Pedestrian Tracking based on 3D Head Point Detection

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Keywords: Pedestrian Tracking, Overhead Camera, Head Detection, 3d Position Estimation, Facial Image Capture.

Abstract: In this paper, we introduce a 3D pedestrian tracking method based on 3D head point detection in indoor environment, such as train stations, airports, shopping malls and hotel lobbies where the ground can be non-flat. We also show that our approach is effective and efficient in capturing close-up facial images using pan-tilt-zoom (PTZ) cameras. We use two horizontally displaced overhead cameras to track pedestrians by estimating the accurate 3D position of their heads. The 3D head point is then tracked using common assumptions on motion direction and velocity. Our method is able to track pedestrians in 3D space no matter if the pedestrian is walking on a planar or a non-planar surface. Moreover, we make no assumption about the pedestrians' heights, nor do we have to generate the full disparity map of the scene. The tracking system architecture allows for a real time capturing of high quality facial images by guiding PTZ cameras. The approach is tested using a publicly available visual surveillance simulation test bed.

1 INTRODUCTION

With the prevalence of video surveillance, face recognition and tracking is drawing more attention and is pursued more rigorously. Usually, a high resolution frontal view facial image is required by most face recognition systems. Accurate 3D tracking of a head is fundamental in capturing close-up facial images. Our camera system architecture consists of a stereo overhead camera set that helps a distributed set of PTZ cameras in effectively and efficiently capturing close-up facial images.

Most existing tracking method uses one side view camera, which cannot handle well occlusions between people. To resolve this problem, multiple side view cameras are used. Orwell et al. (1999) model the connected foreground blobs in multiple views using colour histograms and then the blobs are used to match and track objects. Khan and Shah (2009) use a planar homography constraint that combines foreground likelihood information from different views to resolve occlusions and determine regions on scene planes that are occupied by people. Similar to our approach, Eshel and Moses (2008) focus on tracking people's head. They derive homograghy matrices at different height to align frames from different views and detect 2D patches of a person using intensity correlation at various heights. The highest patch is regarded as the head patch. However, the thresholds of intensity correlation are set manually for each sequence and the method doesn't work on non-planar surface. To localize targets more accurately, more side view cameras are needed. This, in turn, increases the computation and data transmission.

Overhead cameras, which are usually deployed in indoor environment, have their own advantages. An overhead (perpendicular) view is less likely to be occluded compared with a side view where almost no person is viewed by him/herself. Bellotto et al. (2009) use only one overhead camera to localize a person, where the centroid of the foreground blob is taken as the ground position. The method is not accurate especially when people are close to the camera and walk around the boundaries of the field of view (FOV). Oosterhout et al. (2011) detect 3D head positions in highly crowded situations by matching a sphere crust template on the foreground regions of the depth map and then track those using Kalman filters. Boltes and Seyfried (2012) present to build the perspective height field from stereo images which are represented by a pyramid of ellipses. A person is then tracked using the centre of the second ellipse from the head downward.

In this paper, we use two identical horizontally displaced overhead cameras to estimate the 3D position of the pedestrian's head. For each extracted foreground blob a segment that passes through the

Zhang Z. and Cohen F..
Pedestrian Tracking based on 3D Head Point Detection.
DOI: 10.5220/0004232203820385
In *Proceedings of the International Conference on Computer Vision Theory and Applications* (VISAPP-2013), pages 382-385
ISBN: 978-989-8565-48-8

head top is estimated and the disparity of each point on the segment is computed. The 3D head point is determined as the centre of points with largest disparity. To track the pedestrians over time, the pedestrian velocity is used to estimate their next locations. Our approach has several advantages over what is out there: 1) there is no assumption made about people's heights to localize the 3D head point; 2) it does not constrained the walking platform to be flat or planar; 3) lower computation and data transmission load when compared to using several side view cameras; 4) no full disparity map of the scene is needed unlike other methods using stereo vision; 5) better scalability.

2 PEDESTRIAN LOCALIZATION

Our proposed approach is based on the following assumptions, which are the general cases in real world: a) people in the scene are upright; b) the head top is the highest part of a person; c) a human body is symmetrically distributed around an axis, the central vertical axis; d) this axis intersects a person at the ground point and highest point. We define the highest point as the 3D head point which is usually the centre of the head top from an overhead view.

2.1 Potential Head Top Segment Detection

A potential head top segment containing head top points is estimated only for each foreground blob in the left images. The blobs are extracted using background subtraction which is done using HSV rather than RGB colour space to remove the shadow.

Figure 1 shows the geometric relationship when an image of a person is taken by an overhead camera S. A person is modeled as a cylinder with the central vertical axis l. π is the plane perpendicularly intersecting l at the ground point G. If the ground is flat, π is the ground plane since the person is upright. Otherwise π is a hypothetical plane. The optical axis $\overleftrightarrow{OS}$ is vertical with O in plane π. The perspective projection of l lies on the line $\overleftrightarrow{OG}$. Thus with the assumption d), the highest head top point lies on $\overleftrightarrow{OG}$ as well. And the shadow area A, the projected area of the person on plane π, is divided into two halves by $\overleftrightarrow{OG}$. The point C as the centroid of A should be also on $\overleftrightarrow{OG}$ which is denoted as $\overleftrightarrow{OC}$ for later use. F is the furthest point defined as

$$F = \operatorname{argmax}_{F \in A, F \in \overleftrightarrow{OC}} |\overline{OF}| \qquad (1)$$

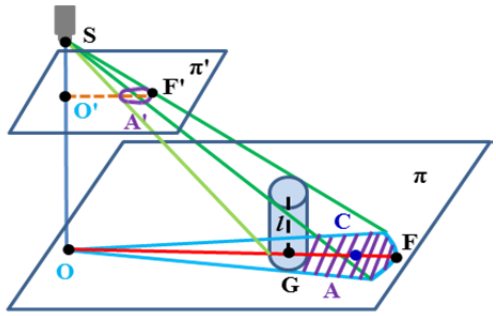


Figure 1: Determination of the potential head top segment.

From assumptions a) and b) we can safely argue that a part of projected head top points lies on the segment $\overline{CF}$ no matter if the walking platform is flat. Plane π' (in figure 1) is the image plane of camera S and A' is the image of A, i.e. foreground blob of a person. F' is the furthest point on the image plane, similarly to equation (1), defined as

$$F' = \operatorname{argmax}_{F' \in A', F' \in \overleftrightarrow{O'C'}} |\overline{O'F'}| \qquad (2)$$

where C' (not denoted in figure 1 because of the limited space) is the centroid of A' and O' the image center. So $\overline{C'F'}$ is the potential head top segment in the image plane, with head top pixels on it.

2.2 3D Head Position Estimation

The 3D head point is the highest point of a person. With the detected potential head top segment, locating the 3D head point reduces to finding the centre of points on the segment which are closest to the cameras and thus have the largest disparity.

To calculate the disparity of each point on the potential head top segment, its corresponding point needs to be established from the synchronized right image. For each pixel on the segment from left image, we compare the RGB values of an N*N region about the point (the template) with a series of the same size regions extracted from the right image (the samples). The centre of each sample, the candidate matching point, has the same row number as the pixel in the left image, since the left and right camera are aligned horizontally. The pixel on the segment is descripted as an N*N*3 vector $\boldsymbol{L}$, containing the RGB values of all pixels in the template, and the candidate pixel is described as the same size vector $\boldsymbol{R}$. The similarity of the two vectors is evaluated by the Euclidean Distance(ED) $d(\boldsymbol{L}, \boldsymbol{R})$ between them. A corresponding point of the point on the potential head top segment is established if

$$d1 < \gamma \cdot d2 \qquad (3)$$

where $d1$ is the closest distance, $d2$ the second-closest distance and γ the distance ratio (typically $\gamma = 0.8$). The disparity of the point on the segment is computed from the image coordinate difference of the two matching pixels.

To get more accurate 3D position, we estimate the sub-pixel disparity by considering the minimum ED that satisfies (3) and the two neighbouring ED values instead of just taking the point of the minimum ED as the matching point. We fit a parabola to the three values and analytically solve for the minimum to get the sub-pixel correction.

The centre of the pixels with the largest rounded disparity instead of only the pixel with largest disparity on the potential head top segment is determined as the head point. Thus both the disparity and the position of the head point have sub-pixel resolution, making the localization of the 3D head point more robust and accurate. With the head point in the image and its disparity (not rounded), the 3D head position can be computed by triangulation.

3 PEDESTRIAN TRACKING

Once the 3D positions of pedestrians, denoted as the 3D head points, are obtained in each frame, they are tracked by assuming constant moving direction and velocity within two consecutive frames. The position of a person is predicted at the next time interval and a search is implemented in a neighbourhood around the predicted point. The position of the person is then updated by the estimated 3D head point that is nearest to the predicted point. If no head point is found in the search area, the person's location is updated using the predicted one. The person is deleted if not found over certain extend period of time. Similarly, if an object is not associated with any object in the previous frame over some frame intervals, it is regarded as a new target.

4 EXPERIMENTS

We test our approach using a publicly available visual surveillance simulation test bed, ObjectVideo Virtual Video. Two virtual scenes of the train station concourse are created, one with flat ground and the other with a small bump, whose cross section is a trapezoid, added on the flat ground. Seven people walk in an area of about 180*160 inches, which is an average crowded scene: the blobs of people don't merge in the overhead view.

The ceiling is 348 inches high from the flat part of the ground. Two identical synchronized cameras are installed on the ceiling with perpendicular views. The baseline is 40 inches. The frame rate is 15 frames per second and the frame size is 640*480 pixels. A PTZ camera is installed on the wall in both scenes with the resolution 320*240 pixels and the height 160 inches. We let a group of people walk on the planar ground and then let the same group walk on the non-planar ground using the same paths.

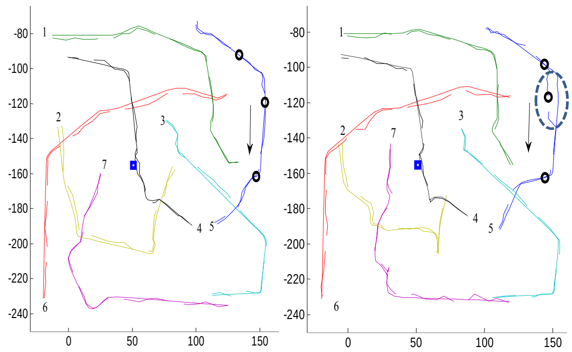
The images in figure 2 are captured by the left camera when people walk on the planar and non-planar ground, respectively. The foreground centroids and the detected head points are marked as in red and white. The detected head points are very close to the head top centres in both scenes. The dashed line square shows the bump area.

(a) Planar ground (b) Non-planar ground

Figure 2: The frames captured by the left camera with people walking on the planar and non-planar ground.

The estimated 3D tracks are projected to the X-Y plane and Z plane (height) separately. The X-Y plane tracking results are shown in figures 3, where the solid lines are the ground truth and the dashed lines the estimated trajectories. The square is the FOV centre. The number at the one end of each trajectory denotes its object ID. The trajectories are very close to the ground truth. Since the bump changes people's speeds, the tracks in the two scenes are a little different though the same paths are set.

The Z plane tracking results are not shown because of limit space. The errors of Z and X-Y plane values in the two scenes are tabulated in table 1. The 3D head position errors can result from the two reasons: a) the estimated potential head top segment is slightly off the head top centre due to pedestrians' movement which makes the foreground blob not perfectly symmetrical about the line from image centre to blob centre; b) robust corresponding points (in section 2.2) are not found on the head top part of the segment or are not established correctly. b) can cause relatively big error in both X-Y and Z plane yet rarely happens. The ellipse in figure 3(b) highlights the relatively big errors due to reason b). The main errors are caused by reason a) instead and are usually smaller than the head radius(see table 1).



(a) Planar ground (b) Non-planar ground

Figure 3: X-Y plane tracking results when people walking on the planar and non-planar ground.

Table 1: The errors of the estimated tracks with planar and non-planar ground (error unit: inch, and 1 inch=2.54 cm).

Object ID	Planar ground		Non-planar ground	
	X-Y errors	Z errors	X-Y errors	Z errors
1	1.35	1.13	1.44	1.14
2	1.87	1.48	1.47	1.43
3	1.07	1.24	0.94	1.21
4	1.70	1.70	1.64	1.46
5	1.29	1.03	2.43	2.06
6	1.88	1.02	1.90	1.53
7	1.04	1.24	1.49	1.20

With accurately estimated 3D head positions, the PTZ camera on the wall is guided to capture close-up facial images. Figure 4 shows the capturing results in the scene with planar (1st row) and non-planar ground (2nd row). The images in the first and second row from left to right are captured when person 5 arrives at the locations marked by the circles in figures 3(a) and (b). The arrows show the walking directions. Our method is very effective in capturing close-up facial image, with almost all the captured faces around the image centre. Even for the point inside the ellipse in figure 3(b) where both X-Y and Z plane errors are relatively big, the whole face is still captured (middle image in the 2nd row).

Figure 4: The close-up facial images captured in the scene with planar and non-planar ground.

5 CONCLUSIONS

We present an approach based on 3D head point detection to track people in an average crowded indoor environment using two overhead cameras. Our mainly contribution is to use the perspective projection to find the potential head top segment and then establish the highest point on the segment to detect the 3D head point. This makes our method work well for accurate 3D tracking without assuming the heights of people, without the constraint that the ground is flat or planar, and without using full disparity map that is computationally expensive. Thus our method is well suited for capturing close-up facial image. The experiments show that the average error of the estimated X-Y and Z plane values of the 3D head point is usually smaller than 2 inches and high quality close-up facial images are captured.

In the future we plan to investigate a global matching method to obtain more accurate and robust disparity along the potential head top segment, thus improving on the 3D head point localization. And we intend to extend our method to very crowded scenes where the foreground blobs of people from the overhead view may merge.

REFERENCES

Bellotto, N., Sommerlade, E., Benfold, B., Bibby, C., Reid, I., Roth, D., Fernandez, C. Gool, L. V. and Gonzalez, J., 2009. A distributed camera system for multi-resolution surveillance. In *ACM/IEEE International Conference on Distributed Smart Cameras, 2009*.

Boltes, M. and Seyfried, A., 2012. Collecting pedestrian trajectories. *Neurocomputing*, [online] Available at< http://dx.doi.org/10.1016/j.neucom.2012.01.036>.

Eshel, R. and Moses, Y., 2008. Homography based multiple camera detection and tracking of people in a dense crowd. In *IEEE Conference on Computer Vision and Pattern Recognition. Anchorage, Alaska, USA 24-26 June, 2008*, pp. 1-8.

Khan, S.M. and Shah, M., 2009. Tracking multiple occluding people by localizing on multiple scene planes, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31 (3), pp. 505–519.

Oosterhout, T. van, Bakkes, S. and Kröse, B., 2011. Head detection in stereo data for people counting and segmentation. In *International Conference on Computer Vision Theory and Applications, 2011*.

Orwell, J., Massey, S., Remagnino, P., Greenhill, D. and G. Jones, 1999. A Multi-agent framework for visual surveillance. In *IEEE International lst Conference on Image Processing, 1999*.