If and When a Driver or Passenger is Returning to Vehicle: Framework to Infer Intent and Arrival Time

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Abstract—This paper proposes a probabilistic framework for the sequential estimation of the likelihood of a driver or passenger(s) returning to the vehicle and time of arrival, from the available partial track of the user’s location. The latter can be provided by a smartphone navigational service and/or other dedicated (e.g., RF based) user-to-vehicle positioning solution. The introduced novel approach treats the tackled problem as an intent prediction task within a Bayesian formulation, leading to an efficient implementation of the inference routine with notably low training requirements. It effectively captures the long term dependencies in the trajectory followed by the driver/passenger to the vehicle, as dictated by intent, via a bridging distribution. Two examples are shown to demonstrate the efficacy of this flexible low-complexity technique.

Index Terms—Intelligent vehicles, object tracking, intent prediction, connected vehicles.

I. INTRODUCTION

A. Background and Motivation

The recent advances in sensing, data storage as well as processing and communications technologies led to the proliferation of intelligent vehicle functionalities and services. This includes Advanced Driver Assistance Systems (ADAS) [1], [2], route guidance [3], [4], driver inattention monitoring [5] and many others [6], [7]. Additionally, whilst the current growing interest in autonomous cars brings a myriad of new technical and human factor challenges [8], [9], it has encouraged expediting the development and adoption of smart vehicle services and their associated technologies. In particular, there has been a phenomenal growth of research into realising a connected cooperative vehicle environment [10], [11], which is key to the success of autonomous driving as well as enhancing transportation efficiency and safety. This encompasses vehicle to vehicle, vehicle to infrastructure, vehicle to devices and vehicle to cloud communications, imposing new requirements on in-vehicle systems and the supporting infrastructure.

Within the context of intelligent vehicles, perhaps in a connected set-up, there are substantial benefits to be gained from determining if and when the driver or passenger(s) is returning to vehicle, as early as possible and before the start of a journey. For instance, it can enable the:

1) timely adaption of the car interior to a priori learnt preferences or driver/passenger(s) profiles (e.g., adjusting seats and pre-configuring the infotainment system, adapting the HMI, warming/cooling vehicle, etc.); thereby delivering a personalised, safer and more pleasant driving experience,

2) efficient activation and/or priming of the key-fob scanner (e.g. for key-less entry or engine start) and exterior-facing vehicle sensors (e.g. cameras for driver/passenger recognition), which can also improve their security features, to name a few.

In this paper, we address the problem of establishing the intent of a driver or passenger (i.e., whether returning to car) and estimating time of arrival from his/her available partial location trajectory, possibly in a connected vehicle environment. This track can be provided by the user’s smartphone Global Navigation Satellite System (GNSS) service or a dedicated user-to-vehicle positioning solution.

B. Contributions

The problem of determining if and when a driver/passenger is returning to vehicle is tackled here within a Bayesian object tracking framework. However, it is emphasised that the objective in this paper is inferring the user’s intent and not accurately estimating his/her position or velocity, as is common in classical tracking applications [14]–[16]. Consequently, a novel simple prediction solution with notably low training requirements, unlike typical data-driven methods [17], is proposed. It facilitates the incorporation of contextual information such as the user’s (learnt) patterns of behaviour, time of day, location, calendar events, etc. Furthermore, it caters for variabilities in the driver/passenger motion en route to the vehicle via assuming a stochastic motion model. The adopted formulation can also treat irregularly spaced and imprecise user location measurements via a continuous-time observations model with a random noise component. Therefore, it is a generic and considerably flexible framework.

The proposed approach capitalises on the premise that the trajectory followed by the driver or passenger has long term underlying dependencies dictated by intent, e.g. returning to the vehicle. Accordingly, a Markov bridge, to the endpoint (i.e. vehicle) of a known location, is built to capture these dependencies in the user’s motion track. If the driver/passenger is not returning to the vehicle, no such bridging is introduced. This postulates the addressed inference task as a hypothesis testing problem, leading to an efficient implementation of the intent prediction procedure. It is shown here that utilising modified Kalman filters suffices, including for the time of arrival estimation. Given the none experimental nature of this
paper and the large number of possible scenarios (e.g. car park layouts, nearby vehicles or obstacles and others), results for two example smartphone GNSS trajectories are presented to illustrate the usefulness and effectiveness of the introduced technique.

C. Paper Layout

The remainder of this paper is organised as follows. Related work is highlighted in Section II and the tackled inference problem is stated in Section III. The proposed Bayesian framework and inference routine are described in Sections IV and V, respectively. Several key considerations are outlined in Section VI and the predictor performance is assessed in Section VII. Finally, conclusions are drawn in Section VIII.

II. RELATED WORK

Knowing the destination of a tracked object (e.g. a pointing apparatus, pedestrian, vehicle, jet, etc.) can offer vital information on intent, enabling smart predictive functionalities and automation. It has numerous application areas comprising, but not limited to,

- Human computer interaction (HCI): early predictions of the on-display item the user intends to select significantly reduces the interactions effort, e.g. whilst driving [18].
- ADAS: predicting maneuvers at intersections [19], pedestrians motion [20], [21], driver behavior [22], etc.
- Surveillance: inferring an object intent (e.g. ship in maritime applications [23], [24]) can unveil potential conflict, opportunities and facilitate automated decision making.
- Robotics: intelligent navigation in general or in the presence of other moving agents such as people [25]–[27].

Several studies in the object tracking area consider the task of incorporating predictive, often known, information on the object’s destination to improve the accuracy of estimating its state $x_t$ (e.g. the object’s position, velocity and higher order kinematics), hence destination-aware tracking [28]–[30]. Furthermore, a plethora of well-established techniques for estimating $x_\tau$ from noisy sensory observations, including the data fusion aspect, exist [14]–[16]. This is referred to by conventional sensor-level tracking. In this paper, we treat the problem of predicting the intent of a tracked object (i.e. driver or passenger) and not estimating $x_\tau$, e.g. his/her position. This operation belongs to a higher system level, thus meta-tracking, compared with the sensor-level algorithms.

A destination-aware tracker with an additional mechanism to determine the object’s intended endpoint is described in [30]. It employs discrete stochastic reciprocal or context-free grammar processes. The state $x_\tau$ space is discretised into predefined regions, which the object can pass through on its journey to destination. This discretisation can be a burdensome complex task, especially if the surveyed space is large. In contrast, in this paper we adopt continuous state space models with bridging distributions, which do not impose any restrictions on the path the object has to follow to its endpoint. It is a simple low-complexity Kalman-filtering-based solution compared with that in [30].

Various data driven prediction-classification methods that rely on a dynamical model and/or pattern of life learnt from previously recorded tracks exist, e.g. [19]–[22], [25], [26]. Whilst such techniques typically involve substantial parameters training from complete labelled data sets (not always available) and have high computational cost, a state-space modelling approach is introduced here. It uses known stochastic motion and measurements models, albeit with a few unknown parameters, as is common in the object tracking area [14]–[16]. We then propose effective predictors, which are computationally efficient and require minimal training. The latter aspect is essential in the studied automotive application since building a sufficiently large and diverse data set of a user approaching a vehicle in a given area such as a car park, i.e. for model learning, can be exceptionally challenging. This is due to the dynamically changing environment, e.g. other parked cars, start position of the user, followed route and even the utilised parking space. It is distinct from set-ups where a pedestrian moves in a confined space of limited viable paths.

Finally, bridging-distributions-based inference was used in [31], [32], mainly for HCI applications. It assumes that the tracked object (e.g. pointing finger in HCI) is heading to one of $N$ possible endpoints of known locations (e.g. selectable icons on a touchscreen). Accordingly, $N$ bridges are constructed to capture the destination influence on the object’s motion. In this paper, a new application related to intelligent vehicles is considered. Most importantly, the scenario where the driver/passenger intended destination is unknown (i.e. not returning to vehicle) is addressed here unlike in [31], [32]; it is dubbed the null hypothesis. This alters the overall problem formulation and subsequently the prediction procedure.

III. PROBLEM STATEMENT

For the $n^{th}$ driver or passenger, the objective is to calculate the probabilities of the following two hypotheses:

$$\mathcal{H}_{0,n}: \text{User } n \text{ is returning to the vehicle},$$
$$\mathcal{H}_{1,n}: \text{User } n \text{ is not returning to the vehicle},$$

and estimate the time $T_n$ she/he reaches the car, i.e. posterior $p(T_n | y_{1:k,n}, \mathcal{H}_{1,n})$ from the available (noisy) measurements of the user’s position $y_{1:k,n}$. Observation $y_{k,n}$ is the 2-D or 3-D coordinates of driver/passenger at the time instant $t_k$, possibly relative to the vehicle. Measurements $y_{1:k,n} = \{y_{1,n}, y_{2,n}, \ldots, y_{k,n}\}$ pertain to the sequential times $\{t_{1,n}, t_{2,n}, \ldots, t_{k,n}\}$. They can be provided by the user’s smartphone GNSS-based or Pedestrian Dead Reckoning (PDR) services and/or any other specialised (proprietary) user-to-vehicle localisation solution. This encompasses vision-based systems and those reliant on existing or dedicated RF technology, e.g. from on/in-vehicle transceivers such as Bluetooth Low Energy (BLE), ultra-wideband, RFID/NFC and others [33]–[39]. This location information can be also based on a suitably equipped (smart) key-fob or any portable device. In general, the proposed approach is agnostic to the employed user-vehicle-positioning solution and can handle noisy irregular spaced observations; see Section IV-D.

We assume that the location of the destination, i.e. vehicle, is known to the inference module, for instance from the vehicle navigation system. To maintain the Gaussian nature
of the formulation and for simplicity, the vehicle is defined by
the multidimensional Gaussian distribution $V \sim \mathcal{N}(a_v, \Sigma_v)$. Whilst
the mean vector $a_v$ specifies the location/centre of the
vehicle, the covariance matrix $\Sigma_v$ (of appropriate dimension)
sets its extent and orientation.

Posteriors $p(H_{d, n}|y_{1:k,n})$, $d = 1, 2$, and $p(T_n|y_{1:k}, H_{t,n})$
are calculated at the arrival of a new observation, hence a
sequential implementation is desired. Additionally, computa-
tional efficiency is crucial to achieve a (near) real-time
response. This is especially critical to smartphones-based
implementation given the ubiquity of their location-based
services. Nevertheless, in a connected vehicle environment,
computations can be performed by the vehicle and/or cloud.
It is noted that the “$n$” subscripts are omitted in the remainder
of this paper for notation brevity.

IV. BAYESIAN FRAMEWORK: MODELLING AND BRIDGING

Within a Bayesian formulation, we have

$$p(H_d|y_{1:k}) \propto p(y_{1:k}|H_d)p(H_d), \quad d = 1, 2,$$

where $p(H_d)$ is the prior on whether a driver/passenger is
returning to the vehicle; it is independent of the current
walking track $y_{1:k}$. This prior can be attained from relevant
textual contextual information $I$, such as the time of day, location
of the vehicle, previous driving times, calender, etc. It can be
linked to $I$, i.e. $p(H_d; I)$. Prior $p(H_d; I)$ can be obtained from
another system (or even from the cloud in a connected set-up)
where the user travel habits can be learnt from historical data,
e.g. based on the smartphone GNSS tracks as in [40], [41].
It can also be gradually and dynamically learnt as the system
is being used, starting from uninformative ones where both
hypotheses are equally probable in equation (2).

This makes the introduced framework particularly appealing
as additional information (when available) can be easily
incorporated. Therefore, the objective of the inference module
becomes estimating the observation likelihoods $p(y_{1:k}|H_d)$,
$d = 1, 2$ in (2).

A. Motion Models

The driver/passenger walking motion towards the vehicle
or under $H_0$ is not deterministic. It is governed by a com-
plex motor system and is likely to be subjected to external
factors such as obstacles. Stochastic continuous-time models,
which represent the motion dynamics by a continuous-time
Stochastic Differential Equation (SDE), are a natural choice
to suitably include the present uncertainties. This is under
the premise that the intent influence on the object’s motion
is captured, e.g. via bridging as in Section IV-C. Here, no
detailed map of the environment is assumed to be available
since obstacles (e.g. other vehicles) or moving agents (e.g.
pedestrians) can dynamically change in a car park.

It is noted that the objective in this paper is not to
accurately model the walking behaviour of a pedestrian. A motion
model that facilitates determining the probabilities of the
driver/passenger returning to the vehicle suffices, how-
ever being approximate, for instance to reduce the predic-
tion/estimation complexities. Consequently, Gaussian Linear

Time Invariant (LTI) motion models are applied below as
they lead to a computationally efficient predictors, compared
with non-linear and/or non-Gaussian models [15], [16], [42].
Upon integrating the SDE, the relationship between the system
state $x_k$ of dimension $s \times 1$ (e.g. the drive/passenger position,
velocity, etc.) at times $t_k$ and $t_{k-1}$ can be written as

$$x_k = F(h)x_{k-1} + M(h) + e_k,$$

with $e_k \sim \mathcal{N}(0,Q(h))$ is the dynamic noise embodying
the randomness in the motion. Matrices $F$ and $Q$ as well as vector
$M$, which together define the state transition from one time
to another, are functions of the time step $h = t_k - t_{k-1}$.

The class in (3) encompasses many models used widely
in tracking applications, such as the (near) Constant Velocity
(CV) or constant acceleration and others that can describe
higher order kinematics. For a CV model in 2-D, $x_k \in \mathbb{R}^4$,
s = 4 for the position and velocity in each dimension. Models
that intrinsically depend on an endpoint, such as the Linear
Destination Reverting (LDR) models [32], are covered by (3),
for example the mean reverting diffusion model (based on an
Ornstein-Uhlenbeck process), with its mean equal to $a_v$.

In general, models, including Gaussian LTI, which better
represent the walking behaviour produce more accurate pre-
dictions as well as estimations of the system state $x_k$. We
recall that estimating $x_k$ is not sought here. Accurate modelling
of a pedestrian walking behaviour is currently receiving notable
attention due to the growing interest in PDR and indoor
positioning from smartphones sensory data [33]–[35].

B. Observation Model

To preserve the linear Gaussian nature of the system, the $k^{th}$
observation of the user position at $t_k$, is modelled as a linear
function of the state perturbed by additive Gaussian noise

$$y_k = Gx_k + \nu_k,$$

where $G$ is a matrix mapping from the hidden state to the observed measurement and $\nu_k \sim \mathcal{N}(0,V_k)$. For example, if
the smartphone GNSS service provides the driver/passenger
2-D position and the system state $x_k$ comprises only position,
then $G$ is a $2 \times 2$ identity matrix. The noise covariance can be
utilised to set the level of measurements noise in each axis.No
assumption is made about the observation arrival times $t_k$ and
irregularly spaced measurements can naturally be processed.

C. Bridging Distribution

For hypothesis $H_1$, the path followed by the
driver/passenger, albeit random, must end at the intended
destination at time $T$ (i.e. he/she reaches the vehicle). This
can be modelled by a pseudo-observation $\hat{y}_T$ at $T$ or an
artificial probability distribution for $x_T$. This prior is equal
to that of the destination $V$ and its geometry modelled by
$\mathcal{N}(a_v, \Sigma_v)$. Its inclusion entails the conditioning of the
motion state model in (5) not only on $V$, but also on the
unknown arrival time $T$. This permits the posterior of the
system state at time $t_k$ to be expressed as $p(x_{k} | y_{1:k}, T, H_1)$,
and hence the observation likelihood $p(y_{1:k} | T, H_1)$ in (2).

The incorporation of this destination prior changes the
system dynamics, where the predictive distribution of the
user’s state changes from a random walk (i.e. with respect to the endpoint) to a bridging distribution, terminating at the vehicle. This encapsulates the long term dependencies in the walking trajectory due to premeditated actions guided by intent as depicted in Figure 1 where endpoint \( \mathcal{V} \) drives the state throughout the walking-to-vehicle action. In other words, it constructs a bridge between the state at \( t \) and destination at \( T \). The approach of conditioning on an endpoint is dubbed bridging distributions (BD) based inference. Thus, Gaussian linear models, whose dynamics are not dependent on the destination \( \mathcal{V} \sim \mathcal{N}(a_v, \Sigma_v) \), e.g. Brownian motion (BM) and CV, can be utilised for intent prediction within the presented Bayesian framework. On the other hand, the motion of the \( \text{CV} \), can be utilised for intent prediction within the presented (BD) based inference. Thus, Gaussian bridging distributions form a bridge between the state at \( t \) and terminates at the \( x_{16} \), via premeditated actions guided by intent (e.g. Brownian motion (BM) and CV) conditioning on the intended endpoint, e.g. vehicle. This encapsulates the long term dependencies in the walking trajectory due to premeditated actions guided by intent.

To demonstrate the impact of incorporating the destination prior on the motion model, the predictive position distributions of the BM and CV models, with and without the use of bridging, are depicted in Figure 2. The figure considers a one dimensional case where the endpoint value is 16 m at time \( T = 20s \). It shows the mean and one standard deviation of the predicted position for \( t^* > t_1 \) such that \( t_1 = 0 \) is the current time instant. It can be noticed in Figure 2 that introducing the bridging assumption has a significant effect on the prediction results. For the non-bridged cases, the prediction uncertainty grows (arbitrarily) as \( t^* \) increases. This illustrates the ability of bridging distributions to promote more accurate predictions of the intended endpoint, e.g. vehicle.

V. INTENT PREDICTION

Here, we detail the means to calculate the sought observation likelihoods \( p(y_{1:k} | \mathcal{H}_d) \), \( d = 1, 2 \), in \ref{eq:likelihood} and time of arrival posterior. The overall inference routine is shown in Figure 3.

A. Hypothesis \( \mathcal{H}_0 \): Not Returning to Vehicle

The observation likelihood in \ref{eq:likelihood} relates to the conditional Prediction Error Decomposition (PED), which is defined by \( p(y_k | y_{1:k-1}, \mathcal{H}_0) \), via

\[
p(y_{1:k} | \mathcal{H}_0) = p(y_k | y_{1:k-1}, \mathcal{H}_0)p(y_{1:k-1} | \mathcal{H}_0), \tag{5}
\]

for hypothesis \( \mathcal{H}_0 \), i.e. without conditioning on \( \mathcal{V} \) (bridging). Based on \ref{eq:likelihood} and \ref{eq:ped}, a Kalman filter (KF) can be conveniently utilised to calculate the PED \ref{eq:ped}, recalling the Gaussian LTI nature of the motion and observation models. This is distinct from the common uses of KF in tracking application, i.e. to estimate the state \( x_k \) and its posterior \ref{eq:ped}. The likelihood \( p(y_{1:k-1} | \mathcal{H}_0) \) in \ref{eq:likelihood} is calculated at the previous time instant \( t_{k-1} \), given the filter’s recursive nature.

B. Hypothesis \( \mathcal{H}_1 \): Bridging Distribution

Similar to \( \mathcal{H}_0 \), the PED under hypothesis \( \mathcal{H}_1 \) is sought. Conditioning on the destination \( \mathcal{V} \) also entails conditioning on the time of arrival \( T \). One approach to introduce this conditioning is by augmenting the system state \( x_k \) with the prior \( \mathcal{N}(a_v, \Sigma_v) \) forming an extended state \( z_k = [x_k', x_T']' \) of dimension \( 2s \times 1 \). This can be shown to lead to the extended linear Gaussian state model

\[
z_k = R_k z_{k-1} + \tilde{m}_k + \gamma_k, \tag{6}
\]

where \( \gamma_k \sim \mathcal{N}(0, \bar{U}_k) \). \( \bar{U}_k = \begin{bmatrix} 0_s & I_s \end{bmatrix} \),

\[
R_k = \begin{bmatrix} H_k \end{bmatrix}, \quad \tilde{m}_k = \begin{bmatrix} m_k \end{bmatrix}, \quad \bar{U}_k = \begin{bmatrix} C_k & 0_s \\ 0_s & 0_s \end{bmatrix}, \tag{7}
\]

\[
H_k = \begin{bmatrix} C_k Q^{-1}(\tilde{h}) F(\tilde{h}) \\ C_k F'(\tilde{h}) Q^{-1}(\tilde{h}) \end{bmatrix}, \quad \bar{h} = T - t_k,
\]

\[
m_k = C_k (Q^{-1}(h) M(h) - F'(\tilde{h}) Q^{-1}(\tilde{h}) M(\tilde{h})), \quad Q(\cdot) \text{ is from equation } \ref{eq:likelihood}.
\]

The observation model of dimension \( k \times 1 \) (e.g. \( k = 2 \) for 2-D GNSS observations) can then be expressed by

\[
y_k = \tilde{G} z_k + \nu_k \tag{8}
\]

with \( \tilde{G} = [G, 0_{k \times s}] \) and where \( G \) and \( \nu_k \) are from \ref{eq:likelihood}.

Therefore, the extended system described by equations \ref{eq:extended_system} and \ref{eq:observation_model} form a Gaussian LTI system. A modified Kalman filter
can then be applied to obtain the time-of-arrival-conditioned PED defined by \( p(y_k \mid y_{1:k-1}, \mathcal{H}_1, T) \) at \( t_k \) and the likelihood \( p(y_{1:k} \mid \mathcal{H}_1, T) = p(y_k \mid y_{1:k-1}, \mathcal{H}_1, T)p(y_{1:k-1} \mid \mathcal{H}_1, T) \) can be subsequently obtained.

However, the arrival time is unknown in practice and typically a prior distribution on \( T \) can be assumed, e.g. from contextual data. Hence, the unknown arrival time \( T \) is treated as a nuisance parameter, which must be integrated over as per

\[
p(y_{1:k} \mid \mathcal{H}_1) = \int_{T \in \mathcal{T}} p(y_{1:k} \mid \mathcal{H}_1, T)p(T \mid \mathcal{H}_1)dt,
\]

where \( p(T \mid \mathcal{H}_1) \) is the a priori distribution of arrival times and \( \mathcal{T} \) is the time interval of possible arrival times \( T \). For example, arrivals might be expected uniformly within some time period \([t_a, t_b] \), giving \( p(T \mid \mathcal{H}_1) = \mathcal{U}(t_a, t_b) \), for instance when the user is within a certain proximity of the vehicle.

Since the integral in (9) cannot be easily solved analytically for all \( t_k \) values, a numerical approximation is applied. This is viable since the arrival time is a one-dimensional quantity. Here, numerical quadrature such as Simpson’s rule, denoted by \( \text{quad}(\cdot) \), is utilised; other numerical methods can be employed. This approximation requires \( q \) evaluations of the arrival-time-conditioned-observation likelihood for the various arrival times \( T_i \in \mathcal{T} \) and \( \mathcal{T} = \{T_1, T_2, ..., T_q \} \), i.e. \( q \) is the number of quadrature points.

Algorithm 1 details the filtering procedure at \( t_k \) where \( \ell_{k,i} = p(y_k \mid y_{1:k-1}, \mathcal{H}_1, T = T_i) \) is the PED for arrival time \( T_i \) and similarly \( L_{k,i} \) is the arrival-time-conditioned-observation likelihood. It is based on Kalman filtering, notated by KF(\( . \)). The filtering is performed \( q \) times at \( t_k \) to estimate \( p(y_{1:k} \mid \mathcal{H}_1) \) in equation (3). This inference approach is particularly amenable to parallelisation, where the calculation of each \( \ell_{k,i} \) and \( L_{k,i} \) can be carried out by a separate computational unit; this is relevant to distributed implementations in a connected vehicle environment; see Section VI.

For simplicity and at time \( t_1 \), the Kalman filtering initialisation for \( \mathcal{H}_1 \) (not shown in Algorithm 1) can be based on

\[
p(z_1 \mid T, \mathcal{H}_1) = \mathcal{N}\left( 0, \Sigma_0 \right),
\]

(10)

where \( \mu_1 \) and \( \Sigma_1 \) specify the initial prior on \( x_1 \), thereby \( p(x_1) = \mathcal{N}(x_1; \mu_1, \Sigma_1) \); \( a_c \) and \( \Sigma_c \) come from the endpoint prior \( V \) assuming independence between \( x_1 \) and \( y \).

After determining the probabilities of both hypotheses according to their calculated observation likelihoods and priors, they are normalised to ensure that their sum to 1 as per:

\[
\hat{p}(\mathcal{H}_d | y_{1:k}) = \frac{p(\mathcal{H}_d | y_{1:k})}{p(\mathcal{H}_d | y_{1:k}) + p(\mathcal{H}_1 | y_{1:k})}, \quad d = 1, 2.
\]

(11)

Algorithm 1 Estimating Probability of Hypothesis \( \mathcal{H}_1 \) at \( t_k \)

**Input:** \( y_k, z_{k-1,i}, \Sigma_{k-1,i}, L_{k-1,i}, i = 1, ..., q \) for quadrature point \( i \in 1, ..., q \)

Calculate \( R_k^i, U_k^i \) at \( t_k \) in (7), and arrival time \( T_i \)

Run Kalman filter:

\[
\{ \ell_{k,i}, \hat{z}_{k,i}, \Sigma_{k,i} \} = \text{KF}(y_k, z_{k-1,i}, \Sigma_{k-1,i}, R_k^i, U_k^i, \hat{G})
\]

Recursive Likelihood Update:

\[
L_{k,i} = \text{quad}(L_{k,1}, L_{k,2}, ..., L_{k,q}) \approx p(y_{1:k} \mid \mathcal{H}_1)
\]

end for

C. Estimating Time of Arrival

The filtering results for inferring the probability of hypothesis \( \mathcal{H}_1 \) in Algorithm 1 can be also be readily utilised to estimate the posterior distribution of the time of arrival of the user at the vehicle as illustrated in Figure 3. It is given by

\[
p(T \mid \mathcal{H}_1, y_{1:k}) \propto p(y_{1:k} \mid T, \mathcal{H}_1)p(T \mid \mathcal{H}_1),
\]

(12)

where \( p(T \mid \mathcal{H}_1) \) is the prior on the arrival time. Prior \( p(T \mid \mathcal{H}_1) \) can be also attained from contextual information including pervious journeys in a given location or the user proximity to the vehicle as provided by a localisation module.

The quadrature procedure is applied to approximate the integral in (9) and estimating the likelihood \( p(y_{1:k} \mid \mathcal{H}_1) \) necessitates calculating the arrival-time-conditioned likelihood \( p(y_{1:k} \mid T = T_i, \mathcal{H}_1) \), for a number of quadrature points \( T_i \). As a result, a discrete approximation of the overall posterior can be obtained via

\[
p(T \mid \mathcal{H}_1, y_{1:k}) \approx \sum_{i=1}^{q} w_i \delta(T_i),
\]

(13)

where \( \delta(T_i) \) is a Dirac delta located at the \( i \)-th quadrature point \( T_i \). To ensure that this approximate posterior distribution in (13) is a valid probability distribution that integrates to 1, it is normalised as per

\[
w_i = \frac{p(y_{1:k} \mid T = T_i, \mathcal{H}_1)p(T_i \mid \mathcal{H}_1)}{\sum_{i=1}^{q} p(y_{1:k} \mid T = T_i, \mathcal{H}_1)p(T_i \mid \mathcal{H}_1)}.
\]

(14)

Thus, the 1-D posterior distribution of the arrival time at the vehicle can be calculated without significant further calculations beyond the already performed filtering operations. Point estimates of \( T \) can be attained, e.g. via a Maximum a Posteriori (MAP) criterion.
D. Decision

Having determined the sought probabilities \( p(\mathcal{H}_d|y_{1:k}) \), a decision on whether the user is returning to a given entity is taken upon minimizing a cost function according to

\[
\hat{\mathcal{H}}(t_k) = \arg\min_{\mathcal{H}_d \in \mathcal{H}} E \left[ C(\mathcal{H}_d, \mathcal{H}^+) \mid y_{1:k} \right] \tag{15}
\]

where \( \mathcal{H} \) is the set of considered hypotheses, e.g. \( \mathcal{H} = \{ \mathcal{H}_0, \mathcal{H}_1 \} \), and \( C(\mathcal{H}_d, \mathcal{H}^+) \) is the cost of choosing a given hypothesis \( \mathcal{H}_d \) whilst \( \mathcal{H}^+ \) is the true hypothesis (intent). It can be easily seen that a binary cost function results in a MAP estimate, i.e. the most probable hypothesis is chosen. Alternatively, a threshold criterion can be used, e.g. \( p(\mathcal{H}_1|y_{1:k}) \geq \gamma \) deems that the tracked object is returning to the vehicle; same can be applied to the not returning hypothesis. This permits quantifying the certainly level of the intent inference process and establishing cases when the system cannot determine, with acceptably high probability, the driver/passenger(s) intent.

VI. Practical Considerations

Here, we address the following key practical aspects of the introduced inference framework:

- **Computational Complexity:** Kalman filters are known to be computationally efficient and the proposed solution has an overall computational complexity in the order of \( \mathcal{O} \left( s^2 + 4qs^2 \right) \). This is a relatively low, especially given the low dimensionality of potential Gaussian LTI motion models, e.g. typically \( s < 10 \). Additionally, a small number of quadrature points usually suffice and the bridging-based inference computational complexity can be further optimised [31], [32]. This can facilitate employing only one filter for both \( \mathcal{H}_0 \) and \( \mathcal{H}_1 \) with an supplementary correction step, in lieu of two.

- **System Implementation and Distributed Architectures:** in a connected vehicle environment (i.e. assuming reliable data links between the smartphone/portalbeen device, vehicle and possibly a cloud service as well as the surrounding infrastructure), the intent prediction calculations can be carried out, partially or fully, by the smartphone or vehicle or cloud. This depends on the availability of: a) the required observations \( y_{1:k} \) and the vehicle information \( \mathcal{V} \) (e.g. position and orientation) and b) adequate computational resources. The latter can be shared by various units within a distribution architecture given the amenability of the introduced algorithms to parallelisation; e.g. each \( \ell_{k,i} \) in Algorithm 1 can be run on a separate computational unit and all results are then aggregated. Figure 4 displays a possible smartphone-based implementation of the intent prediction functionality whom results are shared with the vehicle. Alternatively, the overall system can be implemented by the intelligent vehicle if \( y_{1:k} \) are locally available, e.g. from proprietary user-to-vehicle localisation solution. Ultimately, performing the inference procedure on the same device providing the required measurements \( y_{1:k} \), e.g. on a smartphone, minimises the communications overhead.

- **Training Requirements:** the used motion models, e.g. CV, have a notably small number of parameters; CV has only one (assuming identical motion behaviour in all spatial dimensions). These can be intuitively chosen as in the pilot results below or based on a small number of recorded trajectories; bridging also significantly reduces the models sensitivity to variations in the motion model parameters [32]. This clearly demonstrates the low training requirements of the approach introduced in this paper, compared with a data driven methods, e.g. [20], [21], [25] where prediction models/rules are learnt from available (extensive) data sets.

- **Extensions:** this solution is not confined to a user walking to the vehicle, other means of transport (e.g. a cart, autonomous pod, etc.) can be considered given a representative motion model. Moreover, the prediction formulation can be extended to \( N \) potential destinations of the driver or passenger, instead of one. All endpoints other than the vehicle will collectively constitute the null hypothesis \( \mathcal{H}_0 \). However, such a formulation involves substantially more computations as \( N \) bridges need to be constructed for \( N \) endpoints with their associated (filtering-inference) calculations and the numerical approximations, e.g. with \( q \) quadrature points.

VII. Pilot Results

Figure 5 depicts the sequentially calculated probabilities of a driver returning to the vehicle, \( p(\mathcal{H}_d|y_{1:k}), d = 1, 2 \), and estimated time of arrival for two typical walking trajectories. The measurements of these 2-D tracks were collected using an Android smartphone (assisted) GPS service at a rate of \( \approx 1 \)Hz. A constant velocity motion model, uniform priors on intent and time of arrivals as well as \( q = 40 \) quadrature points are employed. A MAP criterion is utilised to obtain a point estimate of \( T \) from the calculated posterior \( p(T|y_{1:k}, \mathcal{H}_1) \).

Figure 5a shows results for the the scenario when a user returns to car. Whereas, Figure 5b exhibits the inference outcome when the user walks towards then past the car. Please refer to the attached video\(^1\) demonstrating the system response in real-time for these two trajectories.

It can be noticed from Figure 5 that the proposed prediction/estimation approach provides early successful predictions in both scenarios. For instance, the probability of the returning-to-car \( p(\mathcal{H}_1|y_{1:k}) \) becomes significantly high early in the walking track, e.g. after 35s in Figure 5a. For the second

\[^1\] Alternatively, please follow the link: https://youtu.be/0wHG-HqByyl
Figure 5: Inference results for two trajectories for a user walking back/past the vehicle, as a function of time in seconds. First row: a map showing the followed track in yellow; arrows indicate the direction of travel, car is the red circle, start point is the blue cross and selected timestamps of the GPS trajectory are marked in pink. Second row: destination prediction as a function of time, i.e. probability that the user is returning to the vehicle $p(H_1|y_{1:k})$. Third row: depicts the estimated time of arrival $\hat{T}$ (via a MAP estimate from posterior) as a function of time with a confidence interval (one standard deviation); red line is the true time of arrival at endpoint, i.e. vehicle only in (a).

Conventional tracking techniques that can infer the model future state (e.g. user future position) in \[3\], i.e. without bridging, led to arbitrarily erroneous predictions similar to those in Figure 2b. Establishing that the driver/passenger is returning to car based on proximity to vehicle (e.g. when within a $10 - 20$m radius) results in late predictions and/or ambiguous incorrect decisions if the applied proximity range is increased. For instance, when the car is parked relatively near the user’s workplace or home, e.g. within 100m. Contrary to these two basic approaches, the proposed formulation in this paper captures the intent influence on the user motion as he/she walks to car, enabling reliable early predictions of intent and estimates of $T$. Whilst this preliminary testing illustrates the effectiveness of the introduced approach, further evaluation from naturalistic setting is required, possibly for motion models other than the CV.
VIII. CONCLUSIONS

An simple, yet effective, framework for predicting if and when a driver or passenger is returning to vehicle is proposed, within a Bayesian object tracking formulation. Notably, it is: 1) flexible where additional contextual information can be easily incorporated, 2) adaptable where numerous motion and observation models can be used, 3) probabilistic (belief-based) where prescribed certainty requirements can be reinforced via the decision module (or cost function), and 4) leads to low-complexity inference algorithms with minimal training requirements. This paper sets the foundation for further work on this Bayesian approach and its applications in intelligent vehicles, including detailed experimental evaluations.

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