Credibilistic IMM likelihood updating applied to outdoor vehicle robust ego-localization

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Abstract—This paper deals with the ego-localization problem for an outdoor vehicle equipped with proprioceptive sensors. In a current way, the ego-localisation consists in two stages (prediction and updating of the vehicle state) in order to provide a new vehicle state with its associated uncertainty. Previous works have proved the efficiency of several type of algorithms. Among them, we can quote the IMM (Interacting Multiple Model) approach. IMM is based on the discretization of the vehicle motion space modeled by simple manoeuvres, such as Constant Velocity (CT) or Constant Turn (CT) models. This yields a very adapted approach for heavily manoeuvring vehicles. Unfortunately, without GPS data, this approach becomes difficult to use. The idea is to combine different kind of proprioceptive information by using the IMM (Interacting Multiple Model) approach in a credibilistic way for the likelihood model updating in the prediction stage. In our case, data are coming from dead reckoning sensors. This kind of sensors complement the GPS for updating the vehicle state as well as the model likelihood.

Keywords: ego-localization, credibilistic IMM, proprioceptive sensors, behavior modeling

I. INTRODUCTION

Ego-localization techniques based on dead-reckoning sensors can be considered as obsolete since highly precise GPS (Global Positioning System) receivers, like RTK (Real Time Kinematic), which has a centimetric precision, exist. However, automotive manufacturing imposes the use of very low cost sensors, whose reliability and precision must be improved. To achieve it, the strategy is to combine the various sources of information coming from heterogeneous sensors. Moreover, ego-localization cannot be based on only one type of sensor, such as a GPS whose signal can be temporary lost. That is why, data fusion techniques is commonly used [1], [2].

Among various vehicle localization techniques, widely published in the literature [3], Interacting Multiple Model (IMM) approach, in addition to guarantee greater robustness to model unmatching, allows to identify vehicle’s dynamics through various model activation probabilities assessment. Through multiple model adaptation, this contributes to improve localization robustness and integrity [4]. Consequently, IMM is well suited for solving multiple-object tracking problems with strong nonlinear dynamics [5].

However, traditional IMM for road vehicle localization can reveal important drawbacks coming from various sources of error [3]. First, input noisy sensor data can cause the system drift. Secondly, a mismatched Markovian transition matrix, which leads to wrong switching parameters, will generate spurious model probability estimates. Those problems can be solved either through sensors data preprocessing (denoising, unbiassing,...) or through statistical tests applied to the positioning system. However, the most critical aspect, which is treated in this paper, concerns probability model updating when exteroceptive data, such as a GPS signal, are missing. Our idea is to combine both proprio and exteroceptive sensors for precise vehicle localization and for maneuver change detection. Model probabilities are traditionally updated using model likelihoods, derived from innovations and obtained only in presence of exteroceptive sensors data. It is easily understood that in case of GPS outages (for instance in forest, tunnel or urban canyon), probabilities are not updated and system modeling will drift. On the other hand, proprioceptive sensors, like accelerometers, gyrometers or odometers, used for ego-localization lead over time to estimation divergence. These embedded sensors, however, produce very rich information about vehicle’s manoeuvres. For these reasons above, our robust proposed solution will mainly rely on GPS signal for vehicle position estimation and on proprioceptive data for vehicle maneuvering estimation. Moreover, as the GPS sampling frequency is much lower than the one used for proprioceptive sensors, the latters can be used as well for updating model probabilities between two GPS measurements.

In some previous work [4], proprioceptive sensors modeling was proposed by using constrained probabilistic models. In this paper, we propose a more accurate modeling based on Transferable Belief Model (TBM) [6]. Belief functions provide an interesting formalism to manage and to handle imprecision, uncertainty and missing information. Indeed, instead of strictly considering probability distributions over a finite number of hypotheses, belief functions are also computed over all subsets of hypotheses. We will then consider a larger frame of discernment as in probability by adopting the TBM representation, which manages uncertainty at two levels: the credal level, where basic belief assignment (bba) are addressed and the pignistic level, where bba are used to make decisions. With the TBM representation, belief functions are unnormalized and the mass on conflict, \( m(\emptyset) \), can be non empty. In this case, the origin of this conflict becomes an issue (unreliable sources,
missing hypothesis, unappropriate models, open world,...). In our application, combining IMM with belief functions opens a lot of perspective on maneuver identification.

The paper is organized as follows: in the next section, we describe the traditional IMM approach. In section III, our main contribution concerning model likelihood updating with proprioceptive sensors by using the TBM is described. Finally, in section IV, we present experiment results with real proprioceptive data before we conclude the paper.

II. INTERACTING MULTIPLE MODEL APPROACH DESCRIPTION

A. Estimation problem formulation

Our vehicle localization is considered in a local two-dimensional plane. The vector describing the state of the vehicle is given by:

\[ X_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T \]  

(1)

where \((x_k, y_k)\) corresponds to the position and \((\dot{x}_k, \dot{y}_k)\) to the velocity at time \(k\) in the Cartesian plane.

Assuming that the vehicle motion is following the \(i^{th}\) model \((\forall i \in [1, \ldots, m])\), corresponding to the \(i^{th}\) maneuver, represented by the \(f^{(i)}\) function and the process noise \(w^{(i)}\), the vehicle state equation can then be written as,

\[ X_k = f^{(i)}(X_{k-1}, u_k, w^{(i)}) \]  

(2)

where \(u_k\) represents the system inputs.

One sensor \(c\) observes the vehicle dynamics according to measurement function \(h^{(c)}\) in order to produce one measurement \(Y^{(c)}_k\) defined as,

\[ Y^{(c)}_k = h(X_k, v^{(c)}_k) \]  

(3)

where \(v^{(c)}_k\) represents the measurement noise process of sensor \(c\) at time \(k\), here defined as a white Gaussian noise process of standard deviation \(\sigma^{(c)}\).

By considering only one motion model \(M^i\), the state \(\hat{X}^{(i)}_{k|k}\) and covariance \(P^{(i)}_{k|k}\) estimates are calculated according to the Kalman filter as follow:

\[ \hat{X}^{(i)}_{k|k} = E[X_k|Z^k, M^i] \]  

(4)

\[ P^{(i)}_{k|k} = E[(X_k - \hat{X}^{(i)}_{k|k})(X_k - \hat{X}^{(i)}_{k|k})^T|Z^k, M^i] \]  

(5)

where the set \(Z^k\) refers to the cumulated measurements until time \(k\) and \(E[.]\) to mathematical expectation.

In a multi-model context, the global estimation of the state \(\hat{X}_{k|k}\) vector and the covariance \(P_{k|k}\) matrix are calculated as a combination of the different estimates, weighted according to their model occurrence probability \(\mu^{(i)}_{k|k}\) at time \(k\). That is:

\[ \hat{X}_{k|k} = \sum_{i=1}^{m} \hat{X}^{(i)}_{k|k} \mu^{(i)}_{k|k} \]  

(6)

and

\[ P_{k|k} = \sum_{i=1}^{m} P^{(i)}_{k|k} + (\hat{X}_{k|k} - \hat{X}^{(i)}_{k|k})(\hat{X}_{k|k} - \hat{X}^{(i)}_{k|k})^T \mu^{(i)}_{k|k} \]  

(7)

The main issue is now to calculate the model occurrence probability distribution \(\mu^{(i)}_{k|k}\).

B. Model occurrence probability distribution calculation

The main assumption for using IMM is that shifts between the various system models (vehicle’s maneuvers) are following a Markov chain process characterized by the transition matrix \(\pi\). Therefore, the model occurrence probability distribution can be computed with the following four main steps:

- Mixing probabilities \(\mu^{(i)}_{k\rightarrow k}\) are first estimated at iteration \(k\), \(\forall (i, j) \in [1, \ldots, m]\) by using the transition matrix \(\pi\) [7].
- Each model estimate \(\hat{X}^{(i)}_{k|k}\) is mixed with the others model estimates weighted the corresponding mixing probabilities (interaction).
- By using the resulting mixed model estimates, the Kalman filter for each model estimates the corresponding model state \(\hat{X}^{(i)}_{k|k}\) and covariance \(P^{(i)}_{k|k}\) in two steps: prediction and correction. This second step includes the computation of the measurement residual \(Y^{(i)}_{k+1}\) and its covariance matrix \(S^{(i)}_{k+1}\) called the model innovation.
- The model likelihood \(\Lambda^{(i)}_{k+1}\) and probabilities \(\mu^{(i)}_{k+1}\) can be computed as:

\[ \Lambda^{(i)}_{k+1} = \frac{1}{\sqrt{2\pi S^{(i)}_{k+1}}} \exp \left(-\frac{1}{2}Y^{(i)}_{k+1}^T S^{(i)}_{k+1}^{-1} Y^{(i)}_{k+1} \right) \]  

(8)

\[ \mu^{(i)}_{k+1} = \sum_{j} \mu^{(j)}_{k+1} \Lambda^{(j)}_{k+1} \]  

(9)

C. Models linked to ground vehicles

Various vehicle models are used to perform ego-localization with IMM. In order to derive these vehicle models, it is assumed that during some time period, the vehicle dynamics can be split into constant segments. For example, the free motion evolution (no acceleration and no rotation) can be represented by the Constant Velocity (CV) model. The longitudinal dynamics can be described as the Constant Acceleration (CA) model. For the lateral dynamics, a constant yaw rate (CS) model combined with a CV model is used, known as the Constant Turn (CR) model [8], [5].

The CV model is generally used to model stationary situations, such as stop or near to stop situations [9]. However, with low cost noisy sensors, system drift can occur. Therefore, it is very useful to clearly associate stop situations with a dedicated model, which is called the Constant Stop (CS) model. This model is very advantageous because it can allow the autocalibration modules, knowing that accelerations and rotations rates should be zero during stops. Finally, a Constant Rear (CR) model is used to describe backwards driving.
D. IMM parameters

The vehicle’s motion model is modeled as Markovian process, specified by its transition matrix \( \pi \). The estimation quality partially depends on the accuracy of this matrix. Probability transition values are obtained by using statistics on the vehicle motion, knowing that the frame of discernment for models is written as \( \Omega^m = \{CV, CA, CT, CS, CR\} \):

\[
\pi^m = \begin{bmatrix}
0.8 & 0.1 & 0.1 & 0 & 0 \\
0.1 & 0.7 & 0.1 & 0.05 & 0.05 \\
0.1 & 0.1 & 0.8 & 0 & 0 \\
0 & 0.05 & 0 & 0.9 & 0.05 \\
0 & 0.05 & 0 & 0.05 & 0.9
\end{bmatrix}
\]

The initial occurrence model probabilities \( \mu_0 \) following the same state vector as in eq. (10) is set to \( \mu_0 = [0.2, 0.2, 0.2, 0.2, 0.2] \).

III. LIKELIHOOD UPDATING WITH TBM

While the use of belief functions into an IMM become popular [10], [11], our credibilistic approach here is limited to the calculation of the model probabilities. As state estimation and model update are two independent processes, we focus on the latter only.

When no exteroceptive data are available, the model probabilities are not updated and the predicted model probabilities are used, even if the vehicle is subject to further maneuver. We model proprioceptive data with belief functions to update the occurrence model probabilities. In our ego-localization application, we consider four criteria which are the velocity, the yaw rate, the longitudinal and lateral acceleration, all coming from proprioceptive sensors. They constitute the frame of discernment for the following criteria, denoted \( \Omega^c = \{v, \text{AccX}, \text{AccY}, \dot{\theta}\} \) where \( n^c = 4 \) represents the number of criteria.

According to these criteria, we can now describe the model probabilities update, which consists of the following steps:

- **Similarity between criteria and model calculation:**
  On the top sub-figures shown in Fig. 1, similarities for each model belonging to \( \Omega^m \) and each criteria are described. Different options are available to describe the input similarities with models. A Normal distribution \( \mathcal{N}(\mu^c_i, \sigma^c_i) \) is here proposed of mean \( m^c_i \) and of standard deviation \( \sigma^c_i \) for each model \( i \in [1, \ldots, m] \) and for each criteria \( c \in [1, \ldots, n^c] \). Set of means and variances are established by technical expertise. Then the distance \( D \) can be calculated for each input \( Y^c_k \) coming from the sensor corresponding to the criteria \( c \) and for each model \( i \) by using a Mahalanobis distance:

\[
D = \sqrt{\frac{(\mu^c_i - Y^c_k)^2}{(\sigma^c_i)^2 + (\sigma^c)^2}}
\]

If the distance \( D \) is bigger than one, then it is bounded to 1. Finally, the similarity distance \( d_{c,i} \) is calculating for

- (a) CV model - bottom: \(- m(H) - m(\bar{H}) - m(H \cup \bar{H})\)
- (b) CA model - bottom: \(- m(H) - m(\bar{H}) - m(H \cup \bar{H})\)
- (c) CT model - bottom: \(- m(H) - m(\bar{H}) - m(H \cup \bar{H})\)
- (d) CS model - bottom: \(- m(H) - m(\bar{H}) - m(H \cup \bar{H})\)
each input coming from sensor corresponding to criteria \(c\) and for each model \(i\) as:

\[
d_{c,i} = \pi \left( \frac{2}{\alpha} D - 1 \right)
\]

where \(\alpha = 0.5\) is the coefficient of confidence.

- **Initial bba calculation:** The lower series of figures (Figure 1) for each maneuver model from (a) to (e) describes mapping functions from similarity to bba. For each model \(i\), the bba is limited to the power-set \(\Omega_i = \{H_i, \bar{H}_i, H_i \cup \bar{H}_i\}\). Concerning the mapping functions, many options are available. First, if a criteria does not influence the validation of one model, the mapping is said invariant. For example, by considering the CA model, the lateral acceleration \(\text{AccY}\) does not influence our belief into the CA model validation. Consequently, whatever value for \(\text{AccY}\), we have no information on the CA model validation and the belief is entirely reported on the ignorance. The second case occurs when one criteria is discriminative but not incriminating. For example, if the vehicle velocity is close to zero, by exclusion, the CV model cannot be validated \((m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\text{CV}}) = 0)\).

Similarly, if the yaw rate is bigger than zero, the CV model cannot be validated either. In the third case, a single criteria can lead to the validation of a given model (no covering transformation). For example with the CV model, if the longitudinal acceleration is close to zero, the belief transformation lead to the validation of the model \((m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\text{CV}}) > 0)\) and if it is not negligible, then the belief transformation leads to the non-validation of the model \((m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\text{CV}}) > 0)\) because if there is a longitudinal acceleration, then the CA model is more adapted.

Sinusoidals are used as mapping functions [12], which takes into account the model reliability \(\alpha_{c,i}\) for each criteria \(c\). For example, in the CV model transformation with the criterium \(\text{AccX}\), the bba computation is given by:

\[
m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\text{CV}}) = \begin{cases} 
\alpha_{c,i} \left( 1 - \frac{d_{c,i}}{2} + 1 \right) & \text{if } d_{c,i} \leq \alpha \\
0 & \text{ifelse}
\end{cases}
\]

\[
m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\bar{\text{CV}}}) = \begin{cases} 
\alpha_{c,i} \left( \frac{d_{c,i}}{2} + 1 \right) & \text{if } d_{c,i} > \alpha \\
0 & \text{ifelse}
\end{cases}
\]

\[
m^{\Omega_{\text{CV}}}_{\text{AccX}}(\Omega_{\text{CV}}) = \begin{cases} 
1 - m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\text{CV}}) & \text{if } d_{c,i} \leq \alpha \\
1 - m^{\Omega_{\text{CV}}}_{\text{AccX}}(H_{\bar{\text{CV}}}) & \text{ifelse}
\end{cases}
\]

In other words, the basic idea behind the bba computation is to design discriminants for comparing the various models. For example, a strong longitudinal acceleration value with the CV model leads to the exclusion of the CV model because, whereas the CA model is selected. For the CS and CR models, the common incriminating criterium is velocity. But, for the CR model, the similarity is low when the velocity is close to \(\mu_{\text{CR}}^V = 1.5\) for the CR model (during a backward maneuver, the velocity is supposed to be low). Both models can be distinguished by considering longitudinal acceleration as a discriminant. Low longitudinal acceleration (close to \(\mu_{\text{CR}}^V = 0.5\)) validate of the CR model, whereas a strong one will lead to the exclusion of the CS model. As the end of this computation, we obtain a bba \(m^{\Omega_i}_{c}\) for each model \(i \in [1, \ldots, m]\) and for each criteria \(c \in [1, \ldots, n']\).

- **Multi-criteria bba combination for a given model:** each criteria and its associated bba can be seen as an information source. In order to obtain the resulting belief of a given model, we have to combine the different bbas of all criteria for that model. This combination is performed by applying the Conjunctive Rule of Combination (CRC), normalized according to \(\Omega_i\) (Dempster rule of combination). The final bba for a given model \(m^{\Omega_i}\) is obtained by combining the different criteria, which can be written as:

\[
m^{\Omega_i} = m^{\Omega_1}_{c_1} \cdots m^{\Omega_n}_{c_n} = \frac{1}{K} \bigodot_{c=1} m^{\Omega_c}_{c_i}
\]

where \(K\) is a normalization constant and the CRC between two sources of information is written as:

\[
m^{\Omega}_{\bigodot} = \left( m^{\Omega_1}_{\bigodot} \odot m^{\Omega_2}_{\bigodot} \right) (A) = \sum_{B \cap C = A} m^{\Omega_1}_{B} m^{\Omega_2}_{C}
\]

- **Model probability update:** Knowing the model bba \(m^{\Omega_i}\), computed with the CRC, occurrence model probability can be predicted \(\forall i \in [1, \ldots, m]\) using:

\[
\hat{\mu}^{(i)}_{k|k-1} = \pi_i \cdot \hat{\mu}^{(i)}_{k-1|k-1}
\]
and its estimate can be updated by:

\[
p^{(i)}_{k|k} = \frac{\mu^{(i)}_{k|k-1} \cdot m^{(i)}(H_i)}{\sum_{i=1}^{m} \mu^{(i)}_{k|k-1} \cdot m^{(i)}(H_i)}
\]

(17)

IV. EXPERIMENT RESULTS

The tests deal with parking scenario involving stop, forward and backward maneuvers, as shown in figure 2. The data used come from the CVIS/POMA project data collection in Goteborg, Sweden. The selected data correspond to high maneuvering situations as shown on Fig. 2.

Embedded sensors provide measurement at the following sampling frequencies: acceleration and yaw rates at 8 Hz, odometric speed at 25 Hz and low cost GPS position estimate at 5 Hz. Corresponding measurements are shown on Fig. 3. Data suffer a high level of noise as can be seen on Fig. 3. An unexpected velocity residue appears at time \( t = 450 \). Moreover, the acceleration components are non-zero even if the vehicles is immobile. Standard deviations are evaluated as follows: \( \sigma^V = 1 \), \( \sigma^{AccX} = 0.2 \), \( \sigma^{AccY} = 0.2 \), \( \sigma^\theta = 0.1 \).

Similarity is first computed by using pre-defined mapping functions presented in the upper series of figures of Fig. 1 for each model, as shown on Fig. 4. Tab. I summarizes used modeling for each couple model/criteria. Fig. 4 computed for each maneuvering model. As it can be seen, sub-figures 4 (a)-(c) have similar shapes, because the CV, CA and CT models are based on the same pre-defined heuristic functions given each criteria. While the vehicle is at stop (phase 2 and 4 from Fig. 3), similarity for each criteria is very low. That means that the CV, CA and CT models, are not adequate for this particular situation. After this zone (after 1200 s), the similarity functions are heavily mixed, thus leading to very difficult interpretation without the multicriteria bba transformation for each model. Over the all-time frame, sub-figures 4 (d)-(e) shows some differences in the behavior of the similarity curves because the pre-defined function used for the CS and CR model are different. For example, with the CR model, the similarity function for longitudinal acceleration behaves quite differently in the stop zone (phase 2) compared to the other models.

The set of graphics on figure 5 illustrates the multi-criteria bba values for each model as computed with eq. (14).

While the vehicle is still maneuvering, the velocity is non-constant and therefore, the CV multicriteria bba should be mainly attributed to the hypothesis \( \bar{H}^{CV} \), which corresponds to the behavior of our model as illustrated on Fig. 5-(a).

As can be seen on Fig. 5-(b), the CA model multi-criteria bba interacts with most vehicle maneuvers. This is due to the fact that acceleration or deceleration occur during other several vehicle maneuvers (before turning or stopping, the vehicle decelerates ; before having a constant velocity, the vehicle accelerates or decelerates). Therefore, the belief into the CA model increases at the beginning of a vehicle maneuver.

Some maneuvers are clearly identified with the CT model (Fig. 5-(c)). We can see that when the vehicle is at rest (phase 2 and 4 from Fig. 3), the multi-criteria belief is entirely on \( \bar{H}^{CT} \). During the phase 2, while the vehicle is simultaneously turning backwards, the multi-criteria believes into both the CT
model and CR model are non-negligible. Nevertheless, we can see that the belief in this particular time interval is shared between $H^{CR}$ and $\bar{H}^{CR}$. This situation is mainly due to the fact that the vehicle is going backward while turning in the same time. This illustrates a limitation of our approach when only one model is considered at a time.

Concerning the CS model (Fig. 5-(d)), the belief into the $H^{CS}$ hypothesis is very close to one while the vehicle at rest. From these different multi-criteria combined bba's, it is now possible to obtain a clear understanding of the vehicle maneuvers as shown on Fig. 6. Once a normalization and computation of the occurrence model probabilities prediction and update estimation are completed eq. (8) and (9), usable probabilities distribution is available for the final fusion stage of the IMM algorithm. From Fig. 6, it is easy to verify the vehicle maneuvers during the sequence. Moreover it clearly appears that the presented approach allows to reduce the ambiguities compared a classical probabilistic approach [8]. For instance, the CS and CR mode becomes clearly discriminated with our approach.

V. CONCLUSIONS

This paper presents a new credibilistic IMM approach for solving the ego-localisation problem, which exhibits a strong robustness to sensor and modeling errors. The results presented herein constitutes the premisses of a larger work on maneuver identification. In this paper, we limit ourselves to results based on new pre-defined mapping functions used for combining uncertain data coming from different type of sensor. The obtained results, based on real experimental data, conclusively show the relevance of our approach. Our approach allows to take into account both proprioceptive and exteroceptive unperfect sensors, in order to produce an accurate and robust description of vehicle maneuvers. Our credibilistic approach could be further refined for example by consideration simultaneous multi-model combination. It is also possible to consider an extended frame of discernment [13] in order to identify new
models or detect real time system failures.

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