IMAGE BASED STREET LIGHT BLOCK OUT MONITORING

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ABSTRACT

Street lighting system is an essential facility for any civilization. It plays a pivotal role in providing enhanced social security and reducing night time accidents. Therefore, one of the main priorities in Electrical Distribution Companies is timely repair and maintenance of the street lighting, which should be regularly checked. The common mechanized monitoring of the street lighting is based on measuring the consumed current of each lamp and comparing it with the lamp nominal current. In this way, the error in network is identified. Monitoring street lighting is presently conducted by traditional inspection and check-out method. We suggest a new method for monitoring and remote sensing of the street lighting system which is completely isolated from electricity network. It applies picture shooting of the street lighting network, image processing and identifying the off lights in the image. This system conducts monitoring and remote sensing of a large number of passageway lamps which are fed by different branches easily. It monitors the street lights automatically by a system without physical interference. So, the main idea to implement this is by the usage of drones to collect the images of street lighting network continuously. Those images are sent to the system, where they are processed using image processing techniques to identify the off lights in the network.

Keywords: street lights, images, connected components, monitoring, wavelet transform and hough transform.

INTRODUCTION

Street lighting is advantageous to the society in a variety of ways such as reducing night time vehicle accidents and injuries, decreasing street and malicious crimes, increasing the fear to commit a crime, popularizing public transportation, providing the possibility for night time economic, educational and entertainment activities, facilitating rescue missions and enhancing closed-circuit television (CCTV) effectiveness.

An important component of power consumption worldwide is street lighting. India is no different. Global trends in street lighting show that 18-38% of the total energy bill goes towards street lighting and therefore this is one domain that needs major attention if we look at improving efficiency of power consumption with an objective of saving energy. In most of the cities, the street lights are installed and maintained by municipalities. Very often, one notices that the street lights stay on well past sunrise. This is because the lights are switched off based on a pre-decided time rather than lighting needs, which vary based on season and location of the city. There is a need for devising a well thought out way to prevent wastage of electricity.

Owing to the mentioned reasons, the timely repair and maintenance of the street lighting network is one of the major duties of the electrical distribution companies. In general, monitoring of street lighting network is based on measuring the amperage of each lamp and comparing it with the pre-determined reference values. The data collected through power line communication are sent to the local controller and enables identification of the fault in lighting network. But, the installation and maintenance costs for this procedure are high [11],[12],[13],[14],[15].

So, for monitoring of street lighting network and also decreasing installation and maintenance costs, the plan of monitoring and remote sensing of street lighting network using computer vision and image processing techniques has been discussed. Instead of usage of incandescent bulbs as street lights, we can employ LED lights as the street lights because the consumption of energy by LED lights is less. Also, in order to turn on or off the street lights, a person is needed to cover different areas through his vehicle. But, to cover entire city, so many people need to do this, which causes lot of pollution because of usage of those vehicles. Also, time is wasted because of this laborious work. Timely maintenance of street lighting network and examination of the faults of the current systems for street lighting network monitoring is necessary. Implementing the plan of monitoring and remote sensing of street lighting network using computer vision and image processing techniques for mechanized blackouts in some passageways seems to be crucial and economical. This plan can be completely isolated from the street lighting power network and conduct monitoring and remote sensing of a large number of passageway lamps which are fed by different branches using drones and image processing systems. One more advantage of this automatic monitoring of street lights is, the pollution caused due to vehicles used by line men to check the street lights every day is also omitted and the time is also being saved.

So, the motivation behind this work is to reduce both pollution and wastage of time by continuous capturing of street lights images through drones. The images are sent to the server where the monitoring is done through image processing techniques by the system.

MATERIALS

In this work the street light images are acquired using drones in our college at different heights and in different angles. One of the input image acquired is shown in Figure-1.

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Figure-1. Input image with all street lights on.

METHOD

The block diagram of overall drone based street light monitoring system is given in Figure-2. and the steps involved in the image process based proposed street light monitoring using three different methods is given in Figure-3. The detection of street light condition whether it is lighting or not is detected with three methods using Hough transform, Discrete wavelet transform and Radon transform.

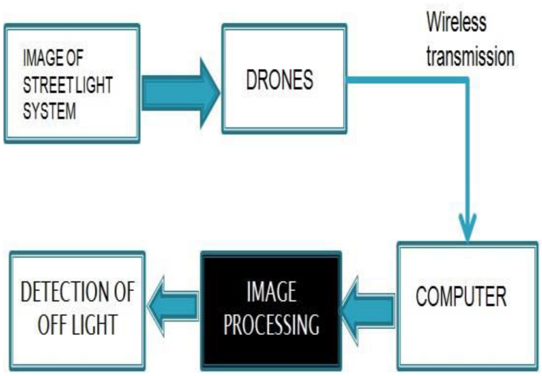

Figure-2. Block diagram for overall drone based streetlight monitoring system.

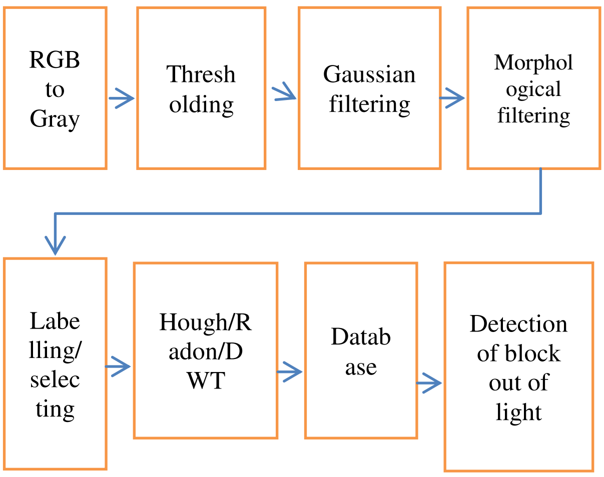

Figure-3. Steps involved in the work.

Images of the street lighting network are obtained as inputs for the system. RGB images are converted to grayscale as we don't require any color information. Threshold filtering is done to convert grayscale images to binary ones. Smoothening of images is carried out using Gaussian LPF. Labeling of the light sources is performed by 8-connected component labelling technique. Using morphological filtering, unwanted light sources are removed. Hough transform is applied for each light source and Hough peak values for each source are stored in a database. The Hough peak values for light sources in the test image are compared with those of values obtained from a reference image with all lights on. Hence, the light sources that are off are identified as their Hough peak values are missing. Thus the off condition of lights are identified in the network from an image.

Preprocessing

In preprocessing the image is converted from RGB to grayscale. Binarization is done using thresholding. Gaussian filtering is applied to eliminate high frequency components. Images are into negatives for further processing.

Hough transform

The Hough transform is a feature extraction technique to find imperfect instances of objects within a certain class of shapes circles or ellipses by a voting procedure [6]. This voting procedure is carried out in a parameter space, from which object candidates are obtained as local maxima in an accumulator space [9]. The Hough transform is used to group the edge points into object candidates. In the Hough transform the characteristics of the straight line is considered not as image points, instead, in terms of its polar coordinate pair, denoted r and Θ (theta). The parameter r represents the distance between the line and the origin, while Θ is the angle of the vector from the origin to this closest point. The equation of the line can be written as

$$y = \left(-\frac{\cos\theta}{\sin\theta}\right)x + \left(\frac{r}{\sin\theta}\right)$$

which can be rearranged to
$r = x\cos\theta + y\sin\theta$

It is therefore possible to associate with each line of the image a pair (r,θ) which is unique if $\theta \in [0,\pi)$ and $r \in \mathbf{R}$, or if $\theta \in [0,2\pi)$ and $r \geq 0$.

The (r,θ) plane is referred to as Hough space for the set of straight lines in two dimensions corresponds to a sinusoidal curve in the (r,θ) plane, which is unique to that point. For each pixel and its neighborhood, the Hough transform algorithm determines if there is enough evidence of an edge at that pixel. If so, it will calculate the parameters of that line, and then look for the accumulator's bin that the parameters fallinto, and increase the value of that bin. By finding the bins with the highest values, by

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looking for local maxima in the accumulator space, the most likely lines can be extracted, and their approximate geometric definitions read off. The simplest way of finding these peaks is by applying threshold determining which lines are found as well as how many. Since the lines returned do not contain any length information, it is often necessary to find which parts of the image match up with which lines. The result of the Hough transform is stored in a matrix called an accumulator. The dimensions of this matrix is the angle θ, distance r, and each element has a value telling how many points/pixels are positioned on the line with parameters (r,θ). So the element with the highest value tells what line that is most represented in the input image.

Hough peaks Identifies peaks in Hough transform. By performing the Hough transform the radius and theta values and the Hough peaks are calculated. The r and theta values of these Hough peaks are extracted into two matrices and the pattern recognition is done on these values.

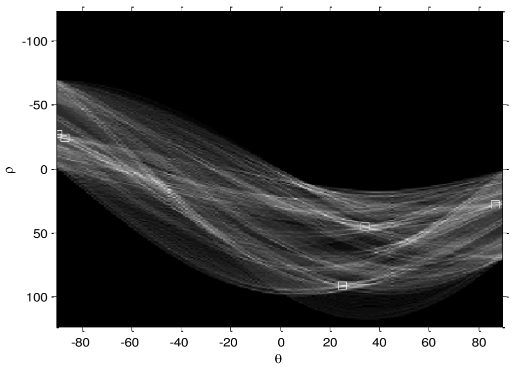

Figure-4. r vs Θ The Hough peaks are represented by the small squares.

Radon transform

The Radon transform is used to create an image from the projection data associated with cross-sectional scans of an object. If a function *f* represents an unknown density, then the Radon transform represents the projection data obtained as the output of a scan. Hence the inverse of the Radon transform can be used to reconstruct the original density from the projection data, and hence it forms the mathematical basis for image reconstruction [10]. The Radon transform data is often called a sinogram because the Radon transform of a Dirac delta function is a distribution supported on the graph of a sine wave. Consequently the Radon transform of a number of small objects appears graphically as a number of blurred sine waves with different amplitudes and phases.

Discrete wavelet transform

The discrete wavelet transform returns a data vector of the same length as the input is with many data are almost zero. This corresponds to the fact that it decomposes into a set of functions called wavelets that are orthogonal to its translations and scaling. Therefore such a signal can be decomposed to a same or lower number of the wavelet coefficient spectrum as is the number of signal data points [8]. Hence a wavelet spectrum is very good for signal processing and compression as we get no redundant information here. The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. This transform decomposes the signal into mutually orthogonal set of wavelets.

Morphological filtering

Morphological opening operation is an Erosion followed by a dilation, using the same structuring element for both operations on a specified neighborhood.

$A \circ B = (A \ominus B) \oplus B$

Opening essentially removes the outer tiny "hairline" leaks and restores the image. The side effect is that it rounds off things. The sharp edges start to disappear.

Labelling of the connected components

Connected-component labelling is an algorithmic application of graph theory, where subsets of connected components are uniquely labelled based on a given heuristic to detect connected regions in binary digital images [1]. When integrated into an image recognition system connected component labelling can operate on a variety of information. Blob extraction is performed on the resulting binary image from a thresholding step. Blobs may be counted, filtered, and tracked [3]. A graph, containing vertices and connecting edges, is constructed from relevant input data. The vertices contain information required by the comparison heuristic, while the edges indicate connected 'neighbors' [2]. An algorithm traverses the graph, labelling the vertices based on the connectivity and relative values of their neighbors. Connectivity is determined based on 4-connected or 8-connected [5],[7]. Once the first pixel of a connected component is found, all the connected pixels of that connected component are labelled before going onto the next pixel in the image. It is assumed that the input image is a binary image; with pixels being either background or foreground and that the connected components in the foreground pixels are desired. Connectivity checks are carried out by checking neighbor pixels' labels neighbor elements whose labels are not assigned yet are ignored [4].

Recognition procedure

The image with labelled light sources is processed for extraction of each light source by eliminating all other. Later Hough parameters, Radon parameters and discrete wavelet coefficients are extracted for all light sources to form the database. Query image is taken by switching off each light source and compared with database for similarity and decision is made which light source is OFF.

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RESULTS AND DISCUSSIONS

The input image with all street lights in ON condition is given in Figure-5,converted gray image is given in Figure-6, binarized image using thresholding is given in Figure-7, filtered image using average filter is given in Figure-8, morphological filtered image is given in Figure-9. Labelling of first light source is given in Figure-10, second light source in Figure-11, third light source in Figure-12, fourth light source in Figure-13 and fifth light source in Figure-14. Image with selection the first light source along with its Hough transform is given in Figure-15, image with selection of the second light source along with its Hough transform is given in figure 16, image with selection of the third light source along with its Hough transform is given in Figure-17,image with selection of the fourth light source along with its Hough transform is given in Figure-18 and image with selection of the fifth light source along with its Hough transform is given in Figure-19. Test image with second street light off is given in Figure-20. Grey converted image is given in Figure-21.Thresholded image and average filtered images are given in Figure-22 and 23 respectively. Morphological filtered image is given in Figure-24. Labelling is shown in Figure-25.

Accuracy

Accuracy is defined as the efficiency of classification of objects in the images.

Figure-5. Input image with all street lights on.

Figure-6. Conversion of input RGB image to gray.

Figure-7. Applying threshold filtering for the gray image.

Figure-8. Filtering the image using average filter.

Figure-9. Morphological filtering of the image.

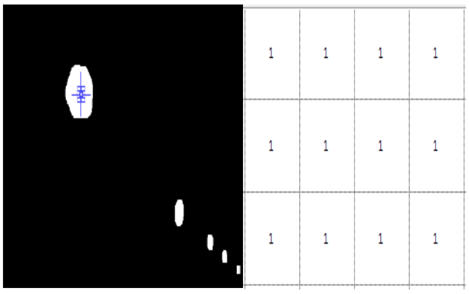

Figure-10. Labelling of first light source.

VOL. 13, NO. 14, JULY 2018 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

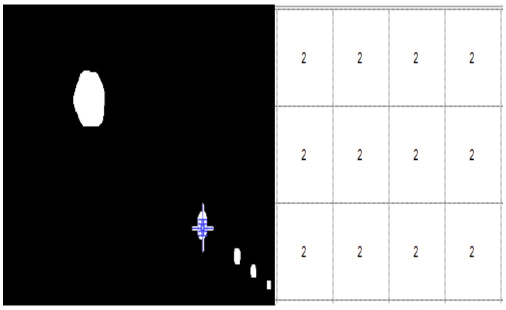

Figure-11. Labelling of second light source.

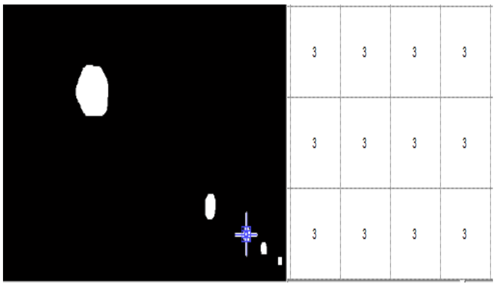

Figure-12. Labelling of third light source.

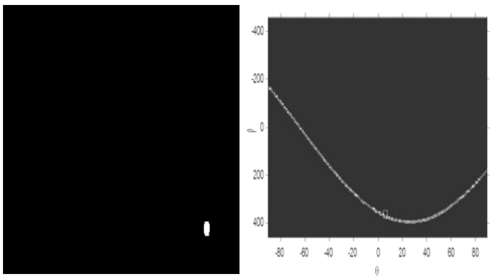

Figure-13. Labelling of fourth light source.

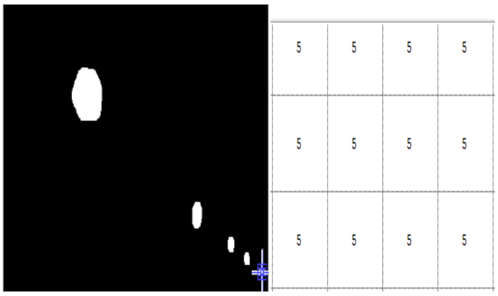

Figure-14. Labelling of fifth light source.

Selection of individual light sources

Light sources are selected individually for testing the working condition. At a time one light source was selected and computed its Hough transform and stored in the database.

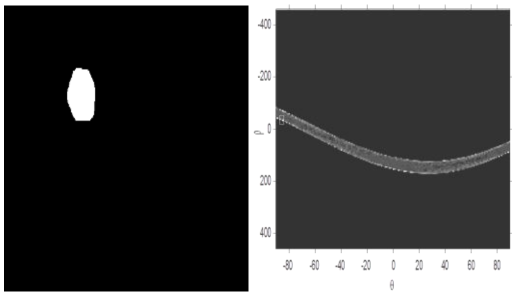

Figure-15. Selecting first light and its Hough transform.

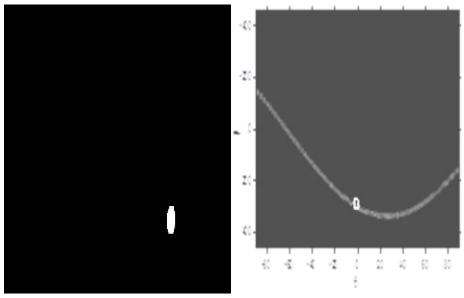

Figure-16. Selecting second light and itsHough transform.

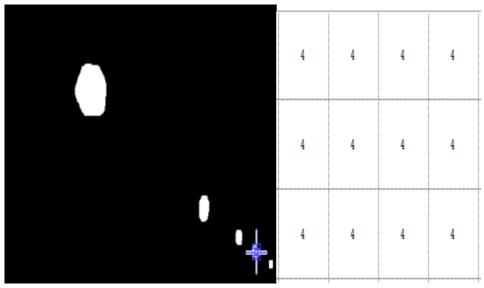

Figure-17. Selecting third light and its Hough transform.

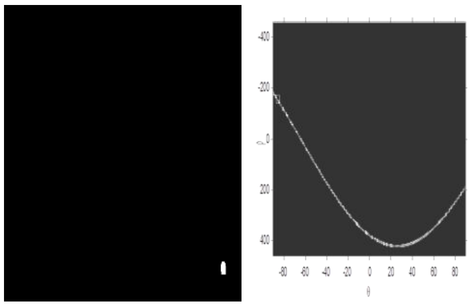

Figure-18. Selecting fourth light and its Hough transform.

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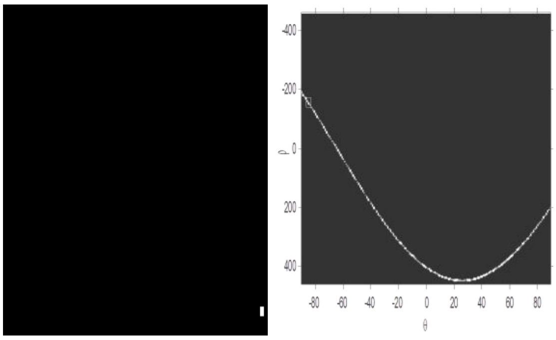

Figure-19. Selecting fifth light and its Hough transform.

Figure-20. Test image with second street light off.

Figure-21. Conversion of test RGB image to gray.

Figure-22. Applying threshold filtering for the gray image.

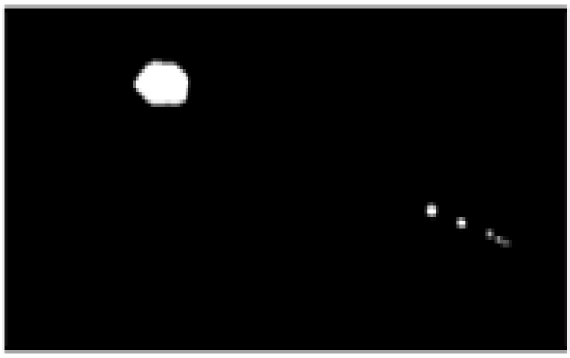

Figure-23. Filtering the image using average filter.

Figure-24. Morphological filtering of the image.

Figure-25. Image labelling.

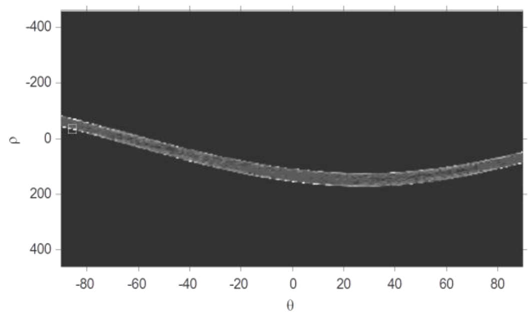

Figure-26. Hough transform of first light source.

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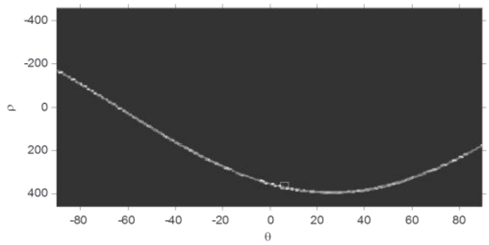

Figure-27. Hough transform of second light source.

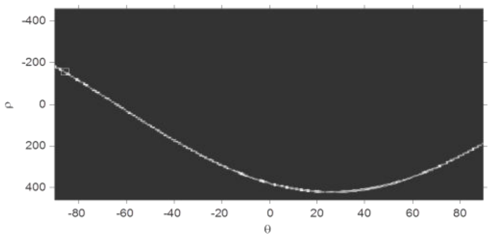

Figure-28. Hough transform of third light source.

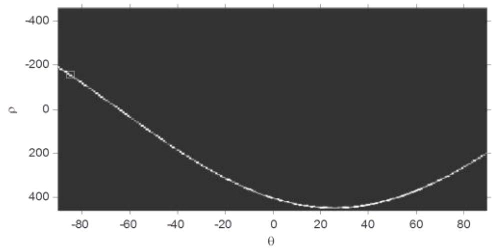

Figure-29. Hough transform of fourth light source.

Table-1. Parameters of hough transform.

	Light 1ρ, θ	Light 2ρ, θ	Light 3ρ, θ	Light 4ρ, θ	Light 5ρ, θ
Refimage	423,5	749,90	823,97	301,5	302,6
Test image Light2 OFF	423,5	----	823,7	301,5	302,6

Table-2. Parameters of discrete wavelet transform.

	Light 1DWT	Light DWT	Light 3DWT	Light 4DWT	Light 5DWT
Ref. Image	0.0085	0.0014	0.0006	0.0004	0.0002
Test image light 1 OFF	----	0.0014	0.0006	0.0004	0.0002

Table-3. Parameters of radon transform.

	Light 1r	Light 2r	Light 3r	Light 4r	Light 5r
Ref. image	3.1339	0.5313	0.2138	0.1555	0.0778
Test image light3 OFF	3.1339	0.5313	---	0.1555	0.0778

Performance of different image transformations

The testing carried out on different views of the images to check for rotation effect and accuracy of block out detection. The results of Radon transform is tabulated inTable-4. Table-5 and Table-6 gives the results of discrete wavelet transform and Hough transform respectively. The comparison of results obtained using Hough, radon and DWT is given in Table-7.

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Table-4. Radon transform.

S. No	View of image	Ref image	Test image	No.of light sources in the image	No.of light sources correctly identified as on/off
1	Front view	p.jpg	p2.jpg	5	4
2	Top view	c.jpg	c1.jpg	5	4
3	Top view	col.jpg	col1.jpg	6	5
4	Side view	d.jpg	d2.jpg	4	0

Accuracy = (13/20)*100 = 65%

Table-5. Test results of discrete wavelet transform.

S. No	View of image	Ref image	Test image	No.of light sources in the image	No.of light sources correctly identified as on/off
1	Front view	p.jpg	p2.jpg	5	5
2	Top view	c.jpg	c1.jpg	5	4
3	Top view	col.jpg	col1.jpg	6	5
4	Side view	d.jpg	d2.jpg	4	0

Accuracy = (14/20)*100 = 70%

Table-6. Test results of hough transform.

S.No	View of image	Ref image	Test image	No.of light sources in the image	No.of light sources correctly identified as on/off
1	Front view	p.jpg	p2.jpg	5	5
2	Top view	c.jpg	c1.jpg	5	4
3	Top view	col.jpg	col1.jpg	6	5
4	Side view	d.jpg	d2.jpg	4	4

Accuracy = (18/20)*100 = 90%

Table-7. Comparison of accuracies.

S. No	Accuracy of monitoring
Hough Transform	90%
Radon Transform	65%
Discrete Wavelet Transform	70%

CONCLUSIONS

The system was tested over an image which contains five street lights. The image containing street lights was pre-processed for removal of high frequency components with the help of averaging filter and morphological filter. The light sources in the image are allotted with labels using connected labelling. Next Hough transform was applied on the extracted light source individually to extract the features. The resulting features namely, **r** and **θ** of the Hough peaks were stored in the database, which became the training set. The same procedure was applied for the image with test light source made off. The extracted features of test image with a particular light source in off condition are compared with the database and decision is made which light source is off. The recognition of outage of light source was also carried out by applying the radon transform and discrete wavelet transform. From the observations, we can conclude that Hough transform was giving maximum accuracy in extracting the data rather than radon and discrete wavelet transform techniques.

REFERENCES

[1] H. Samet and M. Tammineni. 1988. Efficient Component Labeling of Images of Arbitrary Dimension Represented by Linear Bintrees. IEEE Transactions on Pattern Analysis and Machine Intelligence (TIEEE Trans. Pattern Anal. Mach. Intell.) 10(4): 579. DOI: 10.1109/34.3918.

[2] Michael B. Dillencourt and HannanSamet and Markku Tamminen. 1992. A general approach to connected-component labeling for arbitrary image representations. Journal of the ACM (J. ACM) 39(2): 253. DOI: 10.1145/128749.128750.

[3] Weijie Chen, Maryellen L. Giger and Ulrich Bick. 2006. A Fuzzy C-Means (FCM)-Based Approach for Computerized Segmentation of Breast Lesions in Dynamic Contrast-Enhanced MR Images. Academic Radiology.13(1): 63-72. DOI:10.1016/j.acra.2005.08.035. PMID 16399033.

[4] Kesheng Wu, Wendy Koegler, Jacqueline Chen and ArieShoshani. 2003. Using Bitmap Index for Interactive Exploration of Large part Datasets. SSDBM.

[5] A. Rosenfeld. 1970. Connectivity in digital pictures. Journal ofthe ACM. 17(1): 146-160.

[6] P.V.C. Hough. 1962. Method and means for recognizing complex patterns. US patent nr. 3069654.

[7] A. Rosenfeld. 1971. Picture Processing by Computer, Academic Press, New York/London.

[8] P. Bastian and L. Dunn, Global approach to pattern recognition for bubble chamber physics, IEEE T-COMP. 20, 995,

[9] R. D. Duda and P. E. Hart, Use of the Hough transform to detect lines and curves in pictures, CACM 15, 11-15.

[10] Deans Stanley R. 1983. The Radon Transform and Some of Its Applications, New York: John Wiley & Sons.

[11] Pooya Najafi Zanjani and Vahid Ghods. 2013.Monitoring and remote sensing of the street lighting system using computer vision and image processing techniques for the purpose of mechanized blackouts", HCTL Open Int. J. of Technology Innovations and Research. Vol. 4.

[12] VismayPandit *et al.* 2014. Smart Traffic Control System Using Image Processing. International Journal of Emerging Trends & Technology in Computer Science. 3(1): 280-283.

[13] Swathi C A, Hemanth Kumar S, Annappa A R. 2014. Smart Street lighting system based on sensors using plc and scada. International journal of mechanical engineering and technology. 5(9): 44-50.

[14] Omkar Ramdas Gaikwad, Anil Vishwasrao, Prof. Kanchan Pujari, Tejas Talathi. 2014. Image Processing Based Traffic Light Control. International Journal of Science, Engineering and Technology Research (IJSETR). 3(4): 1010-1014

[15] Samir A. Elsagheer Mohamed. 2013. Smart Street Lighting Control and Monitoring System for Electrical Power Saving by Using VANET. Int. J. Communications, Network and System Sciences. 6, 351-360.