involved in this study, we perform an up-scaling of different low-resolution textual images. For lack of space, we give magnification results on a degraded image scanned at 150 dpi. Table 4 compares the Peak SNR (PSNR), the Root Mean Square Error (RMSE), the Structural SIMilarity index (SSIM) [Wan04] results of the up-scaled images recovered by [Wal13b] using HoST descriptor and without using it. According to this table, we can see that the proposed HoST descriptor succeeds in improving the resolution enhancement performance of [Wal13b]. In fact, the image reconstructed by [Wal13b] via the proposed HoST descriptor achieves the highest measures result. In order to have a closer look, Fig.6 illustrates some enlarged regions from the input image, the up-scaled images and the ground truth image scanned at 300 dpi. We can notice improvements in visual quality of the image recov-

Number of Bins	Number of Clusters	Cluster Validity Index	
		DB index	*CH index*
6	16	1.1285	2.2974 e+04
8	**15**	**0.9863**	**2.8466 e+04**
10	15	1.3970	1.8205 e+04
12	18	1.4220	1.5651 e+04

Table 2: Evaluation of the HOG descriptor for pattern clustering with different orientation bins spaced over [0° – 360°].

Local Feature Descriptor	Number of Clusters	Cluster Validity Index		
		Mean of Silhouette	*DB index*	*CH index*
Intensity	13	0.1218	2.0156	7.3503 e+03
First Order Gradients	13	0.1141	2.4600	4.7292 e+03
First and Second Order Gradients	15	0.1348	2.4714	4.0189 e+03
LBP	18	0.2250	2.1024	1.2287 e+04
HOG	15	0.2027	0.9863	2.8466 e+04
HoST	**12**	**0.3338**	**0.8229**	**7.4998 e+04**

Table 3: Comparison between local feature descriptors applied for pattern clustering.

Magnification approach	RMSE	PSNR	SSIM
[Wal13b]	29.460	18.745	0.865
[Wal13b] using HoST	**28.134**	**19.145**	**0.874**

Table 4: Effect of using the proposed HoST descriptor on resolution enhancement results of [Wal13b].

ered by [Wal13b] using the proposed HoST descriptor when compared with the image reconstructed without using it.

5 CONCLUSION

In summary, we mention the main contributions of this paper. First, a new feature descriptor called Histogram of Structure Tensors was introduced to capture the local information of an image. Second, the proposed descriptor was applied for writing pattern clustering task. Experimental results showed its effectiveness in terms of cluster validity indices when comparing it to other local feature descriptors often used in the literature. Third, we demonstrate that the proposed descriptor can improve the performance of clustering based resolution enhancement approaches.

A proposed extension to our work is to include more clustering algorithms for a comparison purpose. Furthermore, the proposed local feature descriptor could be useful to other computer vision tasks such as image matching, object detection and classification.

6 REFERENCES

[Agg12] Aggarwal A., Rani R., and Dhir R. Recognition of devanagari handwritten numerals using gradient features and svm. International Journal of Computer Applications, 48(8):39-44, 2012.

[Alv92] Alvarez L., Lions P.L., and Morel J.M. Image selective smoothing and edge detection by nonlinear diffusion. ii. SIAM J. Numer. Anal., 29(3):845-866, June 1992.

[Ant10] Anthimopoulos M., Gatos B., and Pratikakis I. A two-stage scheme for text detection in video images. Image Vision Comput., 28(9):1413-1426, September 2010.

[Arb13] Arbelaitz O., Gurrutxaga I., Muguerza J., PeRez J.M., and Perona I. An extensive comparative study of cluster validity indices. Pattern Recogn., 46(1):243-256, January 2013.

[Bat95] Batagelj V. and Bren M. Comparing Resemblance Measures. Journal of Classification, 12(1):73-90, 1995.

[Ber97] Berry M. J. and Linoff G. Data Mining Techniques: For Marketing, Sales, and Customer Support. JohnWiley Sons, Inc., New York, NY, USA, 1997.

[Ber13] Bertolini D., Oliveira L. S., Justino Edson J. R., and Sabourin R. Texture-based descriptors for writer identification and verification. Expert Syst. Appl., 40(6):2069-2080, 2013.

[Bul05] Bulacu M. and Schomaker L. A comparison of clustering methods for writer identification and

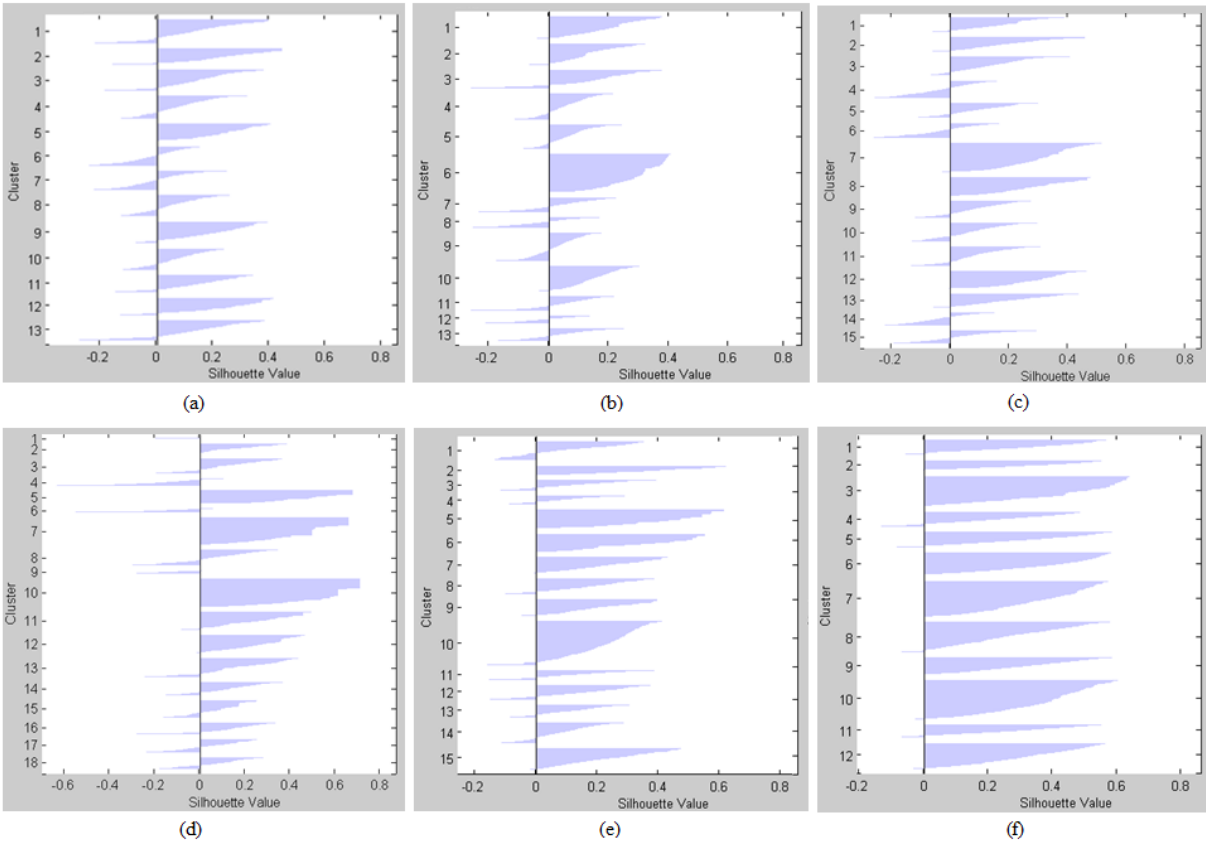


Figure 4: Evaluation of pattern clustering in terms of silhouette measures by using different local feature descriptors. (a) Intensity based descriptor. (b) First order gradients based descriptor. (c) First and second order gradients based descriptor. (d) LBP based descriptor. (e) HOG based descriptor. (f) HoST based descriptor.

verification. In ICDAR, pp.1275-1279, 2005.

[Cal74] Calinski T. and Harabasz J. A dendrite method for cluster analysis. Communications in Statistics-Simulation and Computation, 3(1):1-27, 1974.

[Con01] Connell S. D. and Jain A. K. Template based online character recognition. Pattern Recognition, 34(1):1-14, 2001.

[Dah10a] Daher H., Eglin V., Bres S., and Vincent N. A new approach for centerline extraction in handwritten strokes: an application to the constitution of a code book. In DAS, pp.425-432, 2010.

[Dah10b] Daher H., Gaceb D., Eglin V., Bres S., and Vincent N. Ancient handwritings decomposition into graphemes and codebook generation based on graph coloring. In ICFHR, pp.119-124, 2010.

[Dal05] Dalal N. and Triggs B. Histograms of oriented gradients for human detection. In CVPR (1), pp.886-893, 2005.

[Dav79] Davies D. L. and Bouldin D. W.. A cluster separation measure. IEEE Trans. Pattern Anal. Mach. Intell., 1(2):224-227, February 1979.

[Den11] Deniz O., Bueno G., Salido J., and De la Torre F. Face recognition using histograms of oriented gradients. Pattern Recogn. Lett., 32(12):1598-1603, September 2011.

[Diz86] DiZenzo S. A note on the gradient of a multi-image. Comput. Vision Graph. Image Process., 33(1):116-125, January 1986.

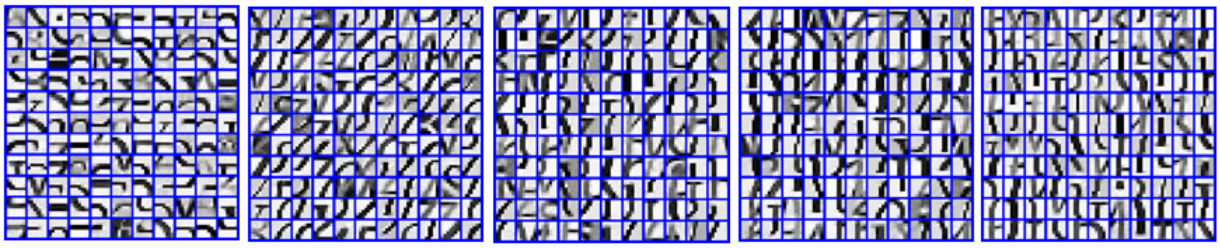
[Dri09] Drira F., Lebourgeois F., and Emptoz H. Document images restoration by a new tensor based diffusion process: Application to the recognition of old printed documents. In ICDAR, pp.321-325, 2009.

[Dri12] Drira F., Lebourgeois F., and Emptoz H. A new pde-based approach for singularity-preserving regularization: application to degraded characters restoration. IJDAR, 15(3):183-212, 2012.

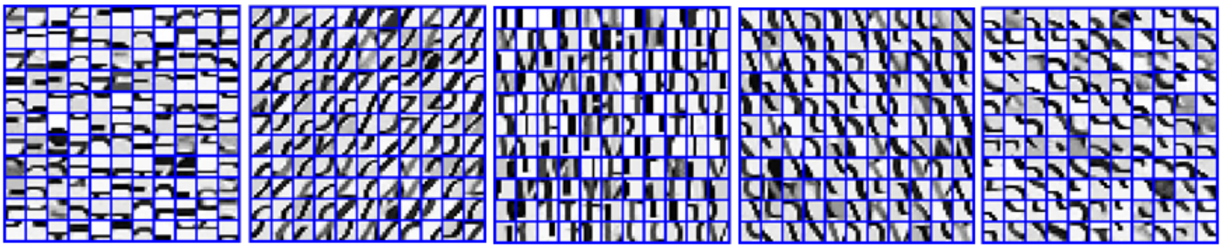
[Kot03] Kothe U. Edge and junction detection with an improved structure tensor. In Krell (Eds.): Pattern Recogn., Proc. of 25 th DAGM Symposium, Springer LNCS 2781, pp.25-32, 2003.

[Liu10] Liu L., Zhang H., Feng A., Wan X., and Guo J. Simplified local binary pattern descriptor for character recognition of vehicle license plate. 10th Conf. CVIG, 0:157-161, 2010.

[Loc12] Lochan D. R., Prasad B. K., and Sanyal G. Article: Hmm based offline handwritten writer

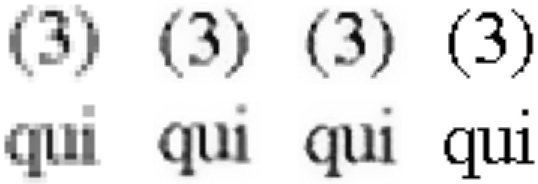


(a)



(b)

Figure 5: High-resolution learned dictionaries using: (a) Intensity based descriptor. (b) HoST based descriptor.



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

Figure 6: Visual comparison of enlarged regions from the input low-resolution textual image (a), the up-scaled images recovered by [Wal13b] (b), by [Wal13b] via the proposed HoST descriptor (c) and the ground truth high-resolution image (d).

independent english character recognition using global and local feature extraction. International Journal of Computer Applications, 46(10):45-50, 2012.

[Min13] Minetto R., Thome N., Cord M., Leite N. J., and Stolfi J. T-hog: An effective gradient-based descriptor for single line text regions. Pattern Recogn., 46(3):1078-1090, 2013.

[Mir05] Mirkin B. Clustering for Data Mining: A Data Recovery Approach. Chapman and Hall/CRC Computer Science Data Analysis, 1 edition, 2005.

[New11] Newell A. J. and Griffin L. D. Multiscale histogram of oriented gradient descriptors for robust character recognition. In ICDAR, pp.1085-1089, 2011.

[Oja96] Ojala T., Pietikainen M., and Harwood D. A comparative study of texture measures with classification based on featured distributions. Pattern Recogn., 29(1):51-59, 1996.

[Rou87] Rousseeuw P. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math., 20(1):53-65, 1987.

[Sid07] Siddiqi I. and Vincent N. Writer identification in handwritten documents. In ICDAR, pp.108-112, 2007.

[Vuo02] Vuori V. and Laaksonen J. A comparison of techniques for automatic clustering of handwritten characters. In ICPR, pp.168-171, 2002.

[Wal12] Walha R., Drira F., Lebourgeois F., and Alimi A. M. Super-resolution of single text image by sparse representation. In Proc. DAR'12, pp.22-29, Published by ACM, New York, NY, USA, 2012.

[Wal13a] Walha R., Drira F., Lebourgeois F., Garcia C. and Alimi A. M. Single textual image super-resolution using multiple learned dictionaries based sparse coding. In ICIAP (2), pp.439-448, 2013.

[Wal13b] Walha R., Drira F., Lebourgeois F., Garcia C. and Alimi A. M. Multiple learned dictionaries based clustered sparse coding for the super-resolution of single text image. In ICDAR, pp.484-488, 2013.

[Wan04] Wang Z., Bovik A. C., Sheikh H. R., and Simoncelli E. P. Image quality assessment: From error visibility to structural similarity. IEEE Trans. on Image Process., 13(4):600-612, 2004.

[Wei99] Weickert J. Coherence-enhancing diffusion of colour images. Image Vision Comput., 17(3-4):201-212, 1999.

[Wei01] Weijer J., Vliet L. J., Verbeek P. W., and Ginkel M. Curvature estimation in oriented patterns using curvilinear models applied to gradient vector fields. IEEE Trans. PAMI, 23(9):1035-1042, 2001.