Real-Time Human Detection in Uncontrolled Camera Motion Environments

Mohamed Hussein Wael Abd-Almageed Yang Ran Larry Davis
Institute for Advanced Computer Studies
University of Maryland
{mhussein, wamageed, rany, lsd}@umiacs.umd.edu

Abstract

In environments where a camera is installed on a freely moving platform, e.g. a vehicle or a robot, object detection and tracking becomes much more difficult. In this paper, we presents a real time system for human detection, tracking, and verification in such challenging environments. To deliver a robust performance, the system integrates several computer vision algorithms to perform its function: a human detection algorithm, an object tracking algorithm, and a motion analysis algorithm. To utilize the available computing resources to the maximum possible extent, each of the system components is designed to work in a separate thread that communicates with the other threads through shared data structures. The focus of this paper is more on the implementation issues than on the algorithmic issues of the system. Object oriented design was adopted to abstract algorithmic details away from the system structure.

1 Introduction

The problem of object detection and tracking in video sequences becomes much harder when the camera is allowed to move uncontrollably. If the object of interest is a deformable object, like a human, the problem becomes even more challenging. Nevertheless, several interesting applications are waiting for solutions to this problem. A modern car prepared with a digital camera and a computer vision software for human detection can automatically avoid running over pedestrians. A military unmanned vehicle equipped with similar technology can automatically detect and deal with an enemy before being attacked.

In this paper, a real-time computer vision system for human detection and tracking in uncontrolled moving camera platforms is presented. The contribution presented in this paper is not in the algorithmic aspect of the system. Rather, our focus is on the system design and implementation aspects. Namely, our design was made to achieve two main goals: robustness and efficiency. Robustness was achieved through integration of algorithms, for human detection, tracking, and motion analysis, in one framework so that the final decision is based on the agreement of more than one algorithm. Efficiency was achieved through multithreaded design and usage of a high performance library. A final merit of our system is its object oriented design. Object orientation was adopted to abstract the algorithmic details away from the system design so that we can easily experiment with different algorithms. Therefore, our system can be regarded as a testbed in testing different algorithms for human detection, tracking, and motion analysis.

The rest of the paper is organized as follows: Section 2 explores some of the related works. Section 3 explains our system design in detail. Section 4 briefly introduces the algorithms used in our implementation. Section 5 presents some experimental results. Finally, Sec. 6 concludes our paper.

2 Related Work

Since our focus in this paper is on the implementation issues of our system, a review of technical approaches in video surveillance will not be much relevant. For a global overview on automated surveillance systems, the reader is referred to [4]. Readers interested in broader and deeper coverage of technical details are referred to any recent survey on video surveillance, such as [8], [13], or [7]. For completeness of the discussion, we selected few systems that are relevant to ours in function to describe briefly here.

Perhaps, a closely related system to ours is the DETER system [9]. DETER can detect and track humans, and can analyze the trajectory of their motion for threat evaluation. The W^4 system [6] detects humans and their body parts and analyzes some simple interactions between humans and objects. In [11], the idea of combining several cues together to enhance the robustness of tracking was utilized. Our system utilizes a similar idea with one step further. It uses different algorithms with different cues instead of one algorithm with different cues. IBM S3-R1 [5] can detect, track, and classify moving objects in a scene, encodes detected activ-

ities, and stores all the information on a database server to enable a broad range of queries on it. We have to make it clear that all these systems, though close to ours in function, work only in a static camera environment, but, our system works in an uncontrolled moving camera environment.

3 System Design

In this section, the details of our system design and implementation are explained. To make the paper self-contained, in Sec. 4, the algorithms used in our current implementation are briefly introduced.

3.1 Objectives

As mentioned before, two main objectives underly our system design: robustness and efficiency. To deliver a robust operation, our system utilizes more than one algorithm to identify a human in a video sequence. Each algorithm uses a different visual cue to make its decision. The final output is based on the agreement of these cues. Namely, our system integrates a human detection algorithm, an object tracking algorithm, and a motion analysis algorithm. The human detection algorithm uses the shape as a cue to decide whether a part of the image contains a human or not. Thereafter, the tracking algorithm uses the intensity cue to track the detected object over time. Finally, the motion analysis algorithm utilizes the motion periodicity cue to verify whether the detected and tracked object moves like a human or not. Each of the three algorithms can be viewed as a filter that filters out false alarms produced by the preceding one.

To confront computational complexity and deliver real time performance, the system was designed to utilize as much as possible from the available computational resources. That is achieved via multi-threading, efficient inter-thread communication, and using a high performance library. Multi-threading removes the unnecessary blocking of a system component when a dependent component is working. For example, the object tracking component does not need to block until the motion analysis is performed. To reduce the communication burden between threads, the shared memory between threads is kept to minimum. Each two communicating threads share a data structure that is accessed only by them in a consumer-producer fashion. Finally, Intel Integrated Performance Primitives (IPP) library [12], which is a highly optimized library for image processing and low level computer vision tasks, is used in our implementation.

3.2 System Architecture

Figure 1 depicts the architecture of our system. The main modules of our system, as they are shown in Fig. 1, from left to right, are: the frame grabbing module, the human detection module, the object tracking module, the motion analysis module, and finally the output module. Input of the system is video frames obtained either online from a video camera, or off-line from a video file or individual video frame files. The output can be shown online or stored to the disk for further analysis.

Each of the modules runs in a separate thread and data is passed from one module to another via a shared data structure. Details of inter-thread communication are given in Sec. 3.4.

3.3 System Components

In this section, we describe the operation of each module in the system.

3.3.1 Frame Grabbing Module

The frame grabbing module is responsible for dealing with the input device. The input device can be a digital video camera connected to the computer, or a storage device on which a video file or individual video frames are stored. This module abstracts the nature of the input device away from the rest of the system so that changing the input device does not affect the rest of the system.

3.3.2 Human Detection Module

This module is responsible for invoking the detection algorithm. Ideally, the detection algorithm is to be run on each input frame. However, this will inhibit the system from meeting its real time requirements. Instead, the detection algorithms in our implementation is invoked every two seconds. The location of the human targets in the remaining time is determined by tracking the detected humans using the tracking algorithm.

To further speed up the process, the detection algorithm does not look for humans in the entire frame. Instead, it looks for humans in the regions determined to be foreground regions. To determine the foreground regions, a stabilization algorithm is used to align the current frame with a preceding frame and with a succeeding frame. After alignment, the current frame is subtracted from the two other frames. The result of each subtraction is thresholded to form a binary image that represents the locations of foreground objects in the two subtracted frames. To know the locations of the foreground objects in the current frame, the results of the two subtractions are combined by an AND operation. The subtraction is performed in the hue channel of the HSV color space.

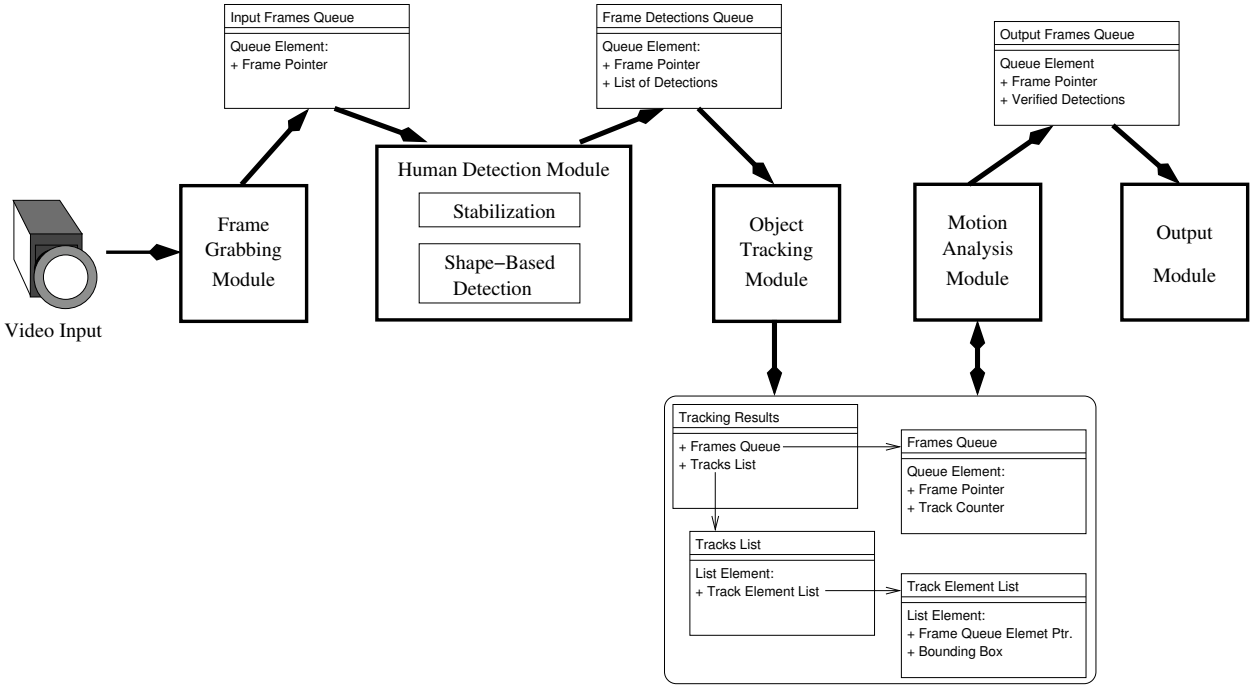


Figure 1. System Architecture

3.3.3 Object Tracking Module

This module processes frames and detections received from the human detection module, and retains information about all the existing tracks. When a new frame is received, the already existing tracks are extended by locating the new bounding boxes locations for each track in this frame. If the frame is received accompanied with new detections, the new detections are compared to the already existing tracks. If a new detection significantly overlaps with one of the existing tracks, it is ignored. Otherwise, a new track is created for this new detection. A track is discontinued if the tracking algorithm fails to extend it in a newly coming frame.

3.3.4 Motion Analysis Module

When the length of a track exceeds some specific length, typically, two seconds, the motion analysis module is invoked. The motion analysis module analyzes the periodicity encountered in the track. Based on the result of this analysis, it decides whether the tracked object is indeed a human or not. This way, the detection results are double checked by the motion analysis. In our experiments, that results in a reduction in the false positives produced by the detector, as shown in Sec. 5.

3.3.5 Output Module

When each track in a frame has been either analyzed by the motion analysis module, or removed because of being too short to be analyzed, this frame is ready for output and passed to the output module. The output module marks the detected human locations in the frame and sends it to the output device, which can be the display monitor or a storage device.

3.4 Inter-Thread Communications

Multi-threading in our system is implemented using the `OpenThreads` open source threading library [1]. Two threads communicate with one another through the shared data structure that both can access. To prevent race conditions between any two threads sharing a data structure, a template class is designed that automatically defines the `OpenThreads` objects that are necessary for mutual exclusion enforcement for any given data type. In this section, the details of the data structures at the interface between each pair of communicating threads are explained. Figure 1 illustrates the various data structures used.

3.4.1 Frame Grabbing and Human Detection Modules

The shared data structure between the frame grabbing module and the human detection module is just a queue of pointers to frames.

3.4.2 Human Detection and Object Tracking Modules

This interface is a queue of structure elements. Each element contains a pointer to the frame along with a list of detections found in it. If the list of detections is empty, then, either the detection algorithm was not run on this frame, or the detection algorithm did not find any human in it.

3.4.3 Object Tracking and Motion Analysis Modules

In the shared data structure of this interface, two lists are maintained: a *frames queue*, which is a queue of *frames queue elements*, and a *tracks list* which is a list of pointers to *track element lists*. Each *frames queue element* contains a pointer to a frame and a counter that holds the number of tracked objects in that frame. Each *track element list* is, in turn, a list of *track elements*. A *track element* represents the location of the tracked object in one of the frames pointed to by an element in the frames queue. A track element contains two items: a bounding box that specifies the location of this track's object in the corresponding frame, and a pointer to the entry of this frame in the frames queue.

When the motion analysis module processes a track, it removes all its track list elements except for the most recent one; so that it can be tracked in the next frame. The object tracking module itself removes all the track list elements of a track if this track is discontinued and its length is not enough to be analyzed by the motion analysis module. When a track list element is removed, either by the object tracking module or by the motion analysis module, the counter of the corresponding frame in the frames queue is decremented. Therefore, when the counter of a frame goes down to zero at any time, that means this frame is completely processed and ready to be sent to the output module.

3.4.4 Motion Analysis and Output Modules

The interface between the motion analysis module and the output module is simply a queue of pointers to frames that has become ready for output. The Motion Analyzer Module is responsible for sending frames ready for output to the output module, along with the bounding boxes that identify the targets that have been verified to be humans.

4 Algorithms

In this section, the algorithms used in our implementation are briefly explained. We do not claim that the algorithms selected are the best ones in their functions. In our system design, any of these algorithms can be safely replaced by others as long as the interfaces between different modules are preserved.

4.1 Stabilization Algorithm

Wolberg and Zokai [14] presented an image registration algorithm which recovers affine motion between a pair of images. The algorithm proposed in [14] uses a log-polar transformation of the image pair to recover translational, rotational and scale misalignments. For a detailed discussion of the stabilization algorithm, the reader is referred to [14].

Briefly, assume that we need to register the image pair I_1 and I_2. A rotation between the two images in the Cartesian space is indeed a translation in the polar space. Therefore, the rotation can be recovered by transforming the image pair to the polar space and location of the maximum cross correlation.

The scale recovery is performed by taking the $\log$ of the polar space values. In the $\log$ space, the scale factor manifests itself as a phase shift in the log-polar domain, which can be computed again using cross correlation methods. To recover the translation, the previous two steps are applied to a small patches cropped off I_1 and registered against I_2. The translation is the location that maximizes the cross correlation.

In our implementation, stabilization is used as a preprocessing stage in the human detection module, Sec. 3.3, to limit the area in which we search for humans. Therefore, precise alignment between I_1 and I_2 is not necessary.

4.2 Human Detection Algorithm

The human detection algorithm used in our implementation was introduced in [3]. This algorithm searches for humans in the image by matching its edge features to a database of templates of human silhouettes. Examples of these templates are shown in Fig. 2. The matching is done by computing the average Chamfer distance [2] between the template and the edge map of the target image area. The image area under consideration must be of the same size as the template. Let the template T be a binary image that is 0 everywhere except for the silhouette pixels where the value is 1, and let the Chamfer distance transform of the edge map of the target image area be denoted by C. The distance between a template T and the target image area I can be computed by

$$D(I,T) = \frac{1}{|T|}\sum_i C_i T_i \ ,$$

where $|T|$ is the number of silhouette pixels in T, T_i is the pixel number i in T, and C_i is the Chamfer distance value at pixel number i in I. The smaller the value of the distance between the template and the target image area, the better the match between them.

For efficient computations, a hierarchal structure, which contains selected templates from the database, is built off-

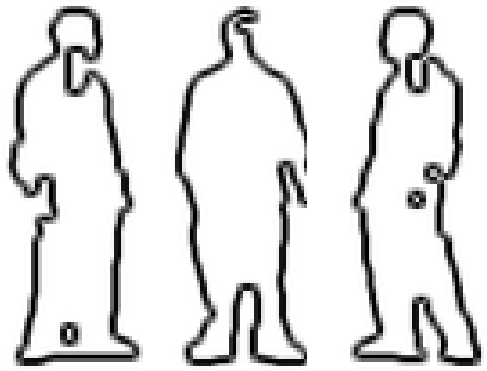


Figure 2. Example Human Silhouette Templates

line. That limits the comparison to a few number of templates and accelerates the search in the database. Details of building the hierarchy and matching the edge features to templates are explained in [3].

4.3 Object Tracking Algorithm

The tracking algorithm used in our system is the one in [15]. The intensity value of each pixel is modeled as a time varying mixture of three Gaussian components, F, S, and W. The F component is the fixed component, which represents the appearance that is expected to be encountered most of the time. The S component represents the stable structure of the object's appearance observed over time. The W component, also called the wandering component, represents the transient changes in the appearance between two successive frames. Let the appearance model at time t be denoted by A_t. A_t is composed of three components $\{F_t, S_t, W_t\}$. Let $\mu_{f,t}, \mu_{s,t}$, and $\mu_{w,t}$, and $\sigma_{f,t}, \sigma_{s,t}$, and $\sigma_{w,t}$, and $m_{f,t}, m_{s,t}$, and $m_{w,t}$ denote the means, the standard deviations, and the mixing probabilities for the F, S, and W components, at time t, respectively. The observation at time t, denoted by Z_t, is the intensity values of the d pixels in the proposed target location at time t . The state at time t, denoted by θ_t, is the affine transformation that transforms the current appearance model to the region of the observation Z_t. The likelihood of a state θ_t with respect to an observation Z_t can be expressed as

$$p(Z_t/\theta_t) = \prod_{k=1}^{d} \left[\sum_{i=f,s,w} m_{i,t} N\left(Z_t(k); \mu_{i,t}(k), \sigma_{i,t}^2(k)\right) \right] ,$$

Particle filtering is used to estimate the current state θ_t based on the previous state and the current observation. The state transition model used is $\theta_t = \hat{\theta}_{t-1} + \nu_t + U_t$, where $\hat{\theta}_{t-1}$ is the estimated state at time $t-1$, ν_t is the predicted shift in the state vector at time t, which is estimated using a first order linear approximation, and U_t is a zero-mean Gaussian noise component. Interested reader is referred to [15] for further details and justifications.

4.4 Motion Analysis Algorithm

Since the human motion is naturally different than other types of motions, the sequence of bounding boxes can be further analyzed to verify whether or not the tracked subject is indeed a human. We use the human motion analyzer proposed by Ran et al. [10].

The algorithm proposed in [10] tests the spatio-temporal pixels in order to prove or disprove the null hypothesis that the signal being tested is periodic. Briefly, for a given pixel location $(x,\ y)$ in the bounding box, the algorithm computes the periodogram of the color value of $(x,\ y)$ across all bounding boxes of subject. A peak in the periodogram proves that the spatio-temporal signal is periodic. On the other hand, a flat periodigram means that the spatio-temporal is a white noise.

The periodicity test is repeated for all pixel locations in the bounding box. If the number of periodic pixels is higher than a certain threshold, then the subject undergoing the test is a human. Otherwise, the null hypothesis that the subject is a human is rejected. For more details on the algorithm, the reader is referred to [10].

5 Experimental Results

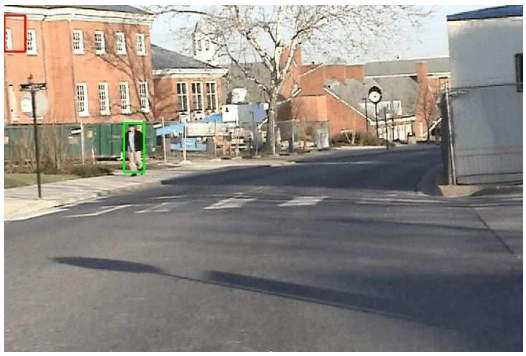
Our system was experimented on a set of challenging video sequences. It has succeeded to demonstrate robustness and close to real time performance (around 15 frames per second.) In this section, we will present the results of two sequences. In the figures presented, rectangular bounding boxes are the output of the detection algorithm. Green boxes are the detections that are verified by the motion analysis algorithm, and the red boxes are the ones that are rejected by it. The reader is referred to the electronic version for clarity of results.

In the sequence shown in Fig. 3, there was only one false detection and it was caught by the motion analysis. On the other hand, the sequence shown in Fig. 4 clearly shows the advantages of the verification step. The shape-based detection algorithm produced many false alarms due to high edge density on the left part of the scene. After tracking these false detections for a period of time, the motion analysis algorithm decided that they did not exhibit the periodic motion of a human.

(a) Frame 1

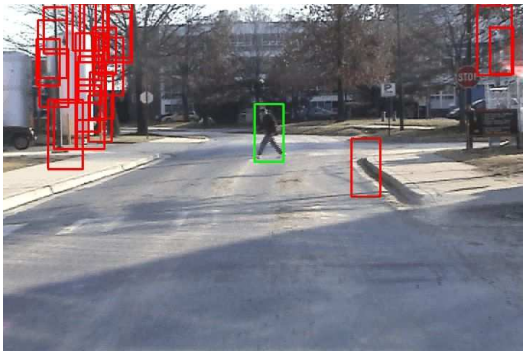
(b) Frame 22

(c) Frame 45

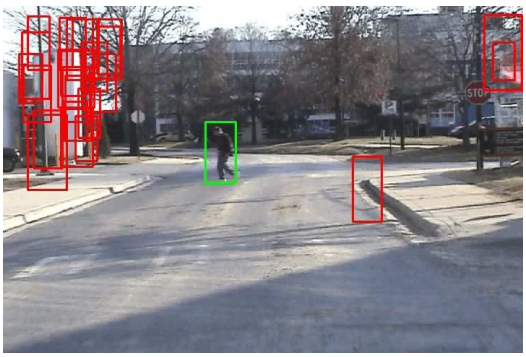


(d) Frame 65

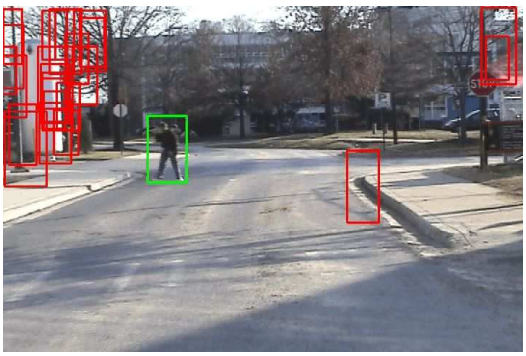
Figure 3. Green rectangles are the detections verified by motion analysis.



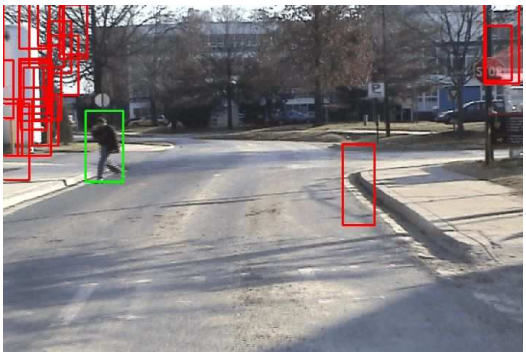
(a) Frame 1



(b) Frame 23



(c) Frame 45



(d) Frame 66

Figure 4. A more challenging example. The verification step removed many false alarams.

6 Conclusion

In this paper, a real-time computer vision system for human detection, tracking, and verification in uncontrolled camera motion environment has been presented. The key features of our system are robustness and efficiency. Robustness was achieved via integration of more than one algorithm, each of which uses a different visual cue to identify humans. The efficiency was achieved via a multi-threaded design with efficient inter-thread communication, and the usage of a highly optimized software library. The system has demonstrated a satisfactory performance on highly challenging video sequences. Our short term plan is to further optimize our system and experiment with other algorithms. Our long term plan is to extend the system to analyze human activities and evaluate threats.

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