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 photo-cells. 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).

In the particular case, this algorithm is used to provide a metric reconstruction of the topology along μ; iii) lens classification based in finding the closest match for the marginal density function of the topology.

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.

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 pixel-distances estimated from the pixel stream correlations.

In order to obtain the embedded raxels directions, Q_L = [q1 q2 ... qN], one follows the steps proposed in [6]: (i) Data binarization using a fixed threshold such that each pixel stream value is either 1 or 0. (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(q1,q2) = 1 - C(f1,f2), f1 corresponds to a time series of brightness values captured by ith pixel. (iv) Using Isomap to compute the topology of the sensor.
Otherwise, it is a perspective lens. The second term is then the lens is tagged as an equidistant lens. Otherwise, of the lens mounted in our camera. The first case that we look at is the cumulative functions, are made using the biggest circle that could fit in the topology.

Based on the value of the first quadratic term we can estimate the type of the camera, 100 pixels, and then subsampled one in every three 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 $100 \times 100$ pixel camera with the three types of lenses one finds that each lens creates a distinct distribution of raxels (see Fig. 3(d)) $^1$.

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.

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 $\Omega \in [0, h(\max(h^{-1}(\cdot)))]$. 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 criterion. 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, $100 \times 100$ 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 $y = 0.0045 \times x^2 + 0.19 \times x + 0.013$. 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.

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