# Review paper: Video processing & its applications.

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**Abstract** - *In this paper various videos processing techniques are considered along with its applications like in traffic environment, real time videos captured through mobile (hand-held) devices. Video stabilization is also considered in this paper. In Video stabilization, video processing technique is used to enhance the quality of input video by removing the undesired camera motions. There are various approaches used for stabilizing the captured videos. Most of the existing methods are either very complex or does not perform well for slow and smooth motion of hand held mobile videos.*

***Key Words***: video processing,motion vector.

## 1.INTRODUCTION

In electronics engineering, **video processing** is a particular case of signal processing, which often employs video filters and where the input and output signals are video files or video streams. Video processing techniques are used in television sets, VCRs, DVDs, video codecs, video players, video scalers , traffic applications and other devices. For example commonly only design and video processing is different in TV sets of different manufactures. The videos taken from hand held mobile cameras suffer from different undesired and slow motions like track, boom or pan, these affect the quality of output video significantly.

*Stabilization is achieved by synthesizing the new stabilized video sequence; by estimating and removing the undesired inter frame motion between the successive frames. Generally the inter frame motion in mobile videos are slow and smooth. Video stabilization techniques can be broadly classified as mechanical stabilization, optical stabilization and image post processing stabilization.*

### 1.1 Mechanical image Stabilization

Mechanical image stabilization involves stabilizing the entire camera, not just the image. This type of stabilization uses a device called “Gyros”. Gyros consist of a gyroscope with two perpendicular spinning wheels and a battery pack as shown in Fig 1. Gyroscopes are motion sensors.When the gyroscopes sense movement, a signal is sent to the motors to move the wheels to maintain stability. The gyro attaches to the camera’s tripod socket and acts like an "invisible tripod".

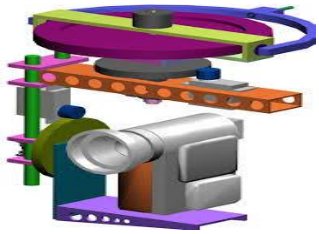

**Fig 1:** Gyroscopic Stabilizer.

### 1.2 *Optical Image Stabilization*

The Optical Image Stabilization (OIS) system, unlike the DIS system, manipulates the image before it gets to the CCD. When the lens moves, the light rays from the subject are bent relative to the optical axis, resulting in an unsteady image because the light rays are deflected. By shifting the IS lens group on a plane perpendicular to the optical axis to counter the degree of image vibration, the light rays reaching the image plane can be steadied [17]. Since image vibration occurs in both horizontal and vertical directions, two vibration-detecting sensors for yaw and pitch are used to detect the angle and speed of movement then the actuator moves the IS lens group horizontally and vertically thus counteracting the image vibration and maintaining the stable picture as shown below.

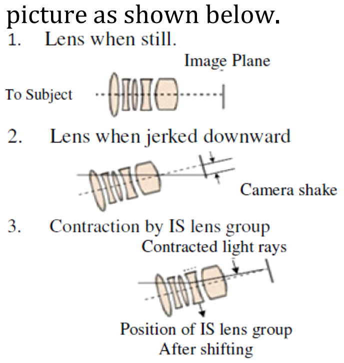


**Fig 2:** Optical Image stabilizer

### 1.3.1. MOTION ESTIMATION

Motion estimation is one of the field of research in video processing. By using different motion estimation techniques, it is possible to estimate object motion or camera motion observed in video sequence. Object motion is defined as the local motion of the scene, and camera motion is defined as the global motion. The motion estimation techniques can be classified as feature based approaches [2, 9, 12, and 14] or direct pixel based approaches [1, 4, 8, 10, and 13]. These feature-based approaches are although faster than direct pixel based approaches, but they are more prone to local effects and there efficiency depends upon the feature point’s selection. Hence they have limited performance for the unintentional motion. The direct pixel based approach makes optimal use of the information available in motion estimation and image alignment, since they measure the contribution of every pixel. The simplest technique is to pick the search algorithm and try all possible matches, that means do the full search. But this method is very lengthy and slow. Hence to make computation faster, image pyramid based hierarchical techniques are used as alternatives. Alternatively To get sub pixel precision in the alignment, incremental methods based on a Taylor series expansion of the image function are often used. These can also be applied to parametric motion models. The differential motion estimation has proven to be highly effective for computing inter frame error. In this the derivatives of the inter frame error is equated to zero and then differential equation is solved to get the parameters. Differential global motion estimation is commonly used with image pyramid based hierarchical video sequence stabilization.

In electrical engineering and computer science, video processing is a particular case of signal processing, where the input and output signals are video files or video streams. Video processing techniques are used in television sets, VCRs, DVDs, video codecs, video players and other devices. For example—commonly only design and video processing is different in TV sets of different manufactures. [13]

In terms of video codecs video filters are divided into three parts:

• Prefilters: used before encoding
• Intrafilters: inside of codec
• Postfilters: used after decoding

Common prefilters are following:

• Video denoising,
• Size conversion (commonly downsampling)
• Contrast enhancement
• Deinterlacing
• Deflicking, etc.

As intrafilter in current standards only deblocking is used.

Common postfilters are following:

• Deinterlacing (to convert interlaced video to progressively scanned)
• Deblocking
• Deringing

## II Application of Video processing:

Video Processing Techniques are also used in Traffic Applications. Section 2 will discuss traffic application in video processing:

### 2. Object detection:

### 2.1. Stationary camera:

In road traffic monitoring, the video acquisition cameras are stationary. They are placed on posts above the ground to obtain optimal view of the road and the passing vehicles. In automatic vehicle guidance, the cameras are moving with the vehicle. In these applications it is essential to analyze the dynamic change of the environment and its contents, as well as the dynamic change of the camera itself. Thus, object detection from a stationary camera is simpler in that it involves fewer estimation procedures. Initial approaches in this field involve spatial, temporal and spatio-temporal analysis of video sequences. Using a sequence of images the detection principle is based essentially on the fact that the objects to be searched for are in motion. These methods prioritize temporal characteristics compared with spatial characteristics, i.e. the detection deals mainly with the analysis of variations in time of one and the same pixel rather than with the information given by the environment of a pixel in one image [15]. More advanced and effective approaches consider object modeling and tracking using state-space estimation procedures for matching the model to the observations and for estimating the next state of the object. The most common techniques, i.e. analysis of the optical flow field and processing of stereo images, involve processing two or more images. With optical-flow-field analysis, multiple images are acquired at different times [16]; stereo images, of course, are acquired simultaneously from different points of view [17]. Optical-flow-based techniques detect obstacles indirectly by analyzing the velocity field. Stereo image techniques identify the correspondences between pixels in the different images. Stereovision has advantages in that it can detect obstacles directly and, unlike optical-flow-field analysis, is not constrained by speed. Several approaches considering different aspects of object and motion perception from a stationery camera are considered.

### 2.2 Moving camera

Autonomous vehicle guidance requires the solution of different problems at different abstraction levels. The vision system can aid the accurate localization of the vehicle with respect to its environment, by means of matching observations (acquired images) over time, or matching a single observation to a road model or even matching a sequence of observations to a dynamic model. We can identify two major problems with the efficient recognition of the road environment, namely the restricted processing time for real-time applications and the limited amount of information from the environment. For efficient processing we need to limit the ROI within each frame and process only relevant features within this ROI instead of the entire image. Since the scene in traffic applications does not change drastically, the prediction of the ROI from previously processed frames become of paramount importance. Several efficient methods presented in the following are based on dynamic scene prediction using motion and road models. The problem of limited amount of information in each frame stems from the fact that each frame represents a non-invertible projection of the dynamically changing 3D world onto the camera plane. Since single frames encode only partial information, which could be easily misinterpreted, the systems for autonomous vehicle guidance require additional information in the form of a knowledge-base that models the 3D environment and its changes (self/ego motion or relative motion of other objects). It is possible from monocular vision to extract certain 3D information from a single 2D-projection image, using visual cues and a priori knowledge about the scene. In such systems, obstacle determination is limited to the localization of vehicles by means of a search for specific patterns, possibly supported by other features such as shape, symmetry, or the use of a bounding box [18–20]. Essentially, forward projection of 3D models and matching with 2D observations is used to derive the structure and location of obstacles. True 3D modeling, however, is not possible with monocular vision and single frame analysis. The availability of only partial information in 2D images necessitates the use of robust approaches able to infer a complete scene representation from only partial representations. This problem concerns the matching of a low-abstraction image to a high-abstraction and complexity object. In other words, one must handle differences between the representation of the acquired data and the projected representation of the models to be recognized. A priori knowledge is necessary in order to bridge the gap between these two representations [21]. A first source of additional information is the temporal evolution of the observed image, which enables the tracking of features over time. Furthermore, the joint consideration of a frame sequence provides meaningful constraints of spatial features over time or vice versa. For instance, Ref. [22] employs smoothness constraints on the motion vectors, which are imposed by the gray-scale spatial distribution. Such form of constraints convey the realistic assumption that compact objects should preserve smoothly varying displacement vectors. The initial form of integrated spatio-temporal analysis operates on a so-called 2.5 D feature space, where 2D features are tracked in time. Additional constraints can be imposed through the consideration of 3D models for the construction of the environment (full 3D space reconstruction) and the matching of 2D data (observations) with the 3D representation of these models, or their projection on the camera coordinates (pose estimation problem). Such model information, by itself, enables the consideration and matching of relative object poses [23]. With the latest advances in computer architecture and hardware, it becomes possible to consider even the dynamic modeling of 3D objects. This possibility paved the way to fully integrated spatio-temporal processing, where two general directions have been proposed. The first one considers the dynamic matching of low-abstraction (2D image-level) features between the data and the model. Although it keeps continuous track of changes in the 3D model using both road and motion modeling (features in a 3 1 2 D space), it propagates the current 2D representation of the model in accordance with the current state of the camera with respect to the road [24]. Thus, it matches the observations with the expected projection of the world onto the camera system and propagates the error for correcting the current (model) hypothesis [11]. The second approach uses a full 4D model, where objects are treated as 3D motion processes in space and time. Geometric shape descriptors together with generic models for motion form the basis for this integrated (4D or dynamic vision) analysis [25]. Based on this representation one can search for features in the 4D-space [25], or can match observations (possibly from different sensors or information sources) and models at different abstraction levels (or projections) [21]. Some relevant approaches for moving object detection from a moving camera are summarized in Section 2.3.

### 2.3 Object detection approaches

Some fundamental issues of object detection are considered and reviewed in this section. Approaches have been categorized according to the method used to isolate the object from the background on a single frame or a sequence of frames.

#### 2.3.1. Thresholding

This is one of the simplest, but less effective techniques, which operates on still images. It is based on the notion that vehicles are compact objects having different intensity form their background. Thus, by thresholding intensities in small regions we can separate the vehicle from the background. This approach depends heavily on the threshold used, which must be selected appropriately for a certain vehicle and its background. Adaptive thresholding can be used to account for lighting changes, but cannot avoid the false detection of shadows or missed detection of parts of the vehicle with similar intensities as its environment [26]. To aid the thresholding process, binary mathematical morphology can be used to aggregate close pixels into a unified object [27]. Furthermore, gray-scale morphological operators have been proposed for object detection and identification that are insensitive to lighting variation [28].

#### 2.3.2. Multigrid identification of regions of interest

A method of directing attention to regions of interest based on multi-resolution images is developed in Ref. [5]. This method first generates a hierarchy of images at different resolutions. Subsequently, a region search begins at the top level (coarse to fine). Compact objects that differ from their background remain distinguishable in the low resolution image, whereas noise and small intensity variations tend to disappear at this level. Thus, the low resolution image can immediately direct attention to the pixels that correspond to such objects in the initial image. Each pixel of interest is selected according to some interest function which may be a function of the intensity values of its adjacent pixels, edge strength, or successive frame differencing for motion analysis [5].

#### 2.3.3. Edge-based detection (spatial differentiation)

Approaches in this class are based on the edge-features of objects. They can be applied to single images to detect the edge structure of even still vehicles [29]. Morphological edge-detection schemes have been extensively applied, since they exhibit superior performance [4,18,30]. In traffic scenes, the results of an edge detector generally highlight vehicles as complex groups of edges, whereas road areas yield relatively low edge content. Thus the presence of vehicles may be detected by the edge complexity within the road area, which can be quantified through analysis of the histogram [31]. Alternatively, the edges can be grouped together to form the vehicle's boundary. Towards this direction, the algorithm must identify relevant features (often line segments) and define a grouping strategy that allows the identification of feature sets, each of which may correspond to an object of interest (e.g. potential vehicle or road obstacle). Vertical edges are more likely to form dominant line segments corresponding to the vertical boundaries of the profile of a road obstacle. Moreover, a dominant line segment of a vehicle must have other line segments in its neighborhood that are detected in nearly perpendicular directions. Thus, the detection of vehicles and/or obstacles can simply consist of finding the rectangles that enclose the dominant line segments and their neighbors in the image plane [2,30]. To improve the shape of object regions Ref. [32,33] employ the Hought transform to extract consistent contour lines and morphological operations to restore small breaks on the detected contours. Symmetry provides an additional useful feature for relating these line segments, since vehicle rears are generally contour and region-symmetric about a vertical central line [34]. Edge-based vehicle detection is often more effective than other background removal or thresholding approaches, since the edge information remains significant even in variations of ambient lighting [35].

### 2.3.4. Space signature

In this detection method, the objects to be identified (vehicles) are described by their characteristics (forms, dimensions, luminosity), which allow identification in their environment [36,37]. [37] employs a logistic regression approach using characteristics extracted from the vehicle signature, in order to detect the vehicle from its background. Alternatively, the space signatures are defined in [38] by means of the vehicle outlines projected from a certain number of positions (poses) on the image plane from a certain geometrical vehicle model. A camera model is employed to project the 3D object model onto the camera coordinates at each expected position. Then, the linear edge segments on each observed image are matched to the model by evaluating the presence of attributes of an outline, for each of the pre-established object positions (poses). In a similar framework, [39] projects the 3D model at different poses to sparse 2D arrays, essentially encoding information about the projected edges. These arrays are used for matching with the image data. Space signatures can also be identified in an image through correlation or template matching techniques, using directly the typical gray-scale signature of vehicles [40]. Due to the inflexible nature of template matching, a specific template must be created for each type of vehicle to be recognized. This creates a problem, since there are many geometrical shapes for vehicles contained in the same vehicle-class. Moreover, the template mask assumes that there is little change in the intensity signature of vehicles. In practice, however, changes in ambient lighting, shadows, occlusion, and severe light reflection on the vehicle body panels generate serious variation in the spatial signatures of same-type vehicles. To overcome such problems, the TRIP II system [38,40] employs neural networks for recalling space signatures, and exploits their ability to interpolate among different known shapes [40]. Despite its inefficiencies, vehicle detection based on sign patterns does not require high computational effort. Moreover, it enables the system to deal with the tracking process and keep the vehicle in track by continuously sensing its sign pattern in real time.

### 2.3.5. Background frame differencing

In the preceding methods, the image of motionless objects (background image) is insignificant. On the contrary, this method is based on forming a precise background image and using it for separating moving objects from their background. The background image is specified either manually, by taking an image without vehicles, or is detected in real-time by forming a mathematical or exponential average of successive images. The detection is then achieved by means of subtracting the reference image from the current image. Thresholding is performed in order to obtain presence/absence information of an object in motion [5,15,18]. The background can change significantly with shadows cast by buildings and clouds, or simply due to changes in lighting conditions. With these changing environmental conditions, the background frame is required to be updated regularly. There are several background updating techniques. The most commonly used are averaging and selective updating. In averaging, the background is built gradually by taking the average of the previous background with the current frame. If we form a weighted average between the previous background and the current frame, the background is build through exponential updating [40]. In selective updating, the background is replaced by the current frame only at regions with no motion detected; where the difference between the current and the previous frames is smaller than a threshold [40]. Selective updating can be performed in a more robust averaging form, where the stationary regions of the background are replaced by the average of the current frame and the previous background [30].

### 2.3.6. Inter-frame differencing

This is the most direct method for making immobile objects disappear and preserving only the traces of objects in motion between two successive frames. The immediate consequence is that stationary or slow-moving objects are not detected. The inter-frame difference succeeds in detecting motion when temporal changes are evident. However, it fails when the moving objects are not sufficiently textured and preserve uniform regions with the background. To overcome this problem, the inter-frame difference is described using a statistical framework often employing spatial Markov random fields [34–36]. Alternatively, in Ref. [34] the inter-frame difference is modeled trough a two-component mixture density. The two components are zero mean corresponding to the static (background) and changing (moving object) parts of the image. Inter-frame differencing provides a crude but simple tool for estimating moving regions. This process can be complemented with background frame differencing to improve the estimation accuracy [37].

The resulting mask of moving regions can be further refined with color segmentation [38] or accurate motion estimation by means of optical flow estimation and optimization of the displaced frame difference [16,37], in order to refine the segmentation of moving objects.

### 2.3.7. Time signature

This method encodes the intensity profile of a moving vehicle as a function of time. The profile is computed at several positions on the road as the average intensity of pixels within a small window located at each measurement point. The analysis of the time signature recorded on these points is used to derive the presence or absence of vehicles [39]. The time signal of light intensity on each point is analyzed by means of a model with pre-recorded and periodically updated characteristics. Spatial correlation of time signatures allows further reinforcement of detection. In fact, the joint consideration of spatial and time signatures provides valuable information for both object detection and tracking. Through this consideration, the one task can benefit from the results of the other in terms of reducing the overall computational complexity and increasing the robustness of analysis [40]. Along these lines, the adaptable time delay neural network developed for the Urban Traffic Assistant (UTA) system is designed and trained for processing complete image sequences [39-40]. The network is applied for the detection of general obstacles in the course of the UTA vehicle.

### 2.3.8. Feature aggregation and object tracking

These techniques can operate on the feature space to either identify an object, or track characteristic points of the object [32]. They are often used in object detection to improve the robustness and reliability of detection and reduce false detection rates. The aggregation step handles features previously detected, in order to find the vehicles themselves or the vehicle queues (in case of congestion). The features are aggregated with respect to the vehicle's geometrical characteristics. Therefore, this operation can be interpreted as a pattern recognition task. Two general approaches have been employed for feature aggregation, namely motion-based and model-based approaches [34]. Motion-based approaches group together visual motion consistencies over time [34,32,33]. Motion estimation is only performed at distinguishable points, such as corners [32,34], or along contours of segmented objects [35], or within segmented regions of similar texture [14,37,40]. Line segments or points can also be tracked in the 3D space by estimating their 3D displacements via a Kalman filter designed for depth estimation [18,34,32,33]. Model-based approaches match the representations of objects within the image sequence to 3D models or their 2D projections from different directions (poses) [24,33]. Several model-based approaches have been proposed employing simple 2D region models (mainly rectangles), active contours and polygonal approximations for the contour of the object, 3D models that can be tracked in time and 4D models for full spatio-temporal representation of the object [33,36]. Following the detection of features, the objects are tracked. Two alternative methods of tracking are employed in Ref. [32], namely numeric signature tracking and symbolic tracking. In signature tracking, a set of intensity and geometry-based signature features are extracted for each detected object. These features are correlated in the next frame to update the location of the objects. Next, the signatures are updated to accommodate for changes in range, perspective, and occlusion. In general, features for tracking encode boundary (edge based) or region (object motion, texture or shape) properties of the tracked object. Active contours, such as snakes and geodesic contours are often employed for the description of boundaries and their evolution over the sequence of frames. For region-based features tracking is based on correspondences among the associated target regions at different time instances [34,37]. In symbolic tracking, objects are independently detected in each frame. A symbolic correspondence is made between the sets of objects detected in a frame pair. A time sequenced trajectory of each matched object provides a track of the object [32].

### Conclusion & Future Scope:

Review of the various video filters, motion estimation, Video Processing Techniques used in Traffic Applications stabilization techniques are presented in the paper. Motion smoothening is the scope for the future the computation cost can also be reduced to improve the efficiency of the estimation and stabilization in future work.

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