A STUDY ON VISUAL ASSESSMENT OF ROAD CONDITION USING RATING METHOD

A Project and Thesis submitted in partial fulfillment of the requirements for the Award of Degree of Bachelor of Science in Civil Engineering

Submitted by
Name: Md. Ibrahim Hossain
(ID :182-47-713)
Name: Mst. Afsana Tasmim Liza
(ID: 182-47-718)
Name: Md. Ashaduzzaman Shawon
(ID :182-47-749)
Name: Safiul Alam
(ID: 182-47-763)
Name:Fariha Jahan
(ID :182-47-798)

Supervised by:
Saurav Barua
Assistant Professor
Department of Civil Engineering
Daffodil International University

DEPARTMENT OF CIVIL ENGINEERING
FACULTY OF ENGINEERING
DAFFODIL INTERNATIONAL UNIVERSITY
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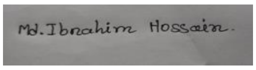
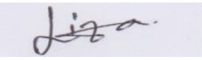
Certification

This is to certify that this project and thesis entitled "A study on Visual Assessment of Road Condition using Rating Method" is done by the following students under my direct supervision and this work has been carried out by them in the Department of Civil Engineering under the Faculty of Engineering of Daffodil International University in partial fulfillment of the requirements for the degree of Bachelor of Science in Civil Engineering. The presentation of the work was held on March 2021.

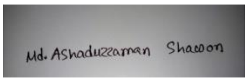
Signature of the candidates



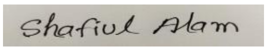
Name: Md. Ibrahim Hossain
ID :182-47-713



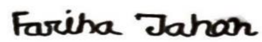
Name: Mst. Afsana Tasmim Liza
ID: 182-47-718



Name: Md. Ashaduzzaman Shawon
ID :182-47-749



Name: Safiul Alam
ID: 182-47-763



Name: Fariha Jahan
ID :182-47-798

Signature of the Supervisor:

Saurav Barua
Assistant Professor
Department of Civil Engineering
Daffodil International University

The project and thesis entitled "A study on Visual Assessment of Road Condition using Rating Method" submitted by Name: Md. Ibrahim Hossain ID :182-47-713, Name: Mst. Afsana Tasmim Liza ID: 182-47-718, Name: Md. Ashaduzzaman Shawon ID :182-47-749, Name: Safiul Alam ID: 182-47-763, Name: Fariha Jahan ID :182-47-798 has been accepted as satisfactory in partial fulfillment of the requirements for the degree of **Bachelor of Science in Civil Engineering** on 31st March 2021.

BOARD OF EXAMINERS

Dr. Miah M. Hussainuzzaman Chairman
Department of CE, DIU

Mominul Haque Internal Member
Assistant Professor,
Department of CE, DIU

Mardia Mumtaz Internal Member
Lecturer,

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At first, we want to thanks almighty God. All praise goes to Almighty God who gives hardworking capability and patience, which guided us to success, which make us possible to complete this thesis successfully.

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Abstract

Visual assessment of road condition is a rapid technique to estimate condition rating. The major advantages is, it requires very few equipment, takes less time and do not need any advance time consuming laboratory test procedure. The study use a rating technique in scale of 0 to 5. Where 0 level stands for no significant damage and level 5 represents ultimate damage of road element. The scale developed by NRA 2008 condition rating method. The method is very easy and rapid with approximate estimation. Since the rating is interpreted into numerical scale and the values of NRA 2008 rating are easily explainable. We study the road area near Kuril Biswa road in Dhaka city. We collected photographs of the various road features and recorded the features in numerical scale. Later, we use Principal Component Analysis (PCA) to implement our analysis on the obtained dataset. Total 13 components were considered while field survey. The PCA study found that 5 major PCs which can explain 79% of variability of the dataset. The most important component is PC1 and PC2. PC1 shows the condition of road surface and PC2 shows the road drainage condition. The study suggests that during repair works, these two issues need to take into account first. Since most of the road maintenance project involve cost and huge budget. There are time constrain and inadequate workers and stuff for road repair work. Therefore, choosing the most important components will help to smooth the road repair works. It also reduce repair cost and lessen repair time. Road repair is a troublesome, since it needs to close lanes and detour traffic. In this context of our road repair technique and PCA implementation to find out the best result will provide good efficacy. The study can be incorporate with existing roads and highway maintenance manual and feasible in context of our country's engineering practices.

Chapter One

Introduction

General

Lack of systematic and appropriate road maintenance in Bangladesh is caused due to lack of proper road condition survey assessment scheme. Budget restriction, instrumentation and equipment shortage, inadequate expertise result in insufficient road condition monitoring. As a result, roads have shorter life span and have more over all maintenance cost. Though Roads and Highway Department, Bangladesh have road condition survey manual. More easier and less time consuming technique adoption along with the existing manual can ease the above mentioned problem.

Background studies

Hanley et al. (2015) performed condition survey of bridges using NRA 2008 manual, Ireland. They adopted Principal Component Analysis for data analysis. Road condition survey manual, 2001, RHD, Bangladesh worked on road inspection guideline and standard practices. They revealed that step by step procedure for road condition assessment and its organogram.Tsai et al. (2017) studied on automated road condition survey. They studied rapid road surface crack detection and classification technique. Sirvio and Hollmen (2008)investigated on spatio-temporal forecasting of road rutting and roughness. They adopt Markov chain and Artificial Neural Network to forecast roughness and rutting. Salau et al.

(2019) used Accelerometer based road survey technique. They detect road anomalies through road bumping experience in accelerometer while travelling over potholes.

Objectives

The purpose of the study is to assess road condition of a road in Dhaka city using NRA 2008 manual and perform principal component analysis to extract information regarding road maintenance scheme.Select a road of Dhaka city to perform road condition survey visually. Study NRA 2008 manual and relevant literature review Prepare a datasheet to record the visual inspection in the proposed rating scale. Perform field survey at the study road segment at every 25m interval

Data analysis of the recorded data using SPSS v. 16.0 and JASP v. 0.13. Perform Principal Component Analysis (PCA) and interpret results.

Summary

We studied NRA 2008 EIRSPAN System Manual No. 3 proposed by Principal Inspection National Roads Authority, Ireland. The technique is very rapid visual assessment method and less time consuming.We also incorporate Principal component analysis (PCA) with the NRA 2008 method to extract valuable information for road maintenance from the road condition survey.

Chapter Two
Literature Review

General

The second chapter discusses on the prior study and theoretical background of the entire research work. The section covers study on the previous works and detail on the principal component analysis models. Principal component technique is the dimension reduction method used for mathematical modeling of large dataset where the dataset have numbers of variables.

Previous studies

We have studied different research articles and journals to find out the relevant research works. Those provide a guideline to ensure our research directives. The following Table describes those topics in a brief.

Topic	Reference	Remark
Condition survey of bridges using NRA 2008 manual, Ireland	Hanley et al. (2015)	Adopted Principal Component Analysis for data analysis
Road inspection guideline and	Road condition survey manual, 2001, RHD,	Step by step procedure for road condition assessment and its

standard practices	Bangladesh	organogram.
Automated road condition survey	Tsai et al. (2017)	Rapid road surface crack detection and classification technique

Topic	Reference	Remark
Spatio-temporal forecasting of road rutting and roughness	Sirvio and Hollmen (2008)	Adopt Markov chain and Artificial Neural Network to forecast roughness and rutting
Accelerometer based road survey technique	Salau et al. (2019)	Detect road anomalies through road bumping experience in accelerometer while travelling over potholes.

Principal component analysis (PCA)

Usage of PCA

We are go through principal component analysis which is known as PCA using singular value decomposition (SVD) method. In this section, we discuss about what PCA does and how it works. We will also discuss how to get deep inside the dataset to use in Principal component analysis. For example, a there are dataset with two variables which are in rows and 4 samples which are in column. Each variable has some contributions within each sample. Variables have some measure in each sample. The sample can be of various tests and variables can be of different subjects in the result of a school. Or, the sample can be different business concerns and variables can be market capacity, nos. of employees involved in those business concerns.

If we consider the variables as genes and samples as various mice, we can explain principal component analysis in genetic point of view. Assume, there are 6 mice sample and 2 genes, gene 1 and gene 2. Mice 1, 2 and 3 have high value in Gene 1, whereas, Mice 4, 5 and 6 have low values in Gene 2. The values can be plotted in simple graph of linear line. If we measure Gene 2, we can plot the dataset in two dimensional graph. Where Gene 1 is in x-axis and Gene 2 is in y-axis. We can see that based on data provided, the mice 1, 2 and 3 are cluster on the right side upper portion and the mice 4, 5 and 6 are cluster on the left lower portion of the graph.

Under the circumstance, if we measure Gene 3, we can plot the dataset in the three dimensional graphical window. The smaller dots in the graph will represent mice data which are further away from Gene 3 axis. On the contrary, the larger one dots will show the mice dataset which are closer to the Gene 3 axis. Similarly, we add 4 genes and measure its value for mice sample 1, 2, 3… 6. The fourth dimension plot can be drawn, however, it is not possible to draw 4-D plot in plain paper. The fourth dimension require 4-D plot to interpret the dataset graphically.

Complex PCA models

Now, we discuss about the way PCA can take 4 or more-dimensional gene measurements or dataset with more than 4 dimension can be interpreted as two dimensional PCA plot. From the dataset, we conclude that which mice or data has more measurement in which variable. There are clustering of data and we can say that which gene or variables are more important for the clustering the data. For example, gene 3 or variable 3 can be the most important to separate the data along the X-axis. The PCA can also tell us how accurate the PCA can interpret the dataset along the 2-dimensional graphical plot.

To understand the way Principal component analysis works, let discuss about the dataset with two variables or genes only. We start plotting the data in 2-dimensional plot. Then we measure the averaging the distance of the data along the X-axis. Similarly, we measure the averaging the distance of the data along the Y-axis. With the average value along X-axis and Y-axis, we calculate the center of the data. It is the centroid of the dataset.

Now, we shift the centroid to the origin of the graph (0, 0). Our centroid will superimpose on the center of the origin. The process of shifting the data does not change the relative position of the data point to each other. Relative distance in-between pair of the data point will remain same. The highest one point will remain the highest one and the rightmost point will same rightmost compare to entire dataset. Now the new shifted data which are centered to the origin can be fit into a line.

Now we draw a line that passes through the origin. And after that we start rotate the line until the straight line fits the data points best. PCA will decide how the straight line passing through origin fit with the data points well or not. Let us begin start back from the random line passing through the origin. To quantify the fitness, PCA projects the data points onto the line. The PCA measure the projection length. Projection length is the distance from the data point to the relative orthogonally projected point onto the line. The target of PCA is to minimize the summation of the projection line length. It also can try to maximize the distance of projected point from origin. The both phenomena is similar. Whenever the projection line lengths are getting smaller, the distance from origin to project points are getting larger. Therefore, aim of both approach is mutually approachable together.

If we consider one data point in the graph, adding the line will not change relative position of data point with respect to the origin. Assume, the distance of the data point from origin is a. The distance from origin to the projection point is c and the projection line length is c. The projection line and the rotating fitting line create a right angle. The value of angle is 90 degree. So, we can apply Pythagoras formula. Where, square of a are equal to the summation of square of b and square of c. The value of b (perpendicular) and the value of c (base) are inversely related.

Sum of squares distances

Assume, the value of a (hypotenuse) is fix. Then whenever the value of perpendicular decreases, the value of base increases. Likewise, if the perpendicular is bigger the base is smaller. The relationship is inverse. Thus the principal component analysis can either minimize the distance of perpendicular i.e. projection line or it can maximize the distance of base i.e. origin to projected point distance. Though, it makes sense to minimize the length of b (perpendicular) i.e. the distance between data point to projected point. However, it is easier to measure the maximization of the length c (base). c is the distance from origin to the projected point.

PCA measures the sum of square of the distance from the projected points to the origin. It finds the best fitting line by maximizing the sum of square of the length c i.e. base. The reference line is drawn passing through the origin. Then, projects the shifted data point to the reference line. After that, measure the distance from origin to the projected points onto the reference line. For each data point assume the distance measured are d1, d2, d3… dn. Where d1 is the distance of origin to the projected point onto the reference line. Similar for d2, d3… dn.

The next thing is to square all the values. Squaring the values will make all negative values to positive. The negative values will not cancel out the positive values. After that, we sum up all the square distance of d1, d2, d3… dn. This will give us the sum of squared value for the distances. For short, we call the value SS (distances). For every choosing reference line, we draw a straight line passing through the origin. Then, we project the data points onto the reference line orthogonally. We measure the distance between the origins to the projected points for all data points. Square each such distances and adding up all the SS (distance). We repeat the whole process again and again until we get a reference line which maximize the sum of squared distance SS (distance). After long iteration we will find a reference line which maximize the sum of square distance from origin to the projected points. The specified reference line will be the best fit line in the PCA.

Axis rotations

We end up with a reference line which has largest SS (distances) at last. The line is known as principal component 1 or PC1. For example, PC1 has slope of 0.25. It means that every 4 units go up to the x-axis will give us 1 unit along y-axis. Here x-axis is the axis for variable 1 and y-axis is the axis for variable 2. It means that the data are mostly spread along x-axis. Vice versa, the data are little bit spread out along the y-axis.

We can imagine in such a way that PC1 is a cocktail recipe. Where to make PC1 we need 4 parts of variable 1 and 1 parts of variable 2. In order to more explain, it can be said that variable 1 is more important than variable 2. And variable 1 can descried the data spread out more illustratively than variable 2. To describe the spread out of data variable 1 is 4 times more important than variable 2. Mathematically, we can say that the cocktail recipe is the linear combination of variable 1 and variable 2. In other word, PC1 is the linear combination of the variables. The recipe of PC1 going 4 on variable 1 axis to catch 1 unit on variable 2. We can solve the length problem of the distance from origin to projected point through Pythagorean Theorem.

Since, a-square is the sum of b-square and c-square, plugging the value we can calculate the value of a. The value a is the distance from origin to the projected line. The value of a will be the square root of the summation of squared b and squared c. Whenever we use singular value decomposition (SVD) the recipe PC1 scaled in such a way that the length of a i.e. the length of perpendicular in the right angle is equal to 1 i.e. unity. The value is scaled to length = 1.

Eigenvalue in PCA

In order to doing such, we have to reduce the length of other arms of the right angle triangle in such a way that the perpendicular a is 1. So, the values of the length are scaled by dividing the length of a to all the length. As a result, the length of perpendicular will be equal to 1. Other base and hypotenuse will be scaled respectively. We divide by the length of perpendicular to all other sides of the right angle. If the value of perpendicular is 4.2, we have to divide both base (1) and hypotenuse (4) by 4.2 value. The scaled new values for perpendicular a = 1, base b = 0.242 and hypotenuse c = 0.97. The new value will change the recipe of the PC1. The mixture of 0.97 of variable 1 and mixture of 0.242 of variable 2 create PC1. However, the ratio between variable 1 and variable 2 will be same as previous. The ratio is still 4:1.

To recap the previous paragraphs, we get through the data, the best fitting line and the unit vector that we calculate in the just prior paragraph. The 1 unit long vector of perpendicular side is consisted with the 0.97 parts of variable 1 and 0.242 parts of variable 2, it is called the singular vector. It is also known as Eigen vector for PC1. The proportion of each variable is called loading scores. For example, the mix of 0.97 of variable 1 and mix of 0.242 of variable 2 are the loading scores.

PCA calls the sum of squared distance for the best fit line the Eigen value for PC1. That is, the sum of square SS (distances for PC1) = Eigen value for PC1. The square root of Eigen value for PC1 is the singular value for PC1. Now, let's work on PC2. PC2 is the simple straight line passing through origin that perpendicular to PC1. We can do this without any further optimization required. It means that the recipe of PC2 is the -1 parts of variable 1 and 4 parts of variable 2. Similarly, if we scale everything we get the unit vector. The recipe for PC2 will be the mixture of negative -0.242 parts of variable 1 and 0.97 parts of variable 2. Since, the graph is a 2-dimensional plot. We draw PC2 orthogonal to PC1 directly.

Singular vectors

The singular vector for PC2 is the distance from origin to the perpendicular point along the reference line 2. It is also known as Eigenvector for PC2. Similarly, the loading score for PC2 is the -0.242 for variable 1 and 0.97 for variable 2. The loading score tell us how the values are projected onto PC2. The variable 2 is 4 times more important that the variable 1. The Eigenvalue for PC2 is the sum of squares of the distances between the projected points and the origin. It means, SS(distances for PC2) = Eigenvalue for PC2. Thus we worked out on PC1 and PC2.

To get the final PCA plot we simply rotate the entire graph. We do the rotation in such a way that PC1 is the horizontal axis and PC2 is the vertical axis. Now we can use the projected points to find where the samples go in the PCA plot. For example, sample 6 is projected on both PC1 and PC2. From the projected point we can get new position for sample 6 in the PCA plot. Similarly, from the projected point of 2 onto both PC1 and PC2, we can retain the position of sample 2 in the new position in the PCA plot. We can retain all the data points to new position in the PCA plot. This is the way PCA is done in singular value decomposition (SVD) method.

The way we get Eigenvalue is recapped here. We get projecting the data point onto the principal components. Then, we measure the distance of projecting point on the principal component axis to the origin. We measure the distances of projecting point to the origin. Then squaring and adding all the data point similar value will give us SS (distances for PC1). Which is the Eigenvalue for PC1. Similarly, measuring and doing same in PC2 axis we will get the Eigenvalue for PC2. We can convert the variation around origin (0, 0) by dividing the SS (distances for PC1) by the sample size minus 1 i.e. n-1. It gives us the variation for PC1. Similarly, dividing the sum of squares distances for PC2 dividing by n-1 gives us the variation for PC2.

Variations of PCs

For example, the variation for PC1 = 15 and the variation for PC2 = 3. It means that total variation around both PCs are 15+3 = 18. Therefore, PC1 accounts for 15/18 = 0.83 = 83% variation of total variation around the PCs. Similarly, PC2 accounts for 3/18 = 0.17 = 17%

variation of the total variation around the PCs. Scree plot is the graphical representation of the percentage variation that each PC accounts for. We will discuss about more on scree plot later.

The PCA for 3 variables are much more similar like previous case. Firstly, we find the best fitting reference line around the data points. Assume that, the recipe for PC1 is now 3 variables or ingredients. Where variable 1 has 0.62 parts, variable 2 has 0.15 parts and variable 3 has 0.77 parts. In this case, variable 3 is the most important ingredients for PC1. Then, we find the PC2 next best fitting line goes through the origin and it is perpendicular to PC1. Assume, the recipe for PC2 is 0.77 parts of variable 1, 0.62 parts of variable 2 and 0.15 parts of variable 3. In this case variable 1 is the most important variable in PC2. Next we find the PC3. PC3 is the best fitting line that goes through origin. It is perpendicular to both PC1 and PC2.

Similarly, if we have more variables, we can find more and more principal components by adding perpendicular lines and rotating them. In theory, there is one PC per variables. However, in practice, the number of PCs is either the number of variables or the number of samples, whichever is smaller. Once we have all the principal components figured out, we can use the Eigenvalues i.e. SS (distances) to determine the proportion of variation that each PC accounts for the total variation. In this case, PC1 accounts for 79% of the variation and PC2 accounts for 15% of the variation. And lastly, the PC3 accounts for 6% of the variation.

Scree plot interpretation

We can see the variation accounts into the scree plot graphically. Where PC1 and PC2 account for the vast majority of the variation. It means that the tow dimensional graph using the PC1 and PC2 just can be a good approximation of the 3-D plot. Since, the combined variation of PC1 and PC2 can explain 94% variation of the dataset. In order to convert the 3-D graph into a two dimensional PCA plot, we just strip away everything, however the data, PC1 and PC2 are retained. Then project the sample onto PC1 and PC2. After that, we rotate so that PC1 will be the horizontal axis and PC2 will be the vertical axis. This is done just to makes it easier to look at. For instance, the projected points onto PC1 and PC2 corresponds to new position of the samples. We retain new position of all data points corresponding to the rotated axis.

In order to review, we started with an awkward three dimensional graph which is hard to read. After that, we calculate the principal components. Then, the Eigenvalues of PC1 and PC2, we get from scree plot that the 2-D plot is good enough informative to retain the variation of the dataset. Lastly, we use the PC1 and PC2 to draw the two dimensional graphical plot with the data points. If we measure 4 variables per samples, we do not able to draw a 4-D graph of the data. However, that does not stop us from doing the PCA math. Because, it does not care about whether we draw the graph or not. We can look at the scree plot.

Data clusters

In the new example, assume PC1 and PC2 account 90% variation of the total variance. We can get the information from scree plot easily. Therefore, we can just use 2- dimensional plot for PCA to interpret the whole dataset. We project the samples onto the first 2 PCs, i.e. PC1 and PC2. Then, projected two points corresponds to any sample will give us the new position of the sample on the 2-D plot. Thus we can retain all points in the similar manner. If we see in the scree plot that PC3 and PC4 account for substantial amount of variation. In that case, we should not consider only first 2 PCs. This will create inaccurate representation of the dataset. Even a noisy PCA plot can be used to identify the data clusters, which is very informative. If there are two cluster of data. The data points in cluster 1 are similar compare to the cluster 2. Similarly, the data points in cluster 2 are similar, however much dissimilar than those of cluster 1.

Summary

This chapter discusses about the prior studies and literature background on the principal component analysis. The key terminology of the PCA are mentioned, defined and describes with the example in this chapter. The next chapter discussed methodology and data collection procedure.

Chapter Three

Methodology and Data Collection

General

In this section, we discuss about data collection and methods used in this study. We studied NRA 2008 EIRSPAN System Manual No. 3 proposed by Principal Inspection National Roads Authority, Ireland. The technique is very rapid visual assessment method and less time consuming.We also incorporate Principal component analysis (PCA) with the NRA 2008 method to extract valuable information for road maintenance from the road condition survey.

NRA 2008 condition rating

The following table describes the NRA 2008 rating scale detail.

Table 3.1: Rating Criteria

Rating Criteria	
0	No or insignificant damage.
1	Minor damage but no need of repair.
2	Some damage, repair needed when convenient. Component is still functioning as originally designed. Observe the condition development.
3	Significant damage, repair needed very soon. i.e. within next financial year
4	Damage is critical and it is necessary to execute repair works at once, or to carry out

5	Ultimate damage. The component has failed or is in danger of total failure, possibly affecting the safety of traffic. It is necessary to implement emergency temporary repair work immediately or rehabilitation work without delay after the introduction of load limitation measures.

Principal Component Analysis (PCA)

Principal component analysis (PCA) is a dimension reduction technique for a set of data. The outcome of PCA is to reduce the input variables as principal components (PC), which is a linear combination of the original variables. However Principal components have a magnitude less than the original data set, but preserve most of the information. PCA examines of the grouping of individuals in n-dimensional space and correlations between variables.

We use the NRA 2008 rating scale to perform visual assessment and conduct PCA analysis to transform the variables i.e. road features of the rating dataset into principal components. We collected data every 25m interval of the study road. Rating data from 40 observation had been recorded from field. The variables or road features of rating dataset were: Potholes (R1), Cracking (R2), Depression area (R3), Rutting (R4), patching/overlay (R5), Raveling (R6), side drain (R7), cross slope (R8), footpath (R9), road marking (R10), Road sign (R11), Roadside garbage/vendor (R12) and footpath garbage/vendor (R13).

Survey site

Location : Kuril Bishwa Road, Dhaka

Chainage :

Start point : Kuril, Progati Sarani, Pubalibank,Dhaka (0+000)

End point :Kuratoli, Purbachal Road, Kuril Flyover, On the East side, Dhaka-1229 (1+000)

Survey Date : 05.12.2020

Survey Time : Start (12:50 PM), End (04:55 PM)

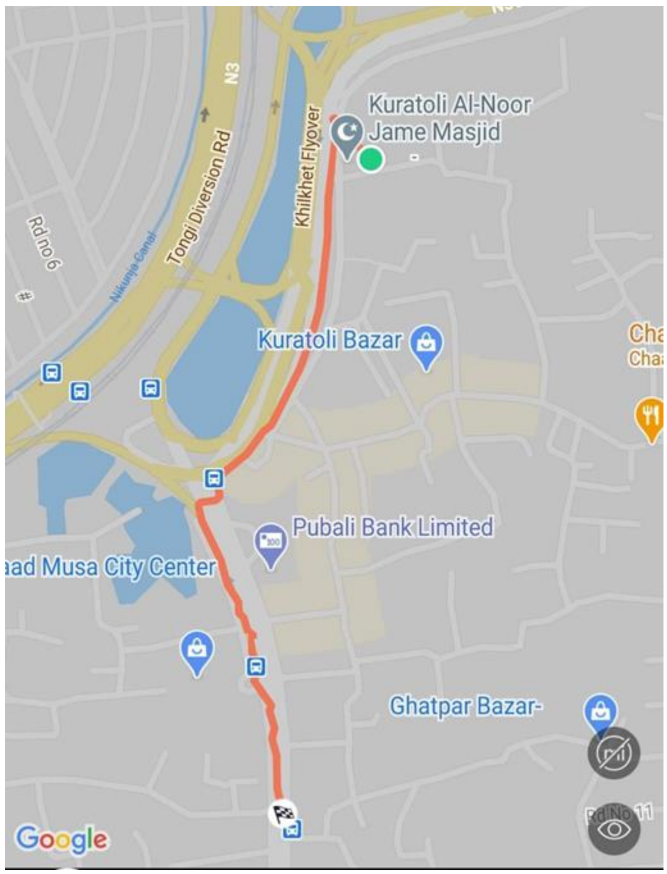

Figure 3.1: Survey site

Survey form is presented in the following section.

RCSF/01

Road Condition Survey Form

The survey is visual inspection of road elements, such as, pavement surface, side drain, footpath, road sign and road marking. This survey performs condition rating of a road segment ranging from 0 to 5 where 0 represents no damage inspected visually and 5 represent ultimate damage. Other numeric are used to rate from good to worse condition of road subsequently. The survey technique is adopted from NRA 2008 EIRSPAN System Manual No. 3, Principal Inspection National Roads Authority, Ireland.

Rating Criteria	
0	No or insignificant damage.
1	Minor damage but no need of repair.
2	Some damage, repair needed when convenient. Component is still functioning as originally designed. Observe the condition development.
3	Significant damage, repair needed very soon. i.e. within next financial year
4	Damage is critical and it is necessary to execute repair works at once, or to carry out
5	Ultimate damage. The component has failed or is in danger of total failure, possibly affecting the safety of traffic. It is necessary to implement emergency temporary repair work immediately or rehabilitation work without delay after the introduction of load limitation measures.

General Information:

Location:

Chainage

Start point: End point:

Survey Date:

Survey Time:

Name of Surveyors:

Figure 3.2: survey form

RCSF/01

Road section	Road features for Visual Inspection												
	Potholes (R1)	Cracking (R2)	Depression area (R3)	Rutting (R4)	Patching/Overlay (R5)	Raveling (R6)	Side drain (R7)	Cross slope (R8)	Footpath (R9)	Road marking (R10)	Road sign (R11)	Roadside garbage/vendor (R12)	Footpath garbage/vendor (R13)
Chainage (m)													
0+000													

2 | Page

Figure: Survey form page 2

Figure: 3.3 Photographs of site

Figure: 3.4 Photographs of site

Figure: 3.5 Photographs of site

Figure: 3.6 Photographs of site

Figure: 3.7 Photographs of site

Chapter Four

Data Analysis

Data Preprocessing

Among the 13 rating road features, we dropped two variables for Principal component analysis (PCA). Those are road marking (R10) and road sign (R11). R10 road feature have 0 variance and R11 road feature has only one data value obtained from field survey. We have total 40 road segments rating data, therefore the dataset for PCA is a 40x11 matrix with 11 variables. We use SPSS v. 16.0 and JASP v. 0.13 software to perform Principal component analysis (PCA).

Descriptive statistics

Average of different road features (variables) ranges from 0.22 (R4, rutting) to 1.41 (R9, footpath). Standard deviation of those road features ranges from 0.52 to 1.28 respectively.

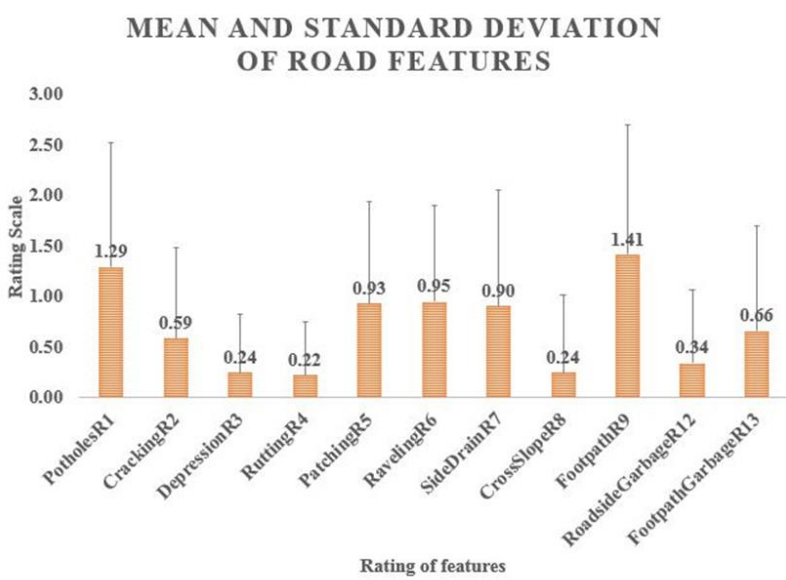

Figure 3.8: Descriptive statistics of road features

Statistical significance

Statistical significance of PCA have been performed through (1) Chi-squared test, (2) KMO adequacy test and (3) Bartlett's sphericity test. Chi-squared test and Bartlett's sphericity test shows statistical significance <0.001 of the PCA model. KMO test has value >0.4, hence the proposed model is significant.

Chi-squared Test			
	Value	df	p
Model	55.873	10	< .001

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.60
Bartlett's Test of Sphericity	Approx. Chi-Square	137.49
Df		55
Sig.		<0.001

Scree Plot and PCA

Scree plot, that is Eigen value vs component plot shows that the rating dataset have 5 Principal components (PC). 13 road features (variables) can be decomposed as 5 PCs, which have Eigen value> 1 in PCA model.

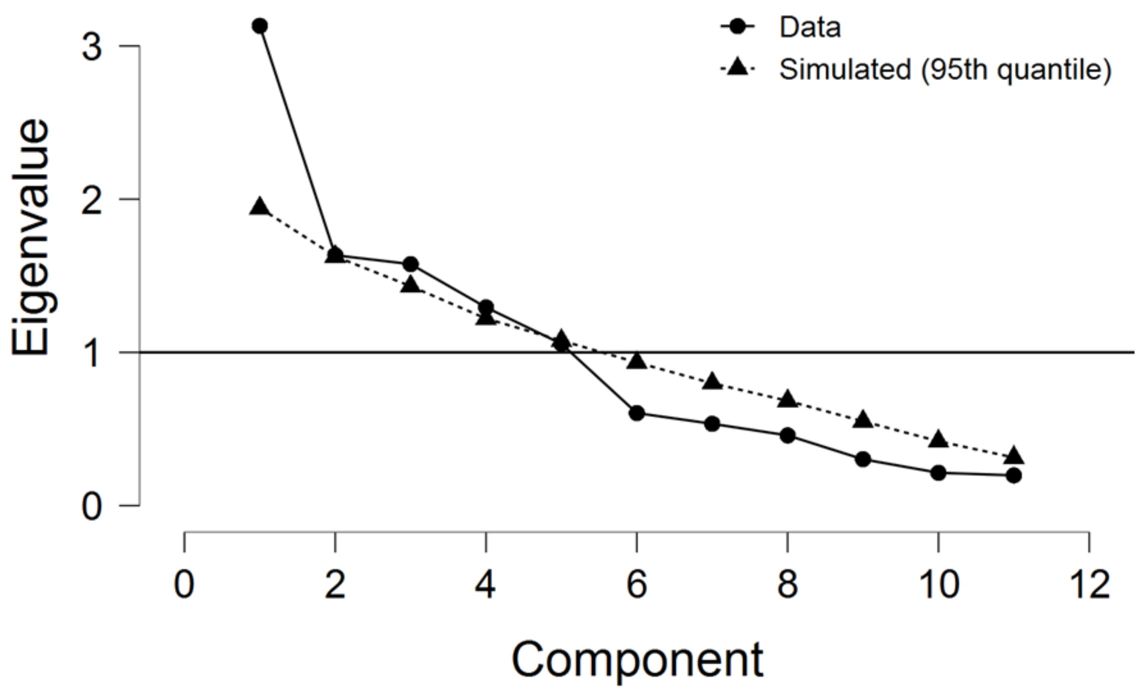

Figure 3.8: Scree plot

Table 3.2: Eigen values and PCA

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.131	28.463	28.463	3.131	28.463	28.463	2.901	26.376	26.376

2	1.634	14.854	43.317	1.634	14.854	43.317	1.478	13.436	39.811
3	1.576	14.326	57.643	1.576	14.326	57.643	1.470	13.364	53.176
4	1.294	11.761	69.403	1.294	11.761	69.403	1.432	13.019	66.195
5	1.056	9.598	79.001	1.056	9.598	79.001	1.409	12.807	79.001
6	.604	5.488	84.490						
7	.534	4.854	89.344						
8	.458	4.164	93.509						
9	.302	2.748	96.257						
10	.214	1.949	98.206						

11	.197	1.794	100.000						
Extraction Method: Principal Component Analysis.									

PC1 explain maximum 26.38% variance of the dataset. PC2 to PC5 comprise with 12.81% to 13.44% variance.

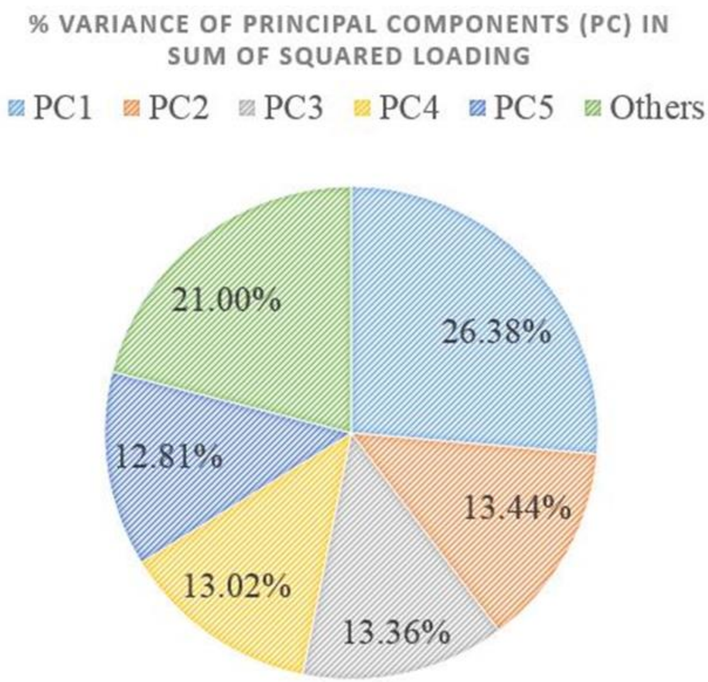

Figure 3.9: % variance in PC

PC1 consists with Potholes (R1), Depression area (R2), Patching/overlay (R3), Raveling (R6) PC2 consists with Side drain (R7) and Cross slope (R8). PC3 comprises with cracking (R2) and footpath (R9). PC4 comprises with rutting (R4) and roadside garbage/vendor (R12). PC5 consists with footpath (R9) and footpath garbage/vendor (R13).

Table 3.3: Component loadings

Component Loadings

	PC1	PC2	PC3	PC4	PC5
PotholesR1	0.845				
CrackingR2			0.876		
DepressionR3	0.697				
RuttingR4				0.861	
PatchingR5	0.881				
RavelingR6	0.775				
SideDrainR7		0.739			
CrossSlopeR8		0.821			
FootpathR9			0.411		0.653
RoadsideGarbageR12			-0.41	0.725	
FootpathGarbageR13					0.848
Note. Applied rotation method is varimax.					

Description of Principal components (PC)

PC1 represents road surface condition. PC2 describes road drainage facilities PC3 comprises with footpath and road cracking. PC4 comprises with road undulation and road side activities. PC5 represents footpath condition.

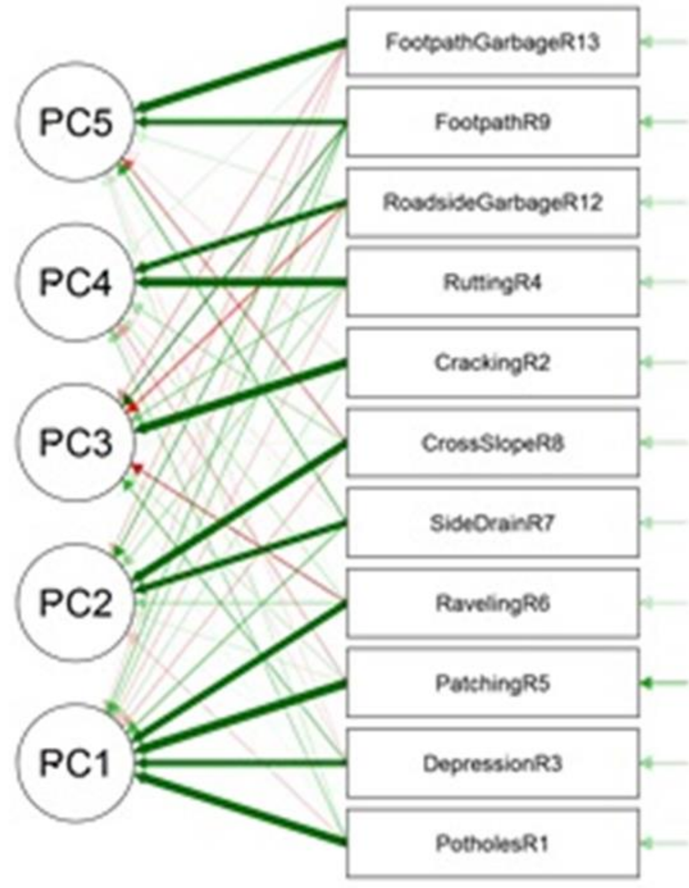

Figure 3.10: Principal components

Features contribution

All the road features have extraction loading 0.76 to 0.86. Any features having loading value >0.5 indicates good contribution to the PCA model.

Table 3.3: Communalities and features

Communalities	
	Extraction
PotholesR1	0.79
CrackingR2	0.79
DepressionR3	0.60
RuttingR4	0.86
PatchingR5	0.83
RavelingR6	0.81
SideDrainR7	0.80
CrossSlopeR8	0.82
FootpathR9	0.83
RoadsideGarbageR12	0.76
FootpathGarbageR13	0.80
Extraction Method: Principal Component Analysis.	

Chapter Five

Conclusion

General

The proposed proportioning of the dataset into Principal Component help to identify features which need more attention than others. Principal Component Analysis (PCA) is a conducive technique to measure feature importance indirectly. The proposed analysis can be extended for other different types of road features including road traffic condition assessment as well. For large scale data interpretation PCA gives us valuable information through feature decomposition and extraction.

Findings

The more rating value in rating scale, the worst the condition of the road feature. Footpath R9 have highest rating 1.41 i.e. minor damage and rutting R4 has average score 0.22 i.e. no or insignificant damage. The Principal component analysis produce statistically significant result, since it has $p<0.05$ for chi squared and Bartlett's sphericity tests and KM) value >0.4. 5 Principal components can explain 79% variability of the rating dataset.

PC1 can explain largest variance of the dataset. It represents road surface condition. PC2 and PC5 represent drainage and footpath condition of the road respectively. Rutting (R4) has the highest 86% contribution (loading) and depression area (R3) has the lowest 60% contribution (loading) into the proposed model.

Recommendations

Overall road features have rating <2 means the study road segments have minor damage most of cases and the road is relatively in new condition. Very few repair work is required as per the observation of field survey.The proposed Principal Component model is statistically significance in terms of Chi squared test, Bartlett’s sphericity and KMO test.Total 13 road features of the rating survey can be decompose into 5 Principal components.

PC3 and PC4 components of the model describes mixed effect of the different types of road features. In-depth study is required to identify relation among different road features. PC1 representing road surface condition is the most important feature for the road condition assessment. Rutting (R4) is the most major concern and depression area (R3) is the least concern issue for the study road area.

Summary

PCA can be incorporated with large scale road condition survey for data analysis. The rating method NRA 2008 system is a rapid and low cost visual assessment technique which can be practiced in Bangladesh along with existing RHD manuals. Road repair and maintenance scheme can be adopted from the decision obtained through NRA rating analyzed through PCA. The proposed method can reduce road maintenance cost and save road rehabilitation time through identifying important features.

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Appendix

Trial 3 cross check in JASP v.0.13

Results

Principal Component Analysis

Chi-squared Test

	Value	df	p
Model	45.513	1	< .001

Component Loadings

	PC1	PC2	PC3	PC4	Uniqueness
PotholesR1	0.863				0.207
CrackingR2		0.776			0.259
DepressionR3	0.866				0.232
RuttingR4				0.896	0.148
PatchingR5	0.646		0.601		0.147
RavelingR6			0.888		0.121
SideDrainR7		0.804	0.500		0.065
CrossSlopeR8			0.721		0.275
FootpathR9		0.898			0.163
RoadsideGarbageR12				0.892	0.181

Note. Applied rotation method is varimax.

Component Characteristics

	Eigenvalue	Proportion var.	Cumulative
PC1	3.218	0.322	0.322
PC2	1.987	0.199	0.520

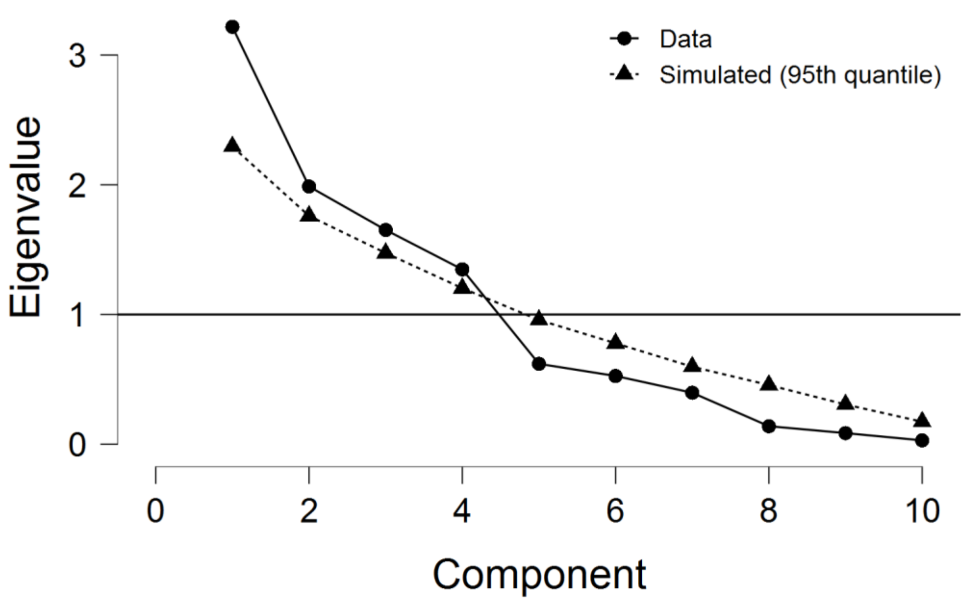
Component Characteristics

	Eigenvalue	Proportion var.	Cumulative
PC3	1.652	0.165	0.686
PC4	1.347	0.135	0.820

Component Correlations

	PC1	PC2	PC3	PC4
PC1	1.000	0.000	0.000	0.000
PC2	0.000	1.000	0.000	0.000
PC3	0.000	0.000	1.000	0.000
PC4	0.000	0.000	0.000	1.000

Scree plot



Trial 3

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
PotholesR1	.8500	1.13671	20
CrackingR2	.7000	.86450	20
DepressionR3	.2000	.52315	20
RuttingR4	.3500	.67082	20
PatchingR5	.5500	.88704	20
RavelingR6	.5000	.76089	20
SideDrainR7	.7000	1.08094	20
CrossSlopeR8	.5000	1.05131	20
FootpathR9	1.2000	1.43637	20
RoadsideGarbageR12	.1500	.36635	20

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.347
Bartlett's Test of Sphericity	Approx. Chi-Square	108.866
	df	45
	Sig.	.000

Anti-image Matrices

	PotholesR1	CrackingR2	DepressionR3	RuttingR4	PatchingR5	RavelingR6	SideDrainR7	CrossSlopeR8	FootpathR9	RoadsideGarbageR12

Anti-image Covariance	PotholesR1	.164	.091	-.112	-.067	.065	-.087	.028	.112	-.105	-.064
	CrackingR2	.091	.362	-.085	-.143	.002	-.020	-.044	.109	-.075	-.014
	DepressionR3	-.112	-.085	.119	.009	-.080	.081	.018	-.117	.065	.099
	RuttingR4	-.067	-.143	.009	.337	.047	-.010	-.047	-.017	.043	-.182
	PatchingR5	.065	.002	-.080	.047	.098	-.088	.004	.080	-.060	-.090
	RavelingR6	-.087	-.020	.081	-.010	-.088	.099	-.025	-.089	.078	.076
	SideDrainR7	.028	-.044	.018	-.047	.004	-.025	.152	-.085	-.096	.082
	CrossSlopeR8	.112	.109	-.117	-.017	.080	-.089	-.085	.246	-.037	-.147
	FootpathR9	-.105	-.075	.065	.043	-.060	.078	-.096	-.037	.155	.016
	RoadsideGarbageR12	-.064	-.014	.099	-.182	-.090	.076	.082	-.147	.016	.316
Anti-image Co	PotholesR1	.287[a]	.375	-.800	-.285	.511	-.681	.178	.558	-.655	-.279
	CrackingR2	.375	.572[a]	-.409	-.408	.013	-.105	-.186	.365	-.317	-.041

rrelation	DepressionR3	-.800	-.409	.250[a]	.045	-.743	.743	.131	-.684	.480	.510
	RuttingR4	-.285	-.408	.045	.483[a]	.257	-.056	-.207	-.059	.189	-.559
	PatchingR5	.511	.013	-.743	.257	.370[a]	-.887	.031	.516	-.483	-.512
	RavelingR6	-.681	-.105	.743	-.056	-.887	.260[a]	-.208	-.566	.629	.428
	SideDrainR7	.178	-.186	.131	-.207	.031	-.208	.596[a]	-.437	-.627	.375
	CrossSlopeR8	.558	.365	-.684	-.059	.516	-.566	-.437	.242[a]	-.187	-.525
	FootpathR9	-.655	-.317	.480	.189	-.483	.629	-.627	-.187	.390[a]	.071
	RoadsideGarbageR12	-.279	-.041	.510	-.559	-.512	.428	.375	-.525	.071	.254[a]

a. Measures of Sampling Adequacy(MSA)

Correlation Matrix

		PotholesR1	CrackingR2	DepressionR3	RuttingR4	PatchingR5	RavelingR6	SideDrainR7	CrossSlopeR8	FootpathR9	RoadsideGarbageR12
Sig. (1-tailed)	PotholesR1		.122	.001	.186	.023	.121	.493	.322	.070	.406
	CrackingR2	.122		.053	.115	.057	.369	.020	.404	.002	.472
	DepressionR3	.001	.053		.401	.007	.289	.378	.500	.258	.244
	RuttingR4	.186	.115	.401		.245	.415	.261	.133	.275	.001
	PatchingR5	.023	.057	.007	.245		.000	.107	.276	.083	.329
	RavelingR6	.121	.369	.289	.415	.000		.047	.042	.343	.346
	SideDrainR7	.493	.020	.378	.261	.107	.047		.005	.000	.269
	CrossSlopeR8	.322	.404	.500	.133	.276	.042	.005		.231	.193
	FootpathR9	.070	.002	.258	.275	.083	.343	.000	.231		.401
	RoadsideGarbageR12	.406	.472	.244	.001	.329	.346	.269	.193	.401	

Communalities

	Initial	Extraction
PotholesR1	1.000	.793
CrackingR2	1.000	.741
DepressionR3	1.000	.768
RuttingR4	1.000	.852

PatchingR5	1.000	.853
RavelingR6	1.000	.879
SideDrainR7	1.000	.935
CrossSlopeR8	1.000	.725
FootpathR9	1.000	.837
RoadsideGarbageR12	1.000	.819

Extraction Method: Principal Component Analysis.

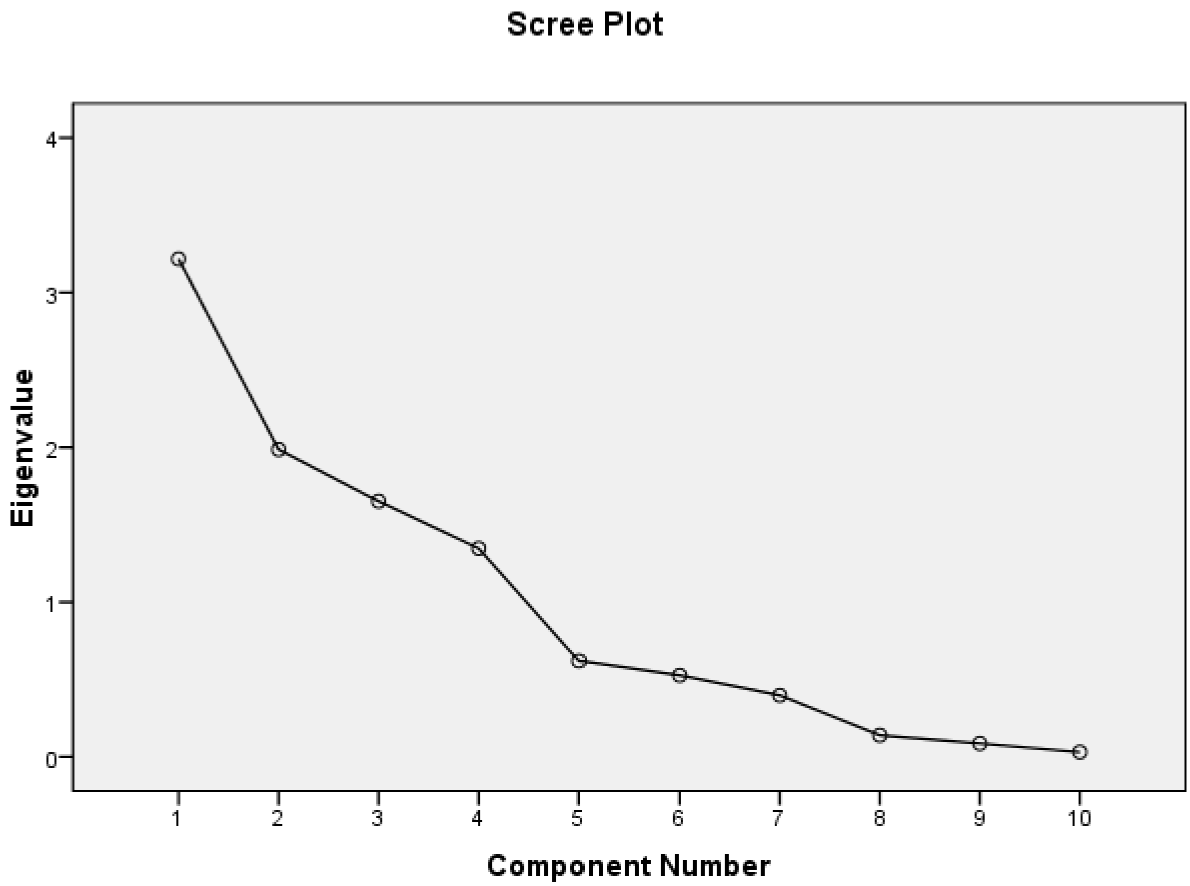
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.218	32.176	32.176	3.218	32.176	32.176	2.240	22.404	22.404
2	1.987	19.867	52.043	1.987	19.867	52.043	2.231	22.314	44.717
3	1.652	16.518	68.560	1.652	16.518	68.560	1.931	19.315	64.032
4	1.347	13.474	82.035	1.347	13.474	82.035	1.800	18.002	82.035
5	.619	6.194	88.229						
6	.526	5.261	93.489						
7	.397	3.968	97.458						
8	.139	1.390	98.848						
9	.085	.855	99.703						
10	.030	.297	100.000						

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.218	32.176	32.176	3.218	32.176	32.176	2.240	22.404	22.404
2	1.987	19.867	52.043	1.987	19.867	52.043	2.231	22.314	44.717
3	1.652	16.518	68.560	1.652	16.518	68.560	1.931	19.315	64.032
4	1.347	13.474	82.035	1.347	13.474	82.035	1.800	18.002	82.035
5	.619	6.194	88.229						
6	.526	5.261	93.489						
7	.397	3.968	97.458						
8	.139	1.390	98.848						
9	.085	.855	99.703						

Extraction Method: Principal Component Analysis.



Component Matrix[a]

	Component			
	1	2	3	4
PotholesR1	.588	-.327	.575	.095
CrackingR2	.680	.133	.206	-.468
DepressionR3	.546	-.537	.424	.038
RuttingR4	.173	.705	.560	.111
PatchingR5	.774	-.378	-.080	.322

RavelingR6	.604	-.115	-.357	.612
SideDrainR7	.675	.445	-.480	-.227
CrossSlopeR8	.384	.549	-.338	.402
FootpathR9	.714	.235	-.049	-.520
RoadsideGarbageR12	-.072	.605	.551	.380

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
PotholesR1	.863	.140	.028	.166
CrackingR2	.355	.776	-.053	.103
DepressionR3	.866	.094	.013	-.098
RuttingR4	.028	.222	-.015	.896
PatchingR5	.647	.171	.601	-.211
RavelingR6	.279	-.006	.888	-.114
SideDrainR7	-.194	.804	.501	-.032
CrossSlopeR8	-.245	.219	.722	.310
FootpathR9	.159	.898	.074	.002
RoadsideGarbageR12	-.018	-.150	.032	.892

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

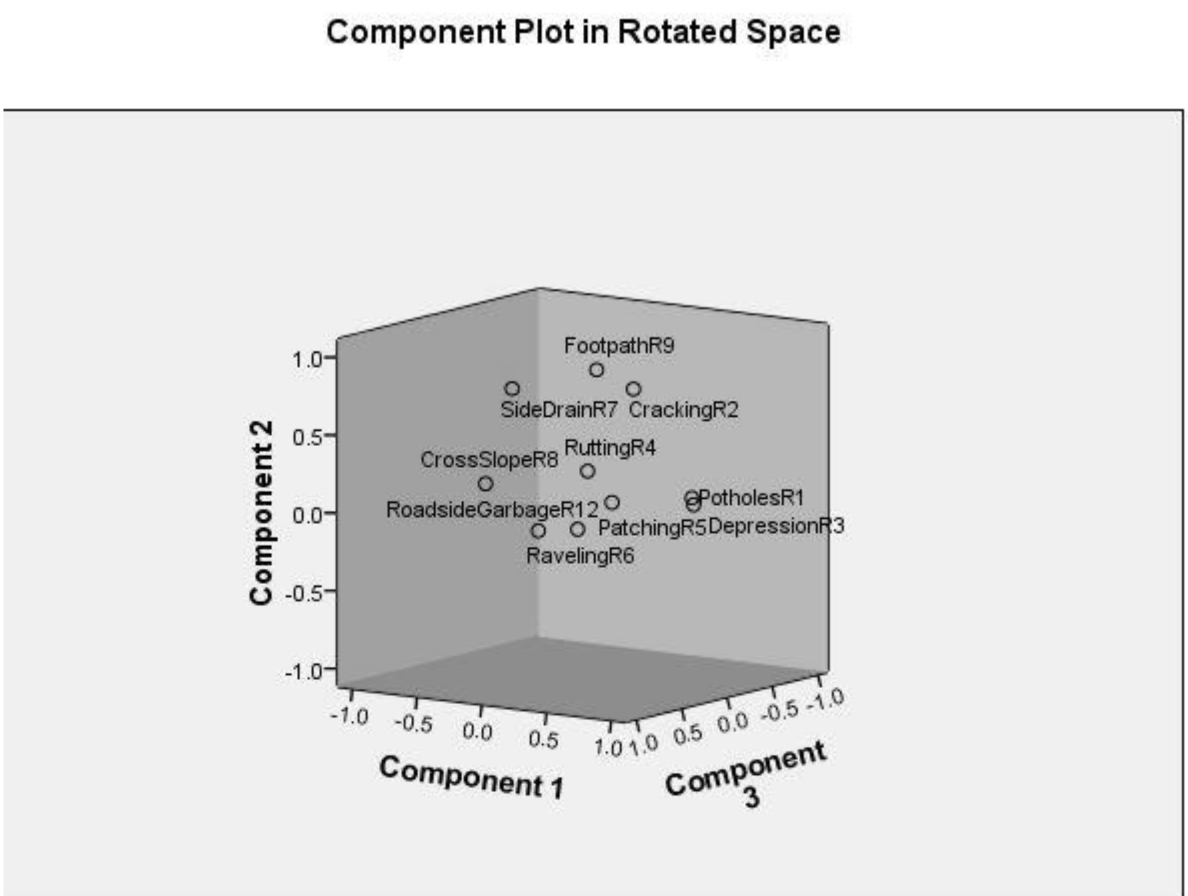
Component Transformation Matrix

Component	1	2	3	4
1	.555	.654	.513	.022
2	-.579	.351	.148	.721

3	.581	-.118	-.505	.628
4	.139	-.659	.678	.294

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.



Trial 2

Descriptive Statistics

	Mean	Std. Deviation	Analysis N

PotholesR1	.8500	1.13671	20
CrackingR2	.7000	.86450	20
DepressionR3	.2000	.52315	20
RuttingR4	.3500	.67082	20
PatchingR5	.5500	.88704	20
RavelingR6	.5000	.76089	20
SideDrainR7	.7000	1.08094	20
CrossSlopeR8	.5000	1.05131	20
FootpathR9	1.2000	1.43637	20
RoadSignR11	.1500	.67082	20
RoadsideGarbageR12	.1500	.36635	20
FootpathGarbageR13	.2500	.55012	20

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.317
Bartlett's Test of Sphericity	Approx. Chi-Square	116.660
	df	66
	Sig.	.000

Anti-image Matrices

	PotholesR1	CrackingR2	DepressionR3	RuttingR4	PatchingR5	RavelingR6	SideDrainR7	CrossSlopeR8	FootpathR9	RoadSignR11	RoadsideGarbageR12	FootpathGarbageR13

Anti-image Covariance	PotholesR1	.141	.085	-.098	-.077	.061	-.079	.017	.105	-.095	-.066	-.066	.091
	CrackingR2	.085	.196	-.076	-.124	.018	-.027	-.037	.106	-.079	-.141	-.034	.194
	DepressionR3	-.098	-.076	.101	.030	-.072	.073	.020	-.104	.064	.072	.093	-.074
	RuttingR4	-.077	-.124	.030	.297	.030	.002	-.032	-.048	.060	.091	-.140	-.119
	PatchingR5	.061	.018	-.072	.030	.095	-.084	.001	.073	-.055	-.030	-.090	.033
	RavelingR6	-.079	-.027	.073	.002	-.084	.095	-.022	-.079	.070	.050	.076	-.025
	SideDrainR7	.017	-.037	.020	-.032	.001	-.022	.149	-.076	-.070	.022	.083	-.029

	Cross Slope R8	.105	.106	-.104	-.048	.073	-.079	-.076	.199	-.053	-.081	-.132	.131
	FootpathR9	-.095	-.079	.064	.060	-.055	.070	-.070	-.053	.127	.084	.027	-.092
	Road Sign R11	-.066	-.141	.072	.091	-.030	.050	.022	-.081	.084	.773	.063	-.062
	RoadsideGarbageR12	-.066	-.034	.093	-.140	-.090	.076	.083	-.132	.027	.063	.307	-.049
	FootpathGarbage R13	.091	.194	-.074	-.119	.033	-.025	-.029	.131	-.092	-.062	-.049	.523
Anti-image C	PotholesR1	.254[a]	.510	-.827	-.377	.532	-.684	.119	.629	-.709	-.200	-.316	.335
	CrackingR2	.510	.372[a]	-.541	-.513	.128	-.196	-.216	.539	-.500	-.363	-.139	.605

orrelation	DepressionR3	-.827	-.541	.226[a]	.172	-.741	.744	.166	-.734	.567	.259	.528	-.321
	RuttingR4	-.377	-.513	.172	.415[a]	.177	.010	-.153	-.199	.307	.189	-.462	-.301
	PatchingR5	.532	.128	-.741	.177	.379[a]	-.888	.009	.532	-.505	-.113	-.526	.147
	RavelingR6	-.684	-.196	.744	.010	-.888	.277[a]	-.180	-.572	.637	.183	.447	-.112
	Side Drain R7	.119	-.216	.166	-.153	.009	-.180	.640[a]	-.442	-.511	.065	.386	-.105
	Cross Slope R8	.629	.539	-.734	-.199	.532	-.572	-.442	.209[a]	-.337	-.206	-.533	.407
	FootpathR9	-.709	-.500	.567	.307	-.505	.637	-.511	-.337	.336[a]	.269	.134	-.359

	Road Sign R11	-.200	-.363	.259	.189	-.113	.183	.065	-.206	.269	.301[a]	.129	-.097
	Road sideGarbageR12	-.316	-.139	.528	-.462	-.526	.447	.386	-.533	.134	.129	.252[a]	-.121
	FootpathGarbage R13	.335	.605	-.321	-.301	.147	-.112	-.105	.407	-.359	-.097	-.121	.311[a]

a. Measures of Sampling Adequacy(MSA)

Correlation Matrix

		PotholesR1	CrackingR2	DepressionR3	RuttingR4	PatchingR5	RavelingR6	SideDrainR7	CrossSlopeR8	FootpathR9	RoadSignR11	RoadsideGarbage R12	FootpathGarbage R13
	PotholesR1		.122	.001	.186	.023	.121	.493	.322	.070	.229	.406	.329

CrackingR2	.122		.053	.115	.057	.369	.020	.404	.002	.366	.472	.046
Depression R3	.001	.053		.401	.007	.289	.378	.500	.258	.353	.244	.220
RuttingR4	.186	.115	.401		.245	.415	.261	.133	.275	.303	.001	.441
PatchingR5	.023	.057	.007	.245		.000	.107	.276	.083	.270	.329	.102
RavelingR6	.121	.369	.289	.415	.000		.047	.042	.343	.257	.346	.089
SideDrainR7	.493	.020	.378	.261	.107	.047		.005	.000	.261	.269	.288
Cross Slope R8	.322	.404	.500	.133	.276	.042	.005		.231	.319	.193	.167
FootpathR9	.070	.002	.258	.275	.083	.343	.000	.231		.203	.401	.500
Road SignR11	.229	.366	.353	.303	.270	.257	.261	.319	.203		.343	.327

RoadsideGarbageR12	.406	.472	.244	.001	.329	.346	.269	.193	.401	.343		.392
FootpathGarbageR13	.329	.046	.220	.441	.102	.089	.288	.167	.500	.327	.392	

Communalities

	Initial	Extraction
PotholesR1	1.000	.813
CrackingR2	1.000	.869
DepressionR3	1.000	.767
RuttingR4	1.000	.852
PatchingR5	1.000	.825
RavelingR6	1.000	.847
SideDrainR7	1.000	.940
CrossSlopeR8	1.000	.724
FootpathR9	1.000	.898
RoadSignR11	1.000	.656
RoadsideGarbageR12	1.000	.814
FootpathGarbageR13	1.000	.700

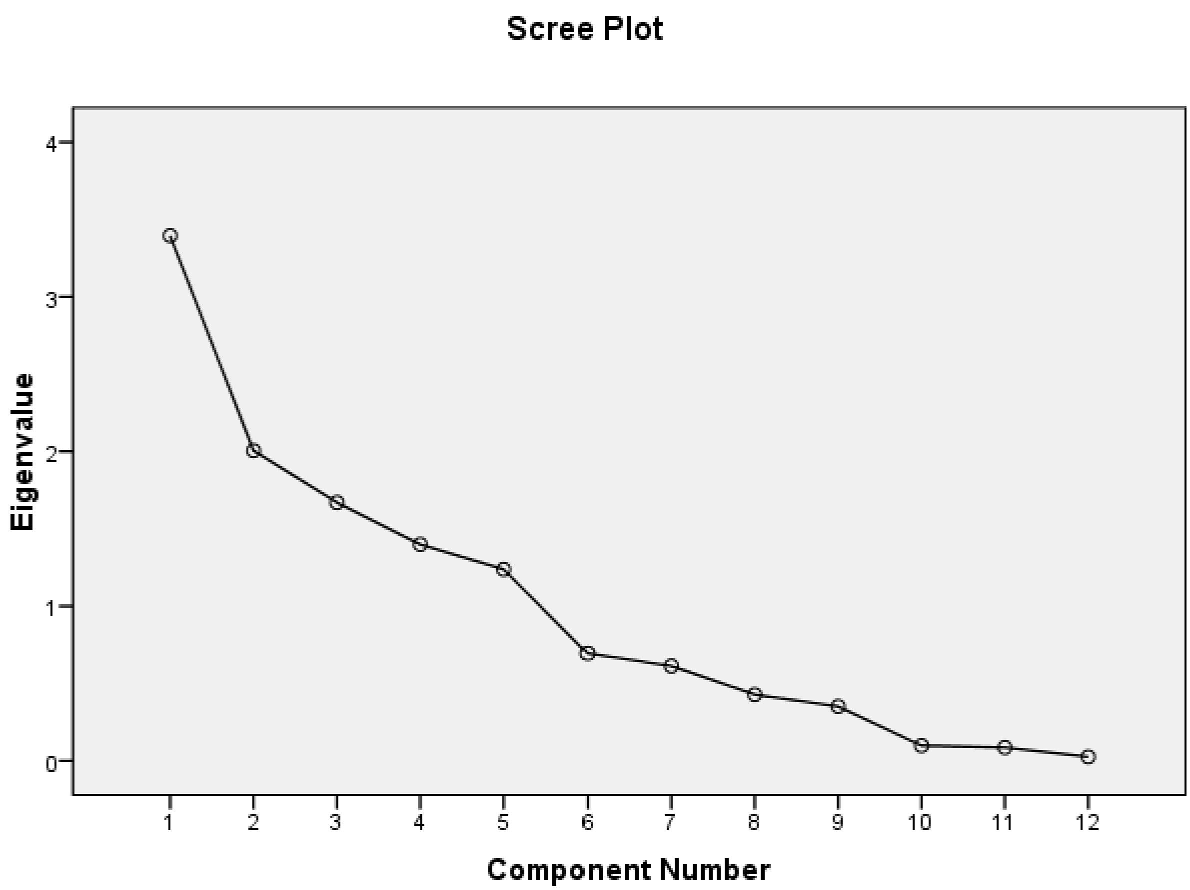
Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.395	28.294	28.294	3.395	28.294	28.294	2.309	19.245	19.245
2	2.005	16.709	45.003	2.005	16.709	45.003	2.238	18.653	37.898
3	1.670	13.916	58.919	1.670	13.916	58.919	2.068	17.237	55.135
4	1.398	11.654	70.573	1.398	11.654	70.573	1.813	15.109	70.243
5	1.237	10.311	80.883	1.237	10.311	80.883	1.277	10.640	80.883
6	.694	5.786	86.669						
7	.613	5.106	91.775						
8	.428	3.564	95.338						
9	.351	2.925	98.263						
10	.098	.815	99.078						
11	.085	.711	99.789						
12	.025	.211	100.000						

Extraction Method: Principal Component Analysis.



Component Matrix[a]

	Component				
	1	2	3	4	5
PotholesR1	.575	-.278	.620	.074	-.121
CrackingR2	.675	.106	.160	-.499	.357
DepressionR3	.543	-.512	.457	.021	.036
RuttingR4	.163	.727	.512	.095	.160
PatchingR5	.781	-.370	-.046	.272	-.052
RavelingR6	.628	-.122	-.345	.562	-.052
SideDrainR7	.658	.436	-.469	-.271	-.156
CrossSlopeR8	.403	.527	-.378	.365	.087

FootpathR9	.674	.261	-.003	-.551	-.270
RoadSignR11	-.231	-.164	-.140	-.259	.699
RoadsideGarbageR12	-.069	.627	.500	.373	.163
FootpathGarbageR13	-.419	.136	.187	-.169	-.665

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
PotholesR1	.871	.115	.030	.155	-.125
CrackingR2	.377	.717	-.025	.139	.438
DepressionR3	.864	.050	.040	-.089	.089
RuttingR4	.036	.208	-.030	.898	-.024
PatchingR5	.628	.173	.596	-.210	.022
RavelingR6	.246	.026	.878	-.119	-.036
SideDrainR7	-.171	.841	.447	-.027	-.065
CrossSlopeR8	-.262	.251	.702	.315	.021
FootpathR9	.206	.911	.020	.002	-.161
RoadSignR11	-.172	-.093	-.229	-.117	.743
RoadsideGarbageR12	-.028	-.155	.026	.885	-.067
FootpathGarbageR13	-.184	-.043	-.438	-.011	-.687

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

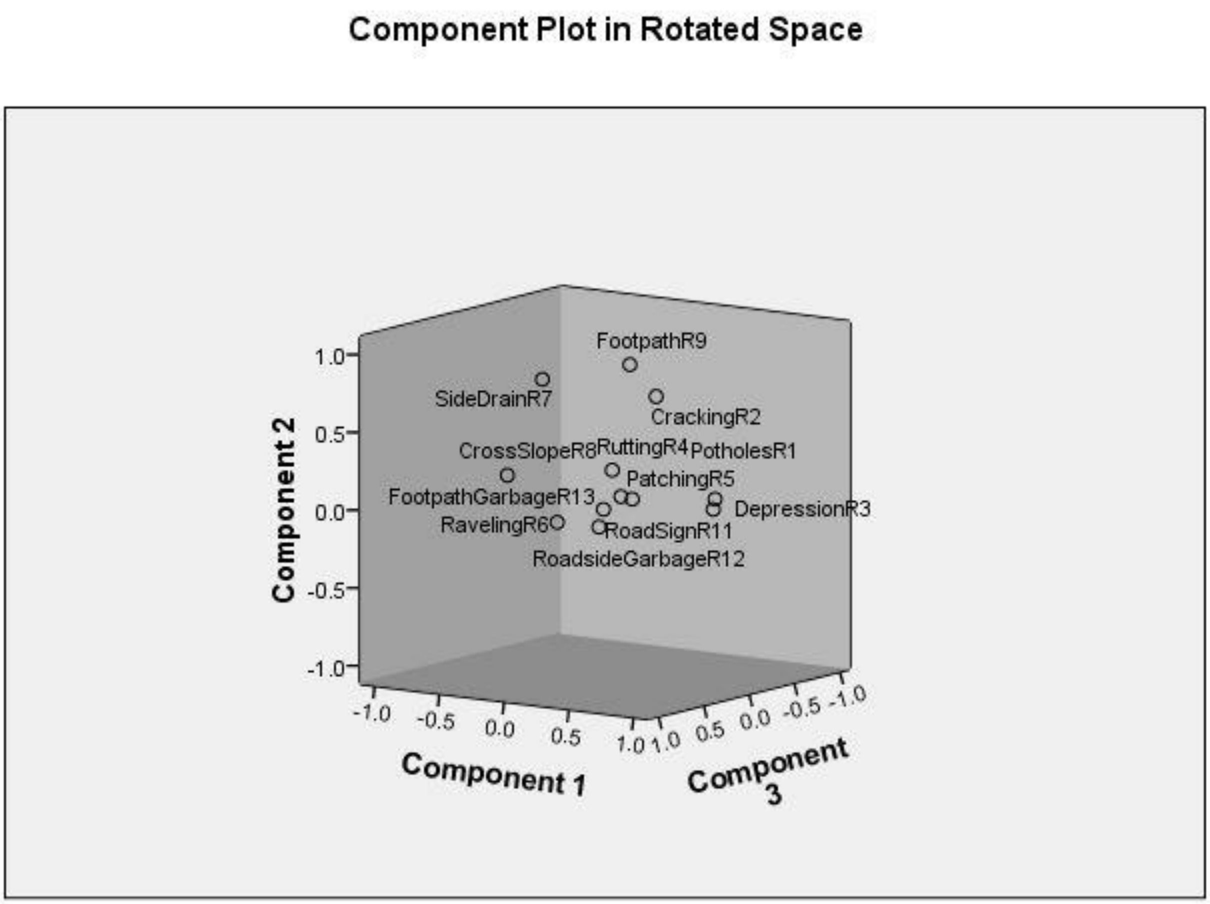
Component Transformation Matrix

Component	1	2	3	4	5
1	.564	.613	.548	.036	.071

2	-.526	.375	.092	.743	-.150
3	.631	-.159	-.494	.562	-.127
4	.078	-.666	.669	.275	-.165
5	-.027	-.121	.023	.234	.964

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.



We drop the variable R11 and R13. R11 is Road sign which has only one non zero value R13 is footpath garbage/vendor, which has all negative loading in components.

Trial 1

Road section	Road features for Visual Inspection												
	Potholes (R1)	Cracking (R2)	Depression area (R3)	Rutting (R4)	Patching/Overlay (R5)	Raveling (R6)	Side drain (R7)	Cross slope (R8)	Footpath (R9)	Road marking (R10)	Road sign (R11)	Roadside garbage/vendor (R12)	Footpath garbage/vendor (R13)
Chainage (m)													
0+000	0	0	0	0	0	0	0	0	0	0	0	0	1
0+025	0	0	0	0	0	0	0	0	2	0	0	0	1
0+050	0	0	0	0	0	0	1	0	1	0	0	0	2
0+075	3	0	0	2	0	0	0	0	2	0	0	1	1
0+100	0	1	0	0	0	0	0	0	0	0	0	0	0
0+125	1	1	0	0	0	0	0	0	2	0	0	0	0
0+150	0	1	0	0	0	0	0	0	0	0	3	0	0
0+175	1	0	0	0	0	0	0	0	0	0	0	0	0
0+200	3	2	2	0	3	1	0	0	2	0	0	0	0
0+225	0	2	0	2	0	0	0	0	0	0	0	1	0
0+250	0	2	0	1	0	0	3	2	4	0	0	0	0
0+275	0	0	0	1	1	2	2	3	0	0	0	0	0
0+300	0	0	0	0	1	1	1	3	1	0	0	1	0
0+325	0	1	0	0	1	0	2	0	3	0	0	0	0
0+350	3	2	1	1	1	1	2	2	3	0	0	0	0
0+375	2	2	0	0	2	2	3	0	4	0	0	0	0

0+400	1	0	0	0	2	2	0	0	0	0	0	0	0
0+425	0	0	0	0	0	0	0	0	0	0	0	0	0
0+450	1	0	0	0	0	1	0	0	0	0	0	0	0
0+475	2	0	1	0	0	0	0	0	0	0	0	0	0

Warnings

There are fewer than two cases, at least one of the variables has zero variance, there is only one variable in the analysis, or correlation coefficients could not be computed for all pairs of variables. No further statistics will be computed.

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
PotholesR1	.8500	1.13671	20
CrackingR2	.7000	.86450	20
DepressionR3	.2000	.52315	20
RuttingR4	.3500	.67082	20
PatchingR5	.5500	.88704	20
RavelingR6	.5000	.76089	20
SideDrainR7	.7000	1.08094	20
CrossSlopeR8	.5000	1.05131	20
FootpathR9	1.2000	1.43637	20
RoadMarkingR10	.0000	.00000	20
RoadSignR11	.1500	.67082	20
RoadsideGarbageR12	.1500	.36635	20
FootpathGarbageR13	.2500	.55012	20

Now we drop road marking R10 variable. It has zero variance and observation is zero.