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The Weibull manifold in low-level image processing: An application to automatic image focusing ☆

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ABSTRACT

In this paper, we introduce a novel framework for low-level image processing and analysis. First, we process images with very simple, difference-based filter functions. Second, we fit the 2-parameter Weibull distribution to the filtered output. This maps each image to the 2D Weibull manifold. Third, we exploit the information geometry of this manifold and solve low-level image processing tasks as minimisation problems on point sets. For a proof-of-concept example, we examine the image autofocusing task. We propose appropriate cost functions together with a simple implicitly-constrained manifold optimisation algorithm and show that our framework compares very favourably against common autofocus methods from literature. In particular, our approach exhibits the best overall performance in terms of combined speed and accuracy.

1. Introduction

Low-level image processing typically involves the application of some type of filter function onto the image data, which results in the extraction of a number of desired feature descriptors. These descriptors are identified, isolated and subsequently evaluated in the later stages of the image analysis pipeline. The analysis step is often carried out in some representation of the resulting feature space (e.g. histogram), an endeavour which can be both difficult and inefficient due to the arbitrary-dimensional, discretised nature and inconvenient form of the space. So for example, distances, angles and directions between elements of the feature space may not always be defined or easily and accurately approximated. Furthermore, notions such as mean and dispersion might not be applicable in certain feature spaces. Therefore, explicit information about the geometry of the feature space is usually desirable, if not necessary, for reliable processing and image analysis.

The responses of difference-based filter functions on image data, are known to be Weibull distributed [16,2,49]. As such, every filtered image may be represented as a single, unique point on a statistical manifold. We exploit this fact and carry out the analysis in the 2-dimensional Weibull manifold, which is much simpler than the original feature space. The 2D, smooth Weibull manifold has well known properties that have been examined in statistical literature, but this is the first time its geometry has been applied to the area of image processing and analysis. In this new lower-dimensional representation, one may easily make use of the established notions of distance, arc-length, curvature and mean, in order to perform basic image analysis tasks in a more principled and efficient manner.

We have devised a modular framework (see Fig. 1) that casts the image processing and analysis tasks as an implicitly-constrained optimisation problem, where we exploit the known manifold geometry to drive the optimisation algorithm to a good solution. For the purpose of feature extraction, we will be using simple line and edge filters in the form of the dihedral filters originally proposed by [27]. These filters, constructed with the aid of representation theory of discrete groups, are both fast and simple and allow for very efficient implementation for parallel execution. Their application in tasks such as content-based image retrieval and classification of high-level scene concepts has been described in a previous publication [49]. We demonstrate the efficacy of our framework and in particular the advantage of the Weibull manifold solution over standard methods, in the well known problem of automatic image focusing.

This paper is organised as follows. In Section 2 we describe in more detail the individual components of our framework. We then continue onto Section 3 with a brief introduction to automatic image focusing and include some of the common approaches from literature. In the same section, we describe how our proposed framework may be applied to the solution of the autofocusing problem. Section 4 follows with a description of the comparative experiments run and a description of the datasets used, as well as an analysis of the results. We conclude in Section 6.

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2. Basic framework

The image processing framework we are introducing in this paper consists of a number of individual components that work together in a loop. First is the *image acquisition* component. This is the module which captures the images to be processed and makes them available to the rest of the system. This could be as simple as a look-up table of a stack of images or some interface to an imaging device. In general, the rest of the system does not have an explicit model of the imaging process, and the contents of and the conditions in the imaged scene. However, modification of some parameters or physical properties of the acquisition system is carried out and is controlled by the rest of the framework.

The next step, is the *filtering* component. This component isolates important characteristic features from the image, such as edges or corners and generates a new representation of the image data in this new feature space. The output of the filtering stage is a vector of magnitudes of filter responses, which is known to be Weibull distributed. The natural next step therefore is to fit a Weibull distribution to the data and describe the filtered image with just two numbers, the Weibull scale and *shape*. Note that this is of course a global application of the filters to the whole image. One may subdivide the image in patches and apply the filters at each patch. The per-patch filtered results are still Weibull distributed, but now they capture the local image properties instead.

Every such scale-shape pair may be considered as a point on the 2D Weibull *manifold*, and the manifold can be given a Riemannian metric, by the Fisher matrix, at every such point. Abstraction of images as manifold coordinates, allows us to turn the image processing task into corresponding operations on points such as curve fitting or optimisation. Using this line of thought, the next component is a *cost function* defined on the manifold, which should obtain an appropriate minimum related to the image processing task at hand. We may recover such a minimum using a manifold-based *optimisation* algorithm.

The image acquisition modification parameters are adjusted, driven by the optimisation component and the main loop (Fig. 1) is repeated until convergence to a good solution. The main framework components are described in more detail in the rest of this section.

2.1. Image filtering with dihedral filters

In the proposed processing scheme we characterise the visual properties of images with the help of low-level filter systems. We use the so-called dihedral filter systems that meet the requirements of both, fast execution times and simplicity. These filters are constructed with the help of the representation theory of discrete groups, which is a generalisation of the theory of the discrete Fourier transform. Their usage is based on three observations: almost all digital images consist of pixels located on a square or hexagonal grid; the transformations that map these grids into themselves are the so-called dihedral groups; The filter functions should be adapted to these transformations. In this paper we will use filters defined on a 5×5 window and on grayscale images. The filters are constructed as follows. First we define two positions in the window as equivalent if there is a group element in the dihedral group (i.e. a rotation or a reflection) that maps one point into the other. As a result we get the six equivalence classes c_1,c_2,a_1,a_2,i and o shown in the matrix

$$\begin{pmatrix} c_1 & i & a_1 & i & c_1 \\ i & c_2 & a_2 & c_2 & i \\ a_1 & a_2 & o & a_2 & a_1 \\ i & c_2 & a_2 & c_2 & i \\ c_1 & i & a_1 & i & c_1 \end{pmatrix}. \quad (1)$$

The value at the origin o will be ignored. For the remaining 24 points we use the tools from the representation theory of the dihedral groups to divide them into six subsets of 4 points each. The first four subsets are the points in the equivalence classes c_1,c_2,a_1,a_2. The other

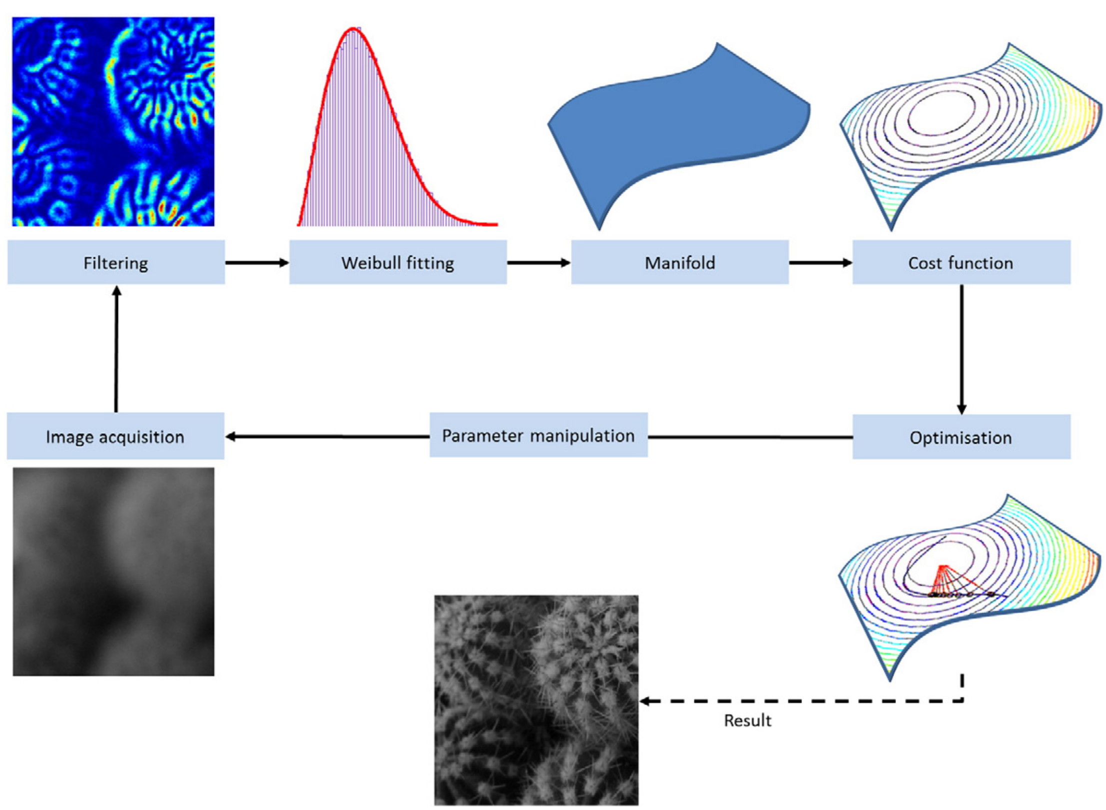

Fig. 1. An outline of the main components of our image processing framework, illustrating the autofocusing problem. The starting point is the image acquisition step.