Expanding Potential Path Geometries for Seam Carving

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Abstract

We consider the refinement of seam carving, or image retargeting, used for "content-aware scaling". This algorithm adds or subtracts seams, continuous pixel paths of minimum importance, to either increase or decrease image size with a minimal impact on relevant image content. Current methods utilize dynamic programming, a technique that imposes some geometric constraints on the range of possible paths. Our method will utilize the A algorithm for seam selection such that more path geometries are allowable. Once the process is altered to accurately utilize the A* algorithm, we will consider additional heuristic measures for evaluating the importance of each seam. The standard has been gradient magnitude, which has been demonstrated to work, but has not been shown as a definitive best choice.*

Traditionally, seam carving results are assessed in a manual and somewhat subjective way; measuring image distortion is currently very challenging for algorithms but is an intuitive part of human perception. In total, we hope to improve upon current techniques by implementing a process which allows for a broader range of viable pahs. This should lead to better results in these demanding situations but not affect performance when unnecessary.

1. Introduction

Image resizing is a ubiquitous tool used in many image processing applications. In general, these operations will either degrade image quality or reduce image content. There have been a number of methods developed over the years in an attempt to reduce the impact and thus provide higher quality output. This has become increasingly important in recent time as media is being consumed on devices with screens of varying sizes (PCs, cellphones, tablets, etc). While many document standards can dynamically scale text and page layouts, they lack this capability for images. As such, important content can become lost or distorted. Seam carving was developed precisely to solve this problem in the work of Avidan and Shamir [1]. A seam is a continuous path of pixels traversing the image in either a vertical or horizontal direction and is characterized by a heuristic for evaluating its importance. As such, when reducing image size, the seams with the lowest importance are removed first in order to minimize the loss of information from the image. The benefit of seam carving, unlike scaling, is that unimportant information in the image is removed instead of introducing distortions. An example can be seen in 1, 2.

Figure 1. Example image before it is retargeted.

Figure 2. Image after it has undergone seam carving, losing 150 pixels in the horizonatl direction. Notice that the original proportions and content of the standing figure and castle are undisturbed.

Seam carving was improved upon by the original authors in their work with Rubinstein et al. [2] by refinement of the energy function used in determining the importance of seams. They used a forward looking metric to calculate the energy increase caused by removing the seam, which yielded stronger results. This was followed by Dong et al. [3] where Image euclidean distance (IMED) and the dominant color descriptor (DCD) metrics were both incorporated and shown to increase performance of the algorithm. It is still, however, an imperfect science.

Other techniques besides seam carving have been investigated for image retargeting. A comparative study, by Rubinstein et al. [4], of different techniques sought to not only compare the different approaches, but also to develop metrics which would be useful in quantifying the quality of retargeted images. While the authors note retargeting is largely a question of human perception, they were able to show that there are some metrics which correlated with the human consensus. These were, in particular, the combination of SIFT flow in the work of Liu et al. [5], [6] and EMD by Pele and Werman [7]. These techniques are heavily used in machine vision, particularly in image recognition. They are the Scale-Invariant Feature Transform, which identifies primary features within an image, and Earth Movers Distance, which is a metric for computing the similarity between two sets of SIFT features (used to measure the similarity between the original and retargeted image). It stands to reason that techniques which could utilize these metrics would be able to produce results more favorable to human perception, outlining another path forward.

Our method will utilize the A* algorithm for finding seams within the image. There are a number of route planning algorithms, but it is our expectation that A* will be one of the most useful. Looking at the field of path planning algorithms in the work of Delling et al. [8], it is clear that A* is not necessarily the fastest in compute time (with respect to multiple calls on a fixed graph). The constraints of our problem, however, dictate that most of the faster techniques are not viable. They predominantly work by reducing the graph structure or finding key nodes. This is counterproductive to our goals, as these nodes would be the ones most likely to be removed (and a new preprocessing step would need to be done on each iteration). There are, additionally, many variants of the A* algorithm seen in in the compilation by Cui and Shi [9]. Here the authors look at path planning within modern video games. Interestingly, grid sizes in many games are on the same order as those for images, so they share some commonalities. Again, however, we see most variants utilize techniques which are inherently counterproductive to our problem - utilizing key nodes or graph reduction would work, but would require recomputation on every iteration and add to the runtime. As such, we will be sticking with a vanilla version of A*. This is not to say that there are no other techniques which could be employed here, bi-directional search being one of them, just that the original is a close approximation of the optimal method. We will start by using energy functions to define the cost associated with each node, as others have done with seam carving. In the future, incorporating more advanced heuristic measures could improve performance. It would be possible to use a combination of SIFT features, E1 energy [1], and the deformation energy defined and studied by Karni et al. [10]. It is likely that by blending these metrics a more perceptually relevant solution could be found. Here, we hope to remedy a geometric issue with using dynamic programming, as was used in the seam carving implementations in [1], [2], and [3]. Dynamic programming is a brute force technique which computes the paths of lowest energy. In this computation, a given pixels possible paths are limited to the three pixels above it - diagonally up and to the left, straight up, and diagonally up and to the right. This constraint forces paths to be cut at angles of at most 45 degrees. By using A* we allow more possible path geometries in order to find more coherent solutions.

2. Algorithm Development

Our current survey of seam carving techniques has revealed that the definition of a seam has not changed since the original paper by Avidan and Shamir. There, they defined a seam as a path of pixels that is both continuous and monotonic. This implies that a seam consists of exactly one pixel per row of the image, and each subsequent pixel can be off horizontal alignment by no more than a single column. As such, for any given pixel along a seam, there are three possible choices for the subsequent pixel. There are strong arguments for why seams should be defined in such a way. Firstly, a seam must be monotonic in order to preserve image size and continuity - each row must have the same number of pixels, otherwise the rest of the image will become misaligned. The connectedness of pixels is also intuitive; removing the pixel with lowest energy within each row would, in most cases, lead to a complete lack of continuity and alignment. We suggest, however, that there are cases when path continuity is detrimental to the resulting seam generation - specifically when the slopes magnitude of the ideal seam is less than 1. This can be seen with an illustrated example, seen in 3. Here it is easy to imagine the path of least energy, yet it is impossible for current algorithms to find this path simply because they do not consider paths of this geometry. As such, the graph structure underlying seam carving needs to fundamentally change in order to explore these geometries.

To explore these additional path geometries we need to break the original constraints on seams, or at least relax them. This is done by permitting horizontal movement. We first break the monotonic requirement but force pixels to

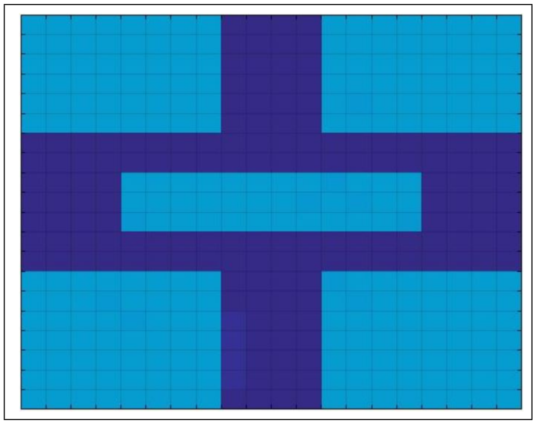

Figure 3. An illustrative test image. We consider a 20x20 pixel image which has an energy function loosely similar to that seen in the figure. The dark blue represents areas of low energy, while light blue is of high energy.

still be continuous - such that there are 5 possible movements options - and now multiple pixels within a single row can be part of a path. This allows us to find the path of minimum energy, even when parts of it have a slope of zero, as seen in 4. After the path has been defined we reimpose the monotonic constraint on the seam. We need to keep this constraint lest the rest of the image become misaligned. In practice, for any horizontal segment of the path, only one pixel within that segment is to be removed, also visible in 4. This satisfies the monotonic constraint but, as far as the seam is concerned, breaks the continuity constraint. Interestingly, continuity was preserved in the path generation portion, so the structure underlying our seams is continuous even if the seam itself is not - which is an important distinction as it will ensure misalignment does not happen in more complex examples.

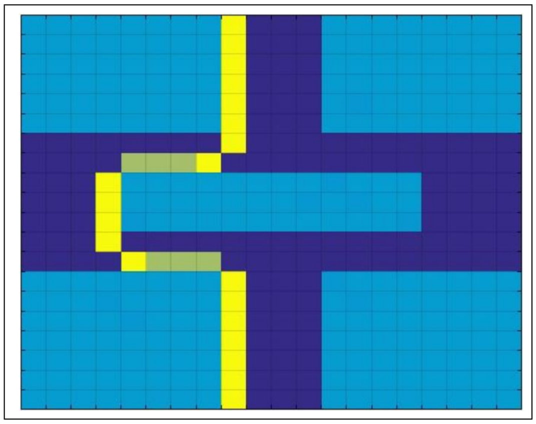

Figure 4. Using our modified process, we find the path of lowest energy. Notice the horizontal segments. Only a single pixel will be removed within each segment, shown in yellow.

We can see the results of removing this seam in 5. We can run the process again to remove another seam, yielding 6. We can compare these results to the output of tradition seam carving, seen in 7. As can be seen, the paths produced by the traditional algorithms cut through the center area of importance and remove 2 columns worth of data from this important region, which does not happen in our modified version. Again, this is because the traditional algorithm can not evaluate paths whose slopes have magnitude less than 1.

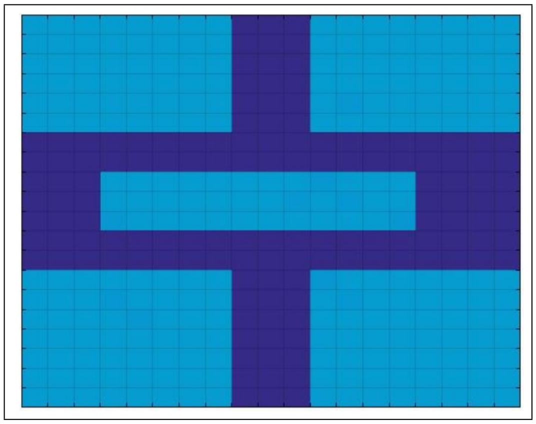

Figure 5. Results of removing the above seam shown ABOVE

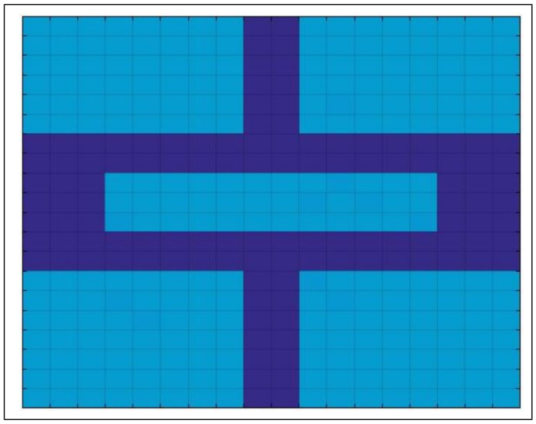

Figure 6. Removal of another seam. Careful examination shows that not a single pixel of high importance has been removed.

Because of the increased complexity, dynamic programming is no longer a viable path planning technique. We utilized the A* algorithm, for which we needed to redefine many parts of the process. First and foremost we define an underlying graphVector structure which our planning algorithm will operate on. Each node holds a multitude of values, including the energy value of the pixel, the list of connected neighbors, and the cost of moving to those neighbors. The A* algorithm needs both a start and goal node, but our seam criteria is that it start anywhere within the top row

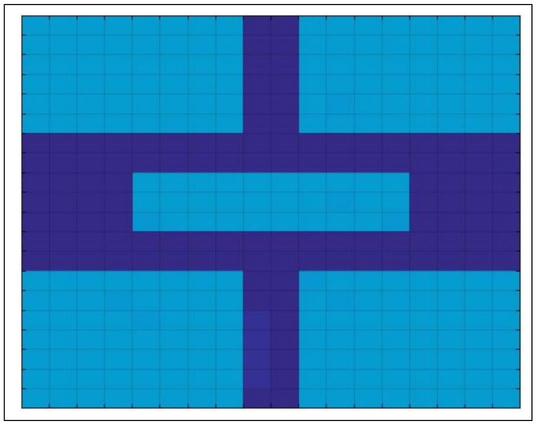

Figure 7. Results of traditional seam carving, using dynamic programming, on our example.

of the image and end anywhere within the bottom row. To facilitate this behavior, we introduce a source node, where the entire first row is considered to be neighbors with zero cost and, similarly, a sink node which is a neighbor of every node in the bottom row of the image, also with zero cost. We can see a layout of this structure in (Graphic to be added here). The A* algorithm will function well on this graph, however we do need to modify our heuristic slightly. In the most basic implementations, the heuristic can rely on the euclidean distance. This is not a useful measure in our case, however, because our sink and source nodes dont have definitive positions - and we dont want them to. We do not prefer seams on the right side of the image over seams on the left, for example, just that they minimize the energy. As such, the heuristic will depend on the vertical position and ignore the horizontal dimension. This represents how many steps away from the bottom row the current node is. Additionally, we need to impose some cost to our movement. This is not necessarily a requirement for finding seams of lowest energy, but we do use this as a tiebreaker for a multitude of equally low-energy paths. An example of an equally low-energy path can be seen in 8. As such, our heuristic is now blending two distinctly different and unrelated measures. This requires a bit of care to pull off properly, and is an area we will be pursuing in future work. Ultimately, we care about the total energy along the path, but do prefer paths of more direct geometry (if only to improve running speed - for which this makes orders of magnitude of difference for). As such, we add the two measures but keep them at different scales. We choose the weighting such that f = sum(movement + alpha*energy).

3. Results

We are currently processing images to show real world effects, but one demonstration is the image seen in our orig-

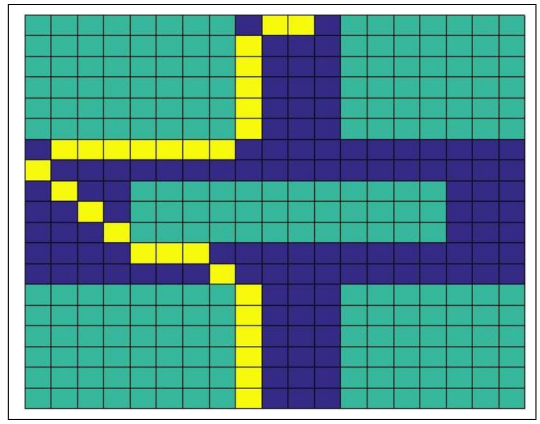

Figure 8. An illustrative test image. We consider a 20x20 pixel image which has an energy function loosely similar to that seen in the figure. The dark blue represents areas of low energy, while light blue is of high energy.

inal example of seam carving, figure 2. This was processed using the algorithm we developed. While it does not exhibit geometry that, on the surface, would appear to particularly benefit by this process we can compare it to the results of the traditional algorithm, seen in 9. Close inspection of the castle, particularly the lower left quadrant, reveals that

Figure 9. Results of traditional seam carving algorithms, again 150 seams have been removed.

4. References

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