EXEMPLAR-BASED INPAINTING WITH ROTATION INVARIANT PATCH MATCHING

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Abstract: In this paper, we propose a novel approach to patch matching in exemplar-based inpainting. Our field of concern is movie restoration, particularly scratch concealment. Here we want to focus on a single frame (still image) inpainting. Exemplar-based approach uses patches from the known areas and copies their content to the damaged area. In case of irregular texture, there might be no patches available, so that the result would be visually acceptable. One way to increase the number of available patches is to rotate them. In most of the exemplar-based approaches, a target patch is not complete and a source patch has to be rotated and compared at every single angle. We overcome this inefficiency using a clue image, which comes from previous processing stages. We use moments of patches from this clue image, normalized to rotation, to reject apparently dissimilar patches, and to calculate the approximate angle of rotation, which has to be performed only once. In this paper, we provide justification for this simplification. We have no ambitions to provide a complete inpainting algorithm here.

1 INTRODUCTION

This paper contributes to the field of movie restoration. Old movies suffer from many defects rising from their extensive usage and from film instability. One of the most frequent defects are scratches. One example is shown in Fig. 1. Scratch concealment is our main research objective.

Provided there is no need to reconstruct fine texture or grain, methods based on solving partial differential equations (PDE's) can be used, see e.g. (Bertalmio et al., 2000; Chan and Shen, 2001; Chan et al., 2002). In movie restoration, it is also important to reconstruct film grain and noise. Therefore, an exemplar-based approach of (Criminisi et al., 2004) is more appropriate. Paper (Bertalmio et al., 2003) is an example of method where the main structure is inpainted by a PDE method and a method for texture synthesis is used to reconstruct the fine details. Sometimes, film scratches do not damage information from all dye layers. It results in color corruption where, to some extent, the texture remains. In that case, Bayesian reconstruction approach of (Joyeux et al., 2002) can be applied.

Figure 1: Example of a typical scratch. The picture is from the movie The Lost World, 1925. By courtesy of Lobster Films.

Exemplar-based inpainting works well in cases of regular textures, where the missing information can be re-filled by suitable patches from the known area. If a unique non-repetitive structure is damaged, there

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are no patches in the neighborhood, which could be used without getting a result with visible artifacts.

It is possible to increase the number and variety of available patches by their photometrical or geometrical transformation. The source patch (the patch from the known area) can be rotated, scaled, flipped, or its intensity can be adjusted to better match the target patch (the patch being reconstructed). There is a large amount of literature using a certain degree of invariance in matching problems (Zitová and Flusser, 2003). For image reconstruction, these techniques have been adopted in (Drori et al., 2003), where five scales and eight orientations of the patches are tested or in (Zhang et al., 2004), where projective transformation of patches are estimated.

This paper focuses on the problem of rotation invariance in patch matching. Rotating the source patch several times and testing the proximity of each orientation to the target patch is a very time consuming task. In matching problems from other fields of image processing, moment invariants are often used to perform the match effectively (Zitová and Flusser, 2003).

In exemplar-based image reconstruction, matching based on moments is normally impossible, since the target patches are incomplete and moments are calculated from the whole patch. Our scratch inpainting algorithm works in multiple resolutions. Inpainting results from previous stages are refined afterwards. Therefore, the mentioned difficulty can be overcome by applying the moment invariants to patches from a pre-inpainted image.

Patch matching and orientation estimation is much faster using moment invariants. This is a novel approach, opening new possibilities in exemplar-based reconstruction. Using the clue image for matching patches containing fine details has to be justified, which is a part of this paper.

This paper focuses solely on the particular problem of rotation invariance in exemplar-based inpainting. The method has been tested on gray-level images, however extension to color images should be straightforward. Detailed explanation of the inpainting algorithm is not our objective. Although, scratch inpainting is a temporal problem, here we limit ourselves to the reconstruction of a single frame.

2 EXEMPLAR-BASED INPAINTING ALGORITHM

In this section, exemplar-based inpainting as described in (Criminisi et al., 2004) is shortly explained. This serves as a starting point for a brief explanation of our algorithm. The main motivation for modifications of the original exemplar-based algorithm was to avoid artifacts in the middle of the inpainted domain, rising from lack of interaction between patches copied to opposite sides of the unknown area. Images shown in Fig. 2 are used in this paper. The scratches are made artificially.

Figure 2: Images used for testing our algorithm. The scratches are made artificially.

Exemplar-based inpainting algorithm according to (Criminisi et al., 2004) works as follows: Pixels along the border of the inpainted domain are sorted according to priority, which is based on structure saliency and on confidence of already inpainted pixels. A block of pixels (due to later usage of rotation invariance, we call it a patch) around the first pixel in the list is called a *target* patch. A *source* patch of the same size as the target patch is searched in a neighborhood of a pre-determined size. The best match based on the known pixels (or its part) is copied to the position of the target patch. The priorities are updated and the whole process is repeated. The algorithm is demonstrated in Fig. 3.

The borders propagate inside the inpainted domain and meet in the middle of it. Since there is no communication between them, it results in artifacts, examples of which are shown in Fig. 4.

Our main improvements to the algorithm proposed in (Criminisi et al., 2004) are using multiresolution, clue images and invariant patch matching. Multiresolution helps to inpaint textures with different characteristic sizes. It also partially alleviates artifacts produced in earlier lower-resolution stages. The image is decomposed into Laplacian pyramid and the lowest-resolution image is inpainted by the PDE method of (Chan and Shen, 2001). The result is upsampled and used as a clue in the next finer resolution.

Figure 3: Principle of the exemplar-based inpainting method. From left ro right: 1) scratched image to be inpainted; 2) the pixel on the scratch edge with the highest priority determines the position of the target patch (white); 3) the most similar patch to the target patch is found (white) - the source patch; 4) the source patch is copied to the position of the target patch.

Distance measure D used in our algorithm can be formulated as follows:

$$D = \beta L_p(T(\omega) - S(\omega)) + (1-\beta)L_p(TC - SC).$$

T, S, TC and SC denotes target patches, source patches, target clue patches and source clue patches, respectively. ω denotes the set of known pixels for a particular patch. Parameters $\beta = 0.5$ and $p = 5$ work best in most cases.

A few results of our algorithm without transforming the patches can be seen in Fig. 5. Results when using rotation invariant patch matching are demonstrated in the following sections.

3 ROTATION INVARIANT PATCH MATCHING

In this section, we propose an efficient solution to rotation invariant patch matching. The task is to take a target and a source patch from the clue image, calculate a few moments of each and answer the following two questions:

- Is the source patch a good candidate for being a match with the target patch after a proper transformation?
- If yes, what is the transformation? Since we model it by rotation, what is the angle to rotate it by to be able to find out if it is a match?

Figure 4: Images from Fig. 2, inpainted by the algorithm of (Criminisi et al., 2004).

Moment rotation invariants are used in the next sections to answer both questions. Information about moment invariants to rotation and about moment invariants by the method of normalization can be found in (Flusser, 2000; Suk and Flusser, 2005).

3.1 Moment Invariants to Rotation

A few relevant results (see e.g. (Suk and Flusser, 2005)) are reproduced here. First, complex moments and invariance are defined and the way to calculate invariants to rotation is explained. Next, a few results which are needed in this paper are emphasized.

A complex moment $c_{p,q}$ of order $p+q$ of an image $f(x,y)$ is defined by the integral

$$c_{pq} = \int_{R^2} (x+iy)^p (x-iy)^q f(x,y)\,dxdy.$$

A moment invariant is a function of moments I such, that the same function calculated from the moments of the transformed image I' can be written as

$$I' = \Lambda I,$$

where Λ depends only on the transformation parameters.

Invariants calculated by the method of moment normalization are used here. After counterclockwise rotation of an image by angle α, complex moments c_{pq} are transformed into

$$c'_{pq} = e^{i(p-q)\alpha} c_{pq}. \tag{1}$$

Thus,

$$c_{00} = m_{00}$$

Figure 5: Images from Fig. 2, inpainted by our algorithm using clue images, but with no invariance.

is one invariant (m_{pq} is an ordinary moment).

Each patch, whose center of gravity is not in the center of the patch, can be rotated by angle α so, that the center of gravity is lying on the positive half of the x-axis. Putting c_{10} real and positive has the same effect. To achieve this, eq. (1) gives the corresponding rotation angle α_1

$$\alpha_1 = -\arctan\frac{m_{01}}{m_{10}} + k\pi$$

for $k = 0, 1$, and condition

$$m_{01}\,\sin\alpha_1 \leq m_{10}\,\cos\alpha_1.$$

Of course, division by zero has to be treated correctly.

After rotation by α_1, patches are aligned to each other and can be compared. The comparison can also be done by calculating their moments m'_{pq} after rotation (normalization). It is possible without rotating the patches using only current moment values. The moments are now independent of rotation (invariant) and can be themselves used for comparison. Since the normalized moment m'_{01} becomes zero, the first order normalization gives one new invariant

$$m'_{10} = \cos\alpha_1 m_{10} - \sin\alpha_1 m_{01}.$$

If the center of gravity is too close to the center, i.e. where

$$|c_{10}| = m_{10}^2 + m_{01}^2 \qquad (2)$$

is smaller than a threshold, the estimation of α_1 becomes unstable. Provided

$$|c_{20}| = (m_{20} - m_{02})^2 + 4m_{11}^2 \qquad (3)$$

is large enough, normalization angle α_2, based on the second order moments can be calculated by the same procedure. Putting c_{20} real and positive gives

$$\alpha_2 = -\frac{1}{2}\arctan\frac{2m_{11}}{m_{20} - m_{02}} + k\frac{\pi}{2}$$

for $k = 0, 1, 2, 3$, and condition

$$2m_{11}\,\sin 2\alpha_2 \leq (m_{20} - m_{02})\,\cos 2\alpha_2.$$

3.2 Inpainting Strategy

Normalization and matching of the source patch to the target patch works as follows: Both patches are multiplied by a circular mask to ensure rotation invariance. Only moments up to the second order are used for orientation estimation.

First, the orientation angle is estimated for the target patch and the normalized moments (invariants) are calculated. For each source patch we try to reject it based on the simplest features, before more complex calculations have to be done.

Therefore, the distance of the mean intensity m_{00} of the target and the source patch are compared at the beginning. The calculation proceeds only if the distance is smaller than a threshold. All the thresholds used in this paper are empirical. The relative distance

$$\delta(a, b) = \frac{|a - b|}{|a| + |b|}$$

is used for invariant comparison (with a small constant in the denominator to prevent division by zero). This is not an optimal measure, however it is only supposed to be approximate to refuse the worst source patch candidates.

After this step, first order moments are calculated. If the value of (2) is larger than a threshold, α_1 is estimated. α_1 is then used for normalization of the first order moments. The relative distance of invariants m_{10} is compared and dissimilar patches are again rejected. Moment m_{11} is calculated, normalized and used to detect if the patch should be reflected.

If the center of gravity should be too close to the patch center, moments of the second order and m_{21} (because of the test of reflection) are calculated. Magnitude of the moment of inertia (3) is tested and the procedure follows analogously.

Either α_1 or α_2 and information about reflection of the patches are used to rotate and eventually reflect the source patch. After it is aligned with the target patch, they are compared based on our distance measure.

4 JUSTIFICATION FOR USING MOMENT INVARIANTS

A few problems are connected with using moment invariants in this work. Some approximations might look too strong and they have to be justified. This is the main goal of this section.

Firstly, both the target and the source patches are square blocks of pixels. On the other hand, invariants to rotation have to be applied to a circular patch to make sense. A circular patch inscribed to the block is used. Thus, it is assumed that pixels in the corners of the block (not covered by the circular patch) are approximate extrapolations of pixels in the middle of the block. If the match for the inner part is good, the same should then work for the corners.

Another problem is, that patches of small sizes are typically used. In this paper, we use blocks of 5×5 pixels. The inscribed circle has to be roughly approximated. Bilinear interpolation is used here. In Fig. 6, an original square block and a circular mask are shown, which are then multiplied to create a circular patch.

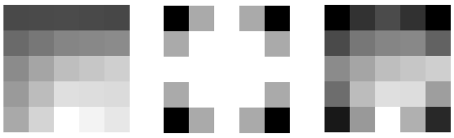

Figure 6: Demonstration of preparing circular patches. From left to right: 1) square patch; 2) circular mask; 3) square patch multiplied by circular mask.

Estimation of the rotation angle is based on clue images. However, the distance measure used in our exemplar-based inpainting algorithm also takes into account higher resolution image, which contains finer texture. Our strategy is to use moments of low orders which are not very sensitive to noise and to finer details.

The following experiment has been performed to justify all the committed approximations. The angle of rotation was first approximated using moment invariants and clue images. Afterwards, the source patches were rotated by a small step and for each single orientation, the complete distance measure was applied and optimal orientation was determined. The histogram of differences α_{dif} of these two values is depicted in Fig. 7. The histogram reveals that our method achieves approximately the same accuracy as the method of (Drori et al., 2003), but it works much more efficiently.

5 RESULTS

A few results are shown here to demonstrate the strength of our inpainting algorithm, see Fig. 8. Exemplar-based inpainting as briefly described in Section 2, together with rotation invariant patch matching is used here. It is obvious, that the results

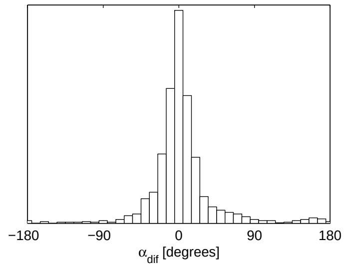

Figure 7: Histogram of differences between angles estimated by moment invariants and those obtained by testing each orientation.

outperform those obtained by previous methods and shown in Figs. 4 and 5. This fact can be attributed to increased offer of available patches in a complex non-textural image.

Figure 8: Images from Fig. 2, inpainted by the proposed algorithm.

In movie restoration, it is also important to restore noise and film grain to keep a natural look. Since the patches are rotated before copying to the target patch positions, they are also resampled. Bilinear interpolation is used for this purpose. For a certain class of noise and grain, there might be a visual distortion. However, in the images used in this paper, we have not observed any perceptually important noise or grain degradation. If the results were bad, a second attempt of exemplar-based inpainting re-graining flat image areas could perhaps be used.

Incorporating rotation invariance does not significantly slow down the inpainting algorithm. The nor-

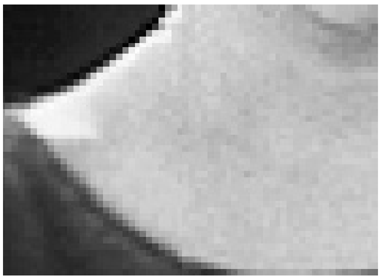

Figure 9: Restoration of a film grain.

malized moments are used as a preliminary criterion to refuse patches for the next comparison step, which comprises resampling and distance transform calculation. The percentage of patches, allowed to be tried as candidates for optimal source patches, depends on the chosen thresholds. In our case it is 2% of all candidate patches.

6 CONCLUSION

This paper uses, for the first time, moment invariants for patch matching in exemplar-based image inpainting. Difficulty with an incomplete target patch is solved by using a clue image.

Justification for orientation estimation from lower resolution images is discussed. Results of inpainting with rotation invariance are demonstrated. They outperform the results of ordinary exemplar-based methods. Since the majority of patches are immediately refused based on moment invariant values, the speed of the algorithm is not significantly decreased.

Other invariance can be used. However, rotation is probably the most appealing transformation. In images with curved edges it significantly improves the results. Our main concern was testing applicability of the method and not the final solution of scratch inpainting in color sequences. Therefore, a simplified problem of gray-value single frame inpainting is analyzed. Extension of the method to color images and usage of other patch transformations is the subject of our next work.

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