ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 2, Issue 1, January 2013

Blind Image De-convolution In Surveillance Systems By Genetic Programming

Miss. Shweta R. Kadu[1], Prof. A.D. Gawande[2]. Prof L. K Gautam[3]

Abstract— **surveillance systems has an important part as a Image acquisition and filtering, segmentation, object detection and tracking the object in that image. In blind image de-convolution .most of the methods requires that the PSF and the original image must be irreducible. Blurring is a perturbation due to the imaging system while noise is intrinsic to the detection process. Therefore image de-convolution is basically a post-processing of the detected images aimed to reduce the disturbing effects of blurring and noise. Image de-convolution implies the solution of a linear equation ,but this problem turns out to be ill-posed: the solution may not exist or may not be unique. Moreover, even if a unique solution can be found this solution is strongly perturbed by noise propagation. In this papers we proposed a genetic programming based blind image de-convolution Blind De-convolution algorithm can be used effectively when of distortion is known. It restores image and Point Spread Function (PSF) simultaneously. This algorithm can be achieved based on Maximum Likelihood Estimation (MLE).**

Index Terms—**Genetic programming, Image blind de-convolution , maximum likelihood , PSF.**

I. Introduction

Surveillance systems involves observation of individuals or groups of organizations. The word *surveillance* is the French word for "watching over". surveillance system has a down-stream stages those are image acquisition, segmentation, detection and tracking the object in that image. Restoration of image data is important for a number of applications, including surveillance video processing ,motion picture restoration, advancements to video capture electronics, up sampling for higher-resolution television monitors, and the removal of video compression artifacts. By de-convolution of optical blur, the quality of image or video is increases. Restoring visual information from the blurred and noisy image is essential in surveillance system. In regards of performance of blind image de-convolution firstly the image is captured. Because of the relative motion between object in the image and camera the blurring is introduce. The addition of blur is formulated by point spread function(PSF). PSF is the degree to which an optimal system blurs a point of light. This function adjust the introduced blur in the image.

In practice, every optical system has its own unique point-spread function. Certainly, our knowledge of quantum mechanics forces us to replace the idea that light is spread evenly through the PSF with a more statistical understanding. In that sense, the PSF is somewhat like a wave-function:

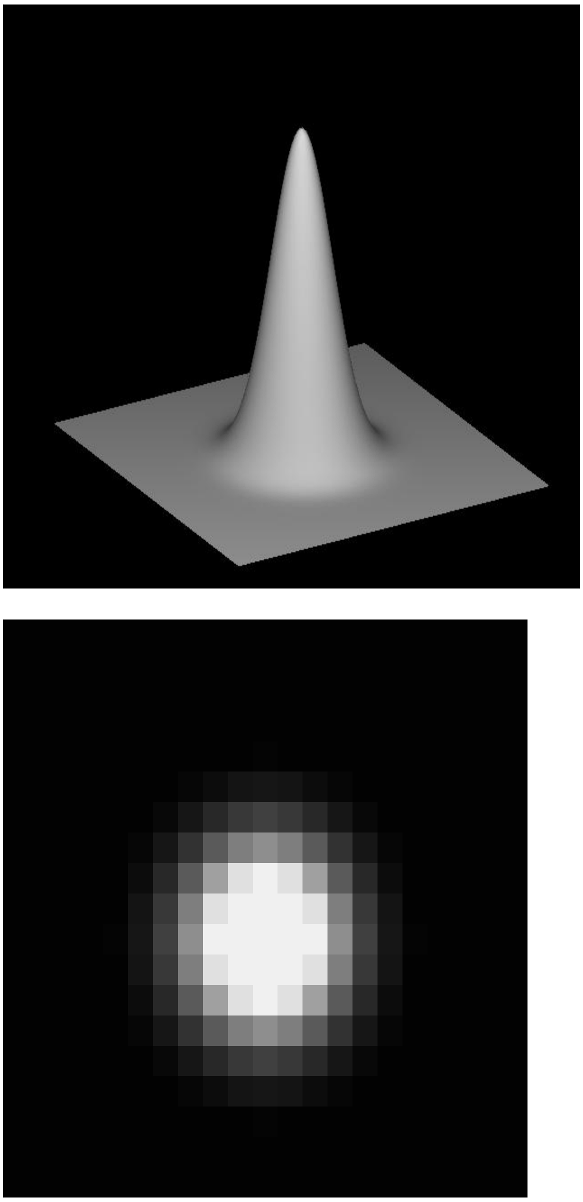

Fig1: Visual representation of a Gaussian point-spread function, left: as a 3-d surface, right: as an image

Usually an imaging system is created in such a way that the point-spread function is over-sampled, meaning its influence is spread over many pixels. It is the PSF, then, that is the limiting factor in resolution. In astronomy, this fact allows the measuring of an optical system's PSF via a long exposure of a star – in practice, a perfect point of light. Certainly, real images are not merely a single point of light. The effect of the point-spread function with a real image is to take every originating point of light from the scene and spread it into neighboring regions.

In this paper blind de-convolution for image restoration is discussed in which recovering the original image from the degraded image and also understand the image without any artifacts errors. The basic tasks of image de-blurring is to de-convolute the blurred image with the point spread function. Beyond image capturing ,the image is degraded using the low-pass filter as a Gaussian Filter and its noise .The Gaussian filter/function is used to smooth the captured image using another certain functions.

A degraded image can be approximately described by following equation[11]: **Gaussian filter g(x, y)= f(x, y) * h(x ,y) + n(x, y) ;**

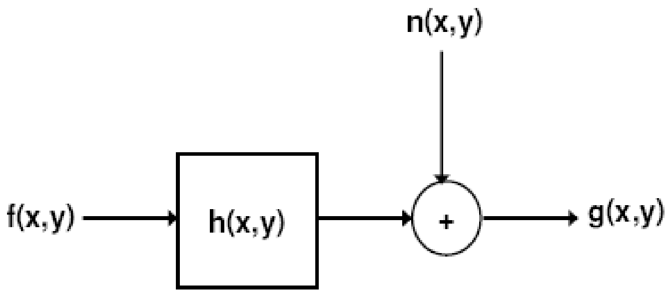

Fig:2: Degradation model

Above figure is also called as a Degradation model. In fig. where g the blurred image, h is the distortion operator called Point Spread Function , f is the original true image and n is the additive noise introduced during capturing the image.

The incomplete knowledge cannot re-store blurred image properly. For restoration of noisy blurred image it requires the fulfilled knowledge of Point Spread Function. PSF is a result of atmospheric effects ,the instrument optics, and anything else that lies between the scene being captured and the camera. The PSF affects the image in a manner called convolution , a particular type of integral. De-convolution is attempt to separate the scene from PSF and digital image .First step in this process is to identify the Point Spread Function ,it can done by careful modeling. The next step is to the actual de-convolution- to find the "truth" given the measured image and point-spread function. There are various type of de-convolution methods as Maximum likelihood Estimate(MLE), Maximum Entropy Method(MEM). But in this paper we used the MLE method. This maximum likelihood estimate(MLE) based on LR algorithm is effective when complete data of point spread function and little information about the additive noise is know. Maximum a posterior method is closely related on the MLE method. After a few iterations the MLE based method begin to amplify the noise. Wiener filtering is used to reconstruct the digital image, de-blurring the image and de-noising. Wiener filter isolates lines in a noisy image by finding an optimal tradeoff between inverse filtering and noise smoothing. it removes the additive noise and inverts the blurring simultaneously so also emphasize any lines which are hidden in the image. It operates in the Fourier Domain so that it eliminates the noise easily as the high and low frequencies are removed from the noise to leave a sharp image.

II. Genetic Programming

Genetic Programming is a stochastic search technique based on natural selection and genetics. It is also a collection of methods for the generation of computer programs that can be solved by specifying problems carefully. It works with population of individuals. genetic programming compounded breeding of computers programs, where only the relatively more successful individuals pass on genetic material to the next generation. Furthermore, GP are difficult to apply to large scale optimization problems due to it requires the large memory.

Genetic programming is a useful technique because it make developing difficult algorithms easier. To involve an algorithm using a preexisting GP , the developer writes a program having a problem-specific algorithm that takes a computer program as input and returns a measurement of how successfully that program solves the problem of interest. This problem-specific algorithm is called the Fitness Function. The solutions provided by the genetic programming may or may not be the fair solutions. So GP is a gradual process. It sort the programs and by selecting a useful part of the program and gives the better solutions. Selection is based on randomly selecting a successful program and placing those parts inside the another useful programs. The basic block diagram of GP is as follow:

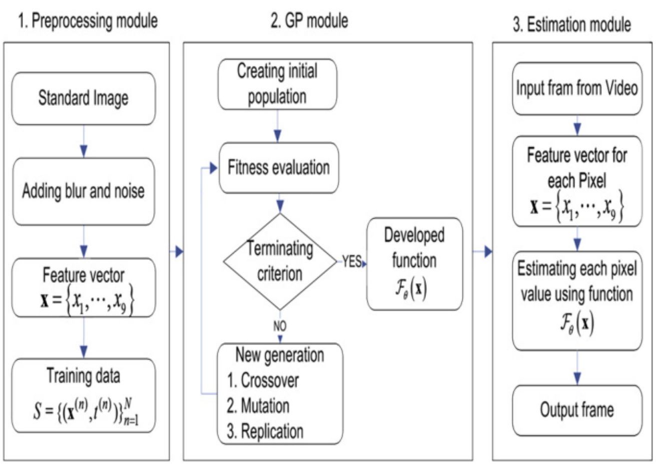

Fig. 3. Block diagram of GP

In the below figure, In initialize step the formation of feature vector is created. The standard image is given as a input to the initialize stage called as preprocessing module. By adding some noise and blur the image is degraded. For each central pixel of a degraded image g(i,j) , we picked local information from a small window W {we prefer to use window size 3×3}. From the degraded image as per pixel a 9-dimenstional feature vector **x={x1,….x9}**. Thus the training data is obtained.

Training data **S** = $\{(x^{(n)}, t^{(n)})\}^{N}_{n=1}$. (1)

The next step is calculating the fitness function. By creating population initially fitness is evaluated. As fitness cases and the actual output of a program are both numeric, the number between both is easily calculated. Conventionally, a fitness functions reports the amount of error between the tested program and the target solution, it means that the zero fitness represents the perfect program. It is standard to evaluate the maximum possible fitness.

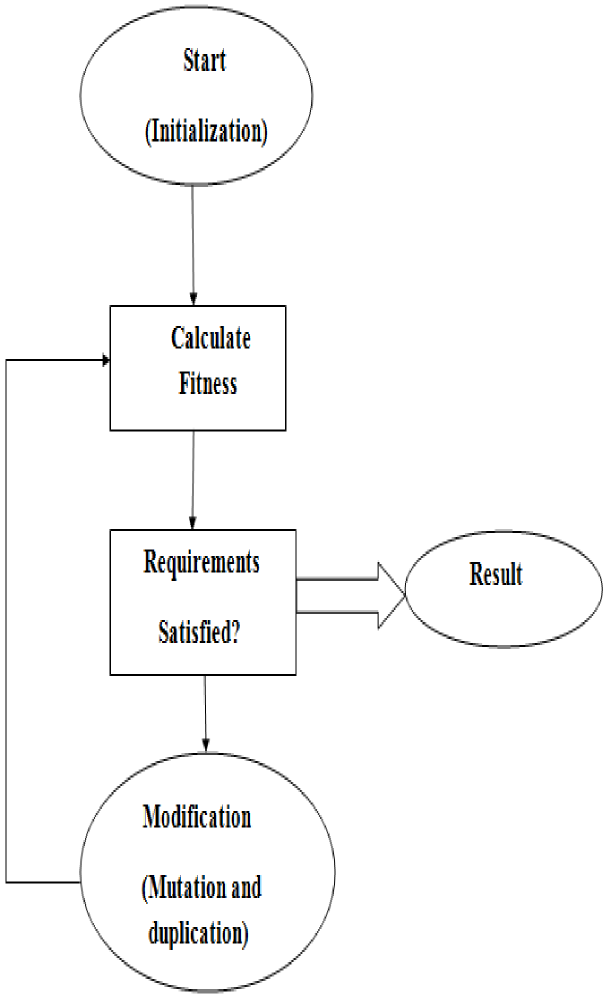

Fig 4:- Flowchart of GP

By calculating the difference between this maximum possible fitness and the measured fitness of the individual we get the perfect individual. For each new member of the population is evaluated using the problem-specific fitness function. The calculated fitness is then stored with each program for use in the next step. Lastly, counting the number of fitness cases it is hard to achieve. Stating with a small number and increase it if evolution fails. This step is called as a GP module. The selected candidates are used for the creation of next generation. Crossover, mutation, and replication operators are applied on the selected individuals to generate new population. The objective of GP module is to develop an improved performance estimator function = F_θ (x) where x$\in R^9$, y$\in R$, and θ represents a set of parameters of GP. GP has an several parameters which controls the operation of evolution that may be changes.

Parameter specification of GP :

Parameter	Value
[1] Number of Generations	30
[2] Population Size	50
[3] Initial Random Tree Creation Method	Ramped Half-and-Half
[4] Reproduction Proportion	30%
[5] Selection Method	Roulette Wheel
[6] Mating (Pairing) Method	Random
[7] CrossOver Proportion	70%
[8] CrossOver Method	SubTree Exchange
[9] Mutation Rate	7%
[10] Mutation Operation	SubTree Insertion
[11] Max Initial Random Tree Depth	3

Table:- 1

In GP module, crossover, mutation, selection, and replication operator are applied to the selected individuals to generate the new population. Crossover operator creates offspring by exchanging the genetic material between two individual parents. Crossover is more successful in the majority of tests. it helps in converging to optimal solution. In mutation process, a small part of individual often brings diversity in the solution space, which help to avoid the local minima convergence. Fitness function plays an vital role to develop the useful solution within a large search space. In next and last step the estimation function F_θ (x) by the GP module is developed, it is easy to restore the degraded image . In order to obtain a complete de-blurred and de-noised image, we need to provide input feature vector for each and every pixel to the estimator in the last module of GP.

Now we are going to discuss the main purpose of this paper, when the blur and noise is added to the image by Gaussian filter due to the high frequency the ringing effect is introduced in that blurred image. This ringing effect should be removed before restoration using edge trapping. In this paper the Maximum likelihood (ML) is the method used for parameters estimation. Its application to image de-convolution is based on the knowledge of the random properties of the detected image. It means that the probability density $P_\eta(g|f)$. If the detected image g, the PSF h, the background b are given , then $P_\eta(g|f)$ is a function only of f and the problem of image de-convolution becomes the problem of estimating these unknown parameters. The ML answers to the problem as[13] :

Definition 1:- For the detected image g the likelihood function is the function of the object f defined by :

$$L_g(f) = P_\eta(g|f) \tag{2}$$

Definition 2:- a maximum likelihood of the object *f* is any object f_{ML} which maximizes the likelihood function**:**

$$f_{ML} = \arg\max_f L_g(f) \tag{3}$$

The probability density of η for a given f is the product of a very large number of factors, so it is used as following log-likelihood function:

$$l_g(f) = \ln L_g(f) \tag{4}$$

So that the ML-estimates is also given by :

$$f_{ML} = \arg\max_f l_g(f). \tag{5}$$

III . Architecture of de-blurring the image by blind de-convolution algorithm[11]:

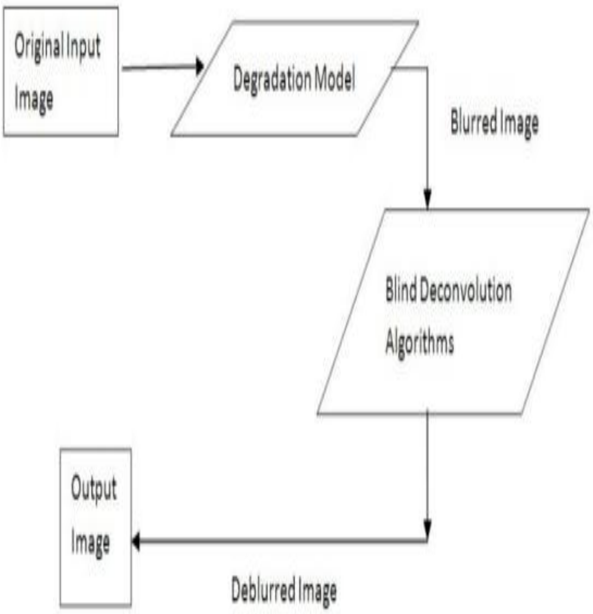

Fig 5:- Systems Architecture

The original image is degraded or de-blurred using degradation model to produce the de-blurred image. The degraded/blurred image should be an input to the de-blurring algorithm. In this paper , we are going to use blind de-convolution by genetic algorithm but the blind de-convolution algorithm is effectively used when no information of distortion is known and it restores image and PSF simultaneously. Blind de-convolution algorithm is also based on MLE.

V. Result and Discussion

The below images fig. 3 represents the result of degradation model using Gaussian blur. The sample image after applying the proposed algorithm will be as follows.

Original Image

Blurring original image

De-blurring with blind De-convolution algorithm

Fig. 5: De-blurring image with no information of PSF

The problem of image restoration by blind de-convolution is ill-posed. To produce a unique solution, *a priori* information must be utilized, such as the support of the image and PSF, non-negativity of the image, the parametric form of the PSF, and other properties of the image and PSF. Due to the ill-posed nature, these algorithms are often lack of the stability, robustness, uniqueness and convergence. With various application backgrounds, blind de-convolution remains a fascinating and challenging field.

The results have demonstrated that the proposed scheme is more accurate, generalized, and robustness as com- pared to the LR algorithm and the Wiener filter. It is anticipated that the performance of the proposed scheme can further be enhanced by including the knowledge of PSF and information extracted from existing de-convolution approaches. Then, GP can effectively combine the advantages of conventional de-blurring approaches by suppressing their weaknesses.

VI. Conclusion

In this paper Blind de-convolution for image restoration is discussed which is the recovery of a sharp version of a blurred image . Genetic programming differs from most other existing methods by only imposing weak restrictions on the blurring filter, being able to recover images which have suffered a wide range of degradations. it can be observed that the objects are detected success- fully in different frames. In order to investigate the robustness of the proposed estimator, we applied it on degraded video by adding different noises and applying different blur kernels. The restoration quality of our method was visually and quantitatively better than those of the other algorithms such as wiener Filter algorithms, and any other algorithms with which it was compared. The advantage of our proposed Blind De-convolution by genetic programming is used to de-blur the degraded image without prior knowledge of PSF and additive noise. But in other algorithms, we should have the knowledge over the blurring parameters.

REFERENCES

[1] Langdon, W.B., 2000. Size fair and homologous tree genetic programming cross- overs. Genet. Program. Evol. Mach. 1 (1/2), 95–119.
[2] Salem Saleh Al-amri et. al. "A Comparative Study for Deblured Average Blurred Images ",journal Vol. 02, No. 03, 2010, 731-733.
[3] D.Kundur and D. Hatziankos, "Blind image de-convolution, " IEEE sig. process. Mag., pp. 43-64, May 1996..
[4] Mariana S.C. Almeida and Luis B. Almeida., Blind and Semi-Blind Deblurring of Natural Images, IEEE Transaction on Image processing, Vol 19, pp.36-52, No.1, January 2010.
[5] D. Kundur and D. Hatzinakos, Blind image de-convolution revisited,IEEE Signal Processing Magazine **13**(6) (November 1996), 61–63.
[6] M.R. Banham and A.K. Katsaggelos, Digital Image Restoration, *IEEE Signal Processing Magazine* **14**(2) (March 1997), 24–41.
[7] Langdon, W.B., 2000. Size fair and homologous tree genetic programming cross- overs. Genet. Program. Evol. Mach. 1 (1/2), 95–119.
[8] Genetic programming based blind image de-convolution for surveillance systems Muhammad TariqMahmooda, AbdulMajid b, JongwooHan a, YoungKyuChoi a,n 13september 2012.
[9] Bes-dok,E.,2004.A new method for impulsive noise suppression from highly distorted image by using Anfis.Eng.Appl.Artif.Intell.
[10] Xu, Z., Lam, E.Y. Maximum a posteriori blind image de-convolution wit hHuber? Markov random-field regularization. Opt. Lett. 34 (9), 1453–1455, 2009.
[11] D. Srinivasa Rao et al. / International Journal of Engineering Science and Technology v (IJEST)-3 March 2011.
[12] Genetic Programming: Theory, Implementation, and the Evolution of Unconstrained Solutions Alan Robinson, pp 11-13, May 2011.
[13] Image De-convolution M. Bertero and P. Boccacci DISI, Universita' di Genova, Via Dodecaneso 35, I-16146 Genova, Italy, pp-8-10 1998.
[14] Petrovic, N.I., Crnojevic, V. Universal impulse noise filter based on genetic programming. IEEE Trans. Image Process. 17 (7), 1109–1120.,2008.
[15] Banzhaf, W., P. Nordin, R. Keller, and F. Francone. 1998. Genetic Programming: An Introduction. Morgan Kaufmann, San Francisco, CA.

First Author Miss S.R. Kadu M.E pursuing Department of Computer Science and Engineering, Sipna College of Engineering and Technology, Amravati, Maharashtra India.

Second Author Prof A.D. Gawande M.E., Ph.d ., Department of Computer Science and Engineering, Sipna College of Engineering and Technology, Amravati Maharashtra India.

Third Author Prof L. K Gautam M.E. ., Department of Computer Science and Engineering, Sipna College of Engineering and Technology, Amravati Maharashtra India.