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Deblurring license plate images with kernel estimation

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Abstract : **A vehicles license plate tracking with sparse representation. A digital image processing method is based on sparse representation to identify the blurred images from the license plate for fast moving vehicles. The detection of fast moving vehicle is an important part in Intelligent Transportation System. A new method for detecting vehicles, which violate rules in real time traffic scenario. The length of the motion kernel with Radon transform in Fourier domain which handles large motion blur even when the license plate is unrecognizable by human. It is used to identify the vehicles which crosses the speed limit and also it is useful in hit and run accidents. Experiment results show that this method can improve the efficiency of the moving vehicles license plate detection without blur greatly.**

Index Terms— **ARMA, ML,PSF, Kernel parameter estimation, license plate deblurring, linear motion blur, sparse representation, Radon transform.**

I. INTRODUCTION

CCTV surveillance, robust trackers (Sparse Representation) these are widely used for searching vehicles reported stolen, pay parking violation and pay tax violation as well as involved in criminal [4-8]. Government officers are increasingly adopting ANPR technologies in CCTV surveillance, which function is to automatically capture an image of vehicle's image, identify (number) license plate location, recognize license plate number, compare the plate number (license) to the database of vehicles of interest, and then alert the officer when a vehicle of interest has been observed in an real-time processing. Commercial ANPR algorithms are very powerful in the area of vehicle access control of parking lot since the vehicle images are very clean which are captured in the environment of low speed and close distance by using trigger signal at the specific entrance points[1].The main Process done in three steps: Moving vehicle detection, Number plate detection and Blur Removal. Firstly, Capture the fast moving vehicle by using novel algorithm, which convert video into image frames. Then license plate extraction of vehicle by using several geometrical features. Finally removing the blur from the vehicle number plate by using blind image DE convolution.

However the vehicle image quality is sometimes poor which are captured by CCTV camera on the road due to blurring effects. When capturing vehicle images by CCTV camera, there are different causes of blur such as the blur due to the motion of camera and the out-of-focus. The degraded vehicle images by blurring effects decrease the accuracy of number plate recognition. In order to increase the recognition accuracy in CCTV surveillance, the deblurring process is selectively performed depend on whether the vehicle images are severely blurred or not. A simple algorithm of sharpness estimation and selective deblurring process for number plate recognition. After number plate location from a vehicle image, image enhancement with de-blurring process which is selectively performed depend on whether the value of sharpness estimation is lower than predefined threshold as shown in Fig. 1. It is known that all characters printed on a license plate are single font and of fixed size. Therefore, it is reasonable to propose a template-based license plate recognition approach to deal with a blurred license plate image. Since the purpose of this study is to provide possible license plate numbers of a suspected vehicle, we can manually crop the license plate region from a suspected vehicle. Since most of the detected vehicles are driven on a smooth road way and therefore we can make an assumption that the grabbed video frames are not seriously influenced by rotation or the perspective effect.

In the last decades, blind image deblurring/ deconvolution (BID) has gained lots of attention from the image processing community. Although some advances have been made, it is still very challenging to address many real-world cases. Mathematically, the model of image blurring can be formulated as:

$$B(x, y) = (k * I)(x, y) + G(x, y)$$

where B, I , and k denote the blurred image, the sharp image we intend to recover, and the blur kernel, respectively; and G is the additive noise

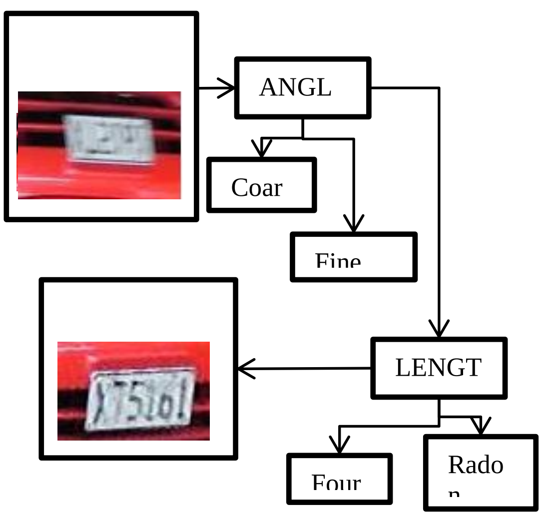

Fig. 1 Block diagram of a kernel estimation

(usually regarded as white Gaussian noise); and $*$ denotes convolution operator. For BID, the kernel k and sharp image I are both unknown. According to whether the kernel k is spatially-invariant or not, the BID problem can be divided into two categories: uniform BID and non-uniform BID. For uniform BID, the kernel k is often called point spread function.

Many cities and districts have developed traffic control systems to help monitor the movement and flow of vehicles around the road network. This had typically involved looking at historical data, estimates, observations and statistics, such as:

- Car park usage
- Pedestrian crossing usage
- Number of vehicles along a road
- Areas of low and high congestion
- Frequency, location and cause of road works

CCTV cameras can be used to help traffic control centres by giving them live data, allowing for traffic management decisions to be made in real-time. By using ANPR on this footage it is possible to monitor the travel of individual vehicles, automatically providing information about the speed and flow of various routes. These details can highlight problem areas as and when they occur and help the centre to make informed incident management decisions.

Some counties of the United Kingdom have worked with Siemens Traffic to develop traffic monitoring systems for their own control centres and for the public.[68] Projects such asHampshire County Council's ROMANSE provide an interactive and real-time website showing details about traffic in the city. The site shows information about car parks, ongoing road works, special events and footage taken from CCTV cameras. ANPR systems can be used to provide average point-to-point journey times along particular routes, which can be displayed on a variable-message sign(VMS) giving drivers the ability to plan their route. ROMANSE also allows travellers to see the current situation using a mobile device with an Internet connection (such as WAP, GPRS or 3G), allowing them to view mobile device CCTV images within the Hampshire road network.

The UK company Trafficmaster has used ANPR since 1998 to estimate average traffic speeds on non-motorway roads without the results being skewed by local fluctuations caused by traffic lights and similar. The company now operates a network of over 4000 ANPR cameras, but claims that only the four most central digits are identified, and no numberplate data is retained.

II. EXISTING METHOD

Existing method of Another interesting approach was offered by Richardson (1972 year) and Lucy independently (1974 year), so this approach is called as method Lucy-Richardson. Its distinctive feature consists in the fact that it is nonlinear, unlike the first three - potentially this can give a better result. The second feature - this method is iterative, so there arise difficulties with the criterion of iterations stop. The main idea consists in using the maximum likelihood method for which it is supposed that an image is subjected to Poisson distribution.

In multi-image based SR approaches used multiple lowresolution images is assumed same size images while in LPR case, there are different sizes of LR images because a license plate is usually captured when the vehicle is moving. Hence, images captured at different time instances may provide different perspectives because they were captured at different angles in the field of view. This makes the registration task even more difficult. Another drawback of previous LPR deblurring researches is that the three parts of license plate recognition are not considered, and the plate is cropped manually.

III. PROPOSED METHOD

1.Notation and Definitions

With the rapid development of highway and the wide use of vehicle, researchers start to pay more attention on the efficient and accurate intelligent transportation systems (ITS). It is widely used for detecting car's speed, security control in restricted areas, highway surveillance and electric toll collection [1]. Vehicle license plate (VLP) recognition is one of the most important requirements of an ITS. Although any ITS and specifically any VLP recognition contains two part in general, license plate detection and recognition, detecting and segmenting VLP correctly is most important because of existing conditions such as poor illumination, vehicle motion, view- point and distance changes. Zhang et al. [9] proposed learning based method using AdaBoost for VLP detection. They used both global (statistical) and local (Haar-like) features to detect the license plate.

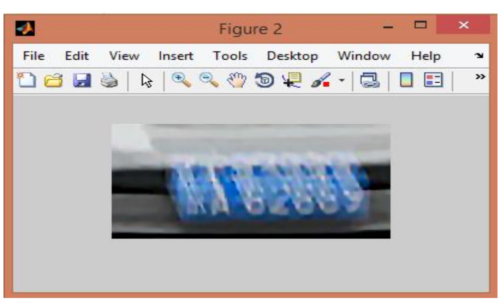

Figure 2. Deblurred image

A Fig. 1 shows an example of cropping a license plate region from a suspected vehicle image. The proposed approach consists of three main steps:

1) determine potential character positions and estimate the most probable character set based on single-character templates;

2) determine the position of any special symbol on a license plate; and

3) perform license plate recognition based on multiple-character templates.

The overall flow of the proposed license number plate recognition consists of number plate location, sharpness estimation, image enhancement with selective de-blurring, layout analysis, character segmentation and character recognition system.

The kernel density estimator (KDE) is a well-known nonparametric estimator of univariate or multivariate densities, and numerous articles have been written on its properties, applications, and extensions (Silverman, 1986; Scott, 1992). However, relatively little work has been done to understand or improve the KDE in situations where the training sample is contaminated. This paper addresses a method of nonparametric density estimation that generalizes the KDE, and exhibits robustness to contamination of the training sample.

1 Consider training data following a contamination model

$$X1,...,Xn \text{ iid}\sim (1-p)f0 + p\ f1,$$

where f0 is the "nominal" density to be estimated, f1 is the density of the contaminating distribution, and p < 1 2 is the proportion of contamination. Labels are not available, so that the problem is unsupervised. The objective is to estimate f0 while making no parametric assumptions about the nominal or contaminating distributions.

2. Data Formation

Let X1,...,Xn ∈ R d be a random sample from a distribution F with a density f . The kernel density estimate of f , also called the Parzen window estimate, is a nonparametric estimate given by fbKDE (x) = 1 n n ∑ i=1 kσ (x,Xi) where kσ is a kernel function with bandwidth σ. To ensure that fbKDE(x) is a density, we assume the kernel function satisfies kσ(·, ·) ≥ 0 and R kσ (x, ·) dx = 1. We will also assume that kσ(x,x ′) is translation invariant, in that kσ(x−z,x ′ −z) = kσ(x,x ′) for all x,x ′ , and z. In addition, we require that kσ be positive semi-definite, which means that the matrix (kσ(xi , xj))1≤i, j≤m is positive semi-definite for all positive integers m and all x1,..., xm ∈ R d . Wellknown examples of kernels satisfying all of the above properties are the Gaussian kernel kσ(x,x ′) = 1 √ 2πσd exp − kx−x ′k 2 2σ2 , (1)

Compared with the classical BID problems, license plate deblurring has its own distinctive characteristics. Fig. 1 shows one example of images on fast moving vehicle in a real scenario. In this scenario, instead of improving the visual quality, we are more interested in generating a recognizable result. The challenges for license plate deblurring lie in three aspects.

1) The surveillance camera is usually designed for captur- ing a big scene that includes a whole vehicle, therefore, the license plate only occupies a small region of the whole image. This leads to insufficient details for kernel estimation.
2) Due to the fast motion, the size of blur kernel is very large. The edge information is degraded severely and is unavailable from blurred images. Therefore, the methods based on large scale edges cannot work robustly and even may fail in some situations [14].
3) The content of licence plate image is very simple, most of edges lie in horizontal and vertical directions. Thus, the methods based on isotropy assumption [12] may also not work well for license plate image.

To target on this challenging BID problem: blind deblurring of fast moving license plate, which is severely blurred and even unrecognizable by human. Our goal is to recover a sharp license plate with confidence that the restored license plate image can be recognized by human effortlessly. Generally speaking, the blur kernel is dominated by the relative motion between the moving car and static surveillance camera, which can be modeled as a projection transform [15].

However, the kernel can be approximated by linear uniform motion blur kernel. The task of blur kernel estimation can be reduced to the estimation of two parameters in the linear motion kernel: angle (θ) and length (l). Given a function of θ and l. We observe that $A(\theta, l)$ shows very useful quasi-convex characteristic under a fixed l. By utilizing this interesting characteristic, we can infer the true angle of the blur kernel efficiently. Once the angle is determined, on the direction parallel to the motion, the power spectrum of blurred image is obviously affected by the linear kernel based on which the spectrum is a sinc-like function, and the distance between its two adjacent zero-crossings in frequency domain is determined by the length of kernel. In order to reduce the effect of noise and improve the robustness of length estimation, we utilize the Radon transform in frequency domain. After kernel estimation, we obtain the final deblurring result with a very simple NBID algorithm.

3.Kernel Estimation

The kernel smoothing function defines the shape of the curve used to generate the pdf. Similar to a histogram, the kernel distribution builds a function to represent the probability distribution using the sample data. But unlike a histogram, which places the values into discrete bins, a kernel distribution sums the component smoothing functions for each data value to produce a smooth, continuous probability curve. The following plots show a visual comparison of a histogram and a kernel distribution generated from the same sample data. Reliable and extremely fast kernel density estimator for one-dimensional data;

Gaussian kernel is assumed and the bandwidth is chosen data automatically fro the database;

Unlike many other implementations, this one is immune to problems caused by multimodal densities with widely separated modes (see example). The estimation does not deteriorate for multimodal densities, because we never assume a parametric model for the data (like those used in rules of thumb).

Alternatively, the kernel distribution builds the pdf by creating an individual probability density curve for each data value, then summing the smooth curves. This approach creates one smooth, continuous probability density function for the data set. The default bandwidth, which is theoretically optimal for estimating densities for the normal distribution, produces a reasonably smooth curve. Specifying a smaller bandwidth produces a very rough curve, but reveals that there might be two major peaks in the data. Specifying a larger bandwidth produces a curve nearly identical to the kernel function, and is so smooth that it obscures potentially important features of the data.

Robust kernel density estimators are nonparametric, making no parametric assumptions on the data generating distributions. However, their success is still contingent on certain conditions being satisfied. Obviously, the percentage of contaminating data must be less than 50%; our experiments examine contamination up to around 25%. In addition, the contaminating distribution must be outlying with respect to the nominal distribution. Furthermore, the anomalous component should not be too concentrated, otherwise it may look like a mode of the nominal component. Such assumptions seem necessary given the unsupervised nature of the problem, and are implicit in our interpretation of the representer theorem and influence functions.

a. Coarse to fine estimation

The recovery of motion information from visual input is an important task for both natural and artificial vision systems. The standard approach to representing motion information is via the image velocity field: that is, the projection of the motion of points in the three-dimensional world onto the image plane. As an approximation to this, computer vision techniques typically compute an estimate of the motion field from the spatial and temporal variations of image brightness. This field of approximate velocities is known as the "optical flow". One common source of difficulty in optical flow estimation systems is temporal aliasing. Motion picture and video imagery is typically sampled below the Nyquist rate in time. Filter-based (including differential) algorithms will typically give erroneous results in these situations. For optical flow algorithms based on matching, the errors appear as "false matches"

4.Length Estimation

Obtain the periodogram of an input signal consisting of a discrete-time sinusoid with an angular frequency of $\pi/4$ rad/sample with additive $N(0,1)$ white noise.Create a sine wave with an angular frequency of $\pi/4$ rad/sample with additive $N(0,1)$ white noise. The signal is 320 samples in length. Obtain the periodogram using the default rectangular window and DFT length. The DFT length is the next power of two greater than the signal length, or 512 points. Because the signal is real-valued and has even length, the periodogram is one-sided and there are 512/2+1 points.

a. Radon Transform

The Radon transform is the integral Ttransform which takes a function f defined on the plane to a function Rf defined on the (two-dimensional) space of lines in the plane, whose value at a particular line is equal to the line integral of the function over that line. The transform was introduced in 1917 by Johann Radon,[1] It was later generalised to higher-dimensional Euclidean spaces, and more broadly in the context of integral geometry. The complex analog of the Radon transform is known as the Penrose transform.

The Radon transform is widely applicable to tomography, the creation of an image from the projection data associated with cross-sectional scans of an object.

b. Fourier transform

The Fourier transform decomposes a function of time (a signal) into the frequencies that make it up, in a way similar to how a musical chord can be expressed as the amplitude (or loudness) of its constituent notes. The Fourier transform of a function of time itself is a complex-valued function of frequency, whose absolute value represents the amount of that frequency present in the original function, and whose complex argument is the phase offset of the basic sinusoid in that frequency. The Fourier transform is called the frequency domain representation of the original signal. The term Fourier transform refers to both the frequency domain representation and the mathematical operation that associates the frequency domain representation to a function of time.

5. Blurring process model

Now let's pass on to more formal and scientific description of these blurring and restoration processes. We will form the blurring process model that can be represented in the following:

$$g(x, y) = h(x, y) * f(x, y) + n(x, y) \qquad (1)$$

The task of restoration of a blurred image consists in finding the best approximation f'(x, y) to the source image. Let's consider each component in a more detailed way. As for functions f(x, y) and g(x, y), everything is quite clear with them. But as for h(x, y) I need to say a couple of words - what is it? In the due to movement. Or we can say otherwise, that each pixel of a blurred image is "assembled" from pixels of some nearby area of a source image. All those overlap each other, which fact results in a blurred image returns into a spot in case of defocusing and into a line segment (or some path) in case of a usual

Figure 2.1. Block diagram of deblurred images

blurring The principle, according to which one pixel becomes spread, is called the blurring function. Other synonyms - PSF (Point spread function), kernel and other.

The size of this function is lower than the size of the image itself - for example, when we were considering the first "demonstrational" example the size of the function was 2, because each result pixel consisted of two pixels.

6. Deconvolution

There are approaches, which take into account the presence of noise in an image - one of the most popular and the first ones, is Wiener filter. Figure 3 shows that deconvolution images for deblurred image. The deblurred image is taken from the deatabase that is shown on the figure 2 It considers the image and the noise as random processes and finds such a value of f' for a distortion-free image f, that the mean square deviation of these values was minimal. The minimum of such deviation is achieved at the function in the Frequency domain:

$$\hat{F}(u,v) = \left(\frac{1}{H(u,v)}\frac{|H(u,v)|^2}{|H(u,v)|^2+S_\eta(u,v)/S_f(u,v)}\right)G(u,v) \qquad (6)$$

Figure 4. Deconvolution image

Figure 2.1 shoes that block diagram of the deblurred images.The next method is "Constrained Least Squares Filtering", other names: "Tikhonov filtration", "Tikhonov regularization". His idea consists in formation of a task in the form of a matrix with subsequent solution of the respective optimization task. This equation result can be written down as follows:

$$\hat{F}(u,v) = \left(\frac{H^*(u,v)}{|H(u,v)|^2+y|P(u,v)|^2}\right)G(u,v) \qquad (7)$$

The last considered method, or to be exact, Calculation formulas are quite simple, without the use of Fourier transform - everything is done in the spatial domain: Here the symbol "*", as before,

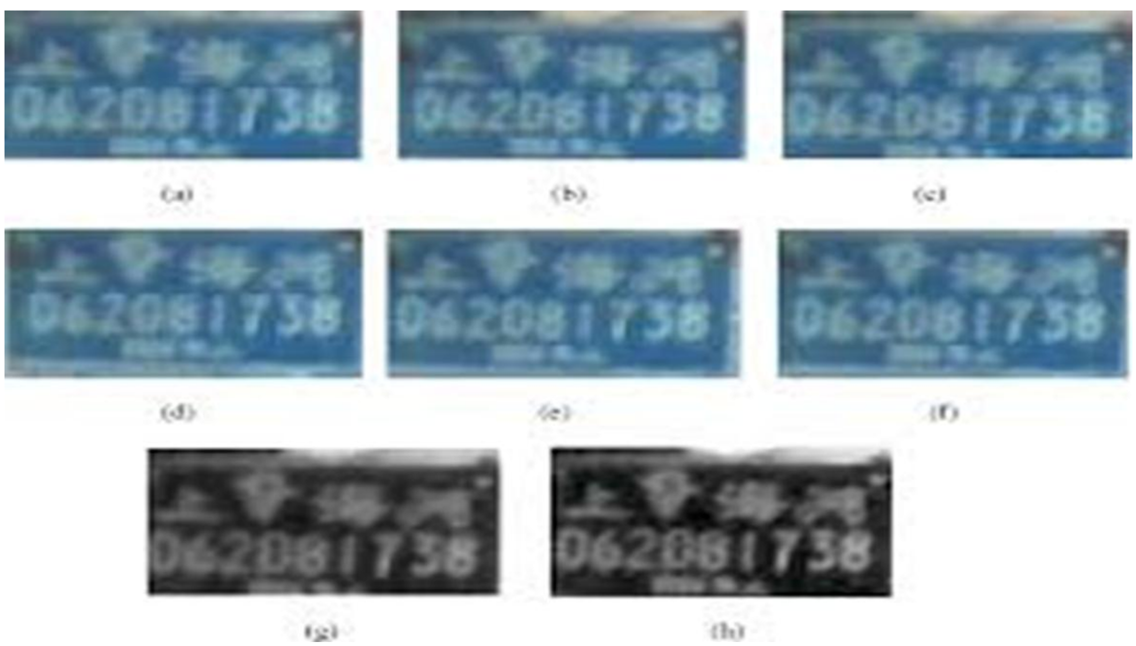

Figure 3. Reconstruction of the given images

is a de-facto standard.

`An example can be Astra Image, these are examples of deconvolution. Computational complexity of the method is quite high - processing of an average photograph, depending on the number of iterations, can take many hours and even days.

$$\hat{f}_{k+1}(x,y) = \hat{f}_k(x,y)\left[h(-x,-y) * \frac{g(x,y)}{h(x,y) * \hat{f}_k(x,y)}\right] \quad (8)$$

the whole family of methods, which are no being actively developed - is blind deconvolution. In all previous methods it was supposed that the blurring function PSF is known for sure, but in practice it is not true, usually we know just the approximate PSF by the type of visible distortions. Blind deconvolution is the very attempt to take this into account. The principle is quite simple, without going deep into details - there is selected the first approximation of PSF, then deconvolution is performed using one of the methods, following which the degree of quality is identified according to some criterion, based on this degree the PSF function is tuned and iteration repeats until the required result is achieved.

IV. EXPERIMENTAL RESULTS

A. Analysis

ANPR uses optical character recognition (OCR) on images taken by cameras. When Dutch vehicle registration plates one of the changes made was to the font, introducing small gaps in some letters (such as P and R) to make them more distinct and therefore more legible to such systems. Some license plate arrangements use variations in font sizes and positioning—ANPR systems must be able to cope with such differences in order to be truly effective. More complicated systems can cope with international variants, though many programs are

individually tailored to each country The cameras used can be existing road-rule

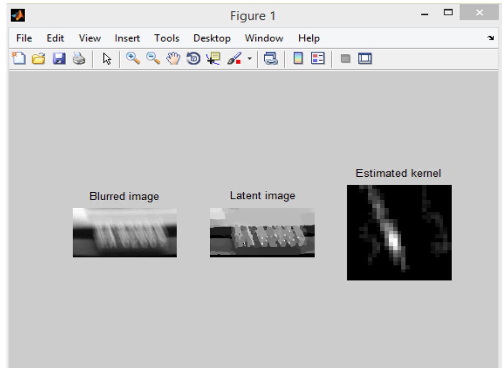

Figure 5. Output for kernel estimation

enforcement or closed-circuit television cameras, as well as mobile units, which are usually attached to vehicles. Some systems use infrared cameras to take a clearer image of the plates.[6][7] Another framework of superresolution image reconstruction is solely based on interpolation where the (only) lowresolution frame is modeled as a down-sampled version of the high-resolution frame, instead of a down-sampled version of the local average of the high-resolution frame.

This framework is also known as intraframe reconstruction. Thus, superresolution reconstruction is simply an up-conversion process. In our notation, This framework corresponds to the case where the averaging matrix C is dropped, or more precisely,
y[3] = Median[80 6 3] = Median[3 6 80] = 6
y[4] = Median[6 3 3] = Median[3

reset to the identity matrix I . Because of the absence of the local averaging processes, the low-resolution frame encodes no information about the missing high-resolution pixels. high-resolution pixels must resort to a form of interpolation, i.e., inpainting. Our model.Thus, any attempt to reconstruct the missing automatically does the inpainting by means of TV minimization.

B. Simulation results

Above fig 2 shows that deblurred images. It is deblurred from the given input images. Figure 4 shows that the simulation result for the blurred images. Figure 2.1 shoes that block diagram of the deblurred images.

C.Algorithm

The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it is filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise . The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries.

The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple todefine: it is just the middle value after all the entries in the window are sorted numerically.

To demonstrate, using a window size of three with one entry immediately preceding and following each entry, a median filter will be applied to the following simple 1D signal:

x = [2 80 6 3]

So, the median filtered output signal y will be:
y[1] = Median[2 2 80] = 2
y[2] = Median[2 80 6] = Median[2 6 80] = 6
3 6] = 3
i.e. y = [2 6 6 3].

Note that, in the example above, because there is no entry preceding the first value is to obtain enough entries to fill the window. This is one way of handling missing window entries at the boundaries of the signal, but there are other schemes that have ifferent properties that might be preferred in particular circumstances:

- Avoid processing the boundaries, with or without cropping the signal or image boundary afterwards,
- Fetching entries from other places in the signal. With images for example, entries from the far horizontal or vertical boundary might be selected,
- Shrinking the window near the boundaries, so that every window is full.

E. Image Reconstruction

Image super resolution refers to a process that increases spatial resolution by fusing information from a sequence of images (with partial overlap in successive elements or frames in, for example, video), acquired in one or more of several possible ways. Figure 7 . Shows that the reconstruction of the deblurred uimages.For brevity,

Figure 6. Super resolution of the blurred images.

in this context, either the term superresolution or high-resolution is used to refer to any algorithm which produces an increase in resolution from multiple low-resolution degraded images. At least two nonidentical images are required to construct a higher resolution version. The low-resolution frames may be displaced with respect to a reference frame (e.g., LANDSAT images, where there is a considerable distance between camera A minimum mean squared error approach for multiple image restoration, followed by interpolation of the restored images into a single high-resolution image has been presented in [51]. Ur and Gross [58] used the Papoulis and the Brown generalized sampling theorem to obtain an improved resolution image from a set of spatially shifted observations.

Figure 7. Image reconstruction of the blurred images.

These shifts are assumed to be known. Bose et al. adapted a recursive total least squares (TLS) algorithm to tackle high resolution reconstruction from low-resolution noisy sequences with displacement error during image registration [5].

V. CONCLUSION

This algorithm is used to show how the evaluation scheme works to identify, accept, Associations of super resolution techniques to the current license plate recognition systems have been reported. Experimental results demonstrate the effectiveness of the Kernel based clustering as a feature selection method for license plate images.

The future scope depends on the restoration of deblurred images. An interesting quasi-convex property of sparse representation coefficients with kernel parameter (angle) is uncovered and exploited. This property leads to design a coarse-to-fine algorithm to estimate the angle efficiently. The length estimation is completed by exploring the well-used power-spectrum character of natural image. One advantage of our algorithm is that our model can handle very large blur kernel. Another advantage is that the scheme is more robust. This benefits from the compactness of our model as well as the fact that our method does not make strong assumption about the content of image such as edge or isotropic property.

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