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Illumination-invariant image matching for autonomous UAV localisation based on optical sensing

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ABSTRACT

This paper presents an UAV (Unmanned Aerial Vehicle) localisation algorithm for its autonomous navigation based on matching between on-board UAV image sequences to a pre-installed reference satellite image. As the UAV images and the reference image are not necessarily taken under the same illumination condition, illumination-invariant image matching is essential. Based on the investigation of illumination-invariant property of Phase Correlation (PC) via mathematical derivation and experiments, we propose a PC based fast and robust illumination-invariant localisation algorithm for UAV navigation. The algorithm accurately determines the current UAV position as well as the next UAV position even the illumination condition of UAV on-board images is different from the reference satellite image. A Dirac delta function based registration quality assessment together with a risk alarming criterion is introduced to enable the UAV to perform self-correction in case the UAV deviates from the planned route. UAV navigation experiments using simulated terrain shading images and remote sensing images have demonstrated a robust high performance of the proposed PC based localisation algorithm under very different illumination conditions resulted from solar motion. The superiority of the algorithm, in comparison with two other widely used image matching algorithms, MI (Mutual Information) and NCC (Normalised Correlation Coefficient), is significant for its high matching accuracy and fast processing speed.

1. Introduction

UAVs (Unmanned Aerial Vehicles) have been developed very rapidly and for ever-widening applications, particularly in the last decade. To achieve full autonomy, the movement of a UAV needs to be self-monitored and self-controlled from a starting point to an end point, known as 'autonomous navigation'. GPS is the most widely used positioning system for UAV navigation. However, in some circumstances, such as military operations, GPS signals may not be available or can be jammed or sabotaged (Zhang et al., 2011). Moreover, for planetary exploration, since GPS service is unavailable, autonomous navigation becomes a crucial issue to UAVs. An UAV flight path usually contains many camera positions allowing the UAV to acquire on-board images and the camera position interval depends on the required image overlapping rates. When GPS data is unavailable or unreliable, vision-based localisation, utilising images from on-board cameras to determine the UAV positions, is a promising alternative for navigation.

Vision-based UAV localisation can be divided into two categories: the frame–frame and the frame-reference approaches. One of the popular frame–frame methods is SLAM (Simultaneous Localisation and Mapping) (Bailey and Durrant-Whyte, 2006), which estimates the camera motion by image matching between the current and the previous frames. Without absolute positioning information, however, these methods suffer from a drift problem which can be moderately reduced by applying filters, such as Kalman filter (Bosse, 1997) and extended Kalman filter (EKF) (Bresler and Merhav, 1986; Merhav and Bresler, 1986). However, these methods rely on the assumption of loop closures which means that UAVs need to fly on the same area twice (Lin and Medioni, 2007). Recent research on SLAM also takes the terrain elevation model as a constraint for avoiding error accumulation, known as the geo-SLAM (Lothe et al., 2009), but the large amount of computation makes it unsuitable for real-time high speed UAV navigation.

Another approach that achieves UAV localisation by image matching between the real time UAV images captured by an on-board camera and pre-installed reference images, is called frame-reference method. One of the advantages of the frame-reference

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approach is that the localisation error does not accumulate with time because the position of the camera is calculated independently at each UAV position. Moreover, by geo-referencing UAV images and reference images, not only can a current UAV position be determined, but also the next UAV position can be predicted because the UAV images cover certain front areas depending on the UAV camera view angles. The localisation of front areas is of great importance for autonomous navigation, because it allows vehicles to know 'where to go'.

The image matching for the frame-reference approach is challenging because the on-board real time images are not necessarily acquired at the same time under the same illumination condition and with the same imaging setting as pre-installed reference images. To achieve robust performance, variation of illumination, scale and imaging geometry are problems to be overcome in frame-reference approaches (Jan et al., 2006). By knowing the flight altitude and camera attitude parameters, the scale difference and geometric distortions in UAV image can be rectified but the appearances of the two images can still be very different because of different illumination conditions. This issue is especially serious in mountainous areas because image matching depends largely on topographic features, which can be greatly altered by changes in solar position. For example, the shadows and shades on a mountain slopes may appear on opposite sides if the reference image was acquired in the morning while the UAV was flying in the afternoon. Several approaches have been proposed to achieve UAV navigation using robust image matching algorithms (Lindsten et al., 2010). However, the searching for optimal image matching in frame-reference is often time-consuming making real-time navigation not always achievable. Matching robustness and speed are two key issues for this type of localisation. In this paper, a Phase Correlation (PC) based UAV localisation approach is introduced and the major research objectives are to develop the following algorithms and functionalities:

- A robust frame-reference localisation algorithm for UAV navigation which is insensitive to local illumination change caused by change in solar position and can tolerate image distortion caused by camera 3D motion.
- Capability to predict the next UAV position based on the current on-board UAV images and the planned flight route.
- A risk alarming algorithm based on self-correction to safe guard the navigation in case the UAV deviates from the planned route.

2. Previous works

As robust image matching is one of the key issues in vision-based navigation, several matching algorithms have been applied in UAV navigation. In this paper, we divided them into feature-based approach and area-based approach.

Features can be corners, edges, and distinctive points which remain their positions and geometry shapes in variant conditions. Feature matching is quick, because only a few points are matched instead of matching the whole images. As one of the most popular corner detectors, Harris operator (Harris and Stephens, 1988) is based on eigenvalues of the autocorrelation matrix. Harris operator is used in feature-based stereo matching for Mars exploration rovers (Mark et al., 2007). However, Harris operator is sensitive to scale and illumination variation. Another popular feature detection algorithm is SIFT (Scale-Invariant Feature Transform) (Lowe, 2004), further improved to SURF (Speed Up Robust Feature) (Bay et al., 2006). Invariant to scale and rotation difference, SIFT and SURF matching algorithms have been widely applied for landmark matching (Ilkyun et al., 2009) and feature-based tracking for UAV images (Pascual et al., 2008). However, both SIFT and SURF, though have been proved to be robust to the global intensity changes in terms of image brightness and contrast, are not truly robust to considerable changes of illumination direction (azimuth and zenith angles of lighting source) (Glover et al., 2010; Maddern et al., 2014). These interest points based approaches are most widely used in frame–frame approaches, because they can tolerate large geometric distortion caused by camera motion. However, they are not robust enough for frame-reference matching, which is the correspondence between UAV images and reference images such as satellite images, because the possible different illumination could be problematic in feature matching (Lee and Lee, 2004). Moreover, in frame-reference approach, these algorithms may fail to find enough correspondences in featureless areas.

Edges are also useful features for tracking and matching. Some commonly used edge detection algorithms are Canny operator (Canny, 1986), zero-crossing operator (Haralick, 1984) and Mar operator (Marr and Hildreth, 1980). Rodriguez and Aggarwal (1990) introduced a cliff map for the image matching between the aerial images and the reference 3D data and Shang and Shi (2007) used the boundary of runway for autonomous UAV safe landing. Edges are considered to be illumination-invariant, because the boundaries of objects remain the same positions under different lighting conditions. However, the edge direction is sensitive to local illumination azimuth and consequently, the number of matchable edges may decrease significantly if the lighting directions are very different. Besides, edge matching is not scale invariant as the number of edges is directly relevant to image resolution. For instance, a road can be a typical edge in a low resolution image but it becomes a patch with two edges in a high resolution image.

In conclusion, most feature-based matching algorithms are based on spatial distribution of local grey values and therefore they are sensitive to illumination variation. Using these algorithms, the features extracted from on-board UAV images may easily lose the correspondence to the reference data if they are under different illumination conditions.

Area correlation based algorithms, such as NCC, MI (Papoulis and Pillai, 2002), LSS (Local Self-Similarities) (Shechtman and Irani, 2007) and PC (Kuglin, 1975) formulates another brunch of image matching. For NCC and MI, correlation coefficient values are calculated consecutively between window pairs of the reference image and the target image that roam within a given neighbourhood in the reference image; the registration is achieved at the position where correlation coefficient value is the maximum among the consecutively calculations. Omead et al. (1999) proposed a visual odometer to determine the position of UAVs by SSD (Sum of Squared Difference) template matching. An auxiliary template was used to calculate the rotation, scale and grey value normalisation between templates. Lin and Medioni (2007) used MI to find the correspondences between the UAV frame and the reference map. In contrast to feature-based algorithms, area-based matching algorithms take global grey value distribution into account and they are expected to be more robust to illumination variation. This is because although the local patterns have been greatly altered by illumination change, the global image texture remain largely unchanged. However, the general perception that area-based matching is slower than the feature-based matching makes it less widely used in vision-based localisation thus far. The searching for optimal matching in frame-reference is often time-consuming making real-time navigation not always achievable. In this paper, we used a Phase Correlation based illumination-invariant matching algorithm to achieve frame-reference based UAV navigation. Research has shown that phase correlation matching can achieve sub-pixel accuracy in estimation of translation, rotation and scale change between resemble images and it is robust to random noise (Reddy and Chatterji, 1996). As a direct matching method, Phase Correlation can calculate the image shifts without roaming search, as done by NCC and MI. Thus, the