Skeleton model-based pose tracking and behavior recognition for pedestrian & cyclists from vehicle scene camera in urban area

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***Abstract*—Pedestrian detection and tracking algorithms have been widely developed and utilized in vehicle pre-crash systems to issue warnings and perform automated braking. However, these safety-oriented functions are not sufficient to read pedestrian gestures and estimate pedestrian intentions, which are critical functionalities to implement autonomous driving in mixed traffic situations with pedestrians. With the significant progress in computer vision research, skeleton model based human pose recognition has become more accurate and time-efficient, although most of the applications are limited in lab-environment or on surveillance videos. This paper is to propose a pose tracking and behavior recognition method from scene camera equipped on vehicle. It will not only detect pedestrians on the road, but also generate their skeleton models describing head, limb, and trunk movements. Based on these more detailed movements of body parts, this method is designed to track poses of pedestrians and cyclists with the potentials to enable automated pedestrian gesture reading and non-verbal interactions between autonomous vehicles and pedestrians. The proposed algorithm has been tested on different databases including TASI 110-car naturalistic driving database and Joint Attention for Autonomous Driving (JAAD) database. Results show that key frames describing different pedestrian and cyclist negotiation gestures are detected from the raw video streams using the proposed method. This will help understanding pedestrian and cyclist's intentions and can be further used for autonomous vehicle control algorithm development.**

Index Terms – pose tracking, behavior recognition, pedestrian, cyclists.

I. Introduction

Autonomous vehicle is among hottest research topics in recent years. Extensive research has already been done to make vehicle running safely without driver involved on highway. They can actively percept surrounding environment and react correspondingly, such as avoid obstacle or change lanes. Nevertheless, situation in urban area is more complex than highway. To further develop algorithm in urban area, more road users should be considered such as pedestrian and cyclists. Existing algorithm focus more on safety purpose and consider less about making vehicle more intelligent and act as a human driver.

Other than tracking surrounding vehicles' behavior in high-way, tracking behavior of pedestrian and cyclists in urban area are much more challenging since there are pose features involved. To understand these features and further to use them for intention analysis, more precise detection and tracking algorithm should be introduced. Tracking Pedestrian and cyclists with bounding box is prevalent in previous research to understand movement of pedestrian and cyclists. Most of these researches start with pose detection of pedestrian and cyclists. Histogram of Oriented Gradients (HOG) [1] and part-based model [2] are previously used for human detection purpose. For their tracking after detection, many strategies have been applied such as Mean-shift [3], globally-optimal greedy algorithm [4] and continuous energy minimization [5]. Tracking pedestrian considering their birth and death state has also been applied by using Markov decision processes [6]. However, tracking with bounding box will only extract position and speed information of pedestrian and cyclists. We will know little about the intention of pedestrian and cyclists largely carried by their pose features.

Furthermore, most of research focus on tracking road users from fixed camera as surveillance [7] by using bounding box. Few research have been done from the perspective of moving scene camera, especially when it is still challenging to track poses of pedestrian and cyclist from moving camera behind the windshield of vehicles. To our best knowledge, our paper is one of the first published studies to propose a method to track and recognize pose of pedestrian and cyclists from a moving camera based on their skeleton model.

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II. Previous Work

Previous work with pedestrian and cyclists tracking are mostly based on bounding box. Different object detection methods have been applied for pedestrian and cyclists' detection. P. Viola *et al.* proposed a motion and appearance based detector in pedestrian detection [8]. HOG detector for pedestrian is further introduced in 2005 by N. Dalal *et al.* [9]. Further extension of HOG method called Deformable parts model (DPM) [10] by P. Felzenszwalb *et al.* in 2008 has been proposed to improve deformation effect. Cyclists detection research, on the other hand, are few and mostly based on HOG, SVM and part-based model [11] [12]. Recent pedestrian and cyclist detection algorithms are improved by applying Faster R-CNN [13] and Mask R-CNN [14] through deep regional CNN. Concurrent detection algorithm by using upper-body detection with bounding box and Fast R-CNN has been proposed to simultaneously detect pedestrian and cyclist from moving camera [15]. Z. Jiang *et al.* introduced a fixed-camera-based tracking algorithm by integrating multiple models with an ellipse bounding box [24]. However, pose information cannot be extracted from these published studies.

Skeleton-based pedestrian and cyclist detection and tracking can help with pose recognition and analysis. One common approach for human skeleton estimation is top-down method, which starts with a single person detection followed with a pose estimation. The pose estimations usually rely on local body parts [16] [17] for articulated model estimation. This method has several drawbacks. Failure of person detection will result in pose estimation loss. Also, running time is proportional to the number of people in each frame which may cost hours to finish processing a single video with crowds. On the other hand, another method has been proposed called bottom-up method. This method could potentially decouple runtime problem from number of people involved in each video. L. Pishchulin et al. proposed a method that labeled candidates of part detected and connected them to individuals using integer linear programming [18]. Based on this work, E. Insafutdinovv et al. further proposed a ResNet based body part detector, image-dependent piecewise score terms, and better optimization strategy [19] which speed up the performance to several minutes per frame. Recently, Z. Cao et al. suggest a Part Affinity Fields based pose estimation which can detect multi-person pose in real time [20]. Pose detection of this paper is based on work of [20].

Skeleton model based tracking algorithms on the other hand have also been proposed. E. Insafutdinov et al. developed a tracking algorithm that simplified body-part relationship graph and applied a feed-forward convolutional architecture to associate parts even in clutter [21]. In another study, an algorithm called PoseTrack has been proposed. It built a graph with both spatial and temporal edges for detection. Then it simultaneously associated body parts within each single frame and each person over different frames by integer linear programming [22]. These methods are more general-purpose pose tracking and are still not time efficient for pedestrian and cyclists tracking and pose recognition.

III. Overall Method

The overall procedure of pose tracking and recognition method in this study is shown as Figure 1 that is composed of 4 steps:

1. Cutting frames from raw videos
2. Generate skeleton model based on generated frames
3. Tracking algorithm will be applied to track each pedestrian and cyclists along frames and assigned them with a unique ID
4. Data of each pedestrian and cyclist will be stored in separate files for pose recognition for crossing intention analysis.

This method is tested based on raw video from two databases. One is TASI naturalistic driving database and an-other one is Joint Attention for Autonomous Driving (JAAD) by York University [23]. TASI naturalistic driving database is collected by Transportation Active Safety Institute at Indiana University-Purdue University Indianapolis and based on driving data of 110 drivers with their cars recruited from the greater Indianapolis area in Indiana, USA completed the proposed naturalistic driving data collection. The duration of data collection process of 12 months and most of data collected including a variety of urban street, suburban, highway with variety of light and weather condition. There are plenty of pedestrian and cyclists' data that can be used for posture tracking and recognition purpose. We randomly select several videos of pedestrian and cyclists from the database for validation. Besides TASI naturalistic database, JAAD database is the database we choose for pose recognition analysis since they are labeled data with pedestrian and cyclists action recorded with time. They have 346 videos with most of them have pedestrian and cyclists involved. We tested the tracking algorithm with this database too.

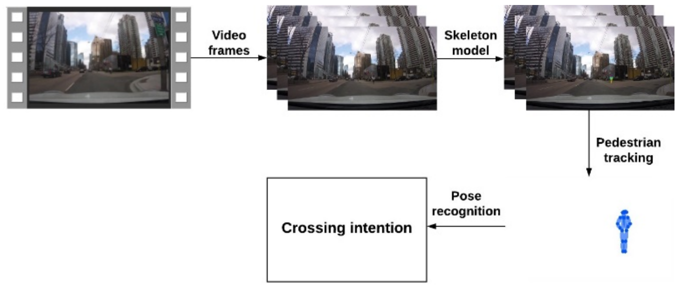

Fig. 1. Overall of pose tracking and recognition method

IV. Pose Estimation And Tracking Algorithm

A. Pose estimation

Pose estimation for tracking algorithm is based on work of [20]. The skeleton model defined in this paper for pose estimation contains 18 points to present human body as figure 2. Points with number 1 and 2 represent head and neck respectively; the tracking algorithm designed for pose recognition is based on coordinates of head and neck. Points with number 15 and 16 represent eyes of a human while points with number 17 and 18 present both ears of a person. Points 3 to 5 and 6 to 8 represent left and right arms and points 9 to 11 and 12 to 14 represent left and right legs. Every pedestrian or cyclist detected by this method is based on this skeleton model. More precise skeleton model can be used for posture recognition to have eyes and ears detected since we will able to know if the object is facing the camera or in opposite position to camera.

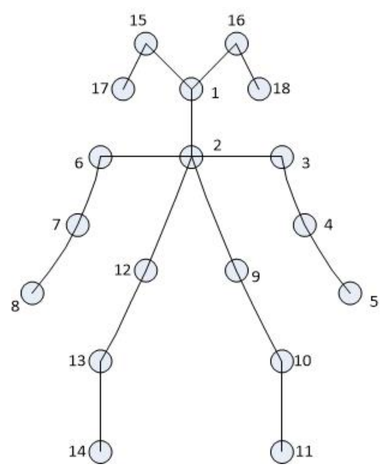

Fig. 2. Skeleton model for pose estimation

To estimate pose of pedestrian and cyclist, heatmap of each body part candidate is generated by convolution neural network from each frame. This algorithm is using bottom up algorithm and no person is detected before parts association. Body parts are further associated based on part affinity field. Redundant parts will be deleted from the graph. Body parts will be connected through certain sequence such that the skeleton model of pedestrian or cyclists can be detected. Speed of pose estimation is fast and pedestrian and cyclist can be detected together in one frame, as shown in following Figure 3.

Fig. 3. Pedestrian and cyclists skeleton model for pose estimation

B. Pose tracking

Pose tracking algorithm is applied after pose estimation. After extracting skeleton model of pedestrian and cyclists from each image, each person should be associated across frames such that their pose can be recognized for next step. Although there is existing tracking algorithm that use skeleton model for human pose tracking from raw video, pedestrian and cyclists tracking could be handled with simpler algorithm since they are heading straight towards the same direction throughout the entire video in rather slow speed with less occlusion happened most of the time.

Our tracking method is based on position of head and neck from the skeleton model. Pose estimation of pedestrian and cyclists is not robust enough for full-body pose tracking in some scenario. With light or weather condition varies, skeleton models of pedestrians and cyclists can be incomplete, which makes it hard to associate people from different frames. However, head and neck of skeleton model can be continuously captured in majority of frames; they are robust compared to other parts of body in skeleton model generated. Also, movement of limbs of skeleton model for each pedestrian and cyclists are drastic compared to movement of head and neck thus they are hard to be chosen as reference for tracking. By only tracking the upper body of each person, we will be able to separate people from each other effectively and assign them with a unique ID. Movement of head and neck of single pedestrian can be shown as below.

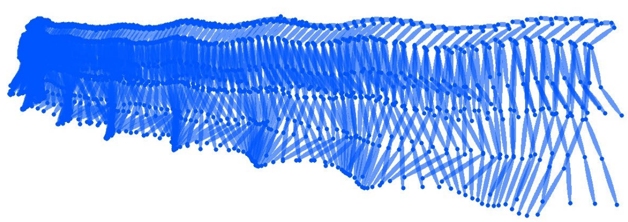

Fig. 4. Movement of head and neck of single pedestrian

Output from pose estimation algorithm need to be cleaned before applying the tracking algorithm. There are two types of common errors in the skeleton model detection process: (1) random noises that do not belong to any pedestrian or cyclists' skeleton models, and (2) false-positive human model detection (usually shown above horizontal line and hanging in the sky detected due to shadows in the tree or dark light conditions). To prevent fault data restored in tracking output, our algorithm neglect head and neck captured on the upper one third height of each frame and will only restore skeleton data corresponding to head and neck. Pseudo-code of data cleaning can be expressed as below.

if *head and neck detected* **then**
  // check if they are in top one third area of image;
  if y_{head} *or* $y_{neck} >$ *image height*$*2/3$ **then**
    neglect data points;
  else
    restore data in candidate pool;
  end
end

Algorithm 1: Data cleaning for pose tracking

Since pedestrian and cyclists are moving limited distances between adjacent frame, calculating distance of head and neck between each frame could be an effective way to distinguish each person from each other for tracking. We record head and neck in certain structure of each person and compare the translational movements of dead and neck location as a group crossing different frames. The data structure of each person's head and neck location is recorded as follow:

[person_ID, (x_head, y_head), (x_neck, y_neck), point_ID]

If x and y coordinates of head and neck of each person are within certain range, it will be classified as same person. The core tracking algorithm can be demonstrated by following Pseudo-code.

for $i \leftarrow 1$ **to** *candid_len* **do**
  $Head\_neck_{candid} \leftarrow candid\_pool[i][:2]$;
  $Head\_neck_{pre} \leftarrow pre\_pool[i][:2]$;
  if $abs[head_{candid} - head_{pre}] < \gamma$ **then**
    if $abs[neck_{candid} - neck_{pre}] < \beta$ **then**
      $ID_{candid} \leftarrow ID_{pre}$;
    else
      swap candidate sequence;
    end
  else
    swap candidate sequence;
  end
end

Algorithm 2: pose tracking algorithm

After matching head and neck coordinates, we save data of each person to separate files. All 18 points of skeleton data are stored along with frame ID and person ID in one frame. If there is no data record from pose estimation output, it will be recorded as -1.

It could be possible that multiple pedestrians and/or cyclists keep cutting in and/or cutting out in video. To track posture of each person precisely, we will need to augment the matrix when new people appear in video and stop recording skeleton data after they cut out. To augment the matrix, we compare the candidate number with maximum candidate number stored. If candidate number is larger than maximum number, we augmented the matrix by adding -1 to previous frames and record data starting from current frame. If one person disappears in one video, we will need to add a penalty value to make sure there will be no data recorded afterwards.

V. Pose Recognition

Purpose of pose tracking is to extract posture information of each pedestrian and cyclists from video such that we can further analyze how pedestrians and cyclists react after seeing a vehicle before or during their crossing. By understanding these, we will be able to know how pedestrians and cyclists communicate with driver. In order to understand more detailed pose intention of pedestrian and cyclists, we first need to extract pose from video and then analyze corresponding crossing intentions.

A. Pose extraction

Pose extraction is based on files recorded from pose tracking. For file of each person, we extract their points of body parts and reconnect them by the same sequence. In this way, we can separate pedestrian and cyclists pose from background and draw them on blank background. It will help us better understand postures of each person throughout whole video. The procedure can be shown as below.

Fig. 5. Pose extraction and recognition

By comparing the results with labelled data from database, we will be able to further separate video into more detailed video clips based on their pose and categorize them base on pose labels.

B. Crossing intention

With pose data extracted from videos, the next step is to read pedestrian or bicyclist gestures and estimate intention. As automatic intention estimation is out of the scope of this study, we adopt manual process to evaluate the crossing intention based on the extracted pose information. Relying on a previous study [23], the videos have been manually processed with different movement and gesture labelled. Key frames of automatically tracked poses are extracted to compare with the manual labels for intention estimation. The main goal is to evaluate the feasibility to use pose detection and tracking data for studying road user intentions.

One example is shown below. We extract pose of one pedestrian crossing the road while vehicle is turning right. When the vehicle is slowing down to let pedestrian cross, the pedestrian is waving hands to let the vehicle pass. It is an implicit pose in one the arm of pedestrian and our method still could capture this pose by skeleton model as Figure 5.

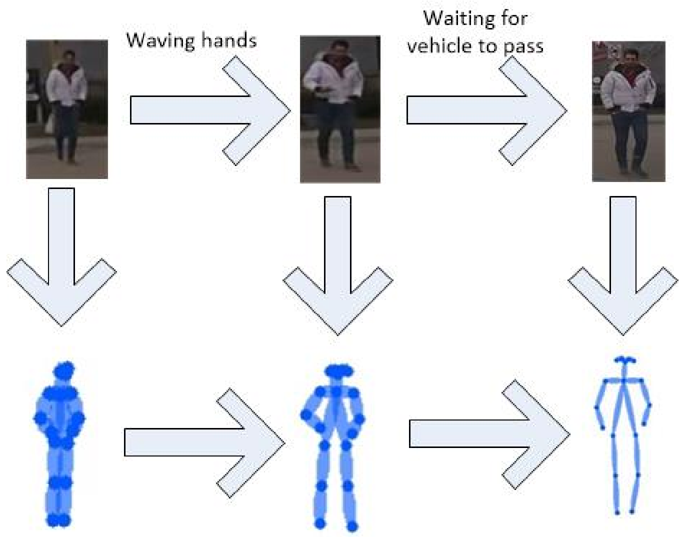

Fig. 6. Waving hand example of Pose extraction and recognition

After detailed pose are extracted from each person along the video, their intention of crossing will be predict based on their pose. It is quite helpful to know crossing intention of pedestrian/cyclist since it will help autonomous vehicle algorithm becoming more intelligent and less conservative beyond safety oriented design concepts.

VI. Result Analysis

We tested 346 videos from JAAD database [23] and some pedestrian videos from TASI naturalistic database [25] [26] [27]. We analyze data manually by separating videos into different categories.: clear path, crossing, waving hand, looking, moving fast/slow, nod, slow down/speed up, stopped.

A. Clear path

Clearing path is pedestrian or cyclist step away from the lane where both they and vehicle occupied. It could happen when both are heading towards each other or going along the same way. In the following figure could we see the clearing path action of a pedestrian or cyclist.

Fig. 7. Clearing path of pedestrian

Orange marked skeleton model of pedestrian represents the clearing path of pedestrian. It happened when the pedestrian saw the vehicle, and then walk towards the side lane to let the vehicle pass. The density of the postures can reflect the change of relative moving speeds of the pedestrian from the vehicle perspective. The speed change can also reflect the likelihood for pedestrian to give up the right of way. By understanding the intention of pedestrian or cyclist, autonomous vehicle can be more intelligent and act more like a human driver by adjusting driving speed and directions correspondingly.

B. Waving hands

Waving hand(s) could happen when pedestrian or cyclist would like to let vehicle go first, as shown in Figure 6. It could also happen when pedestrian or cyclist would like to thank vehicle let them go first. This is a typical interaction between pedestrian /cyclist and the driver.

From Figure 8, the cyclist wave hands towards the driver when the driver is slowing down to let cyclist to go first. It happened during a very short time and it is implicit. By applying our algorithm, this waving posture is successfully captured and shown in the figure. Once vehicle could understand this from their movement, it will be able to communicate with pedestrian or cyclist better and improve overall traffic efficiency. Also, we can see the bicyclist reduced the moving speed before the hand-waving gestures, increased the speed during/after the gestures, and then reduced the moving speeds again (based on the density of the postures illustrated as the sample rate remains constant). This speed-change aligns well with the negotiation process, which shows good potentials to fully model the interaction process based on the pose detection and tracking output.

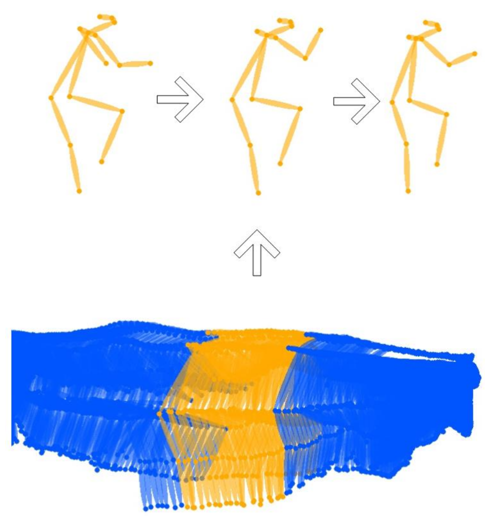

Fig. 8. Waving hands of cyclist to driver

C. Looking

Looking happens commonly when pedestrian or cyclist is crossing the road. Understand if pedestrian or cyclist is looking at the car is very important for estimating their situational awareness and decision making. Some of pedestrian will keep on checking if vehicle is within safe distance between pedestrian/cyclist and vehicle when they are crossing or before crossing; some of pedestrian/cyclist will look at vehicle to make sure they stopped at a stop sign so they can cross safely. Also, some of pedestrian or cyclist may not look at vehicle at all during their crossing, as shown in figure 4.

Similar to waving hands, looking is hard to capture from conventional full-body motion tracking methods. By defining the head model with five points, our pose tracking output could recognize eyes and ears of pedestrian and their movements, as illustrated in the following figure 9. We can tell from the pose tracking results that the pedestrian is looking at the vehicle before crossing; he/she starts to across the street after making sure the vehicle has slowed down its speed.

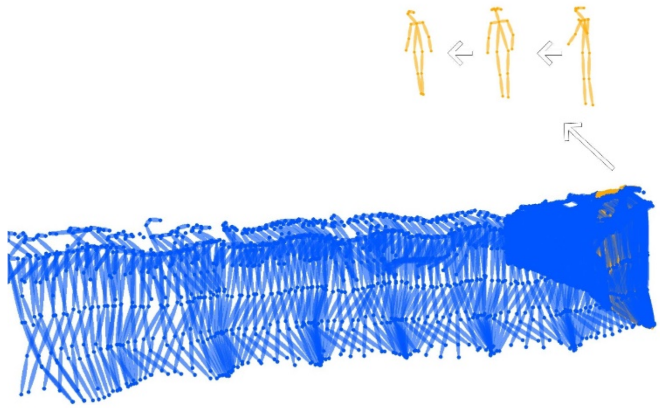

Fig. 9. Crossing pedestrian looking at driver

By using skeleton model for pose recognition, we can clearly recognize some posture of pedestrian or cyclist that cannot captured by using bonding box. Thus, we will be able to further know if the pedestrian or cyclist interacts with driver. In the following section we will show some subtle yet essential posture for pedestrian or cyclist intention analysis.

VII. FUTURE WORK

Our current pose-tracking algorithm is designed for videos with less amount of people and less occlusion happened during crossing, which represents large percentage of pedestrian/bicyclist crossing scenarios. One limitation of the top-down algorithm is to significantly increase runtime for larger number of people involved in one frame. Algorithm therefore could be improved with attention weight added into consideration. The improved algorithm will only focus on crossing pedestrian or cyclists that could potentially be dangerous to driver and neglect those people only walking on sidewalk. Corresponding learning techniques could be introduced.

Based on the results of this study, we have approved the feasibility to read pedestrian and bicyclist gestures and estimate the corresponding intentions for right-of-way negotiation. We are currently working on automatic intention estimation using both spatial and temporal pose tracking results.

VIII. CONCLUSION

This paper proposes a skeleton model based method for pose recognition and tracking from vehicle scene camera. Although pose-recognition and tracking in lab-environment or from surveillance cameras have been studied widely in recent studies, there are very few studies focusing on applying this technique into vehicle scene camera videos. Based on the algorithm develop by [20] and introducing post-processing method including data cleaning and pose tracking algorithm, this study approves that it could be effective to extract pedestrian/bicyclist poses from driving scene video, and the skeleton model of each pedestrian/cyclists can be used for gesture recognition and intention estimation. This technique brings in more detailed information compared to traditional full-body motion tracking methods applied in current safety-oriented vehicle systems, and will be helpful to develop more intelligent control algorithms for future autonomous vehicle.

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