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Adaptive Technique for Contrast Enhancement of Leading Vehicle Tracks

Manoj Kumar Kalra[#,*], Ashutosh Trivedi[$] and Sanjay Kumar Shukla[!]

[#]*DRDO-Defence Geoinformatics Research Establishment, Chandigarh - 160 036, India*

[$]*Department of Civil Engineering, Delhi Technological University, Delhi - 110 042, India*

[!]*School of Engineering, Edith Cowan University, Perth, Australia*

[*]*E-mail: mkkalra.dgre@gov.in*

ABSTRACT

During movement in various unpaved terrain conditions, the track impressions left over by the leading vehicles provide guiding and safe routes in the area. The delineation of these tracks captured by the images can extend immense support for guidance in real time. These tracks that look like edges in coarse-resolution images take the shape of elongated areas in fine-resolution images. In such a scenario, the high pass and edge detection filters give limited information to delineate these tracks passing through different surroundings. However, the distinct texture of these tracks assists in the delineation of these tracks from their surroundings. Gray level co-occurrence matrix (GLCM) representing the spatial relation of pixels is employed here to define the texture. The authors investigated the influence of different resolutions on the distinguishability of these tracks. The study revealed that texture plays an increasing role in distinguishing objects as the image resolution improves. The texture analysis extended to investigate the track impressions left over by the leading vehicle brings out an ample scope in delineating these tracks. The measures could improve the track contrast even better than conventional techniques. To select the most optimal contrast enhancement measure in a given scenario, authors proposed a quantified measure of track index. An investigation is made on the difference-based track index (TI) representing the mean contrast value of the track vis-à-vis off-track areas. The results show an increase in the quantified contrast from 7.83 per cent to 29.06 per cent. The proposed technique highlights the image with the highest track contrast in a given scenario. The study can lead to onboard decision-making for the rut following vehicles moving in low-contrast terrain.

Keywords: Off-road, Vehicular movement, GLCM, Texture, Unpaved, Rut, On-board, Image contrast

1. INTRODUCTION

The movement of vehicles on unpaved terrain is quite common in agriculture, forestry, armed forces, robotics, Unmanned Ground Vehicles (UGV), night safari, etc. Many challenging operations like firefighting, search and rescue, and movement in snow-bound and loose desert soils for many combat missions utilize the unpaved off-road terrain during need. The trafficability condition of the area depends upon the spatial features and the ground state to support the movement of vehicles. Significant resources are available to infer the trafficability condition using spatial data resources. For instance, Pundir and Garg[1] worked on evaluating the impact of terrain features on trafficability employing spatial data resources. However, empirical and experimental models are there for precise evaluation of prevalent soil condition and their inference on trafficability conditions. Vehicles in many places get stuck due to these uncertainties.

Delineation of vehicle tracks on unpaved terrain reflects the wealth of information about trafficable off-road routes for these areas. Moreover, the rut formed by the earlier vehicular movement on unpaved terrain becomes the preferred route for applications like night safari and robotics-based operations[2] for better stability. Tremendous work exists to study the rut formed by vehicles from different perspectives. For instance, Kalra[3], *et al.* investigated the rut contrast improvement using various alternate indices. Liu[4], *et al.* studied the variation in rut width on turnings using military vehicles. In another study, Vennik[5], *et al.* investigated the impact of single and multiple passes of military vehicles. During strategic missions, vehicles move on unpaved terrain in low contrast dark conditions[6]. In such a scenario, the delineation of tracks or the rut impressions by leading vehicles plays an important role.

These days, many vehicular operations make use of vision-based systems. Pierzchala[7], *et al.* used close-range photogrammetry to detect the rut. Salmivaara[8], *et al.* worked on a vehicle-mounted LiDAR system for rut depth detection and measurement. Digital image processing techniques are there to be employed to enhance the features of interest[9]. However, these techniques alone extend limited aid for delineating the tracks from their surroundings in an image. The pattern and texture of these tracks over tonal variation are some appropriate measures that enable the delineation of these tracks. The statistical measures of the GLCM-based texture analysis technique have shown reasonably good results in a wide range of applications[10]. Fauji[11], *et al.* presented one such study for improving the robustness of detection of road surfaces

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in varied environmental conditions using a combination of GLCM measures and local binary pattern (LBP).

In this paper, the authors investigated conventional and texture-based analysis to delineate the tracks. The study used satellite images representing different resolutions and ground-based vehicle tracks formed by leading vehicles. A quantitative track index (TI) based approach is examined in this study to compare and find the most appropriate contrast measure for the delineation of tracks. The paper gives the details of the study.

2. RELATED WORK

Caraffi[12], *et al.* used decision networks and the stereo vision technique for detecting the off-road path and obstacles. Howard and Seraji[13] used a vision system-based mobile robot and applied Artificial Neural Network (ANN) for real-time terrain characterization. Ordonez[2], *et al.* investigated the movement of robotic vehicles by tracking the rut in unpaved areas. Chowdhury[14], *et al.* introduced an algorithm for a line-following robot to achieve the ability to follow the straight-line path autonomously.

There are various techniques used for the enhancement of image contrast. These image-processing-based techniques primarily employ filters and histogram stretching. Janani[15], *et al.* made a compilation of different image enhancement techniques. Babu[16] presented a framework for contrast enhancement. The edge detection techniques that preserve the structural features and the high-frequency components belong to either of the two groups based on the derivates[17]. The first one computes the Gradient or the first-order derivative of an image. The second one, based on the second-order derivative is a Laplacian operator. Both these filters highlight sharp changes or discontinuities in the picture. However, the gradient-based filters emphasize the prominent edges while Laplacian filters enhance the finer details[18]. Based on these, researchers brought out several edge detection algorithms. Shrivakshan and Chandasekar[19] compared the prominent edge detection algorithms covering Sobel, Robert's cross gradient, Prewitt, Canny, Laplacian of Gaussian (LoG), etc. The goodness of edge detection algorithms depends upon measures such as the accuracy of edge detection, the localization of edges, and the minimal response. Canny's edge detection is a computationally more expensive algorithm. However, it performs better than all these operators under almost all scenarios[20].

The track features appear like an edge in the coarse-resolution images. These features take the shape of elongated areas in fine-resolution images. In such a scenario, the high pass and edge detection filters give limited information to delineate these tracks passing through diverse surroundings. However, the distinctive pattern formed by these tracks gives rise to relative variation in its texture from the surroundings.

The relationship of pixels with neighboring pixels reveals worthful information distinctive to distinguish these objects. Various approaches exist that describe the texture in an image. Bharti[21], *et al.* compared different approaches to describe the texture. Humeau-Heurtier[22] presented a survey of various methods of texture feature extraction. GLCM-based texture analysis could delineate well the road boundaries[23]. Measures like energy, homogeneity, entropy, contrast, etc. define the texture using this approach.

The most suitable texture measure that can distinguish the track area more prominently depends upon the surrounding. This paper presents a study to enhance contrast enhancement using different alternate approaches. The proposed method of comparative analysis makes way for selecting the most optimal contrast enhancement measure.

3. METHODOLOGY

Suitable image processing techniques enhance the vehicle tracks and assist in their delineation in an image. The image background, resolution, and noise level in the image containing the tracks form the basis for selecting suitable measures.

3.1 Various Edge Enhancement and High-Frequency Filters

In some course-resolution imagery, the track impressions appear as linear features. In such cases, high-pass and edge-detection filters facilitate the detection of these features.

Edges that form a set of connected pixels create a boundary between two disjoint areas. Edge detection aids in highlighting the high-frequency components in an image. Edge detection usually depends upon the computation of the first or second derivatives of the image[17] and computed as below:

$$\nabla f = grad(f) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (1)$$

here, g_x and g_y are the first derivative or gradients of the image f(x,y) and show the pixel value changes in both x and y directions defined using a column vector ∇f. The second derivative-based edge filter is also defined using Laplacian of the image f(x,y) computed using a second-order differential Eqn. as follows:

$$\nabla^2 f = \frac{\partial^2 f}{\partial^2 x} + \frac{\partial^2 f}{\partial^2 y} \quad (2)$$

Based on the above procedure, a study brings out the comparative analysis of various edge detection algorithms like Sobel, Canny, Prewitt, and LoG. The images processed for highlighting the edges use different high-frequency filters that de-emphasize the low-intensity features. All such operations make use of the convolution of images with filters for representing various edges or other high-frequency filters as follows:

$$Conv(w,f) = w(x,y) * f(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x-s, y-t) \quad (3)$$

here, w(x,y) denotes a filter of dimension (s x t) that scans over the image f(x,y). The symbol (*) stands for convolution- *Conv(w,f)* of image and filter. In these techniques, noise removal can be helpful. Barbu[24] presented the details about using a fourth-degree partial differential equation to remove the noise. Tavakkol[25] showed a spatially adaptive technique that performs when the directional texture is there.

3.2 Image Texture Measures

Most of the techniques mentioned above try to enhance the image contrast using primarily tone-based image classification, which gives limited understanding. This study uses texture measures as a descriptor of the spatial relation of pixels. Several applications employ texture for extracting the required features. Zhou[26], *et al.* and Alsmadi[27] combined edge detection and properties of a co-occurrence matrix for content-based image retrieval. Pradhan[28], *et al.* demonstrated the extraction of flooded areas using a GLCM-based texture analysis based program over TerraSAR- X satellite image. Micheal and Vani[29] employed texture features for automatic mountain detection using DTM data of lunar images. Doycheva[30], *et al.* used texture features for evaluating road distress conditions in real-time. Sudha and Aji[31] used GLCM texture features as the descriptors of features for image retrieval in varied applications. Liu[32], *et al.* employed the local second-order entropy to characterize the variation in the grayscale. Winarno[33], *et al.* applied edge detection with GLCM for fingerprint recognition even though the edges are predominant in such images. Here, the authors used edge detection for preprocessing. Feature extraction is based on the GLCM using measures like energy, contrast, homogeneity, and correlation to improve the results further. Singh[34], *et al.* employed features of GLCM on Sentinel-2 imagery for the identification of avalanche debris areas. Kar and Banerjee[35] used GLCM texture features to evaluate the intensity of tropical cyclones.

This study used GLCM-based measures as a good descriptor of texture features. Haralick[36], *et al.* proposed the GLCM-based concept of measuring texture by computing different texture measures. He introduced 14 features to represent the texture of an image. Subsequently, Conners and Harlow[37] presented that out of 14 parameters, only five are good enough to describe texture. These parameters include Energy, homogeneity, entropy, correlation, and contrast. The following points provide details about the key measures used in the current study.

3.2.1 Energy

This parameter which reflects the uniformity and represents the angular second moment computes the uniformity of texture. This measure considers the pixel pair repetitions and detects the disorders in textures. A constant or periodic form shows high values of energy. The following Eqn. defines this measure:

$$Energy = \sum_{i,j} p(i,j)^2 \tag{4}$$

where, *p(i,j)* is the probability value recorded for the co-occurrence of cell i,j of the GLCM matrix.

3.2.2 Homogeneity

This statistic which reflects the Inverse Difference Moment measures image homogeneity. It assumes larger values for the slight differences in the gray tone of pair elements. It is more sensitive to near diagonal elements of the GLCM. It gives maximum value when the same values of image elements are there. The following Eqn. defines this measure:

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{5}$$

3.2.3 Entropy

This statistic computes the complexity or disorderliness of the image. Complex texture typically has high entropy. The entropy is small for the image containing uniform texture whose GLCM elements have large values. The entropy correlates inversely with energy. The following Eqn. defines this measure:

$$Entropy = -\sum_{i,j} (p_{i,j}) \log_2 (p_{i,j}) \tag{6}$$

3.2.4 Correlation

It measures the linear dependency of the gray level values in the GLCM matrix. It reflects the relation of the reference pixel with its neighbor. The following Eqn. defines this measure:

$$Correlation = \sum_{i,j} \frac{(i-\mu_i).(i-\mu_j).p(i,j)}{\sigma_i.\sigma_j} \tag{7}$$

where μ_i, μ_j, σ_i, and σ_j are the means and standard deviations.

3.2.5 Contrast

This statistic represents the spatial frequency of an image and gives the difference-moment of GLCM. It measures the quantum of local variations and considers the difference between the highest and the lowest values of a contiguous set of pixels. A low-contrast image presents a GLCM concentration term around the principal diagonal and features low spatial frequencies. The following Eqn. defines this measure:

$$Contrast = \sum_{i,j} |i-j|^2 \, p(i,j) \tag{8}$$

GLCM contrast correlates inversely but strongly with homogeneity. Homogeneity decreases when the contrast increases while maintaining constant energy levels.

This study presents the utility of all the above-computed texture measures over the track images. It computes these statistical measures and gives details for optimal selection reflecting maximum contrast.

4. DATA AND TOOLS USED

This study uses filters of suitable size representing different high-pass and edge enhancement filters and texture measures. It convolves them over the image to create the resulting filtered images. This study used GLCM-based measures to define the image texture. More levels imply higher accuracy but with increased computational cost. Clausi[38] provided details about the computational complexity using the GLCM method, which is proportional to O (G2). Suitable selection of displacement value in GLCM is a significant consideration as the large values result in missing the details of textural information[39]. This study uses a kernel of size 5 x 5, a quantisation level of 32, and a horizontal offset of 1 pixel to compute texture. It assigns the value to the center pixel of the filter, which then moves further to cover the whole image. This study used MATLAB and Sentinel Application Platform (SNAP) for further analysis. The google earth images of different resolutions, displaying track areas near Chandigarh given in Fig. 1(a) formed the basis for further study.

5. IMAGE ANALYSIS AND RESULTS

Several conventional techniques can assist detection of various features in the image. Since the idea here is to

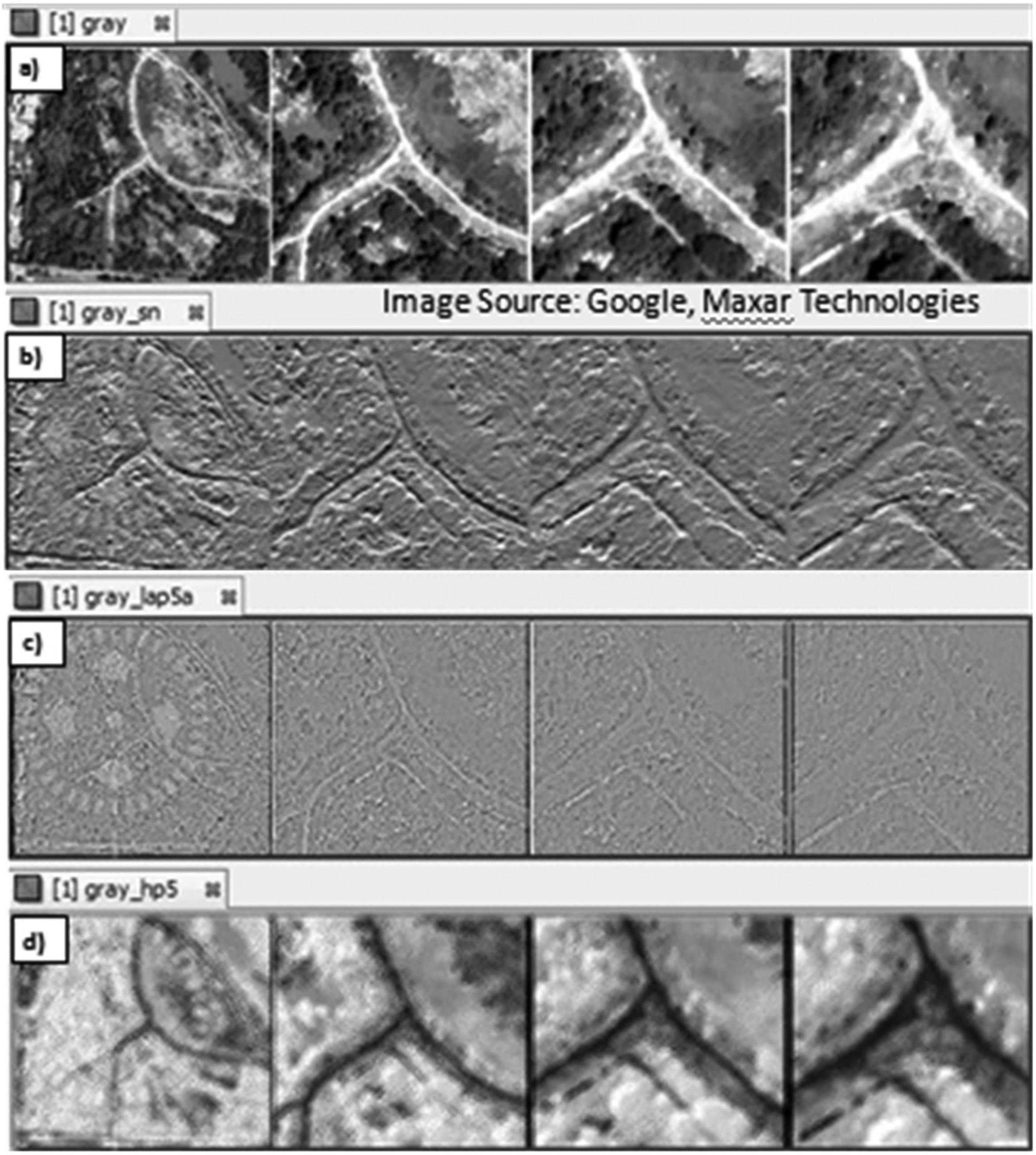

Figure 1. (a) Multi-resolution images of tracks (Source: Google, Maxar Technologies). Result after convolving images, (b) Using sobel edge detection filter, (c) Using second-order Laplacian filter, and (d) using the high-pass filter.

highlight the linear track features and enhance their contrast, the authors analyzed the impact of edge detection and high-pass filters. The convolution using the Sobel gradient and Laplacian filter resulted in images as shown in Fig. 1(b) and Fig. 1(c), respectively. As the track boundaries are delineable using a high-pass filter, its convolution resulted in the image in Fig. 1(d). The figure also shows a comparative effect of these techniques on three different resolutions.

As the tracks have differentiable texture from the surroundings, the texture analysis using GLCM revealed meaningful results. Figure 2 shows the outcome of various statistical measures on images of different resolutions.

The visual appearance of the results at different resolution images brings out the importance of texture as the resolution improves. The texture analysis is carried further on the even finer resolution images captured using ground-level cameras. The illustration in Fig. 3 displays the track impressions of the leading vehicle. The contribution of texture increases as one moves toward the finer level of resolution.

Figure 4 illustrates the results of different contrast enhancement measures and texture analysis on the image of vehicle tracks, as observed in field running conditions.

These results exhibit the role of texture analysis for improved delineation of the vehicle tracks. The authors proposed a quantitative method of computing and comparing the track contrast here. This method considers the relative difference in contrast for on-track and off-track areas and computes the track index for arriving at the most optimal solution.

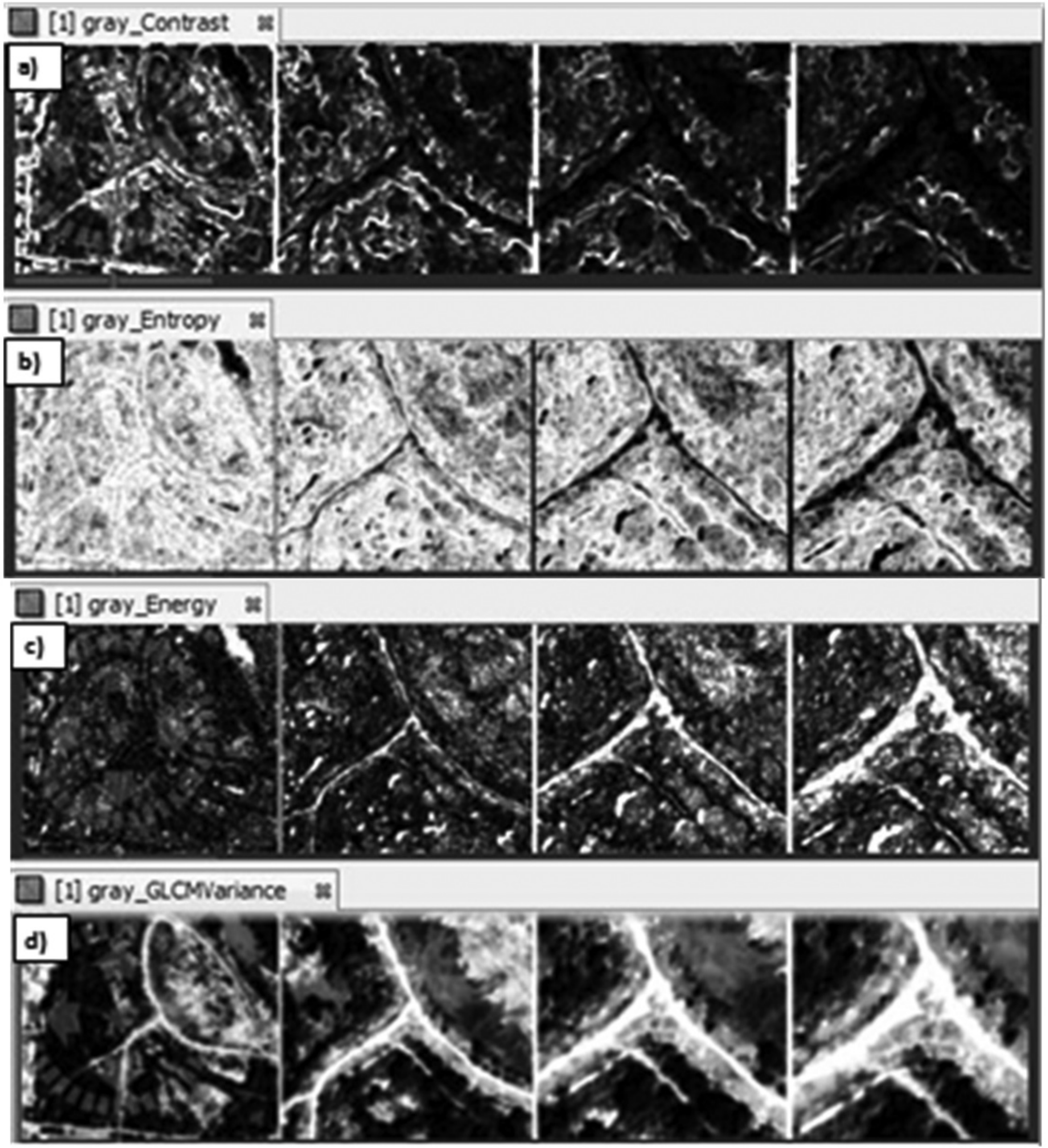

Figure 2. Result of GLCM texture analysis on the multi-resolution images, (a) Contrast image, (b) Entropy image, (c) Energy image, and (d) Variance image.

5.1 Track Index-based Optimal Selection

As illustrated in Fig. 5, the procedure comprises drawing a cross-sectional profile across the tracks on the image.

It selects the Pixels On-track (PT) and Pixels Off-track (POT) in the image for each enhancement measure separately. It considers the average value of pixels in each area to account for the local variation. The authors considered this aspect by choosing a rectangular zone of 11x100 pixels. The average value of the statistical measure (xi) is:

$$P_T = \frac{n_2 x_2 + n_4 x_4}{n_2 + n_4} \tag{9}$$

$$P_{OT} = \frac{n_1 x_1 + n_3 x_3 + n_5 x_5}{n_1 + n_3 + n_5} \tag{10}$$

where, xi, i = [1:5] are the averaged statistical measure of areas around tracks. Here, $x1$, $x3$, and $x5$ are the averaged values for pixels in off-track areas left to the left Track, in-between Tracks, and right to the right Track, respectively. Similarly, the values $x2$ and x4 are the averaged values for pixels on the left and right Track, respectively.

If the focus is to highlight any single track, for instance, the Track by any two-wheeler, the computation for areas representing pixels on the Track is done for the points on one Track. Similarly, the mean value for the area representing Off-track makes the basis on the two zones surrounding the Track.

Data normalisation is an important consideration here for a better comparison of the two measures having different ranges of values. Here, normalisation considers the minimum and maximum values of the pixel value range for various contrast enhancement measures. The following Eqn. explains this computation process:

$$z = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{11}$$

where, z is the normalised value of x data representing contrast enhancement measure, and x_{min} and x_{max} are the minimum and maximum values, respectively. Here the range of numeric data gets normalised between 0 and 1.

The comparison of measures also needs to consider the variance in data for both off-track and on-track zones.

Figure 3. Field Image of vehicle tracks impressions of leading vehicle.

Therefore, it uses the mean value and standard deviation to compute the coefficient of variation defined as:

$$CV = \frac{\sigma}{\mu} \tag{12}$$

where, CV is the coefficient of variation, σ the standard deviation, and μ is the mean value of the Measure. The lower the Coefficient of Variation, the better the reliability of the Measure, representing contrast based on normalized off-track and on-track pixel values. The Track Ratio (TR) for comparing the track contrast used here is:

$$TR = \frac{P_T}{P_{OT}} \tag{13}$$

Since, CV value for each image representing different contrast measures will be different, the equation used for computing the normalized Track Index (TI) here includes:

$$TI = \frac{TR}{CV} \tag{14}$$

Table 1 gives the comparative details of the normalised track index as evaluated using various image enhancement measures.

6. DISCUSSION

Table 1 presents the duly sorted values of the normalised track index. The same suggests that one can achieve better contrast than the original gray Image using one or the other texture images of contrast, dissimilarity, correlation, etc. The track index value for the original gray image increased from 7.83 per cent to 29.06 per cent. The comparative contrast of the Images shown in Fig. 4 confirms this view. It is noticeable that for testing this approach, the areas chosen in off-track and On-rack zones are of size 100x11 pixels. By taking larger areas, the conclusions can improve even further.

The observation reveals that the GLCM texture-based technique effectively addresses the contrast enhancement issue. It also supports the view expressed by Mohanaiah[10], *et al.* that GLCM-based measures give satisfying results in a large domain of applications. The track contrast enhancement achieved here verifies this point. The studies of the rut following

Table 1. Computation of Track Index (TI) quantifying image contrast

Computation of track index						
Contrast measure	**Off_track mean**	**On_track mean**	**Track Ratio (TR)**	**Off_tr_ sigma**	**Coeff of variation**	**Track Index (TI)**
Correlation	0.858	0.793	0.065	0.192	0.224	29.06
Dissimilarity	0.480	0.551	0.071	0.372	0.775	9.11
Contrast	0.291	0.379	0.088	0.294	1.010	8.72
Gray	0.681	0.632	0.049	0.429	0.630	7.83
Entropy	0.803	0.821	0.018	0.272	0.338	5.34
GLCM mean	0.541	0.514	0.027	0.316	0.585	4.65
High Pass Filter	0.328	0.379	0.051	0.498	1.519	3.35
GLCM homogeneity	0.243	0.219	0.024	0.311	1.281	1.86
SobelN	0.452	0.459	0.007	0.433	0.956	0.70
Laplacian	0.515	0.514	0.001	0.512	0.994	0.09
GLCM variance	0.362	0.362	0.000	0.312	0.861	0.02

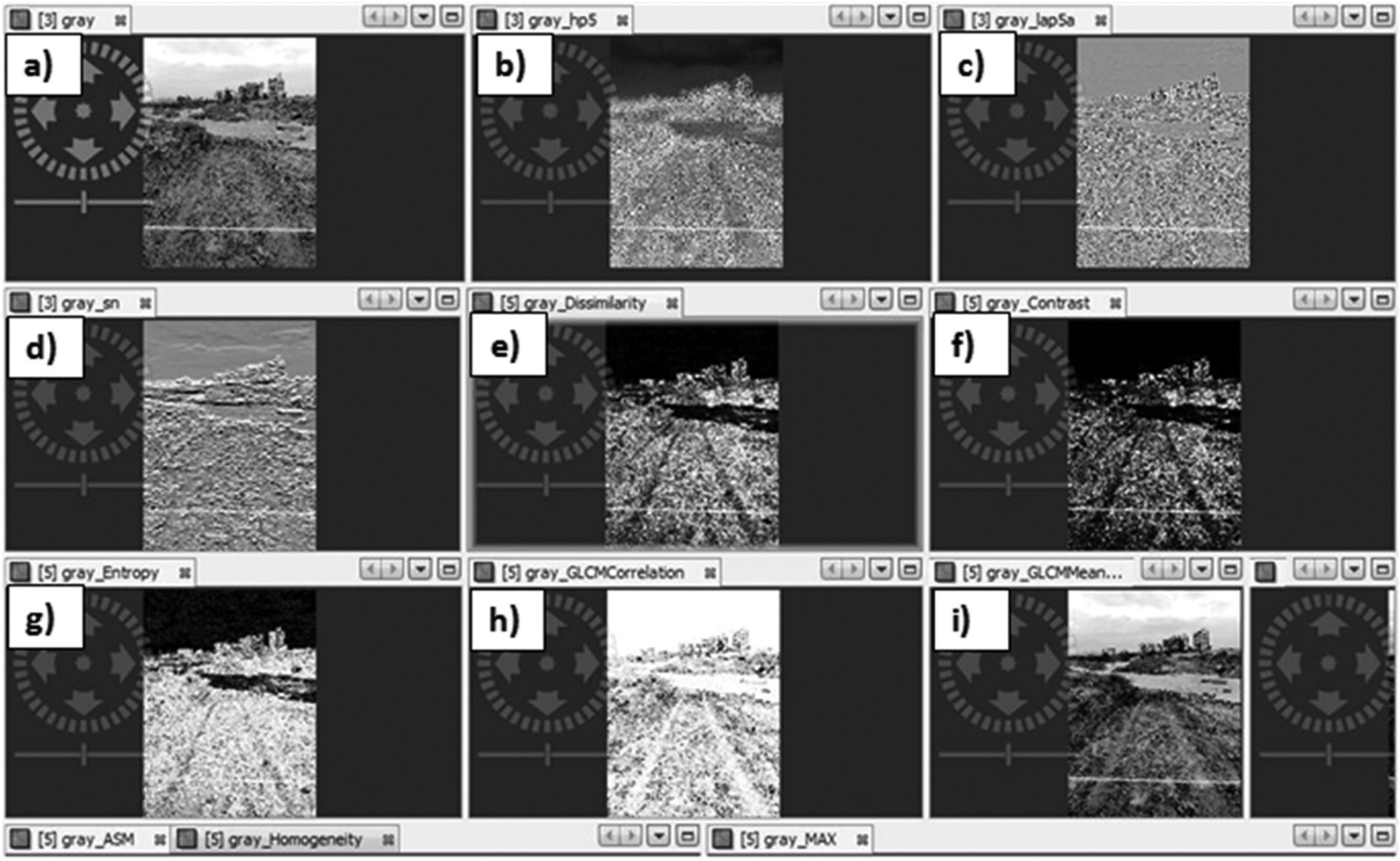

Figure 4. (a) Images of vehicle track impressions as observed in vehicle running condition, (a) In original gray tone and using (b) High-pass filter, (c) Laplacian filter, (d) Sobel edge detection filter and GLCM measures of (e) Dissimilarity, (f) Contrast, (g) Entropy, (h) Correlation, and (i) Mean filter.

robotic vehicles like the ones presented by Ordonez[2], *et al.* and Chowdhury[14], *et al.* can have improved decision-making about the track areas using the proposed technique.

Some related aspects are notable here. If a vehicle moves in a zig-zag fashion or during curves, Liu[4], *et al.* reported in the study of movement on curves that the width of the track portion increases. The localization of the track zones is an important consideration here. The position of the camera capturing pixels data focus around the mid-portion of track zones may not give correct results always. The other way out could be to study the improved localisation of the tracks by employing a deep-learning model. Already attempts are there by various researchers like Stewart[40], *et al.* to identify the road network using CNN. These techniques can improvise the localisation aspects of these tracks. The focus here is to highlight the relative contrast of the track zones w.r.t. the surroundings by quantified comparison.

As per the surrounding terrain, the measure that shows better contrast could vary. There are some other aspects too which need consideration. For instance, the area around the tracks nearer to the vehicle gets captured with better resolution and usually has more variance of pixel values. However, the distant features around the tracks appear smooth to the image captured by the camera. These points may reveal different results at different sections along the track in the same image. This process considers various image enhancement measures, computes the track index in each case, compares, and displays the image with maximum contrast. The technique given in this study considers the effect of generating maximum track contrast and is thus adaptive to the changes in the surrounding terrain.

Further, the index-based computation at different sections along the track shall vary as the vehicle moves. With this, the contrast-based ordered set of images shall also alter. One can apply the probabilistic approach to get the most optimal contrast image set. This aspect, however, demands more computational power from the onboard system. Alternatively, the contrast measure based on a suitably selected section can help to achieve reasonably good image ordering. A better measure of track contrast could also emerge by considering such additional inputs. This aspect, however, needs further study.

The images convolved using high-pass filters and edge detection like the one by Narendra and Hareesha[20] help highlight the boundaries of track areas w.r.t. its surroundings. However, there could also be many high-frequency features in the area that can bar distinguishing exactly the track areas. The role of texture in getting increased track contrast w.r.t. its surrounding becomes noticeable both visually and quantitatively. The GLCM texture-based results presented here support the views of Alsmadi[27] that these measures enrich the content for image retrieval.

An onboard decision-making tool can usefully employ the process given in this study for increased track contrast in both manual and autonomous navigation modes. It may extend as a

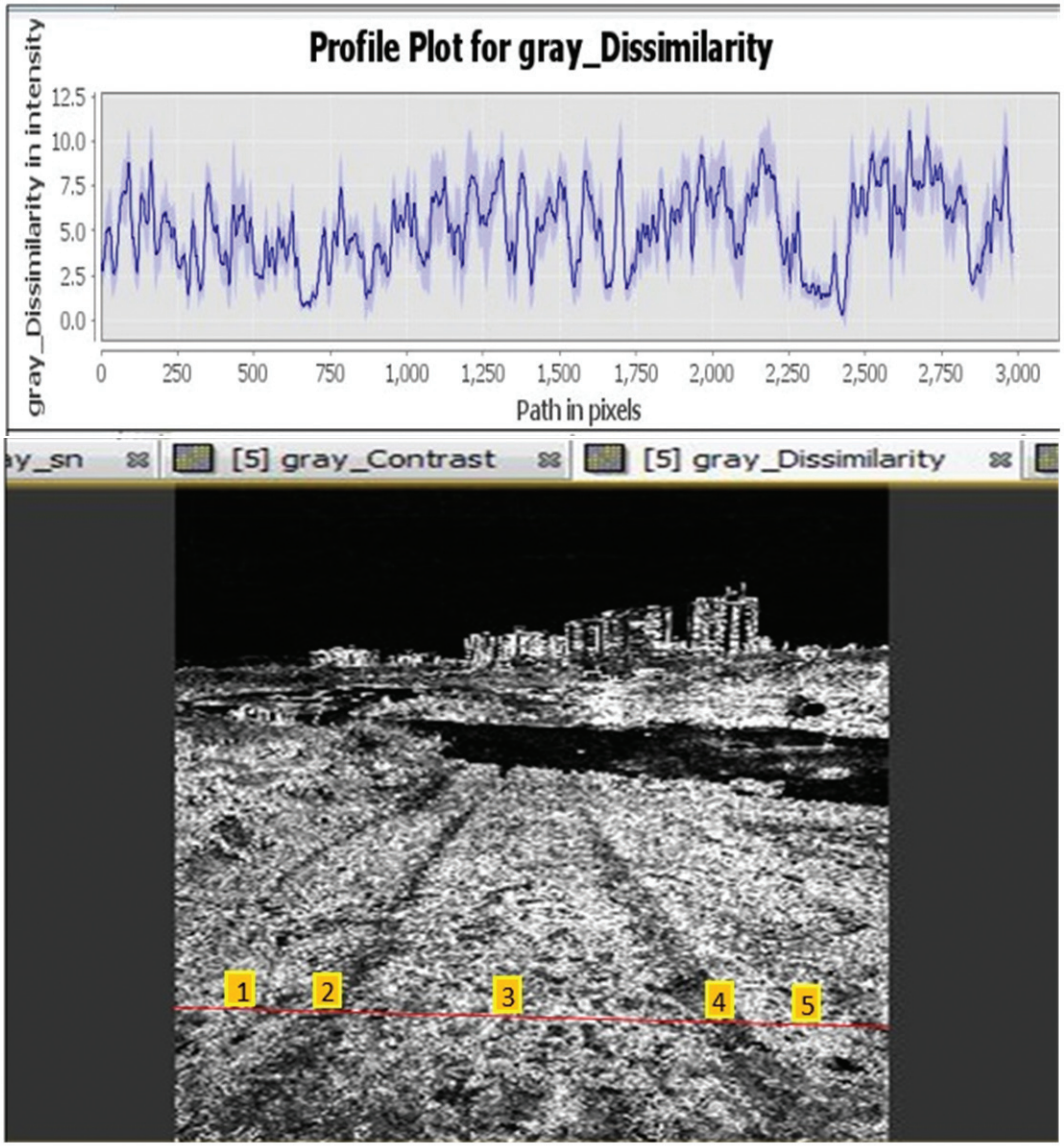

Figure 5. Location of pixels chosen for comparing the contrast of track areas with reference to its surroundings.

vital support for the rut following vehicles, particularly those which operate in the low contrast areas. This study can help many industries like defence, autonomous ground vehicles, robotic vehicles, night safari, etc.

7. CONCLUSIONS

The contrast enhancement study presented here leads to drawing the following key conclusions:

- The role of texture assumes importance and can reveal valuable information as the resolution increases. When the features of interest are of smaller dimensions, the texture analysis may not add much value in delineating the features. This aspect may need further investigation while considering all associated conditions of different surroundings. In the current study, the texture analysis of the image employs a kernel of size 5x5, horizontal displacement of 1 pixel, and 32 quantization levels. Considering other options of these associated parameters can give further insight into the dependence upon these parameters.
- The statistical measures of GLCM-based texture analysis form a strong base for understanding the influence of texture in contrast enhancement. The suitable texture measure for maximizing the contrast could vary with the surrounding. The proposed track index-based technique can quantitatively bring out the variation in track contrast levels w.r.t. its surroundings. The proposed approach that brings out the image with optimal track contrast can thus prove vital for the on-board decision-making.

8. FUTURE SCOPE

The current study used a kernel of fixed size 5x5, horizontal displacement of 1 pixel, and 32 quantization levels for the texture analysis of the image. Considering other options of these associated parameters can give further insight into the dependence upon these parameters.

The area around the tracks nearer to the vehicle gets captured with better resolution, while the distant features appear smooth in the image captured by the camera. This aspect needs further study for better insight and an improved decision on-board vehicle.

The track index-based study presented in this paper considered images in the optical range. However, the comparative analysis of varied input source data could reveal some interesting results.

The proposed technique may also find application in areas like the detection of wake created by ocean-going vehicles. A wake, that causes instability to the vehicles operating in its surrounding can last long and impact other distant vehicles even. Depending upon the vehicle configuration, its speed, etc., the extent and time of wake may vary. A study on the detection of wakes using suitable sensors and various image analysis techniques could give better insight. The proposed track index that comparatively selects the images also seems to have good potential in detecting the most optimal image highlighting the wake.

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CONTRIBUTORS

Mr Manoj Kumar Kalra obtained his Bachelor degree in Civil Engineering from Thapar Institute of Engineering and Technology, Patiala. He is working with DRDO pursuing research in different operational areas. His interest areas also include: Bringing out an integrated solution for different terrain interactive systems by interfacing domain science, instrumentation and computational aspects.
He has contributed in conceptualisation, drafting and writing of the presented manuscript.

Prof A Trivedi is a Professor of Civil Engineering at Delhi Technological University, Delhi, India. He is working as Head of the Department of Civil, Mechanical and Electrical Engineering and Dean IRD. His current interests include: Dynamics of pavements, mobility in unpaved areas, foundations in granular media, bio-cemented soils and rock masses.
He has contributed in this paper by discussing and brainstorming all the key aspects, the results obtained and in shaping the findings as presented.

Prof Sanjay Kumar Shukla working at Edith Cowan University, Australia is also the founding Editor-in-Chief of the International Journal of Geosynthetics and Ground Engineering, Springer Nature, Switzerland.
He has contributed in this paper by discussing and brainstorming all the key aspects, the results as obtained and presented in this paper. He has also contributed in giving shape to this manuscript from editorial aspect.