University of Virginia

Computer Vision

CS 4102

Diminished Reality

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1 Introduction

This report describes our attempted implementation of a diminished reality system incorporating object tracking, removal, and inpainting. The project was originally inspired by a paper written by Herling and Broll. Many challenges, both anticipated and unforseen, were encountered during the course of the project and as a result our goals and approach to these goals changed many times.

2 Past Work

As mentioned in the introduction, the project was inspired by the paper *Advanced Self-contained Object Removal for Realizing Real-time Diminished Reality in Unconstrained Environments* published by Herling and Broll in 2010. We were initially drawn to the paper by the impressive demonstration videos released by the authors and later the company fayteq founded based on this technology. This was a fairly recent paper and was based on a significant amount of previous work.

The paper was divided into three parts regarding object tracking, inpainting, and optimizations respectively. The authors treated the first of these sections as an already solved problem. They mentioned use of active contour algorithms for tracking but didn't discuss the topic further or cite past work in the area. The problem of tracking objects was treated as a necessary prerequisite but largely outside the scope of the paper. The second section of the paper, inpainting, relied heavily on previous work. Most notable of the papers referenced in this section was the 2009 SIGGRAPH publication *PatchMatch: a randomized correspondence algorithm for structural image editing* by Barnes, et al. Professor Barnes discussed this paper and his work in the area in his guest lecture. The authors based their algorithm on PatchMatch's randomized nearest field search and also incorporated elements of the bidirectional similarity function described by Simakov in 2009.

The primary contribution of this paper was a series of optimizations that permitted the system to work in real time. In this section the primary contributing past work was a framework created by the authors that allowed for fast multicore access to video streams.

3 Design and Implementation

Our choice of topic for this project was a last minute one and as a result a number of design decisions were made with an insufficient amount of research to justify them. The choice of this paper at all proved to be a suboptimal decision. While at first reading the high level concepts of the paper are simple to understand, when it came time to implement many of the components the descriptions in the paper were ambiguous. Additionally, because the primary contribution of the paper was an optimization of existing techniques, it assumed a level of familiarity with past work that we did not possess. In retrospect it would have been better to limit ourselves from the beginning to implementing PatchMatch, a more fundamental prerequisite component of Herling and Broll's system that has the benefit of having complete accompanying source code.

We chose to code the project in C++ and make use of the openCV computer vision library. This decision was made with the idea that eventually we would want our code to be as fast as possible in order to run in real time. When that goal was eventually abandoned this choice of language over something more familiar and user-friendly such as Python proved to be a hindrance rather that a benefit.

3.1 Object Tracking

There are two components to the system, object tracking and inpainting. For the first step we initially attempted to use an active contour algorithm to track objects between frames. This was the technique, chosen for its speed, used in the paper. Active contours take an input contour selected by the user and apply a gradient descent approach to minimize an energy function that contrasts properties of the image such as its gradient, with the smoothness of the contour.

We attempted to implement this component of the system by using the openCV function cvSnakeImage. This particular function was the only relevant function in the openCV library but only existed in legacy code. Additionally, after experimenting with different test videos and parameters to the function we found that the results were not adequate on most inputs. For the very simplest videos involving two dimensional objects moving across starkly contrasting backgrounds the results were both accurate and fast but in more complex scenes the contours had a tendency to shrink into nothing and were

too easily waylaid by distracting background elements.

After determining that a new approach was needed we decided to use the CAMshift algorithm. CAMshift is an algorithm based on the Mean Shift object tracking algorithm that is typically used for face tracking in ebedded systems. It tracks objects based on distribution of hue which results in an algorithm that is very fast but is easily thwarted when objects are multi-hued or have a similar hue to their environments.

The first step of the CAMshift algorithm is to create hue histograms for the image as a whole and the particular region that contains the object to be tracked. The mean shift search window begins centered on this region of interest. At each frame a backprojection is created for a variable size window that grows and shrinks with respect to the zeroth moment. The intensity of each pixel in the window then represents the likelihood that it is a member of the object being tracked. Mean shift is iterated and repeatedly centers the tracking window over the centroid of the backprojection until convergence or a maximum number of iterations have been completed.

The algorithm outputs a rotated rectangle which for simplicity in the second step is converted into a standard bounding rectangle.

3.2 Infilling

The paper describes a somewhat complex process by which the portion of the image masked by the tracking stage of the algorithm is filled in. The general approach involves randomly searching for patch correspondances between patches of the image inside of the masked area and patches outside of the mask. After correspondances have been established an iterative function described by Simakov is used to update the value of each pixel inside of the masked region until convergence. In order to do this first the image is scaled down multiple times, then each pixel under the mask is filled in with the average value of its neighboring unmasked pixels. The authors argue that at such low resolution this serves as an acceptable initial approximation. Then correspondances are established as described above, the updating function is run, and results are passed up to the next higher resolution level in the pyramid.

At this point in our implementation we had realized that obtaining real time results was not a feasible goal. In light of this, and in order to maintain simplicity in the code, some of the optimizing components of this process were omitted. In particular, no image pyramid is created. After the mask

is created we immediately fill in the masked pixels with the average values of their neighbors. Then Barnes's PatchMatch is run to establish correspondances. Each pixel in the region of interest is replaced with the average value of the corresponding pixel in every patch that contains it.

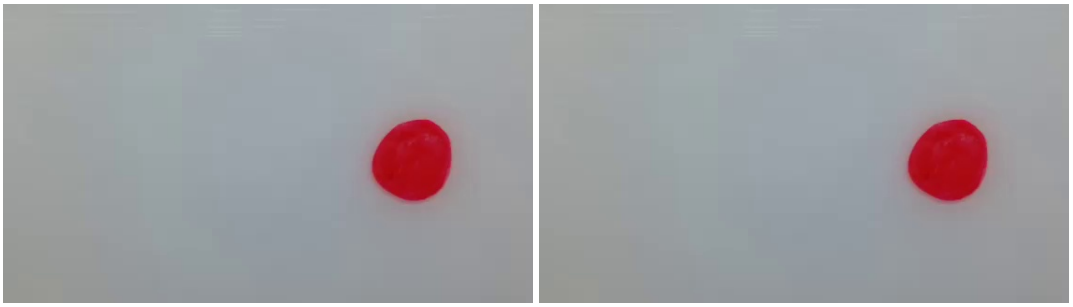
This was not the first approach to inpainting that we attempted. At first, before discovering the iterative pixel-by-pixel update function we attempted to take the information obtained from PatchMatch and use it directly. We set the masked region to contain all 0s and then found correspondances. We gradually filled in the area by pasting in patches that overlapped the boundary by a small amount. We also tried initializing the masked area to contain average values of the neighbors, as we do currently, and then finding correspondances and simply filling in the area by pasting in non-overlapping patches. Both of these approaches suffered from a common problem that seems obvious in retrospect. Although they should all be somewhat similar, patches found in the source image can come from very different locations and pasting them directly into the region of interest creates a very blocky discrete fill. The result is jarringly different than the smooth textures one would hope to see on most surfaces.

4 Results

4.1 Object Tracking

4.1.1 Red Circle

This was the most basic test video that I could come up with. It's a single red dot moving slowly across a solid white background. For this video the original contour tracking method actually works very well and raised my hopes that it would be usable in more general situations. Click on the images below to watch the videos on youtube.



4.1.2 Bowling Ball

For this example I tried to take the smallest step towards a real world scenario. The video consists of a single well definined moving object against a static background. However, unlike the first video, thecontour tracking algorithm fails entirely here. Within the first few frames of the video the contour has shrunk itself out of existance. In contrast, the CAMshift tracking performs to complete satisfaction. The images link to youtube videos.

4.1.3 Business Card

This video attempts to provide a realistic example of a video that might be encountered in the real world. The object being tracked is still simple but it moves in a more complex way in a more realistic environment. I didn't include a video demonstrating the contour algorithm because, as with the bowling video, failure is almost immediate. One thing in particular to note with this video is how the tracking succesffuly follows planar rotations of the objects and even occlusion to some degree while being covered by my hand or rotated away from the camera. The card is briefly lost when it's rotated too far from parallel to the camera but it's picked up again immediately when rotated back into view.

4.2 Infilling

Our infilling results were less successful. Given a single frame and a masked region the ideal result would fill in the masked region in a way that left the fact that the image had been edited undetectable or as unobtrusive as possible. For the most simple case of a clearly defined object on a completely uniform background this result was almost achieved. For more complicated objects in environments with any degree of texture results were very poor.

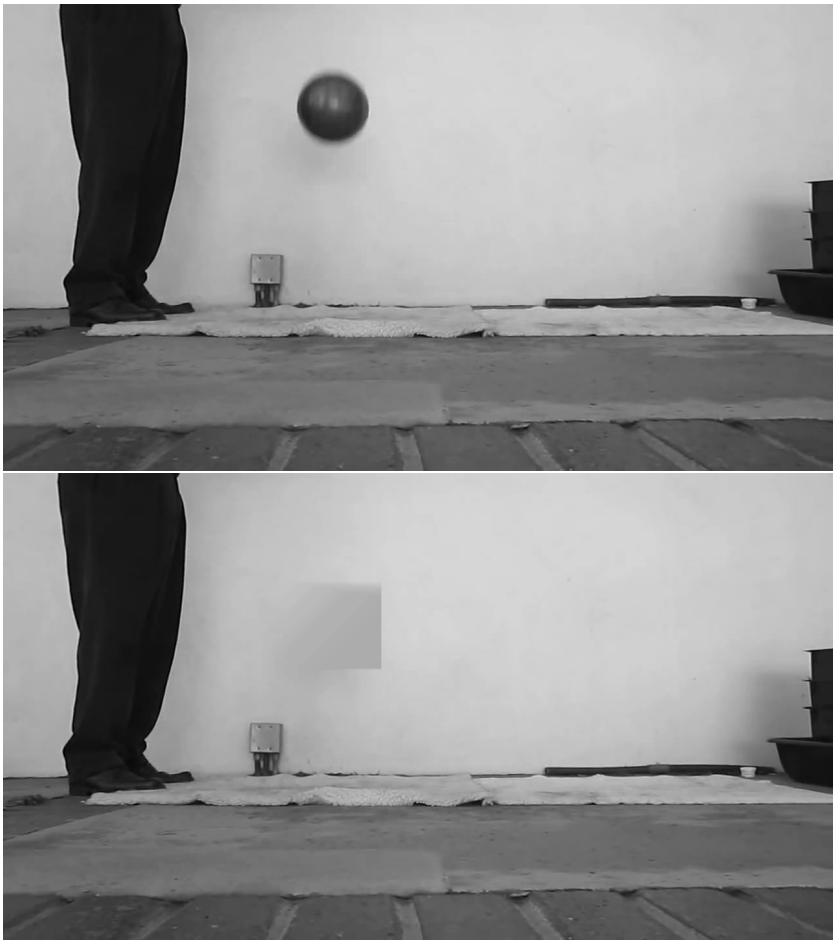
Our general process divided the infilling portion into two steps. The first of these steps involved iterating through each of the pixels in the masked region and replacing it with the average value of its neighbors. The output of this step was not intended to be a satisfactory final output but merely to act as a sufficient initialization for the more in depth following step where PatchMatch is applied. The only complication with this step is that the pixels must be looped through in a valid order. If iteration begins in the middle then it won't be able to fill in any values. Apart from that minor note, because this is merely an approximated initialization step, we concluded that the order was probably insignificant. We loop through the pixel matrix in standard C order. Some images showing examples of this step are shown

below.

One note about the images. They are grayscale. This is because the original Herling and Broll algorithm only does computations on grayscale images in order to reduce computation time. We began our project intending to follow the same model and aspect was never updated.

The first pair of sample images show a case where the average fill step is almost sufficient on its own. The backgroud is of uniform texture and lit in such a way that the fill is almost indistinguishable.

This pair of images shows a situation where the average fill step might be expected to do a good job but small difference in lighting cause the average fill to propogate in a way that produces an incongruous result.



The final pair of test images shows a case when the average fill could not be expected to be sufficient. It is unable to account for the presence of text and my fingers in the environment of the phone.

The next step after the average fill step is to make use of the PatchMatch correspondances in order to refine the results. Our first attempt at this step used the following steps.

1. Run PatchMatch to establish correspondances.

2. For each pixel in the region of interest find every patch that contains the pixel. In each of the corresponding patches for these patches find the average value of the pixels that correspond to the target pixel.

Surprisingly the results of this step tended to produce very minimal changes beyond what occured in the average fill step. The following images show the results of this step on each of the three samples shown above. The only noticeable change is a slight blurring. Otherwise the content of the filled area seems to remain the same.

While checking that the relevant functions were properly implemented the following figs were produced that show how pixels are drawn from areas outside of the patch to fill in the pathc. The white pixels represent the patches containing the target pixel and the black circles indicate the corresponding pixels that are being averaged. Click on the links to view the animated gifs in your browser. The gifs are large and may take a few seconds to load.

1. Starburst
2. Business Card
3. Phone

The animations above raised my confidence that the process was functioning as intended and suggested that a different method for filling the area was needed.

5 Strengths and Weaknesses

The primary strength of the algorithm is the tracking component. Object tracking is fast and accurate even in fairly complicated situations with rotating and fast moving objects. This provides a solid foundation on top of which a real time diminished reality system could eventually be built.

The limitations on the system come primarilly in the implementation of the inpainting component and are fairly evident from the results demonstrated above. Beyond the most simplistic examples the system fails to produce believable results for almost any input. The process needs significant improvements in both speed and accuracy in order to potentially produce acceptable results while running in real time.

Beyond that, there are a few limitations of our approach in general that would have been relevant even if our specific implementation had been more successful. A few of these are a result of the CAMshift tracking process used. In order to run quickly the algorithm is completely dependent on hue distributions in the image. This means that if the object that should be tracked has a similar hue to any object in the background it is impossible for the algorithm to distinguish them. This limitation could be overcome by taking into account channels in the image besides the hue when running the algorithm at the cost of an increased runtime.

There are also limitations imposed by reliance on unmodified PatchMatch. Using PatchMatch as is withouth additional optimizations eans that it is not possible to achieve real time results.