1. Scenario 1: One Nearby Vehicle

The estimated absolute position $\bar{P}^{(j)}$ of the nearby vehicle N_i^j is obtained by maximizing the posterior probability as follows:

$$\bar{P}^{(j)} = \arg\max_{p^{(j)}} f_{P^{(j)}|P^{(ij)}}(p^{(j)}|p^{(ij)}), \tag{1.1}$$

where $f_{P^{(j)}|P^{(ij)}}(p^{(j)}|p^{(ij)})$ is the posterior probability for one candidate position $p^{(j)}$ of the nearby vehicle N_i^j according to the Bayesian theorem as follows:

$$f_{P^{(j)}|P^{(ij)}}(p^{(j)}|p^{(ij)}) = \frac{f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)}) \times f_{P^{(j)}}(p^{(j)})}{f_{P^{(ij)}(p^{(ij)})}}, \tag{1.2}$$

where $f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)})$ is the likelihood of the observed position of the nearby vehicle N_i^j, and $f_{P^{(j)}}(p^{(j)})$ is the prior probability for the candidate position $p^{(j)}$ of N_i^j following the Gaussian distribution from the GPS position g_N^{ij} as follows:

$$P^{(j)} = f_{P^{(j)}}^{GPS}(p^{(j)}) \ \sim N(g_N^{ij}, \sigma^2_{g^{(j)}}), \tag{1.3}$$

where $\sigma_{g^{(j)}}$ is the standard deviation of the GPS measurement errors.

To obtain the denominator $f_{P^{(ij)}(p^{(ij)})}$ in Eq. 1.2, the cumulative probability of $f_{P^{(ij)}(p^{(ij)})}$ is determined as follows:

$$\begin{aligned} &F_{P^{(ij)}(p^{(ij)})} = \\ &\int_{-\infty}^{+\infty}\int_{-\infty}^{d(p^{(i)},p^{(ij)})}\int_{-2\pi}^{a(p^{(i)},p^{(ij)}))} f_{P^{(i)}D^{(ij)}A^{(ij)}}(p^{(i)}, d^{(ij)}, a^{(ij)}) \times \mathrm{d}a^{(ij)}\mathrm{d}d^{(ij)}\mathrm{d}p^{(i)}, \end{aligned} \tag{1.4}$$

where $d^{(ij)}$ and $a^{(ij)}$ are the relative distance and bearing angle between the ego vehicle and nearby vehicle respectively.

After differentiating with respect to $p^{(ij)}$, Eq. 1.5 can be obtained from Eq. 1.4 as follows:

$$\begin{aligned} &f_{P^{(ij)}(p^{(ij)})} = \\ &\int_{-\infty}^{+\infty} f_{P^{(i)}D^{(ij)}A^{(ij)}}(p^{(i)}, d(p^{(i)},p^{(ij)}), a(p^{(i)},p^{(ij)})) \times \mathrm{d}p^{(i)}. \end{aligned} \tag{1.5}$$

Since the position $p^{(i)}$, relative distance $D^{(ij)}$ and bearing angle $A^{(ij)}$ are obtained from different data sources, therefore they are independent, and we have Eq. 1.6 from Eq. 1.5 as follows:

$$\begin{aligned} &f_{P^{(ij)}(p^{(ij)})} = \\ &\int_{-\infty}^{+\infty} f_{P^{(i)}}(p^{(i)}) f_{D^{(ij)}}(d(p^{(i)},p^{(ij)})) f_{A^{(ij)}}(a(p^{(i)},p^{(ij)})) \times \mathrm{d}p^{(i)}. \end{aligned} \tag{1.6}$$

In this work, the candidate position $p^{(i)}$ of the ego vehicle and the candidate position $p^{(j)}$ of the nearby vehicle are assumed to be independent, therefore the likelihood $f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)})$ of the observed position of the nearby vehicle N_i^j can be rewritten as follows:

$$\begin{aligned} &f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)}) = \\ &\int_{-\infty}^{+\infty} f_{P^{(i)}}(p^{(i)}) f_{D^{(ij)}}(d(p^{(i)},p^{(j)})) f_{A^{(ij)}}(a(p^{(i)},p^{(j)})) \times dp^{(i)}. \end{aligned} \tag{1.7}$$

Therefore, the denominator $f_{P^{(ij)}(p^{(ij)})}$ in Eq. 1.2 can be derived from Eq. 1.7 as follows:

$$
\begin{aligned}
f_{P^{(ij)}(p^{(ij)})} &= \int_{-\infty}^{+\infty} f_{P^{(j)}}(p^{(j)}) f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)}) dp^{(j)} \\
&= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f_{P^{(j)}}(p^{(j)}) f_{P^{(i)}}(p^{(i)}) f_{D^{(ij)}}(d(p^{(i)}, p^{(j)})) \\
&\times f_{A^{(ij)}}(a(p^{(i)}, p^{(j)})) dp^{(i)} dp^{(j)}.
\end{aligned} \tag{1.8}
$$

Since the error-free relative distances and bearing angles of the nearby vehicle measured from sensors are not available, we assume that the probability $f_{D^{(ij)}}(a(p^{(i)}, p^{(j)}))$ and $f_{A^{(ij)}}(a(p^{(i)}, p^{(j)}))$ follow Gaussian distributions as follows:

$$
\begin{aligned}
f_{D^{(ij)}}(d(p^{(i)}, p^{(j)})) = f^{Sen}_{D^{(ij)}}(\hat{d}^{(ij)}) \sim N(\hat{d}^{(ij)}, \sigma^2_{d^{(ij)}}), \\
f_{A^{(ij)}}(a(p^{(i)}, p^{(j)})) = f^{Sen}_{A^{(ij)}}(\hat{a}^{(ij)}) \sim N(\hat{a}^{(ij)}, \sigma^2_{a^{(ij)}}),
\end{aligned} \tag{1.9}
$$

where $\hat{d}^{(ij)}$ and $\hat{a}^{(ij)}$ are the measured relative distance and bearing angle of the nearby vehicle N_i^j. $\sigma_{d^{(ij)}}$ and $\sigma_{a^{(ij)}}$ are the standard deviation of the measurement errors of the relative distance and bearing angle.

After that, by substituting Eq. 1.3, Eq. 1.7, Eq. 1.8 and Eq. 1.9 in Eq. 1.2, the posterior probability for the candidate position $p^{(j)}$ of the nearby vehicle N_i^j can be obtained from Eq. 1.10.

$$
\begin{aligned}
& f_{P^{(j)}|P^{(ij)}}(p^{(j)}|p^{(ij)}) \\
&= \frac{\int_{-\infty}^{+\infty} f^{GPS}_{P^{(i)}}(p^{(i)}) f^{Sen}_{D^{(ij)}}(\hat{d}^{(ij)}) f^{Sen}_{A^{(ij)}}(\hat{a}^{(ij)}) dp^{(i)} \times f^{GPS}_{P^{(j)}}(p^{(j)})}{\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f^{GPS}_{P^{(j)}}(p^{(j)}) f^{GPS}_{P^{(i)}}(p^{(i)}) f^{Sen}_{D^{(ij)}}(\hat{d}^{(ij)}) f^{Sen}_{A^{(ij)}}(\hat{a}^{(ij)}) dp^{(i)} dp^{(j)}}
\end{aligned} \tag{1.10}
$$

2. Scenario 2: m Nearby Vehicles (m > 1)

The set containing the absolute positions of the nearby vehicles $\bar{P}^{1...m}$ can be estimated by maximizing the posterior probability as follows:

$$\bar{P}^{1...m} = \arg\max_{p^{(1...m)}} f_{P^{(1...m)}|P^{(i1)}...P^{(im)}}(p^{(1...m)}|p^{(i1)}...p^{(im)}), \tag{2.1}$$

where $f_{P^{(1...m)}|P^{(i1)}...P^{(im)}}(p^{(1...m)}|p^{(i1)}...p^{(im)})$ is the posterior probability for the m nearby vehicles. $f_{P^{(i1)}...P^{(im)}|P^{(1)}...P^{(m)}}(p^{(i1)}...p^{(im)}|p^{(1)}...p^{(m)})$ is the likelihood of the observed position of the nearby vehicles from N_i^1 to N_i^m, and $\Phi(p^{(1)}...p^{(m)})$ is the prior probability for the candidate positions of the m nearby vehicles.

$$\begin{aligned} &f_{P^{(1...m)}|P^{(i1)}...P^{(im)}}(p^{(1...m)}|p^{(i1)}...p^{(im)}) \\ &= \frac{f_{P^{(i1)}...P^{(im)}|P^{(1)}...P^{(m)}}(p^{(i1)}...p^{(im)}|p^{(1)}...p^{(m)}) \times \Phi(p^{(1)}...p^{(m)})}{f_{P^{(i1)}...P^{(im)}(p^{(i1)}...p^{(im)})}}, \end{aligned} \tag{2.2}$$

Since the GPS measurements of the nearby vehicles are assumed to be independent, the prior probability for the candidate positions of the nearby vehicles can be written as:

$$\Phi(p^{(1)}...p^{(j)}...p^{(m)}) = \prod_{j=1}^{m} f_{P^{(j)}}^{GPS}(p^{(j)}), \tag{2.3}$$

where $f_{P^{(j)}}^{GPS}(p^{(j)})$ is the probability for the candidate position of the nearby vehicle N_i^j and it follows a Gaussian distribution $N(g_N^{ij}, \sigma_{g^{(j)}}^2)$.

Similar, the candidate positions of the nearby vehicles are also assumed to be independent, the likelihood of the observations can be written as Eq. 2.4.

$$\begin{aligned} &f_{P^{(i1)}...P^{(im)}|P^{(1)}...P^{(m)}}(p^{(i1)}...p^{(im)}|p^{(1)}...p^{(m)}) \\ &= \prod_{j=1}^{m} f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)}), \end{aligned} \tag{2.4}$$

where $f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)})$ is given in Eq. 1.7.

Following Eq. 1.8, the denominator of Eq. 2.2 can then be determined from Eq. 2.3 and Eq. 2.4. Finally, the posterior probability for the candidate positions of the m nearby vehicles can be determined from Eq. 2.5 by substituting Eq. 1.9, Eq. 2.3, Eq. 2.4 in Eq. 2.2.

$$\begin{aligned} &f_{P^{(1...m)}|P^{(i1)}...P^{(im)}}(p^{(1...m)}|p^{(i1)}...p^{(im)}) \\ &= \frac{\prod_{j=1}^{m} \int_{-\infty}^{+\infty} f_{P^{(i)}}(p^{(i)}) f_{D^{(ij)}}^{Sen}(\hat{d}^{(ij)}) f_{A^{(ij)}}^{Sen}(\hat{a}^{(ij)}) dp^{(i)} \times \prod_{j=1}^{m} f_{P^{(j)}}^{GPS}(p^{(j)})}{\int_{P^{(1)}...P^{(m)}} \prod_{j=1}^{m} f_{P^{(j)}}^{GPS}(p^{(j)}) \prod_{j=1}^{m} f_{P^{(ij)}|P^{(j)}}(p^{(ij)}|p^{(j)}) dp^{(1)}...dp^{(m)}}. \end{aligned} \tag{2.5}$$