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Lens Auto-Classification using a Featureless Methodology

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Abstract

In this work we propose a methodology to find automatically the type of the lens of a discrete mobile camera. The assumption that pixels have approximately uniform density on the sensor allows the classification of different types of lenses, independently of the sensor shape.

1 Introduction

Traditional imaging sensors are formed by pixels precisely placed in a rectangular grid, and thus look like calibrated sensors for many practical purposes such as localizing local extrema, edges or corners. In contrast, the most common imaging sensors found in nature are the compound eyes, collections of individual photo cells which clearly do not form rectangular grids, but are very effective for solving various tasks at hand and thus have inspired the design of many artificial systems.

Recently, Olsson *et al.* [8] proposed a methodology for topologically calibrating a central imaging sensor based on a number of photocells. A metric reconstruction is found by Grossmann *et al.* [5], when the relation between signal correlation values and pixel distance-angles is known. Methods that do not require this relation to be known were presented by Censi and Scaramuzza [2] and Galego *et al.* [6]. In [6] the computational complexity associated to augmenting the sensor resolution is handled by using methods derived from the classical Multi Dimensional Scaling (MDS) [3].

In the cases where the sensor topology is a rectangular grid with a perspective lens one can use traditional calibration methodologies [1, 9, 11]. However, for other type of lenses these methodologies do not work. A methodology to calibrate other types of lens was proposed by Kannala *et al.* [7]. The methodology of Kannala *et al.* requires using a calibration pattern and the specification of the lens type. In our work we propose an automatic method to find the lens type while using natural images.

2 Camera Model

Discrete central cameras, as conventional (standard) cameras, are described geometrically by the pin-hole projection model. Differently from standard cameras, discrete cameras are simply composed of collections of pixels organized as pencils of lines with unknown topologies.

Grossberg and Nayar[4] introduced the concept of raxel as a mathematical abstraction of the pose of a photo-cell. Instead of denoting the real position of the photo-cell, a raxel is just assumed to be along the direction of the chief ray associated to the photo-cell. A raxel can be characterized as a $3D$ position, p, and a direction vector, q, as shown in Fig.1(d). Since we are considering central cameras, all light rays (acquired by photo-cells) converge to the same point, and thus $p_i = p_j$ for any pair of raxels. Therefore, we ignore the position of the raxels, since the only useful information is contained in the direction vector q. As a direction vector, q, we assume that all the vectors have the same norm. This assumption removes one degree of freedom, which allows us to represent q with only two angles, (Ω, μ).

Traditionally the coordinate system of a camera sensor is represented by u_i and v_i, which are the ith pixel position along horizontal and vertical grid. Here we use a polar coordinate system of $[r\ \mu]$, where $r_i = \sqrt{(u_i-u_0)^2+(v_i-v_0)^2}$, $\mu_i = \mathrm{acos}(u_i/v_i)$, and $[u_0\ v_0]$ is the principal point.

In this work we assume that the discrete camera geometric model can be characterized by an unknown radial function h. This function links the angle at which a light ray (raxel) hits the camera lens with the imaged point (pixel coordinates),

$$\Omega = h(r/l), \tag{1}$$

considering that r is the radial distance, in pixels, from the center of an imaging sensor, l is the focal length and Ω is the angle between the principal axis and the incoming ray, as it can be seen in figure 1 (d), note that the μ is the same as in pixels coordinates, since the lens transformation only affect the radius.

In the following we assume that we have three different lenses [7]:

$$\Omega = atan(r/l) \quad \text{perspective lens,} \tag{2}$$

$$\Omega = r/l \quad \text{equidistance projection lens,} \tag{3}$$

$$\Omega = asin(r/l) \quad \text{orthogonal projection lens.} \tag{4}$$

From now on the focal length l will be not considered since it is a constant that will not have impact on the differentiation of a lens type.

In order to classify a lens mounted on a camera we propose a methodology based in three steps: i) topological calibration of a sensor; ii) marginalization of the density of the topology along μ; iii) lens classification based in finding the closest match for the marginal density function of the topology.

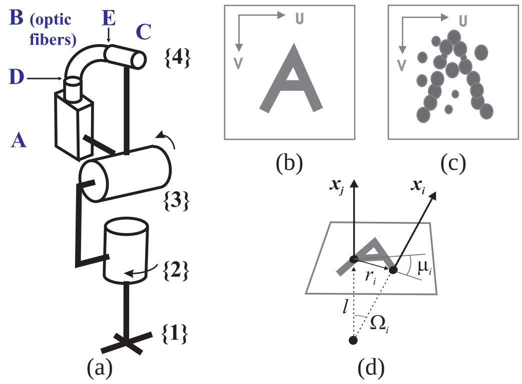
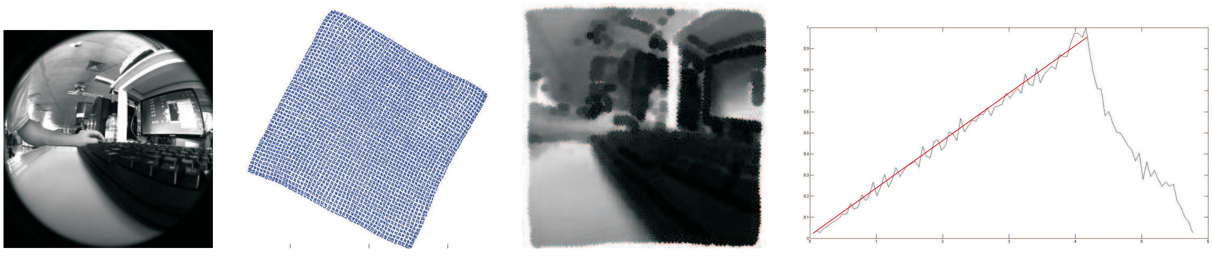


Figure 1: Model of a discrete camera mounted on a pan-tilt basis. The optic-fiber bundle, points E to D in (a), Input image (b). Twisted input image (c). Projection model and raxels notation (d).

3 Auto-Calibration Methodology

The classical Multiple Dimensional Scaling (MDS) algorithm [3] provides a simple way of embedding a set of points in Euclidean space given their inter-distances. It works well when the distances are Euclidean and when the structures are linear, however, when the manifolds are nonlinear, the classical MDS fails to detect the true dimensionality of the data set. Isomap is built on classical MDS but instead of using Euclidean distances it uses an approximation of geodesic distances [10]. These geodesic distance approximations are defined as a series of hops between neighboring points in the Euclidean space using a shortest path graph algorithm such as Dijkstra's. In our particular case, this algorithm is used to provide a pixel embedding given the inter-pixel distances estimated from the pixel stream correlations.

In order to obtain the embedded raxels directions, $Q_f = [q_1\ q_2\ \cdots q_N]$, one follows the steps proposed in [6]: (i) Data binarization using a fixed threshold such that each pixel stream value is either 1 or -1. (ii) Computing the normalized correlation between all the pixel-streams. (iii) Converting the inter-pixel correlations, C, into distances, d, using the linear transformation $d(q_i, q_j) = 1 - C(f_i, f_j)$, f_i corresponds to a time series of brightness values captured by i^{th} pixel. (iv) Using Isomap to compute the topology of the sensor.



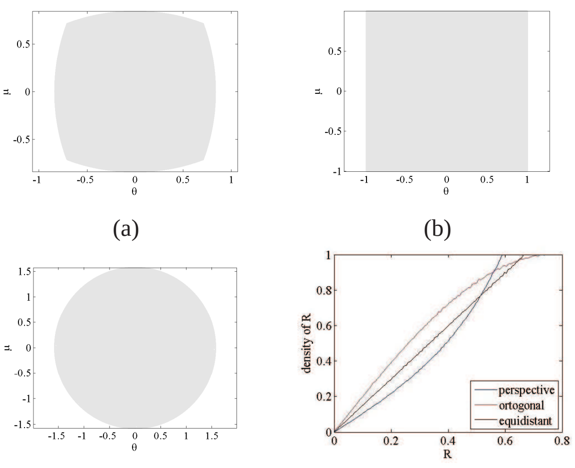
(a) (b) (c) (d)

Figure 2: Detection of the lens type. In (a) we can see a typical image acquired by the camera. (b) the estimated raxels topology. (c) mapping of a image into the topology. (d) histogram of the R density in the topology.

4 Lens Effect and Raxel Densities

Assuming that we have a uniform distribution of the pixels, what is the distribution expected in the raxels space? The marginal density of the pixels would be the solution if we had no lens transformation, however the transformation created by the lens will change the marginal density of the raxels.

Simulating a 100×100 pixel camera with the three types of lens one finds that each lens creates a distinct distribution of raxels (see Fig. 3(d)) [1].



(c) (d)

Figure 3: Effects of a lens in a uniform pixel distribution to the raxels topology. (a) Perspective lens. (b) Equidistant lens. (c) Orthogonal lens. (d) Density of each topology along the radius

Given the previous observation one can now propose a lens classification algorithm. One starts by acquiring the radial distribution of the topology, $h^{-1}(\Omega)$. We truncate the domain of h^{-1} to $\Omega \in [0,\ h(\max(h^{-1}(.))]$. The truncation is done since a random topology is in general not circular (e.g. most of the conventional sensors have rectangular shapes). Then a quadratic curve is fitted to h^{-1} using a minimum squared error criterium. Based on the value of the first quadratic term we can estimate the type of the lens mounted in our camera. The first case that we look at is the equidistant lens. If the first term has a modulus value lower than 10% of the second term then the lens is tagged as an equidistant lens. Otherwise, if the first term is negative the lens on the camera is a orthogonal lens. Otherwise, it is a perspective lens.

5 Results

The experiments have been conducted with a PGR-Flea camera equipped with an equidistant lens type (see Eq. 2). We selected just a central region of the camera, 100×100 pixels, and then subsampled one in every three pixels in both directions. This sensor composed by square pixels forming a regular square grid has a uniform distribution in the pixels space $[u\ v]$. In order to estimate the lens-type of the camera, we reconstruct the topology of the camera using a set of 8500 random images. One of the calibrating images is shown in Fig. 2(a). The topology resulting of the proposed algorithm can be seen in Fig. 2(b). Figure 2(c) shows image (a) remapped according to the reconstructed topology. Since the estimated topology is not perfect, and we have pixel sub-sampling one can see blur in the figure.

Figure 2(d) shows the density function of the estimated topology. The part of the function used for classifying the lens is marked in red. The estimated quadratic curve is $y = 0.0045 * x^2 + 0.19 * x + 0.013$. In this case the ratio between the first and the second term is 2.3%, which means that the lens mounted in the camera is an equidistant lens. This result is confirmed by the datasheet of the lens.

6 Conclusions and Future work

In this work we have shown that is possible to find automatically the type of a lens mounted on a mobile camera. This is useful, for example, to further automate current calibration processes which involve indicating a-priori the type of the lens. Our future work will focus on formalizing the mathematical background of the proposed methodology.

Acknowledgments

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[1] The focal length l is the same in all cases. A square sensor is used, instead of a circle, because it is easier to spot the differences between each case. However the histograms of cumulative functions, are made using the biggest circle that could fit in the topology.