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# ENFORCED INDIVIDUALIZATION OF HUMAN CLUSTER IN TRACKING BY MIXTURE OF GAUSSIAN

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***Abstract- Vision based surveillance system plays an important role in security field. Automatic tracking of objects such as human and vehicle is vital in such a system. In human tracking, it frequently happens that moving people get merged and demerged. When merging occurs, the tracking system should know what and how many humans are in the cluster. When cluster gets demerged into individuals, the tracking system should be able to differentiate among them to cope with correct human following. It will be useful in tracking if we can enforce the human cluster, where multiple humans adhere, to be broken into individual human. In this paper, we propose a novel method for individualization of human cluster in tracking. The method consists of three steps. They are edge finding and edge projection, mixture of Gaussian fitting, and cutting point decision. We applied the method to various scenarios of human cluster and obtained good results.***

***Keywords* –** Gaussian, human tracking, cluster tracking, tracking

## I. INTRODUCTION

Multiple target tracking has many application fields such as defense security, civilian access control, traffic monitoring, etc. Targets may be human, vehicle, missiles, or other moving things. In this work, we are interested in human tracking. When tracking multiple humans, it frequently happens that moving people get merged and demerged in various ways. Merging may be horizontal where merged humans in the cluster do not overlap much and they are aligned horizontally. Merging could be vertical where merged humans do not overlap much and they are aligned vertically. Merging may be in between where humans are aligned diagonally with varying degrees of overlap. Lastly merging may be in the form of partial or complete occlusion. In this work, we consider only horizontal merging. When merging occurs, the tracking system should know what and how many humans are in the cluster. When cluster gets demerged into individuals, the tracking system should be able to differentiate among them to cope with correct human following. It will be useful in tracking if we can enforce the human cluster, where multiple humans adhere, to be broken into individual human. There are some references [1-4] that deal with split and merge of humans in tracking. However, “split” concept was used to mean the breakage of a single object into several fragments. In this paper, we propose a novel method for individualization of human cluster in tracking. The method consists of three steps. They are edge finding and edge projection, mixture of Gaussian (MoG) fitting, and cutting point decision.

The paper is organized as follows. In section 2, related works are discussed. Section 3 presents the proposed method. Results are depicted in section 4 and section 5 concludes the paper.

## II. RELATED WORKS

Sharma [1] proposed a new blob representation where central points are used in addition to centroids. When tracking blobs, blob’s location is usually represented as its centroid. When blobs do not interact, centroids play a sufficient role in applying tracking filters such as Kalman filter. However when blobs merge and demerge, the displacement of centroids in consecutive frames may exceed an expected level and this may cause tracking filter malfunctioning. Sharma[1] proposed to use central points that are local maxima of distance transform values of blob and are a lot less sensitive to merging and demerging. He applied the technique to several well-known database of tracking video and showed the superiority of the method. Though his work outperforms other related works, there was no try to enforce the individualization of human cluster (referred to as merged blob in [1]).

Kumar et al. [2] proposed a cooperative multiple target tracking method consisting of two steps. They are feature extraction and matching based on dynamic programming (DP), and cooperative tracking based on Kalman filter. For features, they use centroid, angularly equidistant control points, and color histogram. They define three match measures based on shape and color. These measures are used to perform matching that can handle split and merge using DP. The DP they used was similar to that for string matching. They adopt to use two Kalman filters, one for tracking position and the other for tracking shape, and these two filters work cooperatively. They showed that their method can handle severe splits and merges while maintaining real time performance. However their method will fail when the motion of object changes greatly before and after merging.

Genovesio et al. [3] proposed a technique where they form a virtual blob made up of actual blobs under splits and merges. They assume one-to-one mapping of blobs between consecutive frames to use joint probabilistic data association

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filter (JPDAF). All possible feasible mappings between virtual blobs and target tracks were enumerated and evaluated to find the mapping that maximizes joint probability. As the number of targets increases, computation complexity increases exponentially. To improve on computational load, Garcia et al. [4] suggested fuzzy logic rule based system with domain-specific heuristics in the presence of splits and merges.

All the related works mentioned above dealt with splits and merges. However the concept of split used above is close to fragmentation where a single object is broken into more than one blob due to misdetection, similarity of object and background colors, or partial occlusion of foreground object by background object.

In this paper, we deal with split (we termed it as individualization or cutting) that breaks human cluster into individual human.

## III.THE PROPOSED METHOD

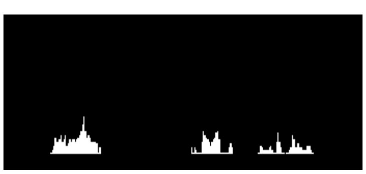
The proposed method consists of three steps. They are edge finding and projection, MoG fitting, and cutting point decision. We describe each step in turn.

### A. Edge finding and projection

In this step we apply sobel edge operator to a blob and get edge pixels having strength greater than some predefined threshold. We apply edge operator only to the upper quarter of the blob since it contains only head and shoulder parts, and gives more clear valleys and peaks after projection. Edge pixels are projected vertically to produce the histogram where horizontal and vertical axes correspond to relative horizontal location in the blob and edge pixel count respectively. Fig. 1 shows the example of step 1. Fig. 1(a) shows three detected blobs, 1(b) edges detected, and 1(c) the projection.

(a)

(b)



(c)

Fig. 1 Example of vertical edge projection (a) Blob Detection (b) Edges (c) Vertical

### B. MoG fitting

We use MoG proposed by [5,6] for fitting. This method was originally proposed for background modeling. We apply the model to iteratively fit a given projection histogram. We duplicate MoG model here for convenience following the notation used in [6].

Let $\theta_k = \{\mu_k, \sigma_k\}$ be the density parameter set of K[th] Gaussian distribution and $\Phi = \{\omega_1 \cdots \omega_k, \theta_1 \cdots \theta_k\}$ be the total parameter set. Here $\mu, \sigma$ and $\omega$ represent mean, standard deviation and priori weight. Then, for MoG, the posteriori probability P (k|X, $\Phi$) of sample X is given by (1).

$$P(k \mid X, \Phi) = \frac{p(k)\, f_{X|k}(X|k, \theta_k)}{f_X(X|\Phi)} \tag{1}$$

Where, sum of Gaussian mixture,

$$f_X(X \mid \Phi) = \sum_{k=1}^{K} P(k)\, f_{X|k}(X \mid k, \theta_k) \tag{2}$$

And p(k) is a priori probability of k[th] Gaussian given by

$$f_{X|k}(X \mid k, \theta_k) = \frac{1}{\sqrt{2\pi}\,\sigma_k} e^{-\frac{(X-\mu_k)^2}{2\sigma_k^2}} \tag{3}$$

Model update is done by (4) through (7).

$$\hat{\mu}_{k,t} = (1-\rho_{k,t})\,\mu_{k,t} + \rho_{k,t} X_t \tag{4}$$

$$\hat{\sigma}_{k,t}^2 = (1-\rho_{k,t})\sigma_{k,t}^2 + \rho_{k,t}((X_t - \hat{\mu}_{k,t}) \circ (X_t - \hat{\mu}_{k,t})) \tag{5}$$

$$\rho_{k,t} = \frac{\alpha_t P(k|X_t, \Phi)}{\hat{\omega}_{k,t}} \tag{6}$$

$$\hat{\omega}_{k,t} = (1-\alpha_t)\,\omega_{k,t} + \alpha_t P(k \mid X_t, \Phi) \tag{7}$$

, where $\alpha_t$ is a learning ratio for weight at time t. To make use of MoG model, we feed values obtained from projection histogram. Suppose the width of blob of interest is W. Then the histogram index goes from 1 to W and each index bin has a projected edge pixel count. We denote by Hist(i) the edge pixel count at index i with $1 \le i \le W$. For example, if W=5, Hist(1)=3, Hist(2)=1, Hist(3)=4, Hist(4)=2, and Hist(5)=6, then the list of values fed into MoG model will be :

1 1 1 2 3 3 3 3 4 4 5 5 5 5 5 5

After all values are sequentially fed in, we will have final model parameter set , $\Phi = \{\omega_1 \cdots \omega_k, \theta_1 \cdots \theta_k\}$ where $\theta_k = \{\mu_k, \sigma_k\}$

.Here $\mu, \sigma$ and $\omega$ represent mean, standard deviation and priori weight.

*C. Cutting point decision*

The cutting point decision is done as in Algorithm I.

**ALGORITHM I**: **CUTTING POINT DECISION ALGORITHM**

Let $\mu_i, \sigma_i, \omega_i$ and $\mu_j, \sigma_j, \omega_j$ be two adjacent distributions with $\mu_j > \mu_i$

If $\mu_j - \mu_i$ < threshold

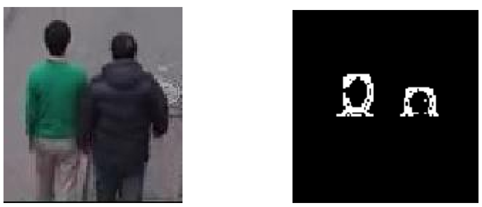
then collapse the two distributions with means $\mu_j$ and $\mu_i$

else cutting point is calculated as

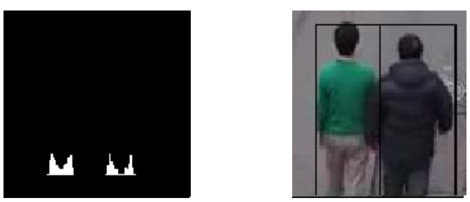
$$\mu_1 + (\mu_2 - \mu_1)(\frac{\sigma_1}{\sigma_1 + \sigma_2})$$

## IV. EXPERIMENTAL RESULTS

The proposed method was tested on different cases of two and three person merging in a video. Below are the figures showing the merging cases along with the results.



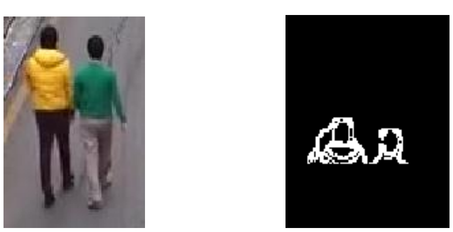
(a) (b)



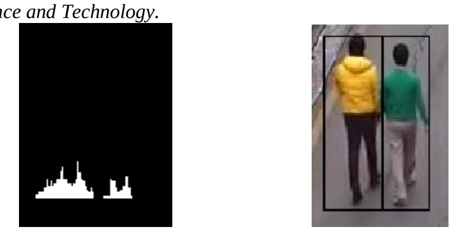
(c) (d)

Fig. 2 Two person merging case (a) Blob Detection (b) Edges (c) Vertical Projection (d) Resulting Image

Figure 2 shows a two person merging case. Figure 2(a) shows the image of the detected blob, 2(b) the edge detection of that blob, 2(c) the vertical projection of edges, and 2(d) the resultant image after cutting. As can be shown, cutting is successfully done in 2(d).



(a) (b)



(c) (d)

Fig. 3 Two person merging case (a) Blob Detection (b) Edges (c) Vertical Projection (d) Resulting Image

Figure 3 shows another two person merging case where cutting into individual object is done accurately.

(a) (b)

(c) (d)

Fig. 4 Three person merging case (a) Blob Detection (b) Edges (c) Vertical Projection (d) Resulting Image

Figure 4 depicts a three person merging scenario. Figure 4(a) is a detected blob, 4(b) the edge detection, 4(c) the vertical projection of edges, and 4(d) the resultant image. As can be seen in Figure 4(d), the proposed method detected two clear valleys in between humans and successfully generated cutting points.

Figure 5 shows another three person merging scenario where successful results are also generated.

(a) (b)

(c) (d)

Fig. 5 Three person merging case (a) Blob Detection (b) Edges (c) Vertical Projection (d) Resulting Image

## V. CONCLUSION

Vision based surveillance system plays an important role in security field. Automatic tracking of objects such as human and vehicle is vital in such a system. In human tracking, it frequently happens that moving people get merged and demerged. It would be very useful if we can break human cluster into individual human. In this paper, we proposed MoG based approach where we extract edges, project them vertically to get projection histogram, feed histogram data into MoG to estimate parameters, and finally decide cutting points. We applied the method to various human clusters and get good results.

The proposed method works only for horizontally merged clusters. Though the method can tolerate some degree of diagonal merging, we need to improve the method to work on other types of merging and it is intended for future research.

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