Obstacle avoidance during aerial inspection of power lines

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Abstract

Gives an overview of a research programme that aims to apply machine vision for guiding a small, unmanned helicopter during inspection of overhead electrical distribution lines. Briefly discusses the background and requirements for aerial inspection of power lines and states the advantages of using a remotely piloted vehicle (RPV). Identifies the main obstacle to the use of RPVs in this application as the ''see and avoid'' principle, which arises from regulatory requirements; it is the underlying motivation for the work described here. Machine vision and automated path planning offer a potential solution. Gives a brief tutorial of the principles involved and describes research in image processing and rapid path planning aimed at detecting and avoiding obstacles in the airspace of a small RPV. Also presents experimental results from a laboratory test rig which was constructed to assess the methods.

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Introduction

The principal voltages used for distributing electricity in the UK are 11KV and 33KV. Of these, the 11KV network is the largest and most electricity companies own between 10,000 and 20,000km of overhead line. The general construction consists of two or three uninsulated conductors supported on glass or porcelain insulators mounted on a cross-arm at the top of a wooden pole (Bayliss, 1996). Plate 1 is a typical three-phase 11KV installation.

For reasons of safety, electricity companies are obliged by Section 24 of the Electricity Supply Regulations (1988) to inspect their networks. Regular inspection also benefits the companies because early detection of defects reduces maintenance costs as well as reducing the number of unplanned outages (power cuts); this contributes to good customer relations and gives competitive advantage. The items inspected vary widely and include sagging conductor spans, leaning poles, tree encroachment, transformer condition, safety guards and notices, broken insulators, discoloration due to corrosion and traces of electrical arcing. It is common to use a helicopter to perform line inspection (Whitworth *et al.*, 2001). A pilot and observer fly over a section of the line, the latter noting defects and potential faults into a tape recorder during the mission. On completion of the mission, the comments are transcribed into codes on an area map and used by the electricity company to plan schedules for repair and maintenance.

So that the observer may obtain a good view it is necessary for the helicopter to fly near to the overhead lines (10-15m from the lines and 15m from the ground). Companies which specialise in electricity line inspection can receive a dispensation from the Civil Aviation Authority (CAA) to fly low; they are required to demonstrate an excellent safety record, have sound operational procedures and use twin-engine helicopters. The main drawbacks of manned helicopter inspection are that it is hazardous, expensive and no visual record of the observations is kept. A crucial problem is that it is often necessary to divert the helicopter in order to avoid flying over livestock and buildings and those parts of the line which have been missed must then be inspected by foot patrol. This is expensive and inconvenient.

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Plate 1 A typical installation on the three-phase 11KV network

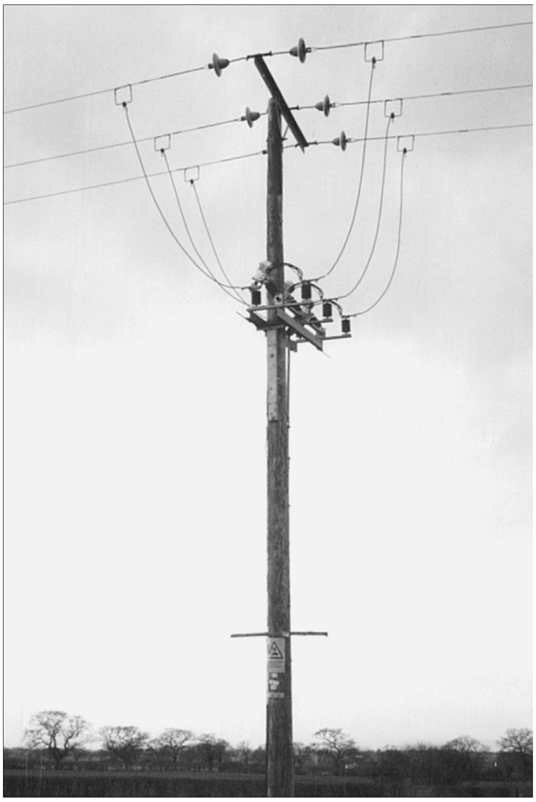


Plate 2 The Sprite RPV is a plan-symmetric helicopter with contra-rotating rotor blades

Using an RPV

Instead of a manned helicopter, Jones and Earp (1996) have proposed the use of a remotely piloted vehicle (RPV) – specifically a small helicopter (approximately 20kg) instrumented with a stability and control augmentation system which makes it easier to "fly" and stabilises it against wind gust disturbances. A close match to this requirement is the Sprite system (*Shephard's Handbook*, 2001) – a photograph of the air vehicle is shown in Plate 2. A small RPV presents no hazard to aircrew and, being very much smaller and lighter than a manned helicopter, less hazard to people and property in the unlikely event of the air vehicle failing completely. Comparative cost studies show that it would be cheaper to run than a manned helicopter. The method of operation of a RPV would be different to current practice. A gyro-stabilised video camera would be used to inspect the lines, transmitting live pictures to a remote observer stationed up to 10km away. Using a telephoto lens, good detail would be available from an operating height of about 40m. As a consequence, the RPV would present a much smaller visual profile from the ground, as well as being quieter, thus allowing it to approach closer to livestock and habitation. With few diversions, the flight path of the RPV would be smoother and more direct than a manned helicopter. The ground-based observer would have the facility to steer the camera onto selected targets and to record sample frames onto an indexed computer-based library for future reference.

Most of the technology to realise this concept already exists in today's RPV industry and continues to improve. For instance, an important development in RPV navigation is the availability of the global positioning system (GPS) and its more accurate extension that includes differential correction (DGPS) which can locate a vehicle's position to within a few meters. The image quality of the inspected item is crucial to the concept, and previous work (Jones and Earp, 2001) indicates that satisfactory images at 30m slant range can be obtained with optical stabilisation of about $100\mu r$ in the frequency range 0.5-2Hz. This is within the capability of current stabilisation packages and recent field trials, conducted with a company shooting digital video from a miniature helicopter, confirmed that very good image quality can be obtained in practice.

The vast majority of RPVs have been developed for a military role and are in general not appropriate for civilian use. In contrast to the hostile environment of battlefield surveillance, a RPV performing overhead line inspection will work within a well-defined area, on pre-planned routes and generally in slow and stable flight. Extreme weather conditions can be avoided for routine work and, with regular flight experience, the pilot and observer will be expert operators. On the other hand, civilian RPV applications make two very demanding requirements which are not as acute in the military case: first, the RPV system must be reliable and safe, complying with CAA regulations and second, it must be relatively cheap to buy and run. The first requirement is dictated by law in the form of the Air Navigation Order (ANO) and the second acts as a severe constraint on admissible technology.

No specific regulations for RPV operation currently exist so the CAA applies the same logic as for manned aircraft. The legislation which affects RPV operation is complex and depends on whether the air vehicle weighs more or less than 20kg, the threshold for "small" aircraft. An aircraft weighing more than 20kg must comply with the ANO which includes holding a certificate of airworthiness and obeying the Rules of the Air (1991); the latter contain restrictions on low flying and, in particular, the "see and avoid" principle for collision avoidance (Clot and Jerome-Smith, 2000; Clot, 2001). Some of these restrictions can be averted by obtaining a CAA exemption order but, in the context of a RPV, it is worth noting that no exemption order has been issued to date which allows flight beyond visual range of the operator. This is normally deemed to be a distance not exceeding 1,500m. It may be concluded that a civilian RPV operating beyond visual range must possess a degree of autonomy that substitutes for the "see and avoid" function naturally fulfilled by the pilot in a manned aircraft. This is the underlying motivation for the work described here which investigates whether collision avoidance and motion planning techniques based on machine vision can fulfil the requirement.

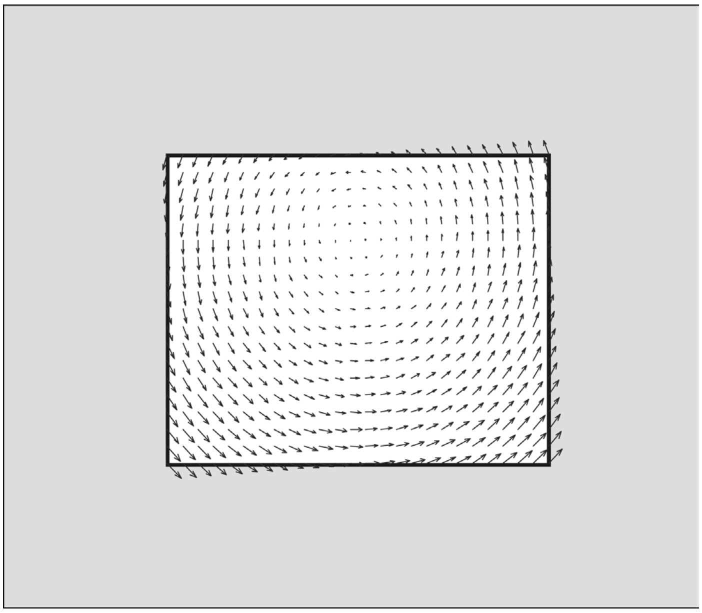
Why machine vision?

Automatic navigation and obstacle detection for manned helicopters has already been an extensive topic of research (Bhanu *et al.*, 1996), usually in a military context, e.g. for "nap-of-the-earth" flight or to aid an incapacitated pilot. These systems often use a number of different sensors to obtain information about the airspace around the helicopter, including millimetre wave radar and laser ranging systems. The use of such active systems has the benefit of providing range information, usually by means of time-of-flight-measurements, which makes it easier to build up a 3D map of the airspace. For this application, they do have serious drawbacks because integrated radar subsystems and scanning laser ranging equipment are not commonly available at present and tend to be expensive. Image processing technology, on the other hand, being driven largely by the volume consumer market, is easily available and relatively cheap. Also, the size, weight and power consumption of active sensors are prohibitive bearing in mind the tight constraints on a small RPV. In contrast, CCD video cameras are now very light and compact, and the use of multiple sensors placed in a ring around the periphery of the RPV to give all-round vision is feasible. Obstacle detection using vision also has the advantage that the visual information can be "shared" with the human (remote) pilot, whose attention can be diverted immediately to the live video picture of the detected obstacle. Dynamic vision is being actively pursued in the robotics, automotive and aerospace industries; for example, autonomous road vehicle guidance and autonomous landing approaches for aircraft (Werner *et al.*, 1996) have been demonstrated, albeit under controlled conditions.

Obstacle detection and location from digitised camera images

Collision avoidance and path planning require that the location and velocity of the obstacle with respect to the viewing camera be deduced in the presence of ego-motion, i.e. the RPV's own motion. Many methods have been described for estimating this information from the camera's 2D image and it is not appropriate to review this vast field of research here. Instead, a brief explanation is given of the principles involved. The key requirement is to estimate, from the digital image, the motion field of the scene being viewed. The motion field is a 2D array of vectors which encode the instantaneous velocity of each point in the scene. For instance, Figure 1 shows the calculated motion field for a rectangular object simultaneously moving from left to right and rotating about its centre. Given the motion, it is possible to calculate the velocity and displacement of the target object, relative to the

Figure 1 Motion flow field for an object moving from right to left and rotating about its centre



camera, in 3D World co-ordinates. This additional information is used to build up a "virtual map" of the obstacle within the vehicle's local environment, allowing a real-time path planning algorithm to be used to change its course in order to avoid the obstacle. While the principle as described is straightforward, it is clear that attempting to "see and avoid" using visual images requires several complex computational stages to be accomplished.

The simpler case is for stationary objects and a moving camera, when the optical flow field is due solely to (known) camera motion. The magnitude of the flow field is then proportional to the distance between the camera and object: a distant object gives a smaller flow field. A threshold function may then be applied to remove objects outside the RPV's local environment. For moving obstacles, a different approach is required. If there is only a small movement of the camera between frames in the captured image sequence, the RPV is approximately stationary with respect to the environment and the generated flow field is entirely due to the motion of the objects. Again a threshold function can be used to bound the local environment. Using a combination of these approaches, an approximation of the local environment can be built up into a map for subsequent path planning.

The first and perhaps most critical stage is to estimate the motion field from a sequence of images. A digital grey-scale image is composed of an array of pixels which encode the intensity (E) of each point in the image. The intensity is therefore a function of the co-ordinates (x, y) of the point and of time, i.e. $E(x, y, t)$. An estimate of the motion field can be obtained from the spatial and temporal variations of the image brightness from frame to frame – this is known as optical flow (Trucco and Verri, 1998). A fundamental assumption of the optical flow method is that there is constant brightness of the observed scene. This means that it is assumed that changes in illumination affect all parts of the image equally. Further, any variation in brightness at two distinct co-ordinates in the image is assumed to be caused by the physical motion of one object rather than a decrease of the intensity of one object and the increase in the intensity of another (thus causing an apparent motion despite both objects being stationary). For a point at (x,y) in the image, this assumed stationarity of the brightness is expressed as:

$$\frac{dE(x,y,t)}{dt} = 0. \quad (1)$$

Differentiation of (1) using the chain rule yields:

$$\frac{\partial E}{\partial x}\frac{dx}{dt} + \frac{\partial E}{\partial y}\frac{dy}{dt} + \frac{\partial E}{\partial t} = 0, \quad (2)$$

where the spatial gradients of brightness $\frac{\partial E}{\partial x}, \frac{\partial E}{\partial y}$ and the time gradient of brightness $\frac{\partial E}{\partial t}$ can be estimated from a sequence of two (or more) images. The objective is to calculate the components, $\frac{dx}{dt}$ and $\frac{dy}{dt}$ of the motion field vector. It is clear, however, that this cannot be done using equation (2) alone because there are two unknowns; in the image processing literature, this is known as the aperture problem. The usual solution is to consider a small patch in the image (say 5 x 5 pixels) and assume that the motion field is the same at all points within this patch. The motion field vector for this patch is then found as the minimum value of a quadratic functional of equation (2) which is expressed as a least squares problem with a standard solution. The optic flow field is built up by considering a grid of overlapping patches covering the whole image.

Once a flow field has been generated – and knowing the camera and lens configuration – the distance from the camera to the obstacle along the optical axis can be estimated by perspective projection. When combined with the object's 2D position in the image, its spatial location in camera co-ordinates can be calculated. If the camera position in World co-ordinates is known (e.g. using GPS), then the obstacle's position can be transformed into World co-ordinates and added to the RPV's internal map. A path-planning algorithm is then used to compute a new course which avoids the obstacle.

Building on this basic principle, a number of methods for generating optical flow fields and deriving 3D motion structure have been developed. Each has its advantages and disadvantages – see Galvin *et al.* (1998) for a comparative review. The method chosen for implementation in the laboratory tests described here is that described by Anandan (1989). The algorithm uses a hierarchical computational framework to determine a dense displacement field from a pair of images. The computational method uses scale-based separation of the image intensity. Initially large-scale intensity information is used to obtain a rough estimation of the image motion, which is then refined using intensity information at smaller scales. The estimates are in the form of displacement (or velocity) vectors for pixels and are accompanied by a direction-dependent confidence measure. A typical result is shown in Figure 2. Note that the lower (later) image has the object slightly displaced to the right of its original position. The optical flow field is shown in the left-hand diagram where the arrows indicating the estimated motion vectors point mostly to the right, as expected, although it should also be noted that there is a substantial amount of "noise" present on the estimates. This can be reduced by averaging over several image frames but involves extra computation and reduced speed of response.

System architecture and path planning

The obstacle detection and avoidance system must have authority to vary the RPV's flight path and therefore must be integrated with its main navigation and autopilot functions. The system architecture proposed for this purpose is based on that of Meystel (1991), as illustrated in Figure 3. There are three levels in the hierarchy, the obstacle detection system being part of the pilot level. In normal operation, the aircraft follows a nominal flight path generated by the navigator level according to an area map; this is prepared off-line before the mission begins. The pilot's map is a high-resolution segment of the navigator's map which is updated as the aircraft moves. When an unexpected obstacle is detected by the vision system, the pilot's map is modified to include the prohibited airspace and a new flight path is generated which avoids the obstacle and then returns to the pre-planned path, once it has been passed. This architecture aids in the design of the component parts of the navigation and guidance system because it defines the information flow between levels and places strict requirements on the type of data used and the software that has access to it.

Path planning is implemented using the distance transform method, first described by Jarvis and Byrne (1986). It does not produce an optimal path, in the sense of least distance or least time of travel, but it always produces a viable path (provided one exists) and it does

Figure 2 The optical flow field produced by two images in a sequence

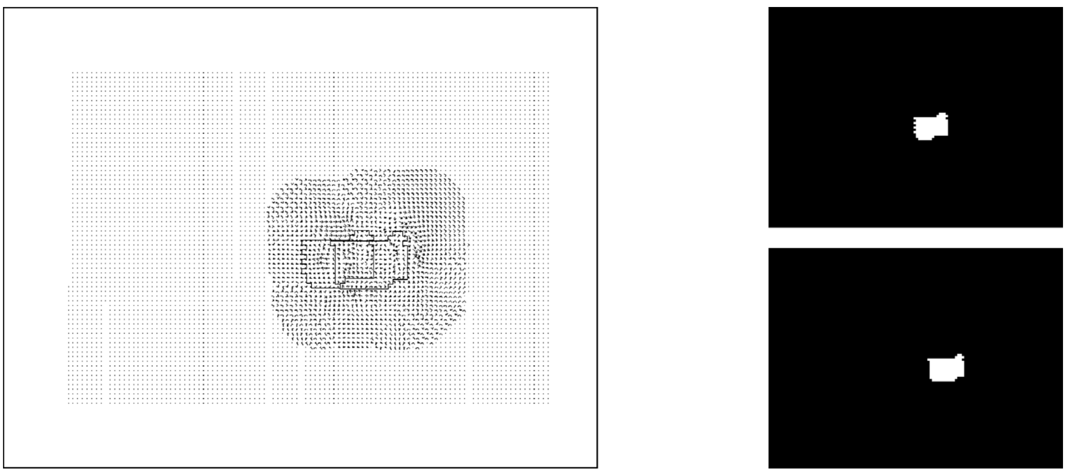
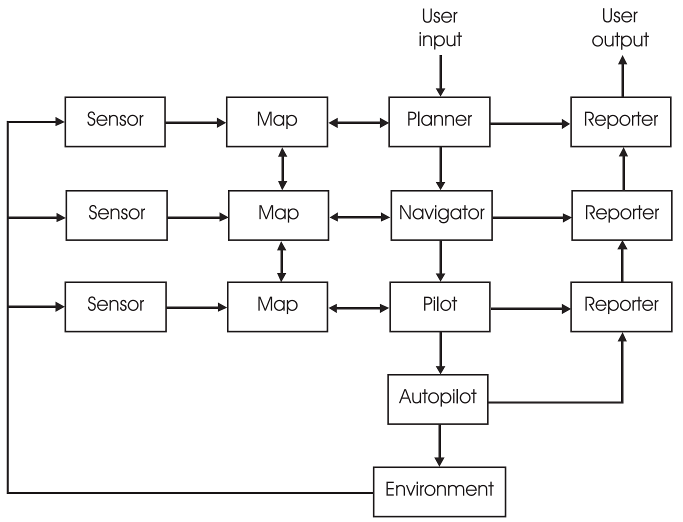


Figure 3 High level system architecture for navigation and guidance



so rapidly. This matches well with the requirements of this application. The concept is simple and best explained by means of a simplified 2D graphical example.

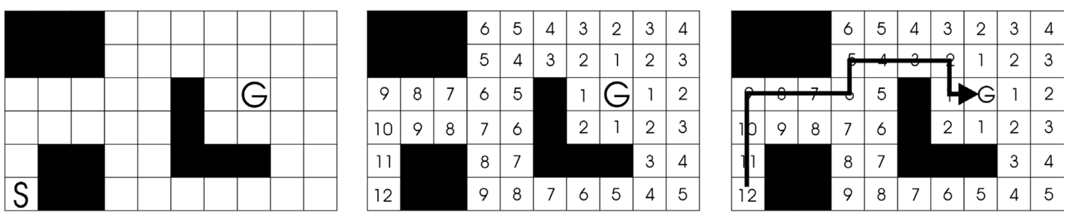
Suppose that the two-dimensional matrix in Figure 4(a) shows the occupancy of an environment where the black nodes of the matrix are obstacles, the white nodes are free-space, S marks the start node and G the goal node. The distance transform is calculated using the connectivity of the node structure. Starting at the goal node, which has a distance transform of 0, successive connected free-space nodes are incrementally labelled with the next positive integer. On completion, all free-space nodes that can be reached from the goal have been labelled with a distance transform value; thus starting at any labelled free space node guarantees that a path exists to the goal. Figure 6(b) shows the distance transform generated for Figure 6(a). Having computed the distance transform, a simple descent search is used to produce a nodal path which is then interpolated and smoothed to give an actual path. In Figure 6, a number of paths from node "S" to node "G" are possible, one of which is shown in Figure 6(c).

For ground-based robots working in locally flat terrain the 2D distance transform is adequate, but this is not the case for this application where the RPV may choose to fly over an obstacle rather than around it. It was therefore necessary to extend the distance transform method to three dimensions. This is straightforward in principle, but effective planning requires a high resolution map which makes substantial demands on computer memory and processing power. A fast and efficient 3D workspace decomposition algorithm which minimises memory requirements is described by Williams and James (2001).

Laboratory tests

Assessing the performance of the proposed methods in a laboratory presents a problem because it is essentially a closed loop system where the scene observed by the camera changes with the pose (i.e. the combined attitude and position) of the vehicle. This, in turn, depends on the output of the path planner and hence the camera image. It is, therefore, impossible to conduct valid tests on recorded sequences (e.g. played back from a VCR). Instead, a 30:1 scale model of the real-life situation was constructed. The laboratory test rig consists of a specially constructed XY table as shown in Plate 3. The RPV and its sensors are represented by two video cameras mounted on the XY table, pointing at 30° either side of the direction of travel. Movement of the "RPV" along its flight path is simulated by pulling the assembly at a constant velocity in the table's *Y* direction, which is approximately 2.5m in length. Variation of the flight path is simulated by moving the camera in the *X* direction by up to 0.5m either side of the centre line, the command being derived from the motion planning software. The test rig is currently

Figure 4 Graphical example of path planning using the distance transform



(a) **(b)** **(c)**

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Plate 3 Photograph of the test rig

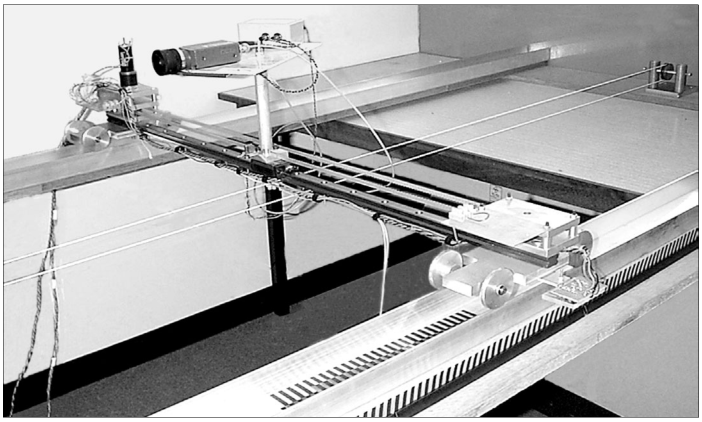
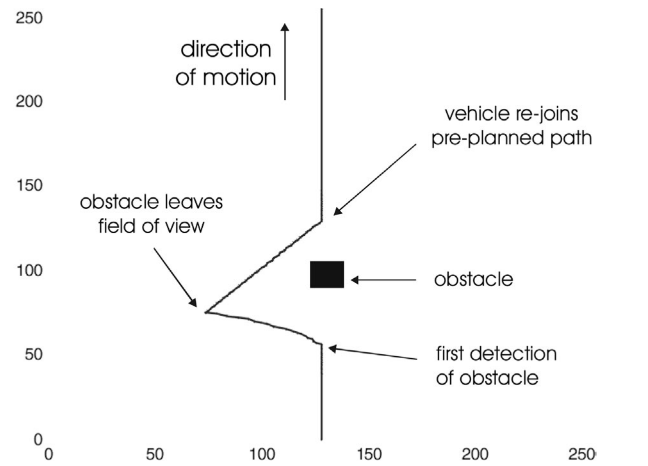


Figure 5 Typical path to avoid an obstacle and return to the pre-planned path



limited to two degrees of freedom, the cameras being at a fixed height and attitude, though these restrictions could be removed in future. One complete cycle of image capture, optical flow, map building and path planning takes one or two seconds on a Pentium II 350MHz PC, the vast majority of this period being taken by the optical flow calculation.

In a typical test, the camera is moved between two way-points and an object is placed on its path. From the sequence of images taken as the camera approaches the obstacle, an estimate of the location and range of the obstacle is formed and projected into the local map. An alternative path is then computed by the planner which the vehicle follows. Figure 5 shows the system detecting the obstacle's presence at $Y = 50$. A path is planned to avoid it and return to the pre-determined flight path and the "RPV" is seen to change its course in the negative X direction. Successive images show the obstacle moving to the right in the camera's field of view and increasing somewhat in size as it is approached so the planned path is modified to accommodate the new situation as the local map of the environment is continuously updated. Finally, the obstacle reaches the limit of the field of view and vanishes, allowing the path planner to generate a direct path that rejoins the nominal course.

Conclusions

This paper has described some image processing and motion planning methods based on commercial, off-the-shelf technology which are suitable for a small RPV. The intended application of the RPV is in power line inspection. An architecture for integrating the obstacle detection and avoidance function with the main guidance system has been proposed.

The laboratory tests have demonstrated that the principles of the methods are correct in a controlled environment but robustness to complex and varying scenes (background, lighting, perspective) still presents major difficulties. Rapid detection and reaction needs fast image analysis, and obtaining sufficient computing power for real-time processing remains a challenge. Evidently, machine vision offers no ready-made solutions to the "see and avoid", problem but both the theoretical techniques and computing power are improving rapidly and, recalling the drawbacks associated with other sensor types in this application, further investigation of vision systems is justified.

In the next stage of this work, the robustness of the algorithms will be assessed in the presence of more realistic background scenes. The test rig will also be extended to include the interaction which takes place between the human (remote) pilot and the machine vision software.

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