Three dimensional dynamic measurements using a stereo vision system and optical flow algorithms for high speed video applications

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Abstract— In this work we present a solution for a specific problems of lateral, radial and depth dynamic measurements using high speed video. By combining optical flow algorithms and stereo vision techniques, we obtain a solution for object tracking, displacement and deformation measurements and also 3d reconstruction. We present the calibration procedure of the system and dynamic test achieved over a random point pattern by using OPENCV library.

Keywords-component; Optical flow; Stereo vision; Deformation; Three dimensional reconstruction.

I. INTRODUCTION

It is known that for the design of new products is necessary to make dynamic measurements of displacements and deformations in solid bodies. For instance; the design of the spin system in a washing machine, safety testing in tempered glass lids and Impact testing in boxes for shipping and packing. In this work we present a solution to a specific problem of dynamic tracking in lateral, radial and depth directions by using images analysis of high speed video of a stereo vision system.

The images are analyzed using optical flow algorithms [1, 2, 3, 4] and stereo vision [5, 6, 7].

The optical flow allows the study of displacement in the time experienced by dynamic objects in two dimensions, when the changes are very small. By using a stereo vision system, we can retrieve the coordinates of the objects observed in the three axes (x, y, z) and therefore the reconstruction of such objects.

A stereo vision system consists of two cameras where the reconstruction of the object is done in four stages in a sequence of images taken from two cameras simultaneously: the first stage is called calibration and leads us to obtain the extrinsic parameters, intrinsic and a model lens distortion. The second stage is by performing the rectification of the stereo images, the third stage is the search for correspondences between the images of the two cameras and the fourth stage calculates the three-dimensional coordinates of the points in the scene. There are several algorithms for solving each of these stages.

The procedure presented in this paper solves them and allow us to follow an object, measure displacement, 3d reconstruction of an object and measure the distortion by analyzing high speed video images.

The following sections show the development of the system calibration and dynamic tests carried out in a pattern of random dots in the above cases using the OpenCV library [8].

II. EXPERIMENTAL SETUP

By using two identical digital cameras with 12mm lens placed in parallel, as seen in Fig. 1. Four sequences were taken at 7.5 frames per second for each camera in sync. The motion sequences were captured for horizontal, vertical, rotational and depth displacement using a random dot pattern (Fig. 2). To calibrate the cameras, we took a sequence of 12 images of a flat chessboard regular pattern (fig.4).

In the next subsection we will present the proper description of both techniques used with its experimental result obtained.

A. Optical Flow

Using Block Matching method [3.4] image was divided, past and present, in small regions of square blocks of pixels. Because the blocks can overlap correlation algorithms are used for matching of the pixels of a previous image with the current, and thus calculate the movement between them.

Applying Sobel filters and using a spiral search algorithm in the current image around a certain number of pixels near the position of the block in the previous image values we are capable of obtain horizontal and vertical scrolling.

Sobel filters are used to note the regions based on texture, then filtered to remove the original image regions where no one has a highly textured according to a threshold value.

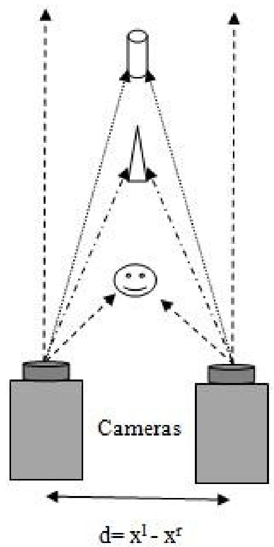


Figure 1. Optical arrangement using two parallel cameras. The depth is inverse inversely proportional to the disparity "d" between the cameras.

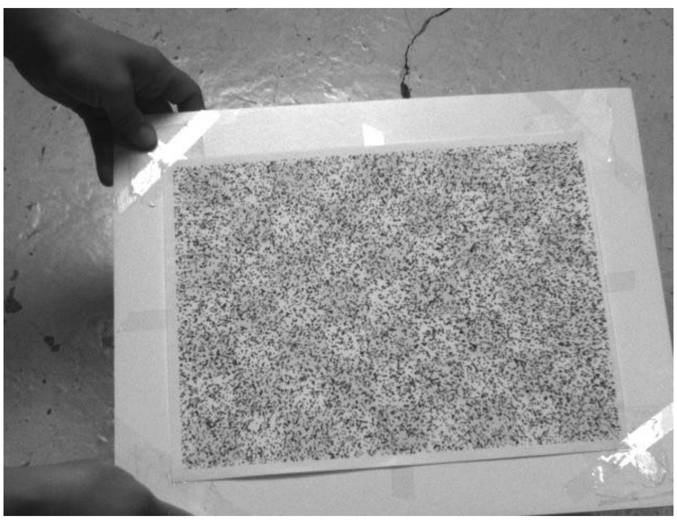
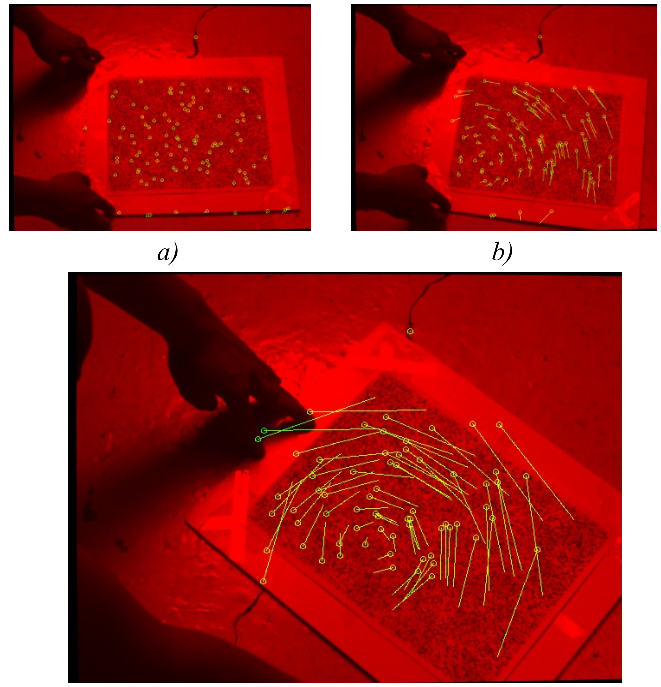


Figure 2. Pattern of random dots.

With this technique we tested 4 motions: horizontal, vertical, rotation and amplitude separately. The most important being the rotation and amplitude, as many optical algorithms cannot recognize these types of movements. For each test is built file cumulative values over the entire sequence, thus we can follow an object at different times (t).

Figure 3 shows tracking results of some points to make rotational movements. Figure 3 (c) shows the displacement accumulated in earlier times.



a) *b)*

c)

Figure 3. Images of the displacement occurred tracking a rotational displacement.

B. Stereo Vision

As mentioned before the stereo vision technique includes several stages, the first and most important is calibration, which relates the two cameras in a single geometry, also gives the internal parameters and distortion parameters of cameras, which are used for the next stage which is the rectification the images. Then we apply the correlation and obtain the disparity maps with which we calculate the depths in the image and lead us to obtain the reconstruction of objects.

B.1 Calibration

The calibration depends on finding the rotation matrix and translation between the two cameras. The procedure is to fix the position of the cameras and take several pictures simultaneously, with the pattern on a chessboard (Fig. 4) from different positions; these changes in the chessboard can be of angle and displacement in three axes and even with a certain degree of rotation. The next step is to find the position (x, y) in pixels of all the inner corners of the chessboard for the 12 images taken from each camera (Fig. 4); To perform the calibration we used the function cvStereoCalibrate() of the OpenCV library [8]. As a result gives us the translation and rotation matrices (better known as extrinsic parameters) of the system. For each camera the four intrinsic parameters are calculated: focal lengths (f_x, f_y), principal points (c_x, c_y) and five distortion parameters: three radial (k_1, k_2, k_3) and two tangential (p_1, p_2).

B.2 Stereo Rectification

From the parameters obtained from the calibration we can eliminate distortions (barrel and pillow) and rectify the images pairs. The rectification is to remap the images in a form that if a point appears in the two images (left and right), this should be in the same row but in a different column, the function to do this is *cvInitUndistortRectifyMap()* [8] the result gives us images without distortion and rectified, as shown in figure 5.

B.3 Stereo Correlation

The correlation allows us to find the position of an object in both images, which becomes an easier task with rectified images. OpenCV provides a function to solve this problem, *sgbm()*. Obtain the disparity maps used to calculates the distance (depth) that are objects from the camera, the depth is given on gray scale, if the object is the closer to the cameras will be clearer tone, otherwise the increases gray scale; black indicates that the correlation could not resolve and therefore no depth (Fig. 6).

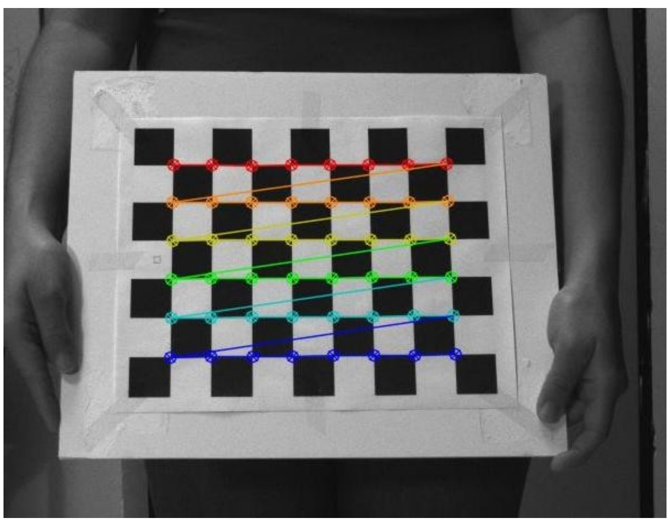


Figure 4. Calibration pattern and results of the search for corners of the board, in this case were 8x6 corners.

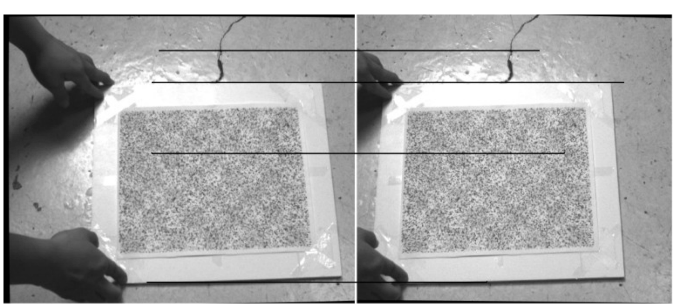


Figure 5. Left and right image rectified. The lines drawn pass over the same object in both images.

Figure 6. Disparity map of a reference plane used. The gray scale indicates the distance of the object (Reference Plane) to the camera.

B.4 Three Dimensional Reconstruction

With the values of the disparity map and the positions (x, y) of each point, we calculate the three-dimensional coordinates of objects within the image, better known as "point clouds", the function used is *cvReprojectImageTo3D()* [8]. In Figure 7 we can see the reconstruction of eight points of the Figure 4. The rectification, correlation and reconstruction are done for all images of the sequences.

C. Tracking spatial and temporal displacements

By using the results of the two techniques used in this work (The cumulative optical flow files and the point cloud coordinates *(x, y, z)*) we can properly measure dynamics distribution as rotation (Fig. 8 and Fig 9) and depth sequence, Fig 10. In Figure 8 we present the tracking of a single point presented in Figure 3 through a sequence of 80 images with their *(x, y, z)* respective positions. In Figures 9 we present the result of tracking all pixels of the image, the rotational displacement suffered by the pixels is shown in colors ranging from gray to blue, the gray color represents the lowest displacement and blue the largest shift obtained. By accumulating the displacements with their respective positions (x, y, z) we can known if an object has deformations. Figure 10 present the case of depth tracking of the plane object used.

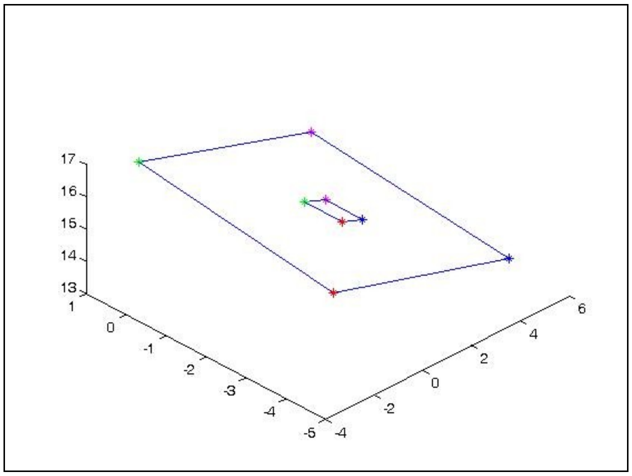


Figure 7. Reconstruction of the corners the pattern of calibration.

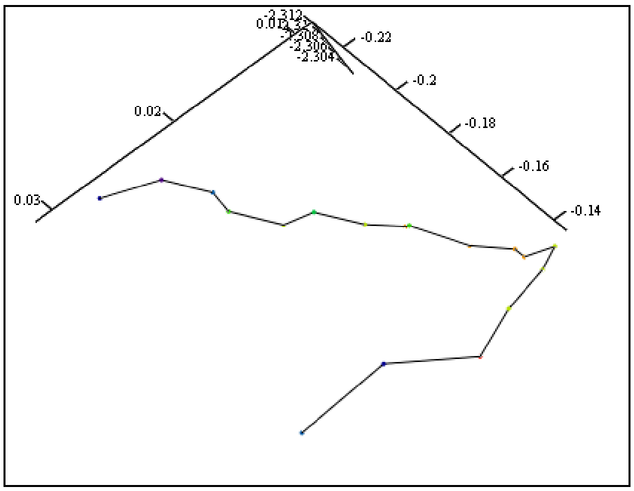
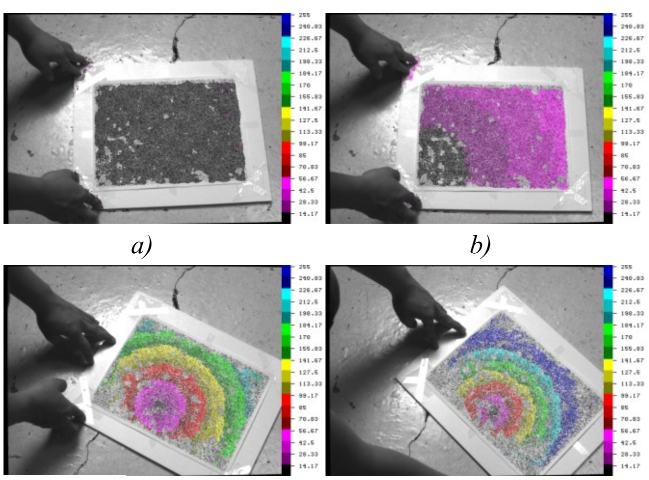


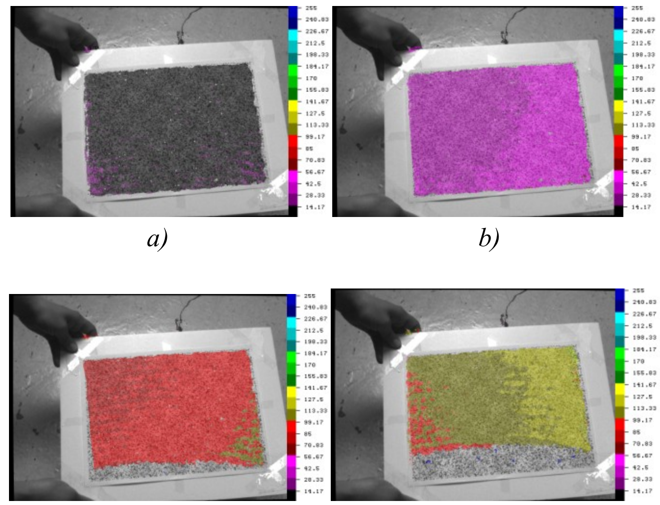
Figure 8. Tracking a point through time and space in rotational and lateral displacement.



a) b)

c) d)

Figure 9. Temporal accumulated of rotational displacement at 64 stages, a) between t=0 and t =1, b) from t=0 to t=9, c) from t=0 to t=40 and d) from t=0 to t=64.



a) b)

c) d)

Figure 10. Displacement accumulated in the time, amplification(Depth) testing for 17 stages. , a) between t=0 and t =1, b) from t=0 to t=9, c) from t=0 to t=12 and d) from t=0 to t=17.

III. Conclusions

We presented and demonstrated the solution for analysis of dynamic systems via high-speed videos, to prove the concept is enough to work at 7.5 frames per second but the technique can work with video much faster, as can be at 1000 frames per second.

On the other hand, the developed system can be easily introduced to the industry because it requires minimal intervention by the operator and not requires high technical information. The system is also an alternative flexible enough to allow the user to adjust the separation between cameras, and even the lenses, depending the experiment to implement.

In conclusion we designed a system capable of analyzing movement and deformation in 3 dimensions for dynamic systems via high-speed video, but it can also be used in biomechanical systems, these systems studied and modeled the human body.

IV. Acknowledgements

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