

MULTI-TARGET TRACKING IN NON-OVERLAPPING SURVEILLANCE CAMERAS USING PREDEFINED REFERENCE SET

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ABSTRACT

In this paper, we consider multi-object target tracking using video reference datasets. Our objective is detection of the target using a novel adaboost and Gentle Boost method in order to track the subjects from reference data sets. Multi-target tracking is still challenging topic which is used to find the same object across different camera views and also used to find the location and sizes of different object at different places. Furthermore extensive performance analysis of the three main parts demonstrates usefulness of multi object tracking. We carried out experiment to analyze discriminative power of nine features (HSV, LBP, HOG extracted on body, torso and legs) used in the appearance model for multicam dataset. For each features the RMSE and PSNR obtained.

INDEX TERMS: AdaBoost, Gentle Boost, HOG, LBP, HSV Color histogram

INTRODUCTION

Nowadays, the demand of tracking system is increases due to maintaining security purpose as well as monitoring. Video surveillance system is also recent concept which is used in tracking. Sometime it is not possible to cover complete area of interest. Such a situation we need to track many objects using multi-target tracking system. In this paper our main aim is to track single target across different camera views, which is very tough task because the appearance of same target in different cameras is very difficult or it is rare. The idea of multi-target tracking which is done by comparing both outputs that are output obtained from different cameras is compared with multi-cam dataset output. Using techniques for human detection, multi-target tracking system can play important role to capture location of people at public areas such as stores and travel sites and then produce congestion analysis to assist in the management of the people [3]. In such a way tracking system can monitor express ways and junctions of the road network. In some cases it is necessary to analyse the behaviour of people and vehicles also and check whether these behaviours are normal or abnormal. For example multi-target tracking system set in parking lots and supermarkets could track abnormal behaviour of theft which is useful to identify any criminals quickly and then contact the police immediately [1].

RELATED WORK

1] ADABOOST METHOD

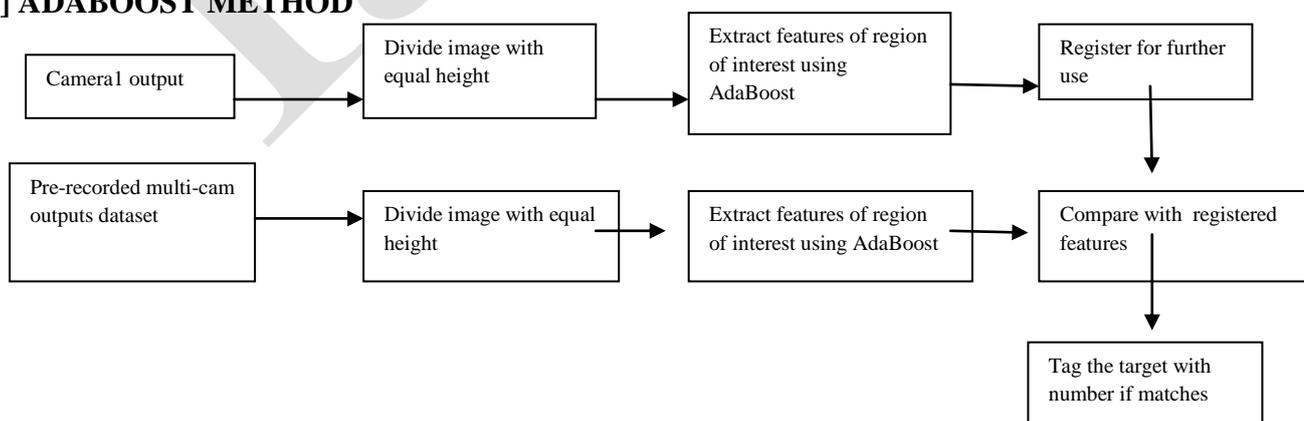


Fig.1 Block diagram using AdaBoost method

1] ADABOOST

Basically, AdaBoost is stands for ‘Adaptive Boosting’. It is good for things with soft edges like facial recognition. It is used for producing a strong classifier. The strong classifier is defined as threshold linear combination of weak classifier outputs. Adaboost is very simple to implement and it does feature selection resulting in relatively simple classifier. It is sensitive to noisy data and outliers. Adaboost improves classification accuracy and it can be used with many different classifiers [17]. It is called adaptive boosting because it uses multiple iterations to generate a single composite strong learner. Adaboost is an ensemble learning algorithm that can be used for classification. It contains many weak classifiers and minimizes overall error. ABOVE figure 1 shows the schematic block diagram of adaboost method.

2] GENTLE BOOST METHOD

In this project the Gentle Boost method is used as a comparative method for adaboost method. We are going to compare the result between these two methods. Basically Gentle Boost is a weak learner whereas adaboost is a strong learner. It is good for things with harder and more symmetrical features and edges like vehicles. Gentle boost is less sensitive as compared to Adaboost. It produce weak classifier. Figure2 shows the block diagram of Gentle Boost method.

▪ CAMERA 1 OUTPUT:

In this block here first track moving objects and take it as a camera 1 output. After this take its features and store it as a reference set.

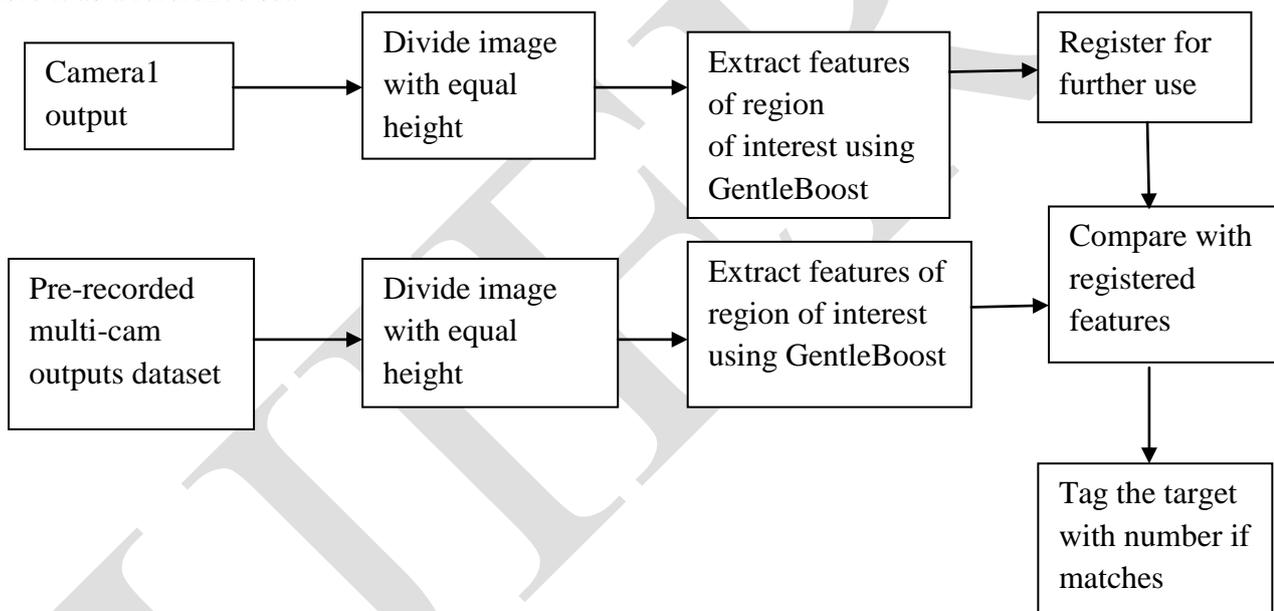


Fig.2 Block diagram using Gentle Boost method

▪ DIVIDE IMAGE WITH EQUAL HEIGHT

After tracking object the whole body is dividing into two parts that are torso and legs. Torso is upper part of detection and legs are lower part of detection. Here whole body is divided into upper and lower part with equal height [2].

▪ REGISTER FOR FURTHER USE:

All above obtained information is stored as a reference set which is used for comparison purpose. This is our register set which is use to comparison with different cameras outputs dataset.

▪ COMPARE WITH REGISTER FEATURES:

In this block compare pre-recorded multiple cameras outputs dataset with the registered features to identify appearance of similar object. For comparison purpose here uses two methods that are as follows [19].

FEATURE EXTRACTION:

The features obtained from first block the features are extracted with using AdaBoost feature extraction method. AdaBoost is stands for 'Adaptive Boosting'. AdaBoost is the method of feature extraction. The role of AdaBoost algorithm is used for selection purpose. It can be used in conjunction with many other types of learning algorithms to improve performance of the system [17]. It is referred as the best classifier. Here we take three kinds of appearance features that are HSV color histograms, Local binary pattern (LBP) and histogram of gradient (HOG). These appearance features are used to capture color, texture, and shape information of object. Here we are partitioning body image into torso and legs for each detection with equal height. For this total nine features are extracted that are Torso HSV, Torso LBP, Torso HOG, Body HSV, Body LBP, Body HOG, Legs HSV, Legs LBP, Legs HOG. For distance measurement the Bhattacharya coefficient is used [2]. To measure the similarity of two discrete or continuous probability distributions the Bhattacharya distance is proposed.

RESULTS:

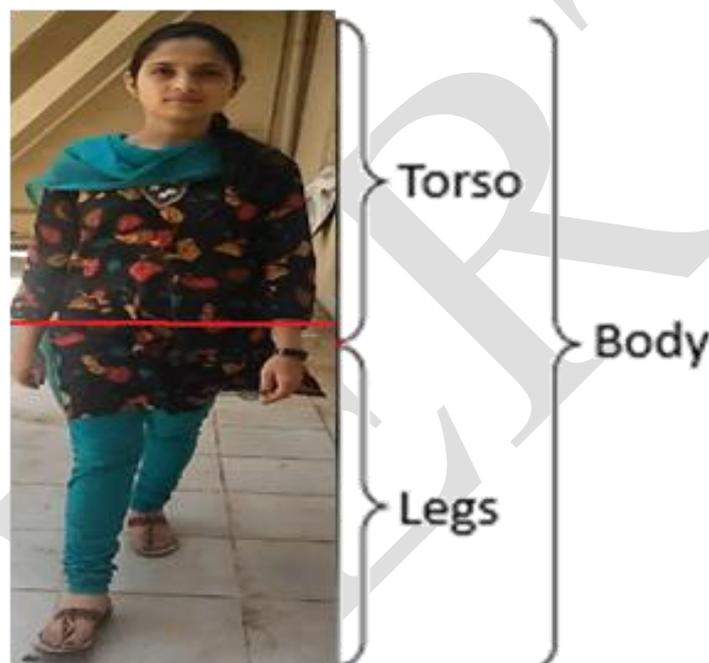


Fig.3 Image division

- 1) Here the upper body part is called as 'Torso' and lower body part is called as 'Legs' which is shown in figure 3 .
- 2) In this method we take 0 to 255 pixels for upper body part (torso) as well as 0 to 255 pixels for lower body part (legs).
- 3) In image division, the division of pixels is also done. Therefore the upper body is used for upper detection and similarly lower body is used for lower detection.

FEATURE EXTRACTION RESULTS:

In this paper three widely used features are extracted that are a follows

- 1) Histogram of gradient (HOG)
- 2) HSV Colour histogram
- 3) Linear binary pattern (LBP)

Here we take one image and then we extract these three features of the camera image which is shown into figure 3. And their corresponding extracted features respectively.

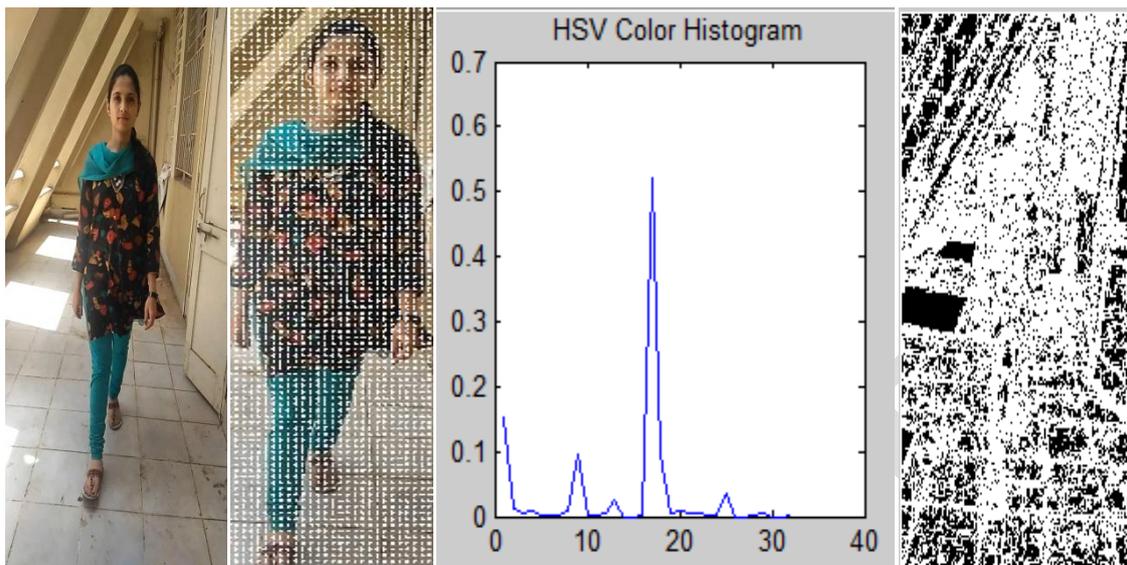


Fig.3 Input image Features

Fig.3a. HOG

Fig.3b. HSV Color histogram Features

Fig.3c LBP Features

ADABOOST RESULTS:



Fig.5 Camera input

Fig.5a Reference set

Fig.5b. Test set

GENTLEBOOST RESULTS



Fig.6 Camera input

Fig.6a. Reference set

Fig.6b. Test set

1] PSNR:

We calculate the Pick signal to noise ratio (PSNR) for each target detection. Here we take three multicam dataset and determine the PSNR value for each dataset which is given in table

Table1. PSNR comparison for AdaBoost and Gentle Boost

Sr. No.	Video	AdaBoost	Gentle Boost
1.	Multicam 1	15.63	32.73
2.	Multicam 2	31.55	41.43
3.	Multicam 3	35.49	49.45

2] RMSE:

Similarly, here we find out the Root mean squared error (RMSE) comparison between AdaBoost and Gentle Boost for three multicam dataset which is given into table2. Reference set is used as the dataset to test AdaBoost and Gentle Boost algorithm. Root Mean Squared Error (RMSE) is used for performance evaluation. It measures the differences between reference set and the prediction result generated by the adaboost and gentle boost appearance model.

The final result is average of three fold cross validation. The comparisons of these algorithms on multicam and video datasets are shown in table 2. It was found that the Adaboost gives the smallest error on both datasets. Also Adaboost algorithm takes less computational time into account. Hence we conclude Adaboost as the feature learning algorithms for the appearance model [2].

Table2. RMSE comparison between AdaBoost and Gentle Boost

Video	AdaBoost	Gentle Boost
Multicam 1	0.151	0.227
Multicam 2	0.242	0.318
Multicam 3	0.273	0.385

3] FINAL ANALYSIS:

In table 3 we evaluate the performance of our reference set based appearance model with two reference subjects. Each time subset of original reference set is randomly selected as new reference set. It is observed that as the size of the reference set reduces the match rate or success ratio degrades.

Table3. Comparison between AdaBoost and Gentle Boost

Sr. No	Video	Viewing Approach	AdaBoost	Gentle Boost
1.	Multicam 1 (Single person video)	Front view	99%	80%
2.	Multicam 2 (Multiple person video)	Front view	99%	60%
3.	Multicam 3 (Multiple person video)	Back view	99%	1%

CALCULATION:

Total no. of frames = 100

Processed frames = 100

Correctly identifying person in all frames

1] Multicam 1 = 99% for AdaBoost

Multicam 1 = 80% for Gentle Boost

Therefore, success ratio = $99/100 * 100$
= 99%

REASONS OBSERVED FOR ERROR IN PREDICTION

- 1) Each frame is processed separately for each video.
- 2) Some of the frames are intensity affected and hence compromising in features extracted.
- 3) The deviation in feature qualities again affects classifier model.
- 4) AdaBoost significantly out performs in terms of success ratio compare to Gentle Boost. As Gentle Boost constitutes weak learner whereas AdaBoost is strong learner.

FEATURE RESULT AND DISCRIMINALITY ANALYSIS

We carried out experiment to analyze discriminative power of nine features (HSV, LBP, HOG extracted on body, torso and legs) used in the appearance model for multicam dataset. For each features the RMSE obtained and when that feature is removed from appearance model is considered as Discriminality measurement. The experimental results for multicam and video datasets are shown in fig.5 and 6 respectively.

For both datasets (reference set and test dataset), it is clear that HSV are more discriminative then HOG and LBP and torso HSV is the most discriminative one. Also legs carry less information for the appearance model compare to torso, probably because two participants are wearing jeans with similar color. Moreover, the RMSE obtained by using all the nine features using AdaBoost and Gentle Boost for multicam1 is 0.151 and 0.227 video datasets respectively.

CONCLUSION

In this paper we proposed AdaBoost and Gentle Boost methods with reference set based appearance model for multi-target tracking in camera with non-overlapping FOVs. It was found that AdaBoost method significantly performs in terms of RMSE, all nine extracted features and success ratio compared to Gentle Boost method.

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