

OBJECT TRACKING USING BRANCHING PARTICLE FILTERS

A Major Project dissertation submitted

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ABSTRACT

In digital video communication systems it is important that a video to be compressed, because of storing capacities as well as bit-rate constraints. The video processing is done using Sum of absolute Differences and with the image processing block set. We first calculate motion vectors between successive frames and use them to reduce redundant information. The method uses optical flow algorithm to calculate changes in the intensity of the pixels of the images. These apparent velocity components are then subjected to various image processing techniques to obtain centroid of the vehicle across the object. Here we are interested in finding spatio-temporal interest points of our object having a significant local variation of intensities of image. Branching particle filtering is a novel technique which is used to reduce the error in and computation time in tracking algorithm and is applied on motion frames to show these results for object detection. The distance traveled by the vehicle is calculated using the movement of the centroid over the frames. The image coordinates of the centroid are mapped to World space. The world coordinate distance is further mapped to actual distance using pixel to distance ratio. Using this information the velocity of the vehicle is estimated. In this Thesis we developed object tracking for real time video which, demonstrates the motion compensated video processing by using key point descriptor. First we have taken an object as reference object or image then the next successive object is compared with the reference object or image. Each time the successive object is compared with the reference object and produces an absolute difference then the summation of all these differences shows its sum of absolute difference.

Keyword: object tracking, Branching particle filter, key point descriptor etc.

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CERTIFICATE

I hereby certify that the work which is being presented in the M.Tech. Dissertation entitled “**Object Tracking using Branching Particle Filters**”, in partial fulfillment of the requirements for the award of the Degree of Master of Technology in **Microwave and Optical Communication** and submitted to the Department of **Electronics and Communication Engineering** of **Delhi Technological University** is an authentic record of my own work carried out under the supervision of **Prof. Rajiv Kapoor** , ECE Department.

The matter presented in this report has not been submitted by me for the award of any other Degree/Diploma elsewhere.

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CONTENTS

I. ABSTRACT.....	i
II. ACKNOWLEDGEMENT.....	ii
III. CERTIFICATE.....	iii
IV. LIST OF FIGURES.....	vi
CHAPTER-1:	
INTRODUCTION.....	1
1.1 Object video tracking.....	1
1.1.1 Introduction to tracking.....	2
1.1.2 Components of Visual Tracking System.....	3
1.1.3 Tracking: Possible Issues and Applications.....	3
1.1.4 Optimization Methods for Tracking.....	4
1.1.5 Direct Optimization.....	4
1.1.6 Probabilistic Inference.....	5
1.2 Video tracking.....	5
1.3 Visual Perception.....	5
1.4 Visual Processing.....	6
1.5 Problem identification.....	7
CHAPTER-2: LITERATURE SURVEY	9
CHAPTER-3: MOTION COMPENSATED VIDEO PROCESSING.....	16
3.1 Overview.....	16
3.2 Frame Segmentation	17
3.3. Search Threshold.....	18
3.4. Block Matching.....	18

3.5. Matching Criteria	20
3.6. Sub-Optimal Block Matching Algorithms	20
3.7. Motion Vector Correction.....	20
3.8. Vector Coding	18
3.9. Prediction Error Coding	22
3.10 Optical Flow	22
3.11. Computation of Optical Flow.....	24
CHAPTER-4: PROPOSED APPROACH.....	26
4.1 Overview	26
4.2 Design and Simulate Video and Image Processing Systems.....	26
4.3 Euclidean system.....	28
4.4 Optical Flow Algorithm.....	29
4.5 Branching particle algorithm.....	29
CHAPTER-5: RESULT AND DISCUSSION.....	32
CHAPTER-6 CONCLUSION AND FUTURE DIRECTION.....	36
REFERENCES.....	39

LIST OF FIGURES

Figure 1.1: A diagram of object tracking

Figure 1.2 : Visual Perception

Figure 1.3: Video Generation

Figure 3.1: Block Diagram of Motion Compensated Video Processing

Figure 3.2: Corresponding blocks from a current and past frame, and the search area in the Past frame

Figure 1.3: Pixel movement from image (a) to image (b)

Figure 4.1 Estimate the Motion Vectors in Each Frame of the Video Sequence

Figure 5.1: Input Original video during framing process

Figure 5.2: features from the first sequence

Figure 5.4: features from the second sequence

Figure 5.5: Resampled particle filter on Test Model

Figure 5.6: Performance evaluation for 3 methods

CHAPTER I

INTRODUCTION

1.1 OBJECT VIDEO TRACKING

In everyday life, there has been an expanding interest for image tracking and movement acknowledgment frameworks; because of huge measure of uses there those compounds can be utilized. Average calculations are not pragmatic to utilize for picture following because of the computational cost that emerges from the high number of degrees of opportunity of moving articles and from the vagueness of the pictures gotten from a solitary camera. Imperatives in the arrangement of the moving items can be utilized to lessen its many-sided quality. The limitations can be concluded from exhibit, in view of various exercises. An image tracking system is created utilizing this sort of requirements and after that assessed. The way that the constraints depend on exercises permits, while doing the tracking, the derivation of the action the object is performing.

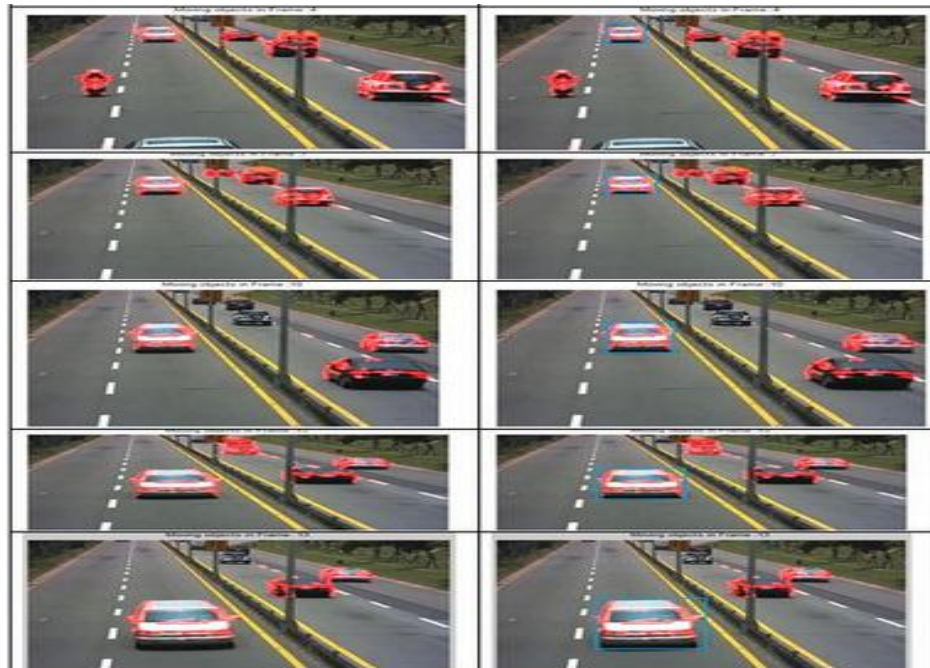


Figure 1.1: A diagram of object tracking

Image tracking and movement acknowledgment are accepting expanding consideration among researchers because of the wide range of uses where they can be utilized, running from athletic execution investigation to video observation. By image tracking we allude to the capacity of a computer to recover the position and introduction of the object from arrangement of pictures. There have been a few distinctive ways to deal with enable PCs to infer naturally the kinematics posture and action from image arrangements.

Video tracking is the way toward finding a moving item (or a few ones) in time utilizing a camera. A calculation examinations the video casings and yields the area of moving focuses inside the video outline. The fundamental trouble in video following is to partner target areas in back to back video outlines, particularly when the items are moving quick in respect to the casing rate. Here, video tracking frameworks ordinarily utilize a movement model which portrays how the picture of the objective may change for various conceivable movements of the object to track. The part of the tracking algorithm is to break down the video outlines to assess the movement parameters. These parameters describe the area of the objective.

1.1.1 TRACKING

Introduction to Tracking

There has been an expanding interest in image tracking and movement acknowledgment frameworks because of the vast measure of uses there those elements can be utilized. Imperatives in the arrangement of the moving items can be utilized to lessen its multifaceted nature. The imperatives can be derived from exhibit, in light of various exercises. An image tracking framework is created utilizing this sort of limitations and afterward assessed. The way that the limitations depend on exercises permits, while doing the tracking, the surmising of the movement the object is performing.

Image tracking and action acknowledgment are getting expanding consideration among PC researchers because of the wide range of uses where they can be utilized, running from athletic execution investigation to video observation. By image tracking we allude to the capacity of a PC to recoup the position and orientation of the object from an arrangement of pictures. There

have been a few distinctive ways to deal with enable PCs to infer consequently the kinematics posture and action from picture groupings.

Video tracking is the way toward finding a moving item in time utilizing a camera. An algorithm examines the video edges and yields the area of moving focuses inside the video outline. The primary trouble in video following is to partner target areas in back to back video outlines, particularly when the articles are moving quick with respect to the casing rate. Here, video tracking frameworks typically utilize a movement model which depicts how the picture of the objective may change for various conceivable movements of the protest track. The part of the tracking algorithm is to investigate the video edges so as to gauge the movement parameters. These parameters portray the area of the target.

1.1.2 Components of Visual Tracking System

Target Representation and Localization is generally a base up process. Normally the computational multifaceted nature for these calculations is low. The accompanying are some basic Target Representation and Localization algorithms:

- Blob tracking: Segmentation of protest inside (for instance blob location, square based relationship or optical stream).
- Kernel-based tracking (Mean-shift tracking): An iterative limitation methodology in view of the expansion of a closeness measure.
- Contour tracking: Detection of protest limit (e.g. dynamic forms or Condensation calculation).
- Visual include coordinating: Registration

1.1.3 Tracking: Possible Issues and Applications

One way to deal with decrease the issue space and to make the issue computationally tractable is to give requirements on the places of the object. Limitations can be founded on fleeting data, camera setup, or any mix of these. Camera arrangement limitations are normally communicated by making presumptions on the relative situating of the subject as for the camera.

Fleeting imperatives allude to the way that an object can just climb to a specific speed, along these lines given a specific arrangement, the protest can just achieve a subset of all the conceivable setups in whenever step. There are sure requirements in tracking the object movement, for instance Joint edges limitations are the imperatives that arrangement with the confinements on the setups of the human body because of its tendency or to some other reality (i.e. movement performed, area of the application, and so forth.). The arrangement of requirements that create the most exact tracking is the one that depicts better the activity performed. Movement acknowledgment frameworks depend on the idea of human tracking. These can be utilized in various applications, going from apply autonomy, PC liveliness, and video observation, and so on to video ordering and even sports.

1.1.4 Optimization Methods for Tracking

Most human movement and posture estimation approaches propose some kind of advancement strategy, immediate or probabilistic, to enhance the stance (and additionally body demonstrate) subject to the picture highlights watched. This area will give a non-thorough review of the strategies utilized.

1.1.5 Direct Optimization

Coordinate advancement strategies regularly formulate a nonstop target work $F(X_t, I_t)$, where X_t is the posture of the body at time t and I_t is the relating watched picture, and after that streamline it utilizing some standard improvement method. Since $F(X_t, I_t)$ is profoundly non-direct and non-curved there is never a certification that a worldwide ideal can be reached. In any case, by iteratively linearizing $F(X_t, I_t)$ and taking after the inclination as for the parameters a nearby ideal can be reached. In the event that a decent gauge from the past time step is accessible, and the posture changes gradually after some time, then instating the pursuit with the past stance regularly prompts a sensible arrangement.

1.1.6 Probabilistic Inference

It is regularly advantageous and normal to define tracking and posture estimation as probabilistic surmising. A probabilistic system has two preferences over the immediate optimization techniques:

- It can encode the certainty of any given enunciated elucidation of the picture.
- It enables one to keep up multi-modular expectations both spatially and after some time. Multi-methodology emerges normally in human movement estimation, since the body in various stances can look fundamentally the same as (if not indistinguishable) in the picture.

1.2 Video tracking

Video is the movement of picture in an edge regarding time by utilizing the property of ingenuity of vision. It is required that more than 15 edges are to be moved per second(fps).For the smoother appearance 30 fps is important.

1.3 Visual Perception

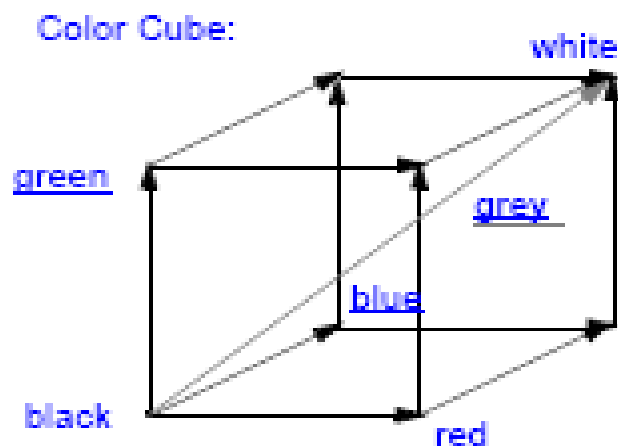


Figure 1.2 : Visual Perception

The human eye comprises of

Cones – to see shading.

Rods – to see brightness

Color defined as a mix of RGB.R for Red ,G for Green and B for Blue.

Video Generation

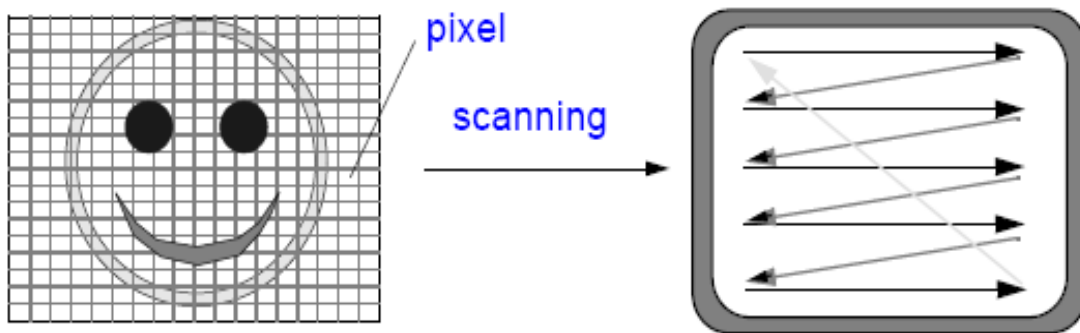


Figure 1.3: Video Generation

As said that a picture is an arrangement of pixels so for the era of a video the filtering of the every last pixel is fundamental .So video is created by checking the pixels and every pixel signified by a value or set of values. The pixels are examined as appeared in the above figure. The filtering begins from the privilege most pixel to one side most pixel in the principal column and afterward returns to the following line and after that begin from the privilege most pixel towards the finish of the line and so on. Once after the filtering whole picture then it again returns back to the beginning stage as appeared. For the best outcomes interweaved examining is utilized in which the picture is isolated into two fields, even field and odd field.

1.4 Video Processing

Video preparing is a critical marvel now a days. Many handling strategies are broadly utilized either in TV frameworks, video after generation or even in like manner life. In spite of the way

that expert equipment video preparing arrangements exist, programming video handling is extremely prevalent mostly on account of the considerable adaptability it offers.

By changing a flag the vitality is isolated into sub groups, by depicting each sub band with various precisions, higher exactness inside high vitality sub groups and less accuracy in low vitality sub groups, the flag can be compacted. The most widely recognized change utilized is the DCT (Discrete Cosine Transform) which has superb in vitality compaction which implies that the vitality of the lattice is concentrated to a little area of the changed framework.

Here in this venture the video handling is done utilizing SAD methods and with the Video and picture Processing Blockset. We initially compute movement vectors between progressive edges and use them to lessen repetitive data. At that point we isolate each casing into sub frameworks and apply the discrete cosine change to each sub-grid. At last, apply a quantization method to accomplish advance pressure. The Decoder subsystem plays out the opposite procedure to recuperate the first video.

1.5 PROBLEM IDENTIFICATION

- The proposed tracker permits managing halfway impediments, ceasing and going movement in exceptionally difficult circumstances.
- Object recognition/tracking and Space-time Interest Points remains an open study problem even after investigation of numerous centuries in which field. A strong, exact and best approach is as yet an awesome test today. The trouble level of this issue exceedingly relies on upon how one characterizes the protest be identified and tracked.
- Object tracking, when all is said in done, is a testing issue. Problems in tracking items can emerge because of unexpected protest movement, changing appearance examples of the object and the scene, nonrigid protest structures, protest and question scene impediments, and camera movement.
- The common difficulties of foundation subtraction with regards to video reconnaissance have been recorded beneath:

1. Illumination Changes

Sudden enlightenment changes can likewise happen in the scene. This sort of progress happens for instance with sudden exchanging on/off a light in an indoor domain.

2. Dynamic Background

Such development can be periodical or sporadic (e.g., activity lights, waving trees). Dealing with such foundation flow is a testing errand.

3. Occlusion

Impediment (halfway/full) may influence the way toward figure the foundation outline. In any case, in actuality, circumstances, impediment can happen at whatever time a subject goes behind an object as for a camera.

4. Clutter

Nearness of foundation mess makes the undertaking of division troublesome. It is difficult to display a foundation that dependably creates the clutter foundation and isolates the moving frontal area objects from that.

5. Motion of the Camera

Video might be caught by unsteady (e.g. vibrating) cameras. The jitter size shifts starting with one video then onto the next.

CHAPTER 2

LITERATURE SURVEY

Hsu-Yung Chen et al. have proposed automobile recognition structure utilizing Dynamic Bayesian Network in Aerial observation. This technique has adaptability and great speculation capacities yet identification results can be settled by performing vehicle following on the vehicle location [1].

Badri-Li Lian et al. have proposed the general approach of voting-based movement estimation, moving article edges recognition and substance based testing coding at transient and spatial scales. These calculations confirmed that, under constrained system transfer speed, the transmitted picture quality can be step by step accomplished and the transmission data transfer capacity usage can be adequately diminished. In any case, the downside of this strategy is that there is no controlled detecting [2].

Bing-Fei et al. Wu have proposed another way to deal with video-based activity reconnaissance utilizing a fluffy cross breed data induction component. There are three techniques for this proposed approach foundation refreshing, vehicle identification with square based division, and vehicle following with mistake remuneration. In this Thesis strategy gives Good execution under congested condition inside passage however the nature of caught picture was poor [3].

Hidetomo Sakaino has presented a developed Markov chain Monte Carlo strategy for following and an augmented shrouded Markov show technique for picking up/perceiving numerous moving items in recordings with jittering foundations. These strategies can adapt to a variable number of moving articles at much lower calculation cost however when diverse points of interest were close and milestone size was too little disappointment happened [4].

Yin-Tsung Hwang and et al. have exhibited highlight extraction and highlight coordinating procedures in this Thesis. In the component extraction four conditions for angle vectors are given [5].

Herminio Chavez-Roman and et al. have presented a new calculation called super determination utilizing wavelet area introduction with edge extraction and scanty portrayal. This strategy addresses the issue of creating a super-determination picture from a solitary lowresolution input picture in the wavelet area. In this Thesis, it has better sharpness and less smoothing at the edges, avoiding pixel blocking, obscured points of interest, and ringing curios around edges yet this technique is not ready to sort better vigor of uproarious pictures [6].

Badri Narayan et al. have proposed a new for moving article discovery and following. This calculation incorporates two plans: one for spatio-transient spatial division and the other for worldly segmentation. This method creates better division comes about contrasted with those of edgeless and JSEG division plans and equivalent outcomes with edge-based approach yet it gives issues with moving camera, does not deliver great outcomes [7].

Marius Leordeanu et al. have proposed a original model and calculation for summed up limit identification. Gb successfully consolidates various low-and mid-level understanding layers of a picture in a principled way, and resolves their requirements together, in shut frame, with a specific end goal to figure the correct limit quality and introduction. This strategy gives the effective estimation of limit quality and introduction in a solitary shut frame calculation yet there is no broad detailing of the issue that incorporates a wide range of limits [8].

In this Theory, the strategy is utilized to recuperate the majority of the downsides contrast and the previously mentioned strategies. The proposed strategy depends on the component based object tracking method. In which technique, object tracking is execution utilizing edge filtering procedure. The vigilant edge finder is utilized to perform separating and afterward by utilizing highlight coordinating item will track.

Vasileios T. Chasanis, Aristidis C. Likas, and Nikolaos P. Galatsanos, proposed a calculation in the region of video ordering, which require the effective division of video into scenes. They utilize run of the mill scene location calculations [9]

Yun Zhai, Student and Mubarak Shah, proposed the recordings, Consist of numerous back to back shots that are caught by various camera operations, e.g., on/off operations and exchanging between cameras [10].

Jiafu Jiang And HuiXiongin, In this Traditional shading histogram Mean-shift (MS)algorithm & that ismeasured just object's shading factual data, and didn't comprise object's space data, so when the focused on protest's shading circulation was like the foundation surface, the conventional calculations effectively brought about question following get incorrect outcome or lost [11].

David A. Ross et al. [12] introduce an appearance based tracker that incrementally takes in a low dimensional subspace portrayal of target question for hearty protest following while target experiences posture, light, appearance changes. To gauge the areas of the objective protests in continuous edges, a testing calculation with probability gauges, which is as opposed to other following techniques that typically tackle complex enhancement issues utilizing inclination drop is utilized. Likewise, it constantly refreshes the model portrayal to reflect appearance variety of target. Despite the fact that it has been appeared to perform well when target objects experience lighting and stance variety, this technique is less viable in dealing with overwhelming impediment or non-unbending contortion subsequently of the embraced all encompassing appearance demonstrate.

S. Avidan et al. [13] introduce a gathering tracker that gives pixel based parallel characterization to separate amongst target and foundation. Group tracker keeps up an understood portrayal of frontal area and foundation utilizing classifiers. In this system, outfit tracker consolidates accumulation of feeble classifier into single solid classifier utilizing Adaboost to present preferred outcome over any of the frail classifier. The tracker always refreshes accumulation of frail classifier to isolate the frontal area and the solid classifier is utilized to mark pixels in next

casing. The solid classifier which is utilized to name pixels in the following edge as either having a place with the protest or the foundation gives a certainty delineate. The pinnacle of the guide, and consequently the new position of the question, is discovered utilizing mean move. In spite of the fact that this technique can separate amongst target and foundation, the pixel-based portrayal is fairly restricted and along these lines obliges its capacity to deal with overwhelming impediment and clutter.

Adam et al. [14] propose a pieces based strategy to deal with impediments. In this strategy, histograms are separated for every layout fix and after that these histograms are contrasted and those extricated from different locales in target picture. The format object is signified to by various picture sections or fixes. The covers are random and that is not founded an object model. Each fix votes on the conceivable positions and sizes of the protest in the present edge, by contrasting its histogram and the comparing picture fix histogram. It limits a strong measurement with a specific end goal to consolidate the vote maps of the various patches. The objective question is situated by a voting map framed by contrasting histograms of the hopeful patches and the relating layouts. Be that as it may, the layout is not refreshed and along these lines this approach is delicate to extensive appearance varieties.

MaheubMurshed et al. [15] show an Edge Sectioncreated tracking process which is utilized to recognize moving items in picture grouping. In this calculation, edge fragment in light of Canny edge guide is utilized by using the edge structure in the moving item district and bend based elements are utilized for moving edge enlistment. A Kalman channel based indicator is utilized for following every individual edge fragments and edge sections are grouped by utilizing weighted mean move calculation. In spite of the fact that this technique can track moving article or some portion of it viably under shifting light and incomplete impediment, it can't manage full impediment.

Mei and Ling [16] exhibit a visual tracking calculation in view of a generative inadequate portrayal of formats. In this strategy, the objective applicant is spoken to as a straight blend of the scholarly layout set made out of both target formats and the minor layout which has just a single nonzero component. The suspicion is that great target applicant can be inadequately

spoken to by both the objective layouts and the inconsequential formats. In this strategy ambiguities are probably going to gather and cause following disappointment.

Liu et al. [17] propose an online powerful and optimizing calculation utilizing a two phase inadequate advancement approach. This following strategy chooses a meager and discriminative arrangement of elements to enhance productivity and power. No shape or movement priors are required for this calculation. Both the preparation set and the layout library models are online refreshed. Two-organize meager streamlining is comprehended together by limiting the objective reproduction mistake and boosting the discriminative power by choosing a scanty arrangement of components. As the quantity of discriminative components is settled, this strategy is less powerful for object tracking in unique and compound scenes.

In [18], **J. Huang et al.** propose propose a calculation in light of histograms of nearby inadequate portrayal for itemfollowing where the objectiveitem is found by means of mode chasing (utilizing the mean shift algorithm) of electivechartsdeveloped by reproduction blunders. That is, this calculation works under the start that the in all probability target question area has insignificant reproduction blunder in view of scanty portrayal. Be that as it may, this technique is less viable in separating the frontal area patches from the foundation ones therefore of generative methodologies in view meagredemonstration.

Lipton et al. [19] proposed outline contrast that utilization of the pixel-wise changes among two edge pictures to extricate the moving districts. In alternative work, Stauffer &Grimson et al. [6] proposed a Gaussian blenddemonstrate in view of foundation model to recognize the protest.

Liu et al. [20] , proposed foundation subtraction to recognize moving locales in a picture by taking the distinction amongst current and reference foundation picture in a pixel-by-pixel. Collins et al. [8], built up a cross breed strategy that joins three-outline differencing with a versatile foundation subtraction demonstrate for their VSAM (Video Surveillance and Monitoring) extend.

Desa&Salih et al [21], proposed a grouping of foundation subtraction and edge distinction which enhanced the past aftereffects of foundation subtraction and casing contrast. Sugandi et al. [22], proposed another method for protest location utilizing outline contrast on low determination picture.

Julio cezaret al. [23] has proposed a foundation display, and join a new system for shadow recognition in dim scale video groupings. Satoh et al. [11], proposed another system for protest following utilizing piece coordinating calculation in light of PISC picture. Sugandi et al. [12], proposed following system of moving people utilizing camera fringe increase sign connection picture.

Beymer&konolige et al. [24] presented in stereophonic camera founded object tracking, utilize kalman channel for anticipating the items position and speed in $x-2$ measurement. Rosals and sclaroff et al., 1999 proposed utilization of stretched out kalman channel to gauge 3D direction of a protest from 2D movement. In question identification technique, numerous scientists have built up their strategies. Liu et al., 2001 proposed foundation subtraction to distinguish moving districts in a picture by taking the distinction amongst current and reference foundation picture in a pixel-by-pixel. It is to a great degree touchy to change in powerful scenes gotten from lighting and superfluous occasions and so on.

In additional work, Stauffer &Grimson, 1997 proposed a Gaussian combination model demonstrate in light of foundation model to identify the question. Lipton et al., 1998 proposed outline contrast that utilization of the pixel-wise contrasts between two casing pictures to remove the moving locales. This technique is extremely versatile to dynamic conditions, yet for the most part makes a less than impressive display with regards to of extracting all the pertinent pixels, e.g., there might be openings left inside moving substances. Keeping in mind the end goal to defeat burden of two-casings differencing, at times three-outlines differencing is utilized. For example, Collins et al., 2000 built up a crossover technique that consolidates three-outline differencing with a versatile foundation subtraction display for their VSAM (Video Surveillance and Monitoring) extend. The half breed calculation effectively sections moving districts in video without the deformities of transient differencing and foundation subtraction.

Desa&Salih, 2004 proposed a grouping of foundation subtraction and edge contrast that enhanced the past consequences of foundation subtraction and edge distinction.

CHAPTER 3

MOTION COMPENSATED VIDEO PROCESSING

3.1 Overview

Square based movement compensation utilizes blocks from a previous casing to develop a reproduction of the present edge. The previous edge is an edge that has as of now been transmitted to the recipient. For each piece in the present edge a coordinating square is found in the past casing and if appropriate, its movement vector is substituted for the square amid transmission. Contingent upon the hunt edge a few squares will be transmitted completely as opposed to substituted by movement vectors. The issue of finding the most reasonable square in the past casing is known as the piece coordinating issue. Piece based movement repaid video pressure happens in various unmistakable stages. The stream outline above represents how the yield from the prior procedures shapes the contribution to later procedures.

Subsequently decisions made at early stages can have an effect of the viability of later stages.

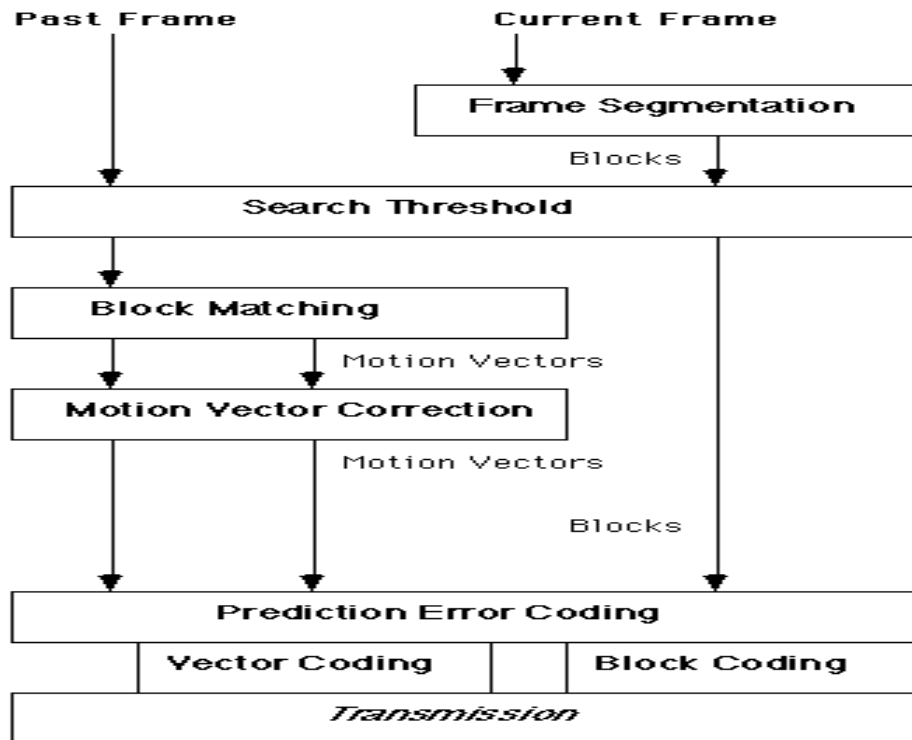


Figure 3.1: Block Diagram of Motion Compensated Video Processing

To completely comprehend the issues required with this sort of video pressure it is important to analyse each of the phases in detail.

These stages can be defined as:

- Frame Segmentation
- Search Threshold
- Block Matching
- Motion Vector Correction
- Vector Coding
- Prediction Error Coding

3.2 Frame Segmentation

The present casing of video to be packed is separated into equivalent estimated non-covering rectangular squares. Preferably the edge measurements are products of the piece size and square pieces are generally normal. Chan et al. utilized rectangular pieces of 16 x 8 pixels, guaranteeing that squares of this shape abuse the way that movement inside video successions is more regularly in the flat heading than the vertical.

Block estimate influences the execution of pressure strategies. The bigger the square size, the less the quantity of pieces, and henceforth less movement vectors should be transmitted. Nonetheless, outskirts of moving articles don't regularly correspond with the fringes of pieces thus bigger squares require more rectification information to be transmitted. Little pieces result in a more prominent number of movement vectors, yet each coordinating square will probably nearly coordinate its objective thus less adjustment information is required. Lallaret found that if the square size is too little then the pressure framework would be extremely delicate to commotion. Accordingly close size speaks to an exchange off between limiting the quantity of movement vectors and boosting the nature of the coordinating squares. The connection between square size, video quality, and pressure proportion has been the subject of much research and is surely knew.

For building details block dimensions of number forces of 2 are favored thus square sizes of 8 and 16 pixels prevail. Both the MPEG and H.261 video pressure measures utilize pieces of 16x16 pixels.

3.3 Search Threshold

On the off chance that the contrast between the objective square and the competitor obstruct at a similar position in the past casing is beneath some edge then it is expected that no movement has occurred and a zero vector is returned. Consequently the cost of an inquiry is kept away from. Most video programmes utilize a limit with a specific end goal to decide whether the computational exertion of a hunt is justified.

3.4 Block Matching

Block matching is the most period consuming portion of the encoding procedure. Through block matching every objective block of the present edge is contrasted and a past edge with a specific end goal to locate a coordinating square. At the point when the recipient recreates the present edge this coordinating piece is utilized as a substitute for the square from the present casing.

Block matching happens just on the luminance part of casings. The shading parts of the pieces are incorporated when coding the casing yet they are not generally utilized while assessing the fittingness of potential substitutes or applicant squares.

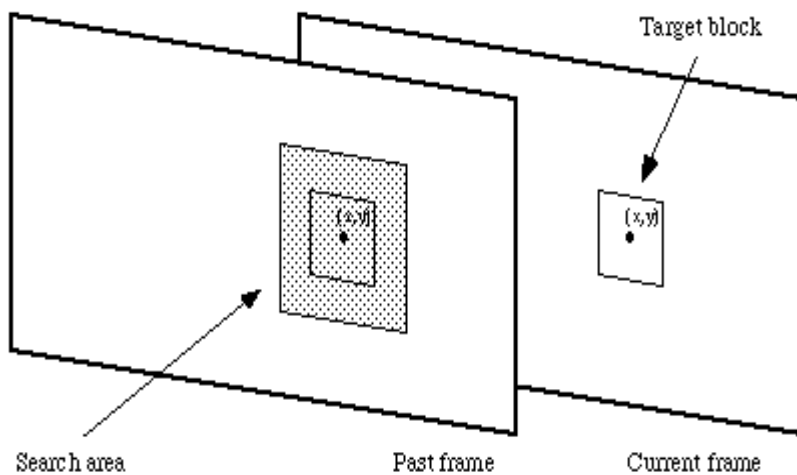


Figure 3.2: Corresponding blocks from a current and past frame, and the search area in the past frame.

The pursuit can be done on the whole past casing, however is normally limited to a littler hunt region fixated on the position of the objective square in the present edge (see above figure). This practice e puts a furthest point of confinement, known as the most extreme uprooting, on how far items can move between casings, on the off chance that they are to be coded successfully. The most extreme dislodging is determined as the greatest number of pixels in the level and vertical headings that an applicant square can be from the position of the objective piece in the first casing.

The nature of the match can frequently be enhanced by adding pixels in the inquiry range, successfully expanding the determination inside the hunt zone by permitting theoretical competitor obstructs with small dislocations.

The hunt zone requirement not be rectangular. Since movement is more probable in the level course than vertical, rectangular hunt territories are prevalent. The CLM460x MPEG video encoder, for instance, utilizes removals of - 106 to +99.5 pixels in the even heading, and - 58 to +51.5 pixels in the vertical. The half pixel exactness is the consequence of the coordinating including inserted pixels. The less expensive CLM4500, then again, utilizes ± 48 pixels in the flat course, and ± 24 in the vertical, again with half pixel exactness. In the event that the piece size is b and the most extreme relocations in the flat and vertical bearings are dx and dy separately, then the pursuit region will be of size $(2dx + b)(2dy + b)$. Barring sub-pixel exactness it will contain $(2dx + 1)(2dy + 1)$ unmistakable, however covering, competitor pieces. Obviously the bigger the reasonable dislodging the more prominent the likelihood of finding a decent match. The quantity of applicant pieces in the pursuit zone, in any case, builds quadratic partner as the dislodging expands, which can bring about countless squares being contrasted with the objective square. Considering each competitor obstruct in the inquiry territory as a potential match is known as an Exhaustive Search, Brute Force Search, or Full Search

3.5 Matching Criteria

All together for the compacted edge to resemble the first, the substitute square should be as comparative as conceivable to the one it replaces. Hence a coordinating model, or contortion capacity, is utilized to evaluate the comparability between the objective square and applicant pieces. On the off chance that, because of a huge hunt zone, numerous hopeful pieces are viewed as, then the coordinating criteria will be assessed commonly. Consequently the decision of the coordinating criteria affects the accomplishment of the pressure. On the off chance that the coordinating paradigm brings about terrible matches then the nature of the pressure will be antagonistically influenced. Luckily various coordinating criteria are reasonable for use in video pressure.

3.6 Sub-Optimal Block Matching Algorithms

The thorough inquiry is computationally exceptionally escalated and requires the twisting capacity (coordinating criteria) to be assessed commonly for each objective square to be coordinated. Significant research has gone into creating piece coordinating calculations that find reasonable matches for target squares yet require less assessment. Such calculations test just a portion of the applicant obstructs from the pursuit territory and picks a match from this subset of pieces. Henceforth they are known as imperfect calculations. Since they don't look at the entire applicant hinders, the decision of coordinating piece won't not be on a par with that picked by a comprehensive pursuit. The quality-cost exchange off is generally beneficial nonetheless.

3.7 Motion Vector Correction

Once the finestextra, or coordinating square, has been found for the objective piece, a movement vector is figured. The movement vector depicts the area of the coordinating square from the past edge with reference to the position of the objective piece in the present casing.

Movement vectors, independent of how they are resolved won't not relate to the real movement in the scene. This might be because of clamour, shortcomings in the coordinating calculation, or neighbourhood smallest amount. The property that is abused in spatially subordinate calculations can be used after the vectors have been computed trying to right them. Smoothing strategies can

be connected to the movement vectors that can distinguish sporadic vectors and recommend choices. The option movement vectors can be utilized as a part of place of those movement vectors.

Smoothing movement vectors, be that as it may, can add extensive unpredictability to a video pressure calculation and ought to just be utilized where the advantages exceed these expenses. In the event that edges will be added by the collector then movement vector amendment is probably going to be beneficial. Smoothing can likewise diminish the measure of information required to transmit the movement vector data, since this data is in this manner packed and smooth vectors can be compacted all the more proficiently.

Vector smoothing causes issues of its own. Smoothing can make little objects be coded gravely in light of the fact that their movement vectors may be viewed as incorrect when they are in actuality remedy. Smoothing such movement vectors can unfavorably influence the nature of the packed video. The averaging plans obscured sharp discontinuities in video arrangements. Since these discontinuities may be the aftereffect of protest limits they ought to be safeguarded. To beat this, a system is utilized which reevaluated each movement vector that did not agree with its quick neighbors to one side.

3.8 Vector Coding

Once decided, motion vectors must be appointed bit arrangements to signify to them. Since such an extensive amount the packed information will comprise of movement vectors, the proficiency with which they are coded greatly affects the pressure proportion. Truth be told up to 40% of the bits transmitted by a codec may be brought up with movement vector information. Luckily, the high relationship between's movement vectors and their non-uniform dissemination makes them reasonable for further pressure. This pressure must be lossless.

Effective coding of motion vectors is a topic of study in its own particular right and many creators have offered proposals on which methods work best. Any of the lossless broadly useful

pressure calculations are reasonable for coding vectors. The calculations are Arithmetic, Adaptive Huffman, and Lepel-Ziv Coding. They found that the number juggling and Huffman procedures performed best and that versatile systems utilizing here and now insights performed superior to anything those utilizing long haul measurements. The ISO/IEC video pressure standard known as MPEG determines variable length codes to be utilized for movement vectors. The zero vectors, for instance, have a short code, since it is the most regularly happening. We tried two strategies for coding movement vectors. The first was a prescient technique where a forecast of the movement vector was calculated in view of its antecedents in a similar line and segment. The forecast blunders were then Huffman coded. The second system gathered the movement vectors into squares. On the off chance that every one of the vectors in a piece were the same, then just a single was transmitted. Blocks that did not contain a homogenous arrangement of vectors were marked and the vectors portrayed according to as their first technique.

3.9 Prediction Error Coding

Despite the fact that the battery of procedures depicted up to this point can code video effectively, they seldom create idealize copies of the first casings. In this manner the contrast between an anticipated edge and the first uncompressed casing may be coded. By and large this is connected on a square by-piece premise and just where parts of the coded edge are altogether not quite the same as the first. Change coding is most much of the time used to accomplish this and totally lossless coding is seldom an objective.

3.10 Optical Flow

Optical is the appropriation of clear speeds of development of shine designs in a picture. Optical flow is an estimate of the neighbourhood picture movement in view of nearby subsidiaries in a given arrangement of pictures. That is, in 2D it indicates how much each picture pixel moves between adjoining pictures while in 3D in determines how much every volume voxel moves between contiguous volumes.

Firmly identified with movement estimation is optical flow, where the vectors compare to the apparent development of pixels. In movement estimation a correct 1:1 correspondence of pixel positions is not a necessity.

Optical flow is the circulation of clear speeds of development of splendor designs in a picture. Optical flow can emerge from relative movement of articles and the watcher [.Therefore, optical flow can give imperative data about spatial course of action of the items saw and the rate of progress of this plan

Arrangements of requested pictures permit the estimation of movement as either prompt picture speeds or discrete picture removals. Armada and Weiss give an instructional exercise prologue to slope based optical flow. John L. Barron, David J. Fleet, and Steven Beauchemingive an execution investigation of various optical stream methods. It underlines the precision and thickness of estimations.

Optical flow technique emerges from relative movement amongst protest and camera.

This strategy figures pixel speed vector which gives the accompanying data:

1. How rapidly is the pixel moving over the picture?
2. In which course is the pixel moving?

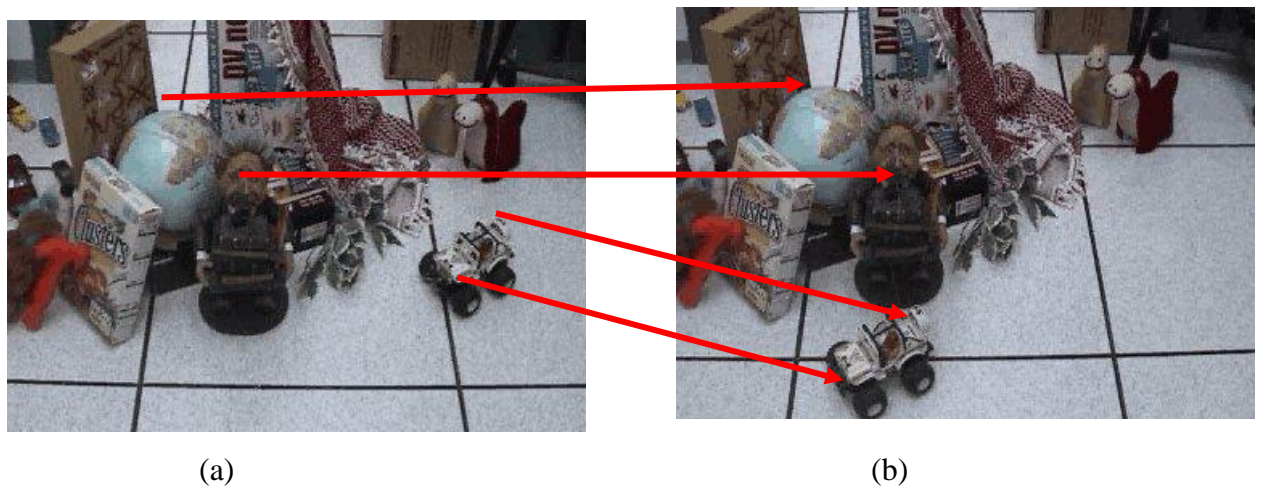


Figure 2.3: Pixel movement from image (a) to image (b)

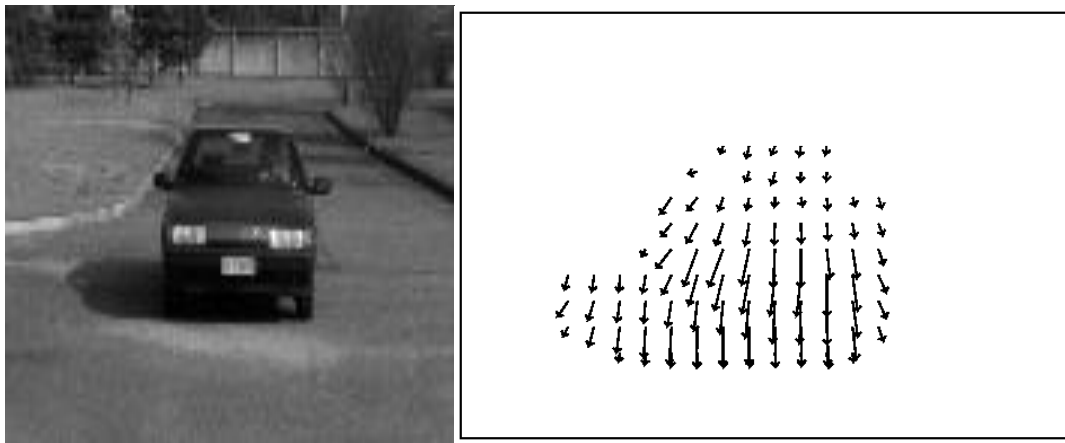
A. Computation of Optical Flow

In a picture, every pixel relates to the force esteem acquired by the projection of a protest in 3-D space onto the picture plane. At the point when the articles move, their relating projections additionally change position in the picture plane. Optical flow is a vector field that demonstrates the heading and size of these power changes from one picture to the next.

Calculation of difference optical flow is, basically, a two-stage methodology:

1. Measure the spatio- transient force subsidiaries (which is equal to measuring the speeds typical to the neighbourhood power structures)
2. Coordinate ordinary speeds into full speeds, for instance, either locally by means of a slightest squares figuring or comprehensively through regularization.

There are clear scientific connections between the greatness of the optic flow and where the object is in connection to you. In the event that you twofold the speed with which you travel, the optic stream you see will likewise twofold. In the event that a object is conveyed twice as near you, the optic stream will again twofold. Likewise the optic flow will change contingent upon the point between your course of travel and the bearing of the question you are taking a gander at. The optic stream is the speediest when the protest is to your side by 90 degrees, or specifically above or beneath you. On the off chance that the question is presented nearer to the or in reverse bearing, the optic stream will be less. A protest straightforwardly before you will have no optic flow, and seem to stop.



(a)

(b)

Figure 3.3: a) Original Video b) Optical Flow representation of (a)

From this figure, we see that the flow vectors seem to exude from a main issue known as the concentration of development [Gibson, 1979], and that focuses nearer to the camera move all the more rapidly over the picture plane. Properties like this are thought to be vital for organic vision frameworks [Gibson, 1979] and have been misused in machine vision to track moving items [Papanikolopoulos and Khosla, 1991], recover spectator movement [Lawton, 1983], distinguish snags [Ancona, 1992], maintain a strategic distance from impacts [Nelson and Aloimonos, 1989] and recoup scene profundity [Adiv, 1985].

There are other, non-automated, utilizations of optical flow too; especially in the ranges of therapeutic imaging and picture pressure [Pratt, 1979].

CHAPTER 4

PROPOSED APPROACH

4.1 Overview

There are two major classes of items in Simulink: **blocks** and **lines**. Blocks are used to generate, modify, combine, output, and display signals. Lines are used to transfer signals from one block to another.

There are several general classes of blocks:

- Sources: Used to generate various signals
- Sinks: Used to output or display signals
- Discrete: Linear, discrete-time system elements (transfer functions, state-space models, etc.)
- Linear: Linear, continuous-time system elements and connections (summing junctions, gains, etc.)
- Nonlinear: Nonlinear operators (arbitrary functions, saturation, delay, etc.)
- Connections: Multiplex, Demultiplex, System Macros, etc.
- Blocks have zero to several input terminals and zero to several output terminals. Unused input terminals are indicated by a small open triangle. Unused output terminals are indicated by a small triangular point. The block shown below has an unused input terminal on the left and an unused output terminal on the right.

4.2 Design and Simulate Video and Image Processing Systems

- The Video and Image Processing Blockset extends Simulink with a rich, customizable framework for the rapid design, simulation, implementation, and verification of video and image processing algorithms and systems. It includes basic primitives and advanced algorithms for designing embedded imaging systems in a wide range of applications in

aerospace and defense, automotive, communications, consumer electronics, education, and medical electronics industries.

- Built-in block libraries provide two-dimensional (2-D) filters, conversions, geometric transformations, morphological operations, 2-D transforms, motion estimation techniques, and input/output (I/O) capabilities. The blockset supports floating- and fixed-point data types for modeling, simulation, and C-code generation. It provides analysis and statistical functions to enable rapid optimization and debugging of your models. These functions include video displays, scopes, and other techniques for visualizing image and video data and validating simulation results.

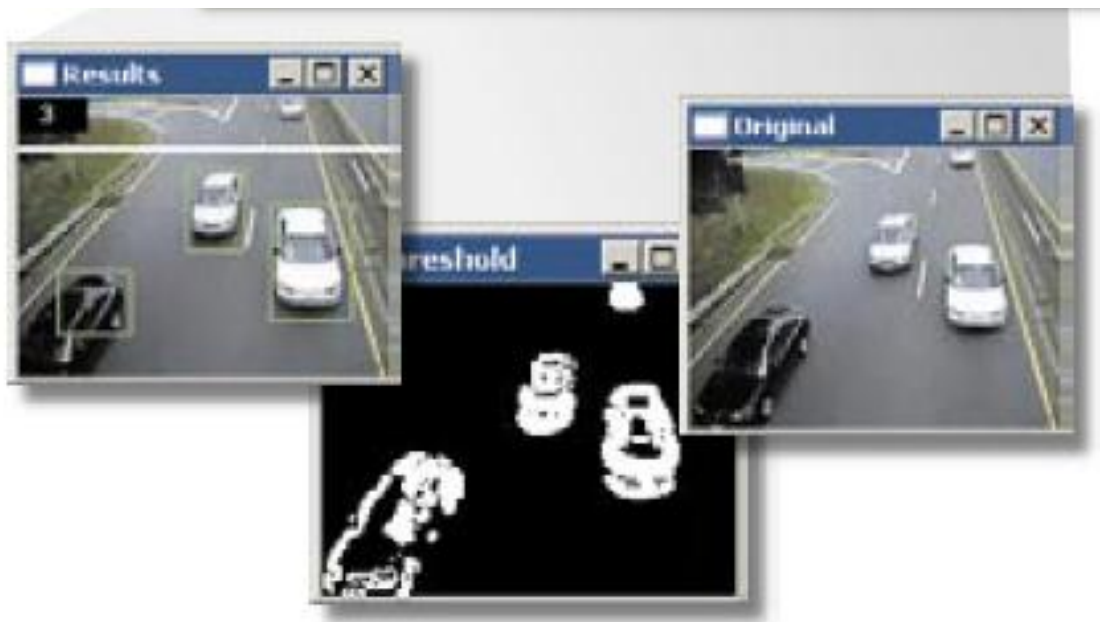


Figure 4.1 Estimate the Motion Vectors in Each Frame of the Video Sequence

The Video and Image Processing Blockset extends Simulink with a specialized library for designing the behavior of your imaging system. The Simulink environment provides tools for hierarchical modeling, data management, and subsystem customization that make it easy to create concise, accurate representations, regardless of your system's complexity.

All blocks in the Video and Image Processing Blockset support double-precision and single-precision floating-point data types. Most also support integer and fixed-point data types. (Fixed-point support requires Simulink® Fixed Point, available separately.)

Simulink and the Video and Image Processing Blockset enable you to run fast simulations for real-time embedded video, vision, and imaging systems. You can create executable specifications for communicating the system to downstream design teams and to provide a golden reference for verification throughout the design process.

4.3 EUCLIDEAN DISTANCE

Euclidean distance is the distance between two points in Euclidean space. Euclidean space was originally devised by the Greek mathematician Euclid around 300 B.C.E. to study the relationships between angles and distances.

Step 1

Compute the Euclidean distance for one dimension. The distance between two points in one dimension is simply the absolute value of the difference between their coordinates.

Step 2

Take two points P and Q in two dimensional Euclidean space. We will describe P with the coordinates (p_1, p_2) and Q with the coordinates (q_1, q_2) . Now construct a line segment with the endpoints of P and Q. This line segment will form the hypotenuse of a right triangle. Extending the results obtained in Step 1, we note that the lengths of the legs of this triangle are given by $|p_1 - q_1|$ and $|p_2 - q_2|$. The distance between the two points will then be given as the length of the hypotenuse.

Step 3

Use the Pythagorean theorem to determine the length of the hypotenuse in Step 2. This theorem states that $c^2 = a^2 + b^2$ where c is the length of a right triangle's hypotenuse and a,b are the lengths of the other two legs. This gives us $c = (a^2 + b^2)^{1/2} = ((p_1 - q_1)^2 + (p_2 - q_2)^2)^{1/2}$. The distance between 2 points P = (p_1, p_2) and Q = (q_1, q_2) in two dimensional space is therefore $((p_1 - q_1)^2 + (p_2 - q_2)^2)^{1/2}$.

Step 4

Extend the results of Step 3 to three dimensional space. The distance between points $P = (p_1, p_2, p_3)$ and $Q = (q_1, q_2, q_3)$ can then be given as $((p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2)^{1/2}$.

Step 5

Generalize the solution in Step 4 for the distance between two points $P = (p_1, p_2, \dots, p_n)$ and $Q = (q_1, q_2, \dots, q_n)$ in n dimensions. This general solution can be given as $((p_1 - q_1)^2 + (p_2 - q_2)^2 + \dots + (p_n - q_n)^2)^{1/2}$

4.4 Optical Flow Algorithm

Optical flow computation is based on two assumptions:

The experimental brightness of any object point is constant over time. Close to points in the image plane move in a similar manner (the velocity smoothness constraint). Suppose we have a continuous image; $f(x, y, t)$ refers to the gray-level of (x, y) at time t . Representing a dynamic image as a function of position and time permits it to be expressed.

- Assume each pixel moves but does not change intensity
- Pixel at location (x, y) in frame1 is pixel at $(x + \Delta x, y + \Delta y)$ in frame2.
- Optic flow associates displacement vector with each pixel.

4.5 Branching particle algorithm

It is known in nonlinear filtering theory [22] that the unnormalized optimal filter $p_t(\phi)$, which is a solution to (4.1), is given by

$$dp_t(\phi) = p_t(A\phi)dt + p_t(h^* \phi)dY_t. \quad (4.1)$$

$$\tilde{E} \left[\phi(X_t) \exp \left(\int_0^t h^*(X_s) dY_x - \frac{1}{2} \int_0^t h^*(X_s) h(X_s) ds \right) \middle| \mathcal{Y}_t \right], \quad (4.2)$$

where the expectation is taken with respect to the measure P which makes Y_t a Brownian motion. This equation is merely a formal expression, because one needs to evaluate the integration $E[\cdot|Y_t]$ with respect to the measure P. However, this equation provides a recursive relation to derive a numerical solution; we will construct a sequence of branching particle systems U_n as in [13] which can be proved to approach the solution pt , that is, $\lim_{n \rightarrow \infty} U_n(t) = pt$.

Let $\{U_n(t), F_t; 0 \leq t \leq 1\}$ be a sequence of branching particle systems on (Ω, F, P) .

Initial condition

(0) $U_n(t)$ is the empirical measure of n particles of mass $1/n$, that is, $U_n(t) = (1/n) \sum_{i=1}^n \delta_{x_i^n}$, where $x_i^n \in E$, for every i , $n \in \mathbb{N}$, and $\delta_{x_i^n}(x)$ is a delta function centered at x_i^n .

Evolution in the interval $[i/n, (i+1)/n]$, $i = 0, 1, \dots, n-1$

(1) At time i/n , the process consists of the occupation measure of $m_n(i/n)$ particles of mass $1/n$ ($m_n(t)$ denotes the number of particles alive at time t).

(2) During the interval, the particles move independently with the same law as in the system dynamics equation (4.3). Let $Z(s), s \in [i/n, (i+1)/n]$, be the trajectory of a generic particle during this interval.

$$dX_t = f(X_t) dt + \sigma(X_t) dW_t \quad (4.3)$$

(3) At $t = (i+1)/n$, each particle branches into ξ_i^n particles with a mechanism depending on its trajectory in the interval. The mean number of off-springs for a particle is

$$\mu_n^i = E(\xi_n^i) = \exp \left(\int h^*(Z(t)) dY_t - \frac{1}{2} \int h^* h(Z(t)) dt \right) \quad (4.4)$$

so that the variance $v_n^i(V)$ is minimal, where the variance occurs due to the off-rounding of $v_n^i(V)$ to compute the integer value ξ_n^i . The symbol $*$ represents complex conjugate (transpose for the real-valued case) here and throughout the paper. More specifically, we determine the number ξ_n^i of offsprings by

$$\xi_n^i = \begin{cases} [\mu_n^i] & \text{with probability } \mu_n^i - [\mu_n^i], \\ [\mu_n^i] + 1 & \text{with probability } 1 - \mu_n^i + [\mu_n^i], \end{cases} \quad (4.5)$$

where $[\]$ is the rounding operator.

Note that the integrals in (4.4) are along the path of the particles $Z(t)$. In the proposed visual tracking application, we only apply the branching mechanism only once per observation interval

(between image frames). We take advantage of the branching particle method in two aspects: the recursive un-normalized conditional density.

CHAPTER 5

RESULT AND DISCUSSION

In this section we present experimental results of our tracking algorithm. The video sequence used in Figure 5.1. The top row of it shows the position measurement. In input video the motion field of object moving, so that the detector measures only one moving object for a of video. Because of the proposed labeling Optical flow and Space-time Interest Points, the branchingparticle filter able to track and label both objects correctly when the motion fields splits again. This can be seen in the bottom row. The center of the green line corresponds to the position information gained by the collecting step after the particle update. The radius of this circle is fixed and only used for presentation.



Figure 5.1: Input Original video during framing process

As part of this research, we had to implement a space-time interest points tracking device that runs entirely on software. Designing things, especially useful things on a piece of software takes effort and time. To avoid any tedious calibrations of algorithms on board and to ensure the algorithms are all properly designed, I wrote a MATLAB program to simulate the environment - grabbing frames from a web camera and track.

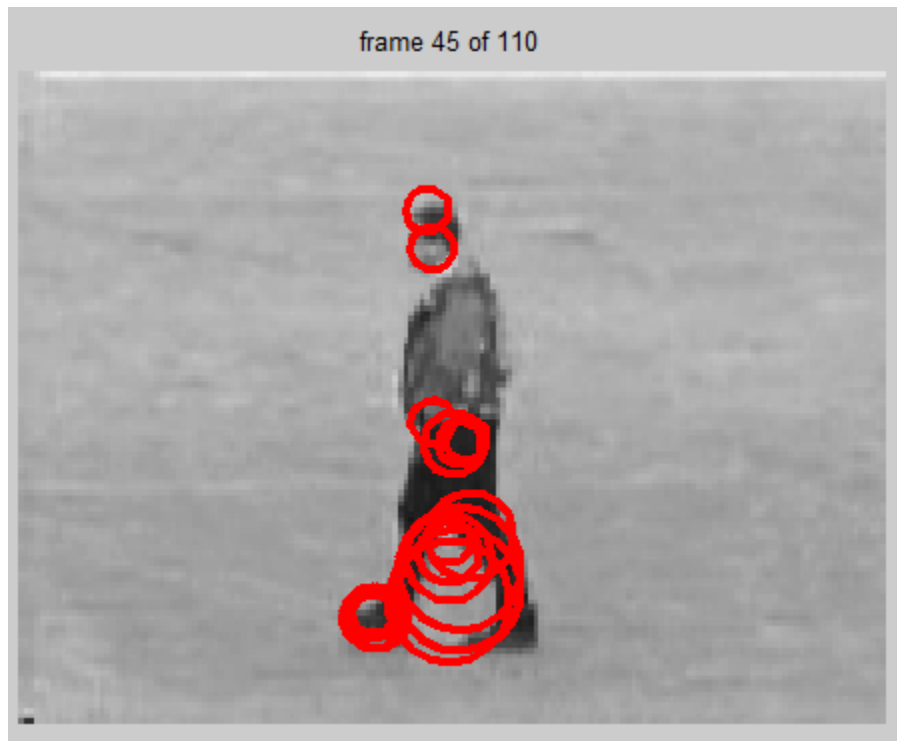


Figure 5.2: features from the first sequence

We calculate the size of input video sequence to determine the total number of rows and columns and apply tracking steps through over all image frames of input video sequence. In order to verify the accuracy of proposed method, we have calculated the centroid and boundary of a tracked object using proposed method and then compare it with the centroid and boundary which we have calculated manually and also with previous algorithm. For this reason, we determine the four corners of tracked objects' boundary and centroid in both ways. we have presented the comparison of tracking only single object of proposed method with manual calculation, where we represent the L, R, T and B as the corners of the boundary. Here L, R, T, B indicates four

boundary properties, where L=Left, R=Right, T=Top, B=Bottom, C_x =Value of centroid at X axis, C_y =Value of centroid at Y axis.



Figure 5.3:

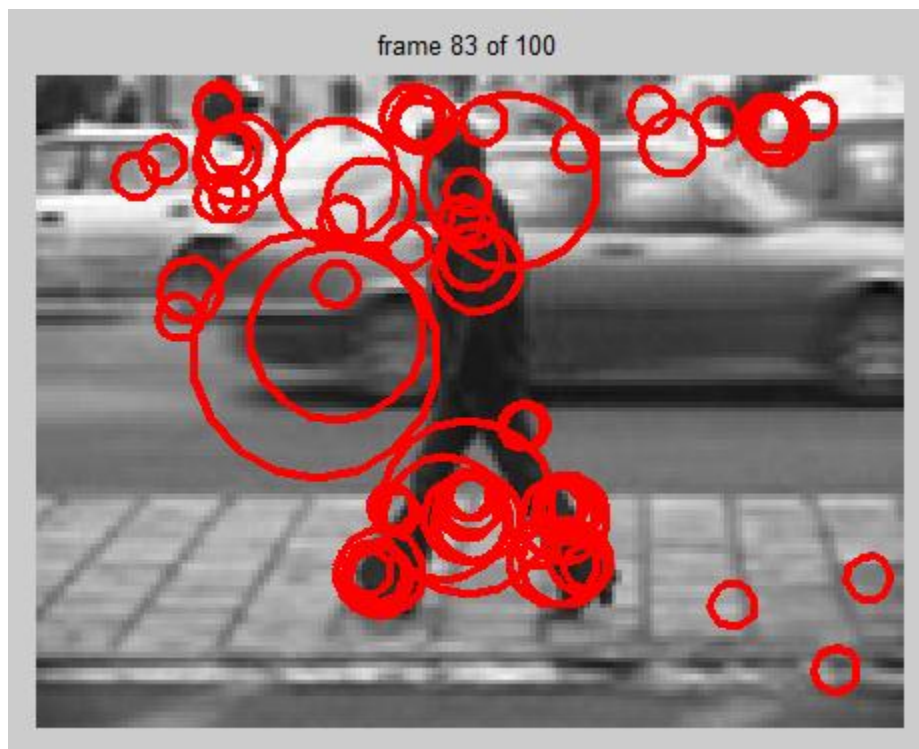


Figure 5.4: features from the second sequence

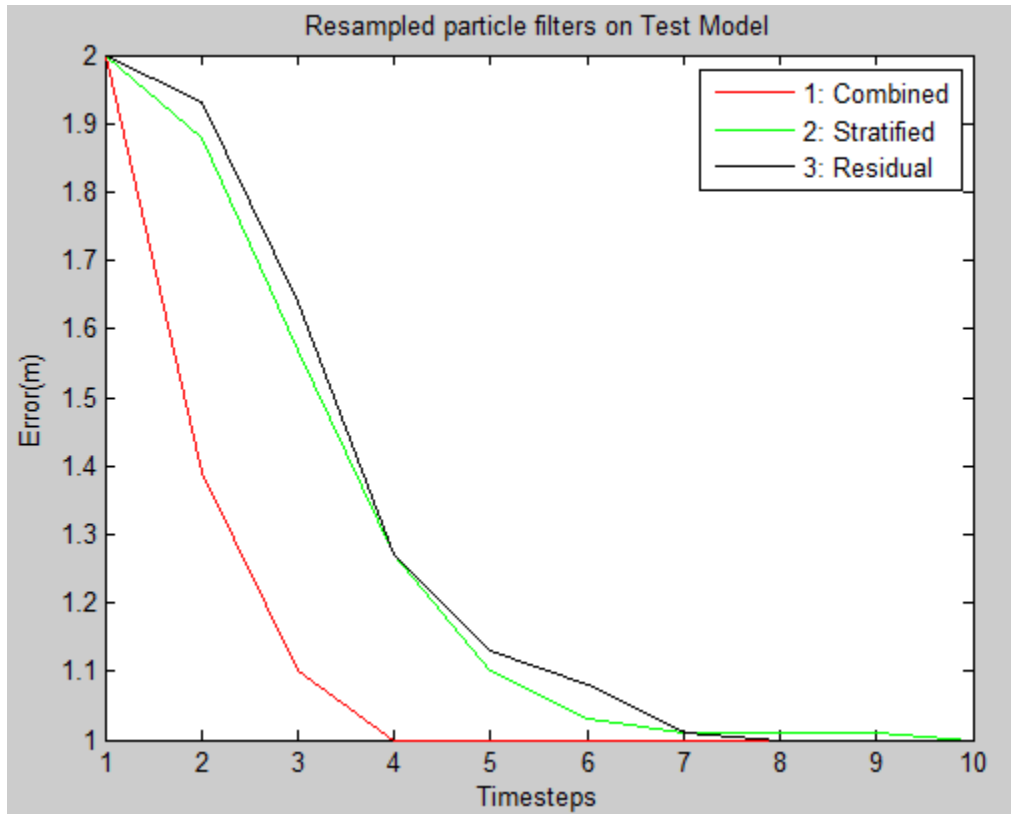


Figure 5.5: Resampled particle filter on Test Model

As shown in above figure we show the final output as motion detected in input video.

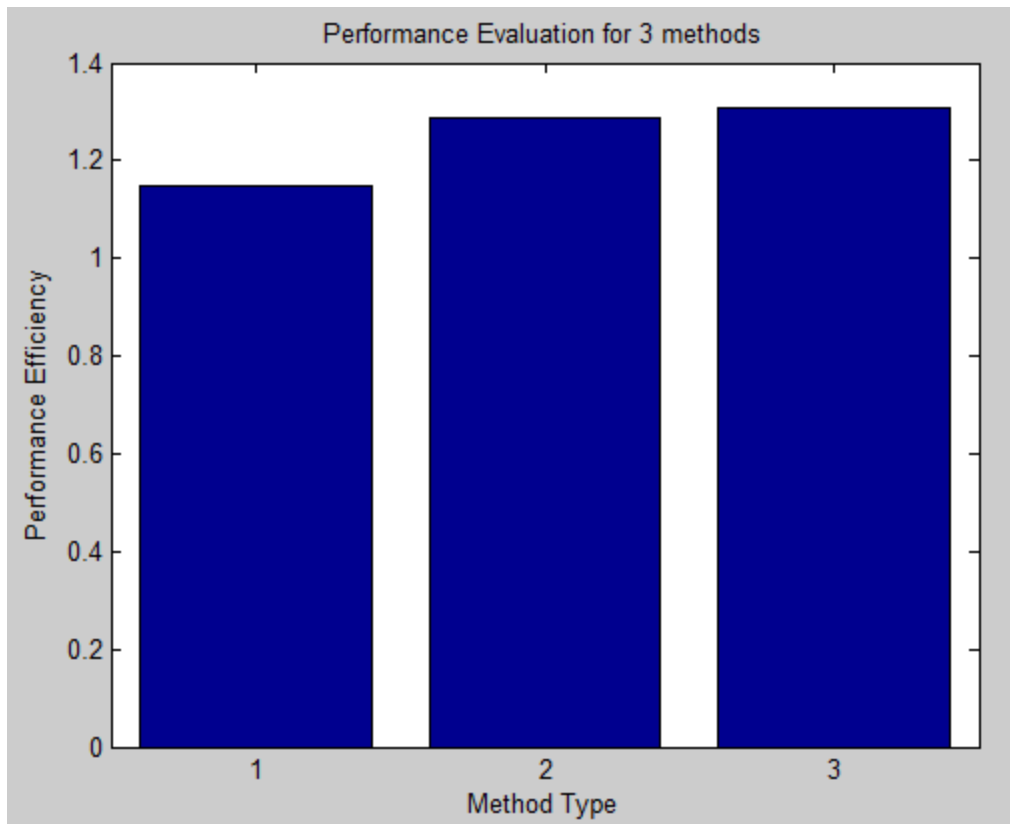


Figure 5.6: Performance evaluation for 3 methods

CHAPTER 6

CONCLUSION

We present a novel method for tracking of both unbending and deformable objects in the video sequences. The proposed tracking algorithm segments object's region based on motion, extracts feature points, predicts the corresponding feature points in the next frame using optical flow, corrects and reconstructs incorrectly predicted feature points, and finally applies space time interest point to handle the occlusion problem. Space time interest point, which has a major contributions in this Thesis, removes the requirement of having a pre-processing step of generating a priori training set. The updation of training set used for model fitting at each frame makes the object's shape more robust under occluded situation. The online updation of training set can help realizing a real-time and a robust tracking system. We have also presented the complete set of the experimental results. These results prove that the algorithm proposed here is capable of tracking objects under various conditions like noisy and low-contrast environment, and is also capable of tracking the object-of-interest having partial occlusion and complicated background.

An efficient and robust automated object tracking and motion system is presented in this Thesis. The proposed idea has been implemented by working on an algorithm that is based on branching particle Filters and dynamic template matching. The algorithm has experimentally been shown to be quite accurate and effective in detecting a moving object even under bad lighting conditions or occlusions. Such an automated object tracking system can be used in applications where accurate tracking is required but good lighting conditions cannot be provided. The video tracking system is furthermore very much applicable to areas like video conferencing and surveillance.

FUTURE DIRECTION

Future work focuses on tracking multiple objects at the same time as well as on improving tracker accuracy during camera motion. The algorithms can be implemented on hardware equipment. These algorithms can be further extended for the use in real-time applications and object classifications. It can be modified to differentiate different class objects in real time video also apply 3D analysis, which allows a more detailed classification of cars. The intention is to identify the type of a vehicle. The height value of the car is, for example, easily to extract from the infrared picture

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