Automatic Blur Detection in Mobile Captured Document Images

Towards quality check in mobile based document imaging applications

Ganesh Nunnagoppula, K Sai Deepak, Harikrishna G. N. Rai, P. Radha Krishna
Infosys Labs
Infosys Limited
India

Noranart Vesdapunt
Computer Engineering Department
Chulalongkorn University
Thailand

***Abstract*— Optical Character Recognition is widely used for automated processing of document images. While character recognition technology is mature, its application to mobile captured document image is still at its nascent stage. Capturing images from a mobile camera poses several challenges like motion blur, defocus and geometrical distortions which are usually not encountered in scanned or calibrated camera captured images. Therefore determining the quality of images automatically prior to recognition is an important problem. Quality check is especially useful in financial transaction instruments like bill payment where accuracy of text recognition for sensitive fields such as "amount due" should be high. Poor quality images can be rejected prior to OCR to avoid incorrect text recognition and save processing time. This paper discusses some techniques in literature for blur detection in mobile camera captured document images. We propose a simple yet elegant method that addresses some challenges faced in these document images. Extensive testing is performed on large dataset containing more than 4000 mobile captured images and optimum parameter values for performing quality check against motion blur and defocus are identified. Our experimental results demonstrate the effectiveness of the proposed method. In addition we realized a smart mobile application for blur detection and report its performance on several mobile devices.**

Keywords—blur detection; document image processing; mobile camera; eigen decomposition; fourier analysis

I. INTRODUCTION

Due to advances in technology and digital revolution, electronic devices are becoming cheaper and smaller in size with increased processing power. This triggered tremendous increase in digital consumers who are using smart devices such as smart phones, tablets, PDAs etc. Image based mobile payment apps such as claim processing, bill payment, check deposit, document enhancement and processing, extensively require mobile camera for capturing the snaps.

Image based mobile payment system is the key focus area in our research where customers use their smart phone cameras to take the snaps of payment slips such as credit card bills, utility bills, invoices etc.(see fig 1). Subsequently these images are processed using intelligent image recognition system capable of extracting the essential fields such as payee name,

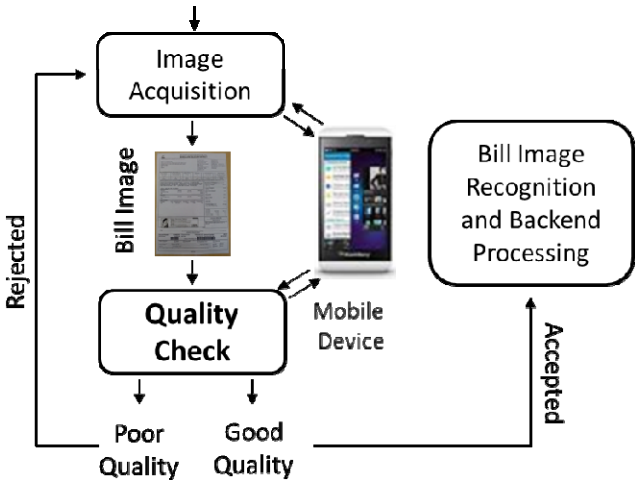


Fig. 1. Workflow for image based mobile payment system.

account number, amount in captured bill snap using document image recognition techniques. Once key fields are extracted form captured document image, mobile apps will initiate backend payment processing using available mobile online banking solution for successful payment. For successful recognition of sensitive bill fields it is essential to provide good quality images to the recognition module.

As images are captured using mobile cameras, there are several imaging challenges such as defocus, motion blur, geometrical distortions, illumination, shadow and rotation. (see fig 2). Several interesting applications for image acquisition and analysis have been proposed using handheld devices [1-4]. In typical imaging systems, images are usually captured in controlled environment such as flatbed scanner and camera with a tripod where the scope of distortion due to defocus and camera motion is limited. Therefore, scope of earlier work has mostly been on noise removal and correction of geometric transformation [5]. As mobile camera is used to capture document images, blur is often introduced due to defocus and camera motion. In this work we focus on detecting blur from mobile captured document images and provide an efficient solution for real time blur detection. This makes entire image based mobile payment solution more efficient as images can be

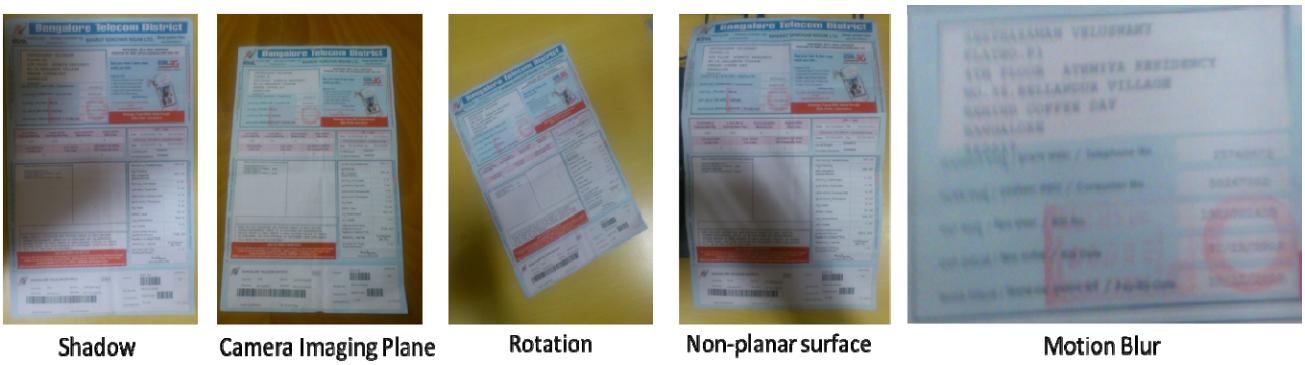


Fig. 2. Various artifacts observed in mobile captured document images.

rejected immediately after customer captures a poor quality image. This efficiency is significant when image recognition and backend processing is performed on a remote server.

Contribution of this work is as follows:

1. Automatic blur detection in mobile camera captured document images is investigated
2. Two popular techniques for blur detection are identified and extended for mobile document images
3. Exhaustive evaluation is performed on synthetically generated document images as well as a collection of utility bill images captured with mobile camera
4. A mobile application is developed for blur detection in document images and results are reported

Rest of the paper is as follows. Section II discusses various blur detection methods in literature and identifies the challenges in using them for mobile captured document images. Section III presents the proposed method used for blur detection followed by rigorous evaluation. In section IV, we realized the proposed system as a mobile application on an open mobile platform. We conclude the paper in section V.

II. Related Work

Methods for blur detection and classification were traditionally developed for scene images [6] with some applications to camera captured document images [6-8]. Required sensitivity of blur detection in scene images for automated processing is not as significant as in the case of document images, where each text field has to be processed through a recognition system accurately. We first review relevant blur detection techniques applied on camera-captured document images and list down various challenges. This is followed by a short review of prominent blur detection techniques developed for scene images.

A. Blur Detection in Document Images

Authors in [9] discussed various challenges in capturing document images from mobile camera and developed a technique, Brick Wall Coding (BWC) for document recognition. Blurry regions in the image due to camera defocus and motion blur can be potentially detected using BWC. While this work is relevant, there is no experimental result to validate the effectiveness of BWC. Images are captured using a stable mobile stand where the scope of motion blur is limited, as complex hand motion is not involved. In addition, only low-resolution images acquired from mobile cameras are considered in this work. [10] performed blur detection from document images using wavelets for estimating the degree of edge strength in the image. Higher the strength of edges lower is the blur degree. A limiting factor in this approach is that it assumes a document to have similar font size, type and contrast with respect to the background. Failing these conditions, estimated blur degree in the same document image will be different in various image regions having similar sharpness. [6] and [11] made use of variance of intensities in the local image region to quantify blur. Eigen values are computed for a local image region where a significantly large first Eigen value is observed in comparison to the remaining Eigen values for blurred image regions. Blur degree is measured as the ratio of the sum of first few significant Eigen values with the sum of all values. Quantitative validation is not performed on document images in [6, 11] and also the method was reported to perform poorly when a large amount of text is present in a region [12]. A significant drawback we have observed in [6, 11] is their inability to distinguish background region from blurred image regions. [12] performed blur detection from historical document images using intensity and edge based technique. It also reviewed few earlier blur detection techniques and identified their drawbacks for camera-captured document images. Primary focus of [12] is on simple documents with white background and black text and does not report results on images acquired under various imaging conditions. Most of the methods discussing blur detection from camera captured document images have not performed rigorous evaluation on representative datasets.

B. Blur Detection from Scene Images

Blur estimation has been widely studied for scene images [13]. Simple localized blur estimation methods based on discrete cosine transform, gradient magnitude, edge thickness, edge strength and response of Gaussian basis filters has been studied [7, 13]. Blind de-convolution of the image to estimate blur and latent sharp images has also been proposed but found to be a severely ill posed problem [13]. [14] performed blur detection to enhance visual tracking. It assumed uniform motion blur and therefore is not appropriate for camera-captured document images.

Local blur detection and classification using Local Power Spectrum (LPS) is performed in [7]. LPS slope acts as an indicator of blur and enables separation of blurred regions from

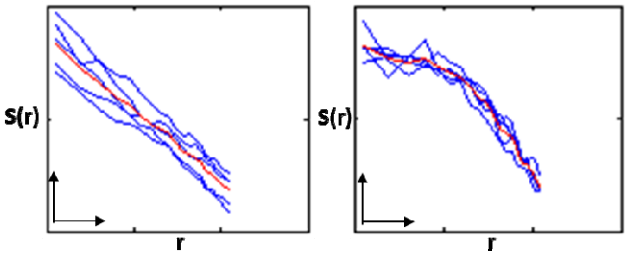


Fig. 3. Plots of normalized S(r) for scene images (left) and mobile camera captured document images (right). Red represents the arithmetic mean of S(r) for all images.

sharp image regions. [6] proposed to use singular value decomposition and apply the estimated Eigen values to detect and estimate localized blur. Some examples on document images are also portrayed in [6] and [11] using this method but there is no quantitative evaluation performed on camera-captured document images. The methods, [6, 7] have been evaluated rigorously on a large scene image datasets and demonstrated to be powerful. We extend these methods for blur detection in camera-captured document images. Similar to earlier techniques in blur detection literature, the two methods cannot separate the blurred image regions from background in document images. Separation of blurred image regions from background is addressed in this work. In addition, we perform extensive experimental evaluation on two large document image datasets for validation. This effort will enable in bridging the research gap for implementing real time quality

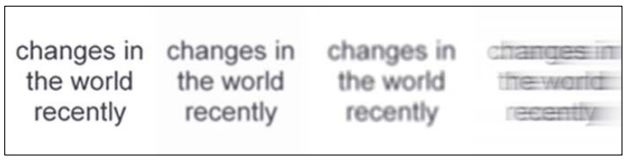


Fig. 4. Images from dataset1 with increasing blur (from left to right)

check in mobile document imaging applications.

III. METHOD

The presence of background in document images is significant in comparison to scene images. Background in document images is mostly observed as bright background against dark text. Existing blur detection techniques end up detecting uniform background regions as blurred. We present, extend and experimentally validate two blur detection techniques on camera captured document images. The first method discussed uses Fourier analysis while the second applies Eigen analysis of images.

A. Local Power Spectrum for Blur Detection

In spatial domain, image blur due to motion or defocus causes smearing of intensities within a local region, resulting in a smoothing effect that is often represented using directional or center-surround filters. Because of smoothing, spatial frequencies within the local region is also affected. For a blurred region, low frequency components tend to have larger amplitude whereas high frequency components have lower amplitude in comparison to a sharp image region, with similar document content. We derive power spectrum in a local region to exploit the elucidated spectral property of blurred and sharp regions.

Discrete Fourier decomposition of image regions are performed and local power spectrum (LPS) is derived. Trend of LPS with increasing spatial frequencies are observed. LPS of a sharp image region tends to have a steeper slope compared to a blurred region [7]. For an image region I and its discrete fourier transform $I(p,q)$, its power spectrum is computed as follows:

$$S(p,q) = \frac{1}{N^2}\left|I(p,q)\right|^2$$

Size of the image region is $N \times N$. p and q are the frequencies in the two orthogonal directions and can represented in polar coordinates (r,θ) as $u = r\cos(\theta)$ and $v = r\sin(\theta)$. A vector representation $S(r)$ is constructed by summing S over all values of θ as follows:

$$S(r) = \sum_{\theta} S(r,\theta)$$

We can observe the average trend of normalized $S(r)$ in fig 3 for a collection of 5 scene images from Corel image dataset [15] and 5 camera captured documents images. The dataset consists of both sharp and blurred regions. While there is a linearly decaying trend of $S(r)$ for scene images, it varies randomly with r for document images. The arithmetic mean plot for documents exhibits a non-linear trend. [7] employs line fitting on $S(r)$ and uses the slope parameter in the linear equation to estimate blur. Eventually a threshold on the slope is applied for classifying the region as sharp or blurred. Since line is not an appropriate representation of $S(r)$ for document images, we fit polynomials with higher degree. It is empirically determined that a quadratic polynomial provides a fast and reasonable fit. The quadratic equation is represented as follows:

$$S(r) \cong \alpha \cdot r^2 + \beta \cdot r + \gamma = 0$$

Threshold on coefficients α and β are determined and applied for detecting sharp and blurred image regions in document images.

B. Singular Value Decomposition for Blur Detection

Eigen analysis generates a lossless orthogonal representation of the data based on the geometric properties of its distribution. For a given image, its first eigen image tends to have maximum information (variance) and also the highest eigenvalue. Therefore, the first few eigen images are usually enough to approximate the original image. The 2nd, 3rd eigenvalues and so on have a decreasing trend. This observation is used for blur detection.

The smoothing effect due to blur leads to loss of information in the document images. Therefore, fewer eigen

Fig. 5. Real Bill images, cropped text region, different patch sizes

images are sufficient to represent a blurred region in comparison to a sharp region, with similar content. [6] generates blur estimate of an image by using the ratio of the sum of first few eigenvalues with the sum of all eigenvalues (n), for each local region. For the first k eigenvalues this ratio tends to be higher for blurred region. The blur estimate for an image region is represented as:

$$B_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i}$$

A threshold on B_k is empirically determined for detecting sharp and blurred regions. One limitation of this approach is its inability to differentiate between severely blurred region and background due to significantly large first eigenvalue than others. Therefore, foreground detection is performed to identify potential regions of interest before generating blur map. Blur map is generated only for the detected foreground. Given a document image, it is first converted to gray scale for further processing. Background pixels constitute most of a document image and typically have significant contrast with respect to foreground containing text. K-means clustering with 2 clusters is performed on the feature vectors derived over a neighborhood for each pixel location in the gray scale image.

Fig. 6. Test cases for square patch size 27 with different degrees of blur

The two clusters of pixels represent foreground and background respectively. Following features are derived at each pixel location for clustering: gradient magnitude, median and intensity. In order to eliminate any bias in the clusters due to non-uniform illumination and shadow in the grayscale image, a large median filter is used to estimate illumination bias and it is subtracted from the image before feature extraction and clustering.

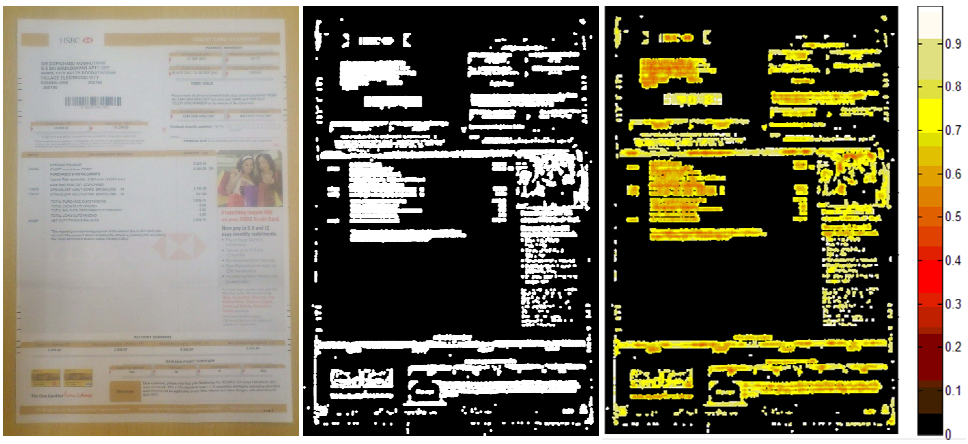
C. *Experiments and Results*

Experiments are performed on two datasets, one comprising of synthetically generated images and the second containing images of utility bills.

Dataset-1: 126 sharp images of size 80 x 80 containing text of font size 12 and font type *Arial* are synthetically generated. Different types of blur, namely average blur, Gaussian blur and motion blur are induced resulting in 2394 images of different blur types (see Fig 4).

Dataset-2: 8 different kinds of utility bills were collected and captured using a mobile camera at 2 megapixels. 90 sharp regions were cropped from these images containing sensitive text. Each of these images were manually verified as sharp by 3 different subjects. Three kinds of blur of various degrees were induced on these images as earlier resulting in 1800 regions. Blur detection was performed using square image patches of sizes 17, 22, 27, 32, 37 and 42 on these regions. Sample bill patches are shown in Fig. 5 and Fig. 6.

We first evaluate blur detection using LPS on dataset-1. Various thresholds are applied on α and β and the best detection performance for blur and sharp image patches are reported. The best classification rate for blur and sharp patches across all patch sizes is 61 *percent* when only parameter α is used. Performance improves to 66 *percent* when parameter β is also used. We also experimented by applying threshold on linear combination of α and β. This leads to poor detection



(a) (b) (c)

Fig. 7. (a) Original bill image (b) Detected foreground (c) Blur map illustrated as heat map.

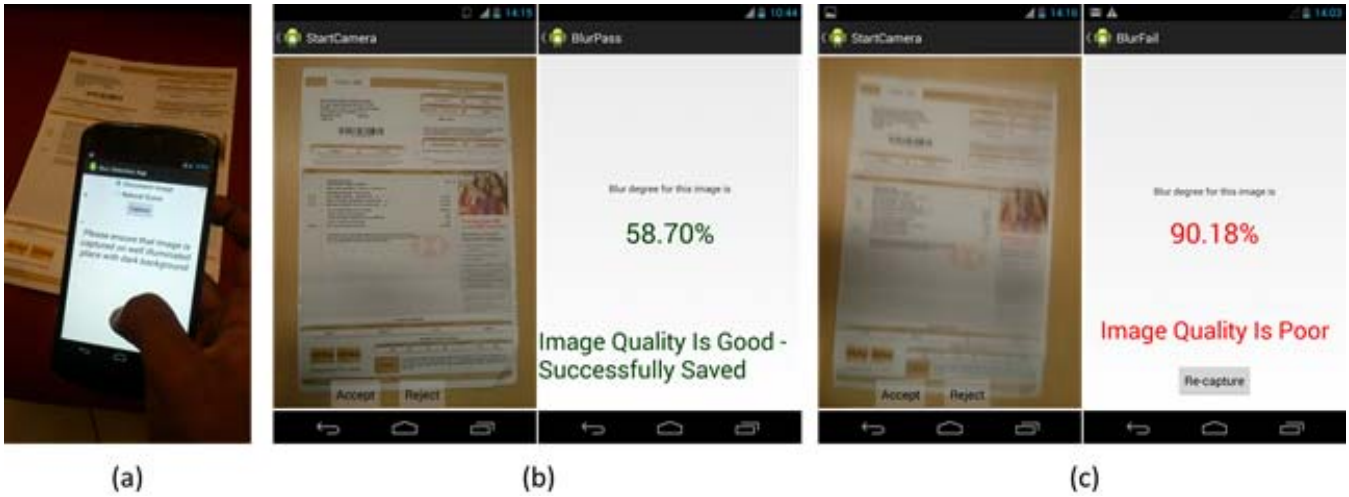


Fig 8. Application screens developed for blur detection (a) Android App and bill (b) Sharp image of a bill (left) and normalized blur degree in percentage (right) (c) Blurred image (left) and normalized blur degree in percentage (right)

performance. We can observe that performance figures are not promising for blur detection in document images using LPS. While linear approximation of $S(r)$ performs well for natural images [7], its non-linear approximation for document image in this work, is not consistent across patches containing different text content. Therefore arriving at a common threshold value on the parameters α and β, which is applicable across different text content is challenging. Evaluation of LPS is not performed on dataset-2 due its poor results on dataset-1, which is generated under controlled conditions.

Second evaluation of blur detection was performed using Eigen analysis on both datasets 1 & 2. On dataset-1 we observe best classification accuracy of 98.8 percent with patch size 27 and $k=1$. Detection performance is lower for other patch sizes in dataset-1.

TABLE I. AVERAGE DETECTION ACCURACY FOR DATASET-2

No. of Eigen Values	Patch Size					
	17	*22*	*27*	*32*	*37*	*42*
1	0.86	0.88	**0.9**	0.87	0.86	0.89
2	0.87	0.87	0.87	0.86	0.86	0.89
3	0.88	0.88	0.88	0.87	0.87	0.89
4	0.91	0.91	0.89	0.88	0.88	0.89
5	0.95	0.94	0.91	0.9	0.88	0.9

Experiments using Eigen analysis are repeated on dataset-2 containing utility bills. Blur degrees using different patch sizes and value of k are calculated and a threshold is identified for maximizing detection accuracy. The best value is determined as $k=1$ with best classification accuracy of 90 percent for blur and sharp images. An important point to note here is the tradeoff between selection of k and the threshold to be applied on B_k. We observe that larger the value of k, the threshold on B_k has to be much higher for better performance. This may lead to over fitting of the blur detection solution. Therefore a lower value of k is suggested for stable results across datasets (see Table II). An example of blur map on a utility bill is shown in Fig. 7. Severe blur is represented in lighter shade of colors whereas sharp text regions are relatively dark. Document background is represented in black color. We can observe that Eigen analysis based method performs well for blur detection on camera captured document images. Fig 9 illustrates blur map for several bill images. Such localized blur maps for text regions can enable the system to selectively accept or reject the document based on quality of sensitive regions in the document.

TABLE II. THRESHOLD USED ON B_k AND PATCH SIZE FOR MAXIMUM DETECTION ACCURACY

No. of Eigen Values	Patch Size					
	17	*22*	*27*	*32*	*37*	*42*
1	0.63	0.64	**0.64**	0.63	0.61	0.6
2	0.78	0.77	0.75	0.74	0.71	0.69
3	0.87	0.86	0.83	0.82	0.78	0.76
4	0.92	0.91	0.89	0.87	0.83	0.81
5	0.95	0.94	0.93	0.91	0.87	0.85

IV. MOBILE APPLICATION

An Android application is developed for testing proposed blur detection method on mobile devices. Java OpenCV library [16] is used for implementing the text detection and blur detection modules for document images. The implementation is optimized for image processing on mobile devices and the application is tested on several devices using the blur detection parameters identified empirically for eigen based approach.

A. Specification

Android version 2.2x (Froyo) and higher was used for development. This was done as there are very few Android phones in the market which use lower versions. There are three screens in the application (see Fig. 8). Screen 1 provides an option to capture a picture of the document. Screen 2 is used to either accept or reject the picture manually. Accepted image is

processed and its quality is displayed in Screen 3. The application is deployed on several Android devices and their average computational performance for different image resolution is shown in table III. Optimum patch size varies according to the image resolution selected. Reported duration is not for an optimized implementation but for an application prototype.

TABLE III. SPECIFICATIONS OF MOBILE DEVICE AND BLUR DETECTION APPLICATION

Device	Processor	Duration (in sec)		
		2MP	3MP	5MP
Nexus 4	1.4 GHz Snapdragon S4 Pro	4	7	11
Fujitsu	1.4 GHz Snapdragon S2	6	10	22
Galaxy S Duos	1 GHz Cortex A5	14	22	39

V. CONCLUSION

Blur detection for camera captured document images is of interest for several mobile applications. Significant effort has been invested on detecting blur from scene and scanned document images in the past. We address the gap in application of blur detection on mobile captured document images. We investigated several techniques as well as extended and evaluated two of them on large representative image datasets. We conclude that the eigen analysis based method performs best for blur detection in a dataset containing utility bill images. In addition, an Android application is developed for real time validation. We plan to investigate Independent Component Analysis for blur detection as eigen analysis assumes normal distribution of data which may not always be satisfied in case of document images.

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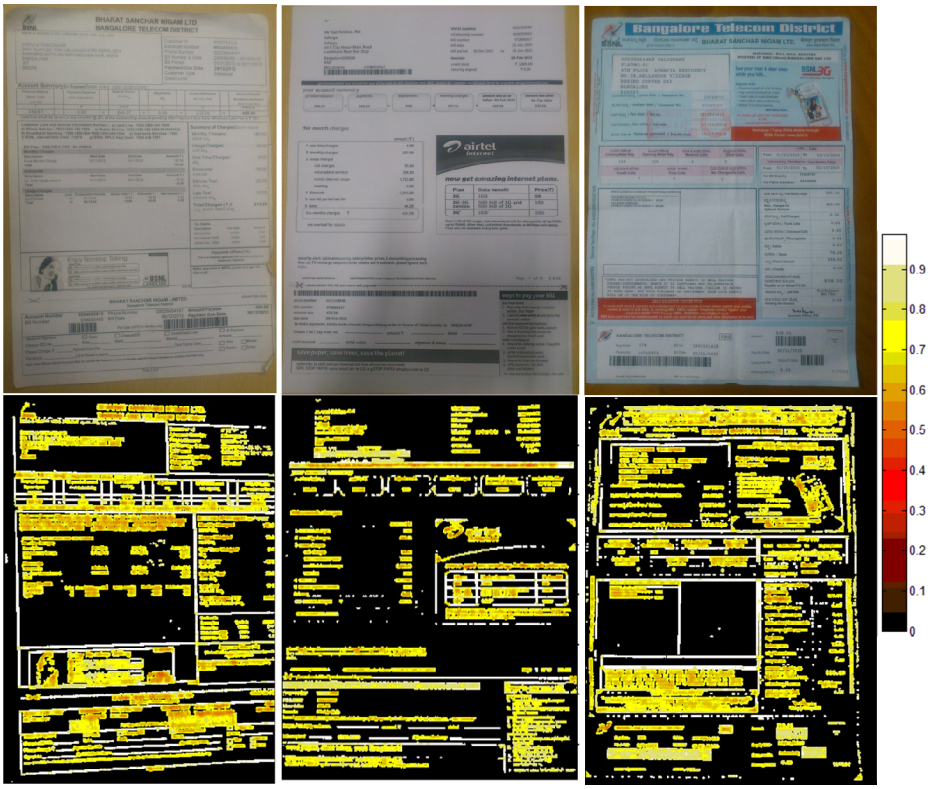

Fig 9. Several bill images (first row) and their corresponding blur map illustrated as a heat map (second row)