ADVANCEMENT OF BLUR DETECTION AND SUBJECT EXTRACTION USING BACKGROUND SEQUENTIAL LEARNING AND ACTION PREDICTION TECHNOLOGY

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Abstract

Super-resolution technologies enable fine magnification of surveillance camera images for purposes such as face and license plate recognition. Conventional technology requires numerous extracted still images to improve the resolution of subjects in video content and enable clear subject magnification. When magnified by more than 2 or 3 times (4 to 9 times the number of pixels), however, these images become blurred. Therefore, there has been significant demand for technologies that could further improve resolution and enable greater image clarity at higher magnification. NEC's new technology creates a super-resolution image from a single extracted image (of a person's face, license plate, etc.) by utilizing a database (library) of categorized images. These images maintain fine details even when magnified by more than 4 times (more than 16 times the number of pixels), making it possible to distinguish small and distant subjects much more easily than with conventional technologies. NEC's new technologies can be efficiently teamed with surveillance cameras to cover such large areas as airports and traffic intersections.

Keywords: - Super resolution technologies, fine magnification, face and license plate recognition, traffic intersections.

1. INTRODUCTION
1.1 Key features of these technologies

Blurring is a form of bandwidth reduction of the image due to imperfect image formation process. It can be caused by relative motion between camera and original images. Normally, an image can be degraded using low-pass filters and its noise. This low-pass filter is used to blur the image using certain functions. In digital image there are 3 common types of Blur effects: - 1) Average Blur, 2) Gaussian Blur, 3) Motion Blur. Out of these, motion blurring is one of the prime causes of poor image quality in digital imaging ([1] - [4]). When an image is captured by a digital camera, the image represents not just the scene at a single instant of time, but the scene over a period of time. If objects in a scene are moving fast or the camera is moving over the period of exposure time, the objects or the whole scene will look blurry along the direction of relative motion between the object/scene and the camera. Camera shake is one main cause of motion blurring ([5] and [6]), particularly when taking images using telephoto lens or using long shutter speed under low lighting condition. Previously, many researchers have been working on removing blurring from motion-blurred images. (e.g. [7] and [8]) The motion blur caused by camera shiver usually is modeled by a spatial invariant blurring process: $f = g * h + n$; Where $*$ is the convolution operator, g is the clear image to recover, f is the observed blurred image, h is the blur kernel (or point spread function) and n is the noise. How to recover the original image g from the

observed image f is the so-called image Deconvolution problem. In the past, there have been extensive research literatures on the nonblind Deconvolution algorithm (e.g. [9] - [18]). Based on the availability of, there are two categories of image Deconvolution problems. First is nonblind, in which the blurring operator i.e. kernel p is given. And blind, in which the blurring operator kernel p is unknown. In general, blind Deconvolution is a very challenging ill-conditioned and ill-posed inverse problem because it is not only sensitive to image noise but also under constrained with infinitely many solutions [19]. There are two broad classes of image restoration concept as Blind Image Deconvolution and Image Deconvolution. Blind Image Deconvolution is a more difficult image recovered where image recovery is performed with no prior knowledge of the degrading PSF. Image Deconvolution is a linear image restoration problem where the specifications of the original image are estimated using the observed or degraded image and a known PSF (Point Spread Function) ([21] & [22]). Point Spread Function (PSF) is the degree to which an optical system blurs (spreads) a point of light. The PSF is the inverse Fourier transform of Optical Transfer Function (OTF).in the frequency domain ,the OTF describes the response of a linear, position-invariant system to an impulse.OTF is the Fourier transfer of the point (PSF). The Blind Deconvolution Algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The algorithm restores the image and the point-spread function (PSF) simultaneously

1. Creates images with fine details when highly magnified these technologies utilize images of subjects from a large library of images stored at various resolutions to create super-resolution images. The best images, at the most appropriate resolution, are automatically selected for use.

2. Creates customized image libraries these technologies can efficiently extract small optimized image libraries from huge libraries of images for specific purposes. Redundant images are eliminated to make the library as small and efficient as possible without compromising image quality.

NEC aims to expand the use of these technologies into a broad range of fields, including the enhancement of satellite and medical images, while actively promoting the development of technologies that contribute to the safety and security of daily life.

1.2 A new algorithm could transfer acclaimed photographers' signature styles to cell phone photos

Celebrated portrait photographers like Richard Avedon, Diane Arbus, and Martin Schoeller made their reputations with distinctive visual styles that sometimes required the careful control of lighting possible only in the studio.

Now MIT researchers, and their colleagues at Adobe Systems and the University of Virginia, have developed an algorithm that could allow you to transfer those distinctive styles to your own cell phone photos. They'll present their findings in August at Siggraph, the premier graphics conference.

1.3 Style Transfer

"Style transfer" is a thriving area of graphics research — and, with Instagram, the basis of at least one billion-dollar company. But standard style-transfer techniques tend not to work well with close-ups of faces, says YiChang Shih, an MIT graduate student in electrical engineering and computer science and lead author on the Siggraph paper.

"Most previous methods are global: From this example, you figure out some global parameters, like exposure, color shift, global contrast," Shih says. "We started with those filters but just found that they didn't work well with human faces. Our eyes are so sensitive to human faces. We're just intolerant to any minor errors."

So Shih and his coauthors — his joint thesis advisors, MIT professors of computer science and engineering Frédo Durand and William Freeman; Sylvain Paris, a former postdoc in Durand's lab who's now with Adobe; and Connelly Barnes of the University of Virginia — instead perform what Shih describes as a "local transfer."

1.4 Acting locally

Using off-the-shelf face recognition software, they first identify a portrait, in the desired style, that has characteristics similar to those of the photo to be modified. "We then find a dense correspondence — like eyes to eyes, beard to beard, skin to skin — and do this local transfer," Shih explains. One consequence of local transfer, Shih says, is that the researchers' technique works

much better with video than its predecessors, which used global parameters. Suppose, for instance, that a character on-screen is wearing glasses, and when she turns her head, light reflects briefly off the lenses.

That flash of light can significantly alter the global statistics of the image, and a global modification could overcompensate in the opposite direction. But with the researchers' new algorithm, the character's eyes are modified separately, so there's less variation in the rest of the image from frame to frame. Even local transfer, however, still failed to make modified photos look fully natural, Shih says. So the researchers added another feature to their algorithm, which they call "multiscale matching." "Human faces consist of textures of different scales," Shih says. "You want the small scale — which corresponds to face pores and hairs — to be similar, but you also want the large scale to be similar — like nose, mouth, lighting."Of course, modifying a photo at one scale can undo modifications at another. So for each new image, the algorithm generates a representation called a Laplacian pyramid, which allows it to identify characteristics distinctive of different scales that tend to vary independently of each other. It then concentrates its modifications on those.

1.5 Future uses

The researchers found that copying stylistic features of the eyes in a sample portrait — characteristic patterns of light reflection, for instance — to those in the target image could result in apparent distortions of eye color, which some subjects found unappealing. So the prototype of their system offers the user the option of turning that feature off. Shih says that the technique works best when the source and target images are well matched — and when they're not, the results can be bizarre, like the superimposition of wrinkles on a child's face. But in experiments involving 94 photos culled from the Flickr photo-sharing site, their algorithm yielded consistently good results. "We're looking at creating a consumer application utilizing the technology," says Robert Bailey, now a senior innovator at Adobe's Disruptive Innovation Group, who was previously director of design at Picasa and, after Picasa's acquisition by Google, led the design of Picasa Web Albums. "One of the things we're exploring is remixing of content. " Bailey agrees that the researchers' technique is an advance on conventional image filtration. "You can't get stylizations that are this strong with those kinds of filters," he says. "You can increase the contrast, you can make it look grungy, but you're not going to fundamentally be able to change the lighting effect on the face." By contrast, the new technique "can be quite dramatic," Bailey says. "You can take a photo that has relatively flat lighting and bring out portrait-style pro lighting on it and remap the highlights as well."

2. Mobile User Guided Adaptation System

To guarantee personalized media consumption with best possible perceptual experience in user-centric multimedia applications, both mobile device access environments and mobile user perceptual experiences are properly taken into consideration in this proposed scheme. The mobile environments include mobile device capabilities and mobile user interfaces, while mobile user perceptual experiences are highly affected by the semantics of media, user individual preference, and presentation of the adaptation results. Therefore, our target is to present the best possible adaptation results by preserving the quality of semantically important and user desired content under the limitation of mobile display capacities and interaction interfaces.
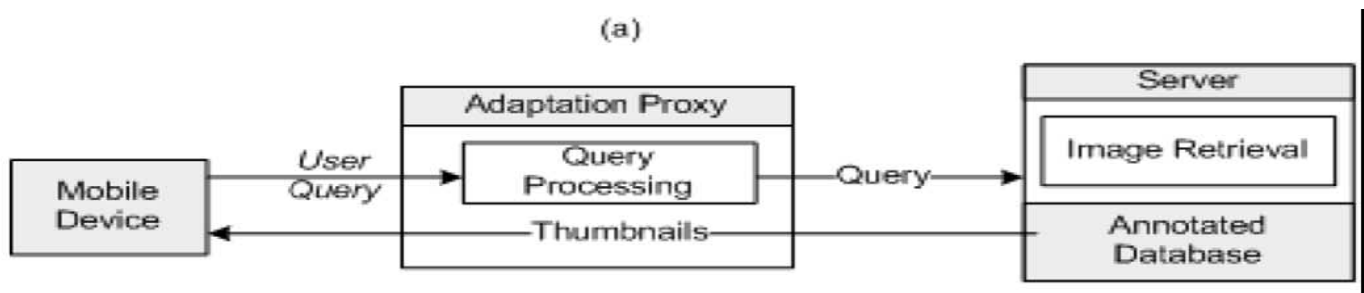

Figure 1: Query Processing

2.1 System Components

As shown in Fig. 1(a), the proposed system consists of 1) an adaptation proxy to process user request and feedback as well as to carry out semantic extraction, user preference learning, and adaptation; and 2) a server/database hosting original consumer photo content. We assume the annotation of the server side media content is processed offline while the user request and feedback processing is carried out in real time. .
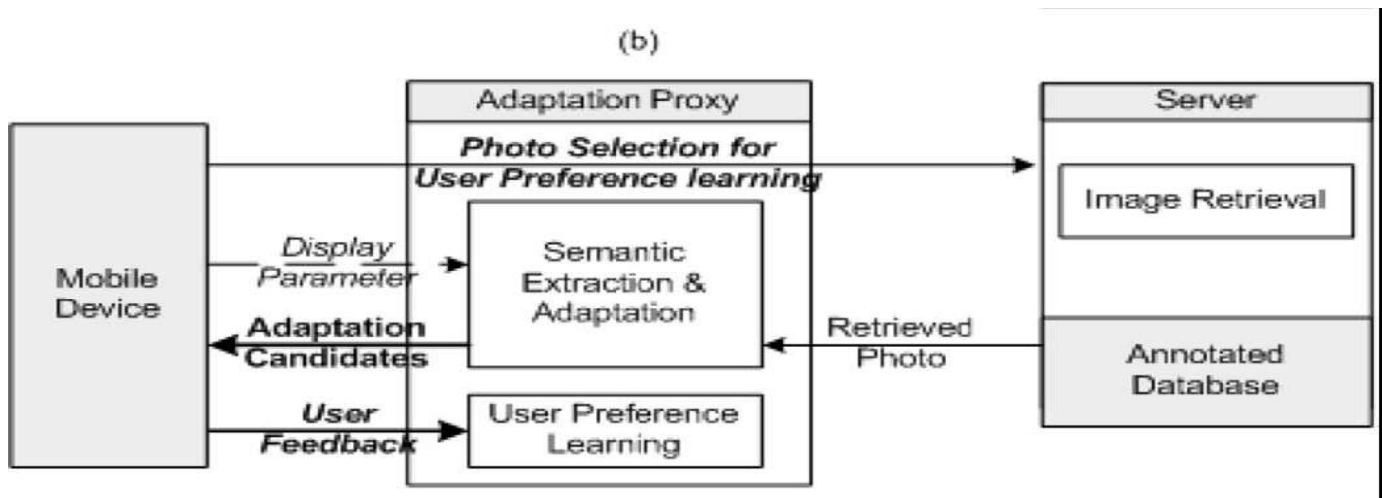

Figure 2: Semantic Extraction and Adaptation Process

2.2 System Workflow

The proposed system works in the following manner. As shown in Fig. 1(b), a user first inputs the semantic request in the form of the keywords for the desired media content through the user interface at the mobile device. These semantic keywords represent the key semantic concept for the desired media content for retrieval and can be used to match the associated annotations representing the semantics of the media content in the database. Such a semantic request is then sent to the query processing module of the adaptation proxy. As most people would like to input the activities or events as the keywords, we assume the system takes queries in the form of events.
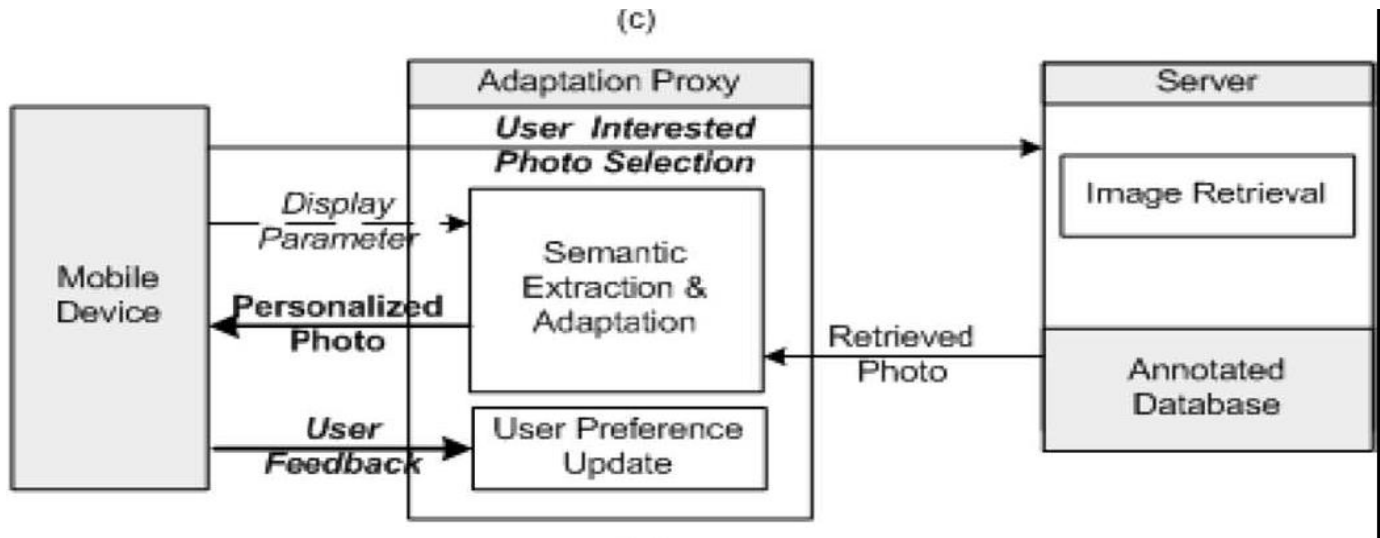
Figure 3: Semantic Extraction and Adaption

3. User Guided Semantic Extraction

Human tends to view and understand images in terms of people and objects associated with underlying concepts in the real world. Hence, semantic analysis is an indispensable step towards extracting semantically important objects and learning user preferences for proper content selection in image adaptation to improve mobile users' perceptual experiences. Semantic gap is still a big challenge in computer vision. Fortunately, in our adaptation scenario, we do not need to perform a full semantic analysis for images, because for a given event, users tend to be interested in only a few objects. Hence, instead of carrying out full image semantic analysis, we extract key objects that users might desire. The key cue we can utilize to narrow down the semantic gap in our application is the user input queries. Although the limited mobile user interface usually does not allow very complicated input as query, the compact keywords provide simple yet useful information about the mobile users' intention. Although sometimes there is a departure between the mobile users' real intention and their query specification, the query is still informative enough to be utilized to extract semantically important objects as user preference relevant object candidates based on concept ontology. It is hence necessary to analyze the user supplied semantic request and determine related major semantic concepts in order to effectively extract semantically meaningful objects. Although the total number of semantic concepts will be numerous in the real world and in general image database, the concepts appearing in consumer domain contains only a small fraction of the general concepts [1]. Moreover, it has been shown that most consumer photos are relevant to one of the events as defined in [1]. Therefore, we adopt these event definitions in the proposed system and focus on the semantic analysis utilizing the user provided event-based semantic keywords to extract the semantically important objects. The limited number of events also leads to an acceptable semantic analysis load.

3.1 Bottom-Up Low Level Feature Extraction

In the bottom-up approach, salient regions are generated based on low level features. First, a raw saliency map is calculated based on low level features such as intensity and color [20], [21]. Then, the image is segmented into regions [22] to produce an efficient representation of the saliency maps for fusion with top-down semantic analysis. Finally, we represent the

original image with regions of different saliency values by averaging the saliency within each region R and use the average value as the initial probability that the region belongs to the desired object.

3.2 User Guided Top-Down High Level Semantic Extraction

In the top-down approach, we develop the event specific classifier to obtain the high level features of the user interested objects with different semantic importance in the given events. We take SIFT [23] and color features as the event based high level semantic features. For each event, an event specific classifier is built offline on a training set that consists of photos of this event. The features for training include quantized color   distribution of the 3-D histogram in HSI space and bag of words [24] of quantized SIFT feature distributions in the training photos with known semantically important objects. Such generic high level semantic feature extraction scheme can be extended to any event by introducing corresponding training process. After the top-down training, the following probabilities are obtained: and , the probability of the SIFT word appears on the object and the non-object area, respectively; and , the conditional probability of the color bin on the object and non-object region, respectively. The training is carried out offline for each event and these probabilities will be used as conditional probability in the following Bayesian fusion module.
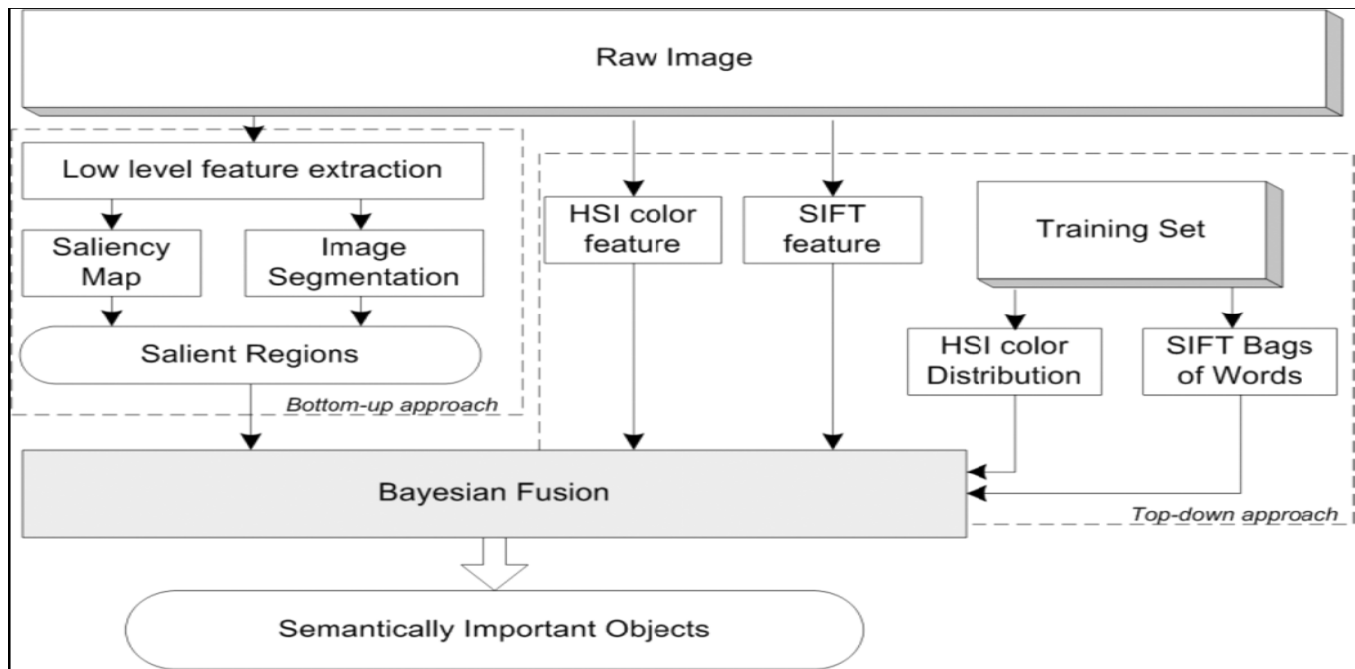

Figure 4: Bayesian Fusion

3.3 Key Objects Localization by Bayesian Fusion

After obtaining the results of bottom-up salient regions and the top-down high level features of main objects using event specific classifier, we fuse them to find the semantically important objects that will likely match with the user's interests. The fusion is designed via Bayesian principle to obtain the posterior belief map of a class of semantic objects. For each region, we consider the bottom-up salient regions as *a priori* of the region belonging to the class of semantic objects. For the conditional

probability, suppose the words are independent, the conditional probability of the region appears on the object class is the joint probability of all the words and colors in the region.

4. User Preference Learning For Adaptation

As discussed earlier, due to the limited mobile device user interfaces, it is usually not allowed to provide complicated inputs for mobile users to describe their desired content details very accurately. Moreover, because of mobile users' different background, they tend to have different interests in concepts even if they input the same query. Even for the same mobile user, his or her intention may vary at different time and circumstance. Therefore, to present content truly consistent with the mobile user's true interest, it is necessary to fine tune the importance of extracted objects and make them gradually matched to the mobile users' preference. However, mobile user preferences are subjective measures varied among individuals. To obtain the user subjective preference value (PV) upon different objects, the only way is to learn them from each individual user. In CBIR systems, to bridge the intention gap in retrieving more relevant images consistent with user's interests, relevance feedback techniques [11] have been developed to capture the subjectivity of human perception of visual content by dynamically updating weights of different features based on the user's feedback. Weights of influential features will be tuned higher to retrieve more consistent images as user feedbacks their judgment towards previous retrieval results.
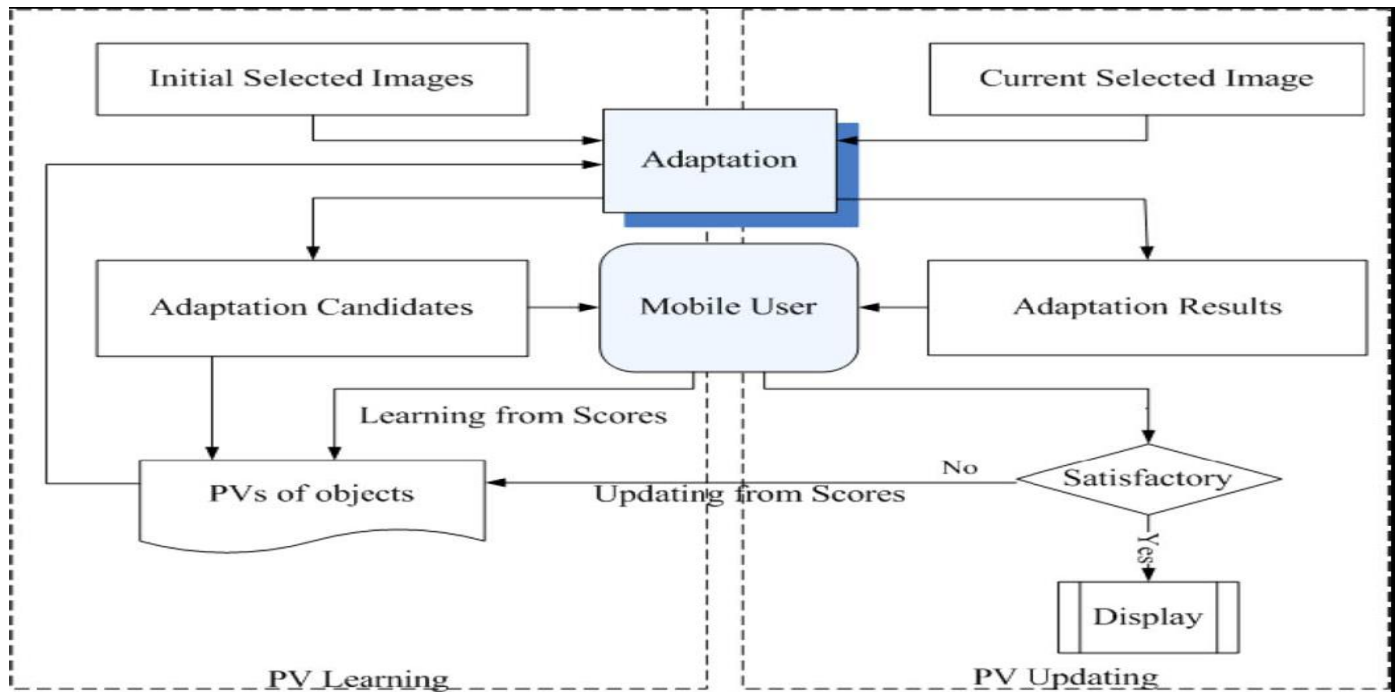

Figure 5: Feedback process for PV learning and updating.

4.1 Feedback Process for PV Learning and Updating

Due to intrinsic characteristics of mobile device interfaces, simple and easy interaction schemes have to be designed for mobile users. Hence, for each query, the system only requires the mobile user to grade a small batch of adaptation candidates initially and few adaptation results subsequently to learn the user's intention. For each grading, the user only needs to type a digit

ranging from 1 to 9 to score whether it is consistent with his preference: 5 means no opinion; scores between 4 and 1 represent the degree of non-relevance, in which 4 is slightly non-relevant and 1 is highly non-relevant.

4.2 User Preference Value Learning and Updating

To handle the variety of mobile user preference, PV learning is performed from the feedback upon the adaptation candidates for the initial selected four images to fine tune the importance of objects from their semantic importance inclined to the individual user preference values of objects. If the PVs learned are not consistent enough with the mobile user's intention, PV updating towards user preference will be further performed from the feedback upon subsequently selected images. Through a limited number of interactions, the PVs can converge to the mobile user intention and the system will be able to perform relevant adaptation for more images, since in one query, the user usually shows stable and coherent interests.

5.   Degradation Model For Blurring Image

In degradation model for blurring image, the image is blurred using filters and an additive noise. The image can be degraded done by using Gaussian Filter and Gaussian Noise. Gaussian Filter represents the Point Spread Function which is a blurring function. The degraded image can be express by the equation f = g * h + n; Where * is the convolution operator, g is the clear image to recover, f is the observed blurred image, h is the blur kernel (or point spread function) and n is the noise. The below Fig.1 represents the formation of degradation model. Image deblurring can be performed by the technique, Gaussian Blur. They are the convolution of the image with 2-D Gaussian function. ([7] and [19])
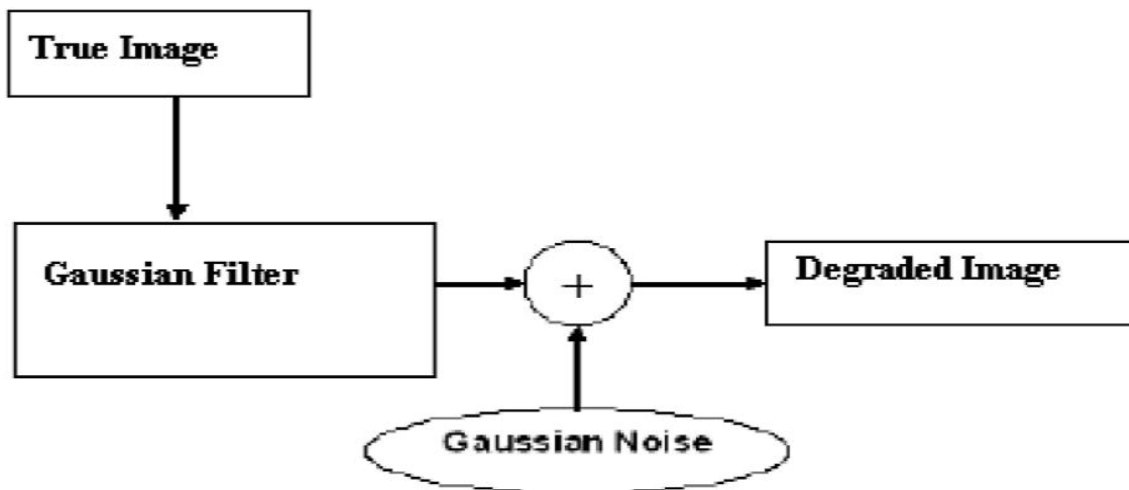

Figure 6: Degradation Model for Blurring Image

5.1 Gaussian filter
Gaussian filter is useful for blur an image by Gaussian function. It requires two specifications such as mean and variance. They are weighted blurring. Gaussian function is of the following form where σ is variance and x and y are the distance from the origin in the x axis and y axis respectively.

5.2 Overall Architecture And Deblurring Algorithm

The original image is degraded or blurred using degradation model to produce the blurred image. The blurred image should be an input to the deblurring algorithm. Various algorithms are available for deblurring. In this paper, we are going to use blind deconvolution algorithm. The result of this algorithm produces the deblurring image which can be compared with our original image. This algorithm can be achieved based on MLE (Maximum Likelihood Estimation).

5.3 User Centric Semantic Adaptation

Given the key semantically meaningful objects contained in a consumer photo, the relevance of different objects for a given user preference can be varied. Moreover, the relevance of the same object for different mobile users may vary substantially Furthermore, there are a variety of mobile devices with various capacities for different users. Given these different PVs of different objects for various mobile users as well as the variety of mobile display capacities, the adaptation module has to decide what content to adopt adaptively according to these varying conditions. The goal of user centric adaptation is to simultaneously panelize the selection of contents not preferred by the user and preserve the user preferred objects with high quality depending on the degree of their relevance to user, under the limited mobile display constraints. By the integration of OSI and feedback, we have already obtained such relevance of different objects to different mobile users which are denoted as PVs. In the following step, we utilize the PVs of objects to guide the adaptation to provide the mobile user the best possible perceptual experience. The optimal adaptation is performed and presented by formulating it into an information fidelity (IF) maximization problem as discussed below.
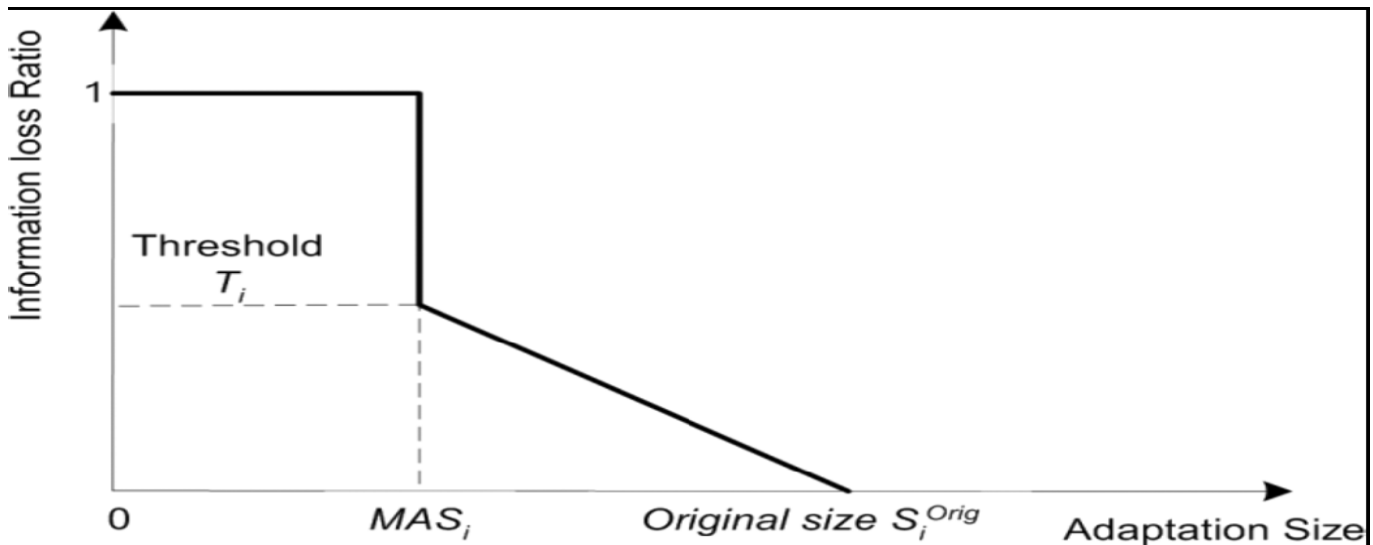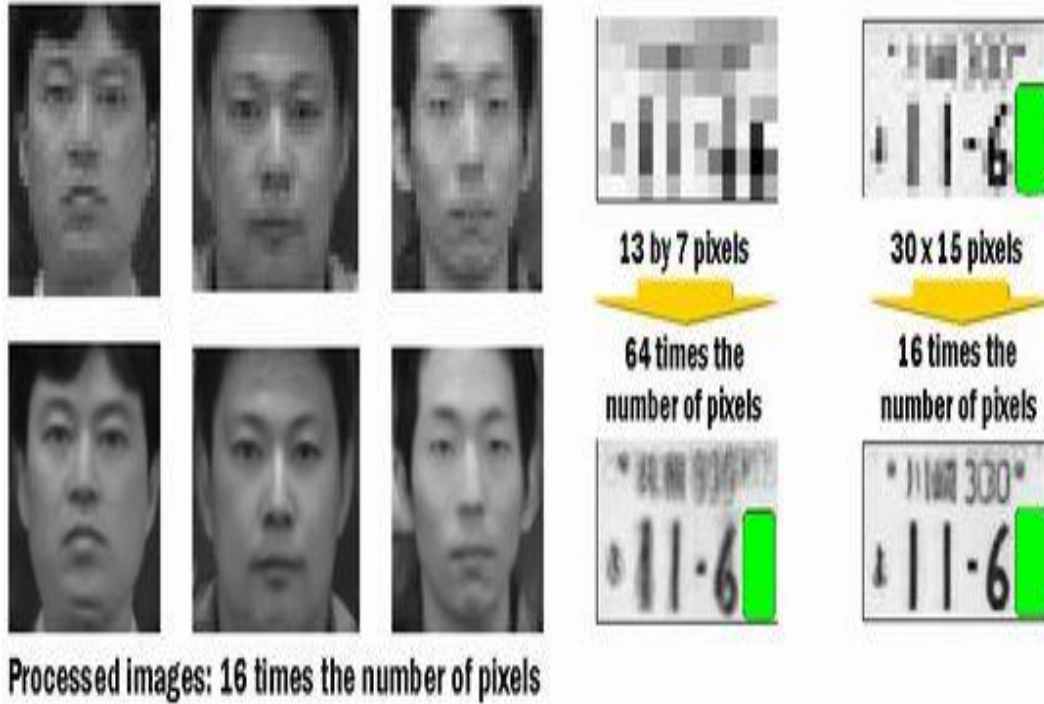

Figure 7: Information loss ratio versus object size after adaptation.

5.4 Experiments

Top row: Original images
Bottom row: Processed images

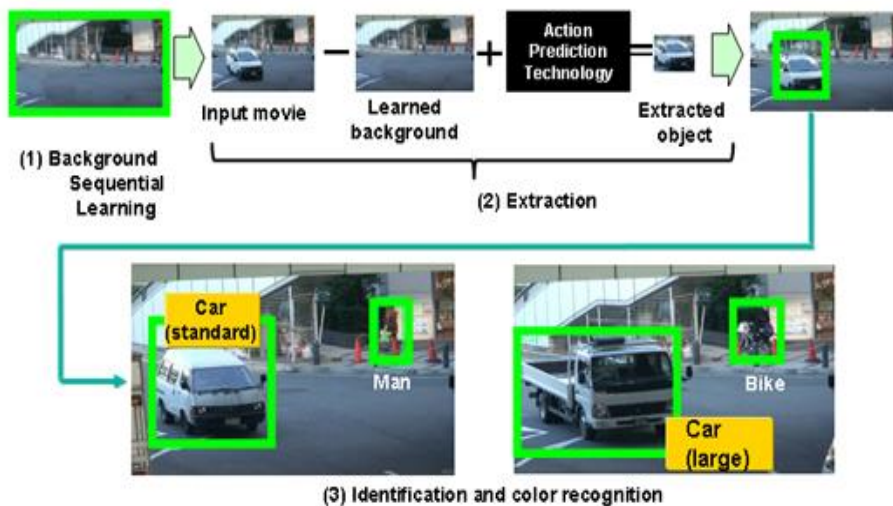Processed images: 16 times the number of pixels

5.5 Contrast Enhancement

Luminance information is analyzed and real-time contrast enhancement (image compensation processing) is performed to effectively extract target objects even from dark images of moving subjects that are otherwise difficult to confirm visually.

6. Extension Of Existing System

The texture of images in scattering media is characterized by speckle. The phenomenon of speckle formation is due to the relatively narrow bandwidth of the transmitted ultrasound pulses and the constructive and destructive interference of echoes backscattered by a volume of tissue which moves on the surface of the receiving transducers. The presence of speckle, causing mottled or granular images, of small contrast in grey level or in texture. However changes in mean grey level and in texture pattern indicate diffuse focal lesions within an organ. Image processing techniques used to improve the visual detect ability of abnormalities in images can be divided into 2 major classes. First of all, speckle detection or grey level filtering techniques are used to reduce the variance of the distribution of the grey levels in an image, thus allowing a better assessment of changes in the mean grey level. To limit the reduction of spatial resolution induced by these filters, adaptive techniques can be used. These techniques, employing the locale image properties to control the settings of the filter, result in both speckle smoothing in regions with a homogeneous texture and preservation of spatial resolution. The second class of image processing techniques consists of parametric imaging techniques. Here parameters, resulting from the local analysis of the echo graphic image, are displayed in a 2D fashion, thus creating a new type of image. This new image may reveal abnormalities more clearly than the original image. The improvement in detecting the abnormal regions may result from an enhanced intensity contrast or from revealing areas which differ only in second order speckle characteristics which are not visually perceptible. It may be mentioned that also parameters resulting from the analysis of the radio frequency signals can be employed in this manner. Besides displaying each parameter separately, also a combination of parameters can be displayed. Cluster techniques or color coding can be used to combine several parameters into a new one to be displayed. This method is called tissue type imaging because the displayed parameter itself is not resulting from the analysis but is a signature of the tissue resulting in the parameters used in the combination.

6.1 Signal to noise ratio imaging

An exception is only borders of the image, the width of which is equal to the blur radius - no complete restoration is possible here. Let's demonstrate it using a small example for a one-dimensional case - let's suppose we have a row of pixels with the following values:

$x_1 \mid x_2 \mid x_3 \mid x_4...$ - Source image

After blurring the value of each pixel is added to the value of the left one: $x'_i = x_i + x_{i-1}$. Normally, it is also required to divide it by 2, but we will drop it out for simplicity. As a result we have a blurred image with the following pixel values:

$x_1 + x_0 \mid x_2 + x_1 \mid x_3 + x_2 \mid x_4 + x_3...$ - Blurred image.

Now we will try to restore it, we will consequentially subtract values according to the following scheme - the first pixel from the second one, the result of the second pixel from the third one, the result of the third pixel from the fourth one and so on, and we will get the following:

$x_1 + x_0 \mid x_2 - x_0 \mid x_3 + x_0 \mid x_4 - x_0...$ - Restored image.

As a result, instead of a blurred image, we got the source image with added to the each pixel an unknown constant x_0 with the alternate sign. This is much better - we can choose this constant visually, we can suppose that it is approximately equal to the value x_1, we can automatically choose it with such a criteria that values of neighboring pixels were changing as little as possible, etc. But everything changes as soon as we add noise (which is always present in real images). In case of the described scheme on each stage there will accumulate the noise value into the total value, which fact eventually can produce an absolutely unacceptable result, but as we already know, restoration is quite possible even using such a primitive method.

6.2 Blurring process model

Now let's pass on to more formal and scientific description of these blurring and restoration processes. We will consider only grayscale images, supposing that for processing of a full-color image it is enough to repeat all required steps for each of the RGB color channels. Let's introduce the following definitions:

$f(x, y)$ - source image (non-blurred)

$h(x, y)$ - blurring function

$n(x, y)$ - additive noise

$g(x, y)$ - blurring result image

We will form the blurring process model in the following way:

$g(x, y) = h(x, y) * f(x, y) + n(x, y)$ (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 process of blurring the each pixel of a source image turns into a spot in case of defocusing and into a line segment (or some path) in case of a usual blurring 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. 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.

6.3 Blurring functions

Let us see what typical blurring functions look like. Hereinafter we will use the tool which has already become standard for such purposes - Mat lab; it contains everything required for the most diverse experiments with image processing (among other things) and allows concentrating on algorithms, shifting all the routine work to function libraries. However, this is only possible at the cost of performance. So, let's get back to PSF, here are their examples: **PSF in case of motion blur functions using: fspecial('motion', 40, 45);**

The process of applying of the blurring function to another function (in his case, to an image) is called **convolution**, i.e. some area of the source image convolves into one pixel of the blurred image. It is denoted through the operator "*", but do not confuse it with a simple multiplication! Mathematically, for an image f with dimensions M x N and the blurring function h with dimensions m x n it can be written down as follows:

Where $a = (m - 1) / 2$, $b = (n - 1) / 2$. The process, which is opposite to convolution, is called deconvolution and solution of such task is quite uncommon.

6.4 Noise Model

It is only left to consider the last summand, which is responsible for noise, $n(x, y)$ in the formula (1). There can be many reasons for noise in digital sensors, but the basic ones are - thermal vibrations (Brownian motion) and dark current. The noise volume also depends on a number of factors, such as ISO value, sensor type, pixel size, temperature, magnetic field value, etc. In most cases there is Gaussian noise (which is set by two parameters - the average and dispersion), and it is also additive, does not correlate with an image and does not depend on pixel coordinates. The last three assumptions are very important for further work.

6.5 Convolution theorem

Let us get back to the initial task of restoration - we need to somehow reverse the convolution, bearing in mind the noise. From the formula (2) we can see that it is not so easy to get $f(x, y)$ from $g(x, y)$ - if we calculate it straightforward, then we will get a huge set of equations. But the Fourier transform comes to the rescue, we will not view it in details, because a lot has been said about this topic already. So, there is the so called convolution theorem, according to which the operation of convolution in the spatial domain is equivalent to regular multiplication in the frequency domain (where the multiplication - element-by-element, not matrix one). Correspondingly, the operation which is opposite to convolution is equivalent to division in the frequency domain, i.e. this can be expressed as follows: Where $H(u, v)$, $F(u, v)$ - Fourier functions for h(x,y) and f(x,y). So, the blurring process from (1) can be written over in the frequency domain as,

6.6 Inverse filter

Here we are tempted to divide this equation by $H(u, v)$ and get the following evaluation $F^{\wedge}(u, v)$ of the source image: This is called inverse filtering, but in practice it almost never works. Why so? In order to answer this question, let us see the last summand in the formula (5) - if the function $H(u, v)$ gives values, which are close to zero or equal to it, then the input of this summand will be dominating. This can be almost always seen in real examples - to explain this let's remember what a spectrum looks like after the Fourier transform. So, we take the source image, convert it into a grayscale one, using Matlab, and get the spectrum:

6.7 Deblurring Algorithm

1) Read an original input image f(x, y).
2) Degrade the original image with Gaussian Blur function to get a blurred image g(x, y).
3) Restored blurred image PSFs of various sizes. This performs three restorations vizi)
Deblurring with undersized PSF
ii) Deblurring with oversized PSF
iii) Deblurring with INITPSF
4) Analyzing the restored PSF.
3) Now restore the degraded image with deconvblind function to get a restored image having ringing effects at its edges.
4) To remove the ringing effect at edges, Canny edge detection technique is used
5) Apply edge taper function to remove ringing effects
6) Finally, we get a restored image

```
% Load image
  I = imread('image_src.png');
  figure(1); imshow(I); title('Source image');
  % Convert image into grayscale
  I = rgb2gray(I);
  % Compute Fourier Transform and center it
  fftRes = fftshift(fft2(I));
  % Show result
  figure(2); imshow(mat2gray(log(1+abs(fftRes)))); title('FFT - amplitude spectrum (log scale)');
  figure(3); imshow(mat2gray(angle(fftRes))); title('FFT - phase smectrum');
```

As a result we will have two components: amplitude and phase spectrum. By the way, many people forget about the phase. Please note that the amplitude spectrum is shown in a logarithmic scale, because its values vary tremendously - by several orders of magnitude, in the center the values are maximum (millions) and they quickly decay almost to zero ones as they are getting farther from the center. Due to this very fact inverse filtering will work only in case of zero or almost zero noise values. Let's demonstrate this in practice, using the following script:

```
% Load image
   I = im2double(imread('image_src.png'));
   figure(1); imshow(I); title('Source image');
   % Blur image
   Blurred = imfilter(I, PSF,'circular','conv' );
   figure(2); imshow(Blurred); title('Blurred image');
   % Add noise
   noise_mean = 0;
   noise_var = 0.0;
   Blurred = imnoise(Blurred, 'gaussian', noise_mean, noise_var);
   % Deconvolution
   figure(3); imshow(deconvwnr(Blurred, PSF, 0)); title('Result');
```

7. Results For Deblurred Images

7.1 Performance Measures And Iteration wise Results Mse

The mean squared error abbreviated as MSE is an estimator that measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated. Mean Square Error can be estimated in one of many ways to quantify the difference between values implied by an estimate and the true quality being certificated.

The proposed approach is experimented using a test image „cameraman.tif" of size 256 x 256.The below images represent the result of degradation model using Gaussian blur.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

Where, m×n monochrome images I and its noisy approximation K.

7.2 PSNR

Peak signal-to-noise ratio abbreviated as PSNR, is a technical term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is usually expressed as decibel scale. The PSNR is commonly used as measure of quality reconstruction of image. High value of PSNR indicates the high quality of image.

Original Image

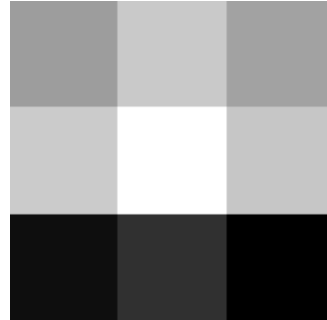**Deblurring with undersized PSF**
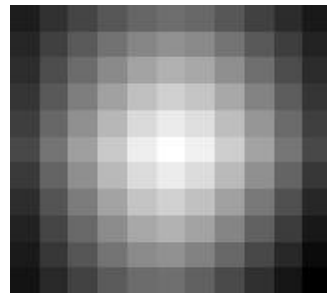

Blurred Image

Deblurring with oversized PSF

Deblurring with initial PSF
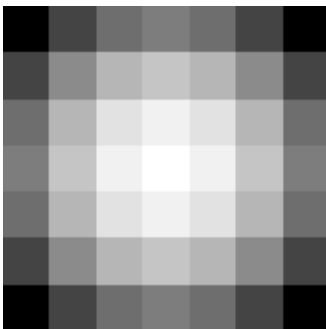

True PSF

Reconstructed Undersized PSF

Reconstructed Oversized PSF
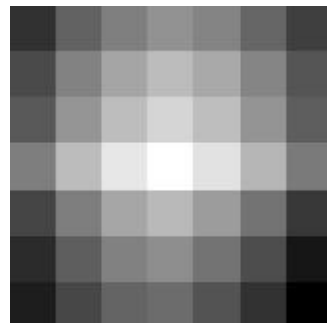

Reconstructed true PSF

Image 1 received after 30 iterations

Image 2 received after 40 iterations

Image 3 received after 50 iterations

8. Conclusion

A semantic image adaptation scheme has been developed for mobile display devices. This scheme aims at providing mobile users with most desired image content by integrating the content semantic importance and user preferences under the limited mobile environment constraints. The main contributions of the proposed scheme are: 1) We have designed a seamless integration of mobile user supplied query information with low level image features to extract semantically important objects. 2) We have designed a integration of semantics and user feedbacks framework to effectively learn and update mobile user preferences. 3) We have developed a perceptually optimized image adaptation scheme to best represent the adaptation according

to mobile user's preference under mobile device constraints. Furthermore, to bridge the semantic gap for adaptation, we have designed a Bayesian fusion approach to properly integrate low level features with high level semantics. To handle the preference variations among different mobile users, mobile user relevance feedback scheme has been developed to learn and update user preferences. Extensive experiments have been carried out to validate the proposed adaptation scheme. The experiments show that by adopting the proposed semantic adaptation scheme with integration of the semantics and mobile user preferences, perceptually highly relevant image adaptation can be effectively carried out to match the user intentions under the mobile environment constraints. For future work, several additional features can be adopted in both the bottom-up and top-down steps in order to improve the detection results of these steps, and thus to further enhance the overall performance of semantic extraction. In addition, object semantic analysis can be developed to further improve the adaptation results, since sometimes the preservation of only part of object of interest is adequate or even better for mobile user perception. Moreover, concept ontology can be exploited further to improve semantic analysis and user preference learning and updating. We expect that the closing of semantic gap and mobile user intention gap will continue to improve the personalized adaptation results to provide mobile users with more satisfactory perceptual experiences.

The blur images can be detected and rectified or cleared using various methods. The method used in this project is, subject extraction and action prediction technology. In these methods first the entire snap has been taken which we have taken using camera or mobile devices. From the snap we have to select the particular image for clearing the blur image. For that we have used extraction method for clearing the blur model. In this method, the background of the blur image will be detected first. Because background clearance only will be giving the clearance of an entire image. So first we should extract the background of an image by pixels. Each and every pixels of a background image will be considered. Pixels consideration will give a good clarity of an image which is present at front.

But this is not applicable for all images. For example if we taken the snap from a camera or mobile devices from too long distance it will be very small to see or not clear to see. So for these kind of images we can provide somewhat clarity only using this background extraction images. Because, the images which are taken from too long distances will very small already. Their background also very small when compared to the image. So for that kind of images it is very difficult to extract the background and clear the blur.

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