A scale invariant detector based on local energy model for matching images

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ABSTRACT

Finding correspondent feature points represents a challenge for many decades and has involved a lot of preoccupation in computer vision. In this paper we introduce a new method for matching images. Our detection algorithm is based on the local energy model, a concept that emulates human vision system. For true scale invariance we extend this detector using automatic scale selection principle. Thus, at every scale level we identify points where Fourier components of the image are maximally in phase and then we extract only feature points that maximize a normalized derivatives function through scale space. To find correspondent points a new method based on the Normalized Sum of Squared Differences (NSSD) is introduced. NSSD is a classical matching measure but is limited to only the small baseline case. Our descriptor is adapted to characteristic scale and also is rotation invariant. Finally, experimental results demonstrate that our algorithm is reliable for significant modification of scale, rotation and variation of image illumination.

Keywords: feature, local energy, phase congruency, detector, invariant, scale space, descriptor.

1. INTRODUCTION

Analyzing a scene, as human beings, our view is focused more on certain points. Human vision is a selective process and some points attract more attention than the others. In computer vision these points are referred as interest or feature points. Many applications like stereo matching, motion tracking, 3D reconstruction and camera calibration rely on the correct feature detection and their results are influenced directly by the accuracy of this operation. Until now a wide variety of image feature detectors have been developed being addressed under different names: corner, interest point, keypoint, 2D feature, junction. In general all these terms describe points that have significant change of the signal in at least two directions.

Apparently, the most representative basic detector was introduced by Harris [Har88a]. This detector use an autocorrelation matrix and Gaussian kernel to weight derivatives inside a considered window. Despite of its well known potency Harris detector has a series of disadvantages. One important drawback of the Harris detector is its variation to image contrast (aperture of the camera). When the sequence of images is large and the illumination conditions vary, setting up the threshold can be very difficult. Another problem of this operator is caused by the Gaussian smoothing which represents an important part of its mechanism. Blurring operation that, mainly performed to eliminate image noise, can easily corrupt useful locations and therefore some potential feature points are completely lost.

As was shown in [Kov03a] a trustworthy alternative for intensity based detectors is the local energy model. This important class of detectors, introduced firstly in [Mor87a], is inspired by the human neurophysiological mechanism and filters merely points with considerable phase congruency of image Fourier components. In other words, extracted key points are only those points where important congruency of the phase signal occurs.

Even though the reported results were incentive, this detector fails for important modification of image scale.

The principal contribution of this paper is a new scale invariant detector based on the local energy model. Invariance property of detectors is essential in computer vision applications like images matching. For a correct matching an important number of detected feature points should be classified in inliers. Robust fitting methods, such as RANSAC or Least Median of Squares, perform poorly when the percent of inliers falls much below 50%.

In our approach, using results of [Koe84a] and [Lin98a] ,we explore images at large range of scales applying Gaussian smoothing that was proved to be the only optimal kernel for multi scale representation.

To validate our detector, the classical image matching application is considered. In order to identify correspondences from images, every feature point should be represented in a convenient way.

The second contribution of this paper is represented by the new matching method based on the Normalized Sum of Squared Differences (NSSD) which was used in general only as a matching measure for the small baseline case. For our problem, where important rotation and scale modification alter images, classical NSSD fails. We extended NSSD to scale space using characteristic scale properties. For rotation invariance a dominant orientation is assigned to every keypoint after a gradient orientation histogram is computed in its neighborhood.

Experimental results demonstrate that this new algorithm is reliable for matching images with significant modification of scale, rotation and variation of image illumination.

Related work: In the last decades a lot of research effort was focused to find more optimal detectors. One of the oldest detectors was proposed in [Bea78a]. His detector uses the Hessian matrix computed with Gaussian filter. Moravec [Mor77a] was the first one who used the intensity of the signal in processing the feature points and his detector is based on the autocorrelation function which measures the difference between a considered window and its shifted value in several directions. [Tom91a] was focused on tracking, considering that interest points are determined only by those points that has a significant magnitude of eigenvalues of the autocorrelation matrix. More recently in [Smi97a] was developed SUSAN detector that thresholds pixels in the neighborhood and computes ratio of areas.

As was presented before, important work was directed to emulate human vision mechanism for detecting special points in images. The local energy model was pioneered [Mor87a],[Mor88b],[Ven90a], [Rob97a],[Kov03a] and represents a reliable technique based on how physical stimuli are perceived by human minds. But all these operators can be seen as basic detectors and are not invariant to scale space.

Scale invariance was intensively studied by Lindeberg [Lin99b]. His automatic scale detection principle forms the base for the majority scale invariant detectors. Feature points are found searching for maxima in 3D scale space of normalized derivatives. Lindeberg used normalized Laplacian of Gaussian for blob detection. Lowe [Low04a] based his detection on multi resolution approach constructing a pyramidal 3D space using DoG where features are determined in local extrema. More recently [Mik04b] introduced the Harris Laplacian operator which has been proven to have excellent results. As its name disclosed, this operator is based on Harris detector used for 2D localization of features and then using the multi scale representation for extraction scale invariant feature points.

The new detector introduced in this paper is based also on the automatic scale selection principle but the main difference consists in using local energy model to find keypoints in scale space images.

Descriptors, seen also as filters, received a lot of attention in computer vision. A large variety of descriptors have been introduced till now. In [Ran99a] filters were compared in the context of texture classification. More recently local descriptor performances were analyzed in [Mik03a]. But the best known one was introduced in [Low04a]. In the last years a lot of work was directed to improve SIFT descriptor. For our problem we adapt NSSD to scale space and in order to have rotation invariance we use a similar approach like in [Thu96a] and [Low04a], assigning a prominent orientation to every keypoint.

Overview. This paper is organized as follows. In Sections 2 and 3 we briefly review local energy model and scale space theory. Implementation of our scale invariant detector is presented in Section 4. Section 5 shows how we use NSSD for filtering feature points and finally experimental results and conclusions are given in Section 6 and 7.

2. LOCAL ENERGY MODEL

Local energy model was introduced in by Morrone [Mor87a]. His operator searched points where maximal phase congruency is reached and observed that these locations present a kind of “order”. A common method for computing local energy is to convolve image with a quadrature pair of filters in the spatial domain. The quadrature pair of filters is composed of one even and one odd-symmetric filter that have zero mean and identical norms and are orthogonal. A general expression of local energy is:

$$LocalEnergy(x) = \sqrt{O_{even}^2(x) + O_{odd}^2(x)} \qquad (1)$$

Where O_{even} and O_{odd} are the image convolved with an even-symmetric filter and with an odd-symmetric filter for a considered point, respectively.

Extension of local energy expression for images is almost straightforward. It necessitates a separate computation for two different directions. Finally, the results are combined in order to express 2D local energy. Following previous steps, points with significant locally maximal variation in at least one orientation are identified. To detect reliably image feature points computation of oriented energy is necessary. This can be imagined as a total energy which takes into consideration several values of local energy computed in different direction:

$$TotalEnergy(x) = \sum_{i=1}^{n} \sqrt{O_{i,odd}^2(x) + O_{i,even}^2(x)} \qquad (2)$$

Using this expression the results are satisfactory but due to the fact that local energy is a dimensional quantity that depends on the image contrast, setting of the threshold to find the proportion of the energy that corresponds to a feature can become a difficult task.

An alternative is to substitute local energy expression by the phase congruency information of the signal. The proportionality between phase congruency and local energy of a signal was proven in [Ven90a]. Therefore, a local maximum of local energy corresponds to a local maximum of phase congruency:

$$PC(x) = \frac{|E(x)|}{\sum_n A_n(x)} \qquad (3)$$

where E is the energy and A_n represents the amplitude of the n^{th} Fourier component. In contrast with local energy, phase congruency is a dimensionless measure that has values between 0 and 1. The lower is the computed value of the phase congruency for a selected point, the higher is the potential of that location to be treated as an interest point. In consequence, points with values of phase congruency close to 1 are classified as ordinary points and points with values of phase congruency close to 0 are filtered as keypoints.

Recently in [Kov03a] was introduced an improved extension of equation (3) that provides better localization of features and also reduces the sensitivity to noise. Our approach of identifying feature points in every image scale is inspired by his expression:

$$PC(x) = \frac{\sum_n W(x)[A_n(x)(\cos\phi_n(x) - |\sin(\phi_n(x))|)] - T]}{\sum_n A_n(x) + \varepsilon} \qquad (4)$$

$W(x)$ is a frequency weight factor (as significant as many frequency congruency are recorded), ε represents a small constant that avoids division by zero and ϕ is the phase angle.

a.

b.

c.

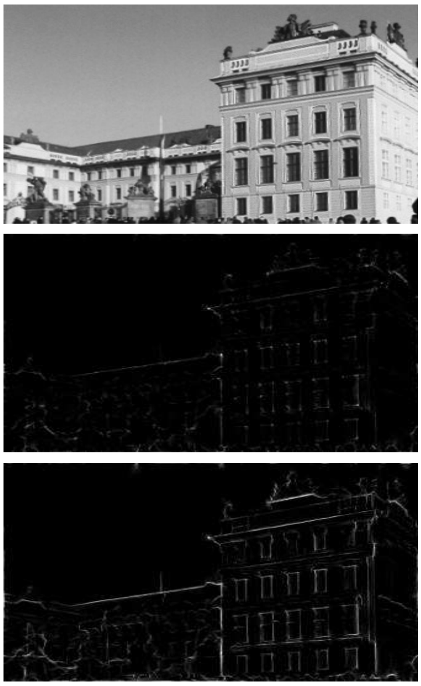

Figure 1. a. initial image b. minimum moment c. maximum moment.

Only the energy values that exceed threshold T, the estimated noise influence, are counted in the final result. In practice the computation of local frequency values is not performed with Fourier transformation but is preferred to be used banks of Gabor wavelets tuned to different spatial frequency. To extract feature points the covariance matrix of phase congruency is computed. Next, performing the singular value decomposition the eigenvalues are extracted. When both of the eigenvalues are larger than a threshold, a point is classified as a keypoint.

The eigenvalues of the covariance matrix corresponds to the minimum and maximum moments computed using the classical moment analysis equation. Interest points are considered only if the magnitude of the minimum moment is larger. Expressing local energy in this way has also an attractive characteristic: from the same expression can be extracted feature points and edges, embedded by the eigenvalues of the phase congruency covariance matrix (see Fig.1).

3. SCALE SPACE

The concept of scale space was introduced in [Lin98a]. Real world objects appear in different ways depending of the selected observation scale. Scale space representation is defined as a solution to the diffusion equation which is equivalent with the convolution of the signal with Gaussian kernel:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (5)$$

The symbol * represents the convolution operator for x and y directions and $G(x,y,\sigma)$ is the Gaussian kernel with σ standard deviation. In the previous work of [Koe84a] [Bab86a] [Lin99b] was proved that under a variety of reasonable assumptions Gaussian is the unique kernel for generating a scale-space. This uniqueness of the Gaussian kernel is emphasized also by the neurophysiologic studies in [You87a] that have shown that mammalian retina and visual cortex present sensitive fields of which the response can be properly modeled by Gaussian derivatives up to order four.

Different levels of resolution of scale space are obtained by convolving the initial image with Gaussian kernels that has different values of the standard deviation. Features are extracted by applying combinations of derivative functions at different scales. A similar method is to use a pyramidal representation of space, where the 3D space is composed by a set of successively smoothed and sub-sampled representation of the original image. This can be performed using difference of Gaussian (DoG) which is a close approximation of Laplacian of Gaussian (LoG). The main difference between these methods is the first one (after smoothing operations) maintains the same number of grid points at all scale levels, while the second one reduces the number of grid points at every next level by subsampling.

One important feature of the spatial derivatives is their amplitude values in general decrease with scale. This can be intuitively understood because the smoothing operation can only decrease the value of the processed signal. This behavior is known as the non-enhancement property of local extrema, which states that values of local maxima cannot increase and respective values of local minima cannot decrease. Therefore, the amplitude values of the signals always decrease with scale. In order to maintain the scale invariance derivative functions are normalized with respect to scale:

$$D_{(m)}(x, \sigma) = \sigma^m L_{(m)}(x, \sigma) = \sigma^m G_{(m)}(\sigma) * I(x) \quad (6)$$

where $L_{(m)}$ and $G_{(m)}$ represent the m^{th} order derivative of the blurred image level L and Gaussian kernel G.

Automatic scale selection principle is built on the relation between images at different resolution levels. Its applicability is extremely important due to the fact that in general, images contain sharp and diffuse features and is almost impossible to identify all kinds of features at the same scale level. Lindeberg [Lin98a] postulates that in absence of other evidence, the selected scale (characteristic scale) is the scale where a function of some combination of normalized derivatives attains a local maximum. The idea behind characteristic scale is borrowed from physics and estimates the characteristic length of corresponding image structures. The characteristic scale is independent of the image scale and the ratio between selected scales of two extrema that represent the same image feature is the same as the ratio between image scales.

4. INVARIANT SCALE DETECTOR

Even if the local energy model based detector proved good results it is not scale invariant. For ratio scales larger than 1.5 this detector cannot be reliable anymore in application like feature matching or object recognition where repeatability rate should be greater than 50%. In order to achieve scale invariance in this paper images are represented at different scales. Our detector is based on the local energy model extended to scale space using the automatic scale selection principle. Combining these two concepts, features are searched in 3D space created by the local energy computed at every resolution level.

The scale space is constructed by successively blurring initial images with a Gaussian kernel with a standard deviation that increase exponentially. After scale space is built our detection algorithm consists of two main steps.

First, using expression (4) at each scale level, locations where the energy has a local maximum are identified and eigenvalues of the phase congruency covariance matrix are computed. As was presented in Section 2, keypoints are localized where the magnitude of the minimum moment is larger. To extract interest points a non maximal suppression of the minimum moment is performed. Due to the fact that standard non maximal suppression can cluster features a better solution is to use adaptive non maxima suppression [Bro05a] which has the advantage to distribute more uniformly detected points.

In the second stage every candidate feature point is verified. Based to the automatic scale selection principle the normalized derivatives are computed at every scale level and the keypoints are identified only in the locations where a maximum over scales is attained. In order to identify which normalized derivative expressions give best results, we have analyzed several combinations of derivatives. Theoretically can be used derivatives till the 4th order. In our experiments we analyzed only the derivative till 2nd order (see Fig. 2).

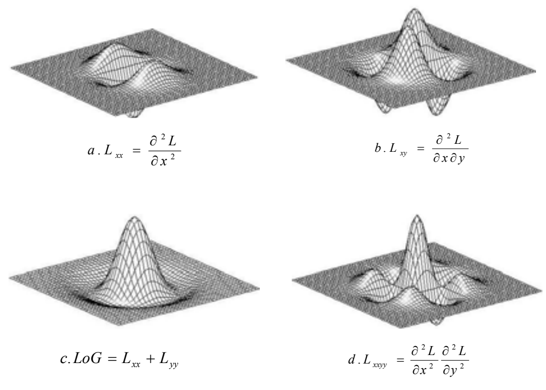

Figure 2. Derivative of Gaussian kernels.

Similar with results reported in [Mik04b] our detector gave best results for Laplacian of Gaussian (LoG) expression which has previously been used for blob feature extraction in [Lin98a] and approximated as DoG in [Low04a] to detect keypoints. To conclude, our detection algorithm can be resumed in three main steps:

1. For a given image, successive levels of resolution are computed. Each k resolution level I_k of image is obtained by smoothing the original image with a Gaussian kernel with a standard deviation (σ) increasing monotonically over the scales ($\sigma_k = \sigma_0^k$). The ratio of sigma between successive scales is considered to be in the range (1.1 to 1.4). Our experimental results were obtained considering a value of the standard deviation of 1.15 with 15 levels of the scale space and σ_0=1.25.
2. Each level is searched for locations that attain a local maximum. Adaptive non maxima suppression of minimum moment of the phase congruency correlation matrix is used for filtering the feature points.
3. Iteratively every candidate point is verified and are withhold only those points that reach a local maximum of the normalized LoG over the scale space.

5. THE NSSD BASED MATCHING

Feature matching problem is a classical problem in computer vision. Even if this task is straightforward for humans, machines still have problems when substantially change of viewing conditions like scale, rotation, variation of illumination degrade the initial information. A correct matching between images corresponds to a reliable extraction of the epipolar geometry, one of the basic steps in 3D reconstruction. A sufficient amount of correspondences between detected keypoints is necessary but still does not need to be perfect since robust estimation algorithms of the geometric transformation between images such RANdom SAmple Consensus will reject eventually mismatches.

In this paper, to identify correspondent detected feature points a new matching method is introduced which can be seen as an extension of the Sum of Squared Differences Normalized (NSSD). This is a classical measure to determine putative correspondences for small baseline images. For our case we introduce an improved version of this measure. Considering two images I_1 and I_2 and the correlation windows W_1 and W_2 of dimension $(2r+1)$x$(2r+1)$ centered on two points p_1 and p_2 the NSSD expression is:

$$NSSD(p_1, p_2) = \frac{\sum_{-r}^{r}\sum_{-r}^{r}\left[(W_1 - \bar{W}_1) - (W_2 - \bar{W}_2)\right]^2}{\sqrt{\sum_{-r}^{r}\sum_{-r}^{r}(W_1 - \bar{W}_1)^2}\sqrt{\sum_{-r}^{r}\sum_{-r}^{r}(W_2 - \bar{W}_2)^2}} \quad (7)$$

with $\bar{W}_1$ and $\bar{W}_2$ represent the means of the selected windows.

We adapt NSSD expression to scale space using the characteristic scale extracted from every detected feature point. Thus, the size of windows W_1 and W_2 should be proportional with the characteristic scale of considered points, having dimensions $(2r_1+1)$x$(2r_1+1)$ and $(2r_2+1)$x$(2r_2+1)$ respectively; where the radiuses r_1 and r_2 should be proportional with the characteristic scales s_1 and s_2 and also with image dimension(e.g. 1.5% of image size). Without losing generality presuming that $r_1 < r_2$ for computing NSSD we need to interpolate values of W_2 to dimension of the window W_1. As is expected, correct results are obtained only if the ratio of image scales and the ratio between characteristic scales of considered feature points are approximately equal.

The next step is to solve the rotation problem. This part of our approach is inspired by [Thu96a] and was also used with success in [Low04a]. In order to determine a prominent orientation for every keypoint the gradient magnitude and orientation is precomputed at every level of scale using pixel differences. Let δ_x and δ_y be the finite differences across x and y directions for a considered pixel.

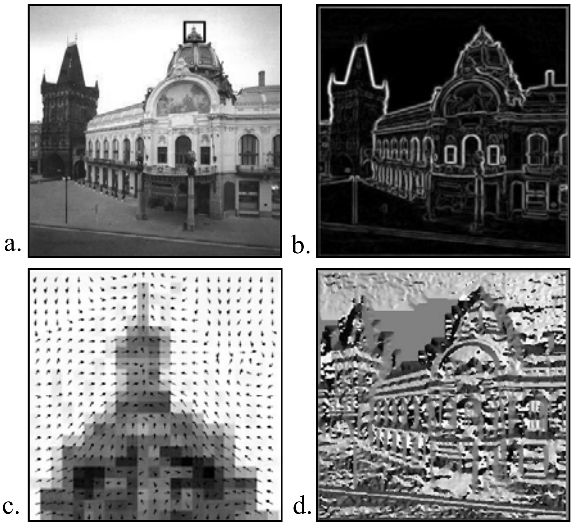

Figure 3. Orientation computed using pixels differences; a. initial image with selected window; b. magnitude image; c. pixel orientation for considered window; d. image with dominant orientation.

The magnitude *m* and orientation φ can be calculated using the following expressions:

$$m(x,y) = \sqrt{\delta_x(x,y)^2 + \delta_y(x,y)^2} \qquad (8)$$

$$\varphi(x,y) = \arctan\left(\frac{\delta_y(x,y)}{\delta_x(x,y)}\right) \qquad (9)$$

The gradient orientation histogram is computed in the neighborhood of every keypoint (see Fig. 3). In our experiments, the histogram is composed by 36 bins with every bin covering a 10 degree range of orientations.

The number of bins represents a tradeoff between computation time and accuracy of the final results. The contribution of each neighbor pixel is weighed by the gradient magnitude and a Gaussian window with σ that is 1.5 times of the respective characteristic scale. Dominant orientation of keypoints is determined by the highest peak of the histogram.

In summary, extracted feature points are described by their centered window proportional with their characteristic scale and rotated according to the computed dominant orientation.

6. RESULTS AND DISCUSSION

Evaluation of our detector is done using the repeatability criterion that was introduced in [Sch00a]. This criterion takes into account locations as well as detected scales of points. The score of repeatability for a pair of images represents the ratio between the number of point-to-point correspondences and the minimum number of points detected in images. Note that only points located in the scene part visible in both of the images are considered. To measure the repeatability rate a unique relation between points from two images has to be known. In this paper we limit the analysis only to planar scenes. Supposing that x_1 and x_2 represent the projected points of a 3D space point the relation between them is given by the homography expression:

$$x_2 = H_{12}x_1 \qquad (10)$$

Whether the homography matrix is known the criterion identifies corresponding points if the error of the relative locations is less than 1.5 pixels and the error in the image surface covered by the neighborhoods is less than 40%.

We compare our detector with some representative scale invariant detectors and also with standard local energy detector. Our detector gives very good results (see Fig.4) having a better repeatability value than DoG(SIFT) operator and similar values like Harris Laplacian detector. Due to the fact that a reliable detector should have a repeatability score greater than 50% our operator can be considered creditable approximately till a scale ratio of 3. As expected basic local energy detector is not invariant to scale and thus it can not be used in applications where important variation of scale occurs.

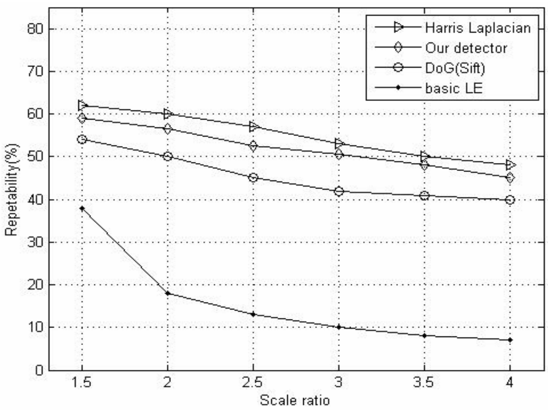

Figure 4. Comparative repeatability scores for considered detectors.

We validate our method by considering the feature matching application is considered in the following. Therefore, several images and obtained results are shown in the next figures.

The first pair of images presented in this paper is taken from INRIA data base. Beside of the scale and rotation (see Fig. 5) a small view angle difference altered images. For this example 53 corresponding feature points were found using our algorithm. Even if visually more points seem to be correct assigned, after applying RANSAC, only 32 correct corresponding features remain.

a.

b.

Figure 5. a. initial corresponding points ; b. correspondences after applying RANSAC.

Next, another set of images with obtained results is illustrated (see Fig. 6). These images were processed synthetically having a scale ratio of 2 and different levels of contrast. As can be observed even if the image foreground contains structures that are repeated (tables, chairs and umbrellas), corresponding feature points are correct identified. For the first pair (+30 units difference of contrast level) 54 correspondent points are identified. If the contrast is increased (+50 units difference of contrast level) 31 matches are filtered in the final.

During our experiments the new detector combined with extended NSSD based matching method gave very promising results when important modification of scale, rotation and illumination affect images. Neither the less important, our method gives correct results if small affine transformation between images is presented.

7. CONCLUSIONS

In this paper a new algorithm for matching images was presented. Our detection of invariant feature points is based on local energy model extended to scale space. Because both of the used principles are based on human neurophysiological mechanism we deem that our detector filters information in a similar way as human vision system perceives reality. The invariance to the scale of our detector was demonstrated by means of the image matching application where correspondences were filtered using NSSD measure adapted to scale and rotation invariant.

Experimental results prove that local energy model can be extended to scale space and based on registered repeatability score our detector can be used in applications where important scale ratio between images occurs.

In future work increasing computation efficiency and more precise feature point localization represent important challenges. Also, extension of our detector in context of the affine transformation will be considered.

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a. b.

Figure 6. Pair of images with scale ratio of 2 and different levels of contrast(a. +30 units difference of contrast level; b. +50 units difference of contrast level).

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