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DETERMINATION OF CRIME PATTERN IN KADUNA STATE USING PRINCIPAL COMPONENT ANALYSIS AND MULTIDIMENSIONAL SCALING

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ABSTRACT

Crime is a complex event occurring in a real spatio-temporal environment. Understanding crime patterns requires both theory and research. The study used secondary data collected from the 23 Divisional Police Headquarters (DPHs) on all the 23 Local Government Areas (LGA) of Kaduna State. The analysis was carried-out using multivariate approaches of Principal Component Analysis and multidimensional scaling. The results shows that three components were retained which collectively accounted for about 85% of the total variability in the data and individually, the first, second and third PC accounted for 42.4%, 25.5% and 16.9% of the total variability in the data respectively. On the other hand, The Euclidean Distance map shows that grievous hurts, assaults, rape, murder and kidnapping are closely compact. This means that these crimes are closely related as people commit them in Kaduna State.It is therefore recommended that further research should be conducted to cover three geo-political zones in the northern Nigeria in particular or the country at large; this would further assist towards addressing the recent problems of insecurity affecting our there country, Nigeria.

Keywords: Crime Pattern, Principal Component, Multidimensional Scaling, Euclidean Distances, Dhat Matrix, STRESS Function.

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1.0 INTRODUCTION

Crime is a complex event occurring in a real spatio-temporal environment. Understanding crime patterns requires both theory and research. In many situations, the requirements of understanding crime patterns lead to the development of new theories or new research methods or techniques. The choice of unit of analysis constitutes a fundamental issue for criminologists interested in spatial patterns in crime. Crime can form very different patterns at different scales of analysis (Brantingham and Brantingham, 1977). Standard spatial aggregations such as census tracts or politically defined neighborhood or city borders often fail to reflect the underlying socio-spatial distributions of people, land uses, or criminal events (Schmid, 1960a; Schmid, 1960b).

Crime is often thought of as a moral threat and injurious to the society. It afflicts the personality of individual and his property, and lessens trust among members of the society (Louis et al., 1981). However, crime is an inescapable reality in human life, therefore no national characteristics, no political regime, no system of law, police or justice has rendered a country exempt from crime. The causes of crime are multiple and could be traced to bio-genetic factors, such as genetic mutation and heredity (Hardle and Sinar, 2003), psychological factors, such as personality disorders (Abramson, 1994), and sociological factors, such as learning and environment. The diverse differences in geographical areas in terms of population density, demographic characteristics, natural vegetation, locations and socio-economic characteristics has rendered crime rate unevenly distributed globally. However, it has been observed that the entire world is experiencing high criminal rate. The report of the International Crime Victim Survey (ICVS) has confirmed the situation. The report which was conducted on six major world regions including Africa, Asia, Central and Eastern Europe, Latin America, and Western Europe for the 1989 - 1996 period has shown that more than half of the urban respondents reported being victimized at least once regardless of what part of the world they inhabit (Ackerman and Murray, 2004).

One of the global concerns is the issue of increase in crime rate. The incidences of organized crimes, corruption, human trafficking, illicit drug addiction and trafficking are continuing to render the world unsecured. The situation in Nigeria is not exceptional (Natsec, 2005). Over the years the rate of crime in Nigeria has been on the increase and these crimes are being carried out with more perfection and sophistication [Sam, 2003; Uche, 2008). Due to inadequate scientific and modern technology and sufficient manpower, the Nigeria security agents have not been able to effectively tackle the issue of crime in the country (Ikiro, 2007). This has led to the formation of various vigilante and civilian join task force (JTF) groups, to combat crimes in some parts of the country. However, these groups have only succeeded in creating other problems instead of solving the existing ones.

In Nigeria, research reports of the crime surveys and the periodical crime Statistical Abstracts have concentrated mainly in either using descriptive statistics or univariate statistics approaches in their statistical analysis, and little attention is focused on using the GIS and the multivariate statistical approaches. The analysis of spatial distribution of crime using GIS mapping helps in better understanding in the dynamic of crime.GIS as a tool for effective crime mapping and management. They further stressed that crime analysis using GIS is today relevant in Nigeria since the rate of crime is very much on the rise. The statistical research would guide security agencies in proper allocation of personnel and in promoting rational decisions by the policy makers. These if achieved, will successfully solve many of the complex crime problems that have bedeviled the country in general and Kaduna State in particular.

The earliest studies that explicitly explored the role of geography in distribution of crime immediately noted various spatial relationships. The growth of interest in crime mapping from police department has thus spurred practitioners to seek out both theoretical explanations for the patterns they see and remedies to the crime problems that plague the communities the police. Many crime prevention practitioners have thus been drawn to environmental criminology researchers, an eclectic group of crime scientist that bringing a fresh and practical perspective to the problem of crime (for a list of the most prominent environmental criminologist/crime scientist (Wortley and Mazerolle, 2008).

However, there is no universal definition for crime. This is as a result of changes in social, political, psychological and economic condition. An act may be a crime in one society, but not in another (Danbazau, 2007). For example, prostitution, adultery and homosexual behavior between consenting adults have been wholly or partially removed from the criminal law in USA, but are considered as crimes in Muslim communities such as Saudi Arabia.

Criminologist concerned not only about the strict legal sense of crime, but also with the potential criminal behaviour. Therefore, they recognize factors such as value systems, and religious attitudes in a given culture in the definition of crime (Danbazau, 2007). The threat of crime to the society is impossible to ignore. Crime undermines the social fabric of society, by first eroding the sense of safety and security. It represents an immediate physical and moral threat to particular individuals (Louis et al., 1981).

Principal Component Analysis is very useful in crime analysis because of its robustness in data reduction and in determining the overall criminality in a given geographical area. If some group of measures constitutes the scores of numerous variables, the researcher may wish to combine the score of the numerous variables in to smaller number of super variables to form the group of the measures. This problem mostly happens in determining the relationship between some socio-economic factors and crime incidences. PCA uses the correlations among the variables to develop a small set of components that empirically summarized the correlations among the variables. In one of the measures, the concentrated disadvantage index, the PCA of the structural measures supported the combination of the following measures: percent of residents who are African American, percent of residents living below the poverty line, percent of families receiving public assistance, percent of residents who are unemployed, and percent of families headed by a single parent with children under 18. Similarly, in a study to examine the statistical relationship between crime and socio-economic status in Ottawa and Saskatoon, the PCA was employed to replace a set of variables with a smaller number of components, which are made up of inter-correlated variables representing as much of the original data set as possible (Exp, 2008).

Multidimensional scaling (MDS) is a statistical method of exploring the level of similarity of individual cases of a dataset. MDS techniques seek to find a low dimensional coordinate system to represent N objects using only a proximity matrix. It refers to a set of related ordination techniques used in information visualization, in particular to display the information contained in a distance matrix (Timm, 2002). An MDS algorithm aims to place each object in *N*-dimensional space such that the between-object distances are preserved as well as possible. Each object is then assigned coordinates in each of the *N* dimensions. The number of dimensions of an MDS plot *N* can exceed 2 and is specified a priori. Choosing *N*=2 optimizes the object locations for a two-dimensional scatter plot. MDS algorithms fall into a taxonomy, depending on the meaning of the input matrix.

Goodwill *et al,* (2012) proposed the Faceted Multidimensional Scaling (FMDS) procedure used in investigative psychology research. Four FMDS themes of street robbery (Con, Blitz, Confrontation and Snatch) were revealed by crossing two underlying axial facets: the offenders' level of violence and interaction with the victim. They compare facet scale method, utilizing offenders' axial facet scores and previous count, proportional and cancroids classification methods in the prediction of offender criminal histories. They used logistic regression and receiver operating characteristic analyses, the axial facet scale method was found to significantly outperform the qualitatively based dominant theme classification methods.

2.0 Materials and Methodology

In every multivariate research, the methods and procedures adopted are critical to achieving the desired objectives. Since this study is concerned with the investigation of crime, its methodology must be carefully outlined. Thus, the study was conducted in the following stages.

2.1 Data Collection

The crime data for the 23 Divisional Police Headquarters (DPHs) on all the Local Government Areas (LGA) of Kaduna State was collected from the Statistics Department of the Nigeria Police Force, Kaduna State Command. For easy statistical analysis and interpretation: the 23 LGAs were categorized according to the three existing Area Commands (ACs): Kaduna, Zaria and Kafanchan ACs.

The data consists of ten major crimes reported to the police from the year 2002 to 2012. The crimes classifications are as follows: Offences against properties which include armed robbery, house and store breakings, theft/stealing and vehicle theft and offences against persons which include grievous hurt and wounding (G.H.W.), murder, rape, cheating, Forgery, Kidnapping and assault.

2.2 Principal Component Analysis

A principal component analysis is concerned with reducing the dimensionality of a multivariate random variable by using linear combinations (the PCs).

2.2.1 Derivation of Principal Components

Let X be a vector of p random variables, and that the variances of the p random variables and the structure of the covariances or correlations between the p variables are of interest. Unless p is small, or the structure is very simple, it will often not be very helpful to simply look at the p variances and all the $\frac{1}{2}\, p\,(p - 1)$ correlations or covariances. An alternative approach is to look for a few ($<p$) derived variables that preserved most of the information given by these variances and correlations or covariances. This explained the basic idea of PC A. This is achieved by transforming to a new set of variables, the PCs, which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables (Jolliffe, 2002).

Algebraically, PCs $Y_1 Y_2,\ldots,Y_p$ are particular linear combinations of the p random variables $X_1, X_2,\ldots,X_p$. Geometrically, these linear combinations represent a new coordinate system obtained by rotating the axes of the original system (the-Xs). The new axes represent the direction of maximum variability.

Let the random vector $X' = X_1, X_2, \ldots, X_p$ have the covariance matrix Σ with eigen values $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$.

Consider the linear combinations

$$
\begin{aligned}
Y_1 &= \alpha_1'X = \alpha'_{11} X_1 + \alpha'_{12} X_2 + \ldots \alpha'_{1P} X_P \\
Y_2 &= \alpha_2'X = \alpha'_{21} X_1 + \alpha'_{22} X_2 + \ldots \alpha'_{2P} X_P \qquad (1) \\
&\vdots \\
Y_P &= \alpha_P'X = \alpha'_{P1} X_1 + \alpha'_{P2} X_2 + \ldots \alpha'_{PP} X_P
\end{aligned}
$$

of the element of X, where α; is a vector *of p* components $\alpha_{j1}, \alpha_{j2}, \ldots, \alpha_{jp}$

Then

$$Var(Y_j) = \alpha'_j \Sigma \alpha_j \qquad j = 1,2,\ldots,p \qquad (2)$$

$$Cov(Y_j, Y_k) = \alpha'_j \Sigma \alpha_k \qquad j,k = 1,2,\ldots,p \qquad (3)$$

The PCs are those uncorrelated linear combinations $Y_1, Y_2, \ldots, Y_p$ whose variances in (15)were as large as possible [Jolliffe, 2002]. Proceeding in this way and writing in matrix notation, the result for a random variable X with $E(X) = \mu$ and $Var(X) = \Sigma = \Gamma \wedge \Gamma'$ is the PC transformation which is defined as

$$Y = \Gamma' X \text{ or } Y = \Gamma'(X - \mu) \qquad (4)$$

In finding the PCs we concentrate on the variances. The first PC is the linear combination with maximum variance. That is, it maximizes $Var(Y_1) = \alpha'_1 \Sigma \alpha_1$. It follows that α_1 could not be taken simply for maximization, since $Var(Y_1) = \alpha'_1 \Sigma \alpha_1$ can be increase by multiplying any α_1 by some constant. We need to put some conditions of choosing α_1 to be a coefficient vectors of unit length, so that $\alpha'_1 \alpha_1 = 1$. We therefore define;

First PC = Linear combination $\alpha'_1 X$ that maximizes $Var(\alpha'_1 X)$

Subject to $\alpha'_1 \alpha_1 = 1$

Second PC = Linear combination $a'_2 X$ that maximizes $Var(\alpha'_2 X)$ subject to $\alpha'_2 \alpha_2 = 1$ and $Cov(\alpha'_1 X, \alpha'_2 X) = 0$.

And so on, so that the K^{th} stage,

K^{th} PC = linear combination $\alpha'_k X$ that maximize var $(\alpha'_k X)$ subject to

$\alpha'_k \alpha_k = 1$ and $\text{cov}(\alpha'_j X, \alpha'_k X) = 0$

$$J = \alpha'_1 X, \alpha'_2 X, \ldots, \alpha'_{k-1} X \quad (5)$$

Up to *p* PC could be found, but it was stopped after the q^{th} stage ($q \leq p$) when most of the variation in X have been accounted for by *q* PCs (Talal, 2016).

Let Σ be the covariance matrix associated with the random vector $X' = [X_1, X_2, \ldots, X_P]$. Let Σ have the Eigen vector – eigen vector pairs $(\lambda_1, \alpha_1), (\lambda_2, \alpha_2), \ldots, (\lambda_p, \alpha_p)$ where $\lambda_1, \lambda_2, \ldots, \geq \lambda_p \geq 0$. The j^{th} PC is given by

$$Y_j = \alpha'_j X = \alpha'_{j1} X_1 + \alpha_{j2} X_2 + \ldots + \alpha'_{jp} X_p' \qquad j = 1, 2, \ldots, P \quad (6)$$

Then

i. The variance of a PC is equal to the eigen value corresponding to that PC,

$$\text{Var}(Y_j) = \alpha'_j \Sigma \alpha_j = \lambda_j \qquad j = 1, 2, \ldots, p \quad (7)$$

ii. The covariance between two different PCs is zero

$$\text{Cov}(Y_j, Y_k) = \alpha'_j \Sigma \alpha_k = 0 \qquad j \neq k \quad (8)$$

iii. The total variance in a data set is equal to the total variance of PCs.

$$\sigma_{11} + \sigma_{22} + \ldots + \sigma_{pp} = \sum_{j=i}^{p} Var(X_j) = \lambda_1 + \lambda_2 + \ldots + \lambda_p = \sum_{j=i}^{p} Var(Y_j) \quad (9)$$

2.2.2 Principal Components obtained from the Covariance and Correlation Matrices

Consider the covariance matrix of a bivariate data

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}, \quad (10)$$

where $\sigma_{12} = \sigma_{21}$ and $\sigma_{22} > \sigma_{11}$ assume $\sigma_{11} = 1$ and $\sigma_{22} = 100$ (a very large difference), and the derived correlation matrix

$$\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix}, \qquad where\ r_{12} = r_{21} \quad (11)$$

Because of its large variance, X_2 will completely dominates the first PC determine from Σ, Moreover, this first PC explains a larger proportion of the total population variance as

$$\frac{\lambda_1}{\lambda_1+\lambda_2}=\psi_{x_1} \qquad (12)$$

When the variables X_1 and X_2 are standardized, however, the resulting variables contributes equally

$$\frac{\lambda_1}{\lambda_1+\lambda_2}=\psi_{x_2} \qquad (13)$$

To the PCs determine from ρ, so that ρ_2, - = p_2Y_1.

Thus $\psi_{x_1} \neq \psi_{x_2}$ the proportion of variance accounted for by the components of ρdiffer from the proportion for Σ.

Since the entries of the covariance and correlation matrices are different, then the coefficients (eigenvectors) of the PC obtained from *p* differ from those obtained from ∑, and therefore $\alpha'_j X \neq \alpha'_j Z$; the PCs derived from *p* are different from those obtained from Σ, (Richard and Dean, 2001).

3.2.3 Procedure for Calculating PCs

For a random vector $X' = [X_1, X_2,..,X_p]$, the corresponding standardized variables are

$Z' = [Z_l, Z_2,...,Z_p]$ so that Cov(Z) = ρ (the correlation matrix of X). The correlation matrix between *p* variables is denoted by

$$\rho = \begin{pmatrix} 1 & r_{12} & \cdots & r_{1p} \\ r_{21} & 1 & \cdots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \cdots & 1 \end{pmatrix} \qquad (14)$$

And the vector of the coefficients (weights or loadings) on the variables for the j^{th} component by

$$\alpha_j = \begin{bmatrix} \sigma_{j1} \\ \sigma_{j2} \\ \vdots \\ \sigma_{jp} \end{bmatrix} \qquad j = 1,2...p \qquad (15)$$

The problem of determining the vectors α_j which maximize:

(1) The variance accounted for by the first component.

(2) The variance accounted for by the second component, orthogonal to the first. The solution for α_j can be solved by this equation

$$(\rho-\lambda_j I)\alpha_j = 0 \tag{16}$$

In which ***I*** is the $(p \times p)$ identity matrix, λ_j's are the characteristics roots or eigen values of ρ and the α_j*'s* are the associated eigenvectors (Louis et al., 1981)

2.3 Multidimensional Scaling of Crime Pattern

Multidimensional scaling (MDS) gives more of pictorial summary of data for easy interpretation. The purpose of multidimensional scaling (MDS) is to provide a visual representation of the pattern of proximities (similarities or distances) among a set of graphs which serves like a map (Talal, 2002). This study is partially concerned with the patterns of crimes in Kaduna State using multidimensional scaling. There are ten types of crimes to perform the multidimensional scaling. From a slightly more technical point of view, what MDS does is finding a set of vectors in *p-dimensional* space such that the matrix of Euclidean distances among them corresponds as closely as possible to some function of the input matrix according to a criterion function called STRESS (Talal, 2002). The index called the Standardized Residual Sum of Squares (STRESS) is given as follows

$$STRESS = \left(\frac{\sum_r \sum_s (d_{rs}^2 - \hat{d}_{rs}^2)^2}{\sum_r \sum_s d_{rs}^2} \right)^{1/2} \tag{17}$$

A simplified view of the algorithm is as follows: (Talal, 2002)

1. Assign points to arbitrary coordinates in *p-dimensional* space.
2. Compute Euclidean distances among all pairs of points, to form the Dhat matrix.
3. Compare the Dhat matrix with the input D matrix by evaluating the stress function. The smaller the value, the greater the correspondence between the two.
4. Adjust coordinates of each point in the direction that best maximally stress.
5. Repeat steps 2 through 4 until STRESS would not get any lower.

2.3.1 Shepard Diagrams (Scatter Plot)

The Shepard diagram is a scatter plot of input proximities (both x_{ij} and $f(x_{ij})$) against output distances for every pair of items scaled. Normally, the X-axis corresponds to the input proximities and the Y-axis corresponds to both the MDS distances d_{ij} and the transformed ("fitted") input proximities $f(x_{ij})$. An example is given in Figure 1. In the plot, asterisks mark values of d_{ij} and dashes mark values of $f(x_{ij})$. STRESS measures the vertical discrepancy between x_{ij} (the map distances) and $f(x_{ij})$ (the transformed data points). When the STRESS is zero, the asterisks and dashes lie on top of each other. In metric scaling, the asterisks form a straight line. In nonmetric scaling, the asterisks form a weakly monotonic function, the shape of which can sometimes be revealing (e.g., when map-distances are an exponential function of input proximities). If the input proximities are similarities, the points should form a loose line from top left to bottom right (Talal, 2002).

2.3.2 Non-Metric Multidimensional Scaling.

In contrast to metric MDS, non-metric MDS finds both a non-parametric monotonic relationship between the dissimilarities in the item-item matrix and the Euclidean distances between items, and the location of each item in the low-dimensional space. The relationship is typically found using isotonic regression. A scatter plot of MDS is displayed below.

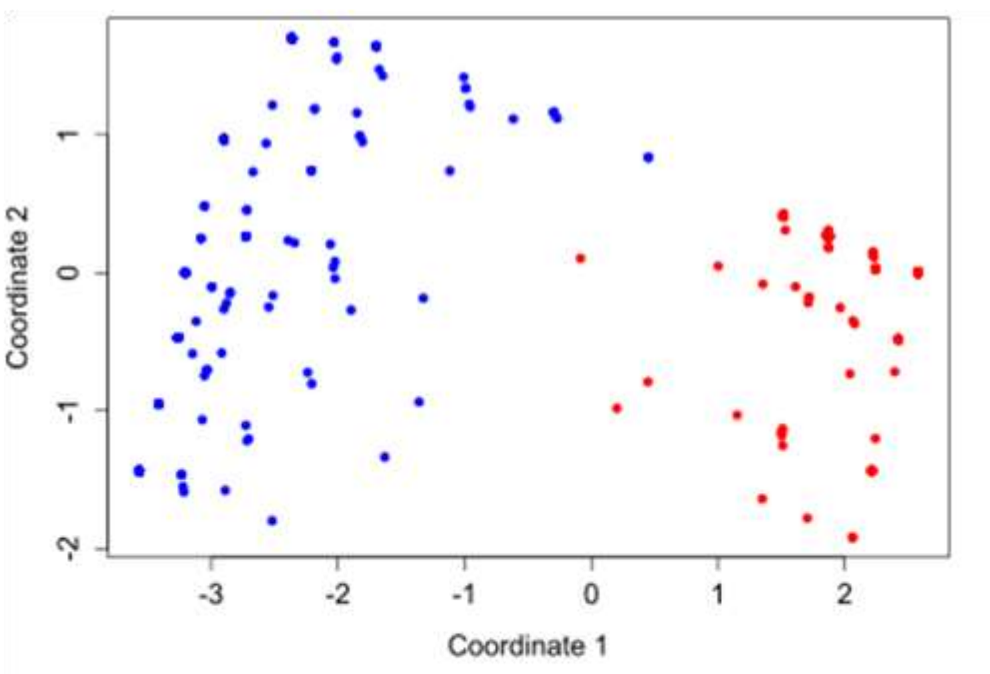

Figure 1*: Shepard diagram of input proximities output distances.*

The data to be analyzed is a collection of I objects on which a *distance function* is defined as

$$\delta_{ij} = \text{Distance between } i^{th} \text{ and } j^{th} \text{ objects}.$$

These distances are the entries of the *dissimilarity matrix*

$$\Delta := \begin{pmatrix} \delta_{1,1} & \delta_{1,2} & \cdots & \delta_{1,I} \\ \delta_{2,1} & \delta_{2,2} & \cdots & \delta_{2,I} \\ \vdots & \vdots & & \vdots \\ \delta_{I,1} & \delta_{I,2} & \cdots & \delta_{I,I} \end{pmatrix}. \qquad (18)$$

The goal of MDS is, given Δ, to find I vectors $x_1, \ldots, x_I \in \mathbb{R}^N$ such that

$$\|x_i - x_j\| \approx \delta_{i,j} \quad \forall i, j \in 1, 2, \ldots, I,$$

where $\| \, . \, \|$ is a vector norm. In classical MDS, this norm is the Euclidean distance, but, in a broader sense, it may be a metric or arbitrary distance function.

In other words, MDS attempts to find an embedding from the I objects into $\mathbb{R}^N$ such that distances are preserved. If the dimension *N* is chosen to be 2 or 3, we may plot the vectors x_i to obtain a visualization of the similarities between the I objects. Note that the vectors x_i are not unique: With the Euclidean distance, they may be arbitrarily translated, rotated, and reflected, since these transformations do not change the pairwise distances $\|x_i - x_j\|$. (Note: The symbol $\mathbb{R}$ indicates the set of real numbers, and the notation $\mathbb{R}^N$ refers to the Cartesian product of N copies of $\mathbb{R}$, which is an N-dimensional vector space over the field of the real numbers.)

There are various approaches to determining the vectors x_i. Usually, MDS is formulated as an optimization problem, where $(x_1, \ldots, x_I)$ is found as a minimizer of some cost function, for example,

$$\min_{x_i, \ldots, x_I} \sum_{i<j} \left(\|x_i - x_j\| - \delta_{i,j} \right)^2$$

A solution may then be found by numerical optimization techniques. For some particularly chosen cost functions, minimizers can be stated analytically in terms of matrix Eigen decompositions.

3.0 RESULTS AND DISCUSSION

3.1 Principal component analysis

The Principal component analysis is a multivariate statistical technique for transforming a set of related (correlated) variables into a set of unrelated (uncorrelated) variables that account for decreasing proportion of the variation of the original observations. This study we used the Kaiser criterion to determine the components to retain. The Kaiser Criterion states that "retain any component with Eigen value greater than one". The components are given in table 1.

Table 1: Total Variance Explained in PCA

	Initial Eigen values		
Component	Total	% of Variance	Cumulative %
1	4.2	42.4	42.4
2	2.6	25.5	67.9
3	1.7	16.9	84.9
4	0.9	8.7	93.6
5	0.5	5.0	98.6
6	0.1	1.4	100.0
7	2.4E-016	2.4E-015	100.0
8	3.4E-017	3.4E-016	100.0
9	-2.2E-016	-2.2E-015	100.0
10	-2.7E-016	-2.7E-015	100.0

We can see from Table 1 that the first three components are to be retain because there Eigen value is above 1. As we can see, the 1st component accounted for 42.4%, the 2nd component accounted for 25.5% while the 3rd component accounted for 16.9% of the variability in the original data. Furthermore, the three components were jointly accounted for about 85% of the total variability in the data set. The matrix for the three retained components is given in table 2; and depicted in figure 2.

Table 2: Component Matrix for Five Components Extracted

	Component		
	1	2	3
Murder/Homicide	0.95		-0.17
Armed Robbery	0.38	-0.86	-0.23
Assaults	-0.33	0.24	-0.69
Theft and Stealing	0.68	0.40	-0.44
Rape Cases	0.76	0.18	0.33
Burglary/House Breaking	0.72	0.66	
Grievous Hurts	-0.71	0.50	0.39
Forgery	0.61	0.67	-0.10
Cheating	0.70	-0.64	
Kidnapping	0.41		0.81

The entries of table 2 represent the explanatory (independent) variables of the regression equations given in (6). Hence, the high dimension of the variables (crime rates) involved in this research had been reduced accordingly (as seen in table 2); therefore, (6) can now be fit without any quagmire.

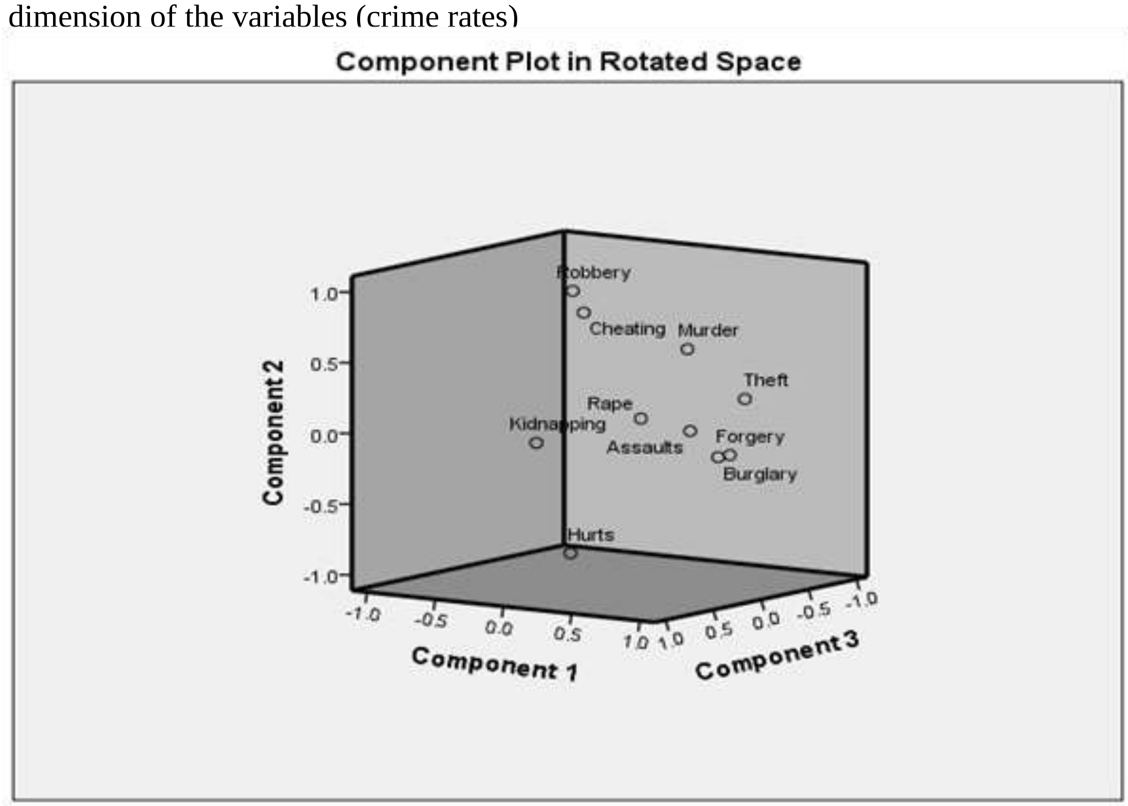

Figure 2: Plot of the three retained components

3.2 Multidimensional Scaling

The Multidimensional scaling gives more of pictorial summary of data for easy interpretation. It gives a matrix made up of dissimilar data converted into multidimensional graphs which serves like a map. This study is partially concerned with spatial distribution of the various types of crimes in Kaduna State using multidimensional scaling. The matrix of Euclidean distances between the various crimes involved in this research is given in figure 3 below.

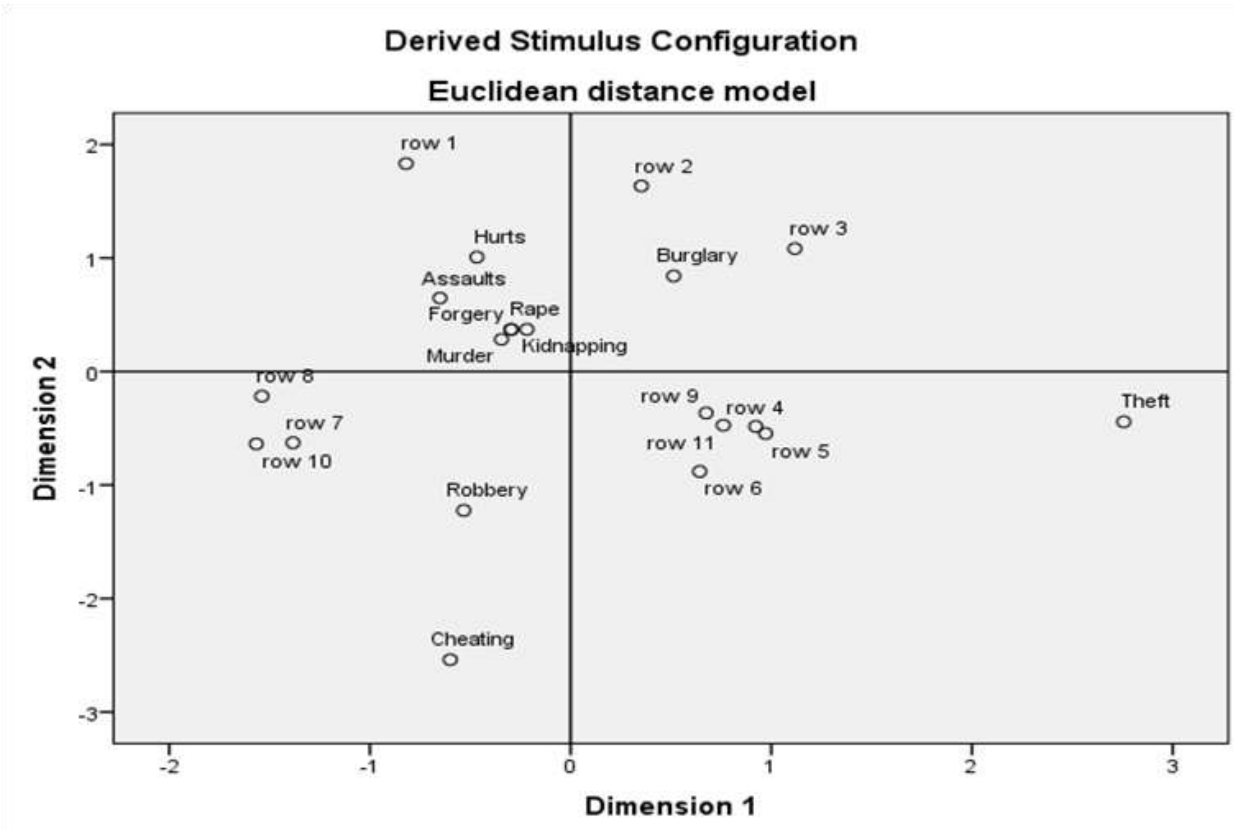

Figure 3: Euclidean Distance Map

The figure 3 above gives a visual representation of the pattern of proximities (similarities or distances) among set crimes in Kaduna state.

5.0 CONCLUSION

By employing the techniques of principal component analysis based on Kaiser Criterion, it shows that three components were retained in which the first, second and third PC accounted for 42.4%, 25.5% and 16.9% of the total variability in the data respectively. And collectively, these components accounted for about 85% of the total variability in the data. This means that any model developed by these retained components to study the relationship, similarity or interdependent that may exist within and between the crimes in Kaduna state, such a model may be able captured and explained about 85% of the scenario, the model may therefore be adequate!

On the other hand, themultidimensional scaling gives more of pictorial summary of data for easy interpretation. It gives a matrix made up of dissimilar data that is converted into multidimensional graphs which serves like a map.The Euclidean Distance map shows that grievous hurts, assaults, rape, murder and kidnapping are closely compact. This means that these crimes are closely related as people commit them in Kaduna State.

Thereafter, as this research is limited only to Kaduna state, it is recommended that further research should be extended to cover three geo-political zones in the northern Nigeria in particular or the country at large; this would further assist towards addressing the recent problems of insecurity affecting our there country, Nigeria.

5.1 Limitations

i. This research is limited only to Kaduna state, it is recommended that further research should be extended to cover three geo-political zones in the northern Nigeria in particular or the country at large; this would further assist towards addressing the recent problems of insecurity affecting our there country, Nigeria.

ii. The data obtained was for the year 2002 through 2012, further researchers may obtained current data and re-perform the analysis to explore and visualize the current experience.

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