Periodic Textures as Distinguished Regions for Wide-Baseline Stereo Correspondence

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Abstract— **This paper addresses the problem of establishing correspondences for wide-baseline stereo, when two images are taken from significantly different viewpoints. Most of the existing approaches avoid using textures for matching as repetitive patterns tend to produce multiple peaks of correlation, which may lead to an ambiguity. We demonstrate that the presence of periodic textures can facilitate wide-baseline matching. The concept of a distinguished region is introduced and discussed. Dominant periodic patterns are used as distinguished regions whose affine-invariant descriptors, regularity feature vectors, are computed to identify regions in a wide-baseline stereo pair. Test results with various images are shown and discussed.**

Keywords— **Wide-baseline stereo, correspondence, periodic textures, invariant features.**

I. Introduction

FINDING correspondences in a set of images of a scene is a fundamental task of computer vision. This task is a basic pattern recognition problem whose successful solution makes more sophisticated problems tractable. In particular, reliable matching is critical for fully automatic reconstruction of 3D scenes from two images taken from arbitrary viewpoints with possibly different cameras and in varying illumination conditions. Such reconstruction is often called **wide-baseline stereo**.

In this paper, we address the problem of region selection for efficient wide-baseline stereo matching. The choice of elements whose correspondence is sought is of primary importance, since in the wide-baseline case, local image deformations cannot be approximated by translation and rotation; an affine model is much more adequate. Photometric variations, shadows and self-occlusion make finding the correspondences even more difficult. Regions selected for matching should therefore possess some distinguishing, highly invariant and stable property. We call such structures **distinguished regions**, abbreviated as DRs.

The main contribution of this paper is the proposal of a new type of distinguished regions based on dominant periodic structures, or regular textures. Most of the existing methods avoid using texture as a tool for matching, since repetitive patterns tend to correlate in multiple positions, which may result in an ambiguity. We argue that the presence of periodic textures can facilitate wide-baseline matching by providing the **periodicity distinguished regions** (PDRs) that efficiently constrain the search for correspondences. Regularity features are proposed as affine-invariant descriptors to identify the PDRs in a wide-baseline stereo pair. Precise correspondences based on local features can then be established within the PDRs.

Our study mainly deals with the texture aspects of the problem. We do not intend to treat the complete chain of 3D scene reconstruction from multiple views. A framework wide-baseline stereo algorithm is only outlined. The paper focuses on the distinguished regions, including finding PDRs and establishing the correspondences of PDRs. Other steps, such as matching local features within the regions or building the epipolar geometry, are discussed briefly.

The paper is organised as follows. In section II, we introduce the concept of a distinguished region and give an overview of related previous work. Section III outlines the process of wide-baseline stereo from distinguished regions. Periodicity DRs and algorithms for their extraction and invariant matching are described in section IV. Test results are shown and discussed in section V.

II. Distinguished Regions

In this section, we present a formal definition of the DR concept and discuss some of its properties.

Definition 1: **Distinguished region**. Let image I be a mapping $I : \mathcal{D} \subset \mathbb{Z}^{\not\models} \to \mathcal{S}$. Let $\mathcal{P} \subset 2^{\mathcal{D}}$, i.e. $\mathcal{P}$ is a subset of the power set (set of all subsets) of $\mathcal{D}$. Let $\mathcal{A} \subset \mathcal{P} \times \mathcal{P}$ be an adjacency relation on $\mathcal{P}$ and let $f : \mathcal{P} \to \mathcal{T}$ be any function defined on $\mathcal{P}$ with a totally ordered range $\mathcal{T}$. A *region* $\mathcal{Q} \in \mathcal{P}$ *is distinguished* with respect to function f iff $f(\mathcal{Q}) > f(\mathcal{Q}'), \forall (\mathcal{Q}, \mathcal{Q}') \in \mathcal{A}$.

In order to be invariant to geometric transformations from a group G, the set $\mathcal{P}$ must be closed under action from G and the extremal property f must be preserved. Let us look at the definition informally. The first two statements define the concept of a region which in this work is simply defined as any subset of the image, not necessarily contiguous. When looking for a 'distinguishing' property, not all regions need to be considered. Instead, one could consider some set $\mathcal{P}$ of regions, e.g. one pixel regions or regions that are circular with a given diameter. The second part of the definition formally states that a distinguished regions is a local extremum of some property f. The adjacency relation $\mathcal{A}$ defines what is exactly meant by 'local'. The requirement on f to have a totally ordered range makes the comparison ($>$) of adjacent regions possible.

Invariance is a theoretical concept assuming typically local planarity and a continuous image domain and range. The practical value of a DR type given by stability w.r.t.

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viewpoint and illumination change must be established experimentally. If a local frame of reference is defined on a DR by a transformation-invariant construction (projective, affine, similarity invariant), a DR may be characterised by invariant measurements computed on any part of an image specified in the local (DR-centric) frame of reference. We use the term **measurement region** (MR) for this part of the image.

Related work. Since the influential paper by Schmid and Mohr [1] many image matching and wide-baseline stereo algorithms have used Harris interest points as distinguished regions. Tell and Carlsson [2] proposed a method where line segments connecting Harris interest points form measurement regions. The MRs are characterised by scale invariant Fourier coefficients. Harris interest detector is stable over a range of scales, but defines no scale or affine invariant measurement region. Baumberg [3] applied an iterative scheme originally proposed by Lindeberg and Garding to associate affine-invariant measurement regions with Harris interest points. In [4], Mikolajczyk and Schmid show that a scale-invariant MR can be found around Harris interest points.

In [5], Pritchett and Zisserman form groups of line segments and estimate local homographies using parallelograms as measurement regions. Tuytelaars and Van Gool introduced two new classes of affine-invariant distinguished regions, one based on local intensity extrema [6] the other using point and curve features [7]. In the latter approach, DRs are characterised by measurements from the inside an ellipse, constructed in an affine invariant manner. Lowe [8] describes the 'Scale Invariant Feature Transform' approach which produces a scale and orientation-invariant characterisation of interest points. In [9], Matas et al. proposed two new detectors of distinguished regions, one based on a watershed-like algorithm, the second selecting a specific type of loops in a graph constructed from an edge map.

Perhaps the first use of texture for wide-baseline stereo is described in the paper of Schaffalitzky and Zisserman [10]. Unlike all the above mention methods, no interest points are detected. Texture properties are used in geometric normalisation of local patches. Exploiting properties of the second moment matrix, effects of affine transformation are compensated up to a rotation. Interest points are then detected by the Harris corner detector which is invariant to rotation.

III. Correspondence from Distinguished Regions

So far we have focused on the selection of the elements to be put into correspondence (the DRs) and on the process of construction of measurement regions. Having two sets of DRs, how can the problem of epipolar geometry estimation by attacked? In problems of realistic size it is clearly impossible to perform a brute-force search for the best globally consistent epipolar geometry. Instead, algorithms described in the literature have adopted strategies with a similar structure whose core is summarised in the following four steps:

Algorithm 1: Wide-Baseline Stereo from Distinguished Regions - The Framework

1. Detect distinguished regions.
2. Describe DRs with invariants computed on measurement regions.
3. Identify DRs and establish tentative correspondences.
4. Estimate epipolar geometry in a hypothesise-verify loop.

Tentative Correspondences. At this stage, we have a set of DRs for each image and a potentially large number of invariant measurements associated with each DR. The most simple situation arises if a local affine frame is defined on the DR. Photometrically normalised pixel values from a normalised patch characterise the DR invariantly. More commonly, only a point or a point and a scale factor are known, and rotation invariants [1], [10] or affine invariants must be used [6]. Selecting mutually nearest pairs in Mahalanobis distance is the most common method [10], [6], [1]. Note that the objective of this stage is not to keep the maximum possible number of good correspondences, but rather to maximise the fraction of good correspondences. The fraction determines the speed of epipolar geometry estimation by the RANSAC procedure [11].

Epipolar Geometry estimation can be carried out by a robust statistical method, most commonly RANSAC. In RANSAC, randomly selected subsets of tentative correspondences instantiate an epipolar geometry model. The number of correspondences consistent with the model defines its quality. The hypothesise–verify loop is terminated when the likelihood of finding a better model falls below a predefined threshold.

IV. Periodic Distinguished Regions

In this section, we introduce the notion of periodic distinguished regions and present algorithms for their extraction and matching. PDRs are distinguished regions with respect to a measure of **periodicity**, or regularity. This measure, called the maximal regularity and denoted by M_R, will be described later in this section.

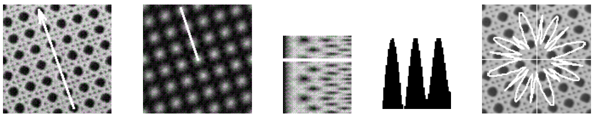
Definition 2: **Periodic distinguished region**. Assume a regularity value $M_R(m,n)$ has been assigned to each pixel of image $I(m,n)$. Let M_R^{thr} be a preset regularity threshold. A *periodic distinguished region* is as a maximal connected region with $M_R \geq M_R^{thr}$.

A method that computes regularity of a texture pattern is outlined below. The approach was introduced in paper [12], where more details are given.

A. Regularity Features

The regularity method quantifies pattern regularity by evaluating, in polar co-ordinates, the periodicity of the autocorrelation function. Consider an $N \times N$ pixel size digital image $I(m,n)$ and a spacing vector (d_x, d_y). Denote by $\rho_{xy}(d_x, d_y)$ the normalised autocorrelation of $I(m,n)$. We obtain ρ_{xy} via the FFT using the well-known relation between the correlation function and the Fourier transform.

The polar representation $\rho_{pol}(\alpha, d)$ is then computed on a polar grid (α_i, d_j) by interpolating $\rho_{xy}(d_x, d_y)$ in non-integer locations. The resulting matrix is denoted by $\rho_{pol}(i, j)$. The negated matrix is then used, referred to as the polar **interaction map**: $M_{pol}(i, j) = 1 - \rho_{pol}(i, j)$.



(a) (b) (c) (d) (e)

Fig. 1. Computing directional regularity $R(i)$. (a) A pattern and a direction within the pattern. (b) Autocorrelation function. (c) Polar interaction map. (d) Contrast function for the direction. (e) Polar plot of $R(i)$ overlaid on the pattern.

A row of $M_{pol}(i, j)$ is called a **contrast function**. A contrast function $F_i(j)$ shows the variation of contrast with spacing d_j along direction i. (See figure 1.) A periodic texture has contrast functions with deep and periodic minima. Our definition of regularity quantifies this property. For each direction i, the algorithm 2 considers the contrast function $F_i(j)$ and computes **directional regularity** $R(i)$. (For simplicity of notation, we omit the direction index i.)

Algorithm 2: Directional Regularity

1. Find relevant extrema of $F(j)$.
2. Calculate amplitudes of $F(j)$ by analysing the descending components of the maxima.
3. Select the largest amplitude $F_{max} - F_{min}$ and define the **intensity regularity** $R_{int} = 1 - F_{min}/F_{max}$.
4. Find positions j_1 and j_2 of the two lowest minima ($j_1 < j_2$) and define the **position regularity** as a measure of how close $2j_1$ is to j_2: $R_{pos} = 1 - |1 - 2j_1/j_2|$.
5. In a similar way, consider also the hypothesis that j_2 is the third rather than the second period.
6. Calculate the directional regularity $R = [R_{int} \cdot R_{pos}]^2$.

$R_{pos}(i)$ describes the periodicity of the layout of the elements comprising the pattern, while $R_{int}(i)$ indicates how regular (stable) the intensity of the elements is. Figure 1 shows an example of the directional regularity $R(i)$. Based on $R(i)$, three **regularity features** are computed by algorithm 3.

Algorithm 3: Regularity Features

1. Find local maxima of $R(i)$. Denote by T_k the sequence of the maxima values. (Positions of T_k within $R(i)$ do not matter.)
2. Select relevant maxima by thresholding T_k at $T_{thr} = 0.15$.
3. For the thresholded sequence, calculate the largest value M_R, the mean μ_R and the variance σ_R.

More features can be defined for other tasks. M_R is called the **maximal regularity**. $0 \le \mu_R \le M_R \le 1$, with 0 indicating a random, 1 a highly regular pattern. $M_R \ge 0.25$ means visually perceived periodicity. It has been shown [12] that the **regularity features are affine-invariant** under the assumption of the quasi-periodic shape of the contrast functions, and up to variations originating from the discrete nature of a digital image.

B. Detection and Matching of PDRs

The regularity feature vector is computed for a set of overlapping windows covering the image. This procedure is called **regularity filtering**. The window size W is determined by the period of the structures to be detected: the filter responds to a structure if at least four periods are observed. When implemented via the FFT, the maximum displacement of the autocorrelation is $W/2$ and $W = 2^k$. In practice, $W \ge 32$. The window shifts with a step $S_W \ge 1$. The algorithm 4 implements the regularity filtering. The operations described are performed in each position (m, n) of the window $\mathcal{W}$.

Algorithm 4: Regularity Filtering

1. Test the homogeneity of $\mathcal{W}(m, n)$.
2. If $\mathcal{W}(m, n)$ is homogeneous, compute regularity features $M_R(m, n)$, $\mu_R(m, n)$, $\sigma_R(m, n)$ by algorithm 3. Otherwise, discard $\mathcal{W}(m, n)$ by setting $M_R(m, n) = \mu_R(m, n) = \sigma_R(m, n) = 0$.
3. If $\mathcal{W}(m, n)$ is homogeneous, but $\sigma_R(m, n) = 0$, also set $M_R(m, n) = \mu_R(m, n) = 0$.

The **homogeneity test** aims at discarding non-textural windows for which the quasi-periodic model of contrast is not valid. The test splits $\mathcal{W}$ into 4 equal subwindows $\mathcal{W}_k$ and checks if the subwindows are statistically similar to $\mathcal{W}$. The statistics used are the mean and variance of the intensity and the mean and variance of the absolute intensity difference between a pixel and its four neighbours. A feature Q passes the test if $|Q_{\mathcal{W}} - Q_k|/Q_{\mathcal{W}} \le T_{inh}$ for all k. $Q_{\mathcal{W}}$ is the feature computed for the entire $\mathcal{W}$. T_{inh} is the inhomogeneity limit; typically, $0.1 \le T_{inh} \le 0.2$.

The **variance test** discards homogeneous but non-textural windows that occasionally appear in cluttered images. $\sigma_R = 0$ means that $R(i)$ has a single maximum that is treated as 'noisy'.

Figure 2 exemplifies the regularity filtering. $M_R(n, m)$ is diplayed intensity-coded, with light regions having higher regularity.

The following algorithm detects PDRs and computes their descriptors.

Algorithm 5: Detection of PDRs

1. Threshold maximal regularity $M_R(n, m)$ at M_R^{thr}.
2. Obtain the connected components of the binarised image.

3. Compute centroids and areas of the components.
4. Remove components with very small areas. The remaining components are PDRs.
5. Assign to each PDR the regularity feature vector of its centroid.

PDRs are detected in both images of a wide-baseline stereo pair. Relatively large, dominant regions are normally detected, whose number tends to be quite small. To identify the same PDR in the two images, that is, to match the regions, we apply the matching procedure presented below. The procedure uses the following **distance** in the regularity feature space: $D(R_1, R_2) = \sum_k w_k |R_{1k} - R_{2k}|$, where R is the regularity feature vector $\{M_R, \mu_R, \sigma_R\}$. The weights w_k were selected empirically as $\{1, 2, 2\}$.

Algorithm 6: Matching of PDRs

1. Compute the distance matrix D_{ij}, where i is the i^{th} PDR of the first image, j is the j^{th} PDR of the second image.
2. Calculate the forward matching matrix C_{ij}: $C_{ij} = 1$ if $D_{ij} < D_{i,k}$ for all $k \neq j$; otherwise, $C_{ij} = 0$.
3. Calculate the backward matching matrix B_{ij}: $B_{ij} = 1$ if $D_{ij} < D_{k,j}$ for all $k \neq i$; otherwise, $B_{ij} = 0$.
4. Match regions i and j if $C_{ij} B_{ij} = 1$.
5. Remove the established correspondences from D_{ij}.
6. Iterate the procedure until no further matching is possible.

The **backward matching** is a standard way to discard unreliable or erroneous links. The **iterative procedure** is based on an algorithm for the Stable Marriage Problem [13].

V. Tests and discussion

Experiments have been carried out to test the applicability of the presented theory. The test imagery included a wide-baseline pair from the well-known VALBONNE set (frames 9 and 13) and four pairs from the RADIUS set [14]. All these pictures contain periodic structures. In some of the selected RADIUS pairs the viewpoints are very different and the corresponding PDRs are in completely different parts of the image.

The VALBONNE pair is displayed in figure 3. In figure 2, the periodic structures of the left image are marked and numbered. First, a **feasibility experiment** was carried out. The periodic patches indicated in figure 2 were manually cut from the image and the regularity features were computed for these patches. Note that the other wall of the tower is poorly visible and its regularity is low.

Table I presents the feature space distances between the patches, with **a** being the left, **b** the right image. (These distances were computed with $w_k = 1$.) The table supports the expectation that the PDRs can be identified. Both within-image and between-image classification seem possible. For example, one could find out that S1a is identical to S2a; or that S1a is identical to S1b.

Fig. 2. Periodic structures and maximal regularity filtering of a VALBONNE image.

TABLE I
Distances between VALBONNE PDRs in feature space.

	S1a	S2a	S3a	S4a	S5a
S1b	0.067	0.095	0.353	0.491	0.304
S2b	0.035	0.035	0.293	0.431	0.244
S3b	0.205	0.177	0.081	0.219	0.162

Results of the **fully automatic experiment** with the VALBONNE pair are shown in figure 3. The window size was 40 pixels, the window step 5 pixels; the maximal regularity threshold was set to 0.3. The PDRs are successfully detected and matched. The lines indicate the correspondences by connecting the centroids of the corresponding regions. The outer contour of a PDR is the outline of the windows in which the PDR was detected. The inner contour shows the region as detected by algorithm 5. (Compare to the filtering result in figure 2.) A neighbourhood of the centroid of the inner area is the measurement region of the PDR method.

Both inner and outer areas can be used to efficiently constrain the search for precise correspondences. Note that the correct correspondences S1a→S1b and S2a→S2b were found by chance: it could have been S1a→S2b and S2a→S1b. At this stage, no spatial reasoning is done and two regions with the same texture cannot be distinguished. Alternative matchings should be considered when estimating the epipolar geometry. As the number of PDRs is small, this does not lead to a significant increase in computation.

Figures 4 and 5 display the results of automatic detection and matching of PDRs in four RADIUS pairs. The parameters were set as follows: $W = 40$, $S_w = 5$, $M_R^{thr} = 0.5$. In some cases, the inner contour is absent, meaning rejection because of very small area. In set J, the objects are usually smaller than in set K. Here, the more robust of the two roof structures exhibits itself as a PDR. In set K, the finer structure is visible and detectable. Note that the structures are non-flat 3D textures.

To summarise the contribution of this pilot study, we hope that the results presented clearly demonstrate that the periodic distinguished regions can be used as an efficient aid to wide-baseline stereo matching. Once the correspondences between the centroids of PDRs have been established, these disparity vectors can serve as starting points for finding a sufficient number of accurate matchings.

It is obvious that the PDR method can only be applied in presence of distinct periodic structures. However, the concept of distinguished regions [9] extends beyond this particular type of DRs. In general, one should attempt finding and matching different types of distinguished regions.

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Fig. 3. PDR correspondences for a VALBONNE pair.

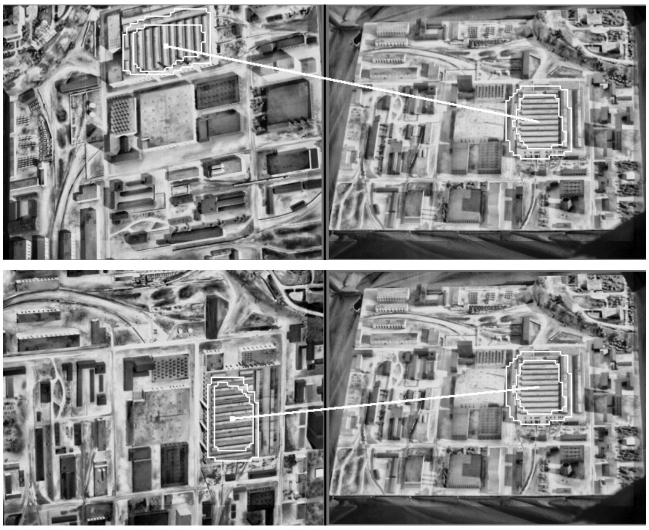

Fig. 4. PDR correspondences for two RADIUS pairs, set J.

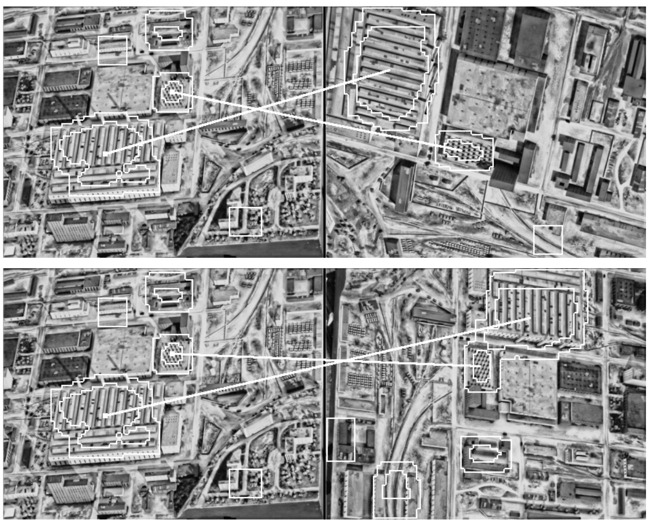

Fig. 5. PDR correspondences for two RADIUS pairs, set K.