# Extreme Intelligent for Laparoscopic Surgery on Medical Deconvolution using Platform Prediction together with Artificial Autofocusing

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Abstract— **This research proposes a new technique for Laparoscopic autofocus as follows: (1) we propose blur area detection in image on Laparoscopic Surgery (LS) by using discrete-time Fourier series together with artificial intelligent recognize in blur image. (2) Plate Resorution Sector Coordinate (PRSC) technique and pattern recognition processing are used for searching blur area. (3) The image enhancement is adjusted by artificial automatic-focus with Kernel Platform Prediction algorithm. This processing is more quickly than hardware so that it is intelligent to solve the image problem in real-time. If system can not found any blur areas the adaptive status is displayed in monitor immediately. (4) This process can be used with any kind of moicroscope. We are study performance $(2D)^2$PCA algorithms for recognition in detect blurring area while move Laparoscopic Surgery . One hundred blur images from Laparoscopic Surgery camera and actualize image enhancement with artificial automatic-focus was used for this experiment. The results shown the accuracy of blur detection 99.67 percentage. The $(2D)^2$PCA algorithm is faster for recognize and detect blur area in real-time. The automatic focus process uses Kernel Platform Prediction algorithm together with Multiscale Pointwise Product has more efficiency than other methods. We use Gaussian Fitting for calculate for short range in adjust by hardware pass the circuit. Moreover, the adjustable by manual hardware that slow and unstable is decreased. The processing's speed of this method is faster than the conservative method (manual adjust) 75.33 percentage base on physical condition of patient. This experimental is working base on Quality Medical Standards (QMS) of Faculty of Medical, Canterbury University.**

***Keywords- Automatic Focusing; Laparoscopic Surgery; real-time ; Deconvolution algorithm; Pattern Recognition Algorithm.***

## I. INTRODUCTION

The medical device development is first priority of modern technology which integrates knowledge in several fields for instant electronic, computer science, medical Engineering etc. Laparoscopic surgery, also called minimally invasive surgery (MIS), is a modern surgical technique in which operations in the abdomen are performed through small incisions. Keyhole surgery makes use of images displayed on TV monitors to magnify the surgical elements. The laparoscopic approach is intended to minimize post-operative pain and speed up recovery time. However , the procedure is more difficult in The special characteristic of Laparoscopic Surgery is high capability to visualize small structures which is established by the quality of the optical visualization and precision lenses. Surgeons often use small camera in operation which has effect to a small lesion and rapidly recover for patients. Laparoscopic Surgery is put into the patient through a small lesion to target organs. The signal image is transferred to TV monitor. The movement of surgeon has affect to the error focus on camera. The image may be blurred for one moment that is normal limitation in hardware and software.

**Figure 1.** Show function of Laparoscopic Surgery

Our method support visualization for Laparoscopic Surgery (LS) on robotic machine. However, it supports the low resolution camera and expands performance for high resolution camera. Laparoscopic always uses in several surgery cases such as Anterior Discectomy, Cholecystectomy, Gallstones. The brightness of visible viewer in existing camera improves surgery procedure with high accuracy but it is costly.

The power of a lens ($P$) which $1/f$ when $f$ as given in meters units so, $P$ is in diopters. By definition, the *focal plane* is that plane in object space where a stare point will form an in-focus visible on the image plane. When stare point moves away from the origin to a position ($x_0$, $y_0$) then the spot image moves to new position ($x_i$, $y_i$) by $x_i = Mx_0$ and $y_i = My_0$ when $M=(d_i/d_f)$ It is the magnification of the system .It has effect to focus distance which must to re-adjust. This event makes distress vision while surgery with Laparoscope. This paper offers the advance algorithms for visible enhancement in Surgical Telescope Visualizes (STV) field which is called Artificial Automatic Focusing Model (AFFM). The AFFM provides the improvement of Laparoscopic images with faster and more accurate.

## II. LITERATURE REVIEW

Laparoscopy is performed to examine the abdominal and pelvic organs to diagnose certain conditions and depending on the condition can be used to perform surgery. Laparoscopy is commonly used in gynecology to examine the outside of the uterus, the fallopian tubes,and the ovaries particularly in pelvic pain cases.

### A. *The lens of Laparoscopic Surgery*

The stare point function for take on specific position in focus of normal medical camera

$$\frac{1}{d_f}+\frac{1}{d_i}+\frac{1}{f} \quad (1)$$

where *f* is focus length of the lens or called the *lens equation.* The focus length is an intrinsic property of any particular lens. It is distance from lens to image plane when a stare point located at infinity is visual in focus as $d_f = \infty \Rightarrow d_i = f$ by symmetry $d_i = \infty \Rightarrow d_f = f$ From problem of magnification *M* of the system we can be manipulated to form a set of formula which useful in the optical setting as

$$f=\frac{d_i d_f}{d_i+d_f}=\frac{d_i}{M+1}=d_f\frac{M}{M+1}, d_i=\frac{fd_f}{d_f-f}=f(M+1)$$

$$d_f=\frac{fd_i}{d_i-f}=f\frac{(M+1)}{M} \quad (2)$$

Where $d_i$ as fixed by the optical tube length of the telescope. The coherent stare point function will taking by a lens with a circular aperture of diameter $a$ in coherent light of wavelength $\lambda$ and $j_1(x)$ is the first order Bessel function.

$$r_0=\frac{\lambda d_i}{a} \quad , \quad r=\sqrt{x_i^2+y_i^2} \quad , \quad h(r)=2\frac{j_1[\pi(r/r_0)]}{\pi(r/r_0)} \quad (3)$$

### B. *Blur detection using low-pass filtering in the Fourier Domain*

The low pass filter can suppress blur area in an image which alternative to spatial domain filtering. It uses to implement the low pass filtering in the Fourier domain. The low pass filter transfer function $H(u,v)$ is multiplied by the Fourier transform $G(u,v)$ of the image as

$$F(u,v)=H(u,v)G(u,v) \quad (4)$$

Where $F(u,v)$ as the Fourier transform of the filtered image *f(x,y)* that we wish to recover. The *f(x,y)* function can be obtained by taking the inverse Fourier transform. An ideal low-pass filter is designed by assigning a frequency cutoff value

$$H(u,v)=\begin{cases}1 & \text{if } D(u,v)\le D_0 \text{ otherwise}\\ 0\end{cases} \quad (5)$$

Where $D(u,v)$ as the distance of a stare point from the origin in the Fourier domain.

### C. *Plate Resorution Sector Coordinate (PRSC)*

Our approach using three places as representative of whole image. Plate Sector Coordinate 1,2,3 tested blur in low-pass filtering in the Fourier Domain. This area will used to make decisions for begin artificial automatic focusing with application algorithm or transfer signal to hardware controler.

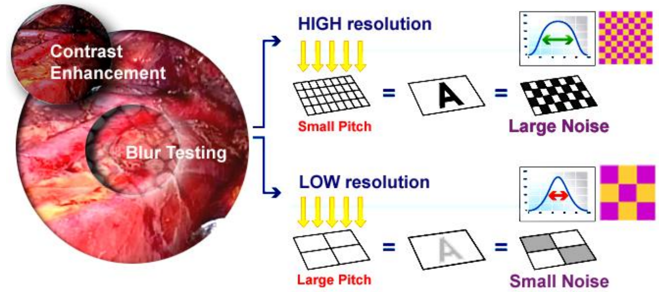


**Figure 2.** Show Resorution Plate Sector Coordinate (PRSC)

The Contrast Enhancement for testing place will help capture blur boundary precisely. We use contrast algorithm together with color remapping as

$$I_v=\frac{I_{x,y}-I_{avg}}{255}, r'=\frac{I_{c,EN}}{\tau}r, g'=\frac{I_{c,EN}}{\tau}g, b'=\frac{I_{c,EN}}{\tau}b \quad (6)$$

Where $\tau$ as the V component pixel value of HSV color space that essentially is the maximum value among the original *rgb* values at each pixel location.

## II. PREPARE METHOD

This research is used four algorithms in pattern recognition in train and testing process for blur detection as follows;

### D. *Two Dimension Principle Component Analysis Algorithm*

Consider an *m* by *n* random image matrix $A$. Let $X \in R^{nxd}$ be a matrix with orthonormal columns, $n \ge d$. Projecting $A$ onto $X$ yields an *m* by *d* matrix $Y = AX$. In 2DPCA, the total scatter of the projected samples was used to determine a good projection matrix $X$ .That is, the following criterion is adopted:

$$\begin{aligned} J(x) &= trace\{E[(Y-EY)(Y-EY)^T]\} \quad (7)\\ &= trace\{E[(AX-E(AX))(AX-E(AX))^T]\}\\ &= trace\{X^T E[(A-EA)^T(A-EA)]X\}\end{aligned}$$

where the last term in this equation as results from the fact that trace ( $AB$ ) = trace ( $BA$ ), for any two matrices [1]. When *image covariance matrix* $G=E[(A-EA)^T(A-EA)]$, which is an *n* by *n* nonnegative definite matrix. Suppose that there are *M* training visual images, denoted by *m* by *n* matrices $A_k (k=1,2,...M)$, and denote the average image as

$$\bar{A}=\frac{1}{M}\sum_k A_k . \quad (8)$$

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then $G$ can be evaluated by

$$G = \frac{1}{M}\sum_{K=1}^{M}(A_k - \overline{A})^T(A_k - \overline{A}) \quad (9)$$

It has been proven that the optimal value for the projection matrix $X_{opt}$ is composed by the orthonormal eigenvectors of $X_1,\dots,X_d$ of $G$ corresponding to the $d$ largest eigenvalues. Because the size of G is only $n$ by $n$, computing its eigenvectors is very efficient. Also, like in Principle Component Analysis the value of $d$ can be controlled by setting a threshold as follows;

$$\left(\sum_{i=1}^{d}\lambda_i / \sum_{i=1}^{n}\lambda_i\right) \geq \theta \quad (10)$$

where $\lambda_1, \lambda_2, ..., \lambda_n$ is the $n$ biggest eigenvalues of $G$ and $\theta$ is a pre-set threshold.

*E. Alternative Two Dimension Principle Component Analysis Algorithm*

$$A_k = [(A_k^{(1)})^T (A_k^{(2)})^T ... (A_k^{(m)})^T]^T$$

$$\text{and } \overline{A} = [(\overline{A}^{(1)})^T (\overline{A}^{(2)})^T ... (\overline{A}^{(m)})^T]^T \quad (10)$$

where $A_k^{(1)}$ and $\overline{A}^{(i)}$ denote the $i$-th row vectors of $A_k$ and $\overline{A}$ respectively.

$$G = \frac{1}{M}\sum_{K=1}^{M}\sum_{i=1}^{m}(A_k^{(i)} - \overline{A}^{(i)})^T(A_k^{(i)} - \overline{A}^{(i)}) \quad (11)$$

This equation reveals that the image covariance matrix $G$ can be obtained from the outer product of row vectors of images, assuming the training images have zero mean. $\overline{A} = (0)_{mxn}$ For that reason, we claim that original of Alternative Two Dimension Principle Component Analysis Algorithm is working in the row direction of images. A natural extension is to use the outer product between column vectors of images to construct $G$.

$$A_k = [(A_k^{(1)})(A_k^{(2)})...(A_k^{(m)})] \text{ and}$$

$$\overline{A} = [(\overline{A}^{(1)})(\overline{A}^{(2)})...(\overline{A}^{(m)})] \quad (12)$$

where $A_k^{(j)}$ and $\overline{A}^{(j)}$ denote the $j$-th column vectors of $A_k$ and $\overline{A}$ respectively. Then an alternative definition for image covariance matrix $G$ is:

$$G = \frac{1}{M}\sum_{k=1}^{M}\sum_{j=1}^{n}(A_k^{(j)} - \overline{A}^{(j)})(A_k^{(j)} - \overline{A}^{(j)})^T \quad (13)$$

Next,we will show how equation can be derived at a similar way as in Alternative Two Dimension Principle Component Analysis Algorithm. Let $Z \in R^{mxq}$ be a matrix with orthonormal columns. Projecting the random matrix $A$ onto $Z$ yields a $q$ by $n$ matrix $B \in Z^T A$. The following criterion is adopted to find the optimal projection matrix $Z$ as

$$J(Z) = trace\{E[(B - EB)(B - EB)^T]\} \quad (14)$$

$$= trace\{E[(Z^T A - E(Z^T A))(Z^T A - E(Z^T A))^T]\}$$

$$= trace\{E[(Z^T E(A - EA)(A - EA)^T]Z\}$$

From this equation will alternative definition of image covariance matrix $G$ is :

$$G = E[(A - EA)(A - EA)^T] = \frac{1}{M}\sum_{k=1}^{M}(A_k - \overline{A})(A_k - \overline{A})^T \quad (15)$$

$$G = \frac{1}{M}\sum_{k=1}^{M}\sum_{j=1}^{M}(A_k^{(j)} - \overline{A}^{(j)})(A_k^{(j)} - \overline{A}^{(j)})^{(T)}$$

The optimal projection matrix $Z_{opt}$ can be obtained by computing the eigenvectors $Z_1,\dots,Z_q$ of this equation corresponding to the $q$ largest eigenvalues. $Z_{opt} = Z_1,\dots,Z_q$ The value of $q$ can also be controlled by setting a threshold. Because the eigenvectors of Equation only reflect the information between columns of images, we say that the alternative 2DPCA is working in the column direction of images.

*F. Double Two Dimension in Principle Component Analysis Algorithm*

$(2D)^2$PCA and alternative 2DPCA only works in the row and column direction of images respectively. $2D^2$PCA learns an optimal matrix $X$ from a set of training images reflecting information between rows of images, and then projects an $m$ by $n$ image $A$ onto $X$, yielding an $m$ by $d$ matrix $Y=AX$ Similarly, the alternative 2DPCA learns optimal matrix Z reflecting information between columns of images, and then projects $A$ onto Z, yielding a $q$ by $n$ matrix $B=Z^TA$ . In the following, we will present a way to simultaneously use the projection matrices $X$ and $Z$ Suppose we have obtained the projection matrices $X$ and $Z$ projecting the $m$ by $n$ image $A$ onto $X$ and Z simultaneously, yielding a $q$ by $d$ matrix $C$.

$$C = Z^T AX \quad (16)$$

The matrix $C$ is also called the coefficient matrix in image representation, which can be used to reconstruct the original image $A$ , by

$$A = ZCX^T \quad (17)$$

When used for face recognition, the matrix $C$ is also called the feature matrix. After projecting each training image $A_k (k = 1, 2, ...M)$ onto $X$ and $Z$, we obtain the training feature matrices $C_k (k = 1, 2, ...M)$. Given a test face image Here the distance between $C$ and $C_k$ is defined by

$$d(C, C_k) = \|C - C_k\| = \sqrt{\sum_{i=1}^{q}\sum_{j=1}^{d}(C^{(i,j)} - C_k^{(i,j)})^2} \quad (18)$$

*G.Artificial Automatic Focus using Rush Deblurring technique and deconvolution in visible inhancement.*

Iterative Van Cittert Algorithm is unstable performance after an additional number of iterations is utilized, and the subsequent image would look shaky. The equation of the Van Cittert algorithm is

$$f^{n+1} = f^n + \vartheta(g - Hf^n) \quad (19)$$

where $f^{n+1}$ is the new estimate from the previous one $f^n$ , $g$ is the blurred image, $n$ is the number of the step in the iteration and $H$ is the blur filter PSF , $\vartheta$ is constant that controls and regularize the sharpening amount of the algorithm.

Iterative Landweber Algorithm ; it has an extra variable $H^T$ which is the transpose of the point spread function (PSF). The use of this variable results a more stable algorithm against noise and more reliable. This equation as follow:

$$f^{n+1} = f^n + \vartheta H^T(g - Hf^n) \quad (20)$$

The equation of the optimized Landweber algorithm can be described in the subsequent equation:

$$f^{n+1} = f^n + \vartheta H(g - Hf^n) \quad (21)$$

Iterative Richardson-Lucy Algorithm ; it does not concern the type of noise affecting the image. In addition, it does not require any information from the original clean image and it is an iterative algorithm.

$$f^{n+1} = f^n \vartheta H^o\left(\frac{g}{Hf^n}\right) \quad (22)$$

where $n$ is the number of the step in the iteration and $H$ is the blur filter PSF,and $H$ is the blur filter (PSF) and $H^o$ is the adjoint of $H$. The first iteration use the value of $f^n = g$

Iterative Poisson Map Algorithm; the Poisson Map uses an exponential operation in the restoration process and, it uses an integer which is (1) for the subtraction operation. The equation of the Poisson Map algorithm as follow:

$$f^{n+1} = f^n e^{[H^o(\frac{g}{Hf^n}) - 1]} \quad (23)$$

Laplacian Sharpening Filters ; it comes to image sharpening; image sharpening is also a term of image deblurring. Laplacian filter is a 3x3 matrix that comes in illustrates the types of Laplacian kernels.

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 1 & -8 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 4 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

The Laplacian formula for the (-4) and (-8) core matrixes as

$$F = I - [I \otimes LK] \quad (24)$$

where $F$ is the restored image, $I$ is the degraded image by blur, $LK$ is Laplacian kernel, and $\otimes$ is the convolution process. Besides, The Laplacian formula for the (9) core matrix can be described as:

$$F = I \otimes LK \quad (25)$$

We use Point Spread Function (PSF) to be computed earlier to the deblurring procedure which is Gaussian PSF:

$$h_g(m,n) = e\frac{m^2 n^2}{2\sigma^2} \rightarrow h(m,n) = \frac{h_g(m,n)}{\sum m \sum n^{hg}} \quad (26)$$

Where $\sigma$ is the restored image is equal to 1.

*H. Artificial Automatic Focusing using Kernel Prediction*

A motion blur is generally modeled as B=KxL+N where $B$ is a blurred image**,** $K$ is a motion blur kernel or a point spread function (PSF), $L$ is a latent image, $N$ is unknown noise introduced during image acquisition, and x is the convolution operator. In blind deconvolution, we estimate both $K$ and $L$ from $B$. The overall process of blind deconvolution method is an algorithm summarizing the process can also be found in the supplementary material to progressively refine the motion blur kernel. Our method iterates two steps are Kernel prediction, and deconvolution process. We is beginning in Kernel prediction step by compute gradient direction platform $\{P_x P_y\}$ of blurred images fallow the $x$ and $y$ directions which predict salient edges in $L$ with noise suppression in smooth regions. The input of the prediction step is the estimate of $L$ obtained in the deconvolution step of the previous iteration. In the kernel estimation step, we estimate $K$ using the predicted gradient direction platform $\{P_x P_y\}$ together with direction gradient platform of blurred medical image $\{P_x P_y\}^T$. We obtain an estimate of $L$ using $K$ and $\{P_x P_y\}^T$ in the deconvolution process with a Gaussian which will be processed by the prediction step of the next iteration. We estimate the image gradient direction platform $\{P_x P_y\}$ of the latent image $L$ in which only the salient edges remain and other regions have zero gradient direction platform which only the salient edges have influences on optimize of the kernel because convolution of zero gradients is always zero regardless of the kernel. We use a shock filter to restore strong edges in $L$ as equation.

$$\ell_t + 1 = \ell_t \text{sign}(\Delta \ell_t) || (\lambda_t) \text{dt} \quad (27)$$

Where $\ell_t$ is an image at time $t$, and $\Delta \ell_t$ and $\lambda_t$ are the Laplacian and gradient of $\ell_t$ , respectively. $dt$ is the time step for a single evolution. The rate estimate an $m*m$ kernel, we need the information of blurred edges in at least $m$ different directions. We construct the histograms of gradient magnitudes and directions for each $\Omega L'$ while $L'$ as

$$\arg\min_L \{|| B-K*L || +_{\rho L}(L)\} \quad (28)$$

by $\rho L$ are regularization terms. We estimate the latent image $L$. In the deconvolution step from a given kernel $K$ and the input blurred image $B$. We will use the energy function.

$$f_L(L) = \sum_{\Omega*} \omega_*[|| K * \Omega * L - \Omega * B ||^2)] + \alpha || \lambda L ||^2 \quad (29)$$

Where $\Omega_* \in \{\Omega_0, \Omega_x, \Omega_y, \Omega_{xx}, \Omega_{xy}, \Omega_{yy}\}$ denotes the partial derivative operator in different directions and orders, $\omega_* \in \{\omega_0, \omega_1, \omega_2\}$ is a weight for each partial derivative, and $\alpha$ is a weight for the regularization term. While a higher resolution we start prediction of sharp edges with an upsampled version of the deconvolved image obtained at a coarser resolution estimate a motion blur kernel using the predicted gradient direction platform $\{P_x P_y\}$ we minimize the energy function

$$f_K(K) = \sum_{(P_*, B_*)} \omega_* || K * P_* - B_* ||^2 + \beta || K ||^2 \quad (30)$$

Where $\omega_* \in \{\omega_1, \omega_2\}$ denotes a weight for each partial derivative. $P_*$ and $B_*$ vary among

$$(P_*, B_*) \in \{(P_x, \Omega_x B), (P_y, \Omega_y B), (\Omega_x P_x, \Omega_{xx} B),$$

$$(\Omega_y P_y, \Omega_{yy} B), ((\Omega_x P_x + \Omega_y P_x)/2, \Omega_{xy} B)\} \quad (31)$$

While $K^* P_* \text{-} B_*$ forms a mapping and we define

$$\| I \|^2 = \sum_{(x,y)} I(x,y)^2 \quad (32)$$

for direction platform $I$, where $(x,y)$ indexes a pixel in $I$. $\beta$ is a weight for the regularization. We can generate to matrix form:

$$fk(\mathrm{k}) = \|\mathrm{Ak} - \mathrm{b}\|^2 + \beta \| \mathrm{k} \|^2 \quad (33)$$

$$= (\mathrm{Ak} - \mathrm{b})^T (\mathrm{Ak} - \mathrm{b}) + \beta \mathrm{k}^T \mathrm{k}$$

where $A$ is a matrix consisting of five $P_*$ and $k$ is a vector of representing the motion blur kernel $K$, and $b$ is a vector in consisting of five $B_*$ the gradient of $fk$, defined by

$$\frac{\Omega fk(\mathrm{k})}{\Omega \mathrm{k}} = 2A^T Ak + 2\beta k - 2A^T b \quad (34)$$

It should be evaluated many times in the minimize process. Kernel Prediction process help range of adjust narrow in $z$-axis focus which increase speed in automatic focusing and decrease adjust from hardware device. It is effect to rapid in processing.

*I.Automatic Focusing using Gaussian Fitting*

The autofocus function is computation to accuracy in adjust visible capability from Laparoscopic Surgery to monitor.The properties of the Gaussian function make it useful for fitting the autofocus function data. Suppose $f_1$,$f_2$ and $f_3$ are the autofocus function values measured at $Z_1$,$Z_2$, and $Z_3$ respectively:

$$f_1 = f(Z_1),\ f_2 = f(Z_2),\ f_3 = f(Z_3),\ Z_1 \neq Z_2 \neq Z_3 \quad (35)$$

Then the fitted Gaussian and its maximum value are

$$f(\mathrm{z}) = \mathrm{A}\ \exp\left(-\frac{(z-\mu)^2}{2\sigma^2}\right) \text{ and } f_{\max}(z) = f(\mu) = A \quad (36)$$

The problem is to find $\mu$ ,which is the Z coordinate to $f_{\max}$ Since we have

$$\ln(f_i) = \ln(A) - \left(-\frac{(z-\mu)^2}{2\sigma^2}\right) \text{ where i=1,2,3} \quad (37)$$

$$\ln(f_2) - \ln(f_1) = \frac{(z_1-\mu)^2 - (z_2-\mu)^2}{2\sigma^2} \quad (38)$$

$$\ln(f_3) - \ln(f_2) = \frac{(z_2-\mu)^2 - (z_3-\mu)^2}{2\sigma^2} \quad (39)$$

The solution can be derived as

$$\mu = \left\{ \begin{array}{l} \frac{1}{2}\frac{B\cdot(z3+z2)-(z2+z1)}{B=1}, if\ (z3-z2)=(z2-z1) \\ \frac{1}{2}\frac{B\cdot(z_3^2-z_2^2)-(z_2^2-z_1^2)}{B\cdot(Z3-Z2)-(Z2-Z1)}, otherwise \end{array} \right\} \quad (40)$$

$$Where\ \mathrm{B} = \frac{\ln(f_2) - \ln(f_1)}{\ln(f_3) - \ln(f_2)} \quad (41)$$

*J .Artificial Automatic Focusing Model*

In the first Step, we are training blur recognition with image in case of previous surgery which has physical characteristics similarity of the patients such as gender, age, physical organisms in disease. This step will beginning use contract image from camera and blur recognition with (2D)²PCA algorithms. Second step, Blur detection on visible image in Plate Resolution Sector Coordinate (PRSC) if find blur in area#1 or area#2 or area#3 then uses Artificial Automatic Focusing with *Rush Deblurring Technic and deconvolution by use range of Kernel Prediction value* If system find blur area in the second time then Artificial Automatic Focusing using Gaussian Fitting. It will re-calculate focusing and sent signal to microcontroller. The system will control with manual hardware which is slowly than software operation.

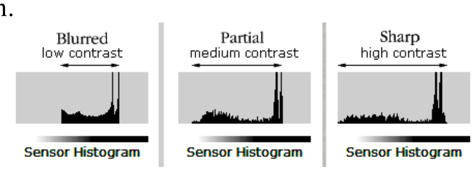


**Figure 4.** Show histogram value difference in three levels.

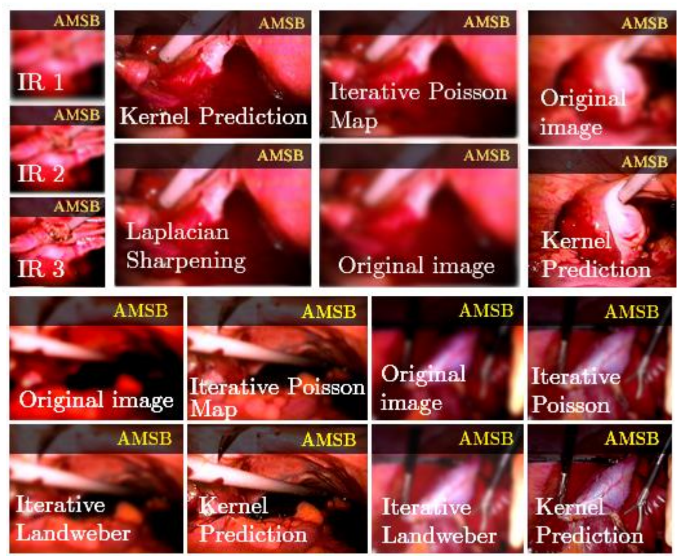


**Figure 5.** Show result of experimental in artificial automatic focusing in Laparoscopic Surgery and deblur processing.

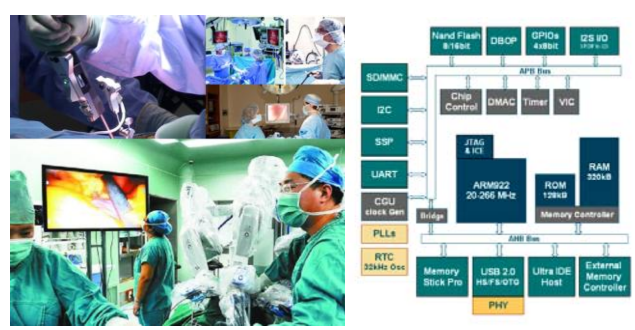

**Figure 6.** automatic focusing in Laparoscopic Surgery and gaussian value transmitter microprocessor

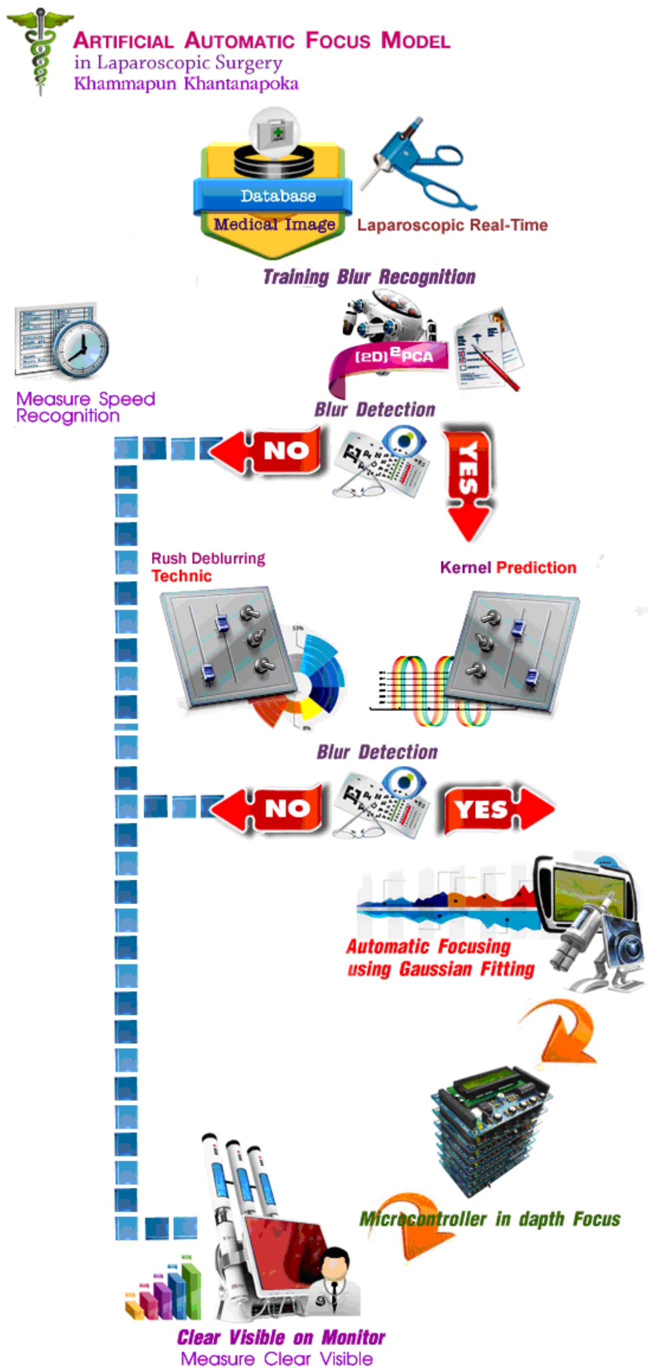


**Figure 7.** Show working in Laparoscopic Surgery

## IV. RESULT OF THE EXPERIMEMT

When $(2D)^2$PCA representation and blur recognition achieves in higher recognition accuracy than 2DPCA generation method while it reduced coefficient set for image representation than other technique. This experimental take PC machine on Intel i5 CPU and 40 GB memory. We are training and testing with 100 medical images which is blurring. It can define blur place in image exactly and classification. It takes less computation. We test with image from Laparoscopic camera. We use data set of patients from medical center AMC.

TABLE 1. SHOW RESULT OF WHOLE EXPERIMENTAL

| Method | Accuracy(%) | Dimension | Time(s) |
|---|---|---|---|
| 2DPCA | 100 | 120 x 100 | 3.98 |
| $(2D)^2$PCA | 100 | 120 x 100 | 2.31 |
| In deblur process of model | | Quality Focus | Time(s) |
| Kernel Prediction | | Excellence | 2.14 |
| Iterative Landweber Algorithm | | Good | 2.82 |
| Iterative Richardson-Lucy Algorithm | | Good | 2.77 |
| Iterative Poisson Map Algorithm | | Good | 2.63 |
| Iterative Van Cittert Algorithm | | Fair | 2.47 |
| Laplacian Sharpening Filters | | Good | 0.92 |
| Gaussian Fitting ( manual adjust ) | | Good | 5.54 |

In summary, we found the various algorithm can solve the problem of deblur image ranking respectively by high to low quality: 1) Laplacian Sharpening Filters 2) Iterative Poisson Map Algorithm 3) Iterative Richardson-Lucy Algorithm 4) Iterative Richardson-Lucy Algorithm 5) Iterative Landweber Algorithm 6) Kernel Prediction which the picture quality is very good but the long time. For images a high degree of blur,it will adaptive to manual adjust with semi manual control pass transmitter microprocessor. Our experiment use Gaussian Fitting when over time 4.00(s). It can be used effectively in the Laparoscopic Surgery. It helps the doctor to be comfortable, accurate and speedy in real-time.

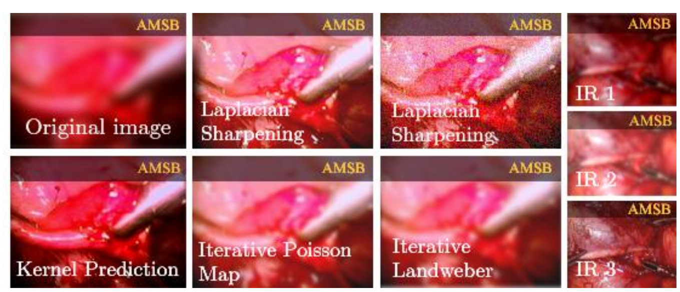


**Figure 8 :** Show result of experimental in artificial automatic focusing in Laparoscopic Surgery

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