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ANALYSIS FOR VISUAL TRACKING VIA CONMF AND PCA

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ABSTRACT

A moving object or multiple object are located through the process of visual tracking over time using a camera. It is one of the most important components in numerous applications such as military, secure control, crime prevention systems, access control and biometric identification etc. of computer vision. In visual tracking, holistic and part-based representations are both popular choices to model target appearance. The robustness and efficiency of CONMF is validated and compared with Principal Component Analysis (PCA) that has been made in recent years.

In past decade there has been made progress for problem of recognizing faces under several unfavorable situations such as changing illumination in an uncontrolled environment. While tracking an object problems such as sparsity and smoothness appear. The tracker is endeavour on various videos, which contain object or targets that undergoing large variations in scale, pose or illumination. Experiments on real video ,including both indoor and outdoor scenes will demonstrate the effectiveness and robustness of the approach that are subjected to occlusion and alteration in addition to scale.

Keywords - Illumination, Non-negative matrix factorization, Object Tracking, Particle filter

I. INTRODUCTION

Today we are all connected worldwide so it is necessary to maintain information which is mainly used for security purpose. While visualizing any object there are variation due to change in illumination and change in pose. There is ample of research work in past decade for Object detection. [1]

The high powered computers, the availability of high quality and inexpensive video cameras and the increasing need for automated video analysis has generated a great deal of interest in object tracking algorithms which are used for many application such as vehicle tracking, surveillance etc. An object to be tracked is selected in the first frame of video and with the mechanism of object detection; the object is tracked in all frames of video which is an important and challenging job [2]

Therefore, the use of object tracking is applicable in the following tasks of:

- Motion-based recognition, that is, human identification based on gait, automatic object detection, etc;
- Automated surveillance, that is, monitoring a scene to detect suspicious activities or unlikely events
- Video indexing, that is, automatic annotation and retrieval of the videos in multimedia databases

- Human-computer interaction, that is, gesture recognition, eye gaze tracking for data input to computers, etc[3,4]

Tracking objects can be complex due to:

- Loss of information
- Noise in images
- Partial and full object occlusions
- Complex object shapes
- Scene illumination changes

1.1. Motivation

It is observed practically that it is really a challenging task in tracking a object from the video when there are environmental changes. The total amount of data in video which has to be sampled is time consuming process. From the literature survey it is found that there are many methods which work efficiently in both indoor and outdoor tracking system for variation in illumination.

1.2. Aim and Objective

The main aim is to have robust tracking of an object in varying or uncontrolled environment or illumination. Even though current recognition system has reached satisfactory level for many applications in a controlled environment; however due to uncontrolled environment such as change in illumination remains a largely unsolved problem . Due to change in illumination which causes vivid changes in object / face recognition system needs to be managed for different applications. It is a very challenging job to model an object continuously, since it undergoes variation due to change in illumination.

Organization of Paper

- 2 - Literature survey.
- 3 - Introduction to NMF and Particle filter.
- 4 - Online constrained NMF , used for on the online learning algorithm.
- 5- Experimental validation.
- 6 – Comparison of tracking using PCA and NMF
- 7- Conclusion and Future Scope

II. LITERATURE SURVEY

Tracking objects in video sequences of surveillance camera is nowadays a demanding application. Tracking objects is much more challenging in video sequences to improve recognition and tracking performances.

2.1 Types of Object Tracking

There are many existing methods of object tracking but all has some drawbacks.

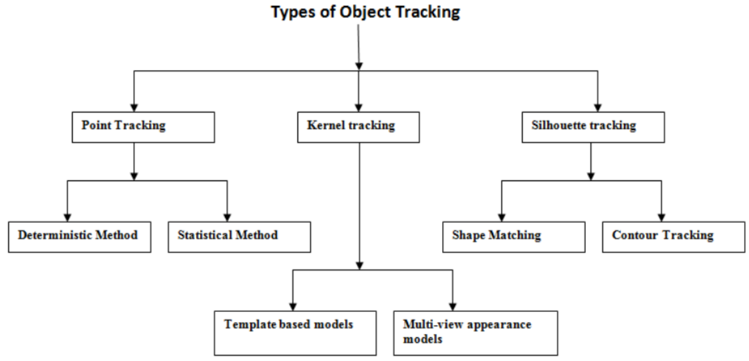

Fig 1. Types of object tracking

Object tracking can be classified as

- Point tracking
- Kernel based tracking
- Silhouette based tracking

To overcome problem related to visual tracking there are tracking methods which is based on non-negative matrix factorization (NMF), novel visual tracker Constrained Online Non-negative Matrix Factorization (CONMF) that achieves robustness to challenging appearance variations and non-trivial deformations while runs in real time.

III. INTRODUCTION TO NMF and PARTICLE FLITER

3.1 Object Tracking

Object tracker is mainly used to generate an outline of an object which has to be located in every frame of the video. Tracking is mainly used to locate a moving object in a video which is captured using a camera. The tasks of tracking an object and establishing a communication between the object instances across frames can either be performed separately or jointly. The detected object is tracked by iteratively updating object location and information obtained from previous frames. There is a huge amount of data which has to be decomposed.

Matrix decomposition is a fundamental part in algebra with has both scientific and engineering significance. For example, a large data matrix can be approximately factorized into several low-rank matrices. Two popular factorization methods extensively used for data analysis are Singular Value Decomposition (SVD) [18] and Principle Component Analysis (PCA)[17] . Many real-world data are nonnegative and the corresponding hidden components convey physical meanings only when the nonnegative condition holds. The factorizing matrices in SVD or PCA can have negative entries, which makes it hard or impossible to obtain physical interpretations from the factorizing results[14,15].

The non-negativity constraints make the representation of images purely additive, allowing no subtractions, in contrast to many other linear representations such as principal component analysis (PCA). Basically PCA are Eigen faces. Eigen face has an advantage of good image representation but has poor discriminatory ability. PCA methods differ from NMF as the later is a part based method of objects including faces.

Nonnegative Matrix Factorization (NMF) [7] imposes the nonnegative constraint on some of the factorizing matrices. When all involved matrices are constrained to be nonnegative, NMF allows only additive but not subtractive combinations during the factorization. Such nature can result in parts-based representation of the data, which can discover the hidden components that have specific structures and physical meanings.

Originally, the NMF approximation is factorized into two nonnegative matrices based on either Euclidean distance or I-divergence. Many numerical algorithms have been developed to optimize NMF objectives. NMF has found a variety of applications in, for example, image processing, text mining, sound or music analysis, bioinformatics [8], etc., among which NMF is mainly used for analyzing multivariate data, i.e. working on features. Recently, NMF has been extended to handle the graph input or similarity matrix between data points, i.e. grouping samples [18].

Even though current recognition system has reached satisfactory level for many applications in a controlled environment; however due to uncontrolled environment such as change in illumination remains a largely unsolved problem [3]. Due to change in illumination which causes vivid changes in face recognition system needs to be managed for different applications. It is a very challenging job to model an object continuously, since it undergoes variation due to change in illumination. To solve this issue part based method is widely used for object detection for variation in the environments. Particle filter is a method based on Bayesian interface filter which is mainly a low dimensional subspace database of an object.

For representing the image Non-negative matrix factorization (NMF) method is used. If a non-negative matrix is denoted by Y, the approximate value of matrix Y by NMF is Y ≈ UV where U and V are non-negative factors of Y. The non-negativity constraints make the representation of images are purely additive. There is no subtraction required as compare with linear methods which are Principal Component Analysis (PCA) and Vector Quantization (VQ) [5]. NMF method is further classified as Local NMF where there spatial locality is added to the standard NMF. This method is called as Topology Preserving NMF. To control sparseness of final matrix Sparse NMF was introduced [6,7]. Thus range of standard NMF is more successful when occlusion is present in face image.

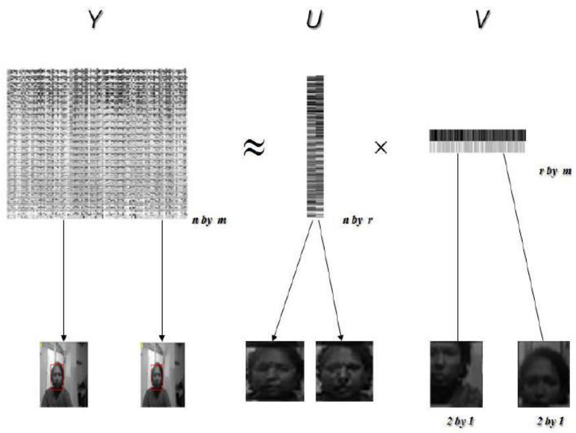

Fig 2. Y≈ UV

NMF is a used for non-negative database. Matrix containing non negative values is made of U and V, where U ≥ 0 and V ≥ 0 where Y≈UV, or

r

$Y_{iu} \approx (UV)_{iu} \approx \sum U_{ia} V_{au}$ ……………………………………(1)

The factorization value of rank r is selected such that (n+m) r < nm, and the product UV is assumed as a compressed form of the data in Y. Matrix factors U and V are all positive values in NMF. So all the data is positive. The actual implementation of the NMF algorithm consists of the update rules for U and V given in equation 2. It can be shown that iteration values of the object which is non-negative.

$$F \approx \sum_{i=1}^{n} \sum_{\mu=1}^{m} [Y_{i\mu} \log(UV)_{i\mu} - (UV)_{i\mu}] \quad \text{………………(2)}$$

The objective function in above equation is related the images in Y from the basis U and encoding V [8,9,10].

3.2 Classification of NMF

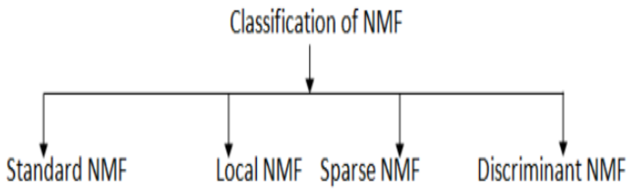

Fig 3. Classification of NMF

3.2.1 Standard NMF

The standard NMF enforces the non-negativity constraints on matrices W and H, thus a data vector are approximated by a non-negative basis vectors. Linearly decomposes the data.

3.2.2 Local NMF

The values which are retained has highest information present in it and which is retained [11].

3.2.3 Sparse NMF

It is mainly used to disclose Local Sparse features in database matrix Y.

3.2.4 Discriminant NMF (DNMF)

Originality of standard NMF algorithm is maintained DNMF keeps the original constraints of the NMF algorithm; it also improves accuracy of discriminant NMF[12,13].

IV. CONSTRAINED ONLINE NON NEGATIVE MATRIX FACTORIZATION (CONMF)

For visual tracking the traditional offline NMF learning algorithm is not applicable. In offline tracking the updated U and V values are stored and then compared with the new frame. It is difficult to handle the sparsity and smoothness, which are very important parameter for tracking. With new advancement U and V can be updated in real time. Analysis of documents and background modeling there are algorithm available. [19]. By using CONMF we can update the basis U with the arrival of new frame.

4.1 Adding Sparseness Constraints to NMF

Sparse coding is referred to represent a scheme only a few units as compared to a large data are effectively used to represent typical data vectors. In result, this implies that values taken are close to zero while few values are non-zero. The concept and sparseness measure is mapped from R^n to R which quantifies how much energy of a vector is packed into only a few components[20].

V. EXPERIMENTS RESULTS

5.1 Online Tracker

- **Observations and Tracking Results by Visual Analysis**

In this subsection, we show some tracking results of our Constrained Online Non Negative Matrix Factorization (CONMF) tracker and the comparison results with other trackers will be illustrated in the future work.

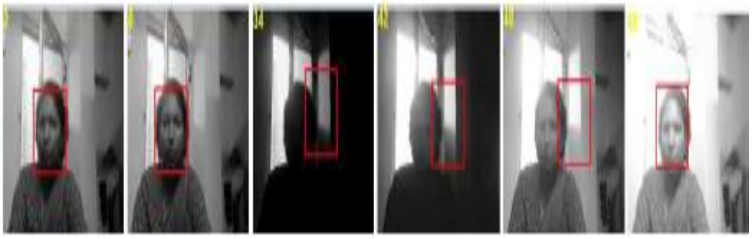

Fig 11. Tracking results of the NMF-Tracker with variation in illumination surrounding the lady

The results on sequence illustrated in Figure 11where there is variation in illumination of the target changes frequently and our tracker can adaptively update the model for these variations. There is a variation in illumination in the surrounding of the lady still the lady is being tracked.

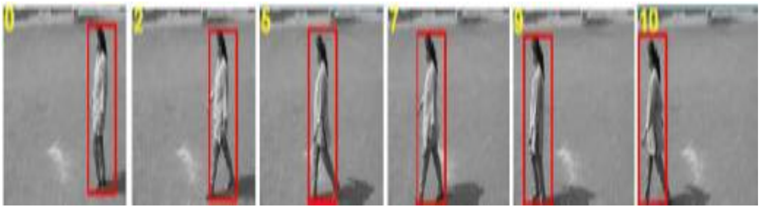

Fig 12. Tracking results of the NMF-Tracker on a girl

Figure 12 illustrates the results on a girl. The pose of the girl changes often and the CONMF can learn these poses into the appearance model. The scale of the target changes which is detected accurately by NMF tracker

Fig 13. Tracking results of the NMF-Tracker on a overlapping image

Figure 13 changes dramatically and the scale is also with large variations. Using the particle filter tracking technique, the target is followed throughout the sequence. The tracker can also track for an overlapping image properly.

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5.2 Observations and Tracking Results by Quantitative Analysis

Table 2. Quantitative Analysis Table

Tracking Percentage	Video 1 Variation in illumination surrounding the lady	Video 2 A girl
90 Percent	15	17
80 Percent	32	30
50 Percent	41	39

Quantitative Analysis basically compares the ground truth of the total object to be tracked. Once the frame of tracking is decided then by using NMF tracker with the change in the frame position. In the video of Variation in illumination surrounding the lady the frame moves around the object but still up to 10 percent it is tracked indicating that even with the variation in illumination the tracking is done. In the video of A girl the girl moves from left to right with change in pose and position still the upto 10 percent it is being tracked.

VI. COMPARISON OF TRACKING USING PCA AND NMF

Some tracking results are shown where there are dramatically changes and the scale is also with large variations. The tracking results of the NMF tracker is shown in RED where as PCA tracker is shown in Green

Fig 14. Tracking results of the NMF-Tracker and PCA tracker on a boy playing with ball

Fig 15. Tracking results of the NMF-Tracker and PCA tracker on a Girl moving from Left to Right.

They measure the performance of their system under several different conditions including: indoor or outdoor, different weather conditions and different cameras/view-points. Results on background subtraction and tracking evaluation are reported. The correspondence between ground truth and detected objects by minimizing distance between the centroids of ground truth and detected objects. They compute a set of performance metrics including false positive track rate, false negative track rate, average position error, average area error, object detection lag, etc. Observation were taken on different videos to compare between PCA and NMF. The ground truth information is represented in terms of the bounding box of object for each frame. Similarly, the results of tracking systems are in terms of the tracked object's bounding box. At the time of evaluation, we tried on different videos to robustly test if the overlap between ground truth and system's results occurs. The simplest form of overlap is testing to see if the system result's centroid lies inside the ground truth object's bounding box. Frame-based metrics are used to measure the performance of surveillance system on individual frames of a video sequence. Each frame is individually tested to see if the number of objects as well as their sizes and locations match the corresponding ground truth data for that particular frame. The results from individual frame statistics are then averaged over the whole sequence. This represents a bottom-up approach. Finally, based on a particular association, success and error rates are computed and accumulated for all the objects.

VII. CONCLUSION AND FUTURE SCOPE

Instead of traditional offline learning, online algorithm, CONMF represents the object on nonnegative basis. The tracker is very efficient even when we take into consideration the sparseness and smoothness constraints.From the result it is observed that we can use Non negative matrix factorization (NMF) as a method for analyzing any video for object tracking. It is used for application such as dimension reduction as well as for video extraction. Using NMF tracker which is one of the best methods to detect an object in an environment which is always subjected to change. In this paper, we present an experimental output of object tracking using CONMF and comparing it with PCA tracker. By using sparse NMF, even with variation in illumination up to 90 percent still we were able to track the object.

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