A New Approach for Secure Transmission and Stabilization of a Video

Anshul Kumar Singh[1] and Prachi Pundhir[2]

[1]R. B. S. Engineering Technical Campus, Bichpuri, Agra, India [2]Ajay Kumar Garg Engineering Collage, Ghaziabad, India akrajawat20@gmail.com prachipundhir1@gmail.com

Abstract. A method of stabilizing and safe transmission of a video was suggested by our study. Without the nervous effect of shaking the handheld cam feature recording, a stable yield function will be achieved. First, from every edge of the data feature, notable focuses. The distinguished and transformed feature was enhanced and settled afterwards. Enhancement incorporates the nature of the adjustment of the feature and less unrelated range after adjustment methodology. The efficiency of using such a method shows great results with regard to other methodologies. The contortion of the yield features recorded in distinctive circumstances is adjusted and disposed of. The initial findings show that the proposed method is suitable for use and provides extraordinary adaptation arrangements. While steganography is defined as the investigation of undetectable correspondences. Secured transmission is achieved in image by installing data into a spread image and generating a stego image.

Keywords: Steganography, stego image, video stabilization.

I. INTRODUCTION

Video stabilization is very demanding and hot topic of research now a days. By re- ducing unnecessary shakes and jitters of an image/video recording system without affecting moving objects or deliberate camera panning, video stabilization technology is used to prevent visual quality loss. In handheld imaging systems, which are more affected by shakes due to their smaller scale, this is especially significant. Usually, unstable images are caused by unnecessary hand jiggling and deliberate camera pan- ning, while unwanted camera angle variations occur in unstable sequences of images. Also under non-optimal settings, the use of video stabilization methods guarantees high visual quality and secure video footage. In certain video cameras, real-time opti- cal image stabilization, also called electronic image stabilization (EIS), is used. This method moves the electronic image from frame to video frame, enough to counteract the motion. To provide a buffer for the motion, it uses pixels beyond the boundary of the visual frame. By smoothing the transition from one frame to another, this method eliminates disruptive vibrations from images. But for the extreme boundaries when the image is extrapolated, this technique does not influence the noise level of the image. It can do nothing with the present distortion of motion, which can lead to a pic- ture apparently losing focus as motion is compensated. Digital signal processing (DSP) is also often used by some to minimize noise in stills, for example by subdivid- ing the exposure into many shorter exposures in fast succession, discarding blurred ones, re-aligning and inserting the sharpest sub-exposures together, and using the gyroscope to detect the right time to take each frame.

II. LITERATURE REVIEW

Omar Hamdoun et.al present and test an individual re-identification scheme for multi- camera surveillance device. Their method uses matching of signatures based on inter- est-points descriptors obtained on short video sequences [2]. In order to capture ap- pearance variability, one of the originalities of their approach is to accumulate interest points on many sufficiently time-spaced images during individual tracking within each camera [1]. The matching method implemented in this paper is very fast: ~ 1/8s for the re-identification of one target person among 10 people previously seen, and a logarithmic dependence on the number of models of stored people making re-identification computationally feasible among hundreds of people in less than ~ 1/5 second [1].

Fayez Tarsha-Kurdi et.al introduced two methods for the detection of automatic roof planes from Lidar data and compared them. 3D Hough-transform and the RANSAC algorithm are these techniques [4]. Each one's theory and pseudocode were compre- hensive. Two sets of point clouds distinguished by different densities and containing different building types were used to evaluate the original and the improved algo- rithms. It is claimed that to detect the best planes from 3D point clouds, both methods are based on pure mathematical principles. This attribute often contributes to the de- velopment of intolerable mistakes. Finally, even with weak point density, the satisfy- ing results obtained for various clouds confirm the suggested processing chain. It becomes easier to complete the processing chain and accomplish the final steps lead- ing to the complete 3D building model once the building roof planes are automatically identified.

"Tree Stem and Height Measurements using Terrestrial

DOI : 10.35291/2454-9150.2021.0080

ISSN : 2454-9150 Vol-06, Issue-12, MAR 2021

Laser Scanning and the RANSAC Algorithm" research paper by Kenneth Olofsson et.al presents terrestrial laser scanning technique for automated measurements of tree stems [5]. The aims of the study were to establish and validate a new method for tree stem and canopy identi- fication, classification and measurement using the Hough transformation and the RANSAC algorithm, and to evaluate the effect of the distance to the scanner on the accuracy of the measurement [5]. As the distance to the scanner increased and fol- lowed the trend of decreasing visible region, the proportion of detected trees de- creased. The proportion of detected trees was 87 percent on average for the plots within 10 m from the scanner and the diameter was measured at breast height with a 14 percent relative root-mean-square-error (RMSE). For oak, which had an RMSE of 7 percent for all the complete 20 m radius plots, the most precise diameter measure- ments were obtained.

Tania Landes et.al discusses the RANSAC algorithm used for the detection of auto- matic roof planes from lidar data [6]. It has detailed its theory and its pseudocode. The algorithm was expanded to adapt its mathematical theory to the geometry of the roof. Two modifications were then proposed in order to increase its capabilities. The first was the improvement by creating a new point cloud of the original results [6]. The second development was the algorithm's adaptation, so that the best roof plane was detected instead of the best mathematical one. In addition, another change was sug- gested for the efficiency of the detected roof planes to be examined. The neighbor- hood relationships between the neighboring aircraft were then analyzed using the neighborhood matrix. Finally, two sets of building point clouds, distinguished by different densities and containing different building shapes, were used to test the ac- curacy of building roof plane detection. Then a comparison was carried out between the number of initial and observed roof planes. In addition, seven factors were calcu- lated which defined the accuracy of the detection of the roof plane compared to a reference model. Finally, even with weak point density, the satisfying results obtained for various clouds confirm the suggested processing chain

III. PROPOSED METHODOLOGY

In this proposed methodology we identified point of interest, it involves finding distortion between two frames, edges and corner is detected by Corner Detector Device Object and then find corresponding point by finding the Sum of Squared Differences (SSD) [3]. After that we applied transform estimation and correct frames with frame correction to get desired stego image. Random Sample Consensus (RANSAC) algorithm is used to solve Position determination problem. It's very interesting and important to find the point of interest to get the corresponding points to work. The transform estimation model contains mathematical formulas or steps which is discussed in the later part. After this whole process our objective is to find stego image by the process of frame correction. Proposed approach is depicted in Fig. 1 with the help of a flow chart.

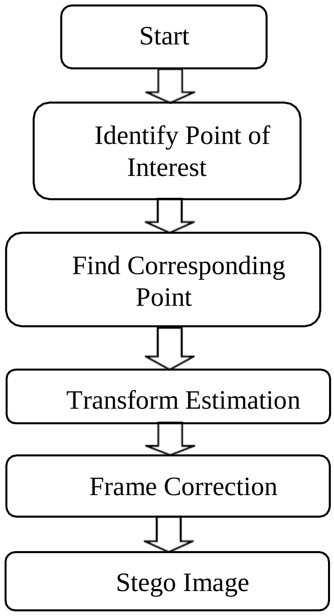

Fig. 1. Proposed Methodology

IV. IDENTIFICATION OF POINTS OF INTEREST

This move involves fixing the distortion between two frames and finding a transformation between them. Firstly it is important to discern the appropriate points from the two chosen frames by choosing the simple correspondence between the edges. Right now the points for each edge are known, so it is important to locate points around striking picture highlights, similar to corners, to check that these points may have comparative points in the second frame. Corner Detector Device Object is used along these lines to discover corner features using Harris Corner Detection, which is one of the easiest calculations to discover corner features.

Fig. 2. Results of point's identification

V. CORRESPONDING POINTS

It will conjure up the introductory correspondence between the points distinguished from the previous phase. Correspondences must be chosen at each point between the summoned points, so a lattice of 9 x 9 fragments would be divided from its continu- ous image outlines around each point. By finding the Sum of Squared Differences (SSD) [3] among the sequential image areas of casings, the most important thing here is to coordinate the cost between points. We ought to identify the lowest costs in these lines

DOI : 10.35291/2454-9150.2021.0080

to take them into account in the agreement. The same positions were seen in Figure 3 for the green shading purposes of the introductory reference points that appeared on both edges.

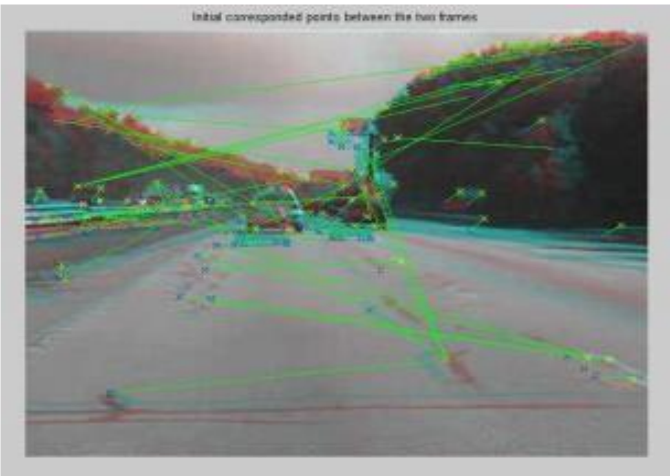

Fig. 3. Corresponding point finding results

Not all points of correspondence are true, but most are outlier points. The SSD is then carried out to ensure that the lowest cost matching points are found in the next step.

VI. ESTIMATION OF TRANSFORM

There are some incorrect point correspondences, but the random sample consensus algorithm (RANSAC) can be used to evaluate good geometric transformation esti- mates between the two frames, as in Figure 4. Random sample consensus (RANSAC) is an iterative method of estimating the parameters of a mathematical model from a set of observable data containing outliers, where no effect on the values of the predic- tions should be allowed to outliers. It can also be viewed as a method of outlier detec- tion. In the sense that it generates a rational outcome only with a certain probability, it is a non-deterministic algorithm, with this probability increasing as more iterations are allowed. The algorithm was first published in 1981 by SRI International's Fischler and Bolles. To solve the Position Determination Problem (LDP), they used RANSAC, where the aim is to decide the points in the room that project onto an image onto a series of landmarks with known locations. The RANSAC algorithm is a learning technique that uses random sampling of observed data to approximate parameters of a model. RANSAC uses the voting scheme to find the optimal fitting answer, given a dataset whose data elements comprise both inliers and outliers. To vote for one or more versions, data elements in the dataset are used.

The RANSAC algorithm can be expressed in the codes as:

Given:

Data – Observation set.

Model – Observed data points is explained by this model.

n – Minimum number of data points required to estimate model parameters. k – Maximum number of iterations allowed in the algorithm.

t – Threshold value to determine data points that are fit well by model.

d – Number of close data points required to assert that a model fits well to data.

```
Return:
   bestFit – model parameters which best fit the data
Iterations = 0
bestFit = Null
bestErr = something really large
While iterations < k do
   maybeInliers := n randomly selected values from data
   maybeModel := model parameters fitted to maybeInliers
   alsoInliers := empty set
  for every point in data not in maybeInliers do
    if point fits maybeModel with an error smaller than t
       add point to alsoInliers
  end for
  if the number of elements in also Inliers is > d then
    // This implies that we may have found a good model
    // now test how good it is.
    betterModel := model parameters fitted to all points in maybeInliers and alsoIn-
ers
    thisErr = A measure of how well better Model fits these points
    if thisErr < bestErr then
      bestFit = betterModel
      bestErr = thisErr
    end if
  end if
  increment iterations
end while
return bestFit
```

The threshold value to be calculated when a data point matches a model t, and the number of near data points needed to assert that a model fits well with data d, are determined on the basis of and likely based on experimental validation, particular implementation and dataset criteria.

Fig. 4. Results after applying RANSAC

The correspondences of the inliers are in the context of the picture from Figure 4. The explanation behind this is that the elements of the context are far enough to behave as if they were on an infinitely distant plane. We should assume that the background plane is unchanged and that between the first and second frames it will not change further, but that this transition catches the camera's motion. The video would thus be stabilized by the correction process.

 DOI : 10.35291/2454-9150.2021.0080

Frame correction:

Fig. 5. Frame Correction

In comparison, as in Figure 4, the raw mean video frames are measured as well as the mean of the corrected frame. The left picture displays the average of the raw input frames due to the intense jittery platform that resembled the warped initial video frame. The median of the corrected frames with less distortion is on the right side. This showed that the algorithm for stabilization performed well.

We use numerous techniques such as spatial domain approaches, mathematical tech- niques, and spread spectrum techniques for data embedding. Here, we used the tech- nique of two stage DWT (discrete wavelet transformation). The hidden message is encoded in this technique in the transition or frequency domain of the cover image. We first add the two DWT levels to the picture here and then create the phase mask. After that, we combined the images and rendered the reciprocal by adding inverse DWT as well.

A Hungarian mathematician, Alfréd Haar, invented the first DWT. In the case of an input represented by a list of numbers {\displaystyle 2^{n}}2^{n}, the transform of the hair wavelet can be considered to pair input values, store the difference, and trans- fer the amount. This method is repeated recursively, pairing the sums to prove the next size, resulting in variations between {\displaystyle 2^{n}-1}2^{n}-1 and the final sum. Wavelets are also used, such as pictures, to denoise two dimensional sig- nals. Three steps for eliminating unnecessary white Gaussian noise from the noisy picture displayed are given in the following example. To import and filter the image, Matlab was used.

It is important to remember that it may result in multiple forms of filtering to pick other wavelets, stages, and thresholding strategies. White Gaussian noise was selected to be omitted in this case. But with various thresholds, it might have been amplified almost as easily.

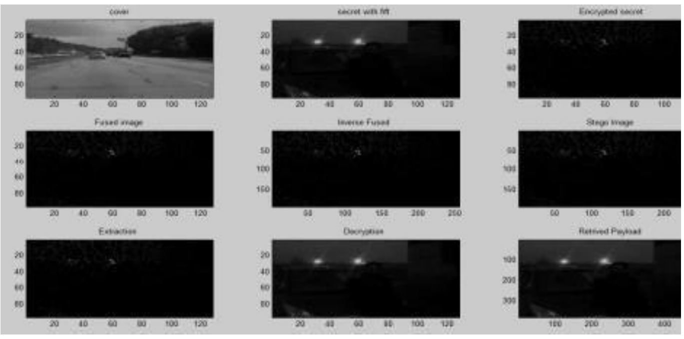

Fig. 6. Results of embedding images

VII. CONCLUSION

We all use mobile devices and cameras to capture the best moment, but while walking and traveling an image which we have taken found to be hazy and shaken or blur. We have worked on image stabilization and safe transmission of a videos by using random sample consensus algorithm (RANSAC). We have used MATLAB to improve the performance with a hazy or blur dataset. And results are embed with frame correction. We have shown that the stabilization approach introduced has performed well and we can quickly extend it to the videos taken on jittery platforms and we can further expand this technique by using certain other approaches in the future. The LSB substitution technique for a day is now commonly used because of its ease of execution, but as a DWT technique it is not properly secured. So using the DWT technique, we can securely transmit our data. And the image and videos may be transmitted with less haziness.

REFERENCES

[1] Omar Hamdoun, F. Moutarde, B. Stanciulescu, B. Steux.: Person re-identification in multi- camera system by signature based on interest point descriptors collected on short video se- quences. 2008 Second ACM/IEEE International Conference on Distributed Smart Cameras 7-11 Sept. (2008).

[2] M. Karkoub,: Development of a Vision non-contact sensing system for telerobotics appli- cations, vol. 44, pp. 1438-1449. International Journal of Systems Science (2013).

[3] F. Zhu, J. Liu: Research on Marine Buoy Surface Reconstruction Algorithm Based on Point Cloud Data. ICISCE (2019).

[4] F. Tarsha-Kurdi, T. Landes, P. Grussenmeyer: Hough-Transform and Extended RANSAC Algorithms for Automatic Detection of 3D Building roof planes from Lidar data. ISPRS Workshop on Laser Scanning and SilviLaser, September 12-14 (2007).

[5] K. Olofsson, J. Holmgren, H. Olsson: Tree Stem and Height Measurements using Terres- trial Laser Scanning and the RANSAC Algorithm, Remote Sensing, ISSN 2072-4292 (2014).

[6] F. Kurdi, T. Landes, P. Grussenmeyer: Extended RANSAC algorithm for automatic detec- tion of building roof planes from LiDAR DATA, The Photogrammetric Journal of Finland. Vol. 21, pp.97-109 (2008).

[7] Morimoto C, Chellappa R: Fast electronic digital image stabilization IEEE Proc, ICPR 3:284–288 (1996).

[8] Yang J, Schonfeld D, Mohamed M: Robust video stabilization based on particle flter track- ing of projected camera motion. IEEE Trans Circuits Syst Video Techno 19(7):945–954 (2009)

[9] Amanatiadis A, Gasteratos A, Papadakis S, Kaburlasos V, Ude :A Image stabilization, ARVRV. IntechOpen, New York, pp 261–274 (2010).

[10] Xu J, Chang HW, Yang S, Wang D: Fast feature-based video stabilization without accu- mulative global motion estimation. IEEE Trans Consum Electron (2012).

 DOI : 10.35291/2454-9150.2021.0080