Pertanika J. Sci. & Technol. 24 (1): 191 - 203 (2016)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Analysis of Bit-Plane Images by using Principal Component on Face and Palmprint Database

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ABSTRACT

The bit-plane feature extraction approach has lately been introduced for face and palm-print recognition. This approach decomposes an 8-bit grey level image into eight groups of bit layers. The assumption of this approach is that the highest order of a bit-plane decomposition, which has the most significant bits of all pixels, contains the most biometric features. Nonetheless, most research has identified bit-plane images illustratively. Hence, in order to endorse the assumption, we performed an analysis on face and palm-print images to identify the bit-plane that contributes most significantly to the recognition performance. Analysis was done based on Principal Component Analysis (PCA). The first principal component was applied as it is defined for the largest possible variance of the data. Next, Euclidean distance was calculated for matching performance. It was observed that bit-plane 6 and 7 contributed significantly to recognition performance.

Keywords: Bit-plane, Principal Component Analysis, face recognition, palm-print recognition

INTRODUCTION

Nowadays, biometric technologies are vital for personal authentication. This technology is able to provide security and privacy for identification because of the unique physical attribute that only an individual can present. Generally, biometrics such as face, finger, voice, iris, eye and palm-print are widely applied. There are two modes of the biometric system i.e. verification and identification, depending on the application (Matyáš & Říha, 2002). Verification is where the identity of an individual is verified as who he claims to be. On the other hand, identification is where the system will identify the unknown person. In order to verify or identify a biometric, significant information has to be extracted. In this relation, feature extraction is very crucial throughout the process of biometric recognition because it is where the distinct interest and significant characteristic of an individual are captured.

Many algorithms have been proposed for feature extraction techniques. In general, there are four basic approaches: geometry, colour

Article history:
Received: 12 March 2015
Accepted: 5 October 2015

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ISSN: 0128-7680

segmentation, appearance and template-based techniques. One example of the geometry-based method is the Gabor wavelets transform approach (Lee, 1996; Lee & Wang, 1999; Lim *et al*., 2009; Bereta *et al*., 2013; Kong *et al*., 2003; Slavkovic *et al*., 2013; Shahamat & Pouyan, 2014) which is applied in face, palm-print and fingerprint recognition. In addition, the edge detection approach is also used on fingerprint and palm-print recognition (Bong *et al*., 2010). Colour-based feature extraction is mostly applied to face recognition where skin region or certain arrays of colour pixels is obtained (Seow *et al*., 2003; Singh *et al*., 2003). It is found to be used on palm-print in Sang, Ma and Huang (2013), where the authors utilised skin-colour thresholding to extract features and also on eye detection (Bong & Lim, 2007; Bong & Lim, 2009). Other than that, Bhoi and Mohanty (2010) used template-based feature extraction by detecting the eyes. Another approach that is commonly applied is the appearance-based technique that is mostly on Principal Component Analysis (PCA) and Independent Component Analysis (ICA). This method has been a favourite of researchers for either face, palm-print or fingerprint detection (Lu *et al*., 2003; Eleyan & Demirel, 2005; Lin, 2010; Ebied, 2012; Mohammadi *et al*., 2014).

In recent years, a new feature extraction technique based on bit-plane has been proposed. The bit-plane approach was recently introduced by several researchers. Most works have been applied for face and palm-print recognition (Lee & Bong, 2013). In (Hoque & Fairhurst, 2000), bit-plane decomposition was applied in face recognition based on the moving window method where every bit level was evaluated for its performance in recognition. This research was further evaluated in Li and Wang (2009) using the same method but emphasised the improvement of diversity of component classifiers, where several mathematical rules were applied for performance evaluation. Also in some works (Ting *et al*., 2008; Bong *et al*., 2009; Ting *et al*., 2013), the authors performed face recognition on single and combined bit planes using feed-forward neural network. Research was also carried out in the work by Ramlan *et al*. (2012) using neural network for thumbprint recognition. The bit-plane extraction approach in face recognition was also proposed by applying PCA (Wang *et al*., 2006; Srinivas *et al*., 2013). In these works, after the bit-plane decomposition, bit-planes were selected visually.

Most of the bit-plane-based biometric recognitions assume that the highest order of a bit-plane decomposition contains the most biometric features. This assumption is supported visually by looking at the decomposed bit planes. Generally, the higher order bit-planes contain binary images that have visual resemblance to the original grey images, whereas the lower order bit-planes do not seem to provide this resemblance. Thus far, not much research has been done to scientifically analyse bit-planes to validate the assumption.

Furthermore, PCA is an established technique for its multivariate analysis. It is used to find patterns in data of high dimension, while expressing data by highlighting their differences and similarities. Other than that, it is commonly applied in pattern recognition such as face recognition and also used for image compression (Jolliffe, 1986). PCA can effectively reduce the image's dimensionality, yet conserve the key identifying information (Turk & Pentland, 1991). It is done by obtaining the principal components that retain the highest variance of the original variables. Since the variance of the principal component indicates the amount of expressed information, bit-plane is analysed with PCA to observe the amount of information in each bit-plane. This is to justify the contribution of each bit-plane in recognition. Hence, in this paper, we used PCA as a model to validate this assumption for face and palm-print recognition. This is different from the technique used by Srinivas *et al*. (2013) and Wang *et al*. (2006), who mainly focused on applying fusion on bit-planes with PCA for feature extraction to enhance recognition rate.

The paper is organised as follows: In Section 2, the idea of bit-plane decomposition is introduced. This is followed by a brief presentation of the PCA algorithm and a description of the database. The experimental results on Yale (Georghiades, 1997), ORL (AT&T Laboratories Cambridge, 1994) and PolyU Palm-print Databases (The Hong Kong Polytechnic University, n.d.) are presented in Section 3. Finally, Section 4 presents the conclusion.

MATERIALS AND METHODS

Bit-Plane Extraction

Schwartz and Barker (1966) presented an idea of decomposing an image from grey-scale to a collection of binary images, and called this the bit-plane decomposition technique. It is based on the conversion of decimal to binary for each pixel. An eight-bit grey level image has pixel values ranging from 0 to 225. Therefore, it can be decomposed into eight layers or bit-planes, whereby the first bit-plane (bit-plane 0) consists of the least significant bits while the last bit-plane (bit-plane 7) comprises the most significant bits.

The general derivation for bit-plane feature extraction is summarised as:

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,N-1) \\ f(1,0) & f(1,1) & \dots & f(1,N-1) \\ \vdots & \vdots & \dots & \vdots \\ f(M-1,0) & f(M-1,1) & \dots & f(M-1,N-1) \end{bmatrix} \qquad [1]$$

To convert to binary, the original image, *f(x,y)* , has to be divided by 2 in order to obtain the remainder, R, which represents the feature of a specific bit-plane. Mathematically, it can be written as in Equation [2]:

$$f_{bpi}(x,y)$$

$$= \begin{bmatrix} R\left(\dfrac{floor(\frac{f(0,0)}{2})}{2}\right) & R\left(\dfrac{floor(\frac{f(0,1)}{2})}{2}\right) & \cdots & R\left(\dfrac{floor(\frac{f(0,N-1)}{2})}{2}\right) \\ R\left(\dfrac{floor(\frac{f(1,0)}{2})}{2}\right) & R\left(\dfrac{floor(\frac{f(1,1)}{2})}{2}\right) & \cdots & R\left(\dfrac{floor(\frac{f(1,N-1)}{2})}{2}\right) \\ \vdots & \vdots & \cdots & \vdots \\ R\left(\dfrac{floor(\frac{f(M-1,0)}{2})}{2}\right) & R\left(\dfrac{floor(\frac{f(M-1,1)}{2})}{2}\right) & \cdots & R\left(\dfrac{floor(\frac{f(M-1,N-1)}{2})}{2}\right) \end{bmatrix}$$

$$= R\left[\frac{1}{2} floor\left(\frac{1}{2^i}\left[f(x,y)\right]\right)\right] \quad ; \text{i=0, 1, 2…7} \qquad [2]$$

where *f(x,y)* is the original image, $f_{bp}(x,y)$ is the bit-plane information, *R* is the remainder, and *floor(x)* rounds the elements to *x* nearest integers less than or equal to *x* (Ting *et al*., 2008; Bong *et al*., 2009; Ting *et al*., 2013).

Fig.1 and Fig.2 show the decomposition of grey images into bit-planes for face and palm-print images. The first row represents the original image, while the second row shows the image of each bit-plane without image enhancement, starting from the least significant plane to most significant plane, and from left to right. From the visual observation in Fig.1, certain bit-planes are shown to have a distinguished face image. The visible face images indicate that the majority of the significant information is present in bit-planes 5, 6 and 7. In contrast, face images that cannot be distinguished indicate the minority of the significant information is present at bit-planes 0, 1, 2, 3 and 4. As for the palm-print image, the palm feature is also observable visually, especially the last bit-plane presented in Fig.2.

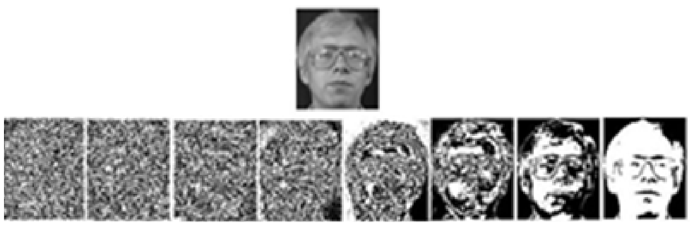

Fig.1: Illustration of an original face image and its 8 bit-planes.

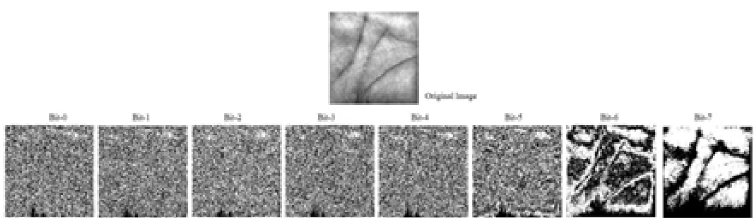

Fig.2: Illustration of a palm-print image and its 8 bit-plane.

Principal Component Analysis

The main idea of PCA is significant information of the data can be represented well by utilising only the first few principal components. The principal components are the new set of uncorrelated variables transformed from the original interrelated variables of the original image. In each principal component, the amount of information is presented as the variance. The ‘first principal component’ has the highest variance, which also means it consists of most information of an image (Jolliffe, 1986). In this work, first principal components for each bit-plane were obtained so as to compare their eigen values. The latter part was proceeded with recognition by using Euclidean distance. The performance shown thereby indicates the amount of information contributed by each bit-plane.

In PCA, the basic algorithm is that, firstl, a digital image can be represented as a matrix with the size of *x* row and *y* column. Let an image be denoted as *f(x,y)* or in short, as *f*. The training set is $f_1, f_2, f_3, \ldots f_M$ where M is the total number of images. Before computing the covariance matrix or eigen vectors, the average of the image set has to be determined. It is defined by:

$$\phi = \frac{1}{M}\sum_{n=1}^{M} f_n \qquad [3]$$

The mean-centred image, which is the difference between each image in the dataset from the average image, is:

$$w_i = f_i - \phi \qquad [4]$$

In order to obtain the largest possible principal component, the *k*th vector, uk, is selected on condition that Equation [5] fulfils the maximum of orthonormality constraint of Equation [6].

$$\tau_k = \frac{1}{M}\sum_{n=1}^{M} (u_k^T w_n)^2 \qquad [5]$$

$$u_l^T u_k = \delta_{lk} = \begin{cases} 1, if(l = k) \\ 0, otherwise \end{cases} \qquad [6]$$

This results as the vectors u_k, which are the eigen vector, and the scalars τk, which are the eigen values of the covariance matrix, and is defined by:

$$C = \frac{1}{M}\sum_{n=1}^{M} w_n^T w_n = AA^T \qquad [7]$$

where A=[w_1 w_2 w_3…. w_M].

Each image in the training set is now represented as an eigen vector. This means the number of eigen vectors produced is equal to the number of training images presented. Next, the eigen vectors are sorted from high to low corresponding to the eigen values. Let *M'* be the selected number of eigen vectors to be used. The *M'* numbers of the largest eigen vectors are then selected as the components of the eigen feature. After that, each of the mean-centred images is projected into an eigen space by using:

$$w_k = u_k^T (f - \phi);\ k=1,2..M'; \qquad [8]$$

Hence, all the training images are now transferred into the eigen space. For recognition purposes, the equivalent process is applied to the testing images. The testing images are to be mean-centred first before being projected into the same eigen space as training images. This enables comparison between the projected testing images with the projected training images in the eigen space. The comparison is done using a Euclidean distance classifier as explained earlier. The matching images would be defined by the closest distance between the training and testing image.

DATABASES

The evaluation was performed using two categories of database: face and palm-print. The specifications of each database are presented below.

Face Databases

For face, Yale and ORL (Olivetti Research Laboratory) face databases were applied. Yale database consists of a total of 165 images from 15 subjects; each subject has 11 images including altered expressions and illumination conditions. The resolution for each image is 100x100pixels (Georghiades, 1997).

The ORL database consists of 400 images from 40 individual subjects; 10 images for each individual in varied poses. In the database, every subject is in an upright, frontal position with facial expression; there are some variations in lighting, facial details etc. The resolution of each image is 112×92 pixels, with 256 grey levels per pixel (AT&T Laboratories Cambridge, 1994).

Palmprint Database

PolyU Palm-print Database was also used for this research. It contains 7,752 greyscale images corresponding to 386 different palms in bitmap format. Approximately 20 samples were collected in two sessions for each palm. The number of the samples is uneven for each set. Around 10 of those samples were captured in the first session and the second session correspondingly. The average interval between the first and the second collections was two months. The original image size was 384 x 284 pixels. In this research, in order to extract the centre of the palm as the region of interest, the images were cropped manually to189 x 182pixels. The samples from the first session were used. Also, in the experiment of the current study, left palm and right palm were treated as two different databases. Some sets of data were filtered and eliminated due to insufficient number of samples or distorted images. Therefore, a total of 3,840 images from 192 subjects were used, with 10 sample images each from the left and right palms (The Hong Kong Polytechnic University, n.d.).

Recognition and Performance Metric

After applying PCA, analysis was continued by evaluating the recognition performance of the bit-planes. Firstly, in order to cluster the features in eigen space, Euclidean distance was applied. Classification was done by measuring the distance between the projection vectors of training images with projection vectors of testing images in the eigen space. The smaller the distance between the images, the more the similarity increased. The shortest distance thereby indicated the subject to be recognised. The mathematical expression for Euclidean distance d_k is:

$$d_k = \sum_{i=1}^{M} \frac{(f(i) - f_k(i))^2}{(s_k)^2} \qquad [9]$$

where f is the feature vector of testing set, f_k and s_k is the kth feature vector and its standard deviation and M denotes the number of eigen vectors.

Next, to observe the performance of recognition for bit-plane, accuracy was computed. Accuracy indicates the percentage of correctly accepted enrolment by the system, which is defined by:

$$Accuracy = \left(\frac{total\ correctly\ classified\ data}{total\ testing\ data}\right) \times 100 \qquad [10]$$

RESULTS AND DISCUSSION

In our experiments, the data were categorised into training set and testing set. The training set consisted of the first five images of each subject. The testing set, on the other hand, was obtained from the remaining images of database.

Two experiments were carried out. Firstly, the analysis was done by extracting the eigen values from the first principal component of each bit-plane to observe the performance of each bit-plane in all the databases. The assumption of bit-planes is that the highest order of bit-plane decomposition contains the most biometric features while the lower order of the bit-plane consists of less information regarding the biometric. Hence, the first experiment was to validate this assumption on face and palm-print; this is further explained below. Furthermore, in order to verify the assumption of bit-planes, analysis of eigenspace for recognition was done.

Principal Components

For our analysis, the first principal components of the bit-planes from all the databases were extracted for comparison. This is because the first principal component is known for the highest variance of the original image. In other words, from the first principal component, the contributed amount of information in each bit-plane can be observed.

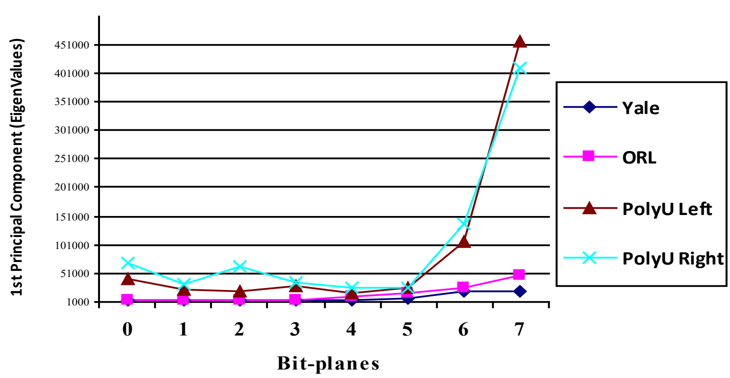

Fig.3: Comparison of eigenvalues of the first principal component for all databases.

Fig.3 shows the comparison of eigen values of the first principal component for all databases. Face and palm-print databases clearly show that the variance has significantly increased starting from bit-plane 5 in the first principal component, and bit-planes 6 and 7 have the most variances compared to others.

Since the first principal component accounts for the largest proportion of the total variance, it also represents the most information of data (Jolliffe, 1986). Hence, although Fig.3 shows stable eigen values from bit-plane 0 to bit-plane 4, the information it provides is insufficient to present data as shown in Fig.1 and Fig.2, where no visible face or palm images can be observed. On the other hand, bit-plane 5 to 7 with increasing variance, show a more discernable face and palm figure as illustrated in Fig.1 and Fig.2. Therefore, the characteristic of the first principal component in each bit-plane corresponds with the bit-plane presented through visualisation where more information is observed at bit-planes 6 and 7 that can contribute to recognition. In order to further verify the contribution of bit-planes, recognition was then continued using the Euclidean distance method.

Face and Palm-Print Recognitions

The bit-planes were then trained using the selected number of principal components. They were then tested for recognition using Euclidean distance. Here, the optimum number of the principal component was selected using the trial-and-error method. To evaluate the recognition performance, Euclidean distance was applied using Equation [9].

Face Database

The experiment was done on two face databases. For both databases, the first five images for each subject were selected in the training set. Therefore, the number of the training images for Yale was 75 (=15x5). The remaining images were then used for the testing set. This gave a total of 90 (=15x6) images for the testing set.

Through the trial and test with 12 eigen vectors, the matching performance showed higher rates for the last two most significant bit (MSB) bit-planes. Fig.4 shows that the last two MSB bit-planes can achieve approximately 86% recognition for bit-plane 6 and 81% for bit-plane 7. The remaining bit-planes showed recognition performance below 50%. It was observed that the lower order bit-planes required more principal components to achieve higher performance rate. Consequently, it was shown that the lower order bit-planes contained less variance than the higher order bit-planes, and thus, contributed less information for the recognition.

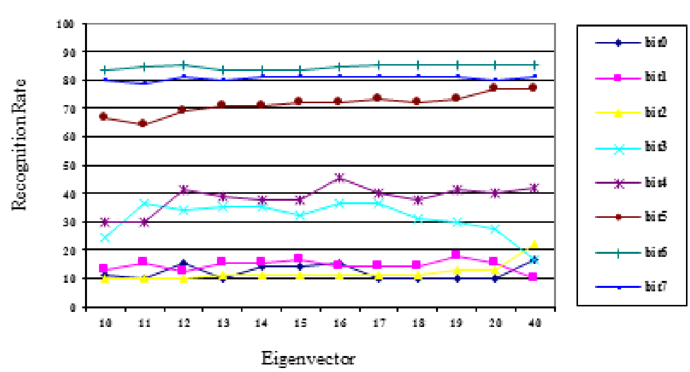

Fig.4: Recognition rate on Yale database.

As for ORL, 35 eigen vectors were selected as the optimum threshold in this study since the bit-planes could achieve 80% of the performance. The results presented in Fig.5 showed that only bit-planes 6 and 7 achieved the matching rate more than 80% while the rest showed higher error rates.

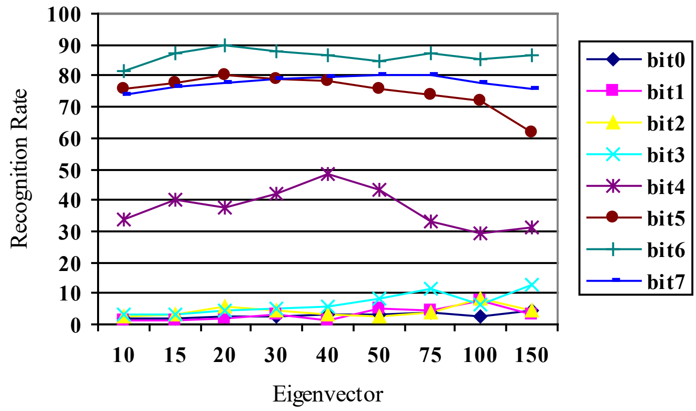

Fig.5: Recognition rate on ORL database.

Palm-print Database

The PolyU palm-print database, which used left and right palms, showed two different orientations, and were separately divided as two distinct databases. For each side of the palm, there were 192 samples with 10 images from each subject. In the experiment, the first five images were used per subject for training while the remaining images were used for testing. This also means that the number of training and testing samples was 960 (=192x5) each.

For the left palms, the experimental results clearly showed that the last two MSB bit-planes provided higher recognition rates than the other bit levels (see Fig.6). Similar to the face database, lower-order bit-planes need more principal components so as to increase the recognition rate. It is clearly shown in Fig.6 and Fig.7, especially for bit-plane 5, that the matching rate increased as more eigen vectors (principal components) were presented. This shows that the lower-order bit-planes consisted of lower variance as compared to the higher-order bit-planes. Hence, less information of the data was presented in the lower-order bit-planes to assist the recognition performance.

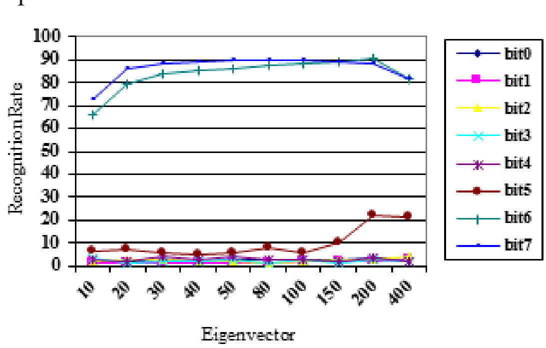

Fig.6: Recognition rate on PolyU left palm database.

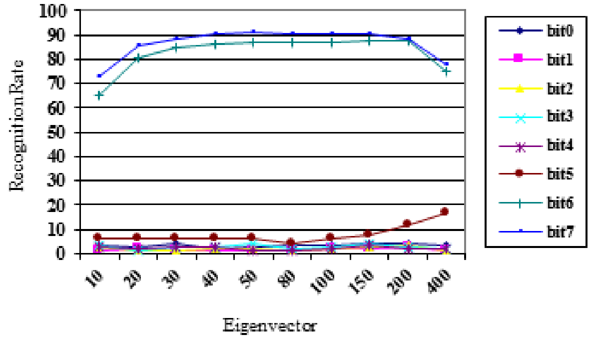

Fig.7: Recognition rate on PolyU right palm database.

BENEFITS OF STUDY

The analyses carried out in this study confirmed that the last two bit-planes, which were bit-plane 6 and bit-plane 7, were able to provide adequate information for feature extraction. No analysis of bit-planes from the perspective of PCA has been done before. PCA as an established technique is thereby eligible to confirm and prove the contribution of each bit-plane for biometric recognition. This analysis also concludes that bit-plane is able to contribute sufficient information for feature extraction in biometric recognition. Furthermore, it is able to overcome database storage limitation and reduce computation time because only the last two bit-planes are needed for biometric recognition.

CONCLUSION

In this paper, the performance of each bit-plane was justified using the PCA approach so as to verify its usefulness in recognition. Experiment was done on two types of biometric: face and palm-print. They were applied on the first principal component with the highest variance, which also showed the amount of information presented. It resulted in the highest variance shown by bit-plane 6 and 7. All the databases were then proceeded for recognition and showed a low matching rate for lower-order bit-planes (0-5), while the last two MSB bit-planes (6 and 7) provided rates above 80%. These verified that more information can be contributed for recognition at bit-planes 6 and 7. In conclusion, for face and palm-print recognition, the bit-plane extraction approach works effectively, as proven by above 80% for face and 90% for palm-print. This further validates the application of bit-planes for biometric recognition.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the Ministry of Education, Malaysia for the provision of research grant FRGS/03(03)/771/2010(52) and the Faculty of Engineering, Universiti Malaysia Sarawak for the provision of research facilities.

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