# Real Time Video Compression and Novelty Detection using HMM Algorithm

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**Abstract**

A new DCT approximation that possesses an extremely low arithmetic complexity, requiring only 14 additions. This novel transform was obtained by means of solving a tailored optimization problem aiming at minimizing the transform computational cost. Second, we propose hardware implementations for several 2-D 8-point approximate DCT. All introduced implementations are sought to be fully parallel time-multiplexed 2-D architectures for 8 *8 data blocks. Additionally, the proposed designs are based on successive calls of 1-D architectures taking advantage of the separability property of the 2-D DCT kernel. Designs were thoroughly assessed and compared. The proposed transform possesses low computational complexity and is compared to state-of-the-art DCT approximations in terms of both algorithm complexity and peak signal-to-noise ratio. The proposed DCT approximation is a candidate for reconfigurable video standards such as HEVC. The proposed transform and several other DCT approximations are mapped to systolic-array digital architectures.

## 1. Introduction

Nowadays, it is seen that surveillance cameras are already prevalent in commercial organizations, with camera output being trace to masking tape that are either rewritten periodically or stored in video records. To take out the greatest advantage from this record digital data, notice any moving objective from the picture is needed without engaging any human eye to monitor things all the time. The wide applications of video surveillance call for automated and efficient analysis, where detection and tracking of moving objects are the essential steps and can be performed in either pixel domain or compressed domain. Since most videos captured nowadays are compressed for storage and program, dense domain method have lately drawn increasing research attention. In video analytics application in observation, motion detection can be base for many other application of analyzing video stream including object recognition, face detection and recognition etc. The hidden Markov model is a popular technique widely used in pattern recognition. It has good capability to grasp temporal statistical properties of stochastic procedure. The spirit of the HMM process is to build a model that explains the occurrence of observations (symbols) in a time sequence and use it to identify other observation sequences. Some researchers have applied HMM for video analysis and classification. This project present a fast and efficient algorithm for moving object detection and tracking for H264 surveillance video for real time applications, in which movement vector and DCT coefficient are used to detect moving object and track it in consecutive frames. Compressed domain processing avoids the full decoding and reconstruction of the video, which present a possible for real time processing of multiple video streams on one server. HMM to detect moving object using spatio temporal spaces. Efficiently reconstruct videos using compressed video approaches. Minimizes the dissimilarity energy and partially decodes frames for tracking the moving object specified by users. Efficiently detect multiple objects detection and tracking.

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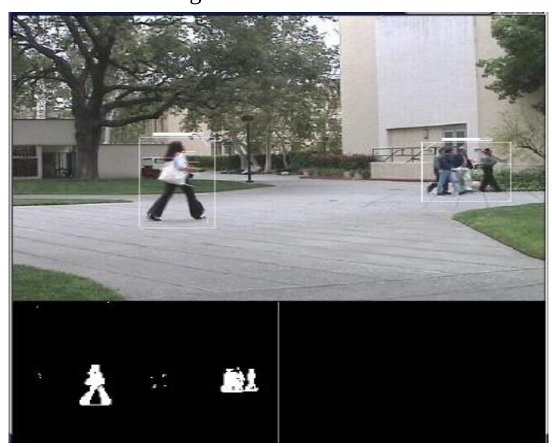

**Fig: 1**. Object Detection in Compression Video

## 2. Related Work

In [1] Asish Kumar Sahu, Abha Choubey et al. This paper presents a novel algorithm for motion detection from a stationary background scene to detect moving object based on background subtraction. The Motion tracking Surveillance has gained a lot of interests over the past few years. We developed a robust and efficiently computed background subtraction algorithm that is capable enough to manage with local illumination changes as well as global illumination changes. The main algorithm being discussed here are those implementing image subtraction methods and background segmentation approach. The report also is aimed to give readers a main idea of the architecture of a human motion detection system in applications. The experiment results show that the proposed method runs rapidly, robustly, exactly and accurate for the concurrent detection. In [2] Vishwadeep Uttamrao Landge et al. This paper proposes a method to detect object based on background subtraction method. A reliable background updating model is established. A optimization threshold method is used to obtain behave our of moving object and tracking. Motion of a moving object and tracking in a video stream is studied and detected. The centroid of object is computed to use in the analyses of the position of the moving human body. The experimental results show that the proposed method runs quickly, accurately and fits for the real-time detection. In [3] Md. Junaedur Rahman et al. In this particular proposed work, a novel real-time motion detection algorithm is proposed for dynamic changing background features. The algorithm integrates the temporal differencing along with optical flow method, double background filtering method and morphological processing techniques to achieve better detection performance. Temporal differencing is designed to detect initial motion areas for the optical-flow calculation to produce real-time and accurate object motion vectors detection. The double background filtering method is obtain and keep a reliable background image to handle variations on environmental changing conditions that is designed to get rid of the background interference and separate the moving objects from it. The morphological processing methods are adopted and mixed with the double background filtering to obtain improved results. The most attractive benefit for this algorithm is that the algorithm does not require to figure out the background model from hundreds of images and can handle quick image variations without prior understanding of the object size and shape.

## 3. Gaussian Mixture Method

Mixture of K Gaussians $\eta(\mu_i, \sigma_i, \omega_i)$ is a model in which independent variables are division of a total. Here $\eta$ is the i-th Gaussian section with intensity mean $\mu_i$ and standard deviation $\sigma_i$. $\omega_i$ is the portion of the data accounted for by the i-th component. It was expectation maximization (EM) algorithm that guarantees to converge to a local maximum in a search space. First it was convolved by Grimson and Stauffer's work. In this way, the model copes also with multimodal background distributions; the number of modes. All weights $\omega_i$ are updated at every new frame. At every new frame, a little of the Gaussians "match" the current value for them, $\mu_i$ and $\sigma_i$ are updated by the running average. The combination of Gaussians essentially models both the foreground and the background: now the question is how to pick only the distributions modeling the background. All distributions are leveled according to their $\omega_i/\sigma_i$ and the first ones chosen as "background".

## 4. Hidden Markov Model (HMM)

In an HMM, there are a finite number of states and the HMM is always in one of those states. At each clock time, it enters a new state based on a transition probability distribution depending on the previous state. After a transition is made, an output symbol is generated based on a probability distribution, depending on the current state. In the formal definition of HMM, the hidden states are denoted Q=$\{q_1, q_2, q_3 \ldots\ldots q_n\}$ where N is the number of states and the observation symbols are denoted V=$\{v_1 v_{,2}, v_3 \ldots\ldots v_n\}$ here M is the number of observation symbols. The state transition probability distribution between states is represented by a matrix A= {a(i,j)}, where a(i,j) = Pr$(q_j \text{ at } t+1 | q_i \text{ at } t)$, and the and the observation symbol probability distribution is represented by matrix B=$\{b_j(k)\}$, where $b_j(k)$ is the probability of generating Observation $v_k$ when the current state is $q_j$. In Initial state distribution denoted by Π=Pr($q_j$ at $t+1$) contains the probabilities of the model being in every hidden state I at time t=1 this is the start point for a HMM. A HMM is always represented by λ = (A, B, Π).

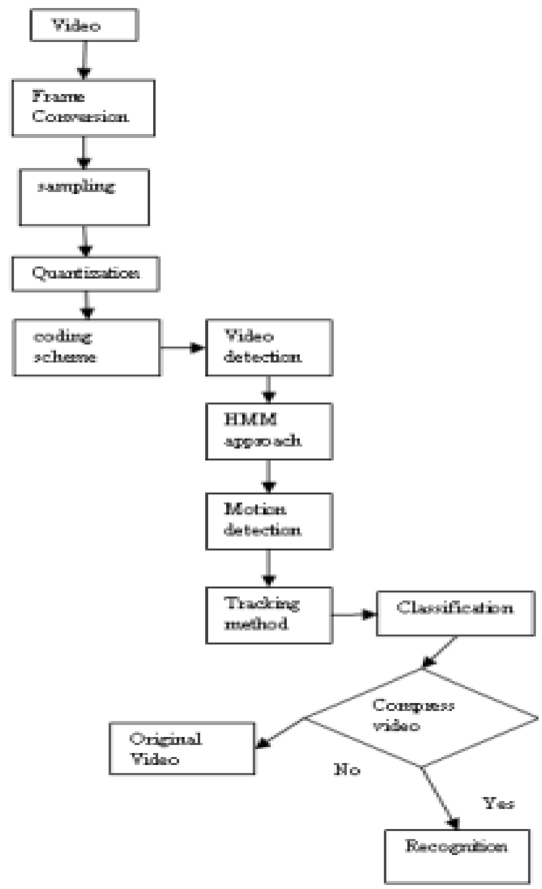


**Fig: 2.** System Architecture

## 5. HMM process

The HMM training step is essentially to create a set of hidden states *Q* and a state transition probability matrix *A* for each video topic category. The other three HMMs are trained in the same way. We first summarize all videos in the basketball game training set to extract chromaticity signatures of key frames. Then we cluster these signatures and take the medoids of resulting clusters as hidden states a video topic category. Here we use the CLARANS clustering algorithm. This algorithm is an improved kmedoids clustering algorithm based on randomized search, which is effective and efficient in spatial data mining with large data sets. The state transition probability matrix includes the probability of moving from one hidden state to another. There are at most $M^2$ (M is the number of states) transitions among the hidden states. Since each of clusters obtained from the above step corresponds to a hidden state and each key frame in these clusters corresponds to a set of frames, we calculate the probabilities based on the number of frames falling into these clusters and the number of frames temporally transiting between clusters.

### 5.1 DWT and PCA Algorithms

Discrete Wavelet Transform has become an important method for image compression. Discrete Wavelet based coding provides substantial improvement in picture quality at high compression ratios mainly due to better energy compaction property of wavelet transforms. Discrete Wavelet transform partitions a signal into a set of functions called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies.

### 5.2 Sub Band Coding

A signal is passed through a series of filters such as DWT. Procedure starts by passing this signal sequence through a half band digital low pass filter with impulse response h(n). Filtering of a signal is numerically equal to convolution of the tile signal with impulse response of the filter

### 5.3 PCA based Video Compression

The video representation and compression algorithms presented in this section are intended for use in two contexts that require the efficient encoding of video sequences. In the case of a distributed multimedia processing and retrieval sys-tem, the query-relevant video shots must be transmitted to the user's location .Within computational considerations; the proposed compression approach can represent the basis for encoding video data at very low bit rates. In both cases, the use of video segmentation, visual change estimation, and object tracking, enables the operation of the PCA-based video representation algorithm. A video segmentation algorithm can be applied to compressed or raw video data.

## 6. Experimental Results

In the experimental results show the video detection and video compression of the existing and the proposed algorithm. The comparison table and the comparison graph are shown below.

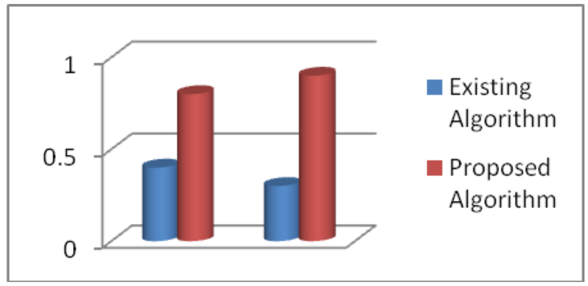


**Fig: 3.** Comparison Graph

**Table: 1.** Comparission Table

| Method | Multiplication | Addition |
|---|---|---|
| BAS 2008 | 2 | 18 |
| CB 2011 | 0 | 22 |
| Proposed Transform | 0 | 14 |

## 7. Conclusion

Emerging video standards such as HEVC provide for reconfigurable operation on-the-fly which makes the availability of an ensemble of fast algorithms and digital VLSI architectures a valuable asset for low-energy high-performance embedded systems. Among these minimal cost matrices, we separated the matrix that presents the best performance in terms of image quality of compressed images according the JPEG-like technique. However, the modified CB-2011 approximation and the proposed transform possess lower computational complexity and are faster than all other approximations under consideration. In terms of image compression, the proposed transform could outperform the modified CB-2011 algorithm. Hence the new proposed transform is the best approximation for the DCT in terms of computational complexity and speed among the approximate transform examined. Introduced implementations address both 1-D and 2-D approximate DCT**8.**

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