

Segmented character recognition using curvature-based global image feature

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Received: 28.06.2018

Accepted/Published Online: 24.05.2019

Final Version: 18.09.2019

Abstract: Character recognition in natural scene images is a fundamental prerequisite for many text-based image analysis tasks. Generally, local image features are employed widely to recognize characters segmented from natural scene images. In this paper, a curvature-based global image feature and description for segmented character recognition is proposed. This feature is entirely dependent on the curvature information of the image pixels. The proposed feature is employed for segmented character recognition using Chars74k dataset and ICDAR 2003 character recognition dataset. From the two datasets, 1068 and 540 images of characters, respectively, are randomly chosen and 573-dimensional feature vector is synthesized per image. Quadratic, linear and cubic support vector machines are trained to examine the performance of the proposed feature. The proposed global feature and two well-known local feature descriptors called scale invariant feature transform (SIFT) and histogram of oriented gradients (HOG) are compared in terms of classification accuracy, computation time, classifier prediction and training time. Experimental results indicate that the proposed feature yielded higher classification accuracy (%65.3) than SIFT (%53), performed better than HOG and SIFT in terms of classifier training time, and achieved better prediction speed than HOG and less computational time than SIFT.

Key words: Natural scene image, segmented character recognition, global image features, curvature, scale invariant feature transform, support vector machine

1. Introduction

The availability of high quality and portable imaging devices today simplifies visual representation of a particular environment through digital images and videos which in turn signify physical and material contents that form a specific scene. Texts can be considered as a piece of a given material content. Natural scene images contain very informative and valuable texts that need to be detected and recognized for various purposes including assisted vehicle auto-navigation [1], vision impairment [2], video indexing and retrieval, text translation, and spam filtering. The task of optical character recognition (OCR) for scanned documents can be considered as a mature technology. The efficiency of current OCR system is supplemented with relative uniform background, font color, and font size of electronically scanned documents. Traditional OCR engine cannot perform well on those unconstrained text images [3,4] when applied directly to natural scene images of various background, lighting, texture, and font. Research in OCR systems specifically designed to recognize scene texts has recently received a great interest [3]. Consequently, classical OCR systems have been substituted by more specialized

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and intelligent approaches over time, ensuring fast and accurate character recognition. These approaches focus on the selection of appropriate image features and description. Features are defined as properties of images that are potential sources of information about the image content. Identification of distinctive image features is among the most nontrivial issues in recognition process. There are two generic image features: the first category is global features that are descriptions of an image pixel in relation to the entire image pixels, or the whole image. The second category, local features, are image patterns which differ from their immediate neighborhood [5]. Among various global features, region and contour-based shape features are used to describe image content. Despite the robustness advantage of local features, global features are still useful in applications where a rough segmentation of the object of interest is available. Fourier and curvature-based descriptors are examples of the most frequently used contour-based shape descriptors. Current trends in segmented character and natural scene image text recognition focus on manipulating either local image features or region-based global, shape features. The literature review discerns that the power of contour-based shape features is overlooked and only a handful of related studies are found accordingly. In this paper, a global curvature-based shape feature is generated and applied for segmented character recognition to demonstrate the description power of contour-based global features. The efficiency of the proposed feature is compared and contrasted with the efficiency of scale invariant feature transform (SIFT) and histogram of oriented gradients (HOG) features. The extraction of the global feature relies mainly on the calculation of curvature information at the detected boundaries of the segmented character image. A comparison between a computed curvature and a fixed threshold determines the qualification of a given pixel as a keypoint. Exploiting the physical relationship between key and boundary points is used as the most significant input in describing the image features through histograms. Support vector machines of different kernels are employed to recognize a given character image. The remaining content of the paper is organized as follows. A literature review of related works is given in Section 2. In Section 3, detailed explanation of the feature extraction and description is presented. Results of experiments on the most widely used datasets, Chars74k introduced in [6] and ICDAR2003 robust reading competition datasets [7] are included in Section 4. Conclusion and future works are outlined in Section 5.

2. Segmented character recognition

The general method for recognizing text in an image is to extract features from the image and classify the characters by feeding them into a machine learning algorithm [8]. Segmented character recognition, a preliminary task in bottom-up natural scene image text recognition, has been studied recently based on hand-designed features as in [1–4,6,9–16] and learned features [17]. Other works such as [18] are based on templates. Both region-based local features and global image features were used in combination for a bottom-up recognition in [1]. The work by Kim et al. [2] proposed a graph matching method for character recognition with structural features. Saidane and Christophe [4] proposed a convolution neural networks-based character recognition system towards cluttered color scene with competing classification accuracy for clear and undistorted images. Random ferns-based character recognition system [5] is claimed to outperform the well-known commercial OCR system ABBYY FineReader. In the study by Campos et al. [6], segmented character recognition is posed as an object recognition task where they affirm a competitive result through the use of multiple kernel learning classifiers along with local and global image features. Other geometric features such as area, width, aspect ratio, and compactness were considered for character/noncharacter classification of a connected component obtained from binarization as described by Milyaev et al. [9]. Linear classifiers along with fisher vectors extracted from Gaussian Mixtures (GM) and spatial information is proposed by Shi et al. [11]. Exemplar-based multilayered

classification approach to the problem was presented by Sheshadri et al. [12]. Neumann and Jiri [13] presented a character recognition system based on maximally stable extremal regions (MSER), in which a support vector machine classifier with radial basis function kernel is employed. Yi et al. [14] proposed a global sampling-based HOG descriptor, GHOG, for character structure modelling which is argued to show better performance than local sampling-based feature representations. Sinha et al. [15] presented an approach that uses image pixels and HOG as features to train three different classifiers. Yang et al. [16] proposed an improved local binary pattern, where it is stated that the use of integral image to search for the best scale lead to find a robust edge descriptor. The work of Coates et al. [17] proclaimed that the use of features learned directly from data leads to a competent performance. A Markov random field-based template matching for natural scene character recognition was proposed by Liu et al. [18]. Gabor filters Local subspace classifier with appearance-based features scheme for recognition of characters in natural images [19] and mixture of HOG-based features for contextual spatial information extraction [20] are among the alternative methods presented. Recently, works such as that by Zhu et al. [21] reported a convolutional neural network-based scene character or text recognition to be more competitive. Extensive review of the literature on segmented character recognition reveals that methods relying entirely on global image feature detection and description are not employed for segmented character recognition in natural scene images. In this paper, a global image feature and its description is proposed based on the calculation of curvature information. Furthermore, a comparison of performance in terms of classification accuracy, classifier training time, and prediction time between the proposed feature, SIFT method, and HOG is presented.

3. Proposed method

In this paper, a global curvature-based feature extraction and description for segmented character recognition is proposed. It is assumed that the input image is already segmented from the rest of the image. The key subtasks that are carried out in the proposed method are image preprocessing, boundary detection, curvature calculation, keypoint identification, feature description, SVM training, and character recognition. The contour or boundary of the character image is used to find the curvature value of each point on the boundary of the image that is considered a curve. Traversing through the boundary points, concavity, and convexity of each boundary point is computed. Results of the calculation can be negative, positive, or zero to imply concave, convex, and straight-line points, respectively. Both concave and convex points are assumed to be keypoints provided that the absolute value of the calculated curvature for each candidate is greater than a predefined threshold. The keypoint identification stage is followed by a feature description where the physical locations of the keypoints, boundary points, and image center are manipulated along with angle measures and image gradient direction. The result of the description is a property of the given character image through which the SVM will learn to classify the character. A general outline of the system is included in Figure 1 followed by a brief description of every subtask.

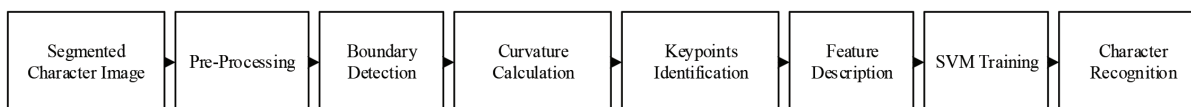


Figure 1. Overview of the proposed method.

3.1. Preprocessing and boundary detection

Segmented character images are put through some preprocessing operations including color to grayscale image conversion, resizing character images to fixed dimensions, and preparing images for boundary retrieval by grayscale to binary image conversion. Figure 2 demonstrates original, resized grayscale, and binary images as given in Figures 2a–2c, respectively.

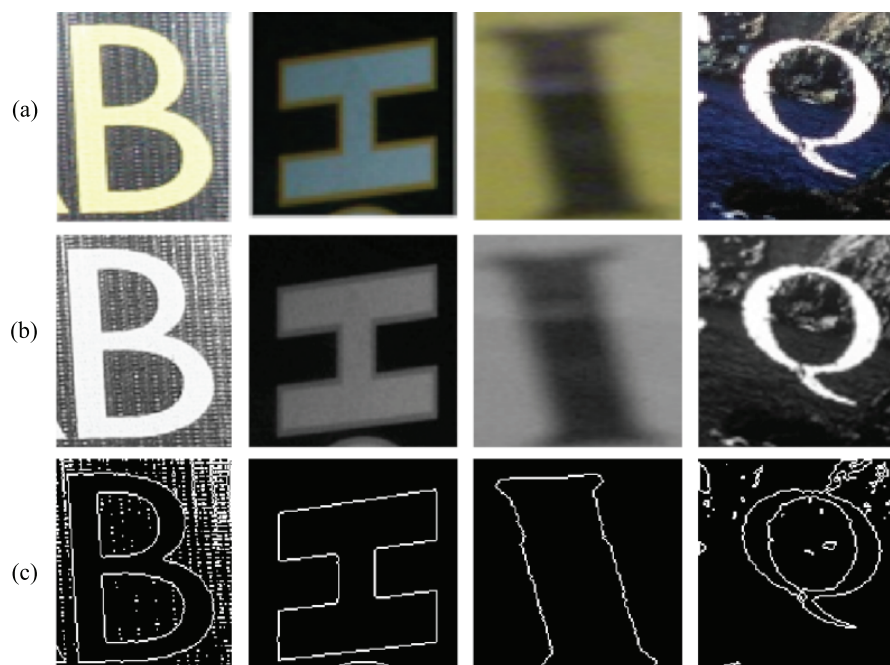


Figure 2. Sample character images: (a) original, (b) preprocessed, and (c) boundary images.

3.2. Curvature calculation

Curvature information is chosen over others such as color and texture mainly because of the following two reasons. Firstly, characters are distinct objects, which can best be described by their shapes. Secondly, curvature provides the most information about shape. The fact that curvature information is independent of local coordinate frames makes curvature to be a more suitable metric [22]. Computation of this metric after plane rotation and translation will always lead to the same value. Curvature can be calculated in various ways such as methods using finite differences, geometric relationships, and moving frames [23]. In this paper, a geometric technique is employed, as it is the only rotation invariant approach among all. The preferred method also does not require the spatial distance between points to be equal. Here, curvature is determined as the reciprocal of the radius of the osculating circle that matches to any three points. The radius is exactly four times the area of the triangle divided by the product of the distances between points. It is assumed that the image boundary is a continuous curve whose length is equal to the extension of the boundary along the X -axis. Three successive points are chosen along the boundary. Consequently, the curvature of the second point is the reciprocal of the radius of a circle passing through three arbitrary points. The calculation of the curvature is given by Eq. (1);

$$crv = \frac{1}{r} = 4 * \frac{(\Delta ABC)}{(a * b * c)}, \quad (1)$$

where $A(x_1, y_1)$, $B(x_2, y_2)$, and $C(x_3, y_3)$ are chosen points, r is the radius of osculating circle, ABC is the area of triangle formed by chosen points and $a = (x_2 - x_1, y_2 - y_1)$, $b = (x_3 - x_2, y_3 - y_2)$, and $c = (x_3 - x_1, y_3 - y_1)$ are the sides of triangle ABC .

That is, for each three subsequent boundary points considered at a time, we tried to compute the curvature value of the second point in each iteration until the whole boundary points are traversed. This value is equivalent to the inverse of the radius of any circle that passes through these three boundary points. Consider three points $A(x_1, y_1)$, $B(x_2, y_2)$, and $C(x_3, y_3)$. These three points, can define a triangle, which can be described by its sides, area, or perimeter. For our purpose, we need to find the area of this particular triangle and the product of the sides of the triangle. Later on, curvature is calculated as the ratio of the area of this triangle to the product of the length of the sides of the triangle multiplied by four.

Curvature is computed for all pixels that compose the boundary of the image. Selection of a particular pixel as a keypoint is based on the evaluation of the curvature as stated in Section 3.3.

3.3. Keypoint selection

Calculating the curvature value for each boundary pixel is followed by a selection procedure where a pixel's curvature is compared to a certain threshold value. In fact, different thresholds are applied to find the optimal keypoints. However, increasing the threshold causes loss of important features especially in cases where the input is low contrast image. On the other hand, decreasing the threshold enables most of the pixels with nonzero curvature value to be accepted as keypoints, which, in turn, leads to poor recognition. In this study, after a series of experiments on different character images, 0.3 is determined to be the most favorable curvature threshold.

3.4. Feature set construction and representation

The description of the keypoints and their interrelationship is used to form a global feature descriptor represented with a 573-dimensional vector, which is passed to the classification learner subsequently. The classifier utilizes this feature to predict the classes of new character images. The feature description phase is dependent mainly on physical Euclidean distance and angle measurement between corresponding point pairs such as keypoints, boundary points, and image centers. These are the major inputs utilized to form the first four set of features including maximum distance between keypoints (MD), distance of each keypoint from the image boundary (DKB), distance between boundary points (DB), and distance of each keypoint from the image center (DC). Both grayscale and binary image gradient direction (GGD and BGD) are used to extract the next three feature sets including image gradient direction on the boundary points derived from GGD and image gradient direction on the keypoints taken from GGD and BGD. The last two feature sets are obtained via computation of angles between key and boundary points with respect to x-axis. A brief explanation of the steps is given in this section.

3.4.1. Distance calculation

Four feature sets; MD (64-dimension), DKB (35-dimension), DB (35-dimension), and DC (32-dimension) are generated through histograms of the specified dimension. Sample keypoints (KP), boundary points (BP), image center, and the distance measure showing distance of keypoints from boundary points and distance of keypoints from the image center is depicted in Figures 3a–3d, respectively.

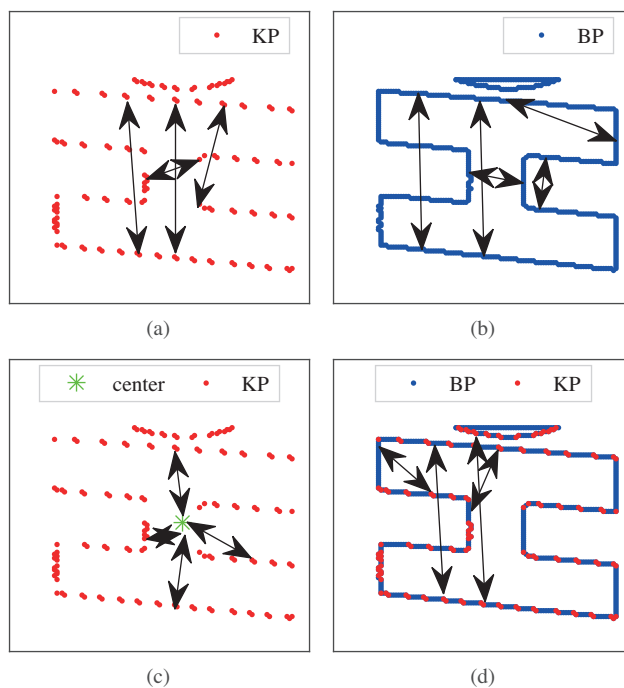


Figure 3. Distance calculations: (a) DB, (b) MD, (c) DKB, (d) DC.

3.4.2. Image gradient direction calculation

The image gradient direction shows the direction to which the image is changing most rapidly (see Figure 4). It is calculated for both key and boundary points resulting in a 192-dimensional vector. For any given point on the input image, gradient direction is computed using Eq. (2);

$$(x, y) = \tan^{-1} \frac{I(x, y + 1) - I(x, y - 1)}{I(x + 1, y) - I(x - 1, y)}, \quad (2)$$

where (x, y) is any point on binary or grayscale input image I.

3.4.3. Angle calculation

Another subfeature is obtained by computing the angle between any successive point pair with respect to x-axis. This value is calculated using Eq. (3);

$$\theta = \cos^{-1} \frac{(x_2 - x_1)}{d}, \quad (3)$$

where x_1 and x_2 represent the x -coordinate values of two successive key or boundary points and d is the Euclidean distance between these two points. From this angle calculation, a 64-bin histogram for each point type (key and boundary points) is created and a 128-dimensional feature vector is obtained. Merging all features derived from distance, gradient direction and angle calculation, a single 573-dimensional global feature vector is created as a final descriptor for any input character image.

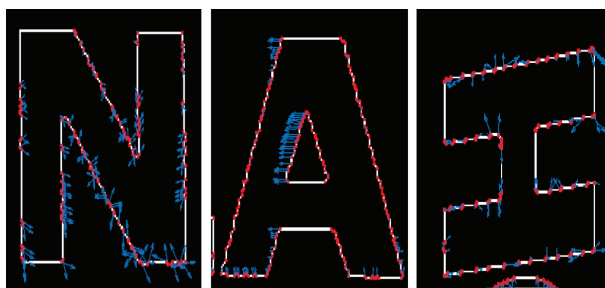


Figure 4. Sample gradient direction representation on binary image.

4. Experiments and results

Affine invariance is an essential prerequisite that ensures the robustness of a given vision algorithm [22]. SIFT is claimed to be scale and rotation invariant and partially invariant to change in illumination and 3D camera viewpoint [24]. Curvature information is also resilient to scale and rotation variations. In order to determine the effectiveness of the proposed feature in terms of these properties, we opt for the most widely known local feature, SIFT. State-of-the-art algorithms such as MSER are reported to show an excellent performance in terms of robustness and localization. However, the proposed method is a keypoint-based local feature, as SIFT, while MSER is a region-based local feature. Other feature sets such as HOG [25] proposed for pedestrian detection are stated to perform equally well for other shape-based objects. Unlike document characters, which usually are in unique appearance, scene characters are better recognized when they are described as objects. The performance of HOG features for scene character recognition is examined. The features perform well when it comes to classification accuracy, but with some limitations such as high training time, low prediction speed and larger feature dimension.

The major stages in the SIFT method performed to create these features are scale space extrema detection, keypoint localization, orientation assignment, and keypoint description. SIFT features transform the given pixel into scale invariant locations relative to detected local interest points. SIFT features are employed in segmented character recognition with the intention of comparing the performance of the proposed global feature developed through this study. Details about the experiments conducted are given in this section. The experiments are conducted using MATLAB R2016a on a PC with Intel i5 CPU, 8GB RAM. The first experiment was done on Chars74k dataset. From this dataset, 1068 images of capital letters in English alphabet are randomly chosen. Figure 5a demonstrates original character images (Q, B, I, H) along with the detected global features given in Figure 5b and SIFT plotted on the boundary and grayscale images shown in Figure 5c respectively.

As depicted in Figure 5b, features detected through curvature thresholding are more reliable and practical than the features detected through SIFT Figure 5c. More keypoints are detected on high contrast images. These keypoints are described as features, which afterwards are used in the classification. Support vector machines [26] have strong theoretical foundations and excellent empirical successes in diversified applications such as handwritten digit recognition, object recognition, and text classification [27]. In order to determine the effectiveness of the constituent features (GD, MD, DK,) obtained through this study, support vector machines of different kernels are trained. The result of classification obtained through LSVM, QSVM, and CSVM trained on each feature set is presented in Table 1.

A single 573-dimensional feature vector is obtained by combining basic feature vectors with various dimensions. Better classification accuracy is achieved after integrating individual features. The reported classification accuracy is basically obtained through 5-fold cross validation. Furthermore, classification results

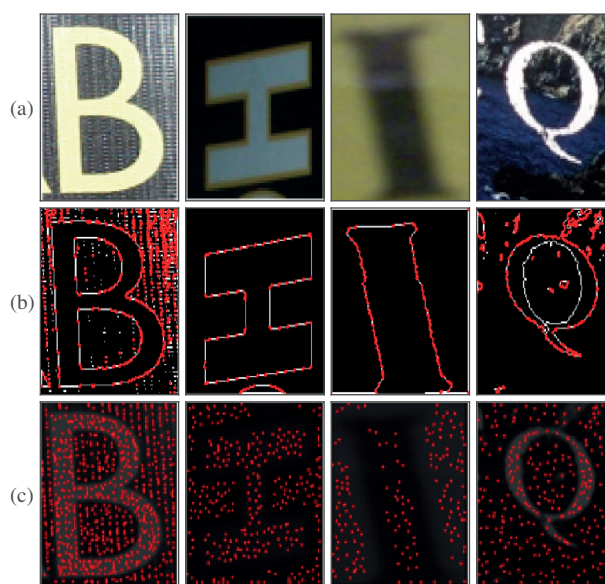


Figure 5. Sample character images: (a) original, (b) proposed method keypoints, (c) SIFT keypoints.

Table 1. Classification accuracy of SVMs before merging features.

Feature types	Classification accuracy		(%)
	LSVM	QSVM	CSVM
GD	32.7	51.2	48.1
MD	37.7	32.6	39.0
DK	27.9	32.5	31.9
ϕ	43.9	45.4	45.1

are compared with the performance obtained from SIFT and HOG features to assess the efficiency of the proposed feature. The results clearly show that curvature-based global features resulted in a higher classification accuracy than SIFT (Table 2).

Table 2. Classification accuracy of SVM on different features.

Feature types	Classification accuracy		(%)
	LSVM	QSVM	CSVM
Proposed feature	63.0	65.3	63.3
SFIT	52	53.7	44
HOG	81	82.3	85

In this work, in addition to the classical performance measure, a comparison between the proposed feature, SIFT, and HOG is done based on feature detection and description time, classifier training time, and classifier prediction speed as is shown in Table 3.

As is shown, the proposed feature is better than HOG and SIFT in terms of classifier training time and it led to better prediction speed than HOG and less computational time than SIFT.

Classifiers such as complex tree (CT), weighted KNN (WKNN), and linear discriminant analysis (LDA)

Table 3. Comparison of features based on computation time, training time, and prediction speeds.

Features	Dimension	Computation time/ Character image (s)	Training time (s)	Prediction speed
Proposed	573	1.68883	66.257	110
SIFT	128	4	68.499	210
HOG	3780	1.358	222.2	17

are also trained and their classification accuracies are compared with the best performing SVM in this study, which is QSVM as shown in Table 4.

Table 4. Classification accuracy of complex tree, KNN, and linear discriminant analysis.

Classification accuracy (%)				
Feature types	QSVM	CT	WKNN	LDA
Proposed	65.3	32.7	52.7	57.3

Other evaluation metrics such as precision, recall, and F-measure are also computed on the classification results obtained from QSVM and the results are reported in Table 5.

Table 5. Comparison of features based on precision, recall, and F-measure on the classification results from QSVM.

Features	Precision	Recall	F-measure
Proposed	0.574	0.471	0.5174
SIFT	0.44	0.46	0.4707

However, these parameters are more meaningful in binary classification problems such as text or nontext and character or not character.

The results included in Table 3 demonstrate that QSVM is highly effective with regard to other methods in segmented character recognition. Therefore, the reported results in Tables 3, 5, and 6 are obtained from QSVM.

The second dataset used for training and testing was ICDAR2003 robust reading competition dataset. This dataset has a small number of samples for some characters such as 'J', 'Q', and 'Z'. As a result, the classification accuracy on this dataset is lower than the results obtained from Chars74k.

Table 6. Comparison of features based on precision, recall, and F-measure on the classification results from QSVM.

Features	Accuracy (%)
Proposed	56.7
SIFT	49
HOG	0.75

5. Conclusions

Images can be described through various features including edges, corners, interest points and regions. In this paper, we intend to investigate the power of global features in scene character recognition. Consequently, keypoint-based image description is proposed. Among the properties of an image, curvature information is used to determine if a given image is qualified as a keypoint or not. This information is further transformed into global description. The resulting 573-dimensional feature vector is used with SVM to classify character images taken from the two most widely used benchmark datasets (ICDAR2003 robust reading competition dataset and CHAR74k). The following conclusions are drawn from the experiments.

- Global image features can be used to effectively recognize a character once it is segmented from the rest of the image. The rotation and scale invariance properties of the proposed features made recognition easy after the cropped image is put through some transformations.
- The dimension of image features has a direct relation with the power of description. Linear increase in feature dimension and diversity in describing the relationships among the key-points improved the classification accuracy linearly with the cost of computational resources. The proposed feature is composed of various properties, which in turn lead to an increase in description.
- Character recognition in natural scene text can yield a better result if the problem is dealt from an object recognition perspective differing from earlier proposals available in document recognition community. As a result, features, which can describe the shape of a given character, is preferable over other features.
- The number of sample images per character affects the classification accuracy of the learner. The classification accuracy of SVM on ICDAR2003 dataset was low when compared to Char74k dataset. This is caused by the lack of enough samples for some characters.

In general, the dimension of a given image feature does not convey significant information to determine the performance of a specific classifier.

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