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Four Projections CMOS Linear Image Sensor Tomographic Image Reconstruction

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Graphical abstract

Abstract

This study focused on developing software for image reconstruction system of optical image data obtained from four projections of CMOS linear image sensors by using MATLAB. Four projections of collimated light beams at least must be used in order to avoid aliasing and smear effect that may be appeared on the reconstructed image obtained. The image reconstruction is based on linear back-projection method where transpose matrix, and pseudo-inverse matrix are used to solve inverse matrix problems in MATLAB. Results were compared between both inverse problem calculation methods selected. It was discovered that transpose matrix method performs better than pseudo-inverse matrix for a high resolution images. A graphical user interface has been implemented, it is capable to reconstruct image from raw data collected from sensor. Reconstruction results demonstrated in most cases are able to produce an adequate image for further analysis by user.

Keywords: Optical tomography; linear back-projection; CMOS linear image sensor

Abstrak

Tumpuan kajian ini adalah untuk membina sistem perisian iaitu sistem penghasilan semula imej daripada data imej optik yang diperoleh dari empat unjuran pengesan oleh pengesan imej lelurus CMOS dengan menggunakan MATLAB. Pemancaran cahaya secara selari harus diambil kira sekurang-kurangnya empat unjuran supaya imej yang lebih berkualiti dapat dihasilkan. Penghasilan semula imej adalah berasaskan kaedah unjuran balik linear yang menggunakan MATLAB untuk menyelesaikan masalah matriks songsang dengan cara alihan matriks dan matriks songsang pseudo. Keputusan tersebut dibandingkan antara kaedah alihan matriks yang dipilih. Ia didapati bahawa kaedah pengiraan songsang menunjukkan hasil yang lebih baik dari matriks songsang pseudo bagi imej resoluti tinggi. Antaramuka grafik komputer telah dirangka bertujuan memudahkan pengawalan oleh pengguna untuk menghasilkan semula imej daripada data mentah yang diperoleh dari sensor. Imej yang direka semula dalam kebanyakkan kes telah dapat dihasilkan untuk analisis lanjut oleh pengguna.

Kata kunci: Tomografi optik, unjuran balik linear; sensor imej lelurus CMOS

■1.0 INTRODUCTION

Tomography process consists of cross-sectioning image system based on particular plane for diagnose purpose adopted from computed-tomography (CT) system in analysis of human body.[1] In fact, several researches already been carried out to investigate a process inside a pipeline or conveyor by measuring particles flow profile, velocity profile, or particle concentration performance noninvasively using process tomography.[2,3,4] However, accuracy of image obtained often depends on the type of sensors used, the image reconstruction techniques applied and the number of projections data collected. The concept of optical tomography involved in this study is the process of measurement taking around the edge of an object to determine the particle distribution, object orientation, or the shape or size of an object presence inside a pipe.

The type of sensor used will determine the characteristics of the object present. CMOS linear image sensor S10077 which designed for image input applications has been used in data acquisitions for this study. There are four projections with collimated light beams through CMOS linear image sensor S10077 need to be considered for image reconstruction problem where the analysis aims to compare two different calculation methods using transpose matrix and pseudo inverse matrix. In order to generate the image as an output, optical tomography deals with mathematical relationship of image reconstruction algorithm. The effectiveness for selected calculation methods can be seen in reconstructed image based on linear back-projection algorithm.[5]

1.1 Optical Tomography

The term tomography was originated from the Greek word, tomos which depicts the idea of "part" or "section".[1] Optical tomography is one of computed tomography system that creates a digital volumetric model of an object by reconstructing images made from light transmitted and then scattered through an object. Optical tomography is also familiar with other term which is diffuse optical tomography (DOT), photon migration tomography (PMT), photon migration imaging (PMI), or diffuse photon density wave (DPDW). This system has very good potentials in medical imaging applications since human tissues are semi-transparent media. Moreover, optical tomography can be considered as an attractive method since it is used as alternative for harmful radiation like X-ray, expensive and not really flexible imaging problem. Optical tomography system now can be found in some other biomedical imaging applications for examples, breast cancer screening, brain tissue oxygenation level monitoring in newborn babies and studies of functional brain activation.[6]

1.2 Linear Back Projection

Linear back-projection or simply called LBP can be classified as the simplest reconstruction algorithms for cross-section of image plane from the projection data. The generation of concentration profile in LBP is the combination of computed sensitivity maps and projections data obtained from each sensor. The sensitivity maps are modeled in matrices form used for image plane representation.[7] The results from reconstruction using LBP methods are the presence of objects or materials where can be seen in form of images. Assigning color values may help in distinguishing different size and shape of materials. However, LBP methods generally can be expected to have a low quality image.[8]

1.3 Aliasing Effect

Most common aliasing effect is staircase effect which images with smooth curves and diagonal lines appear jagged. On display screen, the curves and diagonal lines represented by the pixel with rectangular shaped.[9] Therefore, the curves and diagonal lines data cannot be distributed evenly making some of the data missed and lose the original shape.[10] This usually happens when there is not enough information in term of number of pixel in an image or on a display to represent it realistically. The reconstructed image become inaccurate representation of the original and may give false information about the exact image. Therefore, aliasing can degrade the quality of image with unwanted effect, disintegrating texture and also degradation pattern. Figure 1 image with low resolution has high aliasing effect compared to image with high resolution.

(a) (b)

Figure 1 The image with resolution (a) 1600×1200 and (b) 80×60

1.4 Problem Statement

Image reconstruction system for this study is based on measurement or optical intensity obtained from CMOS linear image sensor S10077 which are arrays of numerous values representing the object scanned. In order to avoid aliasing effect that may be appeared on the reconstructed image obtained, at least four projection image reconstructions must be used, so there will be enough data to distinguish between the real objects and noises. To simplify the software development, the image reconstruction started by manually generating the sensor's sensitivity maps modelled in matrices form starting with small number of pixel at least $\{3 \times 3\}$ pixel. However, the data and sensitivity matrices become very large as the number of pixel increased and it is very difficult to write and do the calculations for solving the inverse problems manually. Therefore, a software programming Matrix Laboratory or simply called as MATLAB is needed to assist in solving various problems arises for this study. In addition, there are two possible methods can be used to solve inverse matrix problem which are the transpose matrix, and the pseudo-inverse matrix (or Moore-Penrose matrix inverse). Moreover, as the number of pixel increased, a higher capacity of random access-memory (RAM) is needed to store the computation data.

2.0 OVERALL PROCESS

2.1 Forward Problem

In image reconstruction there are two main problems need to be indentified and solved. The problems involve are forward problem and inverse problem. The forward problem is to solve the measureable data when all values of variable are given.[11] The purpose of forward problem is to assist in calculation for the measurement values of measureable data before the real experiment for data acquisition is conducted by predicting and estimating the reconstruction data of the object and construct the sensitivity maps.

The most important thing to be considered for the forward problem is to construct sensitivity maps. For example, a square is divided into three crosswise slices and other three slices with perpendicular to the horizontal direction. This produces nine smaller squares with equal size for a simple $\{3 \times 3\}$ pixel image and each square is labeled according to meaningful row and column. It is decided to use at least four projections of collimated light beams through CMOS linear image sensor S10077 in order to overcome the aliasing effect that may be appear on reconstructed image.

Figure 2 shows four chosen paths of collimated light beams through CMOS linear image sensor S10077 to take measurement data projection by projection. The path can easily be known by using a perfect octagon shape to determine the directions for each projection. For a simple $\{3 \times 3\}$ pixel image, supposed there are three collimated lights beams pass through the area under study for each projection. Based on the above figures it is assumed there are two variables which are M for constant measurement data and alpha, α for attenuation coefficient of material or object inside the pipe. Generally from the two variables, a total of n linear algebraic equations can be formed by summing up all variable α_{nm} assigned for crossover lines that present for each measurement line represented by M_n.

1st Projection
$$\alpha_{11} + \alpha_{12} + \alpha_{13} = M_1 \quad (1)$$
$$\alpha_{21} + \alpha_{22} + \alpha_{23} = M_2 \quad (2)$$
$$\alpha_{31} + \alpha_{32} + \alpha_{33} = M_3 \quad (3)$$

2nd Projection
$$\alpha_{11} + \alpha_{21} + \alpha_{31} = M_4 \quad (4)$$
$$\alpha_{12} + \alpha_{22} + \alpha_{32} = M_5 \quad (5)$$
$$\alpha_{13} + \alpha_{23} + \alpha_{33} = M_6 \quad (6)$$

3rd Projection
$$\alpha_{11} = M_7 \quad (7)$$
$$\alpha_{13} + \alpha_{22} + \alpha_{31} = M_8 \quad (8)$$
$$\alpha_{33} = M_9 \quad (9)$$

4th Projection
$$\alpha_{13} = M_{10} \quad (10)$$
$$\alpha_{11} + \alpha_{22} + \alpha_{33} = M_{11} \quad (11)$$
$$\alpha_{31} = M_{12} \quad (12)$$

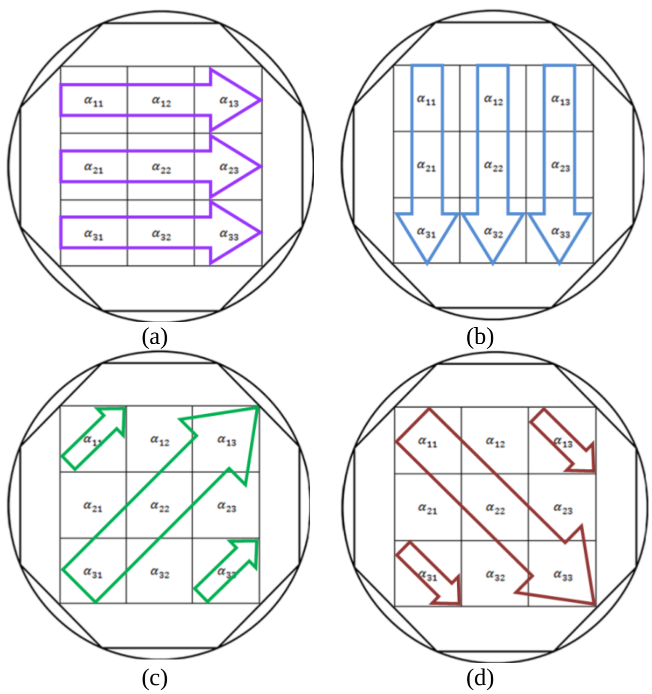


Figure 2 A $\{\mathbf{3} \times \mathbf{3}\}$ pixel image in a pipe: (a) 1st projection, (b) 2nd projection, (c) 3rd projection, and (d) 4th projection

By referring to equations (1) to (12), there are nine data for variable α_{nm} and twelve data for variable M_n can be described in matrix equation. The size of matrices involved in this expression is depending on the value of variable n. Note that the general mathematical equation can be expressed as equation (13).

$$\begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}_{12\times9} \times \begin{pmatrix} \alpha_{11} \\ \alpha_{12} \\ \alpha_{13} \\ \alpha_{21} \\ \alpha_{22} \\ \alpha_{23} \\ \alpha_{31} \\ \alpha_{32} \\ \alpha_{33} \end{pmatrix}_{9\times1} = \begin{pmatrix} \mathrm{M1} \\ \mathrm{M2} \\ \mathrm{M3} \\ \mathrm{M4} \\ \mathrm{M5} \\ \mathrm{M6} \\ \mathrm{M7} \\ \mathrm{M8} \\ \mathrm{M9} \\ \mathrm{M10} \\ \mathrm{M11} \\ \mathrm{M12} \end{pmatrix}_{12\times1}$$

$$\{S\}_{4n\times n^2} \times \{R\}_{n^2\times1} = \{M\}_{4n\times1} \quad (13)$$

where S - Sensitivity matrix of attenuation coefficient
R - Reconstruction vector of object model
M - Measurement vector of CMOS sensor measurement
n - Square factor number of pixel (image resolution)

2.2 Inverse Problem

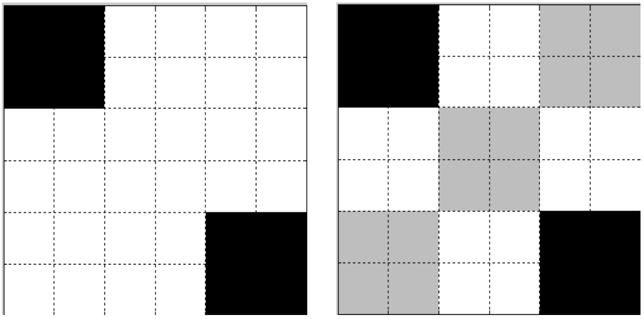
Inverse problem is a process of reconstructing of the theoretical image model given a set of measured value M_n. Therefore, the equation is solved in a reverse way, that is from the inverse matrix of the generated sensitivity matrix multiply with the sensors measurement vector then, an image is reconstructed. There are three variables involved; sensitivity matrix $\{S\}$ is constructed from the forward problem, measurement vector $\{M\}$ is obtained from experiment or from theoretical object model and reconstruction vector $\{R\}$ has to be calculated. Therefore, the inverse problem can be express as equation (14) below.

$$\begin{pmatrix} \alpha_{11}' \\ \alpha_{12}' \\ \alpha_{13}' \\ \alpha_{21}' \\ \alpha_{22}' \\ \alpha_{23}' \\ \alpha_{31}' \\ \alpha_{32}' \\ \alpha_{33}' \end{pmatrix}_{9\times1} = \begin{pmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 \end{pmatrix}_{9\times12} \times \begin{pmatrix} \mathrm{M1} \\ \mathrm{M2} \\ \mathrm{M3} \\ \mathrm{M4} \\ \mathrm{M5} \\ \mathrm{M6} \\ \mathrm{M7} \\ \mathrm{M8} \\ \mathrm{M9} \\ \mathrm{M10} \\ \mathrm{M11} \\ \mathrm{M12} \end{pmatrix}_{12\times1}$$

$$\{R'\}_{n^2\times1} = \{M\}_{4n\times1} \times \{S^{-1}\}_{4n\times n^2} \quad (14)$$

Before can proceed on solving the inverse problem, first the truth of the expression obtained from the forward problem need to be proven. Assume the sensitivity matrix is already constructed, the next step is to determine the theoretical model of the object vector to be reconstructed. The theoretical model or the reconstruction vector is the distribution of data of filled pixel assumed as the image of the object model. The value of reconstruction vector determined the grayscale level for each pixel of the digital image.

The reconstruction vector can be imposed by making some prediction and assumption of a set of attenuation coefficient in $\{9 \times 1\}$ matrix form for a simple $\{3 \times 3\}$ pixel image. Assuming the values of α is 0.003 for a space with an absence of object, while the values of ten for a present of model object in the area under study. An assumption for the values of the reconstruction vector based on the desired ideal output image of the image reconstruction. The value of reconstruction vector is decided based on the presents and the absence of object, and the position of the object by referring to Figure 3(a).



(a) (b)

Figure 3 Object model present at the center of $\{\mathbf{3} \times \mathbf{3}\}$ pixel image: (a) desired image, and (b) reconstructed image

$$\begin{pmatrix} 1&1&1&0&0&0&0&0&0\\ 0&0&0&1&1&1&0&0&0\\ 0&0&0&0&0&0&1&1&1\\ 1&0&0&1&0&0&1&0&0\\ 0&1&0&0&1&0&0&1&0\\ 0&0&1&0&0&1&0&0&1\\ 1&0&0&0&0&0&0&0&0\\ 0&0&1&0&1&0&1&0&0\\ 0&0&0&0&0&0&0&0&1\\ 0&0&0&0&0&0&1&0&0\\ 1&0&0&0&1&0&0&0&1\\ 0&0&1&0&0&0&0&0&0 \end{pmatrix}_{12\times 9} \times \begin{pmatrix} 10.000\\ 0.003\\ 0.003\\ 0.003\\ 0.003\\ 0.003\\ 0.003\\ 0.003\\ 10.000 \end{pmatrix}_{9\times 1} = \begin{pmatrix} M1\\ M2\\ M3\\ M4\\ M5\\ M6\\ M7\\ M8\\ M9\\ M10\\ M11\\ M12 \end{pmatrix}_{12\times 1}$$

Since the assumption of reconstruction vector is already given, the data of measurement vector that should be obtained by data acquisition system from CMOS linear image sensor S10077 can be calculated. The calculated measurement vectors with size $\{12 \times 1\}$ obtained can be used in solving the inverse problem by substituting the values and multiply with transposed sensitivity matrix using dot product into inverse equation as shown above written by referring to equation (14). New values for reconstruction vectors can be calculated and the result of the calculations is shown as follows.

$$\begin{pmatrix} 50.0144\\ 10.0143\\ 20.0230\\ 10.0143\\ 20.0287\\ 10.0143\\ 20.0230\\ 10.0143\\ 50.0144 \end{pmatrix}_{9\times 1} = \begin{pmatrix} 1&0&0&1&0&0&1&0&0&0&1&0\\ 1&0&0&0&1&0&0&0&0&0&0&0\\ 1&0&0&0&0&1&0&1&0&1&0&0\\ 0&1&0&1&0&0&0&0&0&0&0&0\\ 0&1&0&0&1&0&0&1&0&0&1&0\\ 0&1&0&0&0&1&0&0&0&0&0&0\\ 0&0&1&1&0&0&0&1&0&0&0&1\\ 0&0&1&0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&1&0&0&1&0&1&0 \end{pmatrix}_{9\times 12} \times \begin{pmatrix} 10.0057\\ 0.0086\\ 10.0057\\ 10.0057\\ 0.0086\\ 10.0057\\ 10.0000\\ 0.0086\\ 10.0000\\ 0.0029\\ 20.0029\\ 0.0029 \end{pmatrix}_{12\times 1}$$

The calculated values of new reconstruction vector is then, used to reconstruct the digital image with resolution of $\{3 \times 3\}$ pixel. As what can be seen from the results of calculation done, the new calculated reconstruction vector is different compared to the actual values from the assumption earlier. However, image still has contrast between the area with and without model object present. The image reconstruction is illustrated in Figure 3(b).

2.3 Image Reconstruction

In order to reconstruct an image the things need to be considered are both forward and inverse problems which are mathematical problem solving. The mathematical problem is the calculation of matrices. However, the matrices involve in this research all are rectangular matrices with a very large sizes (CMOS sensor contain 1024 pixels). It is impossible to calculate and solve all the matrices manually. In this case, MATLAB programming which is the abbreviation of Matrix Laboratory can assist us to solve the problems. There are various built in function of MATLAB as a calculating tool which can manipulate the matrices involve as desired by programmer.

In image reconstruction for this research, the matrices involved are rectangular shaped matrices. A normal inverse matrix cannot be used to solve the problem since it is only compatible for square shaped matrices. Therefore, two different inverse matrix techniques are used i.e. transpose matrix and pseudo-inverse matrix. Both inverse matrix techniques are tested by solving the inverse problem as described in ~~Chapter 3~~ the previous section and the results obtained from both techniques are compared.

The MATLAB programming for a simple 100x100 pixels image reconstruction using transpose matrix starting with codes to read the data of sensitivity matrix and also reconstruction vector stored in Microsoft Excel. The mathematical relationships of the forward and inverse problem are translated into MATLAB coding listed below. The reconstructed vector [R'] denoted by variable NR is an nx1 matrix need to be reshaped into a square. For this example, the 100000x1 reconstruction vector is changed to a 100x100 matrix in order to plot the data and form a digital image.

```
S = xlsread('S_EvenMatrix.xlsx');
R = xlsread('R_Matrix.xlsx');
RR = reshape(R,100,100);
M = S*R;
NR = S'*M;
NewR = reshape(NR,100,100);
grey = mat2gray([NewR);
X = gray2ind(grey, 256);
RGB = ind2rgb(X,flipud(gray(256)));
```

A new calculated reconstruction vector $[R']$ will be converted into a digital image. However, the image reconstructed from the data in matrix form has a bad quality (Figure 4(b)). The image reconstruction process from matrix data is illustrated as in Figure 4. Therefore, the matrix data need to be changed step by step into RGB. The RGB is actually an abbreviation from red-green-blue color model data which has better quality of coloring than grayscale for an image.

$[R']$ is converted to grayscale image and the data is stored under a variable named *grey*. The grayscale color is divided into 256 scale of colormap and then, once again converted to binary image or indexed image. The variable x is assigned for the indexed image data. The indexed image data, x is converted to corresponding colormap mapped to RGB truecolor format. The actual grayscale color is ranges of color between black-and-white. For example, the highest value 256 is a pure white color and 0 is a pure black color. In this study, the object presents in an image need to be highlighted where the image located is black in color and the space with absence of object is white in color, so the gray colormap is flipped upside down to change the value of scale to be 256 for black color and 0 for white color.

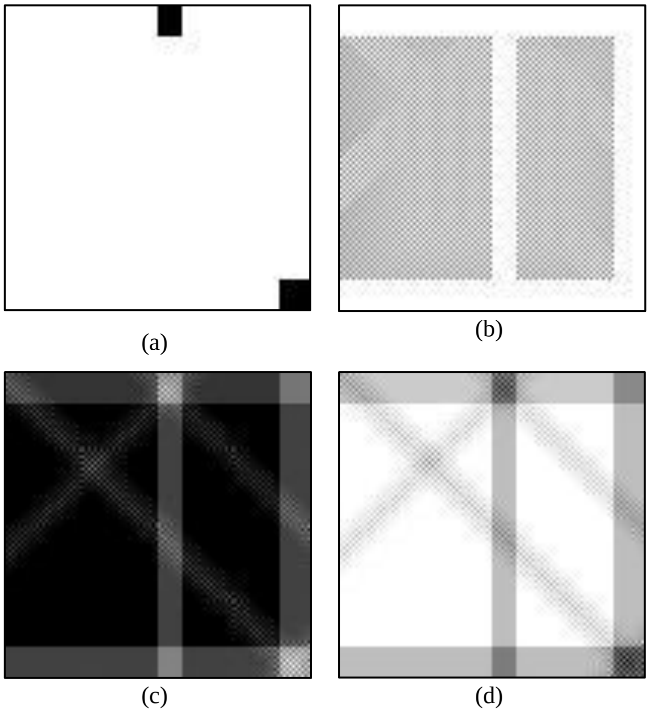


Figure 4 100×100 pixels image reconstruction (a) desired image, (b) reconstructed image using data in matrix format, (c) reconstructed image using data in grayscale format and (d) reconstructed image using data in RGB truecolor format

3.0 RESULTS AND DISCUSSION

3.1 Transpose Matrix and Pseudo-Inverse Matrix

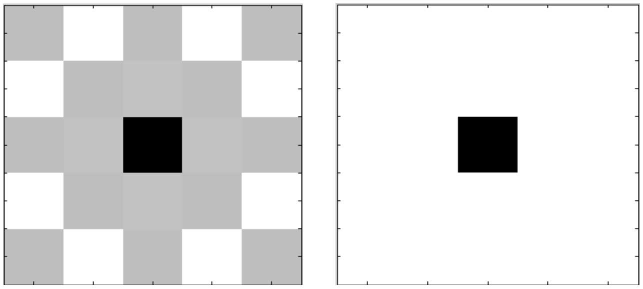
The listed MATLAB codes as follows display the results for simple $\{5 \times 5\}$ pixel image reconstructions. The results consist of ideal values and also calculated values for reconstruction vector. This analysis is done without using auto-generation of sensitivity map where all the data is written manually into Microsoft Excel file format. From listed codes, it can be seen that image is reconstructed using both transpose matrix and Pseudo-inverse matrix in order to solve the inverse problem. These results obtained from transpose matrix and pseudo-inverse matrix.

The values were then, plotted using image scale with colormap of *gray* in order to make the differences of data clearer. There are various colormap can be used in MATLAB. The *gray* colormap was chosen because of its color ranges from white to black or known as grayscale and it is easily be distinguished. The black color represents the highest value while the white color represents the lowest values present in the data obtained.

```
% {5x5} pixel image reconstruction using transpose matrix
S = xlsread('S_OddMatrix.xlsx',2);
R = xlsread('R_Matrix.xlsx',3);
RR = reshape(R,5,5)
RR =

    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029   10.0000

M = S*R;
NR = S'*M;
NR1 = reshape(NR,5,5)
NR1 =

   10.0431    0.0287    0.0459    0.0287   10.0431
    0.0287   10.0488    0.0287    0.0517   10.0258
    0.0459    0.0287   10.0545    0.0287   10.0430
    0.0287    0.0517    0.0287   10.0488   10.0258
   10.0431   10.0258   10.0430   10.0258   40.0344

imagesc(NR3);
colorbar;
colormap(flipud(colormap(gray)))

% {5x5} pixel image reconstruction using pseudo-inverse matrix
S = xlsread('S_OddMatrix.xlsx',2);
R = xlsread('R_Matrix.xlsx',3);
RR = reshape(R,5,5)
RR =

    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029   10.0000

M = S*R;
NR = pinv(S)*M;
NR2 = reshape(NR,5,5)
NR2 =

    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029    0.0029
    0.0029    0.0029    0.0029    0.0029   10.0000

imagesc(NR2);
colorbar;
colormap(flipud(colormap(hot)))
```

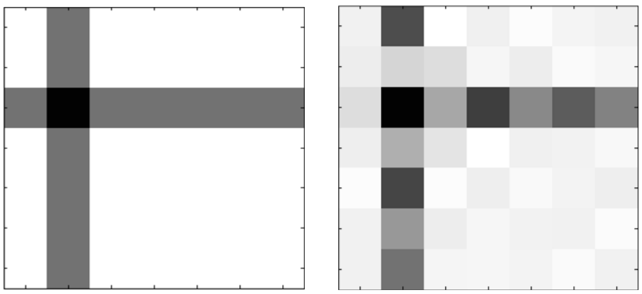
From the calculation of $\{5 \times 5\}$ data for reconstruction vector the differences can be seen clearly among the values obtained from calculation of transpose matrix and pseudo-inverse matrix. When compared the calculated data, (NR1 and NR2), and the ideal data, (RR), it can be said that pseudo-inverse gave an accurate results while transpose matrix is vividly not and even the values are much higher. The differences in values obtained between these two solutions are not even close. The image reconstructions from values obtained are shown in Figure 5.

However, more evidences are needed to proof the pseudo-inverse matrix is the most suitable technique to be used in image reconstructions. The analysis was preceded with more image reconstructions but different values of pixel. The image reconstructions for $\{7 \times 7\}$, $\{21 \times 21\}$, and $\{100 \times 100\}$ pixel are illustrated as in Figure 6, 7, and 8.



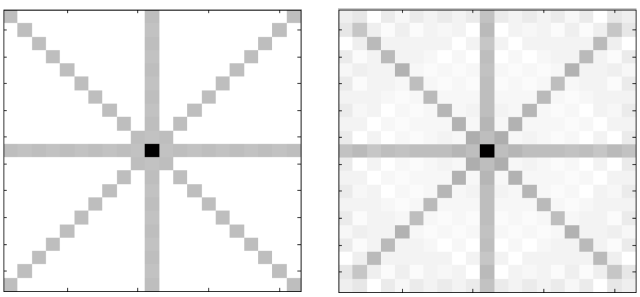
(a) (b)

Figure 5 A $\{\mathbf{5 \times 5}\}$ pixel image reconstruction using: (a) transpose matrix, and (b) pseudo-inverse matrix



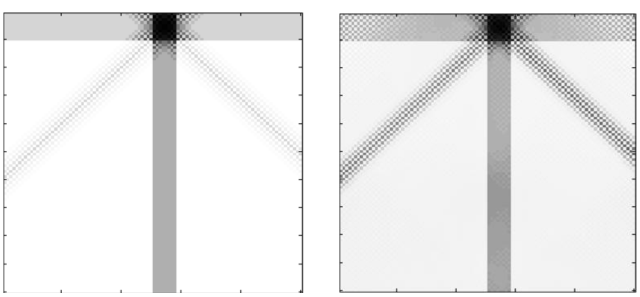
(a) (b)

Figure 6 A $\{\mathbf{7 \times 7}\}$ pixel image reconstruction using: (a) transpose matrix, and (b) pseudo-inverse matrix



(a) (b)

Figure 7 A $\{\mathbf{21 \times 21}\}$ pixel image reconstruction using: (a) transpose matrix, and (b) pseudo-inverse matrix



(a) (b)

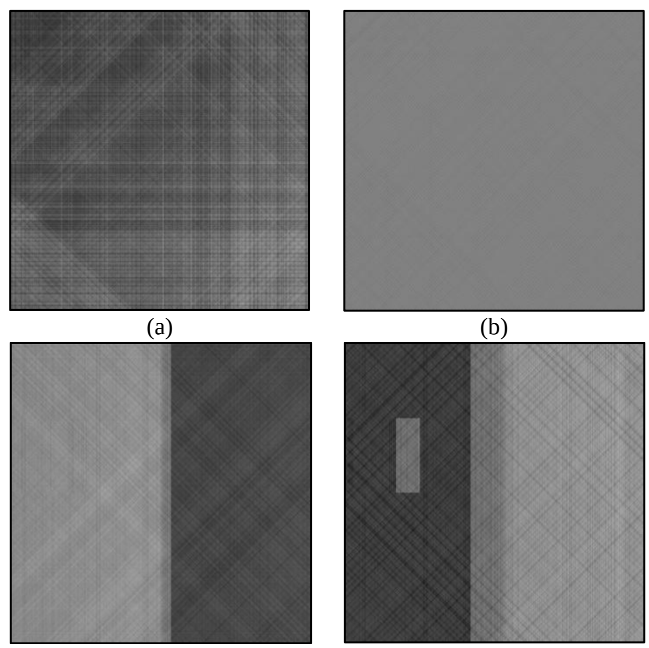
Figure 8 A $\{\mathbf{100 \times 100}\}$ pixel image reconstruction using: (a) transpose matrix, and (b) pseudo-inverse matrix

This study emphasized on the suitability of inverse matrix techniques in image reconstruction for CMOS linear image sensor S10077 without considering the size and shape of the object presents. From the results displayed in Figure 6 to 8, the image reconstructions using pseudo-inverse matrix can distinguished the presents and absences of object. However, the images have darker variation of colors even for the space where model object was absented. This finding implied that pseudo-inverse matrix is apparently good for quantitative analysis, but much so for suitable reconstruction of high resolution image.

On the other hand, the image reconstructions using transpose matrix did not displayed a good results for images with small number of pixel such as $\{5 \times 5\}$ pixel images. But when the number of pixel increased from $\{7 \times 7\}$, $\{21 \times 21\}$ up to $\{100 \times 100\}$, then the color differences were much clearer. This happened because the values of calculated reconstruction data using transpose matrix were much larger than using pseudo-inverse matrix. A very large range of values for a set of data has a smaller change of color in colormap compared with a small range of values that has a larger change of color. That is the reason why the image reconstructions using transpose matrix has better image quality for high resolution than pseudo-inverse matrix. Therefore, transpose matrix is better for qualitative analysis and more suitable to be used in this study.

3.2 $\{1024 \times 1024\}$ Image Reconstruction using Real Data

Measurement vectors obtained from data acquisition system by CMOS linear image sensor S10077 used to reconstruct images. The output images as shown in Figure 9 were produced after several clicks on the GUI implemented. Although the image quality is not very satisfied, but it is clearly can be seen there is contrast on the images between a space with and without object blocking the path.



(a) (b) (c) (d)

Figure 9 A $\{1024 \times 1024\}$ pixel image reconstruction (a) with object fully block the path, (b) without anything block the path, (c) with object blocking at the right, and (d) with object blocking at the left

4.0 CONCLUSION

The goal of this study which is to develop a software based on MATLAB programming to reconstruct images has successfully achieved. In conclusion, the study has successfully reconstructed images using linear back-projection method where the calculations were solved using the transpose matrix and also pseudo inverse matrix techniques. Some image processing methods such as image thresholding and morphology has been used in order to remove imperfections. A graphical user interface was designed using MATLAB as user friendly software for the end user.

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