AUTONOMOUS TRACKING SYSTEM FOR AIRPORT LIGHTING QUALITY CONTROL

J. H. Niblock, K. McMenemy, S. Ferguson and J. X. Peng
School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, United Kingdom

Keywords: Airport approach lighting, autonomous tracking, grey level assessment.

Abstract: The central aim of this research is to develop an an autonomous measurement system for assessing the performance of an airport lighting pattern. The system improves safety with regard to aircraft landing procedures by ensuring the airport lighting is properly maintained and conforms to current standards and recommendations laid down by the International Civil Aviation Organisation (ICAO).

A vision system, mounted in the cockpit of an aircraft, is capable of capturing sequences of airport lighting images during a normal approach to an aerodrome. These images are post-processed[a] to determine the grey level of the approach lighting pattern (ALP). In this paper, two tracking algorithms are presented which can detect and track individual luminaires throughout the complete image sequence. The effective tracking of the luminaires is central to the long term goal of this research, which is to assess the performance of the luminaires' from the recorded grey level data extracted for each detected luminaire. The two algorithms presented are the Niblock-McMenemy (NM) feature tracking algorithm has been optimised for the specific task of airport lighting and to assess its effectiveness it has been compared to the Kanade-Lucus-Tomasi (KLT) feature tracking algorithm. In order to validate both algorithms a synthetic 3D model of the ALP is presented. To further assess the robustness of the algorithms results from an actual approach to a UK aerodrome[b] are presented.

The results show that although both KLT and NM feature trackers are both effective in tracking airport lighting the NM algorithm is better suited to the task due to its reliable grey level information. Limitations, such as the static window size, of the KLT algorithm result in a lossy grey level data and hence lead to inaccurate results.

[a] Algorithms are being developed for real-time processing
[b] Belfast International Airport

1 INTRODUCTION

A substantial increase in the demand for air transport has resulted in the larger size of aircraft and increased frequency of flights. This requires higher performance and better maintenance of the airport lighting pattern (Matsunaga, 1980). One such way of achieving this is to regularly monitor airport lighting with the aim of highlighting and repairing any under-performing luminaires.

Several land based measurement systems such as the Mobile Airfield Light Monitoring System (MALMS[1]) and Photometric Airfield Calibration (PAC[2]) are capable of assessing the performance of inset *runway* lighting through the use of light meters and cameras respectively. Typically these systems work by collecting data as a truck drives over or past the rows of lighting. However, the major limitation of these systems are that they are incapable of assessing the performance of the *approach* lighting were the luminaires are raised a minimum distance of 2m above ground level. Thus, this paper proposes an aerial imaging system that is capable of assessing the approach lighting during an approach to an aerodrome.

Milward (Milward, 1976) was the first person in

[1] http://www.tmsphotometrics.com/

[2] http://www.gsilight.com/ppaclabcombo.htm

H. Niblock J., McMenemy K., Ferguson S. and X. Peng J. (2007).
AUTONOMOUS TRACKING SYSTEM FOR AIRPORT LIGHTING QUALITY CONTROL.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications - IU/MTSV*, pages 317-324

1976 to acknowledge the potential of an aerial imaging system in assessing the performance of airport lighting. With the advance of mobile technology and external storage devices it is easier and quicker than ever to process the lighting patterns performance. It is possible to assess the performance of aerodrome ground lighting (AGL) using aerial based imaging techniques (McMenemy and Dodds, 2003). A vision system is platform mounted, to minimise the effects of vibration, in the cockpit of an aircraft. During a normal approach to an aerodrome a video sequence is captured, approximately 2 minutes in length. The video is split into its component frames and analysed off-line. Not all frames are analysed. For the purposes of this paper a subsection of the acquired images, namely the section including the approach lighting pattern (ALP) are used for the performance assessment.

This paper presents two algorithms. The first termed the Niblock-McMenemy (NM) feature tracking algorithm has been optimised for the application of tracking an airport lighting pattern. To place the algorithm in context, it is compared and contrasted to the KLT feature tracking algorithm which is seen as one of the standard algorithms for tracking applications. Before the autonomous tracking algorithms are detailed, in the following section, an overview of the lighting pattern and the vision system are presented.

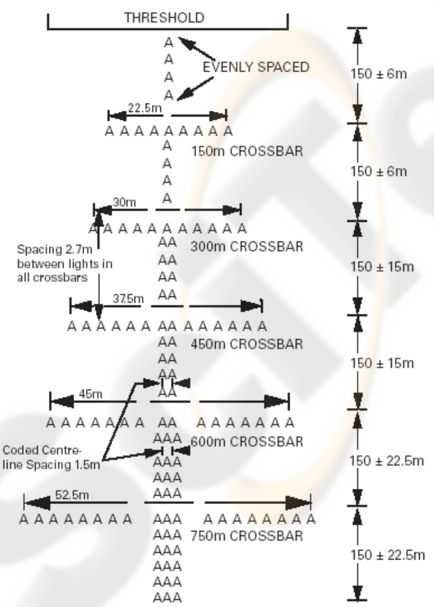

Figure 1: CATI Approach Lighting Pattern.

1.1 Approach Lighting Pattern Layout

Strict guidelines exist for the location and positioning of the luminaires. Such standards are documented in the International Civil Aviation Organisations (ICAO) Standards and recommended practices documents (ICAO, 2004).

Milward presents an overview of the standard Calvert System. This is the standardised lighting system used in the UK and Europe. The approach lighting system consists of a 900m coded line of white lights, on the extended centreline of the runway, and five crossbars at 150m intervals. The bars decrease in width towards the runway threshold, lines through the outer lights of the bars converging to meet the runway centreline 300m upwind from the threshold (Milward, 1976). This is illustrated in figure 1 (ICAO, 2004).

1.2 Vision System Overview

The vision system consists of a monochrome vision sensor with manual lens mounted on a vacuum based platform to minimise the effects of vibration. The vision sensor is connected to an Intel Pentium IV processor. Controller software acts as an interface between the processor and the vision sensor. A USB2.0 medium acts as a communications/power mechanism between computer and vision sensors.

1.3 Autonomous Luminaire Tracking

Tracking has been extended to a number of applications from video surveillance; medical research and image reconstruction (Pollefeys and Gool, 1999) to name a few. This paper is concerned with tracking lighting performance. To this end a lot of research exists for street lighting however this paper is concerned with monitoring an airport ALP. Two tracking algorithms are presented. The first algorithm termed the Niblock-McMenemy (NM) algorithm is introduced in section 2 and is summarised in figure 2. This is a feature extraction algorithm that tracks a series of single pixels through an image sequence.

The second technique termed the Kanade-Lucus-Tomasi (KLT) algorithm (Lucas and T.Kanade, 1981) is a globally recognised feature tracking algorithm and is introduced in section 3. The KLT method defines the measure of match between fixed-sized feature windows in the past and current frame as the sum of squared intensity differences over the windows. The displacement is then defined as the one that minimises this sum. For small motions, a linearisation of the image intensities leads to a Newton-Raphson style minimisation (Tomasi and Kanade, 1991).

Figure 2: NM Tracking Algorithm Overview.

This paper compares and contrasts the NM algorithm with the adapted KLT algorithm. In order to do this a synthetic model of the approach lighting pattern (ALP) has been generated (section 4) in order to simulate a real life approach to an aerodrome. As a means of measuring the performance of an ALP a measure of the total grey level of each luminaire is recorded over the duration of an approach to the aerodrome. This provides the system with information on each luminaires performance which in turn allows the system to make a decision on whether or not the lighting pattern conforms to the relevant standards. Section 5 presents grey level results obtained from actual images captured during a real-life approach to a UK aerodrome[3]. These images are used to assess the robustness of the tracking algorithms and highlight potential improvements. Future work and conclusions are presented in sections 6 and 7 respectively.

2 NM TRACKING ALGORITHM

This section presents the NM tracking algorithm composed of three states: locking state, tracking state and the recovery state. The three states are highlighted in figure 2.

[3]The authors would like to thank Flight Precision (http://wwwflightprecision.co.uk) for allowing us flight time whilst performing maintenance work on Belfast International Airport's lighting.

2.1 Locking State

The objective of the locking state is to *home* in on the target. The target being the approach lighting pattern. When the target is of acceptable size (McMenemy and Dodds, 2003) the imaging system triggers and starts to acquire data. The video segment is currently analysed off-line [4]. A check is performed on the subsequent image sequence to assess if the image is skewed and in need of realignment. A line approximating the horizon is drawn on the first image and the skew angle computed. Using this angle the image is rotated by the appropriate factor ensuring the rows of luminaires are in straight lines. The horizon can have an adverse effect on the extraction process. Stray light can cause the extraction algorithm to detect too many luminaires. Therefore, once the horizon has been used to de-skew the images the region of interest (ROI) i.e. the ALP is cropped, making sure to retain the original positional information.

2.2 Tracking State

Once the target has been identified the next step is to extract the relevant *foreground* information and track it through the image sequence. The following process is undertaken to extract, identify and track the luminaires. Each image contains a set of foreground, bright pixels termed *blobs*. If the extraction process were ideal, each detected blob would relate to a single luminaire in the lighting pattern. The objective of the extraction process is to highlight the useful information, *foreground* information, from a set of dark pixels termed *background* information or *noise*. Background differencing and thresholding techniques are used to minimise the effects of noise in the image.

Connected Component Analysis (CCA) using 8-way connectivity (Haralick and Shapiro, 1993) is used to yield a set of binary points used to segment the image into regions. This process yields a set of smooth *blobs* corresponding to each of the moving objects. The objective of the connected component analysis is to determine the connected set of components in an image and assign a distinct label to each pixel in the same connected component. The number of luminaires (blobs) present depends on the category of lighting pattern. This information is obtained from the standards (ICAO, 2004). For the purposes of this paper a CATI ALP is assumed with a total of 120 approach luminaires.

[4]It is the long term aim to have an imaging system that works in real-time. All algorithms are being developed with this objective in mind.

A center of mass algorithm shown in equation 1 is used to compute the mean *x,y* coordinate for each detected blob in the image.

$$\{\bar{x_i}, \bar{y_i}\} = \left\{ \frac{\sum_{j \in J_i} x_{ij}}{m_i}, \frac{\sum_{j \in J_i} y_{ij}}{m_i} \right\} \quad (1)$$

where $\bar{x_i}, \bar{y_i}$ represents the coordinate of the i^{th} blob, $i \in$I represents the set of detected blobs' in the image and J_i represents the set of m_i individual pixels that constitutes the blob.

In a binary image an unlabelled object is assigned a label based on its (*x,y*) image location. A scan is undertaken of the neighbouring objects until all the blobs have been labelled. The usual notation used to label the blobs is a set of integers $(1...N)$ where N corresponds to the number of blobs detected in the image. The objective of thresholding and image differencing is to minimise the probability that noise in any given image will affect the CCA results. There are occasions when this is not the case:

1. Inadequate sensor resolution can lead to merging of luminaires
2. Reflections may cause stray noise and flag up light sources that should not be present in the ALP
3. Luminaires leaving and entering the field of view of the sensor
4. Occlusions, where a luminaire is obstructed by an *obstacle* from the field of view of sensor. In the case of an occlusion the luminaire must be tracked and only when it has left the screen for 10 consecutive images can it be dropped.

If the expected number of luminaires is not equal to the actual number of luminaires extracted during the CCA a recovery state is required, see figure 2. A count is kept of blobs that fall out of the FOV of the sensor. This count is deducted from the expected number of luminaires to keep the system accurate. detected blobs in the first image (120) so that

2.3 Recovery State

This is a correspondence problem, i.e. given a feature in an image, what is the corresponding feature (i.e. the projection of the same 3D feature) in the other image (Pollefeys and Gool, 1999). Let's assume *p* and *q* to be of the form expressed in equations 2 and 3 respectively.

$$p = x_{fi}, y_{fi} \quad (2)$$

$$q = x_{(f-1)i}, y_{(f-1)i} \quad (3)$$

where *p* is a blob in the current image (f) and *q* is a blob in the previous image $(f\text{-}1)$ and *i* denotes the blob number/id.

For each blob q_i in the previous frame, the objective is to locate the blob p_i which is closest to it in the current frame and assign it the same label. A number of problem scenarios can arise. This happens when there is a mismatch between the number of luminaires in the current frame compared to the previous frame. Two scenarios can occur:

1. Less luminaires are present in the current frame
2. More luminaires are present in the current frame

In the first scenario the 2D Euclidean distance (4) of each blob in the current frame is computed from each blob in the previous frame. When a number of blobs satisfy the Euclidean distance, i.e. $E(p,q) \leq threshold$ where threshold is the maximum displacement a luminaire may shift between consecutive images, their grey level and pixel count are searched to find the closest correlation. The resultant blob is matched and the process repeated for all N blobs in the image frame. If a blob fails to be matched, i.e. $E(p,q) > threshold$, it is assigned a flag '0'. To compensate for this the CCA results $(luminaireNo, position, greyLevel, pixelCount)$ are incremented to accommodate the *missing* blob (Gonzalez and Woods, 2004). Once all the blobs in the current image have been matched the frame number *f* is incremented and the process repeated.

$$E(p,q) = \sqrt{\sum_{i=1}^{N} (p_i - q_i)^2} \quad (4)$$

The second scenario is that of having too many blobs in the current image frame. This is typically caused by extreme cases of vibration and luminaires coming back into the field of view of the imaging sensor from an occlusion. Figure 3 shows an example luminaire that appears to consist of two bright spots with an axon of interconnecting darker pixels. Depending on the threshold this blob can be represented by one/two luminaires. There are two ways of ascer-

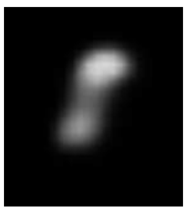

Figure 3: The Effects of Vibration on a Single Luminaire.

taining when a luminaire has split into two parts or *components* due to vibration:

1. There are too many luminaires present in the current frame
2. The pixel count for each component is less than the expected value from the last frame

When the recovery algorithm is called it scans the grey level comparing the current frame with the previous frame. At the same time, the pixel count (that is the number of pixels that constitute a luminaire) is also compared. When a luminaire splits, the value of the grey level and the pixel count decreases. Once the luminaires at fault are identified, the problem is rectified by summing the associated pixel counts and grey levels together for the problem luminaire. The problem luminaire still has multiple locations, due to being split, so a new position is evaluated using equation 1. The aforementioned CCA results are updated accordingly, by decrementing the data one element, so that the effects of vibration are accounted for and the actual number of luminaires is consistent with that of the last frame.

This section has introduced the reader to the NM algorithm and its basic operation. The following section introduces the KLT feature tracker algorithm.

3 KLT TRACKING ALGORITHM

This section introduces the theory behind the Kanade-Lucus-Tomasi (KLT) algorithm before analysing how it performs on the synthetic airport lighting model presented in section 4.

As the camera moves, the platform of image intensities change in a complex way. In general, any function of three variables $I(x,y,t)$, where the space variables x and y as well as the time variable t are discrete and suitably bounded, can represent an image sequence. However, images taken at near time instants are usually strongly related to each other, because they refer to the same scene taken from only slightly different viewpoints.

We usually express this correlation by saying that there are patterns that move in an image stream. Formally, this means that the function $I(x,y,t)$ is not arbitrary, but satisfies the property shown in equation 5.

$$I(x,y,t+\tau) = I(x-\xi, y-\eta, t); \tag{5}$$

where, a later image taken at time $t+\tau$ can be obtained by moving every point in the current image, taken at time t, by a suitable amount. The amount of motion $\mathbf{d} = (\xi, \eta)$ is called the displacement of the point x=(x,y) between the time instants t and $t+\tau$, and is in general a function of x,y,t and τ (Shi and Tomasi, 1994).

An important problem in finding the displacement $\mathbf{d}$ of a point from one frame to the next is that a single pixel cannot be tracked, unless it has very distinctive brightness with respect to its neighbours. In fact, the value of the pixel can both change due to noise, and be confused with adjacent pixels. As a consequence, it is often hard or impossible to determine where the pixel went in the subsequent frame, based only on local information. Due to these problems the KLT algorithm doesn't track single pixels but *windows* of pixels and it looks for windows that contain sufficient texture. Formally, if we redefine $J(\mathbf{x}) = I(x,y,t+\tau)$, and $I(\mathbf{x}-\mathbf{d}) = I(x-\xi, y-\eta, t)$, where the time has been dropped for brevity, our local image model is represented by equation 6.

$$J(\mathbf{x}) = I(\mathbf{x}-\mathbf{d}) + n(\mathbf{x}), \tag{6}$$

where n is noise. The displacement vector $\mathbf{d}$ is then chosen so as to minimise the residue error defined by the double integral over the given window $\mathcal{W}$ shown in equation 7

$$\varepsilon = \int_{\mathcal{W}} [I(\mathbf{x}-\mathbf{d}) - J(\mathbf{x})]^2 w d\mathbf{x} \tag{7}$$

In this expression, w is a weighting function. In the simplest case w could be set to 1. Alternatively, w could be a Gaussian like function, to emphasise the central area of the window. This is user defined. Several methods have been proposed to minimise the residue in equation 7. This paper assumes the linearisation method used when the displacement $\mathbf{d}$ is much smaller than the window size and is detailed in (Tomasi and Kanade, 1991).

3.1 Adapting the KLT Algorithm

By default the KLT algorithm accepts a series of Portable Gray Map (PGM) image files as the input file and outputs a Portable Pixel Map (PPM) results file. A number of alterations, figure 4, were carried out in order to make the airport lighting images, in either Audio Video Interleave (AVI) or uncompressed bitmap (BMP) format, compatible with the KLT tracking algorithm. These alterations allow the KLT algorithm to accept a BMP, AVI or PGM file as the input and store the results in a structure, an AVI video with tracked results superimposed or a sequence of PPM image files with tracked results superimposed. A number of other alterations were performed and are highlighted in later sections.

The next section introduces a virtual model of the approach lighting pattern used to compare and contrast the two tracking algorithms covered in sections 4.1 and 4.2.

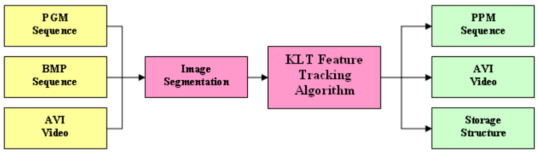

Figure 4: Upgrades to KLT Algorithm.

4 TRACKING VALIDATION

Virtual modelling and scene rendering are particularly useful in cases where it is not viable to continually test developed algorithms on a real life model. To aid testing and comparison of the tracking algorithms a 3D model of the approach airport lighting pattern has been generated. 2D information taken from Belfast International Airport is adapted to include luminaire height information, obtained from the ICAO standards (ICAO, 2004), and rendered into a 3D model using OpenFX software[5]. This model offers a low cost solution to test the tracking algorithms presented in this paper and highlight any limitations the algorithms may have. As strict guidelines are enforced on lighting pattern layout a generic ALP model can be used to represent any CATI lighting pattern. Three assumptions are made about the ALP:

1. All luminaires are present in the lighting pattern
2. All luminaires have equal performance
3. No noise exists in the image sequence - such as horizon, ground and runway markings

4.1 NM Model Response

The model data was tracked using the NM tracking algorithm outlined in section 2. A complete approach to the ALP was simulated over 150 images. All luminaires were correctly identified, labelled and tracked throughout the image sequence. A relationship exists between the total grey level and distance. As the aircraft gets closer to the luminaires, i.e.the frame number increases, so too does the surface area of each luminaire and hence the total grey level. This is represented in 5 where a best fit polynomial is used to represent the grey level data. The grey level information for each extracted luminaire will be used, in later research, to assess the performance of the luminaires'. As such it is important that the tracking algorithm is able to correctly record the grey level information. The NM algorithm was able to track and record the grey level of all the luminaires in the lighting pattern taking a total average time of 355.796 seconds to run, see table 1.

[5]http://www.openfx.org/

4.2 KLT Model Response

In order to adapt the KLT algorithm two variables are varied, namely the *window size* and the *number of features*. When all features are present there is a total of 120 luminaires in the ALP, therefore the number of features to track is 120. The second constant is the window size. For the purposes of this research this was set to 7x7 pixels. As the effects of noise have been ignored in the synthetic data due to the surroundings being controlled no further alterations to the generic KLT algorithm are required.

The KLT algorithm took 378.52 seconds to execute 150 frames, see table 1[6]. The algorithm performs well on the ALP outputting a similar trend of increasing grey level to that the NM algorithm. The results for a random luminaire are presented in figure 5. A problem can arise due to the static window size implemented by the KLT algorithm. If a maximum 8-bit grey level of 220 is used for each pixel (above this value saturation occurs which is not desirable) then a window of 7x7 pixels has a maximum grey level of 17380. This is below the top end of the grey level values obtained in figures 7 and 8 respectively (as much as 45000). At the onset of the approach minimal disruption occurs as the luminaires cover a small number of pixels. However, as the aircraft gets closer to the luminaires the luminaires cover a larger number of pixels (outside the predefined range of the KLT algorithm) and hence the grey level data is termed to be *lossy*. In order to avoid this the window size can be increased. This however has its own problems such as features being merged as the window size is too large. For more details see section 6.

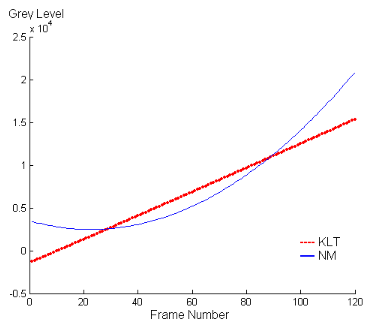

Figure 5: Synthetic Grey Level Data Comparison.

[6]All results are averaged over 5 program executions.

5 ACTUAL APPROACH DATA

This section uses actual approach data to further test the effectiveness of the NM and KLT feature tracking algorithms. The section has two main aims: To test the robustness of the tracking algorithms and to assess whether or not the synthetic model is an accurate representation of an actual approach.

5.1 Sample Results

The NM grey level data for a complete approach is shown in figure 8. The first thing to note is the trend between the simulated results and the actual results. Like figure 7, figure 8 shows how the luminaires go from a low grey level (5000) to a high grey level (30000) as the aircraft gets closer to the luminaires.

For the KLT algorithm a number of alterations have to be made to the system presented in section 4.2, these additions are detailed in figure 4. As the effects of noise, especially the horizon, are more common in the real images a rectangle function is used to *segment* the region of interest (ROI) in the actual images where the ROI is the ALP. If this step is not implemented false features are sent to the KLT algorithm rendering the grey level data meaningless. The results are summarised in table 1. Figure 6 shows how as the NM algorithm accurately captures the grey level data above the 17000 mark. In comparison the KLT algorithm tails off losing valuable grey level and hence performance information. The KLT starts off in frame one with a grey level of approximately 11000 whereas the NM algorithm starts at 4000. The luminaire chosen at random was one furthest away from the vision system. As such the NM algorithm merged it with neighbouring blobs resulting in multiple underperforming luminaires and one over-performing luminaire.

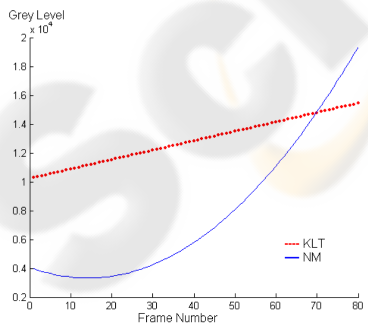

Figure 6: Actual Grey Level Data Comparison.

Table 1: NM versus KLT Results for Actual(A) and Synthetic(S) Data.

Algorithm Name	Time/ Frame(s)	Extracted Features(%)
KLT(A)	1.90	93
KLT(S)	2.52	95
NM(A)	2.04	98
NM(S)	2.4	98

5.2 Discussion

The NM algorithm has an average execution time of 2.04 seconds/frame. This has a strong correlation with the execution time of the synthetic model in section 4.1. However, as the NM is a point tracker on occasions mismatches can occur. An example of this can occur when two luminaires have the same Euclidean distance and similar grey levels. This can lead to luminaire histories being confused. The KLT algorithm performs well on the actual images. It is able to successfully extract 93% of the luminaires and track them through an image sequence. However, it is clear that if this method is to be used to track the airport lighting more advanced noise removal techniques, like that shown for the NM algorithm in section 2.2, are required to minimise the effects of background noise.

6 FUTURE WORK

One of the major limitations with the KLT algorithm is the inaccuracy caused by the static window size. If the window size is too small this will result in inaccurate grey level information. If the window size is too large, the luminaires will be merged. For this application it is essential that the grey level is computed correctly. To this end a *dynamic* window is proposed that will vary according to the aircraft displacement from the lighting pattern. The NM algorithm uses CCA for this purpose. Therefore, if the tracking aspect for the KLT is merged with the performance assessment form the NM algorithm the optimum tracking algorithm will be realised. A second limitation of the KLT algorithm is the effects of background noise. A model of the background noise can be created and using differencing techniques subtracted rom the image data in order to reduce the effects of noise. As a final note, image tracking is only capable of classifying the luminaires into a pass/fail category. Future work has to be done into producing performance assessment information for the ALP.

7 CONCLUSION

Two contributions are presented in this paper. The first is a tracking algorithm that can successfully track the luminaires in an airport ALP. The second is a tool for verifying the tracking algorithms without the need for actual image data.

To satisfy the first objective, two tracking algorithms are presented that assess the grey level of luminaires in a CATI airport ALP. Both the NM and the KLT algorithms are capable of tracking the synthetic and actual approach reliably, with over 90% of the features being successfully tracked. However, a limitation of the KLT algorithm was found to be the static nature of the window size and its vulnerability to background noise. The NM algorithm, being a point tracker, is prone to false matches which can lead to confused luminaire histories. Therefore, it is proposed that a combination of the two algorithms be found for optimum tracking.

The second objective was to assess if the synthetic model proposed is an accurate model for an approach to the aerodrome. The results are conclusive. The model data has a strong correlation with that of the actual data. This is shown in figures 7 and 8 respectively. However, research is still required to make the model more realistic. Accurate correction for noise has to be realised. This can be done in OpenFX by adding rain, fog, ground markings and a horizon.

ACKNOWLEDGEMENTS

The authors would like to thank the European Social Fund (ESF) and the Royal Academy/Society of Engineers for their financial backing. The authors would also like to thank Flight Precision for allowing us flight time.

REFERENCES

Gonzalez, R. and Woods, R. (2004). *Digital Image Processing using Matlab*. Pearson Prentice Hall.

Haralick, R. and Shapiro, L. (1993). *Computer and Robot Vision vol. 2*. Addison-Wesley Publishing Company Inc.

ICAO (2004). *Aerodrome Design and Operations*. Annex 14, Volume 1, Fourth Ed.

Lucas, B. and T.Kanade (1981). An iterative image registration technique with an application to stereo vision. In *Proc. 7th Int Joint Conference on Artificial Intelligence, Vancouver, pp.674-679*.

Matsunaga, N. (1980). Automatic monitoring system for the ccr and aerodrome lighting system on airport system. In *IECI Annual Conference Proceedings (Industrial Electronics and Control Instrumentation Group of IEEE, p411-416)*.

McMenemy, K. and Dodds, G. (2003). Calibration and use of video cameras in the photometric assessment of aerodrome ground lighting. In *The International Society for Optical Engineers, Electronic Imaging, Vol. 5017, pp. 104-115*.

Milward, R. (1976). New approach to airport lighting inspection. In *Shell Aviation News, Vol. 437, pp26-31*.

Pollefeys, M. and Gool, L. V. (1999). Self-calibrated and metric 3d recognstruction from uncalibrated image sequences. In *PhD Thesis*.

Shi, J. and Tomasi, C. (1994). Good features to track. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, p593-600*.

Tomasi, C. and Kanade, T. (1991). Detection and traking of point features. In *Shape and Motion from Image Streams: a Factorization Method-Part 3, Technical Report CMU-CS-91-132*.

APPENDIX

Figures 7 and 8 respectively show the grey level data for an ALP for a synthetic and actual approach.

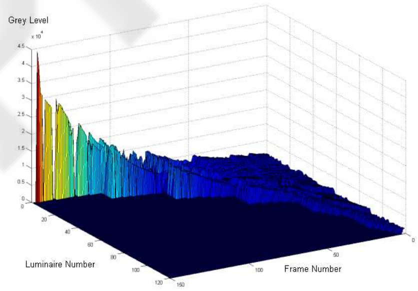

Figure 7: Synthetic Grey Level Data for NM Algorithm.

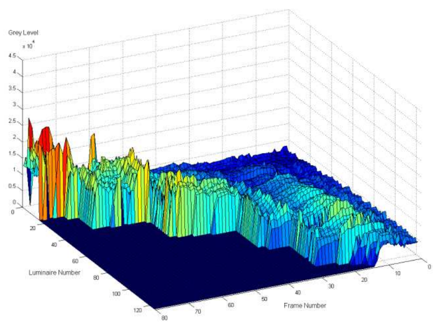

Figure 8: Actual Grey Level Data for NM Algorithm.