Neurocomputing 99 (2013) 358–371

Contents lists available at SciVerse ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Moment-based local binary patterns: A novel descriptor for invariant pattern recognition applications

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ARTICLE INFO

Article history:
Received 2 July 2011
Received in revised form
22 June 2012
Accepted 25 June 2012
Communicated by Qi Li
Available online 11 August 2012

Keywords:
Image moments
Moment invariants
Local binary patterns
Momentgram
Feature extraction
Computer-robotic vision
Pattern recognition

ABSTRACT

A novel descriptor able to improve the classification capabilities of a typical pattern recognition system is proposed in this paper. The introduced descriptor is derived by incorporating two efficient region descriptors, namely image moments and local binary patterns (LBP), commonly used in pattern recognition applications, in the last decades. The main idea behind this novel feature extraction methodology is the need of improved recognition capabilities, a goal achieved by the combinative use of these descriptors. This collaboration aims to make use of the major advantages each one presents, by simultaneously complementing each other, in order to elevate their weak points. In this way, the useful properties of the moments and moment invariants regarding their robustness to the noise presence, their global information coding mechanism and their invariant behaviour under scaling, translation and rotation conditions, along with the local nature of the LBP, are combined in a single concrete methodology. As a result a novel descriptor invariant to common geometric transformations of the described object, capable to encode its local characteristics, is formed and its classification capabilities are investigated through massive experimental scenarios. The experiments have shown the superiority of the introduced descriptor over the moment invariants, the LBP operator and other well-known from the literature descriptors such as HOG, HOG-LBP and LBP-HF.

1. Introduction

A crucial part of a modern intelligent imaging system, which learns from its environment and interacts with it, is the pattern recognition procedure. In general, a pattern recognition process employs four stages: (1) image acquisition, (2) image preprocessing (denoising, filtering, etc.), (3) feature extraction and finally (4) classification. The third step is probably the most complicated and it affects the overall performance of the system. A feature extraction method (FEM) can be termed successful if the resulted features (descriptors) describe uniquely the processed object in a scene. The more successful a FEM is, the more efficient the classification is.

The discrimination power of a descriptor is measured by its ability to capture the particular characteristics of the described pattern, which distinguish it among similar or totally different objects. A difficult pattern recognition task consists of objects being quite similar and differing slightly. In these cases the descriptors need to have strong local nature in order to encode the information that distinguishes them. A considerable performance evaluation of some well-known local descriptors has been performed in [1], with very useful and constructive conclusions.

Among the most widely used local descriptors, the Local Binary Patterns (LBP) operator proposed by Ojala et al. [2], has attracted the attention of the scientists and motivated them to extent its applicability to many disciplines. The LBP operator is initially introduced as texture descriptor but it has been applied, after some modifications, to face recognition [3,4], facial expression [5], pedestrian detection [6], etc. Although there is a specific LBP version being rotation invariant [7,8], its application in traditional pattern recognition tasks where rotated, translated and scaled objects have to be recognized, is not suggested.

Another popular FEM that is used to generate discriminative feature sets is the computation of image moments. Moments have been used successfully in many classification applications [9–12] and their ability to describe an object fully makes them a powerful tool in computer vision applications, like object recognition in robotic applications and object characterization in visual inspection based quality control systems. However, since image moments are region descriptors they provide global information of an object. Although moments of higher orders capture the object's details, their local behaviour is quite poor.

In this work a novel FEM that constructs rotation, translation, scale invariant descriptors of local nature, is introduced.

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http://dx.doi.org/10.1016/j.neucom.2012.06.031

The proposed feature extraction methodology aims to utilize the local behaviour of the LBP and the invariance nature of the orthogonal image moments. The derived descriptors called moment based local binary patterns (Mb-LBP) seem to be effective pattern features, which improve the classification ability of the traditional moment invariants and extend the performance of the original LBP in more general pattern recognition problems.

In order to investigate the behaviour of the proposed descriptors, an exhaustive experimental plan has been arranged, consisting of several pattern recognition tasks (face recognition, facial expression recognition, texture recognition, object recognition) by using several benchmark datasets from the literature.

To summarize, the contribution of this work lies on the construction of a novel LBP-like descriptor which is making use of the invariant properties the moments and moment invariants have. This is achieved by using a novel RST (rotation, scale, translation) invariant image representation called *image momentgram*, which is constructed by applying a straightforward procedure. This new image representation depends on the type of the used moment family and therefore can take several forms, by incorporating different image information. This flexibility helps on finding the most appropriate moment family that better describes the problem at hand. The utility of the momentgram is to combine the main advantages of the moments and moment invariants with those of the LBP method, aiming to construct an invariant local descriptor. Based on this RST image representation the LBP operator can be applied on, in order to extract invariant feature vectors for pattern recognition applications.

The Mb-LBP descriptor shows a global behaviour that comes from the nature of the moment functions to describe the image's content in several components ("bands" - moment orders). On the other hand, the local behaviour of the Mb-LBP descriptor is based on the local information of the constructed momentgram and not that of the original image. This is the reason why the Mb-LBP descriptor is stable under rotation/scaling/translation, since these transformations are filtered by the construction of the momentgram, while the distinctive patterns' information is captured through the LBP histograms of the momentgrams.

The paper is organized as follows: Section 2 describes the most popular moment families and the corresponding moment invariants. The basic theory of LBP operator is presented in Section 3, while the proposed local descriptor along with its definitional principles is discussed in Section 4. An extensive experimental study regarding the classification performance of the proposed descriptor, in comparison with the moments, moment invariants feature vectors, the conventional LBP and other popular descriptors, takes place in Section 5. Finally, the main conclusions are summarized and discussed in Section 6.

2. Moments and moment invariants

Image moments have attracted the attention of the engineering scientific community for several decades, as a powerful tool to describe the content of an image. They have been used in many research fields of the engineering life, such as pattern recognition [9,10], computer vision [11,12] and image processing [13,14] with significant results. The first introduction of image moments for classification purpose was performed by Hu [9], by introducing the concept of moment invariants for invariant pattern recognition applications. By using the geometrical, central and normalized image moments [13], Hu proposed seven measurements invariant to any translation, scaling and rotation transformation of the image be processed, called *moment invariants*. Since then, many attempts to develop improved moment invariants with superior classification performance have taken place lately [15,16].

Recently, the scientists have developed the orthogonal moments and moment invariants, which use as kernel functions polynomials that constitute orthogonal basis and therefore they present minimum information redundancy, meaning that different moment orders describe different image part. Such moment families are the Legendre [13], Zernike and Pseudo-Zernike [17], Fourier-Mellin [18], Tchebichef [19], Krawtchouk [20] moments. These moments can be used as image descriptors after an appropriate normalization procedure in order to achieve translation, scale and rotation invariances.

In the next sections the most representative moment families are described and their invariants are derived. The extracted moment features will be used to construct the proposed Mb-LBP descriptors for the case of each moment family.

2.1. Moments

The general computational form of a $(n+m)$th order moment of a *NxM* image having intensity function $f(x,y)$, is defined as follows

$$M_{nm} = NF \times \sum_{i=1}^{N} \sum_{j=1}^{M} Kernel_{nm}(x_i,y_j) \times f(x_i,y_j) \tag{1}$$

where $Kernel_{nm}()$ corresponds to the moment's kernel consisting of specific polynomials [21] of orders n and m, which constitute the orthogonal basis and NF is a normalization factor (in the case of geometric moments the kernel has the form of a monomial). The type of Kernel's polynomial gives the name to the moment family by resulting to a wide range of moment types. In the following Table 1, the main characteristics of the most representative moment families, the *Geometric Moments (GMs), Zernike Moments (ZMs), Legendre Moments (LMs), Tchebichef Moments (TMs) and Krawtchouk Moments (KMs),* are summarized.

Once a finite number of moments up to a specific order $n_{\max}$ is computed, the original image can be reconstructed by applying a simple formula, inverse to Eq. (1), defined as:

$$\hat{f}(x,y) = \sum_{n=0}^{n_{\max}} \sum_{m=0}^{n} Kernel_{nm}(x,y) \times M_{nm} \tag{2}$$

In theory, if one computes all image moments and uses them in Eq. (2), the reconstructed image is identical to the original one with minimum reconstruction error.

2.2. Moment invariants

Apart from the ability of the moments to describe the content of an image in a statistical fashion and to reconstruct it (orthogonal moments) perfectly according to Eq. (2), they can also be used to distinguish a set of patterns belonging to different categories (classes). This property makes them suitable for many artificial intelligence applications such as biometrics, visual inspection or surveillance, quality control, robotic vision and guidance, biomedical diagnosis, mechanical fault diagnosis, etc. However, in order to use the moments to classify visual objects, they have to ensure high recognition rates for all possible object's orientations.

Mainly, there are two methodologies used to ensure the invariance under common geometric transformations (rotation, scaling and translation) either by image coordinates normalization and description through the geometric moment invariants [13,22] or by developing new computation formulas which incorporate these useful properties inherently [22]. The former strategy is applied next for deriving the moment invariants of each moment family, since it can be applied in each moment family in the same way.

Initially, by applying coordinates normalization [23], the GMs of Eq. (1) are transformed to invariant quantities called Geometric