Commentary
Volume 13:9, 2022

Global Journal of Technology and Optimization

ISSN: 2229-8711 **Open Access**

Lagrange-Fourier Moments for Image Recognition

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Introduction

Recent advances in orthogonal moments' prediction accuracy have made them a vital tool in a variety of pattern recognition tasks, such as object and image detection and classification. The orthogonal Lagrange-Fourier moments (LFMs) for grayscale images, the multi-channel orthogonal Lagrange-Fourier moments (MLFMs), and the quaternion orthogonal Lagrange-Fourier moments (QLFMs) for colour images are three new sets of discrete orthogonal moments and their invariants to translation, scaling, and rotation (TSR) for image representation and recognition that we present in this paper using the orthogonal La Polar coordinates are used to present these orthogonal moments. In order to assess the effectiveness of the suggested invariant moments, we provide a series of numerical experiments in the classification and pattern recognition fields [1].

It is explained how to create an infinite number of independent, algebraic combinations of Zernike moments that are invariant to picture translation, orientation, and size. Two-dimensional image moments with regard to Zernike polynomials are also defined. This strategy is in contrast to the common way of using moments. Within this framework, the broad issue of two-dimensional pattern recognition and three-dimensional object recognition is examined. In terms of a finite set of moments, a unique reconstruction of a picture in either real space or Fourier space is provided [2].

Recent advances in orthogonal moments' predictive performance have made them a vital tool in a variety of imaging and pattern recognition applications, such as object identification, picture classification, and image reconstruction. In this study, we introduce a brand-new class of orthogonal functions known as "Orthogonal helmet functions." We develop three new sets of orthogonal moments and their scaling, rotation, and translation invariants for image representation and recognition using these functions. These sets are referred to as "the orthogonal helmet-Fourier moments" for gray-level images, "the multi-channel orthogonal helmet-Fourier moments," and "the quaternion orthogonal helmet-Fourier moments" (QHFMs) for colour images, respectively. To support the conceptual underpinnings of our strategy, we present a number of actual experiments in pattern analysis and picture analysis [3].

Recent advances in orthogonal moments' prediction accuracy have made them a vital tool in a variety of pattern recognition tasks, such as object and image detection and classification. The orthogonal Lagrange-Fourier moments (LFMs) for grayscale images, the multi-channel orthogonal Lagrange-Fourier moments (MLFMs), and the quaternion orthogonal Lagrange-Fourier moments (QLFMs) for colour images are three new sets of discrete orthogonal moments and their invariants to translation, scaling, and rotation (TSR) for image representation and recognition that we present in this paper using the orthogonal La Polar coordinates are used to present these orthogonal moments. In order to assess the effectiveness of the suggested invariant moments, we provide a series of numerical experiments in the classification and pattern recognition fields [4].

Description

One of the most crucial elements in content-based trademark image retrieval and classification, given a single closed contour trademark image, is form. Therefore, we may extract the contour Fourier descriptor of the target image as a feature vector. Given that Fourier moments are not invariant to image scaling, rotation, and translation, they are used as a feature vector so that the classifier performs better than conventional classification techniques. Poor generalisation performance, local minimums, and overfitting are issues that are resolved by the application of the Support Vector Machine model. Additionally, the training set can be separated thanks to the kernel function used in support vector machines, which translates a linearly inseparable data set to a higher dimensional space. Support vector machine classifiers are therefore frequently employed in pattern recognition.

Due to its qualities of being translation, scaling, and rotation invariant, radial harmonic-Fourier moments (RHFMs) are frequently used for image reconstruction and invariant pattern identification. When compared to Zernike moments and Bessel-Fourier moments, RHFMs have less computational complexity. However, they consistently experience discontinuities, numerical instability close to the image's centre, and reconstruction error, which is especially prevalent for moments of higher order. In order to successfully avoid the issues listed above, an improvement of radial harmonic-Fourier moments (IRHFMs) is suggested in this study. The image matrix in this article is also subjected to a 2D fast Fourier transform technique to produce the IRHFMs. Results from simulation experiments show that the suggested IRHFMs outperform conventional RHFMs and other classic orthogonal moments, such as the most recent image moments, such as polar harmonic Fourier [5].

Although the definition that is commonly found states that it is a mathematical quantity generated from a given quantity by an algebraic, geometric, or functional operation is somewhat more precise in mathematics, it is still somewhat broad or flexible. When we delve a bit deeper, we come across the so-called transform theory, which essentially states that a problem can be made simpler by selecting the right "kernel" function (from the German meaning core or nucleus).

Additionally, a moment is a particular quantitative measure of the shape of a collection of points that is employed in both statistics and mechanics. If the moments are used to represent mass, the centre of mass is represented by the first moment, which is divided by the entire mass, and the rotational inertia is represented by the second moment. The whole probability, or zero, is represented by the zeroth moment where the points stand for probability density. The first moment represents the mean, the second the variance, and the third the skewness.

Conclusion

Lagrange, also known as Giuseppe Lodovico Lagrangia, was the firstborn of eleven children. His paternal great-grandfather was a French cavalry captain whose ancestors were from Tours in France. He had worked for Louis XIV before joining Charles Emmanuel II, Duke of Savoy, and getting married to an aristocratic Roman family member named Conti.Giuseppe Francesco Lodovico, Lagrange's father, was a wealthy doctor of Cambiano in the

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Received: 01 September, 2022, Manuscript No: gjto-22-78957; **Editor Assigned:** 03 September, 2022, PreQC No: P-78957; **Reviewed:** 15 September, 2022, QC No: Q-78957; **Revised:** 20 September, 2022, Manuscript No: R-78957; **Published:** 27 September, 2022, DOI: 10.37421/2229-8711.2022.13.317

countryside of Turin and a professor of law at the University of Torino. He was brought up as a Roman Catholic (but later on became an agnostic).

Acknowledgement

None.

Conflict of Interest

There are no conflicts of interest by author.

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How to cite this article: Kryzhevich, Sergey. “Lagrange-Fourier Moments for Image Recognition.” Glob J Tech Optim 13 (2022): 317.