AUTONOMOUS MODEL-BASED OBJECT IDENTIFICATION & CAMERA POSITION ESTIMATION WITH APPLICATION TO AIRPORT LIGHTING QUALITY CONTROL

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Abstract: The development of an autonomous system for the accurate measurement of the quality of aerodrome ground lighting (AGL) in accordance with current standards and recommendations is presented. The system is composed of an imager which is placed inside the cockpit of an aircraft to record images of the AGL during a normal descent to an aerodrome. Before the performance of the AGL is assessed, it is first necessary to uniquely identify each luminaire within the image and track it through the complete image sequence. A model-based (MB) methodology is used to ascertain the optimum match between a template of the AGL and the actual image data. Projective geometry, in addition to the image and real world location of the extracted luminaires, is then used to calculate the position of the camera at the instant the image was acquired. Algorithms are also presented which model the distortion apparent within the sensors optical system and average the camera's intrinsic parameters over multiple frames, so as to minimise the effects of noise on the acquired image data and hence make the camera's estimated position and orientation more accurate. The positional information is validated using actual approach image data.

1 INTRODUCTION

Airport landing lighting has evolved from the early beginnings when an aircraft's relatively haphazard arrival back to ground was conducted by the light of gooseneck flares. Rapid development took place between 1939 and 1945, when the Drem[1] system was evolved; and subsequent post war developments in omnidirectional low intensity approach lighting culminated in the present state of the art, where high intensity Calvert systems are the order of the day-or rather night (Milward, 1976).

These lighting systems have evolved in the last number of years in order to guide the pilot onto the runway safely. Since the earliest days of flying, pilots have used ground references for navigation when approaching an airport. Pilots need these visual aids in good weather, as well as bad, and during the day as well as at night (Horonjeff and McKelvey, 1993). When visibility is poor and in night time conditions, the visual information is reduced significantly when compared to the clear-weather daytime scene. It is therefore essential to provide visual aids which are as meaningful to pilots as possible (Horonjeff and McKelvey, 1993). Today's state of the art lighting is referred to as aerodrome ground lighting (AGL) and consists of approach lighting, elevated above the ground, to guide the pilot onto the runway lighting pattern and taxi the aircraft into its terminal. In order to ensure the consistency of an airport lighting installation, strict guidelines are enforced on the positioning, uniformity, colour and intensity of the luminaires[2] that make up the complete AGL.

The International Civil Aviation Organisation (ICAO) has published a recommendation that the measurement of luminous intensity, beam spread and orientation of the luminaires, included in the approach and runway lighting systems for a precision approach

[1]Drem Lighting System was developed to assist Spitfire landing in WW2

[2]A complete lighting unit consisting of a lamp or lamps together with the parts designed to distribute the light, to position and protect the lamps and to connect them to the power supply.

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runway category I/II/III, should be undertaken using a mobile measuring unit of sufficient accuracy to analyse the characteristics of the individual luminaires.

To assess the performance and alignment of the luminaires it is necessary to know more about the AGL and how the luminaires are arranged. AGL consists of runway lighting separated from the approach lighting system (ALS) by a row of luminaires termed the runway threshold. Runway and threshold luminaires are usually inset, that is, they are installed at ground level whilst the approach luminaires are elevated above the ground. A typical AGL (CATI (ICAO, 2004)) layout is illustrated in figure 1.

Figure 1: AGL Layout.

This paper presents results from research conducted into creating an aerial-based vision system capable of autonomous performance assessment of the complete AGL pattern. The work proposes mounting one, or more, cameras in the aircraft, capable of acquiring image data of a descent to the airport as the aircraft performs a landing. The function of the camera is to replicate what the pilots see during a standard approach and store the information to an external hard drive for off-line performance assessment.

To assess the performance of luminaires a number of processes need to be undertaken. Firstly, the noise apparent in the camera needs to be quantified in the form of a distortion matrix. The next problem is that of uniquely identifying each luminaire from the acquired image data. Niblock *et al.* compared a basic single pixel image-based tracking method against existing tracking techniques, such as, the KLT and SIFT alternatives (Niblock et al., 2007a). This work highlighted the limitations of such a tracking system and proposed that in order to uniquely identify each luminaire, and thus assess its performance, a model-based approach is required.

In this paper the model-based tracker is briefly discussed before showing how this technique was updated for the purposes of camera position and pose determination. The model-based approach attempts to match a template of the ALS to the set of extracted luminaires from the image, where the template of the ALS is illustrated in figure 2. Strict standards enforced by the ICAO (ICAO, 2004) are in place for the positioning, uniformity, projection angle and colour of these luminaires.

The major advantage of this approach, is that for each successfully matched luminaire, information regarding its position is known, both within the image and real-world coordinate frames. Therefore, projective geometry can be utilised to estimate the camera position and orientation data at the instant each image was acquired. It is essential in this work to have accurate camera position and pose information for the luminaire performance assessment. Existing research indicates that an image of a luminaire can be used to estimate the intensity of a luminaire, providing accurate position and orientation of the camera in relation to the luminaire is known (McMenemy, 2003). The contribution of the paper is to present a model-based methodology for luminaire identification which is extended in order to estimate the position and orientation of the camera (aircraft) during its descent. The theory is validated using actual approach data before concluding remarks and future work are discussed.

2 MODEL-BASED (MB) TRACKING

In order to assess the performance of the luminaires it is first necessary to uniquely identify each luminaire in the ALS and track them through an image sequence in order to build up a profile of the lighting pattern. Once the luminaires have been identified and labelled, these features are then used to estimate the camera's position during the landing. It is essential that the estimated camera position is accurate and robust to noise as any inaccuracies will have a follow on effect with the performance assessment software.

The objective of the MB tracker is one of trying to match a template which consists of the luminaires within the ALS to a set of features extracted from image data acquired during the approach to the airport.

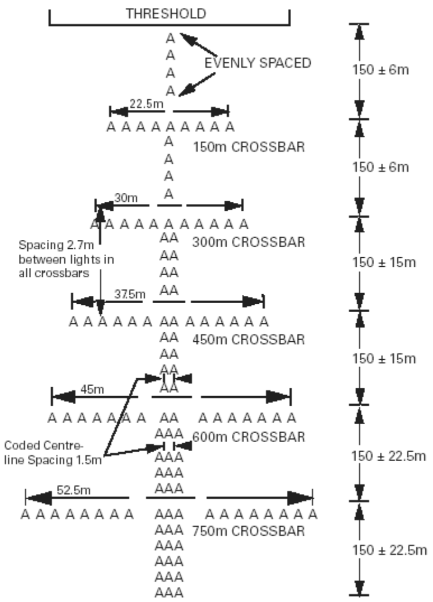


Figure 2: Standard Category I (CATI) approach lighting pattern.

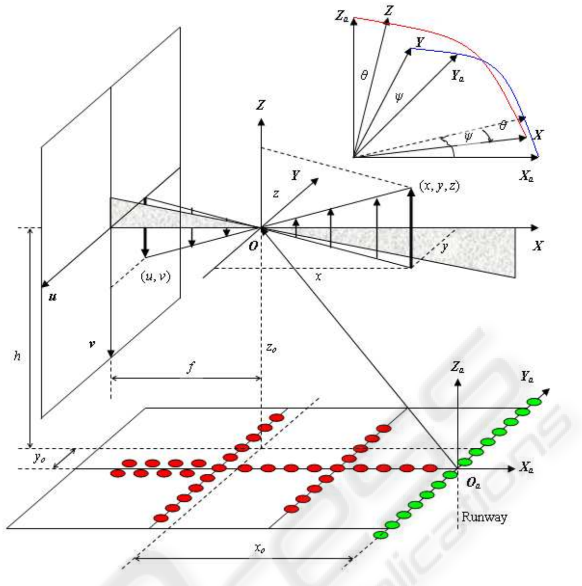


Figure 3: Model-based projection system.

This process is known as planar homography and consists of finding a one-to-one match between a pair of images (Vincent and Laganiere, 2001) or, in this case, a template of the ALS and an image.

In order to project this template onto the acquired image data a pinhole camera projection system is utilised which is mathematically modelled as consisting of a projection system and an imaging system. The projection system projects a 3D-object from the real world (i.e. an ALS luminaire) to the image plane of the camera. The imaging system converts the projected 2D-object on the image plane into a series of pixels through an image sensor array.

According to the pinhole imaging principle depicted in figure 3 a 3D-point (x,y,z) expressed in the camera coordinate system $OXYZ$ is projected to a 2D-point (u,v) on the image plane using a projection system. From figure 3 we can summarise (1).

$$\left.\begin{array}{l} u = fx^{-1}y \\ v = fx^{-1}z \end{array}\right\} \qquad (1)$$

where f denotes the focal length of the camera. It is necessary to allow the focal length of the camera to vary so that the camera will be capable of autonomously locating the AGL and zooming in on the relevant area of the lighting pattern, for example the ALS. This process enhances the quality of the acquired image data.

Assuming that the image sensor array is evenly configured as orthogonal grids, that is to say a series of rectangular-shaped pixels aligned in a grid-like structure in the image plane, the imaging system can then be represented as the linear transformation shown in equation (2),

$$\left.\begin{array}{l} \widehat{p} = k_{u0} + k_u u = k_{u0} + \alpha_u x^{-1} y \\ \widehat{q} = k_{v0} + k_v v = k_{v0} + \alpha_v x^{-1} y \end{array}\right\} \qquad (2)$$

where $(\widehat{p},\widehat{q})$ denotes the coordinates of the pixel corresponding to the 2D-point projection (u,v) in the image plane given in (1); k_u and k_v are the number of pixels per unit distance in the u and v directions respectively, and $\alpha_u = k_u f$, $\alpha_v = k_v f$ represent the intrinsic camera parameters, where f represents the focal length of the imaging system and k_u/k_v represent the scaling factor of the image data and the horizontal and vertical image plane respectively. Finally, (k_{u0}, k_{v0}) represent the image coordinates of the intersection of the optical axis and the image plane, henceforth referred to as the principal point.

However, the approaching template is normally defined with the 3D coordinates of the 120 luminaries given in the airport coordinate system $O_aX_aY_aZ_a$. The transformation from the airport coordinate system to the camera coordinate system includes a translation and a rotation as shown in equation (3).

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = R(\gamma,\theta,\psi) \begin{bmatrix} x_t - x_o \\ y_t - y_o \\ z_t - z_o \end{bmatrix} \qquad (3)$$

where the translation $\mathbf{o} = [x_o, y_o, z_o]^T$ contains the coordinates of the camera position (defined at the original point of the camera coordinate system, see figure 3) in the airport coordinate system. The vector $\mathbf{t} = [x_t, y_t, z_t]^T$ contains the coordinates of an approaching luminaire in the airport coordinate system and (γ, θ, ψ) denote the yaw, pitch and roll of the camera system respectively (i.e. the three rotations around the X,Y and Z axis respectively). Where $\mathbf{R}(\gamma, \theta, \psi)$ is the corresponding rotation matrix, which is formed by three rotations around the $Z, Y$and X axes respectively of the camera coordinate system, as shown in equation (4),

$$\left.\begin{aligned} \mathbf{R}(\gamma,\theta,\psi) &= \mathbf{R}_x(\gamma)\mathbf{R}_y(\theta)\mathbf{R}_z(\psi) \\ \mathbf{R}_x(\gamma) &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & \sin\gamma \\ 0 & -\sin\gamma & \cos\gamma \end{bmatrix} \\ \mathbf{R}_y(\theta) &= \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix} \\ \mathbf{R}_z(\psi) &= \begin{bmatrix} \cos\psi & sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{aligned}\right\} \tag{4}$$

where $\mathbf{R}_z(\psi)$, $\mathbf{R}_y(\theta)$ and $\mathbf{R}_x(\gamma)$ are the corresponding rotation matrices around Z, Y and X axes, respectively (V. Lepetit, 2005).

Using the pin-hole camera projection system illustrated in figure 3 the template of the ALS is superimposed onto the image data and the Levenberg-Marquardt (LM) method used to minimise the error between the two sets of data. This procedure is detailed by Niblock *et al.* (Niblock et al., 2007b) and Peng *et al.* (Peng et al., 2006). Niblock *et al.* show that this process works well and results in successfully identified luminaires in the image sequence (Niblock et al., 2007b).

The major advantage offered by a model-based methodology is its ability to identify luminaires that are missing (or have been turned off) in the ALS. Techniques such as KLT and SIFT only track luminaires that are present in the image data. It is essential, for the performance assessment work, that if a luminaire is missing, for any reason, that its position is still recorded and its associated grey level stored. By using a template of the ALS this is made possible. Furthermore, the model-based methodology produces the best results on the actual image data (Niblock et al., 2007b). As the noise level is increased, it is essential that the algorithms are more robust and have a high tolerance level to noise inherent within the image data. If this is not the case false matches can be made and the grey level profiles of the extracted luminaires can become confused, which is highly undesirable for this application.

These identified luminaires can then be used to estimate the position and orientation of the camera at the instant the image was taken, which as previously mentioned is essential for luminaire performance assessment.

2.1 Camera Positioning

Being able to estimate position and orientation information from image data is a well researched area in computer vision. Indeed, work has already been conducted in the area of aircraft positioning by Soni *et al.* (Soni and Sridhar, 1994) and Sridhar *et al.* (Sridhar et al., 1996; Chatterji et al., 1998) who produced systems that utilise the information provided by the position of individual luminaires in an image for estimating the relative position and orientation of an aircraft. The location of luminaires within the image plane is derived using perspective projection equations based on a pinhole camera model (Faugeras and Toscani, 1987). Differences of features tracked between successive images are used in conjunction with a recursive optimisation algorithm in order to find the optimum position and orientation of the aircraft. The drawback of Soni's work is that the roll of the aircraft is obtained using a roll sensor and is not obtained, like the other variables, from the image sequence. Mostafavi *et al.* use similar techniques with external information such as Differential Global Positioning System (DGPS) data in order to ascertain the position and orientation of the camera with relation to the runway outline and markers (Mostafavi and Malone, 1995).

The work presented in this paper differs from the aforementioned research by presenting novel techniques which average the intrinsic camera parameters over multiple frames, in order to minimise the effects of noise inherent within the image data, and thus make the estimated extrinsic parameters more accurate. A further contribution of this work is that a varying focal length may be used by the imaging system is order to acquire image data of the highest quality, which is essential for the performance assessment of the ALS. The previous work in this area, generally assume constant intrinsic parameters. To realise an accurate imaging system, distortions caused by the sensors optical system also need to be modelled and accounted for.

2.2 Distortion Correction

The model outlined in section 2 makes a number of assumptions regarding the optical system utilised by the imaging system. If the acquired image data has been affected by distortion the image can change in shape and thus the points are no longer assigned to the pixel position that was estimated using the previous model.

That is to say, for real cameras, a pure perspective projection model is not always sufficient to precisely represent the image data. Several types of imperfections in the design, machining and assembly of the camera optical (lens) system may result in small geometrical distortion (Heikkila, 2000). Most commonly the distortion errors are decomposed into radial (figure 4(c)) and tangential (figure 4(b)) components (Faugeras and Toscani, 1987), where the perfect undistorted image is illustrated in figure 4(a). For the distorted image coordinates given by (r_d, c_d), the corrected (or undistorted) coordinates are expressed as equation (5).

$$\left.\begin{array}{l} c_u = c_d + \delta_c(r_d, c_d) \\ r_u = r_d + \delta_r(r_d, c_d) \end{array}\right\} \tag{5}$$

where (r_u, c_u) denote the distortion-free image coordinates (that are unobservable) corresponding to (r_d, c_d) that are observable in the actual image, and $\delta_c(r_d, c_d)$, $\delta_r(r_d, c_d)$ denote the total displacements along the column and row directions respectively. Heikkila gives further details on image distortion and the relevant tangential and radial distortion models (Heikkila, 2000). Utilising these standard techniques the distortion in the image data is corrected for, before any estimates of the camera position and orientation are calculated. In addition to distortion correction, it is important to realise that the focal length of the camera can vary during the approach. A change in the focal length will obviously lead to a change in the projection model, and thus it is necessary to account for this. The algorithms to do this are now discussed.

2.3 Multi Frame-based Estimation

The objective of the multi frame-based estimation technique is to create an algorithm that allows for a varying focal length. The focal length is one of the intrinsic camera parameters modelled in equation (2), represented by the α_u, α_v coefficients. To do this, the technique assumes that the intrinsic camera parameters remain constant for a predefined time period, e.g. 1 second. Therefore, this work estimates the intrinsic camera parameters over a predefined number of images and averages them in order to minimise error caused by noise inherent within the acquired image data. These optimised intrinsic camera parameters are then used to estimate the camera's position and orientation (i.e. extrinsic parameters) during the landing.

Suppose a sequence of F_T images are assessed and the intrinsic parameters and distortion coefficients of the camera are assumed constant over the F_T frames, denoted as $\mathbf{w}_{int} = [k_{u0}, k_{v0}, \alpha_u, \alpha_v, k_1, k_2, t_1, t_2]^T$, where $\mathbf{w}_{int}$ represents the intrinsic camera parameters, where (k_{u0}, k_{v0}) denotes the principal point of the image, (α_u, α_v) are a combination of the focal length and resolution of the camera and the k, t coefficients represent the radial and tangential distortion parameters respectively, as modelled by Lepetit *et al.* (V. Lepetit, 2005). If the camera extrinsic parameters for frame f_c are denoted as $\mathbf{w}_{ext}(f_c) = [t_x(f_c), t_y(f_c), t_z(f_c), \psi(f_c), \theta(f_c), \gamma(f_c)]^T$, where $(t_x(f_c), t_y(f_c), t_z(f_c))$ represent the camera's position in a given frame and $(\psi(f_c), \theta(f_c), \gamma(f_c))$ the orientation, then the cost function is defined in equation (6) as,

$$E(\mathbf{w}_{ext}, \mathbf{w}_{int}) = \sum_{f_c=1}^{F_T} \sum_{k=1}^{N} [e_c^2(f_c; k) + e_r^2(f_c; k)] \tag{6}$$

where $k = 1, ..., N$ and represents the number of extracted luminaires in the image. Equation (6) thus needs to be minimised with respect to w_{int} and $w_{ext}(f_c)$ for $f_c = 1, ..., F_T$,

$$\left.\begin{array}{l} e_c(f_c, k) = c(k)(\mathbf{w}_{int}, \mathbf{w}_{ext}(f_c)) - c_u(f_c, k)(\mathbf{w}_{int}) \\ e_r(f_c, k) = r(k)(\mathbf{w}_{int}, \mathbf{w}_{ext}(f_c)) - r_u(f_c, k)(\mathbf{w}_{int}) \end{array}\right\} \tag{7}$$

where $r(k)(\mathbf{w}_{int}, \mathbf{w}_{ext}(f_c))$ and $c(k)(\mathbf{w}_{int}, \mathbf{w}_{ext}(f_c))$ denote the projection coordinates of the k^{th} ALS luminaire produced in equation (8),

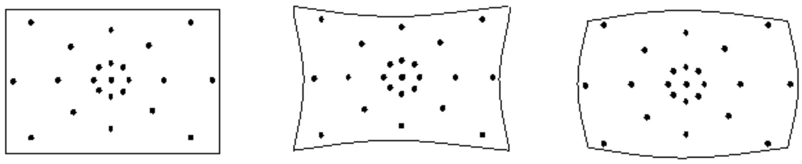
$$\left.\begin{array}{l} c = \alpha_v x_c z_c^{-1} + k_{v0} \\ r = \alpha_u y_c z_c^{-1} + k_{u0} \end{array}\right\} \tag{8}$$

which are functions of the intrinsic parameters $\mathbf{w}_{int}$ and the extrinsic parameters $\mathbf{w}_{ext}(f_c)$ for frame f_c; $r_u(f_c, k)(\mathbf{w}_{int})$ and $c_u(f_c, k)(\mathbf{w}_{int})$ denote the distortion-free image coordinates of the blob corresponding to the k^{th} luminaire extracted from frame f_c, which are functions of the intrinsic parameters $\mathbf{w}_{int}$, or more specifically, functions of part $(k_{u0}, k_{v0}, k_1, k_2, t_1, t_2)$ of $\mathbf{w}_{int}$.

With an optimised multiple frame-based camera parameter estimation now established, section 2.4 details the constraints applied to the software. Once these constraints are defined the software is tested using actual airport lighting data.

2.4 Constraints

A number of constraints are placed upon the camera positioning algorithms. When making a normal 3 degree approach to the airport a number of assumptions



(a) (b) (c)

Figure 4: (a) Original image (b) Tangential distortion (c) Radial distortion.

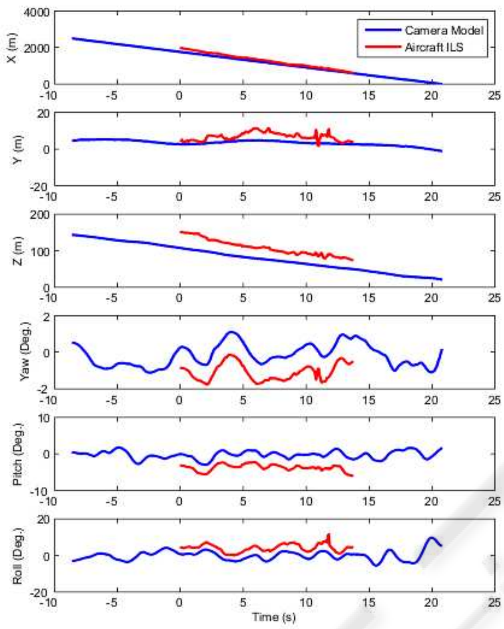


Figure 5: Camera position and orientation for actual approach data using the multi frame-based estimation.

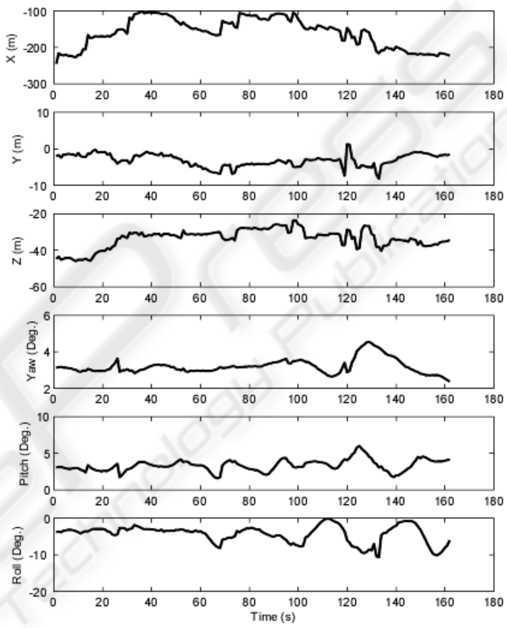


Figure 6: Error profile for the camera's position and orientation for actual approach data using the multi frame-based estimation.

can be made. Firstly the camera starts to acquire image data from roughly 2.5km from the airport. If a 3 degree approach is assumed this means that the height of the aircraft with respect to the AGL is approximately 131m. Therefore, boundaries can be placed on the X,Y and Z data, for example 2500±1000m, 0±50m and 150±150m respectively. However, if it is not possible to assume a 3 degree approach and a different angle of approach is used, then trigonometry can be used to update the starting constraints and their respective upper and lower limits. A second assumption is that the field of view of the camera is set to 45 degrees. This assumption helps with the segmentation of the ALS and ensures the noise from surrounding light sources and general background illumination is kept to a minimum.

With the optimised intrinsic camera parameters estimated over multiple frames, the next section validates the new software using actual airport lighting data acquired during an approach to Belfast International Airport.

3 POSITION & ORIENTATION RESULTS

During a complete flight test a number of approaches are made to the airport. The vision system detailed in this paper was mounted in the cockpit of the aircraft and set to acquire image data during these approaches. The algorithms detailed were used to uniquely identify each of the luminaires in the ALS before using this information to estimate the aircraft's position and orientation during the approach. To assess the accu-

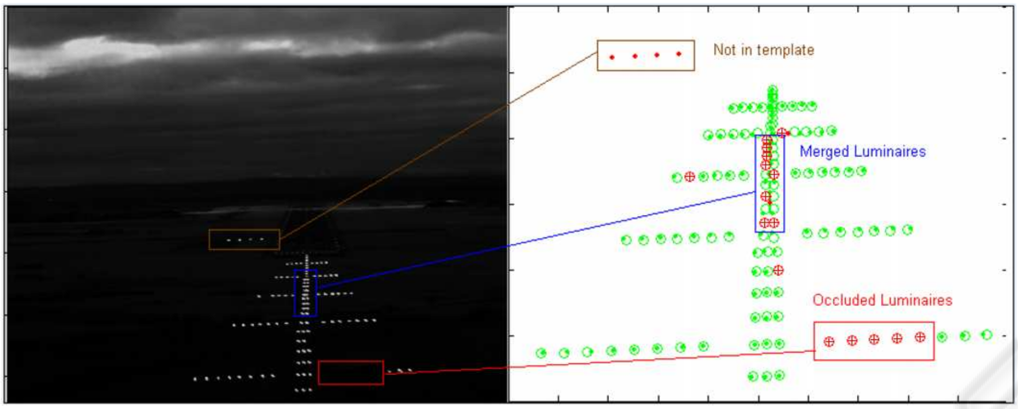


Figure 7: Missing/merged luminaires (left image) and optimisation results (right image). Note how the luminaires are still identified by the model-based matching algorithm even though they are not present in the image data. (Niblock et al., 2007b).

racy of the proposed algorithms, they are compared to the Flight Precision's ILS position and orientation data.

The successfully extracted luminaires were then used to estimate the camera's position and pose. The model-based results for a sample image are shown in figure 7. The dots represent extracted luminaires present in the image data, using the connected component analysis technique outlined in (Niblock et al., 2007a). Most luminaires have been successfully identified and these are represented by the dot with a circle around it. However, a number of the circles have a cross ('+') inside them, which indicates a luminaire that is missing or hasn't been extracted from the image data. These can be caused by merged luminaires (illustrated at the top of the image), or because the luminaires are actually missing or occluded (as illustrated in the bottom right of the figure where 5 consecutive luminaires are occluded by a temperature meter housed outside the aircraft).

Figure 5 shows how the camera parameters estimated using the multi frame-based software, compared with the Flight Precision ILS data. The results show a good comparison in terms of the estimated camera position. There is also a good correspondence between the pose information. More importantly there is a strong correlation between the profiles, with a constant offset apparent between the two sets of position and pose data illustrated in figure 5. The reason for this offset (and why both sets of data are not superimposed on top of each other) is that the ILS data shows the aircraft's position and pose with respect to the PAPI luminaires (illustrated in figure 2), whereas the model-based positioning software calculates the position and pose of the camera with respect to the centre of the threshold.

The error profile, which is the difference between the two sets of data, is shown in figure 6. The figure shows that the positional error is largest for the X parameter. Note that the errors shown in figure 6 include the constant difference between the two reference systems of the ILS and image-based data. For example, with the camera pose information, the error between the two sets of data is negligible with the highest error set at 5 degrees which is explained by the two difference reference coordinate frames utilised. It is also worth highlighting that the error profile is minimised because the camera's intrinsic parameters are averaged over multiple frames thus causing the error of the camera's extrinsic parameters (caused by factors such as stray noise) apparent in any given image to be minimised.

4 CONCLUDING REMARKS

This paper presents results from research conducted into creating an aerial-based vision system capable of autonomous performance assessment of the complete AGL pattern. The work proposes mounting one, or more, cameras in the aircraft, capable of acquiring image data during a typical descent to the aerodrome as the aircraft performs a landing.

To date algorithms have been produced in order to robustly extract the luminaires present within the image data and identity them using a model-based methodology. A pin-hole camera projection system was then used to estimate the position and orientation of the camera, during the descent, from the acquired image data. The results obtained from the new software were compared against the positional information supplied by the Flight Precision ILS data and a strong correlation was found between both sets of data. In particular the profiles of the two sets of positional and orientation data were found to have a strong correlation with the constant error offset explained by the different reference systems utilised by both techniques.

The final goal of this work is to realise an autonomous image processing system capable of assessing the performance of the complete AGL pattern. Thus far, MATLAB has been used for the software with a mean execution time per frame of approximately 3 seconds and a standard deviation of 0.3s/frame achieved using a standard CPU with a 3GHz processor and 1GB RAM. This timing information could be dramatically reduced with a C++ setup and further reduced if the algorithms were programmed with a GPU as implemented by Sinha *et al.* (Sinha et al., 2006).

Future work includes assessing the performance of the lighting pattern. To this end two methodologies are proposed. Firstly, uniformity, which assesses the performance of the complete lighting pattern and secondly, assessing the luminous intensity of each individual luminaire within the lighting pattern. This work will add negligible time onto the execution time per frame as the memory inefficient and time consuming tasks of reading in an image sequence and extracting the luminaires/eatimating the aircraft's position have already been determined. Thus, this paper shows that it is possible to assess the performance of the AGL using an aerial-based imaging methodology.

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