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INTERACTIVE INTENT ESTIMATION MODEL

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Abstract

With the rise of collaborative robots, the need for safe, reliable, and efficient physical human–robot interaction (pHRI) has grown. High-performance pHRI requires robust and stable controllers suitable for multiple degrees of freedom (DoF) and highly nonlinear robots. In this article, we describe a cascade-loop pHRI controller, which relies on human force and pose measurements and can adapt to varying robot dynamics online. It can also adapt to different users and simplifies the interaction by making the robot behave according to a prescribed dynamic model. In our controller formulation, two neural networks (NNs) in the "outer-loop" predict human motion intent and estimate a reference trajectory for the robot that the "inner-loop" controller follows. The inner-loop imposes a prescribed error dynamics (PED) with the help of a model-free neuroadaptive controller (NAC), which uses a NN to feedback linearize the robot dynamics. Lyapunov stability analysis gives weight tuning laws that guarantee that the error signals are bounded and the desired reference trajectory is achieved. Our control scheme was implemented on a Personal Robot 2 robot and validated through an exploratory experimental study in point-to-point collaborative motion. Results indicate fast convergence of our controller, and the resulting tracking error, motion jerk, and human control effort are comparable with other methods that require prior training, knowledge, and calibration

Keywords: Interaction, intent, model

Introduction: Advanced driving assistance system (ADAS) and autonomous driving system (AD) are expected to be at the center of future transportation systems as well as highly enhance traffic safety. To successfully bring autonomous vehicles (AVs) into our lives, they must be capable of managing complex urban environments, including various participants and complex traffic infrastructure. Among them, intersections are one of the most dangerous urban traffic infrastructures. It is reported that 21.5% of fatalities and even 40% of all accidents in the United States occur at intersections [**1**]. Although recent commercialized vehicles are equipped with ADAS functions, human drivers still need to focus on complex driving situations such as urban intersections. To deal with this, the predict-and-plan approach is typically applied; during the 'predict' step, the ego vehicle integrates numerous signals from sources such as sensors or traffic infrastructure and predicts future actions of several agents in the vicinity. In the planning step, the ego vehicle generates maneuvers based on the trajectory from the predict step. Therefore, the predict step is essential in the entire decision-making process, so several researchers have tried to develop methods to predict the intention of other traffic agents which not only have behavior patterns but also inherent uncertainty.

Recently, most of cars that have been newly released have a certain level of ADAS built into the vehicle. For instance, in the most recently released GV80, Hyundai Motors group provides general ADAS functions such as forward collision-avoidance assist (FCA) and lane keeping assist (LKA) by default. The FCA offers a more diverse range of recognition options, including when a vehicle passes through an intersection or is laterally approaching. It also provides Highway Driving Assist II (HDAII), which includes machine-learning-based adaptive cruise control (ACC), automatic lane change assist when operating direction indicator lamps, and near-field vehicle recognition technology [**2**]. Hyundai Motors Group also announced that they have a plan to mass-produce highway driving pilots (HDPs) in the near future, which enables the vehicle to drive on its own, even if the driver leaves the steering wheel when driving on highways [**3**]. Practically, it is equivalent to SAE (Society of Automotive Engineer) Level 3, which is often compared to Tesla's Navigate on Autopilot (NOA). Tesla's autopilot is capable of steering, acceleration, and deceleration of the vehicle. In addition, the most recently updated feature, NOA, based on autopilot, enables the vehicle to change lanes and overtake other cars using map data [**4**]. As such, the vehicles on the market with most advanced ADAS are assessed to be within the SAE Level 2–3. Now, most of the conventional carmakers and vehicle technology providers are testing AD vehicles that are equivalent to SAE Level 4 within a certain area, and they have claimed that these verified AD vehicles can be used as shuttles and taxis, for example, 'Waymo One' of Waymo [**5**], Google's subsidiary, 'Robotaxi' of Tesla [**6**], and 'Pilot Project' by Mercedes Benz, and Bosch [**7**]. This trend of technological advancement once again confirms that the vehicle's responsibilities are increasing, and the perception and control technology must ensure a certain level.

As stated above, since obtaining effective vehicle behavior analysis is critical for urban autonomous driving, tracking and calculating of the expected trajectory must be conducted. To better estimate the trajectory of vehicle movement, the performance of the state of estimation algorithms is one of the most significant factors. Thus, various approaches that have been theorized in literature have been tested, such as dynamic Bayesian networks (DBN), hidden Markov models (HMM), support vector machines (SVM), interacting multiple model (IMM), and vehicle-to-vehicle (V2V) communication [**8**,**9**,**10**,**11**,**12**]. Traditional learning methods like DBN and HMM are frequently used since they are simple, fast, and do not require lots of data to become trained [**13**]. For instance, S. Lefèvre et al. uses DBN, combining probabilistically uncertain observations on the vehicle's behavior and local characteristic information to estimate driver maneuvers [**14**]. In addition, Streubel et al. proposed a prediction framework based on HMM using a database of real driving data such as speed, acceleration, and yaw rate [**15**]. As a discriminative approach, SVM is used as a learning framework for binary classification. Aoude et al. present a comparison and validation of performances of SVM, HMM, and other traditional approaches consisting of TTI-, RDP-, and SDR-based algorithms [**16**]. In recent years, along with the advancement of information and communication technologies, V2V communication is often applied to the prediction protocol. Aoki et al. introduce a decentralized intersection protocol for mixed traffic environments where all automated vehicles use V2V communications [**17**]. Since this information-driven control research area is active, not only V2V but also vehicle-to-infrastructure (V2I), vehicle-to-pedestrian (V2P), technologies are arousing interest.

As stated above, the IMM algorithm is a method used to determine the expected target trajectory in selecting among filter models derived from the behavior of targets. To select the best hypothesis, the IMM consists of four main steps: interaction, filtering, update, and combination. At the interaction step, the initial values of each model for the filtering step are calculated by receiving signals from sensors. These initial values are transferred to the filtering step. In the filtering step, each model independently conducts the calculation and deduces the state prediction. Typically, a Kalman filter (KF) is applied at this step. Then, the probabilities of models are updated at the update step, and by combining the probabilities and sending them to the interaction step again at the combination step, one cycle of the IMM is finished.

Since the IMM was introduced in the late 1980s, it is generally known and has been implemented on a wide range of conditions. Tsunashima et al. used IMM to estimate vehicle state differing road friction [**18**]. Rubin et al. illustrate that the noble IMM estimator works accurately with the external disturbances and inputs of steering [**19**]. As the IMM is verified in plenty of conditions, the IMM algorithms are also often modified. Wang et al. presents an adaptive IMM which utilizes the models for an adaptive turn rate in order to track a target for maneuvering [**20**]. In addition, the IMMs are classified depending on how they use multi-model fusion criteria as scalar weight IMM (SIMM), diagonal-matrix-weight interacting multiple model, and matrix weight interacting multiple model [**21**,**22**]. These new approaches weigh differently when mixing beginning model values with states and corresponding covariances at each step of the IMM algorithm. Fu et al. also introduced $H\infty$ filtering into the distributed interacting multiple model (DIMM) algorithm instead of KF, for target tracking of maneuvering during which the measurement noise is statistically unknown [**23**]. Park et al. propose a new algorithm suitable for multi-object tracking using multi-data fusion by applying centralized KF to a typical IMM. Since it is reasonable and easily adaptable, the IMM is applied in a variety of fields which require tracking of the maneuvering target. The

IMM filter is often applied in aircraft tracking problems, such as in the study by Li et al. [**24**]. Tong et al. used IMM for 3D human motion tracking [**25**]. For application to autonomous vehicles, an IMM filter that integrates market commercial GPS and vehicle local sensors is implemented to develop a vehicle localization algorithm [**26**]. Since the IMM algorithm is incorporated in both the kinematic and dynamic model of the vehicle, the positioning performance is improved demonstrating high accuracy under the various driving conditions.
Thanks to the advantages described above, we propose an intersection-target-intent estimation algorithm based on IMM [**27**].
In this research, we focus on the target intent estimation algorithm at urban intersections, and the paper is structured as follows. The next section demonstrates use of the intersection driver behavior model to represent the intent of the driver's maneuvering at the intersection. In **Section 3**, an IMM-based target intent classification algorithm is demonstrated by reflecting continuity of driver behavior while improving the accuracy of state prediction. The target intent estimation algorithm for urban intersections is verified via simulation studies in **Section 4**. Finally, conclusions are provided in **Section 5**.

1.1 The role of Pro-search Context in Exploratory Information-seeking

A ' context' can be defined as a description of aspects of a situation and an internal representation in the cognitive state of knowledge. In ideal information system, context technology mechanism captures the concepts and relation and co-relation among in different user contexts, which is easy to reuse across searches/domains. Context information can be used to facilitate the communication in human-computer interaction [49]. The use of context is becoming important in interactive computing. Recently, there has been much discussion about the meaning and definition of context and context -awareness. However, this kind of information (context) is still not utilized much and the concept of context is not yet well understood or defined. Additionally, there exists no commonly accepted system that supports the acquisition, manipulation and exploitation of context including information units and data [49].
When discussing the information retrieval process, often the focus is on the individual activities such as formulating queries, searching document collections and presenting returned documents. However, there are situations where we need to go beyond analyzing these individual activities in isolation, and consider the groups of these activities. Traditionally, nearly 60% of users had conducted more than one information retrieval (IR) search for the same information problem. In their research, they refer to the process of repeatedly searching over time in relation to a specific but possibly evolving information problem as the successive search phenomenon.
Contextual information plays a more important role in the study of successive searches than that of isolated searches since the contexts behind a series of successive searches are probably closely related to each other, if not the same. However, finding contextual information is a complex, even for successive searches. Previous studies have demonstrated that less information is available about the users and their information needs, not to mention the fact that searches are shorter and search statements contain fewer terms than their counter parts in traditional IR searches. An individual retrieval task may be informative sometimes, but a collection of search activities provides much more information about the topic and the context if they are organized according to their time order and related search topic. It is likely that consecutive activities related to one topic can share the same context. It is, therefore, reasonable to say that the information about search topics is an important component of the context behind the users' searches or retrieval need.
For example, a search for the word "Jaguar" should return car-related information if performed from a document on the motoring industry, and should return animal-related information if performed from an Internet website about endangered wildlife. Guiding user's search by the context surrounding the text eliminates possible semantic ambiguity and vagueness.
Keyword-based search engines are in widespread used today as a popular means for Web-based information retrieval [51, 110]. Although such systems seem deceptively simple, a

considerable amount of skill is required in order to satisfy non-trivial information needs. The thesis presents a new conceptual paradigm for performing search in context that largely automates the search process, providing even non-professional users with highly relevant results. This paradigm is implemented in practice in the proposed system 'IIM', where search is initiated from a text query marked by the user in a document she views, and is guided by the text surrounding the marked query in that document ("the context"). The context-driven information retrieval process involves semantic keyword extraction and clustering to automatically generate new, augmented queries. The latter are submitted to a host of general and domain-specific search engines. Search results are then semantically re-ranked, using context. The experimental results testify that using context.

In the thesis, an interactive intent-model based exploratory search system is designed and referred to as 'IIM'. Here, a client application running on the user's computer captures the context around the text highlighted by the user. The server-based algorithms analyze the context, via selecting the most important document and eventually, keywords/terms. The 'IIM' system assists the user to modify the intent to which context guides any given search, by modifying the amount of context considered. The context can be reliably classified to a predefined set of search states. A dedicated re-ranking module ultimately reorders the results received from all of the engines, according to semantic proximity between their summaries and the original context. Systems as an information specialist acting on behalf of the user, which automatically performs the search steps, from query expansion, to search engine selection, to re-ranking the results.

The proposed system, adapts the significance of the new context-based approach lies in the improved relevance of search results even for users not skilled in Web search. We achieve this by applying natural language processing techniques to the captured context in order to guide the subsequent search for user-selected text. Existing approaches, either analyze the entire document the user is working on, or ask the user to supply a category restriction along with search keywords. As opposed to these, our proposed method automatically analyzes the context in the immediate vicinity of the focus text. This allows analyzing just the right amount of background information, without running over the more distant (and less related) topics in the source document. The method also allows collecting contextual information without conducting an explicit dialog with the user.

1.2 Intent Estimation for Exploratory Information-seeking

The 'Intent' is a topical dimension of user search and characterizes 'why' the user is searching, and 'how' his search evolves during search progression [76]. Characteristically, intent defined as 'immediate reason, purpose, or goal' that motivates a user to initiate or conduct a search [88] and co-exist in three aspects, i.e. Pre-search, In-search and Pro-search of the user search context. A significant fraction of user searches is influenced by the user's primary search aim i.e. 'Pre-search' context and others due to intermediate query or result in understanding 'In-search' context. An ideal information system would be able to predict the estimation of future intent (also known as 'Pro-search' context) based on the captured 'Pre-search' and 'In-search' context. The prediction of search context of futuristic search 'Pro-search' requires identification of co-relations between all three aspects of user search, therefore understanding 'why' users start searches and 'how' to predict search intent are multifaceted tasks [33, 134].

The primary focus of Information system (IS) systems has been to optimize the user-centric information retrieval and supplement the interaction related support. Conventional retrieval strategies are primarily based on term statistics, e.g. term-frequencies, inverse-document frequencies, document lengths, for the retrieval and subsequent ranking of the query results [23,30, 101]. Intuitively, the proximities instances of query terms within matched results or document can also be utilized, and proximity score could be amalgamated with traditional document-term based score in retrieval framework.

1.3 Proposed Retrieval Framework and Intent Estimation Model

The proposed strategy assigns more weights on exploration aspects, during initial iterations of data retrieval, and adapts to the best-efforts matching, rather exact matching. The focal point of retrieval shifts towards exploitation of related data objects, in later stages, eventually to extract highly related objects. Each intermediate user search interactions are utilized to solve the exploration/exploitation tradeoffs, and incorporated into search intent estimate. Figure 1.1 shows the evolution in the exploitation-exploration circle for a user query with retrieved objects.

In initial algorithmic iterations, the focuses is on exploration rather exploitation, as a user is uncertain of real search needs thus retrieval on the best-efforts basis is prompt. Later, the exploration circle is spanned in larger than exploitation circle, to indicate the user's state of knowledge on the current search, and this growth indicates the enhanced state of knowledge of the users' search needs, and eventually end up to a narrowed exploration circle, which implies the lesser space of uncertainty. Though, data objects under exploration circle are potential to navigate the search towards new search interest.

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