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# A Modified Principal Component Analysis Technique For Recognising African Bust

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**ABSTRACT**
*This study identified and analysed the pattern recognition features of African bust. It also developed and evaluated a Modified Principal Component Analysis (MPCA) for recognizing those features. The developed MPCA used varying number of eigenvectors in creating the bust space. The characteristics of the bust in terms of facial dimension, types of marks, structure of facial components such as the eye, mouth, chin etc were analysed for identification. The bust images were resized for proper reshaping and cropped to adjust their backgrounds using the Microsoft Office Picture Manager. The system code was developed and run on the Matrix Laboratory software (MatLab7.0). The use of varying values of eigenvectors has proven positive result as far as the system evaluation was concerned. For instance, a sensitivity test carried out revealed that thirteen out of seventeen bust's images were recognized by selecting only vectors of highest eigenvalues while all the test images were recognized with the inclusion of some vectors of low energy level. That is, the modification made to the Conventional PCA gave rise an increment of about twenty five percent (25%) as far as recognizing the test images was concerned. The study concluded that the Modification made to the conventional PCA has shown very good performance as far as the parameters involved were concerned. The performance of the MPCA was justified by the identification of all the test images, that is, the MPCA proved more efficient than the Conventional PCA technique especially for the recognition of features of the African busts.*

***KEYWORD:*** *Eigenvectors, Bust recognition, Modified Principal Component Analysis, African Bust.*

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## I. INTRODUCTION

The typology of traditional African sculpture share a different style compared with those in other continents of the world. For instance, African busts usually portray African identities such as tribal marks, beads, body painting, tattooing and others. Basically, a bust is an art work that depicts the human head. It is of symbolic importance and also shares visual values across tribes in Africa. One major functional area of the basic African Sculptural works that really differentiate them from others (European, Asian etc) is their theme. Sculptural themes are meant to convey messages which the sculptor intends to communicate with the work. These sculptures embody numerous expressive contents which manifest in the manner and style of the work. Most African Arts express African cultures, which are known to be expressed in a variety of styles ranging from absolute abstraction, stylization, naturalism and or a cross-breed of the above. The sculptural theme in the African arts enables the sculptors to consider what is called 'African motif' in their various designs. These motifs include the use of lines, stitches and basic shapes, which are sometimes used to represent tribal marks, tattoos and other forms of African mode of body adornment.

Recognition is a peculiar process as far as the Human Visual System (HVS) is concerned. This is as a result of the fact that, every human being carries with him from his cradle to his grave certain physical marks which do not change his character and by which he can easily be identified. On the other hand, many different techniques are involved in recognizing different objects (including faces) in the area of Computer Visual System (CVS). In recent times, face recognition has being a popular issue under consideration in this area of pattern recognition. Faces and busts share some relationships being items that both relate to the characteristic features of human facial structure. The face is defined as the frontal part of the head in humans from the fore head, to chin including the hair, eyebrow, eyes, nose, cheek, mouth, lips, teeth, and skin. It is used for expression, appearance and identity among others even though, no two faces are alike in the exact same way, not even twins. In the same vein, a bust is used to clearly represent the various characteristic features of the human face with the aim of passing some messages related to culture and tradition especially here in Africa.

As a result of this, a typical bust is usually made to be composed of some additional unique features that have direct relations to the nature of message it is meant to pass. Researches have shown that faces are made up of pretty standard components that are somehow similar in nature and thus difficult to distinguish using computers. This as a result makes developing a computational model of face recognition more difficult because faces are complex multidimensional and meaningful visual stimuli. The reverse seems to be the case in sculptural designs which are noted to be man-made unlike faces. Busts usually bear on them features that easily distinguish them from one another since they are majorly made to either show an action, or a condition that is culture-related. The following characteristics of the African bust i.e. facial dimension, types of marks, structure of facial components such as the eye, nose, mouth and chin are to be considered as the pattern recognition features for designing a workable system that will be suitable for identification and recognition of a typical African bust. The efficient recognition of these features would be achieved by developing a simple system that is characterized by a clear and easily modifiable algorithmic steps. This shall give room for the merging of newly discovered features (if any) in future times.In this work a Modified Principal Component Analysis (MPCA) algorithm to identify and recognize African bust is presented. Principal Component Analysis (PCA) is a straight forward pattern recognition techniques possess the needed procedural steps and qualities that simply need to be modified to cater for the proper recognition of the African bust.

## II. OVERVIEW OF THE PRINCIPAL COMPONENT ANALYSIS TECHNIQUE

The PCA according to Turk and Pentland (1991) is an approach considered as one of the most successful representations for recognition (Marian *et al.,* 2002). By PCA, we mean only the main features of a given image are considered and analysed, thus, faces are captured into basic features and stored as vectors in a face space after being normalized as required. This process involves a phenomenon called Normalization which is said to be the remapping of images in space (Undrill, 1992). The idea of using eigenvectors was first put into being by a technique developed by Sirovich and Kirby (1987) for efficiently representing pictures of faces using Principal Component Analysis. Starting with an ensemble of original faces, Sirovich and Kirby (1987) collected the best coordinate system for image compression, where each coordinate was actually an image that was termed as eigenpicture. PCA is also called the (discrete) Karhunen-Loeve Transformation (or KLT, named after Kari Karhunen and Michael Loeve) or the Hotelling Transform (in honour of Harold Hotelling) (Turk and Pentland, 1991). The process of Karhunen-Loeve transformation is simply to find the vectors that best account for the distribution of face images within the entire image space (Turk and Pentland, 1991). These vectors define the face space, thus, each vector of length N describes an N by N image which is a linear combination of the images in original face image. These vectors are the eigenvectors of the covariance matrix corresponding to the original face image and they also are face like-in nature as revealed by Turk and Pentland (1991). PCA seeks a linear combination of variables such that the maximum variance is extracted from the variables. It then removes this variance and seeks a second linear combination which explains the maximum proportion of the remaining variance (Dennis, 1973). According to Lindsay (2002), PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Meanwhile, once these patterns in the data are found, they can be compressed, i.e. by reducing the number of dimensions, without much loss of information (Lindsay, 2002). The technique has been described by Burton *et al* (1999), as a promising image processing approach to face recognition.

### 2.1 Reasons for Choosing Principal Component Analysis

The conventional PCA algorithm (Eigenface algorithm) has successfully been used to recognize human faces with fewer variations and under simple conditions. This has proven very efficient especially when features are not to be treated on higher order level of analysis. Meanwhile, researches have shown that the behaviour of human faces in response to external conditions such as expressions, feelings, pose, illumination etc has been the major factor that led to the development of more robust recognition systems that could be used to tackle most of the identified issues related to human facial recognition.

As far as the issue of bust recognition is concerned, PCA remains the best algorithm to be looked at due to the fact that features on African bust have certain qualities that are better treated using it. Features on African busts are direct functions of what is been conceived by the sculptor in charge. In other words, bust's features are meant to portray the message intended to be passed by the designer. This makes these features' existence permanent thus making their analysis more accurate at a lower-order level of data abstraction. Many different algorithms have later emerged to complement the workability of the Eigenface algorithm but in diverse areas of research interest. An example is the Linear Discriminant Analysis (LDA) developed by Kamran and Rama (1997), which centered on the need for a face recognition system that caters for the Discriminant power of human facial features such as gender. Another area of interest was emphasized in the Hidden Markov Model (HMM) for face recognition.

According to Ara and Monson (1998), the HMM dealt with the effects of face Orientations and expressions and was proven to be more efficient than the Eigenface algorithm in that respect. In 1999, Burton *et al.,* introduced the Interactive Activation and Competition (IAC) model attached to a front-end. The resultant model provides the facility to examine the phenomena outside the range of either perceptual or cognitive models thus emphasizing the need for a system to provide information about a person suffice to recognition. Meanwhile, in some researches, it has been observed that both the independent Component Analysis (ICA) technique and the Bayesian (Bayes) approach developed by Marian *et al.,* (2002) and Babback *et al.*, (2002) respectively served as improvement on PCA. While the ICA technique treated the issue of high-order dependencies among images' pixels, the Bayesian approach dealt with intra-personal and inter-personal variations between face images. Other approaches are 3D-Morphable model and Kernel Clustering-Based Discriminant which were developed in the years 2003 and 2007 respectively.

Meanwhile, the working definition of the term 'African Bust' in this research implies a particular bust *(i.e. art work depicting the human head)* that is made of features which do not only display the characteristic features of the human face but also speak about African culture and tradition. The fact remains that African art demonstrates the African characteristic, as it tends to express harmony, unity and balance according to Nasry (2007). In summary, since the African Busts (Figure 1) have many different characteristic features, and that only the unique among them are needed for their easy and quick identification, the analysis of the images' principal components are needed to serve the purpose. Hence, PCA, which gives room for such analysis, has an advantage over others in this regard because the technique gives room for reduction of dimensions and makes the entire process more efficient. Finally, there is no issue of gender specification, expression representation, object deformation and the likes (conditions responsible for what is termed as 'Feature Dynamism') in bust recognition as opposed to face recognition. These are the problematic areas of face recognition that can be better solved using other recognition algorithms such as Independent Component Analysis, Linear Discriminant Analysis, Bayes Algorithm, Hidden Markov Model, and Artificial Neural Network etc. However, some of these algorithms mentioned have their own major flaws, for instance, the Linear Discriminant Analysis Technique, according to Kresimir *et al. (*2006) and Wendy (2000), is observed to be less effective in a situation whereby the training set is small. Meanwhile, busts are never to be treated as we do on faces. Faces are purely natural in nature and as a result, have no other basis for their creation other than to represent human beings. Busts on the other hand, are noted to be man-made. They have most of their creation associated with a particular theme. That is, the message the artist/sculptor intends to pass using the bust design which in this case relates to beliefs, tribal styles etc which are all part of African culture. This fact makes them to contain features such as tribal marks, beads, and veils among others.

**Fig. 1:** Examples of African busts' images

## III. MODIFIED PCA DESIGN

Five replications of seventeen African busts images were taken with the use of a digital camera with resolution of 10.00 Mega-pixel. The following characteristics of the bust: facial dimension, types of marks, structure of facial components such as the eye, nose mouth and chin were analysed for identification and recognition. At the pre-processing stage, the images were resized for proper reshaping and cropped to adjust their background using the Microsoft Office Picture Manager. The images were the splitted into two groups namely: *trainingt and test images.*

Four of the five images of each bust were used to form the *training set* while the *test image* was composed of a single image of each bust. According to Standberg (2000), digital image is composed of pixels, which can be thought of as small dots on the screen. Therefore, the numeric forms of the said pixels for each of the images were extracted and the data corresponding to the features, collected using MatLab. The input data were transformed into a reduced representation set of features (also named features vector) since bust images have very large sizes. This transformation of the input data into the set of features is called *features extraction.* The logic behind this is that, if the features extracted from a given image are carefully chosen, it is expected that the features set will extract the relevant information from the input data in order to perform the desired task. Meanwhile, a Modified PCA algorithm, which facilitates varying eigenvector and non-square image processing, was developed. The corresponding eigenvectors was designed to take into account both the magnitude as well as varying number of those eigenvectors.

**3.1 Algorithms Analysis: *PCA* Versus *MPCA***

Next we present the PCA algorithm and our modified PCA

**3.2 Principal Component Analysis**

The PCA algorithm always begins with the initialization operation followed by the recognition of testing images. The initialization procedure (bust recognition) is as follows;
Acquire an initial set of face images (to form the training set)
Calculate the Eigenface from the training set. That is, calculate the eigenvalues from the covariance matrix and use it to calculate the eigenvectors.Form the bust space by selecting only vectors with highest eigenvalues.
Having initialized the system, the following steps are used to recognize a test image;
Determine its eigenvectors and eigenvalues representation
Calculate the image's distance from the space and also its distance from the face classes
Determine whether or not the image is a face and determine its class.
The above steps are illustrated in Figure *2* as a flowchart with instance of three bust images with three replications each as an example.

**3.3 Modified Principal Component Analysis *[MPCA]***

This modification *(*shown as flow chart in figure *3* is a way of retrieving certain useful information ignored using Conventional PCA technique. In this case, the bust space is to be formed by making use of some vectors with low energy level together with those with highest energy level. This is as a result of some additional non-facial features ignored in face recognition which were not properly considered because they do not form part of what was termed *"major features"* in the Eigenface algorithm. However, MatLab took charge of converting digital images from their original coloured form to their grey-scale equivalent during processing; with the aid of the Modified PCA code. The grey-scale level is the degree of whiteness and blackness of a particular picture, which is usually represented with numeric values that range between 0 and 255. The digit 0 denotes perfect white while 255 denotes perfect dark. The algorithm in term of flowchart for both the pre-processing carried out on the images and the MPCA are shown in appendices A and B respectively.

**INITIALIZATION**

Acquire an initial set of bust images and form the training set
Calculate the images corresponding eigenvectors and eigenvalues
Classify the images' vectors i.e. group the various vectors into classes based on the closeness of the respective eigenvalues Create a bust space comprising of vectors of varying eigenvalues.

**RECOGNITION**

Input the test image
Determine its eigenvector and eigenvalues form
Calculate the image's distance from the space and its distance from the bust classes
Determine whether or not the image is a bust.
Determine the test image class if recognized to be a bust.

**3.4 Feature Analysis and its Relevance to the PCA Modification**

PCA makes use of only the major components of a particular image for analysis and as a result, its image representation and analysis procedure require only vectors with highest eigenvalues leaving aside those with low eigenvalues. That is, the higher the eigenvalues, the higher the magnitude of information contained. The modification theory centers on the need to retrieve part of the information contained in those ignored vectors.
This is simply because some of these features ignored while treating human faces carry certain information vital to the issue of bust recognition. Therefore, while only vectors of highest eigenvalues are considered in the Conventional PCA, the MPCA gives room for the use of vectors of varying number of eigenvaluesHowever, the analysis of the pattern recognition features of African bust needs to be based on two inter-related issues namely human representation and passing of messages. This aspect of human facial recognition is very important in determining the features of African bust simply because busts are designed through the characteristic structure of the human face and as a result share the same aspect of features composition. Based on this, a typical bust is expected to be composed of features that together make up the human face. Examples of such features are eyes, nose, mouth, the forehead etc. In addition to these features, certain portions of the human face which are considered minor facial parts

play greater role in the area of bust recognition. Being elements used to speak about the African culture and tradition, African busts do possess certain featural qualities such as tribal marks, tattoos, scarifications etc. These are very important features which are mostly located on salient portions such as chin, cheeks etc. These portions form the minor parts in human facial recognition. Therefore, the issue of African busts recognition is quite different from that of the human face. Being a man-made material, a typical African bust is not only created to represent human being but also to pass some very important messages. These messages could be about a tribe, tradition, event, cultural activity or race. This makes it to be composed of certain salient features, which don’t form part of the major features considered in human face recognition. Also, human faces are made up of facial features that make most human being closely related in terms of recognition unlike African busts, where features are based on the theme *(i.e. the message the artist intends to communicate)*. This, in some senses, makes the recognition of a typical bust less difficult.Also, to the popular facial features such as eyes, nose and mouth, some of the most important pattern recognition features that make up a typical African bust which are usually employed in communicating the African message include lines and stitches which also gave rise to the consideration of features such as tribal marks, tattooing and scarification and are mostly located on special areas of the face such as chin, cheeks as well as the forehead. In other words, there are certain important information needed for recognizing a typical African busts which are not really found on most features considered in human facial recognition.

Examples are tribal marks, stitches, lines etc. Hence, the use of a varied number of eigenvectors in addition to their respective eigenvalues, serves as the necessary tool for clearly determining the correctness of the African bust recognition system. Lastly, most African bust images are somehow different in sizes making their resizing into square dimensions very difficult. This results as a result of image background elimination since most African busts employed in this system were found in places it was possible to take their photographs without minor coverage of their respective backgrounds. This thereby led to some of the modifications earlier mentioned in order to have an efficient system design.In summary, this modification made to PCA serve as an improvement on the algorithm and can probably be used to solve recognition issues of human faces especially those with deformed size and distinct features such as tribal marks.

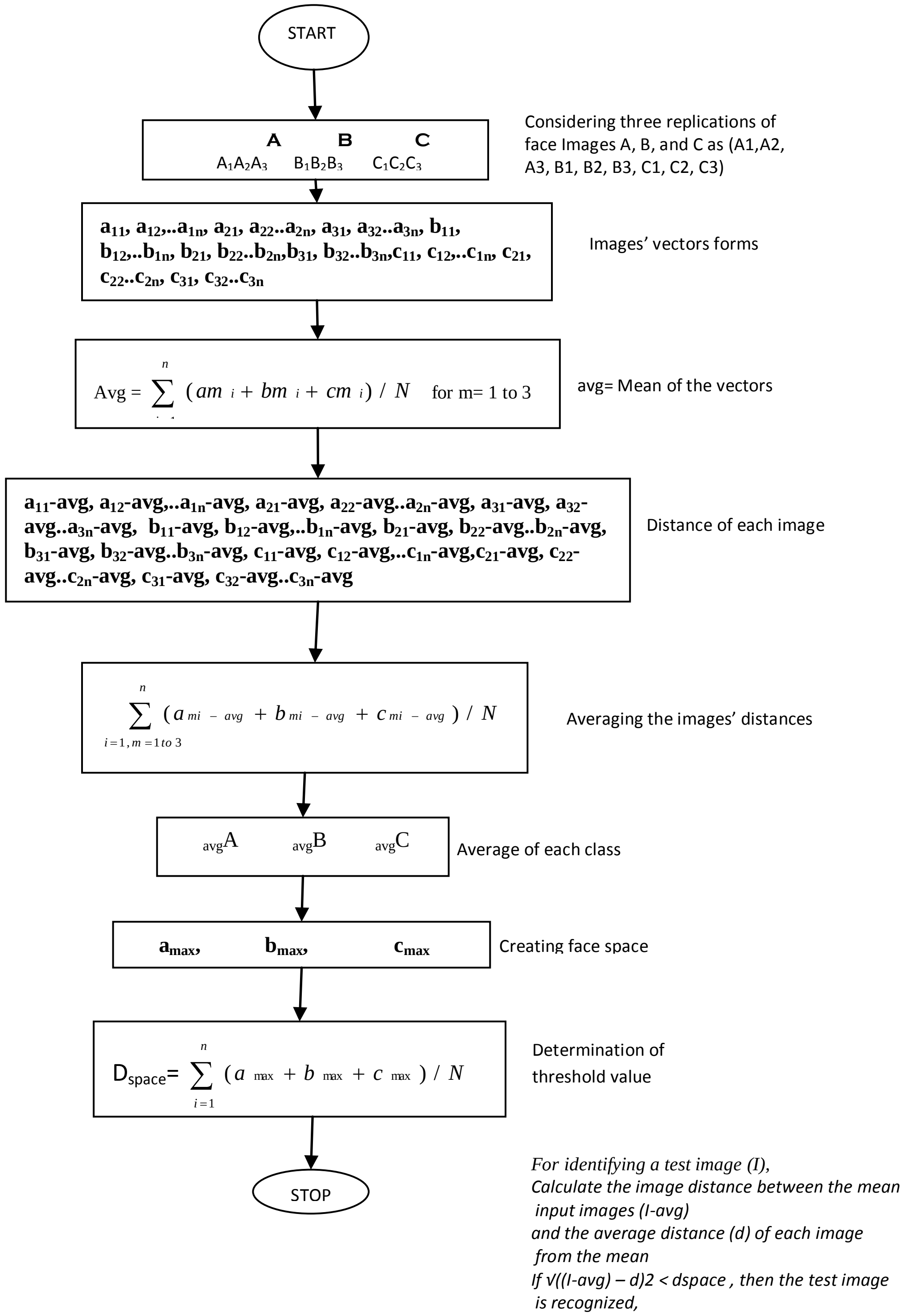
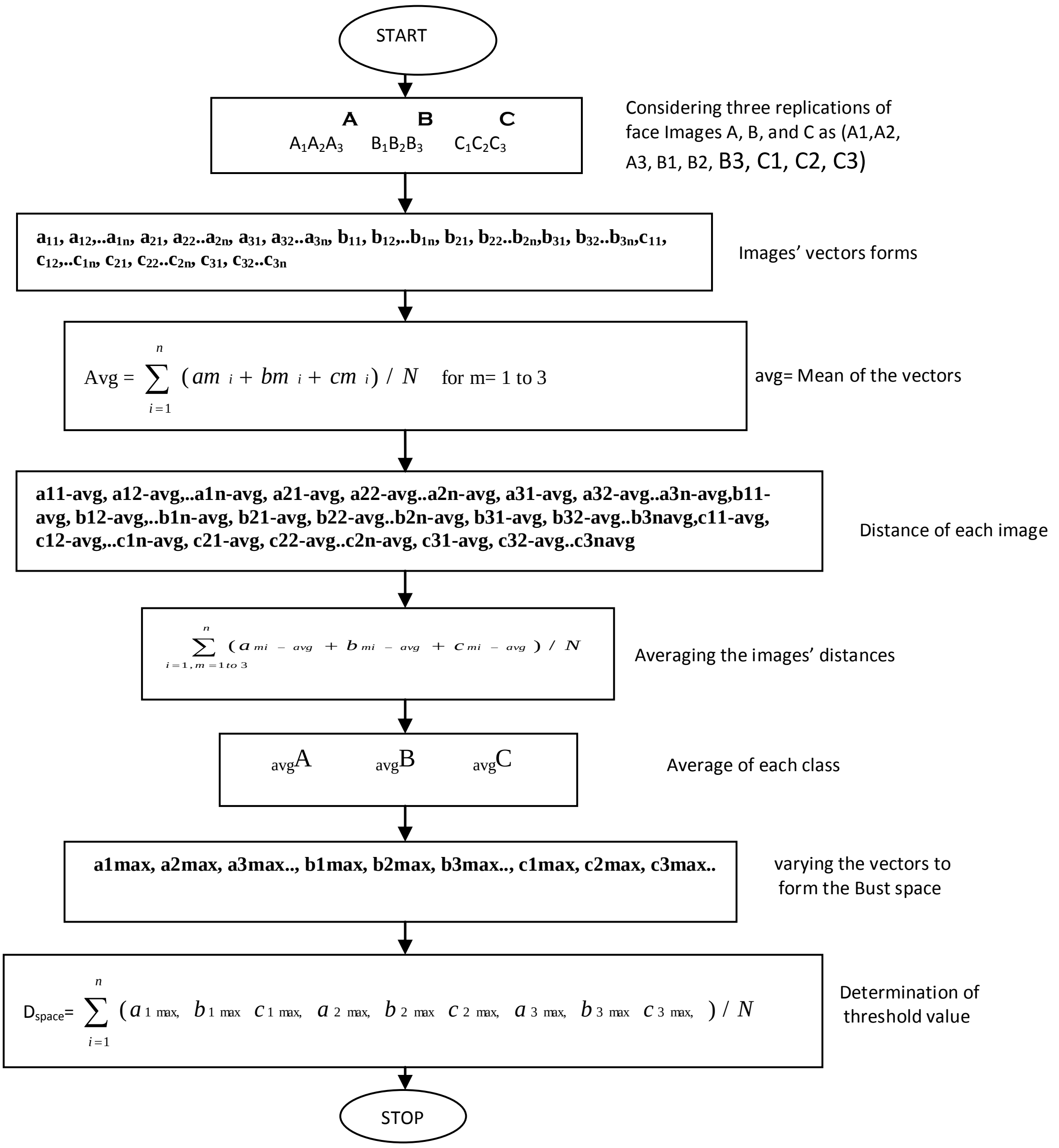



Figure. 2: Illustration of the PCA




For identifying a test image (I),
Calculate the image distance between the mean input images (I-avg) and the average distance (d) of each image from the mean If √((I-avg) – d)2 < dspace , then the test image is recognized, Else, it is not.

Fig. 3: Illustration of the MPCA steps

**3.5 Processes Involved in the Modification and Merits**

The first process is the cropping of images which is the process of eliminating the background of an image to stay clear of foreign (unwanted) portion(s) of a particular image. This was considered necessary due to the following reasons:The first reason is the issue of background that makes it difficult for most graphics packages to accurately represent digital images in terms of their exact features knowing fully that image representation is a function of the colouring of the picture elements (pixels) of a particular image. Meanwhile, with background on images, the process of allocating numbers to each of the image pixels based on their colour seems ambiguous hence poses serious threat as regards the accuracy of result. This is because the consideration (i.e. allocation of numbers) will be extended to that unwanted part of the (i.e. background). That is, each pixel forming up the image background shall also be allocated numbers thus affecting the result of the representation. The fact remains that pixels are the discrete elements used to capture the image created by the camera or scanner lens system on the device's imaging chip (Reichmann, 2008). Meanwhile, the use of well-cropped images for processing in this research has greatly has led to the speed up of the image processing rate in the sense that it took the processor less time to centre each bust image thus making it easier to locate the corresponding features. This result also tackled the issue of background elimination, which forms part of the constraints in the Eigenface Algorithm.The second reason is the inclusion of some vectors of low-energy level: The theorem in PCA explains that the number of selected eigenvectors (Eigenfaces) forming up the face space must not be greater than the number of original face images. This is mathematically expressed as follows;

$M_{(v)} < = N_{(I)}$

Where $M_{(v)}$ = No of selected eigenvectors and

$N_{(I)}$ = Total number of vectors from the training set of images.

This is better explained in the algorithm that follows:

- *Let K = Total number of original image*
- *Let M (v) = Number of selected vectors*
- *Calculate the eigenvalues of bust images*
- *Calculate the corresponding eigenvectors*
- *Determine the maximum eigenvalue for each image*
- *FOR M (v) <=K DO*
- *Select the vector with the maximum eigenvalue for each of the image*
- *Group the vectors to form the space*
- *Calculate the average of the vectors (i.e. threshold value)*

Also, the MPCA envisaged that the selection of vectors should be extended beyond the total number of original images in order to include some vectors with certain information ignored in face recognition but needed in bust recognition. This step gave rise to an improved PCA system that was able to recognize all the test images. This is explained in the algorithm below:

- *Let K = Total number of original image*
- *Let M (v) = Number of selected vectors*
- *Let N= total number of vectors generated from the training set*
- *Calculate the eigenvalues of bust images*
- *Calculate the corresponding eigenvectors*
- *Determine the maximum eigenvalue for each image*
- *FOR K< M (v) <N DO*
- *Select vectors that satisfies the statement above*
- *Group the vectors to form the space*
- *Calculate the average of the vectors (i.e. threshold value)*

**3.6 Relevance of MatLab to the System Design**

Digital images have different formats and as a result, require several procedural steps in making them usable for processing with most programming languages. These sets of digital formats are not easily readable by most programming packages since most important functions needed to perform operations on them, such as reading and writing of digital images, performing mathematical operations on digital images, etc, are not readily available in most conventional programming languages such as *C*-language, *C++* language among others.

Knowing fully that most digital images are in form of two-dimensional *(2D)* discrete signals, *(3D in some cases)* which are mathematically represented as functions of two independent variables, MatLab rendered help by providing suitable tools for any operation on the digital images of African bust together with some in-built functions for their transformations when needed.

This made the design of the system and the development of the Modified PCA code comprehensive. It also reduced the processing time. However, images are most commonly stored in MatLab using the *logical, uint8, uint16* and *double* formats. Many standard MatLab array manipulations can be performed on *uint8* and *uint16* image data, including basic arithmetic operations, such as addition, subtraction, and multiplication. MatLab stores most data in arrays of *class double*. The data in these arrays are stored as *double-precision (64-bit) floating-point* numbers. All MatLab functions and capabilities work with these arrays. For images stored in one of the graphics file formats supported by MatLab, this data representation is not always ideal. The number of pixels in such an image can be very large; for example, a *1000-by-1000* image has a million pixels. Since each pixel is represented by at least one array element, which would require about 8 megabytes of memory if it were to be stored as *class double*. Therefore, to reduce memory requirements, MatLab supports storing image data in arrays of class *uint8 and uint16*. The data in these arrays is stored as *8-bit*s or *16-bit*s unsigned integers. These arrays require one-eighth or one-fourth as much memory as data in *double* arrays. For the purpose of this research, the bust's images were converted into their *greyscale* forms from their original *Joint Photographic Expert Group (JPEG)* forms. However, the various pixels forming up each of the images were represented using the class *Unit8* because of their very large sizes. This gave room for each pixel colouration to be represented between the range of *0 to 255* with *0* representing *total blackness, 255* for *total brightness* while the numbers in-between stand for the different colouration aside *blackness* and *brightness*. The bust images were finally converted into class *'double'* being the only class on which most mathematical functions can be applied in MatLab. However, displaying the eigenvectors of such bust images were impossible since the class *'double'* in which they were converted to for calculation purposes has its colouration between the *integer 0 and 1* which cannot be employed to reference information for images of very large sizes such as the bust image. An analysis of the conversion is shown in figure 4.

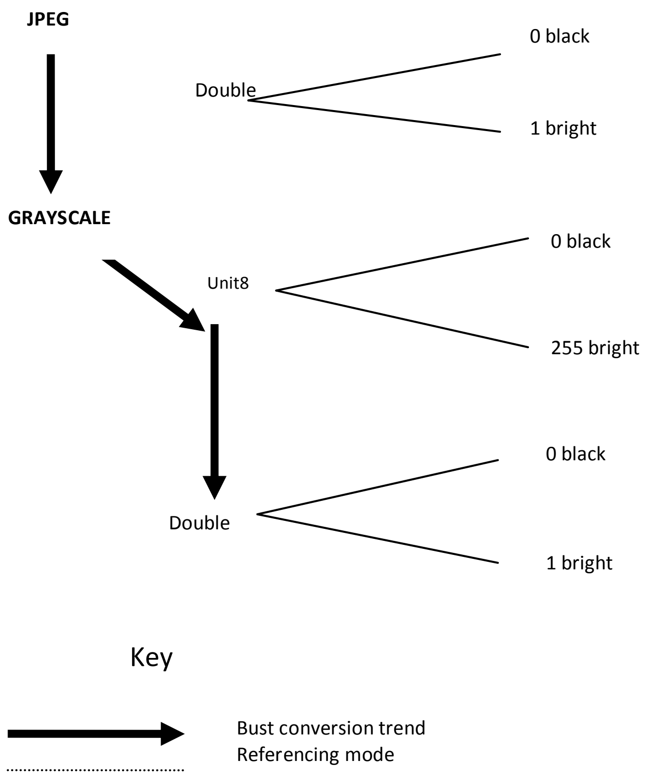



Figure 4: Bust Conversion

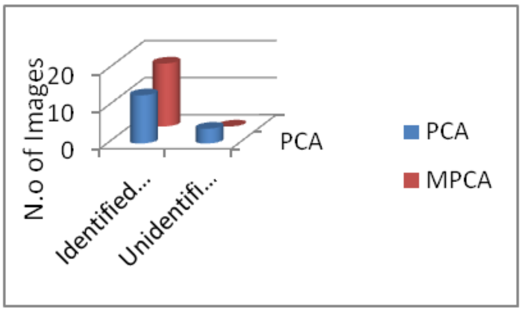
Next we discuss the evaluation of the proposed approach to the recognition of African bust under two sub-heading namely;

1. The performance evaluation of the MPCA in comparison with the Conventional PCA on the set of bust images.
2. The determination of the effects of varying pixel resolution on the developed system.

## IV. PERFORMANCE EVALUATION: PCA VS MPCA

The essence of this evaluation is to clearly determine the impact of the modification on the PCA technique. In other words, this evaluation is a way of showcasing the merits of the MPCA with respect to the introduction of eigenvectors of varying number of eigenvalues in forming the bust space for recognizing a typical African bust image. The Eigenvectors are the carriers of information about a typical digital image and as a result, considered as the main elements employed in classifying and identifying images in the PCA technique. Therefore, testing the effects of these eigenvectors as mentioned above remains the main evaluation procedure in the Modified PCA. To ensure this, a total number of eighty five (85) bust images were involved with sixty eight (68) used for training and seventeen (17) as test images. This same set of data was run on both PCA and MPCA codes and their results displayed in Table 1 with the corresponding sketches in Figure 5. However, with test data as the main benchmarking parameter, it was discovered that the performance of the MPCA outweighed that of the PCA in terms of the total number of identified images.

**Table 1: :** Evaluation Details Using Number of Identified Images




| PARAMETERS | PCA | MPCA |
|---|---|---|
| Total Number. of Images | 85 | 85 |
| Images for Training | 68 | 68 |
| Images for Testing | 17 | 17 |
| Identified Images | 13 | 17 |
| Unidentified Images | 4 | 0 |

### 4.1 The Effects of Pixel Resolution on the MPCA

Evaluation using pixel resolution implies the determination of the effect of pixel resolution of a particular African bust image on the MPCA performance. This was considered both in terms of the number of identified images and also the average time taken. The term ‘pixel resolution’ of a digital image is the arrangement of the various picture elements forming the image which is usually in rows and columns. The system was tested by varying the resolution of images’ picture elements (square-wise) to determine its effect on the recognition performance. The resolution numbers of pixels used in this case and their corresponding results are tabulated in table 2 and graphically displayed in Figure 6. The system performance was also checked by varying the values of pixel resolution (i.e. rows of non-square values) with a view to determining the possible change in the identification performance whenever the selected number for both the rows and that of columns are not the same. It is therefore observed that the system performance accuracy is being affected whenever there is a mis-match between the rows and the columns. This simply implies that the performance declines with a slight difference between the value of rows and that of the columns. The results of varying the rows are shown in table 3 and Figure 7. In essence, it was generally observed that the performance of the MPCA was observed to be at best whenever the rows and columns in the bust image pixel resolutions were the same.

**Table 2:** Effect of Pixel Resolution (Square-wise)

| Pixel Resolution | No. Of Identified Images | Average Time Taken |
|---|---|---|
| 55x55 | 17 | 9.5785 |
| 60x60 | 17 | 9.4021 |
| 65x65 | 17 | 9.3133 |
| 70x70 | 17 | 9.1261 |
| 75x75 | 17 | 9.9373 |

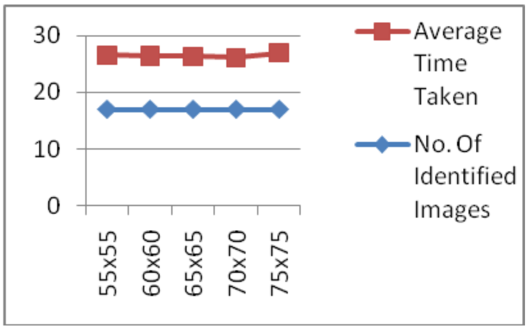
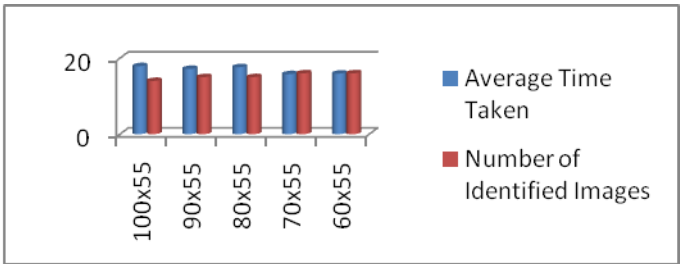



**Figure 6:** Effect of Pixel Resolution (Square-wise)

Table 3: Effect of varying pixel resolutions (row-wise)

| Pixel Resolution | Average Time Taken | No. Of Identified Images |
|---|---|---|
| 100x55 | 17.8777 | 14 |
| 90x55 | 17.1601 | 15 |
| 80x55 | 17.6125 | 15 |
| 70x55 | 15.7717 | 16 |
| 60x55 | 15.9121 | 16 |




## V. CONCLUSIONS

The developed MPCA in this research has been an improvement on the Conventional PCA technique (Eigenface algorithm) at both the pre-processing as well as processing stages. The Modification made to the conventional Principal Component Analysis of human facial recognition has shown better performance compared with the Conventional PCA as far as the parameters involved were concerned. One observed fact in this research is that the Conventional PCA has somehow shown noticeable performance to some extent based on the nature of the used data. Finally, the system performance was highly justified by the nature of the various results obtained in each of the evaluation stages. That is, the system has proven very efficient and reliable in recognizing the features of the African busts.

## VI. FUTURE WORKS

Although, the MPCA developed has proven to be very efficient in terms of accuracy of results, there are certain things left untreated which could have made it more robust than it is presently. The MPCA designed only takes care of the primary features of the African busts, examples of which are eyes, mouth, nose, tribal marks and stitches. However, features such as veil, beads, hats which are noted to be external to the main facial features of the African busts, were not really taken into consideration during the course of the design. Another area of interest includes the issue of African busts of different sizes and poses, which could take care of any African bust irrespective of its structural forms and locations, if properly handled.

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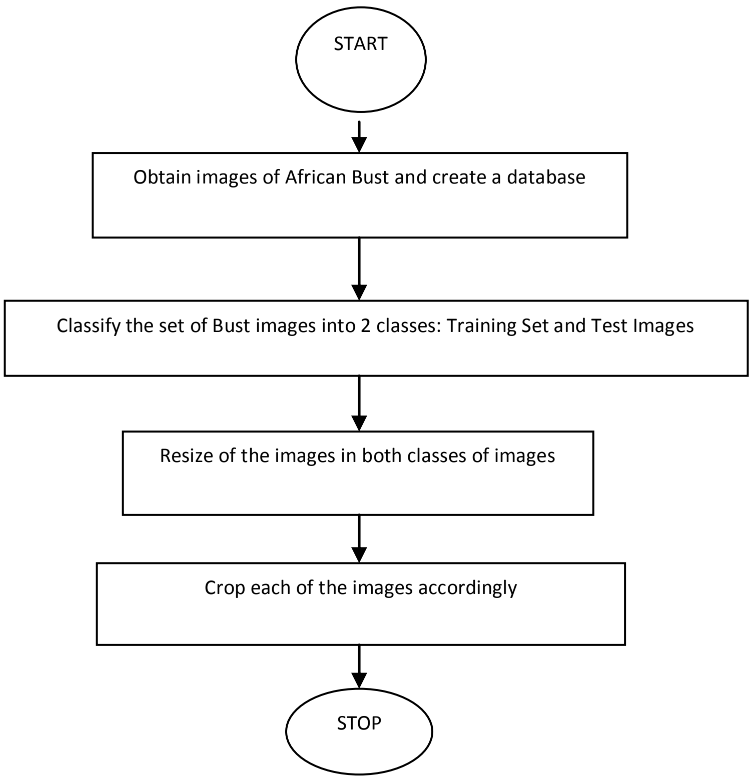
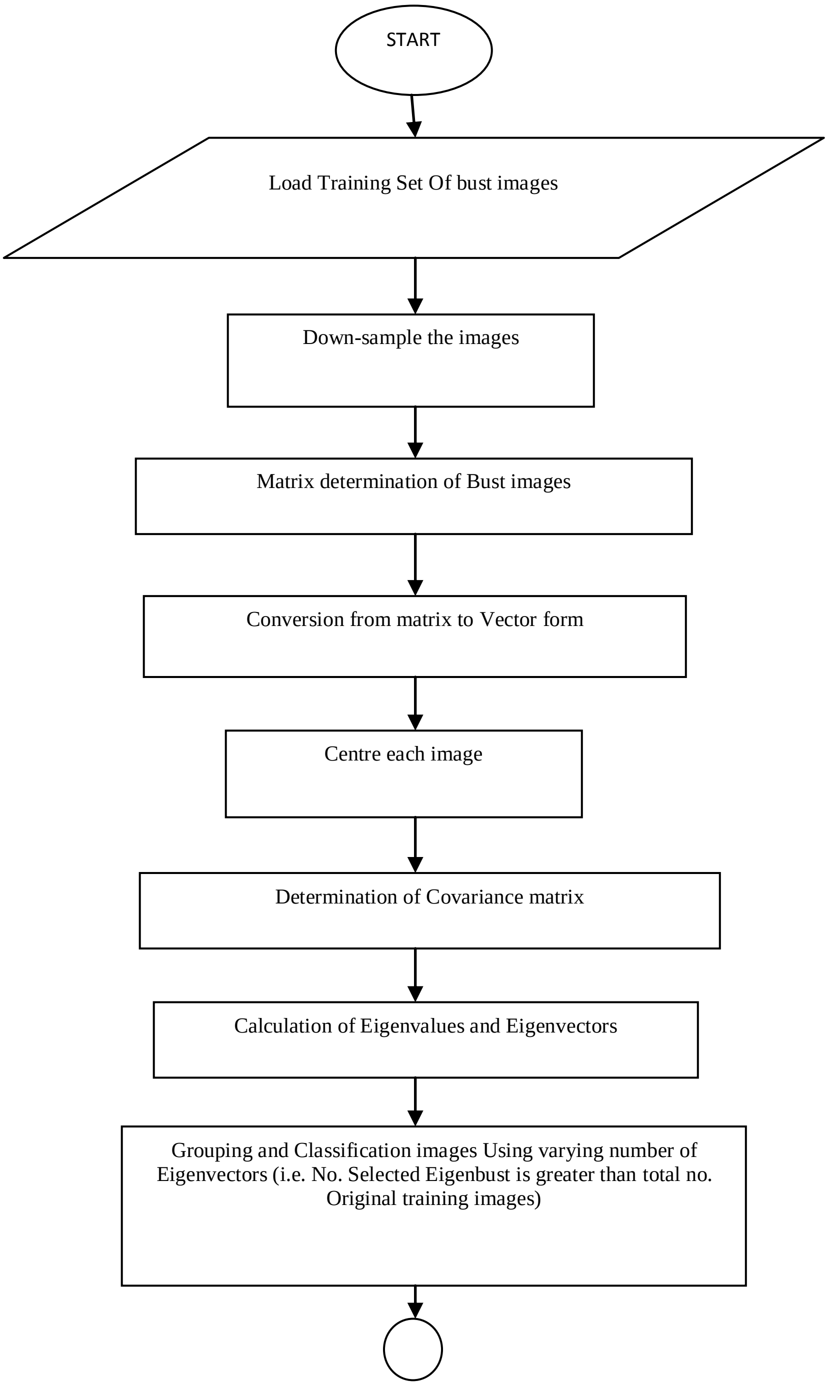
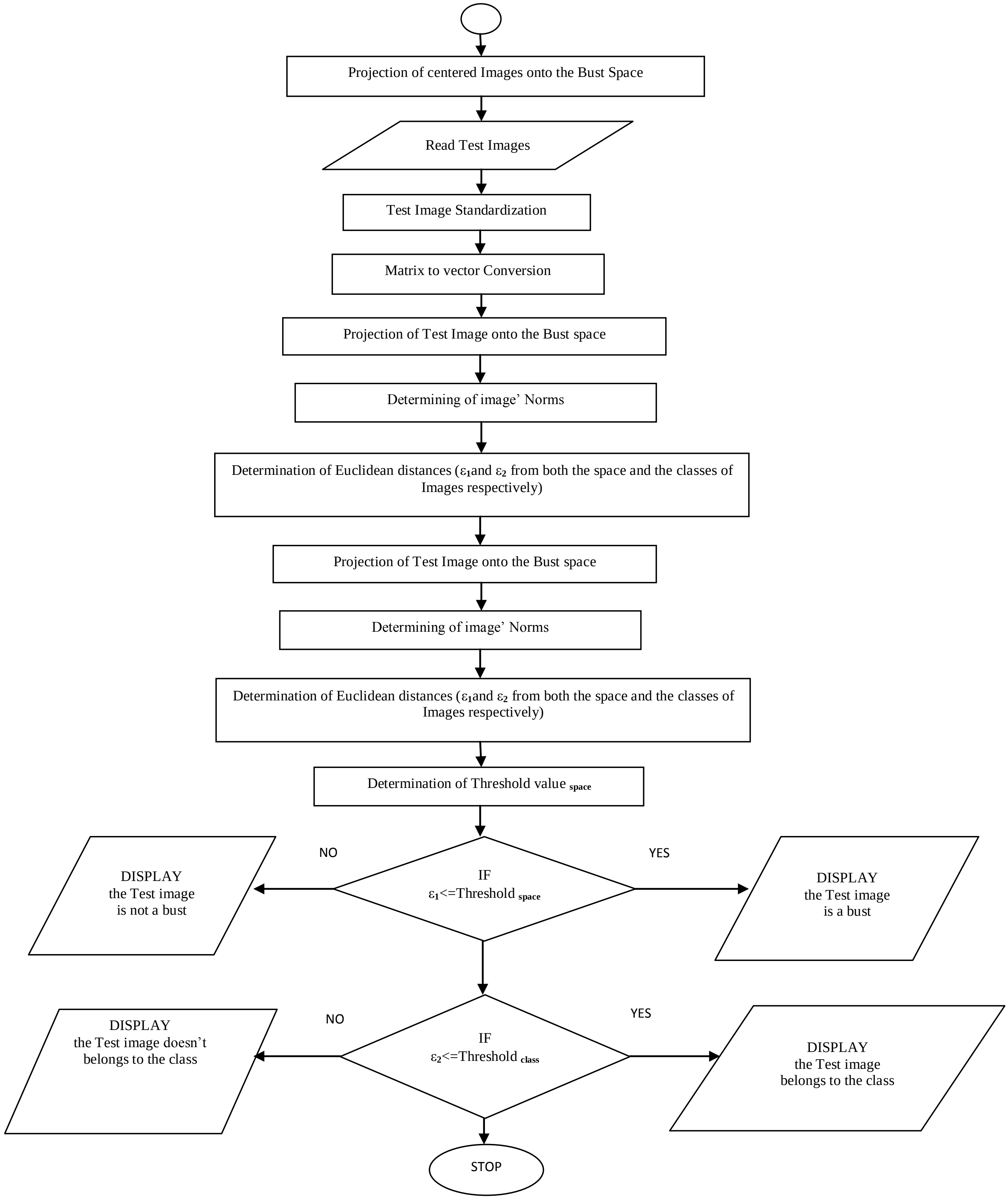
**[14]**

## APPENDICES

**APPENDIX A:** Pre-processing Flowchart




START
Load Training Set Of bust images
Down-sample the images
Matrix determination of Bust images
Conversion from matrix to Vector form
Centre each image
Determination of Covariance matrix
Calculation of Eigenvalues and Eigenvectors
Grouping and Classification images Using varying number of Eigenvectors (i.e. No. Selected Eigenbust is greater than total no. Original training images)


Projection of centered Images onto the Bust Space
Read Test Images
Test Image Standardization
Matrix to vector Conversion
Projection of Test Image onto the Bust space
Determining of image' Norms
Determination of Euclidean distances ($\varepsilon_1$and $\varepsilon_2$ from both the space and the classes of Images respectively)
Projection of Test Image onto the Bust space
Determining of image' Norms
Determination of Euclidean distances ($\varepsilon_1$and $\varepsilon_2$ from both the space and the classes of Images respectively)
Determination of Threshold value $_{space}$
NO
YES
DISPLAY the Test image is not a bust
IF $\varepsilon_1$<=Threshold $_{space}$
DISPLAY the Test image is a bust
NO
YES
DISPLAY the Test image doesn't belongs to the class
IF $\varepsilon_2$<=Threshold $_{class}$
DISPLAY the Test image belongs to the class
STOP