Image Data Restoration for Prominent Point's Resolution

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Abstract: In this paper we present a procedure for prominent point's resolution based on color prominence. Prominent points are locations in an image where there is a significant variation with respect to a chosen image feature. Since the set of prominent points in an image capture important local characteristics of that image, they can form the basis of a good image representation. Prominent features are generally determined from the local differential structure of images. They focus on the shape prominence of the local neighborhood. Most of these detectors are brightness based which have the problematic condition that the distinguishing feature of the local color information is completely ignored in determining prominent image features. To fully take advantage of the possibilities of prominent point detection in color images, color distinguishing feature should be taken into account in addition to shape distinguishing feature. The color and texture information around these points of interest serve as the local descriptors of the image. In addition, the shape information is captured in terms of edge images computed using Gradient vector flow fields. Constant moments are then used to record the shape features. The combination of the local color, texture and the global shape features provides a strong feature set for image restoration. The experimental results exhibit the efficacy of the procedure.
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1. Introduction

Prominent point's resolution is a technique used for extracting similar images from an image database. The most challenging aspect of this procedure, bridges the gap between low-level feature layout and high-level semantic concepts. In this procedure, applications, the user typically provides an image (or a set of images) with no mark of which portion of the image is of interest. Thus a search in classical model of this procedure often relies upon a global view of the image. Confined to a particular place of THIS PROCEDURE, has been defined as a task where the user is only interested in a portion of the image and the rest is impertinent. [1, 2].

To capture the local characteristics of an image, many of these systems either divide the image into fixed blocks [3, 4], or more commonly partition the image into different meaningful regions by applying a segmentation algorithm [2, 3, 4]. In both the cases, each region of the image is represented as a feature vector of feature values extracted from the region. Other systems extract prominent points (also known as interest points) [10], which are locations in an image where there is a significant variation with respect to a chosen image feature. With prominent point procedures, there is one feature vector created for each prominent point. These representations enable a restoration procedure, to have a representation of different local regions of the image, and thus these images can be searched based on their local characteristics.

Usually the performance of a segmentation based procedure depends highly on the quality of the segmentation. Especially, a segmentation based representation usually measures features on a per-segment basis, and the average features of all pixels in a segment are often used as the features of that segment [3, 4]. Therefore, this representation requires high quality segmentations because small areas of incorrect segmentation might make the representation very different from that of the real object. Moreover, the incorrect segmentation also impedes the shape analysis process. The object shape has to be handled in an integral way in order to be close to human intuition. Shape has been extensively used for restoration systems [8, 9].

The prominent point procedure, s for restoration assign features to a prominent point based on the image features of all the pixels in a window around the prominent point. Traditionally prominent point detectors for this procedure, often use the brightness component of the image for prominent point computation, and thus, ignore the color information. The problematic condition of this procedure is that the prominent points often gather at textured portions of the image or on the edges where the change of intensity is significant, so that many prominent points capture the same portion of the image. This inspired us to develop a technique for image restoration that uses color distinguishing feature in determining the prominent points and also that uses shape features in terms of the object edges. Different sized windows are used to capture the texture and color information around the prominent points. Gradient vector flow fields are used to compute the edge image, which will capture the object shape information. GRADIENT VECTOR FLOW fields give excellent results in determining the object boundaries irrespective of the concavities involved. Constant moments are used to serve as shape features. The combination of these features forms a strong feature set in retrieving applications. The experimental results are compared with those in [7, 8].

2. Proposed Procedure

The efficiency of prominent point detection depends on the distinguishing feature of the extracted prominent points. At the prominent points' positions, local neighborhoods are extracted and described by local image descriptors. The distinguishing feature of the descriptor defines the succinctness of the representation and the uniqueness power of the prominent points. The distinguishing feature of points of interest is measured by its information content. Most prominent point detectors focus on two dimensional structures, such as corners, which are stable and distinctive at the same time. Color is also considered to play an important role in attributing image prominence. In our approach, the color prominence is based on the work reported in [6]. To achieve the color prominence, the color axes are rotated followed by a rescaling of the axis and, the oriented oval-shaped figure are transformed into domain. Thus, the vectors of equal prominence are transformed into vectors of equal length. The Harris detector detects points based on black and white events, while the proposed procedure, uses color prominence to detect the events. It can be seen from the results that the Harris detector detects prominent points that typically cluster around textured areas, while the proposed procedure, and spreads them according to color prominence. In our experiments we have considered 40 prominent points. The texture features were captured in a window of size 9 x 9 around every prominent point and the color features in a window of size 9 x 9 around each prominent point. Active contours are used extensively in computer vision and image processing applications, particularly to locate object boundaries. Problems associated with their poor convergence to boundary concavities, however, have limited their utility. Gradient vector flow is a static external force extensively used in active contour procedure; gradient vector flow is computed as a diffusion of the gradient vectors of a grey-level or binary edge map derived from the images.

The gradient vector flow uses a force balance condition given by

$$F_{\text{int}} + F_{ext}^{(p)} = 0$$

where F_{int} is the internal force and $F_{ext}^{(p)}$ is the external force.

The external force field $F_{ext}^{(p)} = V(x, y)$ is referred to as the gradient vector flow field. The gradient vector flow field $V(x, y)$ is a vector field given by $V(x, y) = \left[u(x, y), v(x, y)\right]$ that minimizes the energy functional

$$\varepsilon = \iint \mu\left(u_x^2 + u_y^2 + v_x^2 + u_y^2\right) + \left|\nabla f\right|^2 \left|V - \nabla f\right|^2 dxdy$$

This variation formulation follows a standard tenet that of making the results smooth when there is no data. In particular, when $\left|\nabla f\right|$ is small, the energy is dominated by the sum of squares of the partial derivatives of the vector field, yielding a slowly varying field. On the other hand, when $\left|\nabla f\right|$ is large, the second term dominates the integrand, and is minimized by setting $V = \left|\nabla f\right|$. This produces the desired effect of keeping V nearly equal to the gradient of the edge map when it is large, but forcing the field to be slowly-varying in homogeneous regions. The parameter μ is a regularization parameter governing the tradeoff between the first term and the second term in the integrand.

For our purpose Gabor filter responses are used as texture features. 6 orientations and 4 scales are considered for this purpose [7]. A window of size 9 x 9 around every prominent point is considered to capture the local texture features. First and second order statistical moments of the 48 filter responses. The responses were normalized over the entire image database. The first and second order statistical moments of the color bands, a and b, in the CIE-Lab color space of the image, are computed around every prominent point within a window of size 9×9, as color features. A total of 64 features are computed for each prominent point. A total of 40 prominent points are considered. Going beyond 40 prominent points, did not yield considerable improvement in restoration result worth the computational overheads involved.

The overall similarity distance D_j for the j th image in the database is obtained by linearly combining the similarity distance of each individual feature:

$$d_j = \sum w_i s_j(f_i)$$

with $S_j(f_i) = (x_i - q_i)T(x_i - q_i)$, $j = 1, \cdots, N$ and $i = 1, \cdots, M$, where N is the total number of images in the database and M the total number of color and texture features. The low level feature weights w_i for color and texture are set to be equal.

Shape: Translation, rotation, and scale constant one-dimensional normalized contour sequence moments are computed on the edge image [15]. The gray level edge images of the R, G and B individual planes are taken and the shape descriptors are computed as follows:

$$F_1 = \frac{(\mu_2)^{\frac{1}{2}}}{m_1}, \quad F_2 = \frac{\mu_3}{(\mu_2)^{\frac{3}{2}}}, \quad F_3 = \frac{\mu_4}{(\mu_2)^2}, \quad F_4 = \bar{\mu}_5$$

Where

$$m_r = \frac{1}{N}\sum_{i=1}^{N}[z(i)]^r, \quad \mu_r = \frac{1}{N}\sum_{i=1}^{N}[z(i) - m_1]^r,$$

$$\bar{\mu}_r = \frac{\mu_r}{(\mu_2)^{\frac{r}{2}}}$$

And $z(i)$ is set of Euclidian distances between centred and all N boundary pixels.

A total of 12 features result from the above computations. In addition, moment constant to translation, rotation and scale is computed on R, G and B planes individually considering all the pixels [15]. The transformations are summarized as below:

$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}$ where $\gamma = \frac{p+q}{2} + 1$ (Central moments) $\phi = \eta_{20} + \eta_{02}$, (Moment constant).

The above computations will yield an additional 3 features amounting to a total of 15 features.

Canberra distance measure is used for similarity comparison in all the cases. It allows the feature set to be in unnormalized form and is given by:

$$CanbDist(x, y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|}$$

where x and y are the feature vectors of database and query image, respectively, of dimension d. The distance between two images is computed as $D = D_1 + D_2$ where D_1 is the distance computed using color and texture information around the prominent points and D_2 is the distance resulting from shape comparison.

3. Experimental Results

The results are produced with standard systems namely, using the same database as in [3, 4]. The quantitative measure defined is average precision as explained below:

$$p(i) = \frac{1}{100} \sum_{1 \le j \le 1000, r(i,j) \le 100, ID(j) = ID(i)} 1$$

Where $p(i)$ is precision of query image i, $ID(i)$ and $ID(j)$ are category ID of image i and j respectively, which are in the range of 1 to 10. The $r(i,j)$ is the rank of image j (i.e. position of image j in the retrieved images for query image i, an integer between 1 and 1000). This value is the percentile of images belonging to the category of image i in the first 100 retrieved images.

The average precision pt for category t ($1 \le t \le 10$) is given by

$$p_t = \frac{1}{100} \sum_{1 \le i \le 1000, IID(i) = t} p(i)$$

Table 1. Comparison of average precision obtained by proposed procedure, with other standard restoration systems

Class	Simplicity [4]	Proposed Procedure	
		With prominent points detected by Harris Corner Detector	With color prominent points
Asia	0.58	0.48	0.49
Beaches	0.30	0.34	0.37
Tower	0.45	0.39	0.39
car	0.36	0.47	0.52
lion	0.85	0.92	0.93
Rooster	0.38	0.32	0.41
Flower	0.52	0.58	0.62
Horses	0.62	0.68	0.73
lake	0.31	0.32	0.33

The results are illustrated in Table 1. The results of restoration obtained using the Harris corner detector is also provided for the sake of comparison. In most of the categories our proposed procedure, has performed better than other systems. The results are considerably improved by considering color prominence in prominent point detection as compared to grey scale prominent points detected by Harris corner detector.

4. Conclusion

In this article, we have proposed a novel procedure, for image restoration using color, texture and shape features. Prominent points based on color prominence are computed on the images. Texture and color features are extracted from fixed sized windows around these prominent points to serve as local descriptors. Gradient vector flow fields are used to extract edge images of objects. The results are considerably improved by considering color prominence in prominent point detection as compared to grey scale prominent points detected by others detectors. Constant moments are used to describe the shape features. A combination of these local color, texture and global shape features provides a strong set of features for image restoration. The experiments exhibit the efficacy of this procedure.

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