

# Efficient Local Texture Regularity Estimation

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## Introduction

Automatically detecting regular image textures is a challenging task. A regular image texture can be represented by two vectors, a vector *pair*, that describe the lattice of the texture [Hays et al. 2006]. However, natural images can contain *multiple* textures that are often only *near-regular*, i.e. images can be described as being *locally* regular. To provide such description, the regularity should therefore be estimated at each location. This poster describes an algorithm, Recursive Search Regularity Estimation (*RSRE*), that *efficiently* estimates *local* regularity vectors.

Regularity estimators in the literature are often based on the auto-correlation function. This has two disadvantages: it is computationally expensive and typically estimates only global regularity. Consequently, it only describes one regular texture per image and cannot describe an image containing multiple (near-)regular textures. An improved method with some similarity to our work is presented by Hays et al. [2006]. There the lattice of near-regular textures is detected by iteratively growing the lattice from an initial seed point driven by local correspondences between texture elements and higher-order lattice geometry. However, also this method is demonstrated only on single textures and it has a high computational complexity. Our method, RSRE, is more efficient and can detect multiple textures. On the other hand, it gives local regularity vectors (see Figure 1) and does not detect the texture lattice.

RSRE is derived from an *efficient, local* motion estimator, using the notion that estimation of local regularity and motion is very similar. Both estimates require correspondences between groups of pixels: motion estimation relates pixels between video frames, whereas regularity estimation searches for correspondences within an image or a video frame.

## Algorithm design

The RSRE algorithm is based on the extremely efficient 3-Dimensional Recursive Search algorithm for motion estimation, or *3DRS* [de Haan and Biezen 1994]. 3DRS uses block matching to estimate local motion between video frames, while reducing computational effort substantially by testing only a few *candidate* motion vectors per block (some 3 orders of magnitude less candidates than Full-Search). This efficiency has been key in enabling real-time frame rate conversion for television sets.

3DRS selects candidate vectors from previously calculated vectors in the *spatiotemporal* (hence 3D) neighborhood. This is based on the assumptions that moving objects are larger than pixel blocks and that objects have inertia [de Haan and Biezen 1994]. A single additional candidate vector is generated by adding noise to one of the neighborhood candidates allowing the algorithm to converge.

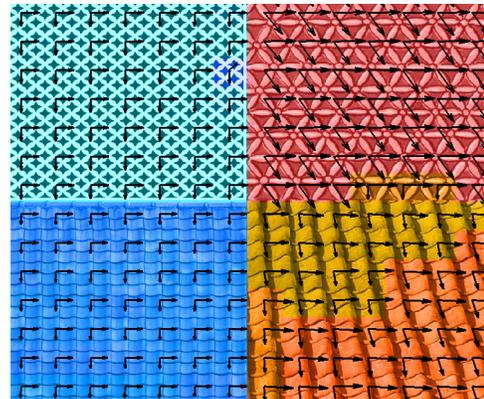
RSRE is basically running 3DRS with vector *pairs* on a *single* frame. However, constraints need to be incorporated to avoid redundant and trivial solutions. Estimating regularity in a texture is inherently ambiguous as it yields multiple solutions for each block: a block can be matched to several locations in a regular texture, including the current location. Length and angle dependent *penalties* were therefore added to the error function of the candidate vectors

to introduce preferences in the vector candidate selection. A length penalty avoids near-zero and very long vectors. In order to find two vectors that point in different directions, an additional angle penalty favors non-aligned vectors.

## Experiments

Penalty parameters are determined heuristically. To assure convergence, the image is scanned up and down twice. Vector candidate pairs are predicted from four neighboring blocks, two already updated in the current scan and two from the previous scan. This candidate set is doubled by additionally using slightly perturbed versions of the vector pairs.

In our experiments, we used images from the PSU near-regular texture database (<http://vivid.cse.psu.edu/texturedb/gallery/>). A result is shown in Figure 1, where the local regularity vectors are depicted in black and the summed length of each pair is color coded. The color illustrates the possibility of additional image segmentation based on local regularity. The borders between the textures are handled well and the perspective in the bottom right texture is tracked.



**Figure 1:** Result of local regularity estimation using RSRE on a single image containing four textures.

## Conclusion

RSRE is a new approach that enables very efficient (96 ops/pixel) detection and segmentation of multiple (near-)regular textures within a single image or video frame. This enables the use of texture regularity analysis for (real-time) video applications, such as video compression, object segmentation, 3D-shape reconstruction, improved motion estimation, and video enhancement.

## References

- DE HAAN, G., AND BIEZEN, P. W. A. C. 1994. Sub-pixel motion estimation with 3-d recursive search block-matching. *Signal Processing: Image Communication* 6, 3, 229–239.
- HAYS, J. H., LEORDEANU, M., EFROS, A. A., AND LIU, Y. 2006. Discovering texture regularity as a higher-order correspondence problem. In *9th European Conference on Computer Vision*.

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