Digital Video Stabilization through Curve Warping Techniques

Angelo Bosco¹, Arcangelo Bruna¹, Sebastiano Battiato², Giuseppe Bella², and Giovanni Puglisi²

Abstract — The widespread diffusion of hand-held devices with video recording capabilities requires the adoption of reliable Digital Stabilization methods to enjoy the acquired sequences without disturbing jerkiness. In order to effectively get rid of the unwanted camera movements, an estimate of the global motion between adjacent frames is necessary. This paper presents a novel approach for estimating the global motion between frames using a Curve Warping technique known as Dynamic Time Warping. The proposed algorithm guarantees robustness also in presence of sharp illumination changes and moving objects¹.

Index Terms —Video Stabilization, Dynamic Time Warping, global motion estimation.

I. INTRODUCTION

Imaging devices offering video recording capabilities have gained significant popularity in the recent past. Frames resolution, movie-clips length and video quality are all factors of which users are becoming progressively more conscious. Hence, the request for high-quality video is increasing even when small portable devices, such as mobile phones, are concerned [1]-[3].

The assessment of video sequences involves many factors and the quality of the single frames is just one of the elements to be considered. Temporal incongruities such as compression artifacts occurring during scene changes, frame dropping and low frame rates are the major annoyances related to video quality perception. Nonetheless, even after reducing or eliminating the aforementioned problems, it is also necessary to consider the way in which video sequences are inherently acquired by the user.

Video quality obtainable using small hand-held devices is obviously intrinsically affected by the unsteadiness of the user's hands; therefore, without any correction, the acquired video will show unbearable jerkiness. Hence, the removal of unwanted camera vibrations is a fundamental element to be considered.

Basically, two main approaches for removing nonintentional camera motion exist: *mechanical* and *software* based methods. Mechanical solutions consist in moving the lenses to align frames onto the image sensor thus compensating for jerky motion. Similarly, another mechanical solution consists in moving the image sensor instead of lens.

The software based stabilization is more cost-effective in that it relies exclusively on image processing techniques, avoiding the cost of mechanical moving parts. Software solutions generally require the estimation of the global motion between frames so that the opposite motion can be applied to counteract image shake and realign frames. Hence, the estimation of the global motion vector is a critical part of the system since this vector must correctly describe the amount of unwanted motion between frames.

In [4] we proposed a method that derives the global motion between frames by analyzing the motion vectors obtained using block based motion estimation. This paper introduces a novel solution that estimates the global motion using a technique that finds matches between two curves known as *Dynamic Time Warping (DTW)*[5].

Our solution addresses the problem of stabilization in relation to the translational model [6][7].

The paper is organized as follows: sections II-III provide a description about the frame signatures and *DTW*. Section IV describes the proposed architecture. Section V ends the paper showing experimental results.

II. FRAME SIGNATURE CURVES

Before giving full description of the *DTW* approach, we introduce frame signatures; they are simply obtained by processing the rows and the columns of each frame. The basic technique to compute frame signatures is known as *integral projections* [8].

In its simplest form, the method consists in summing up the pixel values of each row and each column generating two characteristic curves for each frame as depicted in Fig. 1. The value of each summation can be normalized to avoid too big values.

Formally, given a frame F with m rows and n columns, two curves C_x and C_y are determined, according to the following equations (1):

$$C_{x}(j) = \frac{1}{m} \sum_{i=1}^{m} P(i, j), \ j = 1,...,n$$

$$C_{y}(i) = \frac{1}{n} \sum_{i=1}^{n} P(i, j), \ i = 1,...,m$$
(1)

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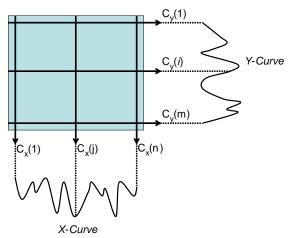


Fig. 1. X and Y signatures for a frame with n rows and m columns.

The integral projections method allows estimating the global motion between two consecutive frames by shifting their C_X -curves (C_Y -curves) in order to find the best alignment. The displacement used to determine the best match of the curves is representative of the global motion between frames.

Figure 2 shows the C_X -curves of two consecutive frames. The two test frames are very similar; hence the shape of the two curves is almost equal. The displacement of the two curves is caused only by the hand-shake of the user. By analyzing the amount of displacement between the two curves it is possible to determine the relative component of the global motion vector.

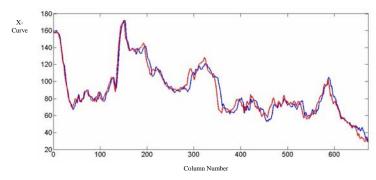


Fig. 2. C_X -Curves of two consecutive frames. The curves displacement in pixels gives the corresponding global motion vector component.

III. DYNAMIC TIME WARPING

A significant limitation of the simple *integral projection* technique is that it cannot provide accurate results when the dynamics of the acquired scene become complex, as for example under fast varying illumination conditions and in presence of large moving objects. In these cases, the shape of the curves, even between consecutive frames, can be quite different and an accurate alignment becomes almost impossible to achieve.

For example, Fig.3 shows the C_X -curves relative to two similar frames in which a large object moves in the center of scene. Under these conditions it is not easy to estimate the correct displacement between the curves: there is a large displacement in the center and very small displacement at the periphery.

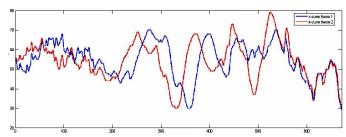


Fig.3. Critical curves for the integral projection method.

In order to properly cope with complex scenes, a more robust solution is necessary. *Dynamic Time Warping (DTW)* can provide the required level of robustness [5][9].

In general, the *DTW* method is used to warp and match generic sequences of numbers that can be viewed as curves in a proper coordinate system; the aim of *DTW* is to obtain a precise matching along the temporal axis, maximizing the number of point-wise matches between two curves.

Formally, given two sequences X and Y of length n and m respectively (2):

$$X = x_1, x_2, ..., x_i, ..., x_n$$

 $Y = y_1, y_2, ..., y_j, ..., y_m$ (2)

A distance between the elements of the two curves is computed; the Manhattan difference can be used for efficiency in that it requires very little computational effort (3):

$$d(i,j) = |x_i - y_j| \qquad (3)$$

The computed differences are stored into a nxm matrix as defined in (4):

$$M(i,j) = d(i,j) \tag{4}$$

A subset of the elements in M defines a warping path W (5):

$$W = w_1, ..., w_l, ..., w_K$$
 (5)

Each element $w_l \in W$ is a pair of indices (i, j) that associate an element of the X-series with an element of the Y-series.

The length K of the warping path is defined is such that (6):

$$\max(m, n) \le K < m + n - 1 \tag{6}$$

Clearly, many warping paths exist inside M, but we choose the one that minimizes the following functional (7):

$$DTW(X,Y) = \min\left(\sqrt{\sum_{l=1}^{K} w_l} / K\right)$$
 (7)

The elements of the matrix that are chosen for the best warping path define an association between the sequences X and Y, see Fig. 4.

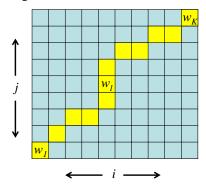


Fig. 4. A warping path example between two generic curves. The x(y)-axis spans the elements of the first (second) curve. Each marked item in the matrix represents a matching between a point of the first curve with a point of the second one.

The q-th element of the warping path $w_q(i,j)$ indicates that the i-th element of the first curve matches with the j-th element of the second curve.

IV. PROPOSED ARCHITECTURE

The proposed method extracts the digital signatures from pairs of consecutive frames and warps them to find the best point-wise matching. The global motion information from frame t-I to frame t is inferred by analyzing the warping parameters that maximize the point-wise matching.

For any pair of frames t-l and t, the horizontal and vertical digital signatures are extracted:

$$H^{t-1}, V^{t-1}, H^t, V^t$$

The process starts by storing the two *current H/V*-signatures in memory so that when the next frame carrying its own H/V-signatures is processed, a DTW warping step is performed:

$$DTW(H^{t-1}, H^t)$$

 $DTW(V^{t-1}, V^t)$

Each warping step produces two warping paths: W_H , W_V , relative to the horizontal and vertical dimensions respectively.

The block diagram and data-flow of the algorithm are shown in Fig. 5. The process in then repeated for each pair of consecutive frames.

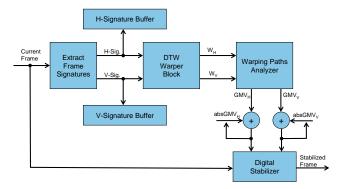


Fig.5. Block Diagram of the algorithm

The point-wise matching associated to the horizontal signatures of two consecutive frames is illustrated in Fig. 6:

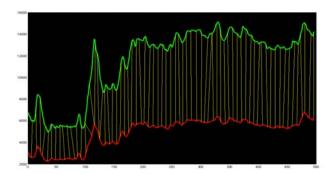


Fig. 6. X-Curves of two consecutive frames having different illumination.

By analyzing how matching is distributed and how frequently it occurs, the components of the *Global Motion Vector* (GMV_H , GMV_V) are determined and added to the *Absolute Global Motion Vector* (AbsGMV) which is the motion computed in relation to the reference frame (9):

$$AbsGMV_{H} = AbsGMV_{H} + GMV_{H}$$

$$AbsGMV_{V} = AbsGMV_{V} + GMV_{V}$$
(9)

Hence, the vector *AbsGMV* accumulates the global motion starting from the reference frame. Finally, the digital stabilizer block stabilizes the current frame according to the new *AbsGMV*. It is worth mentioning the fact that not all detected motion is unwanted; the user may intentionally move the device to perform panning. To this end, a low pass filtering of the detected motion is usually performed [10].

V. EXPERIMENTAL RESULTS

In order to confirm the validity of the proposed algorithm, a series of experiments have been performed comparing our approach with other digital stabilization techniques based on integral projections [8] and block matching [4].

The sequences used for the experiments were taken from two different sets:

- SET 1: sequences containing large moving objects;
- SET 2: sequences showing fast illumination changes.

The video sequences of both sets do not originally contain jerky motion.

In order to scientifically measure the effectiveness of the proposed solution, hand-shake motion was artificially added to the original sequences by using a series of known global motion vectors representing typical real user hand vibrations.

The difference between the true motion vector used to introduce jerkiness and the *DTW*-estimated motion indicates the precision of the proposed solution (10):

$$\Delta^{t}(x) = \left| GMV_{true}^{t}(x) - GMV_{est}^{t}(x) \right|$$

$$\Delta^{t}(y) = \left| GMV_{true}^{t}(y) - GMV_{est}^{t}(y) \right|$$
(10)

where $GMV_{true}^{t}(\bullet)$ and $GMV_{est}^{t}(\bullet)$ are the real and the estimated motion vector components respectively.

A. Experiment with large moving objects.

The first illustrated experiment is relative to a sequence from SET 1; it contains a crowd moving from right to left (Fig. 7). Figures 8 and 9 show that both integral projections and block matching approaches do not correctly estimate the motion vector components. On the contrary, the *Dynamic Time Warping* based solution generates a better estimate of the motion vector components (Fig. 8).







Fig. 7. A frame taken from a SET-1 sequence presenting large moving objects (sequence 1). The crowd is moving from right to left.

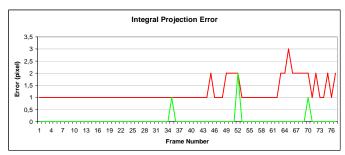


Fig. 8. Integral projection estimation error along x (red) and y (green) axes for sequence 1.

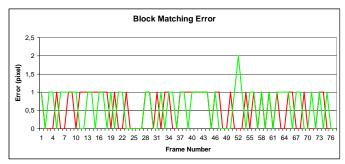


Fig. 9. Block based estimation error along \mathbf{x} (red) and \mathbf{y} (green) axes for sequence 1.

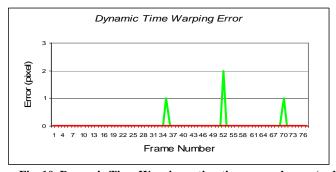


Fig. 10. Dynamic Time Warping estimation error along \boldsymbol{x} (red) and \boldsymbol{y} (green) axes for sequence 1.

B. Experiment in fast changing illumination conditions.

Our second illustrated experiment is relative to a sequence of SET-2. Fast illumination changes are exaggerated by dropping frames and increasing the speed at which the sun goes beyond the horizon (Fig. 11).

The integral projection approach, finds incorrect matching between the frame signatures yielding inaccurate global motion estimation (Fig. 12). On the contrary, both Dynamic Time Warping and block matching based approaches, yield better results (Figg.13 and 14). In particular, it can be seen that no errors occurred along the x-direction.







Fig. 11. A frame taken from a sequence with brightness variation in the scene due to the sunset (sequence 2).

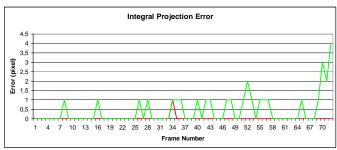


Fig. 12. Integral projection estimation error along x (red) and y (green) axes for sequence 2.

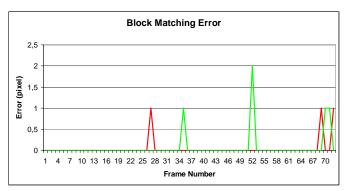


Fig. 13. Block matching estimation error along \mathbf{x} (red) and \mathbf{y} (green) axes for sequence 2.

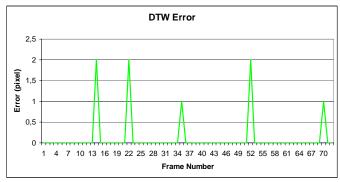


Fig. 14. Dynamic Time Warping estimation error along x (red) and y (green) axes for sequence 2.

The experiments proved that the integral projection technique suffers in presence of sharp brightness variations or large moving objects in the scene. Conversely, Dynamic Time Warping is robust enough and obtains results similar to, or better than, the block based approach. The proposed *DTW*

technique also allows using only one frame buffer instead of two.

VI. CONCLUSIONS

A new approach for the estimation of global motion between frames has been proposed. The solution can be incorporated in a system for video-stabilization for hand-held devices. The proposed technique is based on the *Dynamic Time Warping* techniques; hence it is robust in case of changing illumination conditions and moving objects which interfere with the shape of the frame signatures. Future work consists in optimizing the method in terms of speed and memory consumption.

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