SKCS - NEW KERNEL FAMILY WITH COMPACT SUPPORT

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ABSTRACT

Extraction of pertinent data from noisy document images with complex backgrounds remains a challenging problem in character recognition applications. It depends on the quality of the character segmentation. Over the last few decades, mathematical tools have been developed for this purpose. Several authors show that the Gaussian kernel is unique and offers many beneficial properties. In their recent work Remaki and Cheriet proposed a new kernel family with compact supports (KCS) that achieved good performance with accurate information extraction and reducing drastically time processing with regard to the gaussian kernel. In this paper, we focus in further improving its efficiency by proposing a new separable version which itself has a compact support. Experiments, on real life data, from noisy gray level images, show fast and high performance with accurate results of such a kernel. A practical comparison is established between results obtained by using the KCS and the SKCS operators. Our comparison is based on the information loss and the gain in time processing.

Key words— **Kernel with Compact Support, Separable Kernel, Multi-scale representation, Image segmentation, Handwritten data extraction.**

1 INTRODUCTION

In handwriting recognition, visual shapes are very important to improve systems performance. Handwritten data contains characters of different sizes and with variable distances; its corresponding image intensity changes occur over a wide range of scales. When such a gray scale image is processed there is a great information loss resulting in broken characters, touched characters with the presence of noise and unnecessary information. Several works have been presented in order to improve data quality and to extract visual shapes with good noise immunity [11][12]. The use of LoG convolution masks was first suggested by Marr and Hildreth [4]. Cheriet et al. have presented in [5][6] a generalization in using the Laplacian of Gaussian (LoG) operator for extracting full shape data segmentation. They proposed in [1] a new kernel family derived from the Gaussian, by deforming the plane into a unit ball. Hence, they obtained Kernel family with Compact Support (KCS). This KCS has been introduced in order to recover the information loss and reduce drastically the prohibitive time processing when Gaussian Kernel is used in scale-space representation [2][3]. They have shown that with the KCS there is no need to cut off the kernel while processing time is controlled because the mask is the support of the kernel itself. Furthermore, this kernel guarantees the most important proprieties required to perform image segmentation properly without contradicting the uniqueness of the Gaussian [7] [8] for such a purpose. In this paper, we propose a new Separable version of the KCS, denoted SKCS, in order to be able to apply the recursive algorithm used for the Gaussian [9], to the new version of KCS, and hence to increase the performance of the KCS and to further minimize the processing time.

2 SEPARABLE VERSION OF THE KCS

To design the new proposed method, we define an implementation based on the decomposition of the Laplacian of the new KCS shape, as the sum of two filters. In addition, since we are interested in segmenting visual data (full objects as perceived in the scene), we consider the second derivatives of such a kernel as decision criteria in scale-space [10]. The KCS construction, formulation, and analysis are presented with details in [1].

To derive the Laplacian of KCS operator (LoKCS), we recall first the 2D KCS formula:

$$KCS(x,y)=\begin{cases}\dfrac{1}{C_\gamma\sigma^2}e^{\gamma\left(\frac{\sigma^2}{x^2+y^2-\sigma^2}+1\right)} & \text{if } x^2+y^2<\sigma^2\\[2ex] 0 & \text{elsewhere}\end{cases} \qquad (1)$$

Where C_γ : is the normalization constant
σ : is the standard deviation KCS
γ : is the width parameter.

The above formula is not separable. However, the product of 1D KCS following x and y, leads to a new 2D operator, namely SKCS, as in the following:

$$SKCS(x,y)=KCS(x).KCS(y)$$

$$=\begin{cases} \lambda^2 e^{\left(\frac{\gamma\sigma^2}{x^2-\sigma^2}\right)} e^{\left(\frac{\gamma\sigma^2}{y^2-\sigma^2}\right)} & if\ x^2<\sigma^2\ and\ y^2<\sigma^2 \\ 0 & elsewhere \end{cases} \quad (2)$$

with $\lambda=\dfrac{e^{\gamma}}{C_{\gamma}\sigma}$ (3)

As we will discus it below, this kernel family has also a compact support as its analogous KCS, with nice features.

To derive the LoKCS, let ∇^2 be the 2D Laplacian operator,

$$\nabla^2=\frac{\partial^2}{\partial x^2}+\frac{\partial^2}{\partial y^2} \quad (4)$$

So, the Laplacian of KCS is :

$$LoKCS=\nabla^2 KCS(x,y)$$

$$=\begin{cases} \frac{4\gamma}{C\gamma}\left[A(x,y)\right] e^{\gamma\left(\frac{\sigma^2}{x^2+y^2-\sigma^2}+1\right)} & if\ \ x^2+y^2<\sigma^2 \\ 0 & elsewhere \end{cases} \quad (5)$$

with

$$A(x,y)=\frac{(x^2+y^2)^2+\gamma\sigma^2(x^2+y^2)-\sigma^4}{(x^2+y^2-\sigma^2)^4} \quad (6)$$

In the same way, we are interested by computing the Laplacian of the SKCS (LoSKCS), as in the following:

$$LoSKCS=\nabla^2 SKCS(x,y)$$

By re-writing the 2D SKCS formula:

$$SKCS(x,y)=\begin{cases} \lambda^2\cdot e^{h(x)}\cdot e^{h(y)} & if\ x^2<\sigma^2\ and\ y^2<\sigma^2 \\ 0 & elsewhere \end{cases} \quad (7)$$

with

$$h(s)=\frac{\lambda\cdot\sigma^2}{\left(s^2-\sigma^2\right)} \quad (8)$$

We then have:

$$LoSKCS=\nabla^2 SKCS(x,y)$$

$$=\begin{cases} K.[A(x)+A(y)]e^{[h(x)]}\cdot e^{[h(y)]} \\ if\ \ x^2<\sigma^2\ and\ y^2<\sigma^2 \\ 0\quad elsewhere \end{cases} \quad (9)$$

With

$$k=2\gamma.e^{\gamma} \quad (10)$$

$$A(s)=h'(s)^2-h''(s) \quad (11)$$

$$h'(s)=\frac{2\cdot\gamma\cdot\sigma^2\cdot s}{\left(s^2-\sigma^2\right)^2} \quad (12)$$

$$h''(s)=\frac{-2\gamma\sigma^2[(s^2-\sigma^2)(3s^2+\sigma^2)]}{\left(s^2-\sigma^2\right)^4} \quad (13)$$

Hence, the LoSKCS operator is written as a sum of two one-dimensional filters (one column vector and one row vector). Its equation can be rewritten as the sum of two filters as follows:

$$\nabla^2 SKCS(x,y)=H(x,y)+H(y,x) \quad (14)$$

where $H(x,y)=\mu.A(x).e^{[h(x)]}.e^{[h(y)]}$ (15)

with $\mu=\dfrac{e^{\gamma}}{\sigma^2}$ (16)

Figure 1 and figure 2 show the two dimensional profiles of the LoKCS and the LoSKCS.

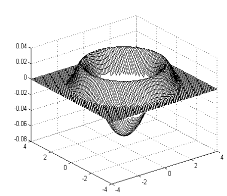


Figure 1. 2D profile of LoKCS

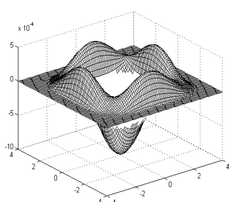


Figure 2. 2D profile of LoSKCS

We notice that the LoKCS operator has a compact support of a circular form while the LoSKCS have a compact support of a square form. Furthermore, the LoSKCS operator has a central excitatory region [9] larger than of the LoKCS (see figure 3) and the KCS has the smaller inhibitory region, and hence the SKCS has the large bandwidth.

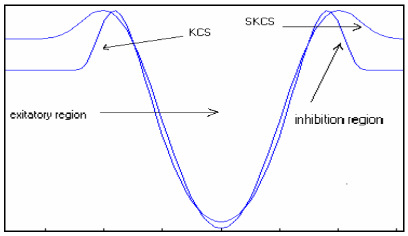


Fig.3: The KCS filter cross-section and the closest possible equivalent SKCS Filter cross-section.

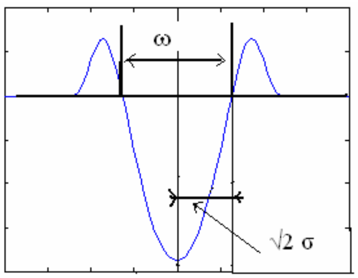


Figure 4: One dimensional profile of the mask and the associated parameters

The detection of shapes with accurate position depends on the width **ω** of the operator excitatory region (see figure 4). Since the SKCS has a larger **ω**, it would be the better in recovering the information loss.

3 EXPERIMENTAL RESULTS

For the practical aspect, in order to investigate the SKCS impacts on extracting handwritten data from degraded and noisy images, experiments were conducted on real data , from CEDAR, at SUNY Buffalo, data base, that contains Zip codes scanned in US Postal offices on live mail and images scanned in our local mail.

The filters implementation is performed using a PIV-700MHz computer, under Matlab software.

The performance of the proposed method is judged by visual inspection using criteria of image shape, such as thickness, intensity and connectivity of strokes of character shapes with a weight given to each.

To achieve this purpose, we have used the algorithm proposed in [6] and replaced the LoG operator by the LoKCS operator and the LoSKCS respectively.

For both kernels, KCS and SKCS, we have chosen the same width parameter and the same mask size contained in the interval]-σ,+σ[, then the mask size is equal to 2σ.

For the multi-scale representation, we have decreased the σ value from 4 to 2 with a step of 0.5. In terms of mask dimension from (8x8) to (4x4).

3.1 Image segmentation

We focus the discussion on two sets of images.

a- In the first set (see figure 5), we produce the original image and the results achieved by the KCS and the SKCS operators.

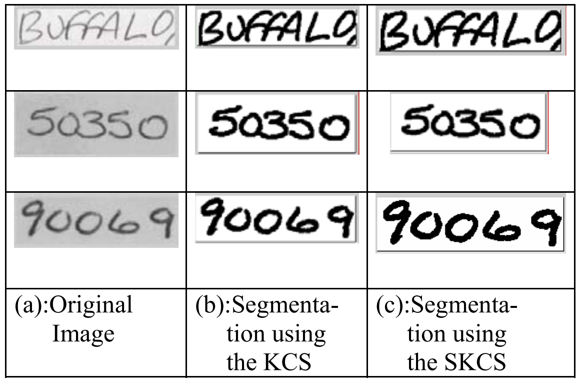


Figure 5: Segmentation of gray level images

In this case, we can confirm that both operators give good results with high visual quality.

b. In the second set (see figure 6); we use the same parameters as in (a), and we produce a degraded image for the two operators.

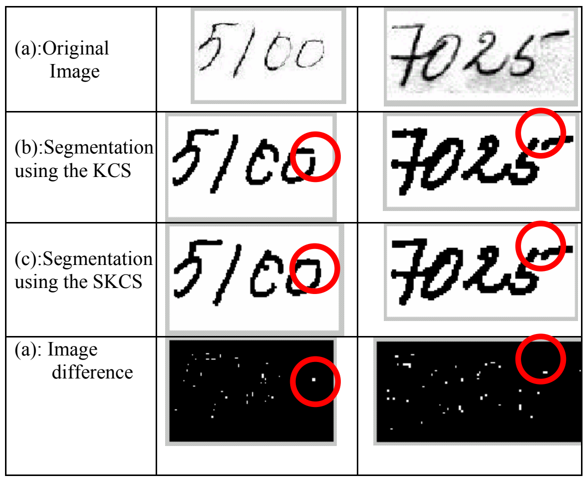
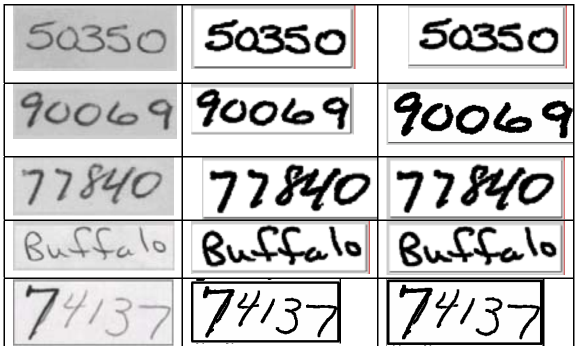


Figure 6: Segmentation of a degraded image

In figure 6, if we focus on the segmented images, we can appreciate the segmentation results given by the SKCS operator with regard to KCS operator especially for its capability in extracting more details of the target information and in the way the image is smoothed. We notice that certains degradations appear on the image segmented by the LoKCS and we appreciate the capability of the LoSKCS operator to recover it. This effective segmentation of the SKCS is due to the width of its excitatory region and to its larger bandwidth.

3.2 Processing time evaluation

In this set (see figure7); we use the same parameters as in (a), and we produce the different images for the two operators in order to evaluate the processing time of the KCS and the SKCS operators.



(a):Original Image	(b):Segmentation using the KCS	(c):Segmentation using the SKCS

Figure 7: Some sample images and the segmented images obtained by applying the KCS and the SKCS operators.

In figure 8, we summarize the results of the different images to illustrate the processing time using the KCS and the SKCS operators.

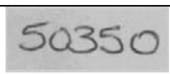
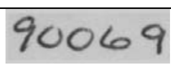
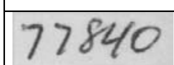
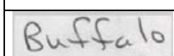
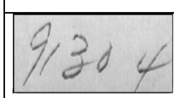
Original Image	Processing time for KCS	Processing time for SKCS
	**55.04**	**17.69**
	**54.88**	**17.56**
	**62.64**	**20.20**
	**50.65**	**16.32**
	**61.08**	**19.89**

Figure 8: KCS and SKCS processing time

We notice that the processing time required for the LoSKCS operator is distinctly less than that required for the LoKCS operator. Indeed for the separable version of the KCS each of the convolutions is realized as successive one dimensional row and column convolutions, the result is equivalent to two-dimensional convolution but is faster because it requires fewer computations. The total number of operations required at each pixel is reduced from M^2 to 2M, where the size of the filters is MxM pixels.

4 CONCLUSION

In this paper, we have presented a new Separable version of kernel with compact support. This new kernel is used to segment visual data in variable contrasted images, with the presence of noise. Our main purpose is to achieve significant improvements in the time required to perform convolutions without loss of information. The new kernel support remains compact and has shown interesting results in extracting visual shapes, in performing accurate information and considerable savings in processing time are achieved. Our tests are conducted on a set of approximately 200 gray-scale images from CEDAR data base and from our local zip code data base.

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