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Motion Detection and Optical Flow

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***Abstract*— In this paper Ransac algorithm is used to detect the motion is happened or not and this is by finding out the matching features between the two images. And then finding out the motion using optical flow algorithm. A common problem of optical flow judgment is fine motion structures cannot always be correctly estimated, especially for regions with significant and abrupt displacement variation. To address this issue introduce Lucas Kanade's optical flow method. This method is very fast and easy calculation. And it is also very fast method.**

***Keywords*—Ransac,Motion,LucasKanade's, Optical flow, matching features**

INTRODUCTION

Motion analysis and estimation is one of the most challenging tasks in digital video processing and computer vision [8]-[12]. Optical flow presents an apparent change of a moving object's location or deformation between frames. Optical flow estimation yields a two-dimensional vector field, i.e., motion field, that represents velocities and directions of each point of an image sequence [8]. As it is an illposed problem, so far a wide variety of constraints between frames have been introduced in optical-flow modeling. Such constraints are based on image brightness and velocity. In particular, assumption of image brightness constancy between frames is one of the mostly used constraints**.**

Optical flow is an approximation of the local image motion based upon local derivatives in a given sequence of images. That is, in 2D it specifies how much each image pixel moves between adjacent images while in 3D in specifies how much each volume voxel moves between adjacent volumes. The 2D image sequences used here are formed under perspective projection via the relative motion of a camera and scene objects. The 3D volume sequences used here were formed under orthographic projection for a stationary sensor and a moving/deforming object. In both cases, the moving patterns cause temporal varieties of the image brightness. It is assumed that all temporal intensity changes are due to motion only. The computation of differential optical flow is, essentially, a two-step procedure:

1. Measure the spatio-temporal intensity derivatives (which is equivalent to measuring the velocities normal to the local intensity structures) and
2. Integrate normal velocities into full velocities, for example, either locally via a least squares calculation [1, 3] or globally via a regularization [2, 3].

In general, the use of optical flow in a generic machine vision system will probably require a sophisticated analysis of image content and motion in order to determine that all of the algorithmic assumptions are likely to be met. Quantitative use of the data will also require quantitative predictions of accuracy. In optical flow, a motion vector of each pixel is computed and entire image could be imagined as a vector field. The motion vector of each pixel represents the brightness of the pixel.

The region of the image where brightness change is observed is considered as a candidate for moving object. The method based on optical flow is complex, but it can detect the motion accurately even without knowing the background. This approach results in good performance, however this
algorithm need one more than image to be stored, thus resulting in higher memory requirements, in-turn resulting in high cost.

RELATED WORK

In [4] optical flow can benefit from sparse point correspondences from descriptor matching. The local optimization involved in optical flow methods fails to capture large motions even with coarse-to-fine strategies if small subparts move considerably faster than their surroundings. Point correspondences obtained from global nearest neighbor matching using strong descriptors can guide the local optimization to the correct large displacement. Conversely, also shown that weakly descriptive information, as is thrown away when selecting keypoints, contains valuable information and should not be ignored. The flow field obtained by exploiting all image information is much more accurate than the interpolated point correspondences.

Moreover, outliers can be avoided by integrating multiple hypotheses into the variational approach and making use of the smoothness prior to select the most consistent one. This work extends the applicability of optical flow to fields with larger displacements, particularly to tasks where large displacements are due to object rather than camera motion. Here expect good results in action recognition when using the dense flow as a dynamic orientation feature correspondingly to orientation histograms in static image recognition. However, with larger displacements there also appear new challenges such as occlusions.

In [5] presented a new optical flow estimation framework to reduce the reliance on the coarse level estimation in the variational setting for small-size salient motion estimation. Differing from previous efforts mainly to improve the model, instead revise flow initialization in the coarse-tofine setting, which yields a unified framework to preserve motion details in both small- and large-displacement scenarios. The proposed method also takes advantage of the accurate variational coarse-to-fine framework and of nonlocal search/matching.

Other main contributions include the selective combination of the color and gradient constraints, sparse feature matching and dense patch matching to collect appropriate motion candidates, the mean field approximation to simplify optimization, and a variable splitting technique to enable fast and reliable flow estimation.

There are several limitations. First, although sparse feature matching and dense patch matching complement each other in proposing new flow candidates, they could still be insufficient especially for motion in textureless or regularly-patterned regions, where large matching ambiguity could occur. Second, motion inference for large occluded regions is still an open problem due to lack of correspondence. Current occlusion handling relies on a heuristic smoothness assumption, which could fail in texture- or color-rich regions when occlusion is significant.

In [6] tested the performance of this algorithm when a threshold based on the magnitude of the image gradient was used The original formulation of this algorithm uses a two-point central difference approximation to image derivatives. And also evaluated performance when a four-point central difference approximation was used, and when this was used in conjunction with thresholding. It is assumed as an additional constraint that the optical flow is varying smoothly in the sense that neighboring object points have almost the same velocity. Here also use Ransac algorithm to detect the motion and then using this optical flow algorithm. Its advantage is smooth flow global information accurate time derivatives, using more than two frames, possible. Disadvantage is iterative method is slow and unsharp boundaries.

Finally Lucas Kanade's optical flow algorithm use. In this paper also use Ransac algorithm and then find out the motion using optical flow algorithm. This method is very fast and accurate when compared to Horn and Schunck's optical flow algorithm.

PROPOSED SYSTEM

In our method first we want to find the motion of the object and then plot the optical flow to find the motion happened or not we use Ransac algorithm and for ploting optical flow here using Lucas kanade's optical flow algorithm.

The RANdom SAmple Consensus (RANSAC) algorithm proposed by Fischler and Bolles [7] is a general parameter estimation approach designed to cope with a large proportion of outliers in the input data. Unlike many of the common robust estimation
techniques such as M-estimators and least-median squares that have been adopted by the computer vision community from the statistics literature, RANSAC was developed from within the computer vision community.

RANSAC is a resampling technique that generates candidate solutions by using the minimum number observations (data points) required to estimate the underlying model parameters. As pointed out by Fischler and Bolles [7], unlike conventional sampling techniques that use as much of the data as possible to obtain an initial solution and then proceed to prune outliers, RANSAC uses the smallest set possible and proceeds to enlarge this set with consistent data points [7].

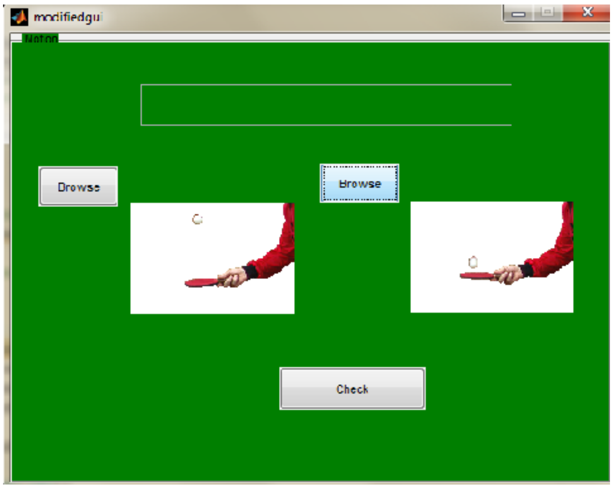
One of the more popular methods for optical flow computation is Lucas and Kanade's local differential technique. This method involves solving for the optical flow vector by assuming that the vector will be similar to a small neighborhood surrounding the pixel. It uses a weighted least squares method to approximate the optical flow at pixel (x, y). This technique has numerous advantages. Firstly, the support for the flow vector is local rather than global like the iterative technique of Horn and Schunk. This means that a good estimate without having to rely on the entire image. For some images with large homogenous regions, a global method may produce satisfactory results but for most cases, the flow vectors of different regions should not impact separate regions. Iterative techniques such as Horn and Schunk allow vector information to spread out over the image to possibly different regions. Reinforcement of the constraint equation can serve to mitigate this, but the problem remains. Imagine two occluding objects passing, both with similar spatial gradients but with different orthogonal components.

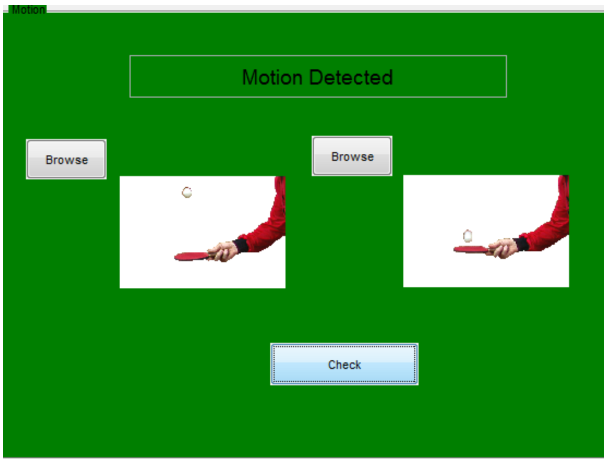
The iterative scheme will merge these two flow field regions at the boundary and will not preserve the sharp discontinuity. The vectors produced by local techniques will not suffer this problem. The downside is that the homogeneous regions will not be filled in. The task of deciding and filling in homogenous regions is obviously important but should be accomplished at a later stage in the process, using the initial local estimates as input. In this way, the user has more control over the final optical flow field and will probably produce better results.

EXPERIMENTAL RESULT

In our approach first we have to find out correspondence between the images, for this we use Ransac algorithm. This algorithm is use to recognise the motion is happened or not. For this we use two consecutive images and it is put in to the Ransac algorithm. Here use the SURF (SpeedUp Robust Featurs)features. RANSAC is used for further localization and identification of the most prominent motions within the frame.

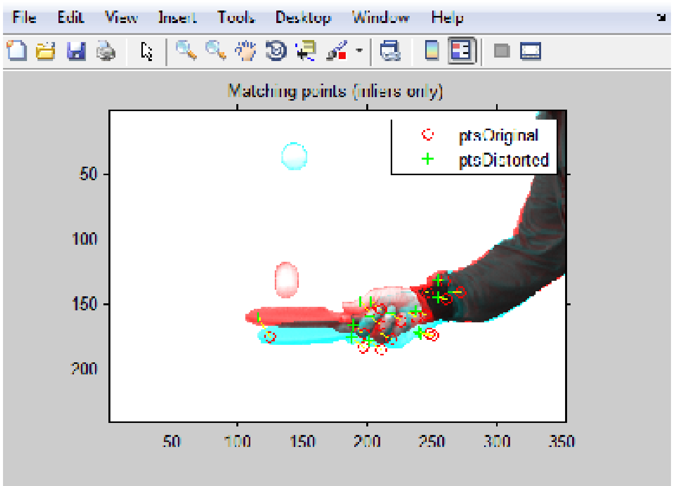
For finding out the movement we have to know the scale and theta value. Scale is use to detect the horizontal and vertical movement and theta is use to detect the angle. For this we use the similarity or affine transformation. And then matching features is find out using Ransac algorithm and find out the movement is happened or not. Here the motion of tennis is find out by using these algorithm. There is an option for browsing the images and field for showing the motion is happened or not. If two images are same then display no motion detected.

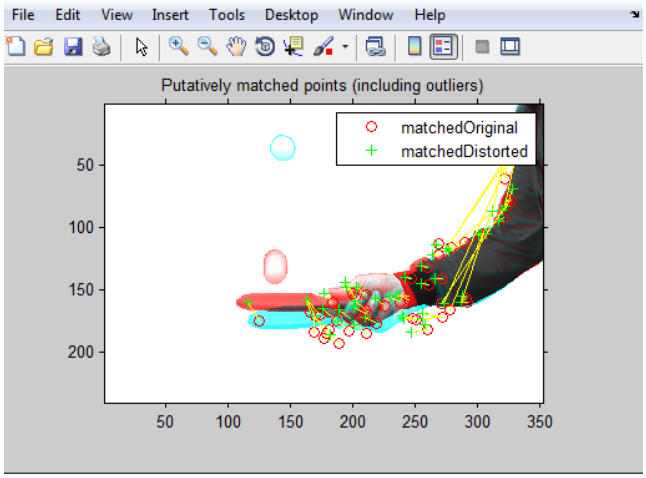




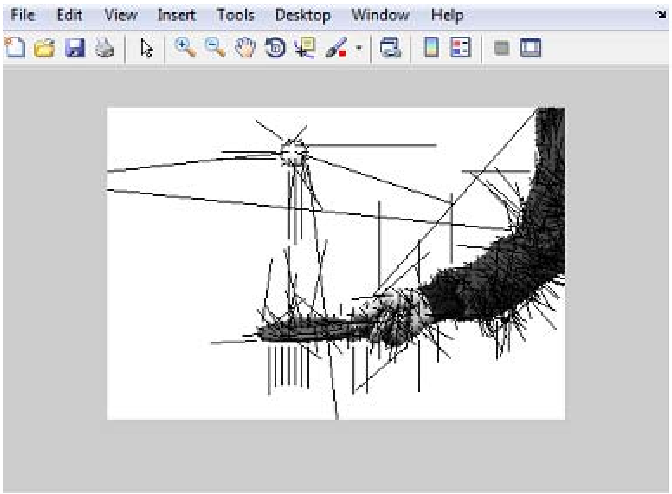
According to these images we detect the motion and optical flow. Here using the optical tool box and computer vision toolbox. For motion detection Ransac algorithm is used here and Lucas Kanade algorithm for optical flow. In Ransac first feature is detect then extract the feature and then find out the matching points and find out the motion is happened or not. Then plot optical flow, for this lines are using here and show the movement of pixels. Here display the possible movement of pixels.

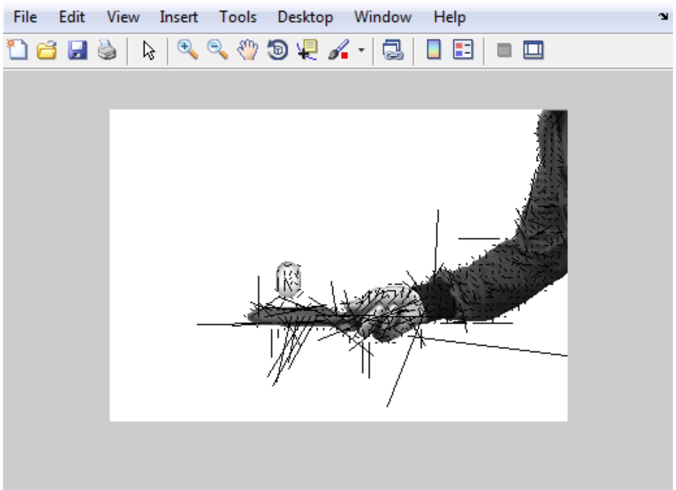
The output of Ransac algorithm and optical flow is shown below.





Here more points shown the movement and next figure only required points is displayed .And after that optical flow is shown in the figure. optical flow display the movement of pixels in the object. The lines shows the movements of the pixels. The output of Lucas Kanade algorithm are given below.





CONCLUSIONS

This paper presented an implementation of Ransac and Lucas and Kanade's [2] differentiation method for computing optical flow in video. The implementation has been shown to compute motion and flow in real-time for small image sizes and presents a desirable level of flow accuracy, capable of distinguishing regions varying in activity level. The algorithm does consume a large amount of system resources, however it is predicted that continuing technological improvements in computer hardware will resolve this problem Overall, the algorithm based on Lucas and Kanade when used with a threshold had the best performance. It consistently produces accurate depth maps, has a low computational cost, and good noise tolerance. On the down side, it produces quite sparse depth maps. Barron et al.[8] also concluded that this algorithm had the best performance.

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