Supplementary Material: Pedestrian Models for Autonomous Driving Part II: high level models of human behavior

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I. Quality of citations

These linked papers (Part I and II) review over 450 papers from high quality journals and conferences such as *CVPR, ICRA, PAMI, IROS, ITSC, ECCV, IV*. It is common in Computer Science fields including machine vision and machine learning for conferences to be considered higher quality or similar quality to journals, while psychology and sociology fields typically consider journals to be more authoritative. The following figures give some ideas about the quality of the cited papers.

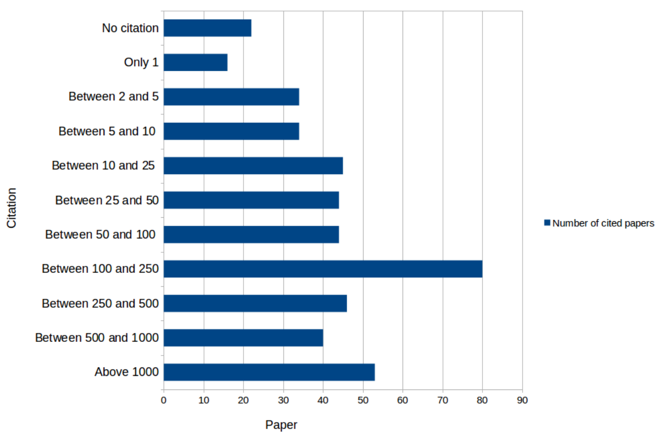

Fig. 1. Number of citations per paper

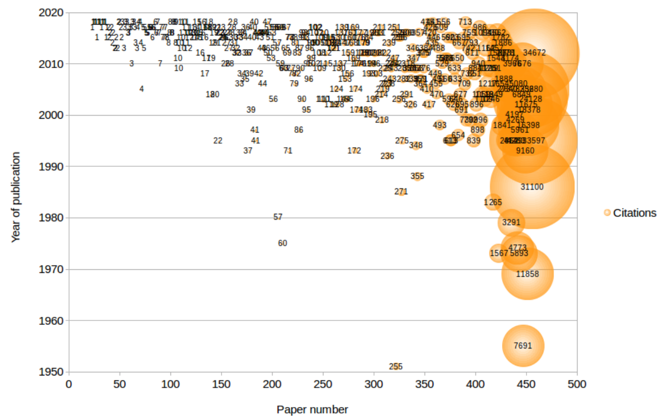

Fig. 2. Number of citations per paper and per year of publication

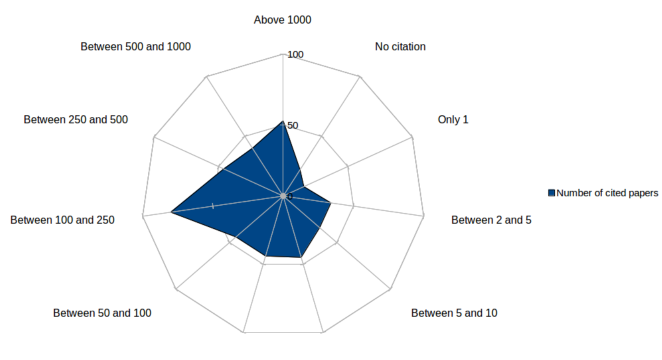

Fig. 3. Number of citations per paper

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II. Summary of pedestrian trajectory and interaction models

TABLE I: Summary of pedestrian trajectory prediction models

Study/Paper	Input/Evaluation	Method	Trajectory Prediction Models	SAE Level
Hoogendoorn et al. [1]	Simulated trajectories	Optimal control theory	Unobstructed walking paths	Level [4,5]
Antonini et al. [2]	Pedestrian movements (video sequence)	Discrete choice model	Unobstructed walking paths Two agents interaction	Level 3
Borgers et al. [3]	Pedestrian movements (manual)	Discrete choice	Unobstructed walking paths	Level 3
Taylor et al. [4]	CMU Graphics Lab Motion Capture Database	Conditional Restricted Boltzmann Machine (CRBM)	Unobstructed walking paths	Level 3
Puydupin-jamin et al. [5]	Pedestrian trajectories dataset Arechavaleta et al. [6]	Unicycle model with inverse optimal control	Unobstructed walking paths	Level 3
Habibi et al. [7]	Pedestrian trajectories dataset from two intersections [7]	Gaussian Process with a Transferable ANSC algorithm	Route prediction around obstacles Gaussian Process methods	Level [3,4]
Kitani et al. [8]	92 videos (80% for training)	Inverse reinforcement learning with inverse optimal control theory	Uncertain destination models Dynamic graphical models	Level [3,4]
Ziebart et al. [9]	Predicted trajectories used in an incremental motion planner	Maximum entropy with inverse optimal control	Uncertain destination models Dynamic graphical models	Level [3,4]
Vasquez et al. [10]	14 pedestrian trajectories dataset [8]	Markov decision process (MDP) with a Fast Marching Method (FMM)	Uncertain destination models Dynamic graphical models	Level 4
Gockley et al. [11] Topp et al. [12]	Laser data	Direction-following and Path-following with Curvature velocity method	Route prediction around obstacles	Level 3
Bennewitz et al. [13] [14]	Laser range data from Pioneer robots	Clustering with Expectation Maximization (EM) algorithm	Uncertain destination models Dynamic graphical models	Level 3
Wu et al. [15]	Pedestrian trajectories from Rutesheim dataset	Markov chains with an heuristic method	Uncertain destination models Dynamic graphical models	Level 3
Karasev et al. [16]	Pedestrian dataset [16]	Markov decision process (MDP) with Rao-Blackwellized filter	Uncertain destination models Dynamic graphical models	Level [4,5]
Bai et al. [17]	Autonomous golf car	Partially observable Markov decision process (POMDP)	Uncertain destination models Dynamic graphical models	Level [4,5]
Rehder et al. [18]	Pedestrian trajectories (stereo video dataset)	Inverse reinforcement learning	Uncertain destination models Deep learning methods	Level [4, 5]
Garzon et al. [19]	Simulations and real-world data	Fast Marching Method (FMM) and A Star (A*) algorithm	Uncertain destination models	Level 4
Kooij et al. [20]	Pedestrian trajectories dataset [20]	Dynamic Bayesian network (DBN) with a switching linear dynamic system (SLDS)	Event/activity models Dynamic graphical methods	Level [4,5]
Schulz et al. [21]	Pedestrian dataset [22]	Interacting Multiple Model (IMM) with a latent-dynamic conditional random field (LDCRF)	Event/activity models Dynamic graphical methods	Level [4,5]
Dondrup et al. [23]	Laser and RGB-D data	Qualitative Spatial Relations (QSR) with Hidden Markov model (HMM)	Event/activity models Dynamic graphical methods	Level [4,5]
Bonnin et al. [24]	Pedestrian datase [24]	Inner-city model with 'Context Model Tree' approach	Event/activity models	Level [4,5]
Borgers et al. [25]	Pedestrian dataset from the city of Maastricht	Discrete Choice Model	Event/activity models	Level 3
Camara et al. [26] [27]	Pedestrian-vehicle interactions dataset [26]	Regression models Filtration analysis	Event/activity models	Level [4,5]
Völz et al. [28]	LIDAR pedestrian trajectories	Support vector machine (SVM)	Event/activity models	Level 3
Duckworth et al. [29] [30]	Pedestrian dataset from a mobile robot [30]	Qualitative Spatial Analysis (QSR) with a graph representation	Event/activity models	Level [4,5]
Mögelmose et al. [31]	Pedestrian trajectories from a monocular camera	Particle filter	Route prediction around obstacles Dynamic graphical methods	[Level 3,4]
Schneider et al. [22]	Pedestrian dataset [22]	Extended Kalman filter (EKF) and Interacting Multiple Model (IMM)	Event/activity models Dynamic graphical methods	Level [3,4]
Quintero et al. [32] [33]	CMU Dataset with 129 video sequences	Balanced Gaussian process dynamical models (B-GPDMs) and Naive Bayesian classifiers	Event/activity models Dynamic graphical methods	Level[3,4,5]
Fragkiadaki et al. [34]	Motion capture data: H3.6M dataset [Ionescu et al. 2014]	Encoder-Recurrent-Decoder (ERD)	Uncertain destination models Deep learning methods	Level [4,5]
Martinez et al. [35]	Motion capture data: H3.6M dataset [Ionescu et al. 2014]	Recurrent neural network with a gated recurrent unit (GRU)	Uncertain destination models Deep learning methods	Level [4,5]
Doellinger et al. [36]	Simulation and real world data from a mobile robot	Convolutional neural network	Uncertain destination models Deep learning methods	Level [4,5]
Goldhammer et al. [37]	Camera data	Multilayer perceptron (MLP) with polynomial least square approximation	Uncertain destination models Deep learning methods	Level [4,5]
Kruse et al. [38]	Camera data	Statistical analysis	Route prediction around obstacles	Level [3]
Cosgun et al. [39]	Real robot	Motion planning with curvature velocity method	Uncertain destination models	Level [3,4]
Koschi et al. [40]	Real world data from a moving vehicle	Set-based method Reachability analysis	Uncertain destination models	Level [4,5]

TABLE I: Summary of pedestrian trajectory prediction models

Study/Paper	**Input/Evaluation**	**Method**	**Trajectory Prediction Models**	**SAE Level**
Tang et al. [41]	Motion capture data: H3.6M dataset [Ionescu et al. 2014]	Deep neural network (modified High-way Unit (MHU))	Uncertain destination models Deep learning methods	Level [4,5]
Ghosh et al. [42]	Motion capture data: datasets in [Ionescu et al. 2014] and [Holden et al. 2016]	Dropout AutoEncoder LSTM (DAE-LSTM)	Event/activity models Deep learning methods	Level [4,5]
Bock et al. [43]	Dataset in [43]	LSTM	Event/activity models Deep learning methods	level 5
Hug et al. [44]	Synthetic test conditions	LSTM with a mixture density output layer (LSTM-MDL) model and particle filter method	Uncertain destination models Deep learning methods	Level [4,5]
Cheng et al. [45]	Pedestrian datasets: ETH [46] and UCY [47]	Social-Grid LSTM based on RNN architecture	Uncertain destination models Deep learning methods	Level 5
Bhattacharyya et al. [48]	CityScapes dataset [49]	Two-stream recurrent neural network (RNN)	Uncertain destination models Deep learning methods	Level [4,5]
Broz et al. [50]	Simulated data	Time-state aggregated partially observable Markov model (POMDP)	Two agents interaction	Level 4
Rudenko et al. [51]	Simulated and real data	Markov decision process (MDP) with a joint random walk stochastic policy sampling	Two agents interaction Graphic dynamical models	Level 5
Kretzschmar et al. [52]	Turing test with human participants	Markov chain Monte Carlo (MCMC) sampling	Two agents interaction Graphic dynamical models	Level [4,5]
Kawamoto et al. [53]	Pedestrian datasets: ETH [46] and [54]	Kriging (Gaussian process) model	Two agents interaction Gaussian Process methods	Level [3,4]
Alahi et al. [55]	Pedestrian datasets: ETH [46] and UCY [47]	Social LSTM	Two agents interaction Deep learning methods	Level [4,5]
Hoogendoorn et al. [56]	Simulations	Optimal control theory	Two agents interaction	Level [4,5]
Ikeda et al. [57]	Shopping mall data	Social force and sub-goal concept	Two agents interaction	Level [3,4]
Chen et al. [58]	Experimental vehicle ALSVIN	Extended Kalman filter (EKF)	Two agents interaction Graphic dynamical models	Level [3,4]
Bera et al. [59] [60]	Indoor and outdoor crowded videos	Ensemble Kalman filter (EnKF)	Group interaction Graphic dynamical models	Level [4,5]
Deo et al. [61] [62]	Crowded unsignalized intersection dataset	Variational Gaussian mixture models (VGMM)	Group interaction Graphic dynamical models	Level 5
Pellegrini et al. [46] [63]	Pedestrian dataset with birds-eye view images [46]	Linear Trajectory avoidance model (LTA)	Small Group interaction Graphic dynamical models	Level [4,5]
Sun et al. [64]	L-CAS Pedestrian dataset [64]	Temporal 3DOF-pose LSTM (T-pose LSTM)	Group interaction Deep learning methods	Level [4,5]
Yi et al. [65]	Crowded scenes video data	Behaviour convolutional neural network (CNN)	Group interaction Deep learning methods	Level [4,4]
Radwan et al. [66]	6 public datasets comprising ETH, UCY, L-CAS	Interaction-aware trajectory convolutional neural network (IA-TCNN)	Group interaction Deep learning methods	Level [4,5]
Moussaid et al. [67]	Pedestrian trajectories [67]	Heuristic model	Group interaction	Level 5
Turner et al. [68]	Simulations	Exosomatic visual architecture	Group interaction	Level [4,5]
Vasishta et al. [69]	Real world scenes dataset [69]	Natural vision model	Group interaction	Level [4,5]
Zhou et al. [70]	Pedestrian dataset from New York Central station	Mixture model of dynamic pedestrian-agents (MDA)	Group interaction Graphic dynamical models	Level [4,5]
Henry et al. [71]	Crowd flow simulator	Inverse reinforcement learning (IRL) and Gaussian process (GP)	Crowd behaviour models	Level 5
Trautman et al. [72]	Pedestrian dataset: ETH [46]	Gaussian process (GP)	Group interaction Gaussian Process methods	Level 5
Ali et al. [73]	Video from Google videos and National Geographic documentary	Lagrangian particle dynamics model	Macroscopic models Crowd behaviour models	Level 5
Mehran et al. [74]	Dataset of escape panic scenarios and web videos	Particle advection with social force model	Macroscopic models Crowd behaviour models	Level 5
Monokrousou et al. [75]	Open Street data	Syntactic analysis	Macroscopic models Crowd behaviour models	Level 5
Ma et al. [76]	UCY Zara Dataset, the Town Centre Dataset and the LIDAR Trajectory Dataset.	Fictitious game and reinforcement learning	Game theoretic models Two agents interaction	Level 5
Isaacs [77]	/	Homicidal taxi driver problem	Game theoretic models Two agents interaction	Level 5
Turnwald et al. [78] [79] [80]	Pedestrian trajectories from motion capture system [78]	Finite set of single-shot games	Game theoretic models Two agents interaction	Level 5
Fox et al. [81] [82]	Simulations and dataset in [26]	Game of Chicken	Game theoretic models Two agents interaction	Level 5
Vascon et al. [83]	Public datasets	Game theory	Game theoretic models Small group interaction	Level 5
Johora et al. [84]	Simulations	Stackelberg games	Game theoretic models Small group interaction	Level 5
Mesmer et al. [85]	Experiments	Game theory with velocity vector	Game theoretic models Crowd interaction	Level 5
Shi et al. [86]	Experiments	Modified lattice model	Game theoretic models Crowd interaction	Level 5

TABLE I: Summary of pedestrian trajectory prediction models

Study/Paper	Input/Evaluation	Method	Trajectory Prediction Models	SAE Level
Dimitris et al. [87]	Video data	Two-dimensional classification model	Signalling models	Level 5
Katz et al. [88]	Controlled experiment	Statistical analysis	Signalling models	Level 5
Guéguen et al. [89]	Controlled experiment	Statistical analysis	Signalling models	Level 5

III. Datasets

TABLE II: Summary of pedestrian datasets

Dataset	Data type	Viewpoint	Applications	Quantity of data
The Caltech Pedestrian Benchmark [90]	Urban video data (Resolution: 640x480)	Moving car	Detection, Tracking, Trajectory Prediction	10 hours of 30Hz video with 250,000 annotated frames, 350,000 labeled bounding boxes and 2300 unique pedestrians
ETHZ Benchmark [91]	Urban video data using a stereo pair of cameras (Resolution: 640x480)	Children's stroller	Detection, tracking, Trajectory prediction	2,293 frames with 10958 annotations
TUD-Brussels [92]	Image pairs	Hand-held camera and Moving car	Detection	Training set: 1,092 positive image pairs (resolution: 720x576) with 1,776 annotations and 192 negative image pairs (resolution: 720x576). Additional 26 image pairs with 183 annotations Test set: 508 image pairs (resolution: 640x480) with 1,326 annotations
Daimler Benchmark [93]	Grayscale camera images	Moving car	Detection	Training set: 15,660 positive samples (resolution: 72 pixels height) and 6,744 negative samples Test set: 21,790 images with 56,492 annotations including 259 trajectories of fully visible pedestrians
INRIA Pedestrian Dataset [94]	Camera images	Any	Detection	1805 images (resolution: 64x128)
CityPersons [95]	Camera images	Moving car	Detection	5k images with 35k bounding boxes of pedestrians and 20k unique persons
Edinburgh Informatics Forum pedestrians overhead dataset [96]	Pedestrian Trajectories	Surveillance camera	Trajectory prediction	Over 92k pedestrian trajectories
ETHZ BIWI Walking Pedestrian dataset [46]	Video	Bird-eye view	Detection, Tracking and Trajectory prediction	650 tracks over 25 minutes
UCY Zara pedestrian dataset [47]	Synthesized crowd data	Bird-eye view	Tracking and Trajectory Prediction	1 video 2-min long with 5-6 persons per frame 1 video with 40 persons per frame Trajectories
Town Center Dataset [54]	Video data	Bird-eye view	Detection, Tracking and Trajectory Prediction	Video (resolution: 1920x1080) with 71500 annotations
MARKET-1501 [97]	Camera images	Moving car	Detection and Re-identification	32k bounding boxes with 1,501 individuals and 500k non-pedestrian (street windows)
VIPER Benchmark [98]	Video data	Moving car	Optical flow, semantic instance segmentation, object detection and tracking, object-level 3D scene layout, visual odometry	250k video frames
CUHK01 [99]	Camera images	Surveillance camera	Detection and Re-Identification	971 persons with 2 camera views
CUHK02 [100]	Camera images	Surveillance camera	Detection and Re-Identification	1,816 unique persons with 5 pair of camera views
CUHK03 [101]	Camera images	Surveillance camera	Detection and Re-Identification	13k images with 1,360 pedestrians
DUKEMTMC dataset [102]	Video and trajectories	Surveillance camera	Detection, Tracking, Trajectory Prediction, Re-Identification	6,791 trajectories for 2,834 unique persons over 85 minutes video per camera (8 cameras in total) (resolution: 1080p)
DUKEMTMC-reID dataset [103]	Video and bounding boxes	Surveillance camera	Detection and Re-Identification	Over 36k bounding boxes of 1,812 unique individuals
MOTChallenge Benchmark [104] [105]	Video	Any	Detection, Tracking, Re-Identification, Trajectory Prediction	Composed of parts of other datasets and new data (videos, bounding boxes) website: motchallenge.net/
Daimler Pedestrian Benchmark [20]	Annotations	Moving car	Trajectory prediction [crossing, stopping]	58 annotated pedestrian-vehicle interactions data
PETA dataset [106]	Images	Any	Detection and Recognition	19,000 images with 8,705 persons
L-CAS 3DOF Pedestrian Trajectory Prediction Dataset	Pedestrian trajectories	Mobile robot	Trajectory prediction	50 trajectories
L-CAS 3d-point-cloud-people-dataset [?]	3D LiDAR point clouds	Mobile robot	Pedestrian detection and tracking	5,492 annotated frames with 6,140 unique persons and 3,054 groups of people
IAS-Lab People Tracking dataset [107]	RGB-D video sequences + ground truth given by a motion capture system	Mobile Pioneer P3AT robot	People detection and tracking	4,671 frames with 12,272 persons
Porch experiment dataset [6]	Motion capture system	Any	Trajectory prediction	1,500 person trajectories
UCLA Pedestrian dataset [16]	Video data	Moving car	Trajectory Prediction	17 annotated video sequences, ranging from 30 to 900 frames, and containing 67 pedestrian trajectories
LIDAR Trajectory dataset [76]	Lidar data	Top view	Trajectory Prediction	20 interacting person trajectories
Joint Attention in Autonomous driving (JAAD) [108]	Videos and annotations	Moving car	Detection, Tracking, Trajectory Prediction	346 video clips with annotations extracted from 240 hours of driving videos
MoCap database [109]	Motion capture system	Any	Detection, Recognition	500k frames with persons in many different poses

TABLE II: Summary of pedestrian datasets

Dataset	Data type	Viewpoint	Applications	Quantity of data
The Multi-Person PoseTrack Dataset [110]	Video data	Any	Detection, Recognition, Tracking	60 videos with 16k annotated persons with different poses
CMU dataset [8]	Video data	Any	Detection, Tracking, Trajectory Prediction	92 videos
Pedestrian-Vehicle Interactions dataset [26] [27]	Annotations	Human observers	Trajectory Prediction (crossing, stopping)	204 annotated pedestrian-vehicle interactions at an unsignalized intersection

TABLE III: Summary of vehicle datasets

Dataset	Data type	Applications	Quantity of data
Berkeley DeepDrive Video dataset (BDDV) [111]	Video and GPS/IMU data	Detection, Tracking, Identification	10k hours of driving videos around the world
Compcar [112]	Images	Detection, Identification	136k entire car images and 27k parts of car images, all views, labels, bounding boxes, car models
Stanford fine-grained car dataset [113]	Images	Detection, Identification	16k car images with 197 car models
EPFL multiview car database [114]	Images	Detection, Identification	2k images with 20 different car models
The vehicle image database [115]	Images	Detection	3k rear car images and 3k ”noncar” road images
The Car dataset [116]	Images	Detection	500 car images
KITTI dataset [117] [118]	Video data	Detection, Tracking, Identification, Localisation	About 1 hour in one city in daytime
Cityscape [49]	Video data	Detection, Tracking, Identification	About 100 hours videos in multiple cities in daytime
Commai.ai [119]	Video data	Detection, Tracking, Identification	7.3 hours videos in highway during daytime and night
The Oxford RobotCar Dataset [120]	Video data	Detection, Tracking, Identification	214 hours videos in Oxford in daytime
Princeton TORCS DeepDriving [121]	Synthetic video data	Detection, Tracking, Identification	13.5 hours videos in highways
Honda Research Institute Driving Dataset (HDD) [122]	Video data	Detection, Tracking, Identification	104 hours videos in one city
Udacity [123]	Video data	Detection, Tracking, Identification	8 hours of videos

TABLE IV: Summary of pedestrian and vehicle simulators

Simulator	Type	Applications
Technical University of Munich (TUM)	• Pedestrian simulator: Head-mounted display with a motion capture system • Driving Simulator software	• Pedestrian behaviour understanding • Driver behaviour analysis
Institute for Transport Studies (ITS), University of Leeds	• HIKER Lab : pedestrian simulator • Driving Simulator • Truck Simulator	• Pedestrian behaviour understanding • Pedestrian interaction with the environment • Driver behaviour understanding
Japan Automobile Research Institute (JARI)	• JARI-ARV (Augmented Reality Vehicle) • JARI-OVDS (Omni Directional View Driving Simulator)	• Road running driving simulator • Driving simulator with 360-degree spherical screen and rocking device
French Institute of Science and Technology for Transport, Development and Networks (IFSTTAR)	• Driving Simulator • Immersive Simulator • Driving Simulator with human assistive devices • Bicycle Simulator	• Driver behaviour analysis • Road user behaviour understanding
University of Iowa	Driving Simulator	Driver behaviour understanding
Pedsim [124]	Synthetic simulator	Crowd behaviour understanding

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