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A Survey on Hybrid Algorithm for Image Deblurring Techniques

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Abstract: This paper concern on image deblurring has a major impact in Digital Image processing, but the main drawback in digital image is presence of noise and degradation during the camera shack, long exposure time, movement of object, and not focus the target. Image deblurring and restoration is very important and necessary in digital image process avoid the blur. Image deblurring is a technique which is used tomake picture sharp and useful by using mathematical model. Blur found in the digital image can be two types blind convolution and non-blindde convolution, that need the estimation of point spread function (PSF) to recover the blur.There have been many methods that were proposed in this paper we studied various image deblurring method and hybridization of the two methods for better resolution.

Keywords: image deblur, blur, PSF, degradation model, motion blur, blind deconvolution.

I. INTRODUCTION

In Modern generation Digital Image are widely used in many kind of application such as everyday photography, monitoring, medical imagining, astronomy, microscopy and remote sensing. Digital Image made of lots of pixels that organized in a grid. Each pixel contains an intensity value which determines the tone at a specific point. Unfortunately, all capture image end up more or less blurry. Image blur usually devastate there is a lot of interference in the Environment. The blur is defining the values of PSF (Point Spared Function). We take a digital image and each pixel has a specific value, blur disturbance the value of pixel so avoid the blur we can estimate the PSF and reduce the blur and get original image.

Generally image deblurring can be classified into two types, blind deconvolution and non-blindde convolution [1]. Blind deconvolution is a difficult task to remove blur, as the PSF is an unknown. Non-blind deconvolution is more effective as the PSF is known. Hence, deblurring regimes can be developed than those when no prior information for the PSF is available. Recent deblurring methods have been developed by incorporating the mechanisms of point spread function (PSF) and non-blind deconvolution.

A. Blind deconvolution:

The common approaches of blind deconvolution are basedon the availability of more than two images of the samescene. With a close temporal position, these approaches can be particularly implemented in way finding applications. Developed a blind deconvolution using two blurred images with two motion captions of which the correlation between the two captions is used for determining the deblurring function [2]. Used a twoimages of which one is blurry and one is noisy, in order to perform deblurring in low light conditions. However, these approaches cannot be applied on real-time systems such as road navigation or way finding as the required computational time is high[3].Developed a method using a single image for handling slight blurring such as camera tremble. It attempts to determine the camera motion based on the initial blur kernel, which is estimated by the heuristic information of camera motion[4]. Based on a unified probabilistic model consisting of both blur kernel estimation and de-blurred image restoration. However, both these methods have complex computational costs and are therefore not suitable for implementing on microcontroller, which has limited computational power [5].

B. Non-blind deconvolution:

Modern electronic communication devices, such as smart phones and tablets commonly have embedded inertial sensors such as gyroscopes, accelerometers which can be used to capture inertial data in order to determine the geometric information for the camera motion. proposed a de-blurring methodusing the IMU data captured by the gyroscope, accelerometer and depth sensor installed on the camera. The computational cost required for this method is high, as it requires a microcontroller with high computational power to control the position of the depth sensor making it unsuitable for implementation in real-time applications [6]. A more effective deblurring method was developed based on the geometric information captured by accelerometer, gyroscopic sensor data and digital single-lens reflex (DSLR) camera [7-8]. However, this approach requires the expensive DSLR camera and can only be used for offline deblurring.

A deblurring method based on the IMU sensor in this method, boththe anti-blur feedback and IMU sensor data are used for the camera stabilization. It is useful in the area of image acquisition but synchronizing the IMU data with the image capture is a challenging task as the accelerometer and the gyroscopic sensor capture IMU data and the camera captures the image within the exposure

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time. As the exposure time is small, the synchronization task, which attempts to align the image sensor with IMU data, is problematic.

This paper proposes a deblurring methodology, which uses the IMU data, captured by accelerometer and gyroscopic sensor data. A hybrid optimization method has been developed to synchronize the IMU data and the captured image in order to improve the image quality of the blurred images. The resulting deblurring methodology will benefit our research project, which aims to develop an embedded system for way finding purposes for vision-impair people [9].

II. PSF ESTIMATION

The point spread function (PSF) describes the response of an imaging system to a point source or point object. A more general term for the PSF is a system's impulse response, the PSF being the impulse response of a focused optical system. The PSF in many contexts can be thought of as the extended blob in an image that represents an unresolved object. In functional terms it is the spatial domain version of the transfer function of the imaging system. It is a useful concept in Fourier optics, astronomical imaging, electron microscopy and other imaging techniques such as 3D microscopy (like in confocal laser scanning microscopy) and fluorescence microscopy. The degree of spreading (blurring) of the point object is a measure for the quality of an imaging system. In non-coherent imaging systems such as fluorescent microscopes, telescopes or optical microscopes, the image formation process is linear in power and described by linear system theory. This means that when two objects A and B are imaged simultaneously, the result is equal to the sum of the independently imaged objects. In other words: the imaging of A is unaffected by the imaging of B and vice versa, owing to the non-interacting property of photons. The image of a complex object can then be seen as a convolution of the true object and the PSF. However, when the detected light is coherent, image formation is linear in the complex field. Recording the intensity image then can lead to cancellations or other nonlinear effects.

If the imaging system is linear, the image of an object can be expressed as:

$$g(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x,y;\alpha,\beta) f(\alpha,\beta)\, d\alpha\, d\beta + \eta(x,y) \quad (1)$$

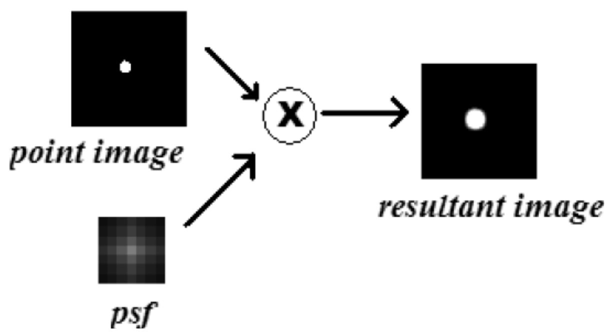

Figure1: Image formation with PSF

Where η(x, y) is the additive noise function, f (α,β) is the object, g(x, y) is the image, and h(x, y; α,β) is the Point Spread Function (PSF). The “;” is used to distinguish the input and output pairs of coordinates in this case.

III. TYPES OF BLUR

A. MOTION BLUR:

When a photograph is taken of any moving object or the imaging system itself is moving then the degradation caused is motion blur. Motion blur caused significant degradation of the image. This is caused by the movement of the object relative to the sensor in the camera. The motion blur occurs if any of the following condition persists,

I. Moving Object captured by static camera,
II. Static Object captured by camera in motion
III. Both Object and camera are in motion,
IV. Shutter movement, film is exposed in a camera by the movement of the shutter across the film plane.

The two types of motion blur have been studied. They are:

Linear-Horizontal Motion Blur: The motion blur arising either to camera moving or the object moving horizontally is given as, L being the blur length. More precisely, L is the number of additional points in the image resulting from a single point in the original scene [10].

$$d(x) = \begin{cases} \frac{1}{L} & \text{if } \frac{-L}{2} \le x \le \frac{L}{2} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Angular Motion Blur: When the scene to be recorded translates at a constant velocity,V, with an angle of θ degrees from the horizontal axis during the exposure interval, [0 T], then the PSFobserved is given as[11]:

$$d(x,y) = \begin{cases} \frac{1}{L} & \text{if } 0 \le |x| \le L\cos\theta,\ y = L\sin\theta \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

B. Gaussian Blur:

A Gaussian blur is the result of blurring of an image byGaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. Gaussian blur is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales. The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve. The blurring is dense in the centre and feathers at the edge. Apply Gaussian Blur to an image when you want more control over the Blur effect [12].

C. Average Blur:

The Average blur is one of several tools you can use toremove noise and specks in an image. Use it when noise is present over the entire image. This type of blurring can be distribution in horizontal and vertical direction and can be circular averaging by radius R which is evaluated by the formula:

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$$R = \sqrt{g2 + f2} \quad (4)$$

Where: g is the horizontal size blurring direction and f is vertical blurring size direction and R is the radius size of the circular average blurring.

D. Out-of-focus Blur:
When a sight is captured by the camera in a two-dimensionalfield, it may happen that some parts are in focus while other parts are not. The degree of defocus depends upon the effective lens diameter and the distance between the object and the camera [13].

IV. DEBLURRING TECHNIQUE

A. Lucy- Richardson Algorithm Technique:
The Richardson–Lucy algorithm, also known as Richardson Lucy deconvolution, is an iterative procedure for recovering a latent image that has been the blurred by a known PSF [14].
Ci = Σjpijuj
Where: p_{ij} is the point spread function (the fraction of light coming from true location j that is observed at position i), u_j is the pixel value at location j in the latent image, and ci is the observed value at pixel location i. The statistics are performed under the assumption that u_j are Poisson distributed, which is appropriate for photon noise in the data. The basic idea is to calculate the most likely uj given the observed ci and known p_{ij}. This leads to an equation for u_j.

B. Neural Network Approach:
Neural networks is a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, adaptive interaction between elements, When an element of the neural network fails, it can continue without any problem by their parallel nature[15]. ANN provides a robust tool for approximating a target function given a set input output example and for the reconstruction function from a class a images. Algorithm such as the Back propagation and the Perceptron use gradient- decent techniques to tune the network parameters to best-fit a training set of input-output examples. Here we are using Back propagation neural network approach for image restoration. This approach is capable of learning complex non-linear functions is expected to produce better structure especially in high frequency regions of the image. We used a two-layer Back propagation network with full connectivity.

C. Wiener Filtering:
One of the most common techniques for image deblurring is wiener filtering. The wiener filter has a large ability to remove the blur in images caused by linear motion or unfocussed optics. The blurred image can be seen as a result of poor sampling. Each pixel in the image should contain intensity value for a single stationary point in front of the capturing device (camera). Unfortunately, if the camera is moved or the shutter speed is very slow, a given pixel will be an amalgam of intensities from points along the line of the camera's motion [16, 17]. The Wiener filter performs an optimal trade-off between inverse filtering and noise smoothing because it removes the additive noise and inverts the blurring simultaneously. Some of the techniques that used Wiener filtering the model work as described in equations 5.

$$B\,(x, y) = h(x, y) * s(x, y) + n(x, y) \quad (5)$$

Where s(x, y) is the unknown sharp image, h(x, y) is the known impulse response of a linear scale-invariant system , n(x, y) is some unknown additive noise independent of s(x, y) and b (x, y) is the observed blurred image. The Wiener deconvolution filter finds g(x, y) and use it to estimate s(x, y), as expressed in equation 6.

$$s(x, y) = g(x, y) * b(x, y) \quad (6)$$

Where s(x, y) is an estimate of s(x, y) that minimizes the mean square error, the filter works in the frequency domain. The first step is to calculate the frequency domain version of g(x, y), as expressed in equation 7.

$$G(u,v) = \frac{H(u,v)\,W(u,v)}{|H(u,v)|^2 W(u,v) + N(u,v)} \quad (7)$$

Where G(u, v) is the Fourier transform of g, H(u, v) is the Fourier transform of h, W(u, v) is the mean power spectral density of s(x, y), N(u, v) is the mean power spectral density of the noise n(x, y). Finally, the filtering is performed in the frequency domain, as expressed in equation 8.

$$S(u,v) = G(u,v)B(u,v) \quad (8)$$

Where S(u, v) is the Fourier transform of the estimated sharp image and B(u, v) is the Fourier transform of the observed blurred image. If three pixels in a line contain info from the same point on an image, the digital image will seem to have been convolved with a three-point boxcar in the time domain[17]. It is seen that the technique is based on inverse filtering. Unfortunately, there are a number of drawbacks associated with the wiener filter: (i) H is unknown. It can be guessed for a given image but it requires a lot of trials and efforts to give a good estimation of H; (ii) it is failed in some cases because the sine function equal 0 at some values of x and y.

D. Deblurring With Blurred/Noisy Image Pairs:
In this approach the image is deblurred with the helpof noisy image. As a first step both the images the blurred and noisy image are used to find an accurate blur kernel. It is often very difficult to get blur kernel from one image. Following that a residualdeconvolution is done and this will reduce artifacts that appear as spurious signals which are common in image deconvolution. As the third and final step the remaining artifacts which are present in the non-sharp images are suppressed by gain controlled deconvolution process. The main advantage of this approach is that it takes both the blurred and noisy image and as a result produces high quality reconstructed image. With these two images an iterative algorithm has been formulated which will estimate a good initial kernel and reduce deconvolutionartifacts. There is no special hardware is required. There are also disadvantages with this approach like there is a spatial point spread function that is invariant [18].

E. Deblurring With Motion Density Function:
In this method image deblurring is done with the helpof motion density function. A unified model of camera shake blur and a framework has been used to recover the camera motion and latent image from a single blurredimage. The camera motion is represented as a Motion Density Function (MDF) which records the fraction of time spent in each discretized portion of the space of all possible camera poses. Spatially varying blur kernels are derived directly from the MDF. One limitation of this method is that it depends on imperfect spatially invariant deblurring estimates for initialization [19].

F. Deblurring With Handling Outliers:
In this method various types of outliers such as pixels saturation and non-Gaussian noise are analysed and then a deconvolution method has been proposed which contains an explicit component for outlier modelling. Image pixels are classified into two main categories: Inlier pixels and Outlier pixels. After that an Expectation-Maximization method is employed to iteratively refine the outlier classification and the latent image [20].

G. Deblurring by ADSD-AR:
In this approach ASDS (Adaptive Sparse Domain Selection) scheme is introduced, which learns a series of compact sub-dictionaries and assigns adaptively each local patch a sub-dictionary as the sparse domain. With ASDS, a weighted l1-norm sparse representation model will be proposed for IR tasks. Further two adaptive regularization terms has been introduced into the sparse representation framework. First, a set of autoregressive (AR) models are learned from the dataset of example image patches. The best fitted AR models to a given patch are adaptively selected to regularize the image local structures. Second, the image nonlocal self-similarity is introduced as anotherregularization term [21].

H. Deblurring by PSO & Gradient Search:
Which is, incorporated the mechanisms of particle swarm optimization (PSO) and gradient search method, in order to optimize PSF parameters. It aims to incorporate the advantages of the two methods, where the PSO is effective in localizing the global region and the gradient search method is effective in converging local optimum. Experimental results indicated that deblurring can be successfully performed using the optimal PSF. Also, the performance of proposed method is compared with the commonly used deblurring methods. Better results in term of image quality can be achieved.

V. DENOISING PROCESSES

The original meaning of noise is unwanted signal. Noise in images are mainly due to capturing instruments, transmission medium, recording medium, image quantization for storage, sources of radiation and compression. It is an unwanted signal that interferes with the original signal and degrades the quality of digital image. The introduced noise may of different kinds upon which the amount of degradation varies. There are different types of noise models for different types of noises. Noise is present in image either in additive or multiplicative form.

A. Image Noise:
The main source of noise in digital images arises during image acquisition (digitization) or during image transmission

1. Additive Noise Model
Noise signal that is additive in nature gets added to the original signal to produce a corrupted noisy signal and follows the following model:

$$W(x, y) = s(x, y) + n(x, y) \tag{9}$$

2. Multiplicative Noise Model
In this model, noise signal gets multiplied to the original signal. The multiplicative noise model follows the following rule:

$$W(x, y) = s(x, y) \times n(x, y) \tag{10}$$

Where, $s(x, y)$ is the original image intensity and $n(x, y)$ denotes the noise introduced to produce the corrupted signal $w(x, y)$ at (x, y) pixel location.

3. Uniform noise
The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise. It has an approximately uniform distribution. In the uniform noise the level of the gray values of the noise are uniformly distributed across a specified range. Uniform noise can be used to generate any different type of noise distribution. This noise is often used to degrade images for the evaluation of image restoration algorithms.

4. Gaussian noise
The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity. Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value.

5. Salt-and-pepper noise
An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. It is generally caused due to errors in transmission. This is caused generally due to errors in data transmission. It has only two possible values, a and b. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged.

6. Speckle noise
Speckle noise is multiplicative noise. Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar images. Speckle noise in SAR is generally more serious, causing difficulties for image interpretation. It is caused by coherent processing of backscattered signals from multiple distributed targets. The source of this noise is attributed to random interference between the coherent returns.

B. Denoising Techniques:

Various denoising techniques are used which are basically dependent on the type of image and type of noise model. There are two approaches to image denoising.

1. Spatial Domain Filtering

The traditional way to remove noise from the digital image is to employ the spatial filters. Spatial domain filtering is further classified into linear filters and non-linear filters.

i. Linear Filters

Linear filters tend to blur sharp edges, destroy lines and other fine details of image. It includes Mean filter and Wiener filter [22].

Mean Filter: Mean filter is a simple sliding window spatial filter that replaces the centre value in the window with the average of all the neighbouring pixel values including it. It is also called a linear filter. The mean filter is useful when only a part of the image needs to be processed.

Weiner Filter: Weiner filtering method requires the information about the spectra of noise and original signal and it works well only if the underlying signal is smooth. Weiner method implements the spatial smoothing and its model complexity control corresponds to the choosing the window size. Wiener Filter assumes noise and power spectra of object a priori.

ii. Non Linear Filters

With the non-linear filter, noise is removed without any attempts to explicitly identify it. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median, rank conditioned rank selection, and relaxed median have been developed to overcome this drawback.

Median Filter: The Median filter is a nonlinear digital filtering technique, often used to remove noise. The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighbouring entries. Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possiblemedian. A major advantage of the median filter over linear filters is that the median filter can eliminate the effect of input noise values with extremely large magnitudes.

2. Transform domain filtering

The transform domain filtering can be subdivided into data adaptive and non-adaptive filters. Non-adaptive filters includes Wavelet domain.

i. Wavelet Domain

Noise reduction using wavelets is performed by first decomposing the noisy image into wavelet coefficients i.e. approximation and detail coefficients. Then, by selecting a proper thresholding value the detail coefficients are modified based on the thresholding function. Finally, the reconstructed image is obtained by applying the inverse wavelet transform on modified coefficients. Filtering operations in the wavelet domain can be subdivided into linear and nonlinear methods. Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE).

The most investigated domain in denoising using Wavelet Transform is the non-linear coefficient thresholding based methods. The procedure exploits sparsity property of the wavelet transform and the fact that the Wavelet Transform maps white noise in the signal domain to white noise in the transform domain. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is this important principle that enables the separation of signal from noise.

ii. Data-Adaptive Filters

Widely used Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the independent component analysis method all the pixels in the image work independently which means they work in their own and they are not dependent on the neighbour's pixel value. So it gives the best result while finding in the denoising techniques.

VI. OPTIMIZATION TECHNIQUE

The optimization techniques are useful in finding the optimum solution or unconstrained maxima or minima of continuous and differentiable functions. These are analytical methods and make use of different+ial calculus in locating the optimum solution.

A. Optimization using PSO:

Optimizings w is difficult due to the huge number of possible poses of the camera in the pose space, and the problem is converted to searching the optimized weighted parameters in a high dimensional space. In this paper, we propose to use the PSO algorithm to solve this issue.

x^i_k-Particle position
u^i_k- Particle velocity
p^i_k- Best "remembered" individual particle position
p^g_k- Best "remembered" swarm position
c_1, c_2- Cognitive and social parameters
r_1, r_2- Random numbers between 0 and 1

Position of individual particles updated as follows:

$$x^i_k+1 = x^i_k + u^i_{k+1} \qquad (11)$$

With the velocity calculated as follows:

$$u^i_{k+1} = u^i_k + c_1\, r_1(p^i_k - x^i_k) + c_2\, r_2\, (p^g_k - x^i_k) \qquad (12)$$

- **Initiaze**
  - Set constant k_{max} c_1 c_2
  - Randomly initialize particle position $x^i_0 \in D$ in IR^n for i = 1……p
  - Randomly initialize particle velocity $0 \le v^i_0 \le v_0^{max}$ for i = 1……p
  - Set k = 1.

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- **Optimize**
- Evaluate function value f^i_k using design space coordinatesxik
- If $f^i_k f^i_{best}$ then $f^i_{best} = f^i_k$; $p^i_k = x^i_k$
- If $f^i_k f^g_{best}$ then $f^g_{best} = f^i_k$; $p^i_k = x^i_k$
- If stopping condition in satisfied then goto 3
- Update all particle velocity u^i_k for i = 1……p
- Update all particle position x^i_k for i = 1……p
- Increment k
- Goto 2 starting
- **Terminate.**

B. Optimization using GA:

In this work, a GA technique [23] was used due to its generality and capability to heuristically overcome situations where an exhaustive solution would be too computationally demanding. Its goal was to identify the correct bottle among those whose properties are stored in the database, as well as its initial and final positions. The correct solution should be able to recreate the blurred image as it was captured.

1. Population

The information needed to accurately describe the motion of a bottle during the image capture could be provided by 4 parameters. The bottle species was identified by an integer index which referred to its position in the database, in which the bottles were recorded by increasing size. Nearby indexes pointed to bottles of similar size, albeit not necessarily similar shape. Two parameters consisted of the coordinates of the displacement vector Δx, Δy of the centroid measured in pixels, while the last indicated the total angle of rotation Δθ around the centroid of the bottle. In this GA, individuals consequently consisted of ordered vectors k P of 4 components each. To speed up the process, a small subset of all bottles in the database was considered for the GA algorithm. All bottles whose area was out of the range 70% - 105% of the area of the blurred image were considered too unlikely as solutions and not included as possible candidates. Furthermore, a small number of individuals were selected out of a larger initial population. Typical values were 50 individual out of which only 8 to 20 were kept for the actual GA iterations.

2. Cross-over

The cross-over is performed on randomly selected couples by performing a linear combination of the corresponding components:

$$\{\mathbf{P}_a, \mathbf{P}_b\} \rightarrow \mathbf{P}_{new} = \boldsymbol{\alpha} \cdot \mathbf{P}_a + (1 - \boldsymbol{\alpha} \cdot \mathbf{P}_b) \quad 13)$$

The components of the random parameter vector α were selected as $\alpha_i \in [-0.5,\ 1.5]$ in order to access partsof the population space not lying in between the twoparent vectors. The first component of Pnew was roundedto the nearest integer index among those accepted as possible candidates. The diversification arising from this cross-over procedure does not guarantee that new individuals inherit or improve the fitness value of their parents. For this reason the best two or more individuals of a population are transmitted to the new generation without changes, in a process known as elitism.

3. Mutation

The mutation is coded as a vector of random changes ΔP in all components of the offspring individuals:

$$\mathbf{P}_{new} \rightarrow \mathbf{P}_{new} + \Delta\mathbf{P} \quad (14)$$

The first component of ΔP is chosen out of the set [−1, 0, 1], while the others are limited to a predefined maximum equal to 10% of the largest value of all corresponding components. This mutation is applied to all new individuals in order to explore the vicinity of groups of similar individuals rather than explore different and faraway bottle motions.

4. Fitness

The fitness of an individual had to be related to the effectiveness in reproducing the geometrical features of the blurred image of the object. For each individual, the binarized image of the relevant bottle was obtained from the database and treated as the initial position. According to the translation and rotation values, the final and three intermediate positions (at each quarter of the motion) were calculated and the resulting images were superposed to the initial one. The resulting image was first tested on its area and discarded if the difference with the area of the blurred image was bigger than a pre-set value, typically 15% of the latter. If the areas were comparable, the resulting image was rotated to make its principal axes parallel to those of the blurred image and then superposed. The cost function was calculated as the amount of inaccuracy of the superposition, in terms of the area of the nonmatching parts, by means of the XOR operator on the two binarized images[24].

VII. COMPARISON OF DIFFERENT DEBLURRING TECHNIQUES

This work makes a comparison between different deblurring techniques. Following are tabular results obtained after the comparison.

Table 1 Comparative parameters

Algorithm	Types of blur	Performance	PSNR Value
Winner Filter	Gaussian	Worst Result	17.06
Lucy-Richardson	Gaussian	Good	21.02
Blind Image Deconvolution	Motion	Better	26.76
Using MDF	Motion	Good	24.30
Using Handling Outliers	Gaussian	Good	21.91
Using ASDSAR	Gaussian	Best	31.20
Neural Network	Gaussian, Out-of-focus	Best	30.10
PSO	Motion	Good	21.33
Median	Gaussian	Better	26.69
PSO & Gradient Search	Motion	Better	28.53
Genetic Algorithm	Gaussian	Better	25.45

VIII. DISCUSSION AND CONCLUSION

In this survey paper the various image deblurring techniques and hybrid optimization technique for imaged blurring proposed by different researchers have been discussed. It is concluded that removal of blur and noise from the image is difficult problem and the performance of deblurring technique is based on the applicant approach. The performance of deblurring algorithm is measured using quantitative performance measured such as PSNR and SNR. A higher value of PSNR is good because it means that the ratio of peak signal -to- noise is higher. The above table shows the performance of various deblurring techniques. After the survey it was observed that there are still existing scope of enhancing and handling the more sophisticated problems.

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