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STUDY ON AN EVALUATION OF TRAJECTORY PREDICTION APPROACHES AND HUMAN MOTION TRAJECTORY PREDICTION IN CROWDED SPACES

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ABSTRACT

The capacity of intelligent autonomous systems to see, comprehends, and predicts human behaviour becomes more crucial as the number of such systems grows. Self-driving cars, service robots, and high-tech surveillance systems all face the challenge of accurately anticipating future locations of dynamic agents and making plans based on that information. This study surveys the field of predicting human motion trajectories. Only observed tracklets are used in the deep network analysis, which is similar to previous methodologies. To classify current approaches based on the motion modelling methodology and the quantity of contextual information employed, we study, analyse, and organise a significant collection of work from a variety of groups. An overview of the current datasets and performance metrics is provided here. In addition, we examine failure scenarios and provide reasons for observed events, as well as some ideas for resolving the inadequacies that have been proven.

Keywords: *"Trajectory Forecasting, Path Prediction, Trajectory-based Activity Forecasting, Survey, review, motion prediction, robotics, video surveillance, autonomous driving."*

I. INTRODUCTION

Intelligent systems must be able to comprehend human movement in order to live in harmony with and interact with people. Motion analysis, representation, and motion perception all play a role in it. Because it's possible to anticipate how an event involving several agents will play out over time, anticipating it is an essential aspect of human motion analysis: this information may be used to improve active perception, predictive planning, model predictive control, or human-robot interaction. This has led to a rise in interest in human motion prediction across several fields. "Self-driving automobiles, service robots, and enhanced surveillance systems are just a few of the many key application areas." Due to the complexity of human behaviour and the diversity of its internal and external influences, it is difficult to accurately anticipate human motions. "The presence and actions of other agents, social interactions between agents, social laws and conventions, or the environment, with its topology, geometry, affordances, and semantics, may all influence motion behaviour in various ways." A large number of elements are not immediately visible and must be inferred or modelled from context knowledge. Motion prediction also has to be strong and real-time to be useful in practise. "Full-body movement, gestures and facial expressions, or movement across space via walking, using a mobility device or driving a vehicle are all examples of human motion." Prediction of human motion trajectory is the focus of this study. We are particularly interested in ground-level 2D pedestrian trajectory prediction, as well as bicycle and vehicle-related literature. Despite the fact that many of these tasks depend on the same motion modelling ideas and trajectory prediction techniques that are discussed here, they are beyond the scope of this paper. A wide range of works from various groups are surveyed and a new taxonomy based on motion modelling methodologies and contextual signals is proposed. As a first step, we classify the current state of the art and identify common characteristics, benefits, and disadvantages of each category, as well as unsolved problems that need further investigation. In the end, we ask the following questions: Do prediction performance assessment procedures follow best practises and are they adequate? Are all prediction systems now at the same degree of accuracy and it doesn't matter which one you use? Is motion prediction a thing of the past? [1]

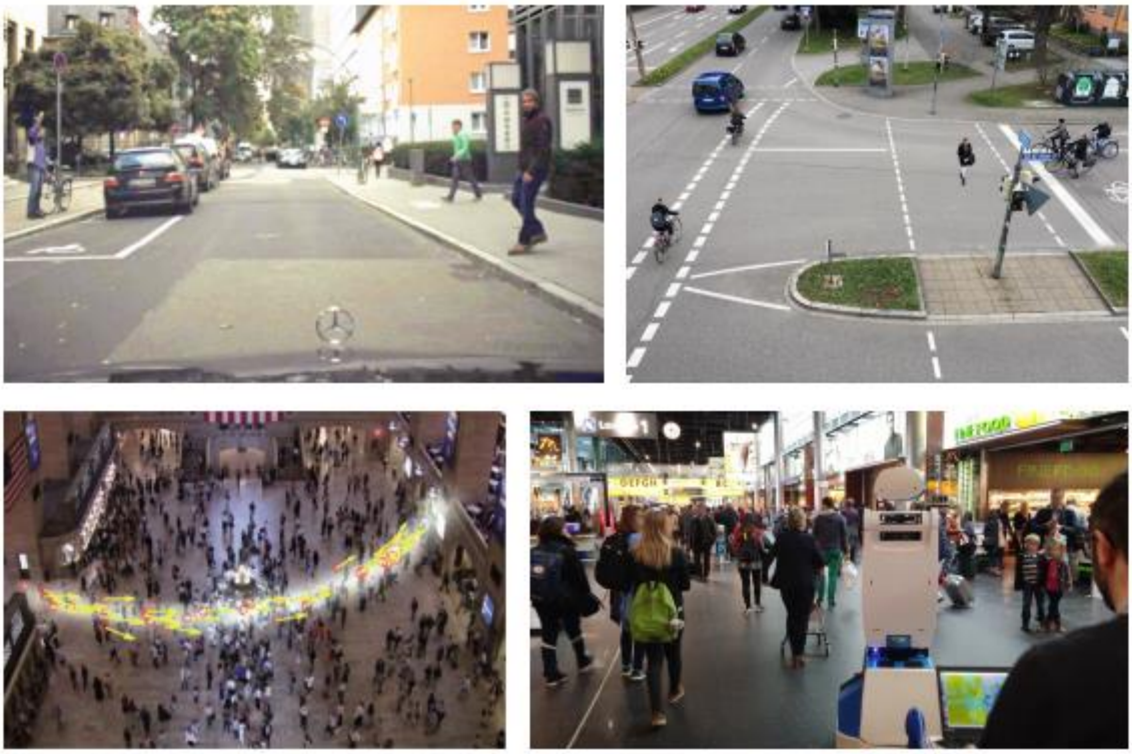


Figure 1. Human motion prediction applications. Is the pedestrian going to make a right turn? A self-driving car must be able to swiftly determine the intents and future positions of other traffic players, such as pedestrians (Illustration from (Kooij et al. 2019)). Using communication technology, advanced traffic monitoring systems may deliver real-time warnings of impending crashes. Below: Human mobility in public settings is analysed by advanced surveillance systems for the identification of suspicious conduct or crowd management (Illustration from Zhou et al. 2015). For robots to navigate through crowded areas safely and effectively, they need to be able to accurately anticipate the movements of humans in the immediate vicinity.

A. *Overview and Terminology*

The motion prediction issue consists of the following three components at the highest level of abstraction (Fig. 2):

- **Stimuli:** motion intent, as well as other directly or indirectly visible effects, are examples of inputs that impact motion behaviour. "Partial trajectories, or sequences of agent state data such as velocities, body joint angles, or characteristics are used in most prediction algorithms." In most cases, this information is given by a tracking system, and it is typical to presume that the track ID is accurate across the observation time. "Contextual signals from the surroundings such scene geometry, semantics or cues that relate to other moving things in the surrounding are further examples of additional types of input." Sensor data sequences are the foundation of end-to-end techniques [2].

- **Modeling approach**: Methods for human motion prediction vary in the representation, parametrizing, learning, and solving of the problem they attempt to model. "This study focuses on identifying and assessing relevant categories, hidden commonalities, common assumptions, and optimal assessment procedures in the rapidly expanding literature on the topic."
- **Prediction**: For example, a Gaussian over agent states, a probability distribution over grids, or an unique or multiple trajectory may all be predicted using various approaches.

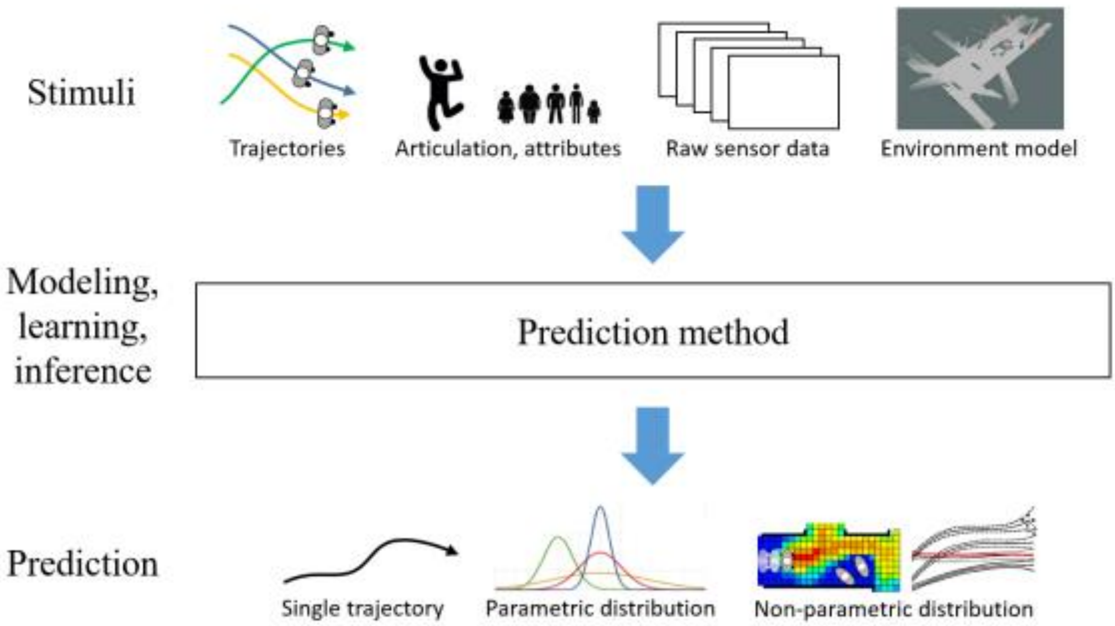


Figure 2. Internal and external inputs that affect motion behaviour, technique, and various parametric and non-parametric or structured prediction forms are typical components of a motion prediction system.

Agents are dynamic objects of interest, such as human-driven vehicles such as automobiles and bicycles, as well as robots. Predicting the actual movements of a dynamic item is called "targeting." Agents are presumed to behave in a predictable and purposeful manner in order to achieve a desired result, whether it the best possible or close to it. The motion prediction issue would be substantially more difficult or perhaps impossible without this assumption. Trajectories are paths paired with timing laws or velocity profiles, whereas paths are defined as sequences of (x, y)-positions. "Prediction horizons as short as 1-2 s and as far ahead as 20 s are described by the terms short-term and long-term, respectively st is the state of an agent at time t, ut is the action that the agent does at time t, ot O is the observation of the agent's state at time t, and is used to represent trajectories." Subscripts t are used to denote the passage of time between various states, activities, or observations: T [3].

B. Application Domains

Motion prediction is an essential part of service robots, self-driving cars, and sophisticated surveillance systems (Fig. 1).

- Service robots It's becoming more commonplace for mobile service robots to function in open-ended areas shared with humans. The ability to anticipate the mobility of other agents in the environment is essential for both human-robot interaction and safe and efficient motion planning. An on-board computer and first-person sensors make this a difficult job.

- Autonomous cars. Automated driving requires the capacity to predict the movement of other road users. When it comes to autonomous cars, the risks are similar to those faced by service robots; however, the damage that may be caused on the most vulnerable road users, such as walkers and bicyclists, is much greater (i.e. pedestrians and cyclists). In addition, cars must function in dynamic, semantically rich outside traffic environments and must meet strict real-time operational limits. This is especially true for autonomous vehicles. Traffic infrastructure (such as lanes and curbside markers) and regulations (such as zebras) may aid with motion prediction.
- Surveillance. The capacity to properly monitor a large number of objects over scattered networks of fixed cameras is essential for visual surveillance of automobile traffic or human gatherings. "People retrieval, perimeter security, traffic monitoring, crowd management, and retail analytics may all benefit from long-term motion prediction by lowering the amount of false positive tracks and track ID changes in dense crowds or across non-overlapping field of views [4]."

II. REVIEW OF LITERATURE

Based on human-aware motion's comfort, naturalness, and socialability, Kruse et al. [5] present an overview of techniques for wheeled mobile robots. Motion prediction is classified as either reasoning-based or learning-based in the context of a humanaware navigation system. "Predictions in reasoning-based approaches are based on basic geometric reasoning or dynamic models of the target agent, respectively." Predictions are made using motion patterns acquired from observed agent trajectories in learning-based systems.

Chik et al. [6] present an overview of frameworks for socially-aware robot navigation. These frameworks include a number of planners and approaches for predicting human movements.

For example, the four themes of safe human-robot interaction are outlined by Lasota et al. [7] in a review of the literature. Robotic arms, drones, and self-driving cars may also be found in this collection of works. Goal-intention or movement-characteristic-based techniques are the two main approaches to human motion prediction in the literature. Using goal intent approaches, we may infer a user's intention and then anticipate a path that the user will follow to get there. Observations regarding human movement and natural route planning are used by the latter set of techniques, which do not explicitly depend on objectives.

Vehicle motion prediction and risk evaluation in an autonomous driving setting are examined by Lefevre et al. [8]. As a result of this discussion, they identify three types of models for prediction: physics-based, ad hoc-based, and interaction-based. "Physicists use forward simulation of a vehicle model to forecast future trajectories, often under kinodynamic limitations and uncertainty in starting states and controls." According to these techniques, car motion is defined as the total of a sequence of predetermined moves that may be deduced from observable partial agent trajectories. Additionally, inter-vehicle interactions and traffic laws are taken into consideration when making joint forecasts via intention-aware algorithms.

Pedestrian motion models for car safety systems are reviewed and compared by Brouwer et al. [9]. "Methods for motion prediction based on environmental cues are divided into four categories: dynamics-based models that only use the target agent's motion state, methods that use psychological knowledge of human behaviour in urban environments (e.g. probabilities of acceleration, deceleration, switch of the dynamical model), and methods that use head orientation and semantic map of the environment." Ridel et al. [10] examine pedestrian crossing intention inference strategies based on this classification.

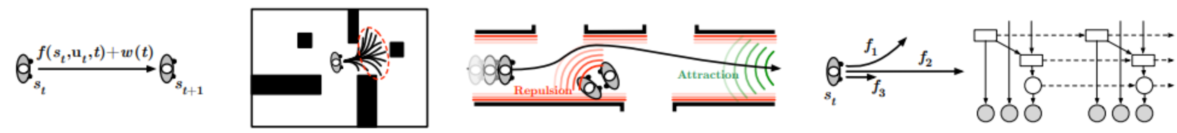
Methods for trajectory learning and analysis for visual surveillance are examined by Morris and Trivedi [11]. As a case study in online activity analysis, they look at measurements, strategies, and models for identifying archetypal motion patterns (referred to as "activity routes"). To tackle this complex topic, the researchers at Murino et al. [12] look to the social sciences as well as computer vision and pattern recognition. Many contemporary techniques for monitoring and predicting human mobility in crowds are reviewed by the authors. There are a variety of video-based approaches for extracting semantic features and predicting human trajectory, according to Hirakawa and colleagues [13]. “The literature is classified into Bayesian models, energy reduction techniques, deep learning methods, inverse reinforcement learning methods, and other ways based on the motion modelling approach.”

We've discussed benchmarking approaches in relation to the datasets for motion trajectories and metrics for assessment of prediction in a few publications [14]. “Several datasets of human trajectories in crowded environments, used to explore social interactions and assess route prediction algorithms, are described by Poiesi and Cavallaro [14] and Hirakawa et al [13].” Pedestrian motion datasets in metropolitan areas are discussed by Ridel et al [10]. In motion prediction, Quehl et al. [15] discuss many measures for comparing trajectory similarity.

These surveys, on the other hand, focus on a single application domain and a single agent type. Our taxonomy contains the categories suggested by Kruse et al. [5], Lasota et al. [7], and Lefevre et al. [8] and extends them with a systematic classification of contextual cues. “Furthermore, we suggest that modelling and contextual cues are two fundamentally independent parts of the motion prediction issue and should be categorised separately, Using this strategy, for example, it is possible to distinguish between physics-based systems that are not aware of any external stimuli and others in the same category that are extremely situational aware.” This differs from prior studies, which classified respondents along a single dimension based on various modelling methodologies and increasing degrees of contextual awareness.

III. PHYSICS-BASED APPROACHES

Using Newton's principles of motion, physics-based models predict future human motion based on a hand-crafted, explicit dynamical model f. One of the most popular ways to express the formula for the process noise (f) is to write it as the sum of the (unknown) input and the (known) output. While motion prediction may seem like an inductive process, it may really be thought of as an inference made from multiple observed or estimated inputs. “Most of these physics-based models are employed as building blocks for Bayesian filters or multiple-model algorithms in target tracking and automated control to explain the motion of dynamic objects on the ground, in the sea, in the air, or in space.” It's important to note that these models vary in the sort of motion they depict, such as manoeuvring or non-maneuvering motions, as well as their complexity. [16] Provide an overview of physics-based tracking models. “A single-model method relies on a single dynamical model, whereas a multi-model approach incorporates several modes of dynamics, We classify physics-based models in these ways (see Fig. 3).”



(a) single dynamical model (b) reachability-based model with static environment cues (c) potential field model with dynamic environment cues (d) multiple modes of dynamics

Figure 3. Following are some real-world examples of physics-based solutions: the DBN switching mechanism, (d) a multi-model technique with many modes of dynamics and the DBN switching mechanism, (a) a single dynamical model.

A. Single-model Approaches

Early designs and prototypes Position, velocity, and acceleration (PV&A) are often used to characterise the target agent's motion state in human motion prediction techniques. Kinematic models that do not take into account the forces that regulate the motion are among the simplest. “For example, there's the piecewise constant velocity model (CV), which assumes a constant speed with white noise jerk, and the piecewise constant acceleration model (CA), which assumes a constant speed with white noise linear and white noise turn acceleration.” There's also the coordinated turn model (CT), which assumes a constant speed with white noise jerk (1997). According to Schubert and colleagues [17], the bicycle model is a common approximation to represent vehicle dynamics.

Kinematic models are widely used because of their simplicity and good performance under moderate circumstances, such as tracking with low motion uncertainty and short forecast horizons. Both pedestrians and dynamic obstacles may be predicted using linear motion predictions [18], while Kalman filters can be used to forecast dynamic obstacles using a constant acceleration model (Elnagar 2001). “To follow incoming cars from point clouds produced by an in-car stereo camera, Barth and Franke [19] employ the coordinated turn model for one-step forward prediction using an Extended KalmanFilter (EKF).” For one-step vehicle motion prediction in an Unscented KF, Batz et al. [20] adopt a coordinated turn model version based on expected mutual distances between vehicles. According to Newton's laws, motion is characterised by the presence of forces. When describing the mechanics of wheels, gearboxes, engines, or friction effects, these models may get complicated. Other agents' motions are not immediately detectable by sensory data because of the intricacy of the forces that regulate their movement. For motion prediction, dynamic models are more difficult to use. It was determined by Zernetsch et al. [21] that the trajectory of cyclists can be predicted using a dynamic model that incorporates the driving and resisting forces caused by acceleration, slope, rolling, and air. When compared to a normal CV model, long-term predictions up to 2.5 seconds in the future are more accurate empirically. It has also been possible to forecast motion using autoregressive models (ARM), which, unlike first-order Markov models, take into consideration the history of states. Moving obstacles may be predicted using a third-order ARM by Elnagar and Gupta [22], who use maximum likelihood estimate of the ARM parameters. “Second-order ARM motion prediction in a particle filter is used by Cai et al [23] for visual target tracking of hockey players, Zhu (1991) used an autoregressive moving average model as a transition function of a Hidden Markov Model (HMM) to estimate the occupancy probability of moving barriers across several time steps with applications to predictive planning in his early work.” To forecast the target agent's movements, a physics-based model, such as f, is applied to the present state of the target. Only Zhu's [24] work has so far been able to provide predictions that are more than one step in the future, and it does so by ignoring environmental context. Additional forces, model parameters, or state restrictions may be added to the dynamics model f to account for context.

B. Multi-model Approaches

A single dynamical model f fails to capture the complexities of complex agent motion. Such techniques, despite the integration of map information and inputs from numerous actors, remain intrinsically constrained. Modeling the generalized motion of moving objects is often done by combining many prototype motion modes, each characterised by a distinct dynamic regime f. Sequences of motion may be described using a variety of modes, including linear motions, turns, and rapid accelerations. We require strategies to express and reason about motion mode uncertainty since the motion modes of other agents are not immediately visible. Multi-model (MM) and hybrid estimate [25] are the key approaches to this purpose. Continuous-valued (x) is supplemented by discrete-valued modes (s) in the hybrid system state (= (x,s)). Model selection and filter selection are two of the four main components of MM methods. The first is the model set, which is either fixed or adaptive, and the second is a strategy for dealing with discretized uncertainty, such as a Markov or semi-Markov assumption. “Finally, a mechanism is used to generate the overall best estimate from a combination or selection of the individual filters. Prediction is done in a variety of ways using MM approaches, such as including context information from other agents and the map, as well as more complicated motion representations, Cyclists' future motion is predicted using a homogenous blend of five linear dynamic systems (LDS) dynamics-based motion strategies: travel straight, turn 45 degrees or 90 degrees to the left or right, respectively.” If the anticipated route does not follow the topology of the road where it is predicted, the probability of each approach is set to zero. An inference method extensively utilised in tracking [26] and making predictions based on MM models is the interactive multiple model filter (IMM). Examples of such methods include the one proposed by Kaempchen et al.[27], which transitions between constant acceleration and simplified bicycle dynamical models for the assessment of future vehicle states Gaussian noise is explicitly used to describe the following transition's uncertainty. Pedestrian trajectory prediction is made easier by Schneider and Gavrila [28] using an IMM that incorporates numerous motion models (constant velocity, constant acceleration and constant turn). “The technique proposed by Schulz and Stiefelhagen [29] uses an IMM framework with constant velocity, constant position, and coordinated turn models to forecast the future route of a pedestrian.” An intention recognition system based on Latent-dynamic modelling governs model transitions in this study. A person's purpose is characterised as crossing, halting, or moving in the same direction based on the aspects of their dynamics (position and velocity) and situational awareness (head orientation). “For Kuhnt et al [30] an approach that uses pre-defined environment geometry to estimate the potential paths taken by each individual vehicle includes joint vehicle trajectory prediction utilising IMMs as well.” A Bayesian Network used to forecast traffic condition development incorporates contextual interaction limitations.

There are a variety of IMM approaches that take road limits into consideration, such as the variable-structure IMM for ground vehicles [31]. “Kinematics-based consistent turn rate and acceleration and IMM-based lane holding and changing manoeuvres mixing were merged in a recent study by Xie et al [32].” As a consequence of taking into account the route geometry, the approach generates results with various time horizons in mind.

IV. PATTERN-BASED APPROACHES

Instead of depending on clearly stated, parametrized functions, pattern-based approaches may learn motion dynamics from data, as outlined in the "Sense - Learn - Predict" paradigm. “Different function approximators (e.g. neural networks, hidden Markov models, Gaussian processes) are fitted to data in order to learn human motion habits.” Many of the technologies now utilized in robotics and autonomous navigation were initially used in behavior cloning and video surveillance. “Based on the kind of function approximator used, we classify pattern-based methods into one of two categories:”

(1) When employing sequential methods, it is often held that the current state (e.g. position, velocity) is conditionally reliant on a sufficient statistic from the whole history of past states. “If an Nth order Markov model is deemed to be adequate, then a limited state history of N time steps is sufficient for all states in the model”. Denoting the state st+1 as a one-step prediction and a function named "f(stn:t)" are examples of sequential strategies that attempt to develop a one-step predictor based on a sequence of states known as a "sufficient statistic of history." A single long-term trajectory is built up from a succession of shorter-term forecasts that, taken together, project a sequence of state changes.

(2) Two, non-sequential methods don't force a factorization of dynamics (i.e. the Markov assumption) on the data, while sequential models do.

V. CONCLUSION

A detailed investigation of the human motion trajectory prediction issue is presented in this paper. We conduct a literature review in a variety of fields and put out a classification system for motion prediction methods. “It is based on the two main parts of the motion prediction problem: the model of motion and the input context, Trajectory prediction challenges in service robots, self-driving automobiles and advanced surveillance systems are discussed in this paper.” As a final step, we summarised and discussed the state of the art along the lines of three key issues and identified various possible future research paths. The art of foreseeing the future is particularly challenging, as the saying goes. Even after more than two decades of study and the inclusion of more than 200 prediction techniques in our survey, this comment (which has been ascribed to several persons) remains relevant to motion trajectory prediction. This is a fast developing topic, and we hope that our study will raise awareness of it and encourage additional research in the lines described.

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