

# Robust Image Retargeting via Axis-Aligned Deformation

## Supplemental Material: User Study

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### 1. Setting

We conducted a user study with 305 participants, following the paired-comparisons protocol of [RGSS10]. Eight methods have been compared: manual crop (CR), nonhomogeneous warping (WARP) [WGO07], Scale-and-Stretch (SNS) [WTS08], MULTIOP [RSA09], shift-maps (SM) [PKVP09], streaming video (SV) [KLHG09], energy-based deformation (LG) [KFG09] and our algorithm (AA). All datasets in the study have been created by the authors of the respective methods, manually tweaking parameter values and sometimes the saliency to show the strengths of their retargeting algorithm and produce the best possible result.

The benchmark is made of 37 images and every image is tagged with one or more of the following attributes: people and faces, lines and/or clear edges, evident foreground objects, texture elements or repeating patterns, specific geometric structures, and symmetry. To better understand the strength and weakness of every retargeting algorithm, all the statistics of this study are grouped according to these attributes, and we also give the aggregate results for the entire dataset.

We note that the study participants had no reason to prefer a retargeted image over a (manually) cropped one since the study did not place the images in any semantic context. This biases the study in favor of manual cropping as it does not introduce any distortion. For this reason, cropping should be considered as a reference, not as a proper retargeting algorithm (for more details see the original paper [RGSS10]).

The gathered data is attached to the submission in the form of a MySQL database that uses the RETARGETME schema. Scripts to automatically analyze the data can be found at the RETARGETME website.

### 2. Votes and Ranking

Figure 1 provides the study statistics, showing that our deformation subspace is a good choice for content-aware re-

targeting. Our results have ranked higher than the other six state-of-the-art methods. In particular, they achieved a quality slightly superior to SV [KLHG09], while being simpler to implement, faster and not requiring a GPU implementation to obtain interactive frame rates. Our study is in accordance with the original [RGSS10], providing further validation of the consistency of users' preferences.

Table 1 shows the ranking according to the rank product method [RGSS10] (the smaller the number, the better).

| CR   | AA   | SV   | MULTIOP | SM   | SNS  | SCL  | WARP |
|------|------|------|---------|------|------|------|------|
| 1.41 | 2.04 | 2.88 | 2.88    | 5.15 | 6.32 | 6.92 | 7.65 |

Table 1: Rank product of all methods.

### 3. Agreement and Statistical Significance

We computed the Kendall coefficients of agreement  $u$  [KS39] to study the similarity of choices between participants. All participants would be in complete agreement if they voted the same way, and then  $u = 1$ . The minimum value of  $u$  is attained by an even distribution of answers and is given by  $u = -\frac{1}{8}$  in our case.

The coefficients of agreement are shown in Table 2, and they indicate that users have more agreement when people or strong symmetries are present in a scene. It is interesting to note that the participants reacted inconsistently to distortion in textures and geometric structures.

| Lines / Edges | Faces / People | Texture | Foreground Objects | Geometric Structures | Symmetry | Total |
|---------------|----------------|---------|--------------------|----------------------|----------|-------|
| 0.113         | 0.261          | 0.090   | 0.216              | 0.113                | 0.220    | 0.148 |

Table 2: Coefficients of agreement.

The statistical significance of the coefficients can be determined by testing the null hypothesis that the comparisons are assigned randomly (no agreement amongst users). A  $\chi^2$

|         | Total       | Lines/<br>Edges | Faces/<br>People | Texture    | Foreground<br>Objects | Geometric<br>Structure | Symmetry   |
|---------|-------------|-----------------|------------------|------------|-----------------------|------------------------|------------|
| CR      | 2106        | 1376            | 973              | 308        | 1119                  | 895                    | 310        |
| SV      | 1926        | 1274            | 745              | 287        | 908                   | <b>850</b>             | 340        |
| MULTIOP | 1826        | 1189            | 761              | <b>314</b> | 879                   | 746                    | 336        |
| AA      | <b>2000</b> | <b>1320</b>     | <b>911</b>       | 295        | <b>1055</b>           | 790                    | <b>350</b> |
| SCL     | 1019        | 751             | 323              | 192        | 383                   | 512                    | 214        |
| SM      | 1429        | 985             | 569              | 250        | 698                   | 650                    | 185        |
| SNS     | 1226        | 829             | 408              | 212        | 590                   | 543                    | 162        |
| WARP    | 900         | 676             | 350              | 158        | 416                   | 390                    | 119        |

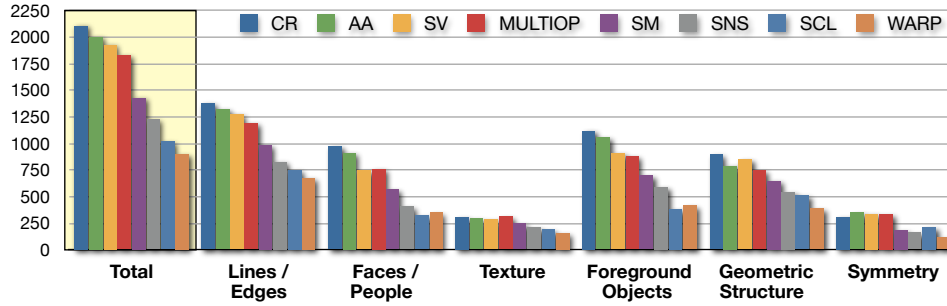


Figure 1: The number of votes for the eight methods considered in our user-study. A method gets a vote if a user picked a result by that method in a single paired-comparison question.

test shows that the coefficients of agreement are statistically significant at the significance level of 0.01 in all seven categories.

#### 4. Grouping

Following [RGSS10], we group the 8 methods in statistically equivalent groups. Two methods in the same group are considered indistinguishable, since the difference in the votes they received is not sufficient to elect a clear winner.

Figure 2 shows the groups computed over the entire survey (marked as “Aggregate”) and for each attribute.

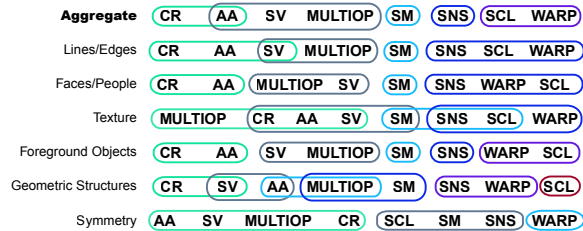


Figure 2: Grouping of the methods in statistically indistinguishable groups.

Note that our method is considered indistinguishable from CR, showing that the participants’ preference towards it is strong. The grouping for the other methods is similar to the previous study. The main competitor of our method is SV, that always ranks lower than our method or is statistically indistinguishable from it.

#### 5. Conclusions

Our study shows that the space of axis-aligned deformations is a good candidate for content-aware image retargeting. Furthermore, our study validates the study of [RGSS10], since our results are very similar to theirs. We release all the gathered data to the public in the hope that it will be used by other researchers to validate their results.

#### References

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