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Outdoor Visible Light Positioning Using Artificial Neural Networks for Autonomous Vehicle Application

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***Abstract*—In this paper, a novel outdoor 2-D vehicular visible light positioning (VLP) using a linear array of streetlights and artificial neural network (ANN) is proposed. The classical position methods which are mostly based on triangulation will not work with the linear array of the street light. Hence, we proposed a spatial diversity receiver with ANN to overcome the collinearity condition. The proposed system is simulated for a realistic outdoor condition and provides an accurate positioning with an average RMS error of 0.53m.**

***Index Terms*—visible light positioning, outdoor positioning, Artificial neural network, receiver diversity**

I. INTRODUCTION

Autonomous vehicles are expected to benefit the intelligent transport system (ITS) through improved efficiency, reduced traffic congestion and increased road safety. The practical realization of these expected benefits requires autonomous vehicles to have efficient communication, perception (to identify the surrounding and obstacles), precise localization and control functionalities [1]. The vehicles need to have precise localization often at centimeter accuracy for safety requirement. Widely used outdoor localization method such as Global positioning systems (GPS) and differential GPS (dGPS) used by autonomous vehicles relies on artificial satellites transmitting position information using the radio frequency (RF) spectrum. The localisation accuracies of these technologies are in the meter range and worsen in adverse conditions [2], [3]. Although recent developments of dGPS for autonomous vehicles provide decimeter-level accuracy [4], these signals do not extend to tunnels and underground areas. Hence, there is a need for alternative localisation techniques to either complement or replace GPS (in the case of GPS failure) to improve the current localisation availability and accuracy for safety requirements and also to facilitate indoor navigation for smart parking.

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The popularity and wide availability of solid-state lighting (SSL) such as light emitting diodes (LEDs) for indoor and outdoor illumination, traffic signalling and display provide a unique platform to utilize them for high-speed communication and accurate localisation [5]. The current energy-saving schemes funded by the European Commission aiming to replace current street lighting solutions with LED streetlamps is attractive for outdoor positioning systems due to its ubiquity, especially in tunnels and underground roads.

Though several of studies already proved that VLP system can provide unparallel accuracy in centimetre range for indoor positioning, the use of VLP for outdoor positioning, especially for autonomous vehicle application is relatively at infancy. Outdoor localisation for vehicular applications is challenging due to the unavailability of a distributed light network. Streetlights are generally in a straight line and thus techniques such as triangulation or similar algorithms cannot be applied. This is because a reference plane equation is formed for each transmitter which is required not to be collinear for the algorithms to compute any valid output. Hence, most of the outdoor localisation strategies are on estimating the relative position or separation between vehicles (using the streetlight with head and tail light of vehicles) which is only adequate for vehicle collision avoidance. However, autonomous navigation requires accurate absolute positioning that these techniques fail to offer. A study in [6] demonstrated the feasibility of accurate localisation using tunnel infrastructure and car tail lamp. The work uses a camera sensor receiver and image processing to extract information. However, this is based on the assumption that there is always a neighbouring car on the road several meters ahead continuously sending its updated position information. In [7], the vehicle position was estimated using traffic light and TDoA of optical signal estimated using two photodiodes. The TDoA, however, requires the time synchronization among traffic light which may be difficult in heterogeneous environments. Furthermore, for accurate positioning, the receiver separation needs to be comparatively large in the meter range (2m in this particular study, which is not practical in all the case) so that TDoA can be estimated. Moreover, the algorithm is accurate only for a known fixed speed of the vehicle moving towards or away from the traffic light. Hence, to provide a ubiquitous and accurate position for an autonomous and intelligent transportation system, there is a need for highly accurate VLP using existing infrastructure such as streetlights. As the streetlights are located linearly, this makes triangulation or other existing algorithms challenging due to collinearity condition [8]. Moreover, modification in the location of the streetlights is not an option as it is not cost-effective.

To overcome these issues, in this work, we propose outdoor VLP localization based on the existing streetlight with supervised artificial neural network (ANN). Receiver diversity is later introduced in an effort to reduce the effect of collinearity in VLP. To the best of the authors' knowledge, this is the first work to use ANN with receiver diversity to mitigate the collinearity condition and further provide accurate outdoor positioning. Though there are some prior work on use of ANN for indoor VLP (see [9], [10]), they are mostly for indoor localisation using distributed transmitters. For example, a three-dimensional indoor localisation was proposed in [9] using ANN. However, [9] assumes the availability of distributed receivers. As described above, this is not practical for outdoor ITS application.

The rest of this paper is structured as follows; the system description is provided in Section II. Section III describes the proposed application of supervised feed-forward back propagation multilayer perceptrons (MLP) for 2-D localization. The performance of the proposed system is discussed in Section IV. Finally, conclusions are drawn in Section V.

II. SYSTEM DESCRIPTION

The proposed VLP system configuration is given in Fig. 1. Streetlights are the most consistent and available light sources in urban areas thus considering them as transmitters for the model. Each transmitter transmits time division multiplex (TDM) or frequency division multiplex (FDM) signals as outlined in [11]. The generic scenario adopted is that the streetlights are only located at the side of the road. The vehicles are assumed to have two degrees of freedom by travelling on the x-axis and changing lane across the y-axis. Hence, we consider 2D localisation in both x-axis and y-axis.

The proposed model is based on received signal strength (RSS), which prompts the estimation of the received power $P_{r,i}$ at various locations. The latter is given by:

$$P_{r,i} = H_{los}(0) P_{t,i} \tag{1}$$

where $P_{t,i}$ is the transmitted optical power from the i^{th} LED, $H_{los}(0)$ is the DC channel gain between the PD and the i^{th} LED.

The DC channel gain depends on the channel configuration (line of sight (LOS), the angle of incidence and the link distance. For a LOS link with Lambertian radiation pattern, the DC channel gain is given by:

$$H_{los}(0) = \begin{cases} \frac{(m+1)A}{2\pi d^2} \cos^m(\phi) T_s(\phi) g(\psi) \cos(\psi) 0 \leq \psi \leq \Psi_c \\ 0, \qquad\qquad\qquad\qquad\qquad\qquad \psi > \Psi_c \end{cases} \tag{2}$$

where m is the Lambertian emission order, A is the PDs physical area, ϕ is the irradiance angle, $T_s(\psi)$ is the optical filter gain, ψ is the angle of incidence, $g(\psi)$ as the optical concentrator gain, d is the distance between the receiver and the transmitter, Ψ_c is the PDs field of view. The Lambertian emission order is calculated as:

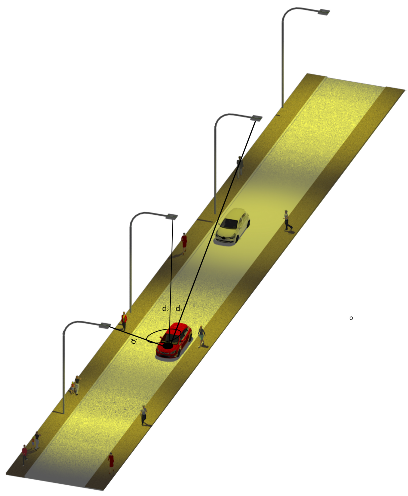

Fig. 1. Street light localization model for VLP

$$m = \frac{-\ln 2}{\ln(\cos\phi_{1/2})} \tag{3}$$

where $\phi_{1/2}$ represents the half power angle of the LED. The optical concentrator gain is calculated as:

$$g(\psi_i) = \frac{n_c^2}{\sin^2\Psi} \tag{4}$$

where n_c is the refractive index of the concentrator.

As the simulation is considered to be in an outdoor environment, sunlight is expected to increase the noise level. Hence, the scenario adopted aims to demonstrate the effectiveness of the system at extreme conditions under the assumption that streetlights are turned on all the time. The noise comprises thermal noise and shot noise. This type of noise is generally modelled as additive white Gaussian noise (AWGN) [12]. The background light and the photo-current generated by the desired signal is known as the shot noise and its variance is calculated as:

$$\sigma^2_{shot,i} = 2qI_{bg}I_2B + 2qR_pP_{r,i}B \tag{5}$$

where B represents the bandwidth, R_p is the receiver responsivity, I_2 is a noise bandwidth factor of the current, I_{bg} is the background current and q is the electronic charge. The thermal noise that arises from the amplifier at the receiver is given as:

$$\sigma^2_{thermal} = \frac{8\pi k T_k}{G}\eta A I_2 B^2 + \frac{16\pi^2 k T_k \Gamma}{g_m}\eta^2 A^2 I_3 B^3 \tag{6}$$

where k represents the Boltzmann's constant and q represents the electronic charge. G, T_k and η, represent open-loop gain, absolute temperature and fixed capacitance of the PD.

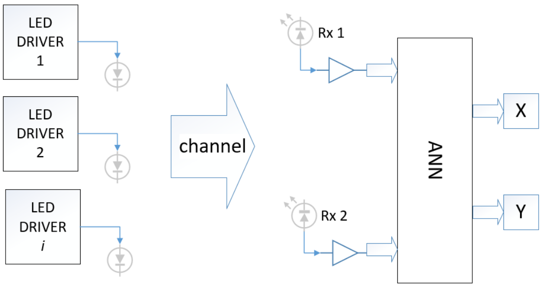

Fig. 2. Schematic of proposed VLP using ANN

I_3 is the noise bandwidth factor. Γ and g_m represent FET channel noise factor and FET trans-conductance, respectively. Hence, the total noise variance is given as:

$$\sigma^2_{noise} = \sigma^2_{shot} + \sigma^2_{thermal} \tag{7}$$

Therefore, the received signal is given by:

$$P_{rec,i} = P_{r,i} + P_{n,i} \tag{8}$$

where P_n is the AWGN signal, with power spectral density (PSD) of σ^2_{noise} as given by (7).

III. Outdoor Localization Based on Artificial Neural Network

This section describes the supervised feed-forward back propagation MLP ANN for 2-D localization as shown in Fig. 2. A two-layer ANN with $M \times N$ neurons in the input layer, 60 neurons in the hidden layer and two neurons in the output layer is considered. Two neurons are in the output layer corresponding to the (x, y) coordinates required for 2-D positioning. This ANN uses Log sigmoid transfer function at the hidden layer and a linear transfer function at the output layer. The received signal given by (8) through free space optics with respect to the receiver position is simultaneously fed to the network. The ANN is trained with 1000 random samples within the road to estimate the x and y co-ordinates of the vehicle. The Levenberg-Marquardt supervised training algorithm was adopted to train a feed-forward back-propagation network. Once the ANN is trained, the ANN can predict the unknown vehicles position based on the received signals. Up to $28,704$ random locations across the road were used to test the trained network. The details of the ANN structure and training algorithm can be found in [13].

IV. Results and Discussion

The performance of the proposed ANN algorithm is evaluated in this section. The method used to evaluate the results is root mean square (RMS) error and cumulative distributive function (CDF) of the RMS error. The RMS error is given by:

$$RMSerror = \sqrt{(x-\hat{x})^2 + (y-\hat{y})^2} \tag{9}$$

where (x, y) is the real position and $(\hat{x}, \hat{y})$ is the estimated position of the receivers.

TABLE I
PARAMETERS USED FOR SIMULATION

Parameter	Value
Road parameters $[L \times W \times H]$ (m)	$60 \times 5 \times 7$
Number of neurons	60
Number of transmitters (M)	3
Transmitter power P_t (W)	90
Transmitter semi-angle (degree)	60
No. of receiver (N)	2
Receiver area, A (cm^3)	1
Optical filter gain	1
Noise bandwidth, B (MHz)	1
Noise bandwidth factor (I_2)	0.562
FET channel noise factor Γ	1.5
Fixed capacitance of PD (pF/cm^2)	112
Temperature T_k (K)	295
FET transconductance (mS)	30
Background current (I_{bg}) (mA)	5.1
Noise bandwidth factor (I_3)	0.0868

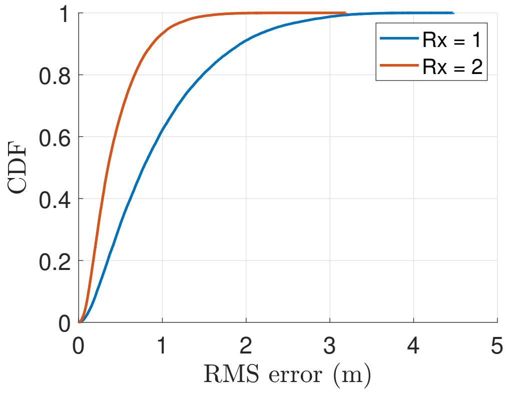

Fig. 3. CDF of VLP as a function of number of receiver.

We consider a road with dimensions of 60m$\times$5m$\times$7m with each transmitter located 30m apart from each other and a height of 7m at the side of the road [14]. The generic scenario adopted is the streetlights are only located at the side of the road. Up to 1000 randomly distributed locations within the road are considered to estimate the 2-D position using the MLP-ANN. We consider up to 2 receivers and compared the performance of the system with single and multiple receivers to evaluate the impact of receiver diversity. Note that due to the large separation of the transmitters, the receiver is able to obtain signals from up to 3 transmitters in the majority of the cases. The main parameters used for the simulation are shown in Table I [12], [15] .

Fig. 3 shows the RMS error versus CDF for scenarios using 1 and 2 receivers. Using a single receiver, at 0.95 CDF, an RMS error of 2.34m is noted. However, when receiver diversity is introduced, the RMS error is seen to drop 1.06m at 0.95 CDF. Hence, this shows the effect of receiver diversity gain on the accuracy in VLP. Therefore, the diversity technique is adopted for the rest of the studies.

The models performance was studied using different receiver field of view (FOV). A CDF analysis is done for these results to identify the best receiver FOV. The optical gain at all the FOVs are considered as unity in an effort to differentiate

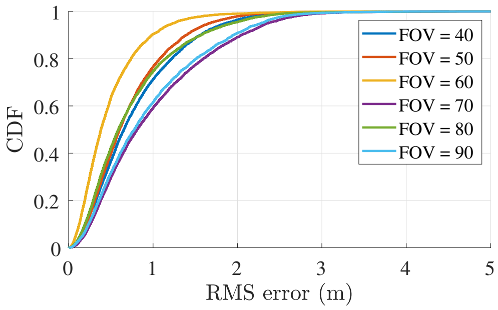

Fig. 4. CDF of VLP as a function of receiver FOV.

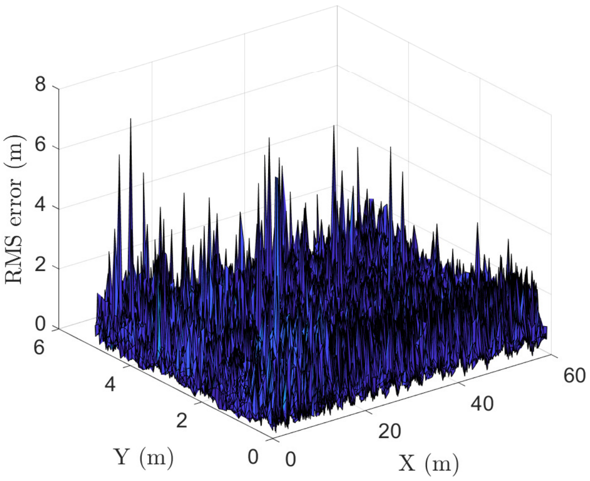

Fig. 5. RMS error distribution across the road.

the performance improvement due to FOV. Fig. 4 shows the CDF analysis starting from $40°$ to $90°$ with a step size of 10. A significant improvement is noticed when the FOV is increased from $40°$ to $60°$. However, increasing the FOV beyond $60°$ does not offer any improvement in RMS error. Increasing receiver FOV increases the chance of signal reception across the road, but at the cost of increased noise; leading to an overall reduction in the accuracy of the system. From this results it can be concluded that $60°$ FOV provides the best trade off between signal to noise ratio.

Having evaluated the impact of key simulation parameters, the performance of the model is now analysed across the road. Fig. 5 shows the RMS error distribution across the road using the receiver diversity. An average RMS error of 0.53m is calculated even when the effect of sunlight is considered. The rise in RMS error is noticed at the side of the road. This is due to the lower received power reception at the receivers as the light intensity drops at the edges of the road. Moreover we evaluate the systems performance in the absence of sunlight (at night). With the absence of ambient noise, an average RMS error of 0.41m is calculated. A percentage difference of 25.5% shows the impact of sunlight on the performance of the system.

V. CONCLUSIONS

In this paper, we propose a novel outdoor positioning algorithm using receiver diversity for autonomous vehicle application. The linear transmitter array setup of street lights makes traditional positioning methods inadequate for VLP. Hence, we introduce the use of ANN and receiver diversity to solve this problem. The error performance of the VLP system using MLP-ANN is studied by considering receiver diversity and different receiver FOV. The optimum receiver FOV of $60°$ and 60 neurons in the two-layer neural network, an average RMS error of 0.53m is achieved at the presence of sunlight. Future works include the study of different road scenarios at different transmitter setup. In addition, the impact of receiver tilting with a different number of receivers in VLP will be investigated.

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