Fuel Adulteration Estimation using Image Processing

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Abstract - *Nowadays the urban conurbation growth is associated with increased number of automobiles to meet human requirements. Since the establishment of automobile industries, air pollution has increased due to the consumption of fossil fuels. Automobile fuel adulteration is a stealthy and profit oriented operation, which leads to increased tailpipe emissions, damaging engines and adverse impact on the environment. In the past few years the problem of fuel adulteration has grown into dangerous proportions. Fuel adulteration estimation using image processing method is one of the efficient methods. The first step of image processing is the image acquisition, where sufficient amount of images are captured and read into MATLAB. The texture analysis is performed directly on the colored image. Image preprocessing is not done here, because the texture features extracted directly from colored images vary a lot with the texture features extracted after preprocessing of the images, which may leads to drastic change in the results of estimation of fuel adulteration. An important approach for describing a region is to measure its texture contents. Texture analysis refers to the class of mathematical measures and models that characterize the spatial variations within imagery as a means of extracting information. Here statistical texture analysis method is used. A statistical method of investigating texture that considers the spatial relations of pixels in the gray level co-occurrence matrix (GLCM), which is also called as gray level spatial dependence matrix. Texture classification is done using Minimum distance classifier.*

Key Words: Fuel Adulteration, Texture Analysis, GLCM, Minimum Distance Classifier, MATLAB

1. INTRODUCTION

The importance of fuel as well as their purity plays a prominent role in the present world. Hence, it is necessary to check fuel adulteration as may damage the appliances and may affect the performance of automobiles. Nowadays the urban conurbation growth is associated with increased number of automobiles to meet human requirements. Since the establishment of the automobile industries, air pollution has increased due to the consumption of fossil fuels. Adulteration is defined as illegal introduction of foreign or subservient substance into fuel. The subservient substances are called adulterants, which when introduced remold and deteriorate the quality of the base transport fuels. The major

transport fuel in India is gasoline [6]. Transport fuels i.e., gasoline and diesel are frequently adulterated with cheaper products or by-products or waste hydrocarbon stream for financial gains. The most commonly used adulterant for fuel in kerosene. The excepted fuel adulteration is around 15% to 35% by volume. Adulteration beyond this range can be noticed by the automobile users by lowering engine performance. Automobile fuel adulteration is a stealthy and profit oriented operation, which leads to increased tailpipe emissions, damaging engines and adverse impact on the environment [1]. Experts say that health problems could result from harmful tailpipe emissions and cancer causing pollutants, though not all forms of adulteration are harmful.

In the past few years the problem of fuel adulteration has grown into dangerous proportions. Monetary incentives arising from distinctive taxes are generally the primary cause of fuel adulteration. In South Asia, petrol carries a much higher tax than diesel, which in turn is taxed more than kerosene. To neutralize adulteration successfully, it is necessary to determine the fuel superiority at the distribution source. The devices implemented to detect fuel adulteration should be transportable, computationally fast, it should be quickly practical and effective, should be inexpensive so that all the automobile users can implement it in their vehicles [6]. There are many methods to detect fuel adulteration namely Distillation Test, Evaporation Test, Gas Chromatography, fiber grating sensor technology, filter paper method, emission testing, density measurement method, image processing techniques [1] etc.

1.1 Types of adulteration

The types of adulteration may be broadly classified as follows [6]:

i. Mixing small amount of distillate fuels than properly maintained kerosene into gasoline.
ii. Mixing industrial solvents such as hydrocarbons into gasoline.
iii. Mixing small amounts of waste industrial solvents such as used lubricants which may be costly to dispose off in an environment into gasoline and diesel.
iv. Mixing kerosene into gasoline in range of 10 – 20 percent.

v.   Mixing small quantity of heavier fuel oils into diesel.

1.2 Factors encouraging fuel adulteration

The factors which mainly encourage the practice of fuel adulteration are as given below [6]:

i.   Difference in cost of automobile fuels which may be due to the existence of distinctive tax levels amongst the intermediate and byproducts and base fuels.
ii.   Easy accessibility of adulterants in the market.
iii. Lack of observation and consumer awareness.
iv.   Lack of translucency and unlimited regulations in the merchandise chain and production-supply for byproducts and intermediates of refineries.
v.   Inaccessibility of instruments and mechanisms for spot checking of the quality of automobile fuels.

1.3 Consequences of fuel adulteration

Fuel adulteration is currently a boom business in our country, which leads to economic losses, increased tailpipe emissions and worsening of performance and parts of engines using the adulterated fuels. One conventional estimate is that the country losses more than 50,000 crores per year just from the adulteration loss, not considering the health cost and other indirect loss of efficiency [6].

Some of the effects of fuel adulteration are as follows:

i.   Increased exhaust tailpipe emissions of carbon monoxide, hydrocarbons, particulate matter and oxides of nitrogen (NOX particles).
ii.   Fuel adulteration worsens the engine components. This problem gets further exaggerates for modern engines with high performance.
iii. Adulteration can also cause air borne diseases directly due to the air pollution caused by the tailpipe emissions. As the common adulterant used is kerosene, it indirectly leads to indoor air pollution due use of biomass as domestic fuel.
iv.   Major loss to tax revenue: There is huge financial loss to the national gross Domestic Product (GDP), as well as to the oil companies as there is diversion to the use of kerosene as adulterant for both petrol and diesel.

2. OBJECTIVES

The objective of this project is to estimate fuel adulteration. Thereby leading to the following, direct as well as indirect positive outcomes.

i.   To increase engine lifetime with good performance
ii.   To reduce emission of harmful pollutants from vehicles
iii. To reduce tailpipe emissions, which leads to decrease in air borne diseases and green house gases
iv.   To increase the overall economy of the country by contributing to the enhanced GDP

3. METHODOLOGY

Fuel adulteration estimation using image processing method is one of the efficient methods. The first step of image processing is the image acquisition, where sufficient amount of images are captured and read into MATLAB. The texture analysis is performed directly on the colored image. Image preprocessing is not done here, because the texture features extracted directly from colored images vary a lot with the texture features extracted after preprocessing of the images, which may leads to drastic change in the results of estimation of fuel adulteration.

An important approach for describing a region is to measure its texture contents. Texture is a property represents the structure and surface of an image. Image textures are composite visual patterns poised of regions with sub-patterns involving the characteristics such as brightness, color, size, shape, etc. Texture analysis refers to the class of mathematical measures and models that characterize the spatial variations within imagery as a means of extracting information [7].

Texture analysis mainly consists of two steps: Feature extraction and Texture classification. The texture analysis is divided into statistical, structural using Transform methods and stochastic methods. Here statistical texture analysis method is used. A statistical method of investigating texture that considers the spatial relations of pixels in the gray level co-occurrence matrix, which is also called as gray level spatial dependence matrix. Texture classification is done using Minimum distance classifier.

3.1 Gray Level Co-Occurrence Matrix

The co-occurrence matrix is used to capture the numerical features of a texture using spatial relationship of related gray tones. The GLCM functions distinguish the texture of an image by calculating how often pairs of pixel with particular values and in a specified spatial relation occur in an image, creating a GLCM and then statistical measures are extracted from this matrix.

A GLCM is a matrix which has equal number of rows and columns to the number of gray tones or gray levels, G, in an image. The matrix element $Q(i, j \mid \Delta a, \Delta b)$ is the relative frequency with two pixels, separated be a pixel distance (Δa, Δb), that occur within a neighborhood, with intensity i and j,

respectively [8]. Given an input image matrix of size M x M containing G gray tones from 0 to G – 1, let f(c, d) is the intensity at sample c, line d of the neighborhood. Then,

$$Q (i, j \mid \Delta a, \Delta b) = W \, S (i, j \mid \Delta a, \Delta b)$$

Where, $W = \dfrac{1}{(M - \Delta a)(M - \Delta b)}$

$$S (i, j \mid \Delta a, \Delta b) = \sum_{d=1}^{M - \Delta b} \sum_{c=1}^{M - \Delta a} X$$

And,

$$X \text{ is } \begin{cases} 1 \text{ if } f(c, d) = i \text{ and } f(c + \Delta a, d + \Delta b) = j \\ 0 \text{ elsewhere} \end{cases}$$

The numerical features extracted from the GLCM are used to represent, evaluate and categorize textures. The subsets of standard features derivable from a normalized GLCM are as follows [8]:

i.   **Maximum Probability:**
     The maximum probability is defined as the measure of computing the strongest response of the co-occurrence matrix. It is the simple static value in the center pixel of the window. Maximum probability is higher if one combination of the pixel dominates the other.

$$\text{Maximum probability} = \max (Q_{cd})$$

Where, (Q_{cd}) is $(c, d)^{th}$ entry in a gray level spatial dependence matrix

ii. **Correlation:**
     Correlation is a measure of how correlated a pixel is to its adjacent pixel over the entire image. The range of correlation is (-1 1). It is -1 or 1 for a perfectly negative or positively correlated image, respectively. It is NaN for a constant image.

$$\text{Correlation} = \sum_{c=1}^{L} \sum_{d=1}^{L} \frac{(c - nr)(d - ns) Qcd}{\sigma r \, \sigma s}$$

Where,
Q_{cd} = c, d element of normalized symmetrical Co-occurrence matrix
L = Number of gray tones in the image as specified by number of levels in under quantization.
n = GLCM mean, calculated as
$nr = \sum_{c=1}^{L} c Q(c)$
$ns = \sum_{d=1}^{L} d Q(d)$
σ = variance of intensities of all reference pixels in relation to that contributed to GLCM, calculated as
$\sigma_r^2 = \sum_{c=1}^{L} (c - nr)^2 * Q(c)$
$\sigma_s^2 = \sum_{d=1}^{L} (d - ns)^2 * Q(d)$
$Q(c) = \sum_{c=1}^{L} Q cd$ and $Q(d) = \sum_{d=1}^{L} Q cd$

iii. **Contrast:**
     Contrast is defined as a measure of intensity of an image between a pixel and its neighbor. The range of contrast is normally [0 (size (G, 1) – 1)²]. Contrast is zero for a constant image. It is used to measure the local intensity variation.

$$\text{Contrast} = \sum_{c=1}^{L} \sum_{d=1}^{L} (c - d)^2 Qcd$$

iv. **Energy:**
     Energy is defined as the measure of homogeneity or uniformity of an image. It is also known as angular second moment. It is used to give the sum of squared elements in G. The range of energy is (0 1). Energy is 1 for a constant image.

$$\text{Energy} = \sum_{c=1}^{L} \sum_{d=1}^{L} Q \, cd^2$$

v.   **Homogeneity:**
     Homogeneity is used to measure the value of closeness of distribution of elements in G to the diagonal of G. The range of homogeneity is (0 1). It is 1 for a diagonal G.

$$\text{Homogeneity} = \sum_{c=1}^{L} \sum_{d=1}^{L} \frac{Q \, cd}{1 + |c - d|}$$

vi. **Entropy:**
     Entropy is defined as measure of randomness. Entropy measures disorganization of an image and achieves its largest value when all elements in matrix Q are equal. When the texture of an image is not uniform then many GLCM elements have very small values, which imply that entropy is very large. Therefore, entropy is inversely proportional to GLCM energy.

$$\text{Entropy} = -\sum_{c=1}^{L} \sum_{d=1}^{L} Qcd \, \log 2 \, Qcd$$

3.2 Minimum Distance Classifier

Texture classification is done using supervised learning, which is Minimum Distance Classifier. It is used to classify unknown image data set to classes which minimizes the distance between the image dataset and the test image. Minimum distance classifier is a samples kind of supervised classification. The method:

i.   Calculate the mean vector for every class
ii. Calculate the Euclidean distance from each pixel to class mean vector
iii. Later it assigns each pixel to the class it is closest to

3.3 Algorithm

1) Capture sufficient samples of petrol and diesel such as Pure Petrol, Pure Diesel, 10%, 20%, 30%, 40% and 50% adulteration of petrol and diesel with kerosene respectively, and create a database.
2) Read the images in MATLAB.
3) Perform texture analysis on each image and extract image features.
4) The texture analysis is performed by using statistical method i.e., Gray Level Co-Occurrence Matrix.
5) The algorithm for GLCM is as follows:
a) Quantize the image data: Each sample is treated as a single image pixel and its value gives the intensity of that pixel. These intensities are further quantized into a specific number of discrete gray levels known as Quantization.
b) Create the GLCM: It is a square matrix of size M x M, where M is the number of Levels specified under Quantization.
c) Let A be the sample under consideration for the calculations.
d) Let B be the set of samples surrounding the A which fall within a window centered upon sample A.
e) Define each element i, j of the GLCM sample present in set B, as the number of times two samples of intensities I and j occur in specified spatial relationship.
f) Make the GLCM symmetric: This produces a symmetric matrix in which the relationship I to j is indistinguishable for the relationship j to i.
g) Normalize the GLCM: Divide each element by sum of all elements.
h) Calculate the selected features. E.g., Maximum probability, Correlation, Contrast, Energy, Homogeneity and Entropy.
i) Texture classification is done using supervised learning, which is Minimum Distance Classifier.
6) The algorithm for Minimum Distance Classifier:
    a) Estimate class mean vector and covariance matrix from training samples i.e., in code class mean vector is the feature and covariance matrix is the test image features, feature_vector.
    b) Compute Euclidean distance as, Euclidean distance = [sqrt (sum (feature – feature_vector) ^{2})]
    c) [min index] = [sqrt (sum (feature – feature_vector) ^{2})] gives the test image results by checking the minimum values of the obtained.
7) Adulterations of petrol as well as diesel are estimated by using image processing technique and minimum distance classifier.

3.4 Flowchart
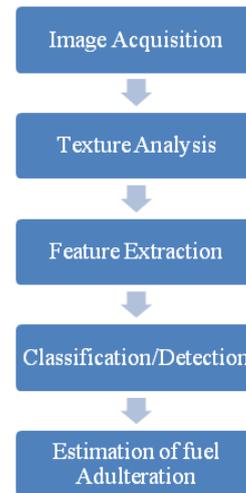
4. RESULTS AND DISCUSSIONS

The samples of images captured for petrol and diesel are as shown below:

4.1 Petrol

Fig-1: Pure petrol   Fig-2: 10% adulterated

Fig-3: 20% adulterated   Fig-4: 30% adulterated
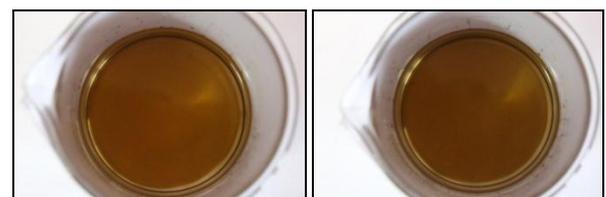

Fig-5: 40% adulterated   Fig-6: 50% adulterated

Sample Tests:

Let us take 30% adulterated petrol. As seen from the table, the texture analysis features for test image using GLCM is given as follows:

Maximum Probability = 0.0344
Correlation = 15.602
Contrast = 0.9983
Energy = 0.0035
Homogeneity = 0.4780
Entropy = 10.5308
Let us take these values as Feature_vector:

$$Feature\_vector = \begin{pmatrix} 0.0344 \\ 15.6072 \\ 0.9983 \\ 0.0035 \\ 0.4780 \\ 10.5308 \end{pmatrix}$$

To perform Minimum Distance Classifier, the training data is prepared as shown below:

Feature = [Pure petrol 10%A 20%A 30%A 40%A 50% A]

Feature = [1   2   3   4   5   6]

Where A = Adulterated

Therefore, training data set is given as,

Feature =

$$\begin{pmatrix} 0.0190 & 0.0049 & 0.0143 & 0.0274 & 0.0160 & 0.0392 \\ 2.3665 & 16.8234 & 15.6003 & 15.3705 & 15.2764 & 14.1076 \\ 0.9997 & 0.9976 & 0.9982 & 0.9983 & 0.9985 & 0.9988 \\ 0.0038 & 0.0010 & 0.0015 & 0.0027 & 0.0018 & 0.0043 \\ 0.6028 & 0.4110 & 0.4441 & 0.4629 & 0.4572 & 0.4897 \\ 9.3010 & 10.9087 & 10.8300 & 10.5642 & 10.7485 & 10.4165 \end{pmatrix}$$

Calculate Euclidean distance,

Sqrt (sum ((Feature - Feature_vector). ^2))

We get,

E = [13.2982 1.2757 0.3018   0.2396   0.3969   1.5039]

Where E = Euclidean distance

Now apply minimum distance classifier method,

Min (sqrt (sum ((feat1 - feature_vector). ^2))) = 0.2396

[Minimum index] = [E] gives,

Minimum = 0.2396

Index = 4

Hence, petrol is 30% Adulterated.
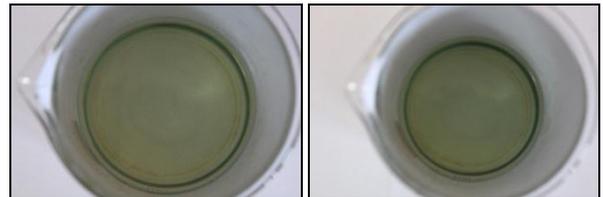
4.2 Diesel

Fig-7: Pure diesel   Fig-8: 10% adulterated

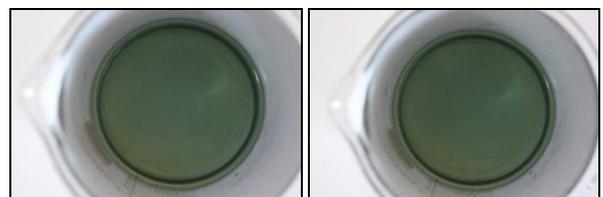Fig-9: 20% adulterated   Fig-10:30% adulterated

Fig-11: 40% adulterated Fig-12: 50% adulterated

Sample test:

Let us take 40% adulterated diesel. As seen from the table, the texture analysis features for test image using GLCM is given as follows:

Maximum Probability = 0.0067
Contrast = 16.2492
Correlation = 0.9978
Energy = 0.0035
Homogeneity = 0.4297
Entropy = 10.9679

Let us take these values as Feature_vector:

$$Feature\_vector = \begin{pmatrix} 0.0067 \\ 16.2492 \\ 0.9978 \\ 0.0035 \\ 0.4297 \\ 10.9679 \end{pmatrix}$$

To perform Minimum Distance Classifier, the training data is prepared as shown below:

Feature = [Pure diesel 10%A 20%A 30%A 40%A 50% A]

Feature = [1   2   3   4   5   6]

Therefore, training data set is given as,

Feature =

$$
\begin{pmatrix}
0.0035 & 0.0068 & 0.0057 & 0.0081 & 0.0058 & 0.0064 \\
17.4183 & 6.0799 & 11.3562 & 12.9482 & 16.0545 & 15.8693 \\
0.9944 & 0.9989 & 0.9979 & 0.9981 & 0.9979 & 0.9979 \\
0.0012 & 0.0016 & 0.0011 & 0.0013 & 0.0010 & 0.0010 \\
0.3861 & 0.4976 & 0.4578 & 0.4471 & 0.4300 & 0.4323 \\
10.4345 & 10.1767 & 10.6729 & 10.6574 & 10.9112 & 10.9518
\end{pmatrix}
$$

Calculate Euclidean distance,

Sqrt (sum ((Feature - Feature_vector). ^2))

We get,

E = [1.2857 10.2003 4.9020 3.3157 0.2028 0.3803]

Now apply minimum distance classifier method,

Min (sqrt (sum ((feat1 - feature_vector). ^2))) = 0.2028

[Minimum index] = [E] gives,

Minimum = 0.2028

Index = 5

Hence, diesel is 40% Adulterated.

5. CONCLUSIONS

Image processing technique using MATLAB is a simple and effective technique used for fuel adulteration estimation. By applying statistical texture analysis which uses Gray Level Co-Occurrence Matrix, image features are extracted for different proportions of adulteration of both petrol and diesel. Texture classification uses Minimum Distance Classifier which gives an efficient result in estimating fuel adulteration.

Estimation of fuel adulteration results in:

i. Reduced exhaust tailpipe emissions
ii. Reduces the wear and tear of engines which in turn leads to improved performance and lifetime of engines
iii. Reduces air pollution which leads to lesser air borne diseases
iv. Increases overall economy of the country and national GDP
v. It leads to lesser use of biomass for domestic appliances which reduces indoor air pollution
vi. Reduces green house effects on the environment

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