Current Trends on Visible Light Positioning Techniques

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***Abstract*— This paper presents a survey on visible light positioning techniques. The paper briefly reviews conventional positioning methods based on Rx signal strength (RSS), time difference of arrival (TDOA) and angle of arrival (AOA). Then it focus on the current research trends, relying on the machine learning techniques, sensor fusion and communication requirements.**

Keywords—Visible light positioning (VLP), Machine learning, Neural networks, Modulation schemes.

I. Introduction

The need for accurate indoor positioning systems (IPSs) and location-based applications are developing day by day. IPS offer surveillance, navigation and object tracking services, which have an increasing number of applications in numerous areas, for example, indoor parking facilities, shopping malls, manufacturing, supermarkets, big warehouses, and autonomous navigation, to mention a few. Even though, global positioning system (GPS) has become one of the most popular example for outdoor positioning systems, it is unable to provide high precision in indoor environments, because the GPS signals (i.e., radio frequency (RF)) do not penetrate well through the building walls, which results in disruptive errors and cannot be used in mines and underground environments [1-3]. Already, a few different technologies, for example, ultrasound [4], radio waves [5], [6], radio frequency identification (RFID) [7], [8], Zigbee, Bluetooth [9] and ultra wide band (UWB) [10] have been investigated for IPSs. Indoor positioning systems (IPS) based on ultrasounds have large ranging and localization errors (the accuracy is 10 cm range) because of the fact that its wavelength is generally large, and the speed of sound is influenced by the temperature of environment [11]. RF based localization faces several problems including electromagnetic (EM) radiation, which restrict the use of RF based systems in some areas (i.e., medical, etc.). Moreover, RF signals are (*i*) affected by multipath effects in the indoor environment which increase localization errors; and (*ii*) constrained by the available spectrum, which is highly congested. RFID and UWB recognize signals for positioning with the help of dedicated infrastructure and special devices. Other positioning methods, such Zigbee and Bluetooth based systems are vulnerable to fluctuations in signal sources.

On a different edge, light has been used to infer location for a long time. Our ancestors used the stars to navigate the globe. The astrolabe and the quadrant are perhaps within the first tools to measure angles based on the light from the stars – a precursor of angle of arrival. More recently, the light intensity and pulsation of distant stars, widened our perception of how immense is the universe we live in. This was accomplished with the discovery of Cepheid stars, by Henrietta Leavitt, and used by Edwin Hubble, to reveal that the universe is much larger than our local galaxy [12-13].

Light emitting diodes (LEDs) based visible light positioning (VLP) techniques become more prominent for indoor positioning systems compared to other positioning systems because of advantages offered by the LED technology such as [14-17]: (*i*) free from EM interference; (*ii*) compliance with RoHs recommendations; (*iii*) longer lifetimes when compared with other light sources; (*iv*) energy efficient; and (*v*) low cost and allow fast switching – a feature which enables data transmission. In VLP systems, photodetectors (PDs) or camera (i.e., image sensors (ISs)) are commonly used at the Rx [18–22]. The formers are widely reported in the literature, whereas the latter offers higher positioning accuracy, but at the cost of complex positioning algorithm and the limited positioning speed. Currently, VLP technologies, are based on the triangulation technique where the distance or angle between transmitter (Tx) and receiver (Rx) needs to be estimated. The distance or the angle can be determined in a number of ways including received signal strength (RSS), angle of arrival (AOA), time of arrival (TOA) and time difference of arrival (TDOA) [20], [23]. These methods present their intricacies. The major drawback of AOA is that the system need expensive sensor arrays or ISs to measure the incident angle with high accuracy, which is needed in indoor environments [24]. TOA need accurate synchronization between Tx (LED) and Rx, which increases the deployment cost [25]. On the other hand, RSS needs accurate determination of the incident signal power, thus being strongly dependent on signal to noise ratio (SNR) [16]. Simple approaches, rely on proximity based and scene analysis, which trades simplicity with the accuracy [23]. These are suitable for low accuracy systems, not demanding high location precision.

Machine learning has been widely used for position estimation of RF-based IPSs, for example Wi-Fi, ZigBee and UWB. In [26], machine learning has been introduced for VLP for the first time. The system is capable of reaching 0.31 m of average accuracy in an indoor environment of dimension of 4.3×4×4 m. In [27], a VLP algorithm based on artificial neural network (ANN) was considered where positioning was achieved by a trained ANN in a diffuse channel. The sensor fusion and multi-technology approaches are also reported in the literature [34]. Additional sensors like compass or gyroscopes, are useful to provide attitude correction and heading of the sensor. Hybrid technologies are also a means to achieve higher positioning accuracies [37].

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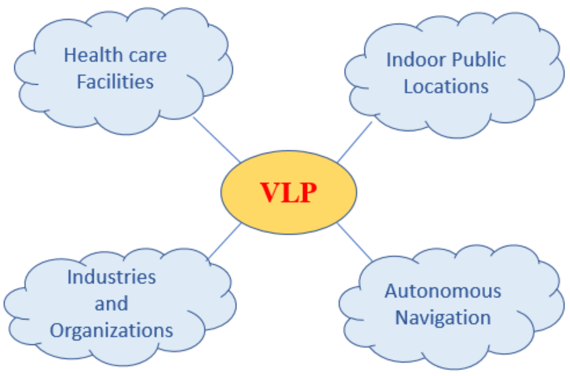

Fig. 1. Indoor VLP system applications.

The rest of the paper is organized as follows: Section II explains the VLP applications. In Section III, conventional positioning techniques are introduced for IPSs. Section IV explains the current research implied on VLP systems. In Section V, communication constraints are considered. Finally, we make a conclusion/discussion of our review in section VI.

II. VLP Applications

The VLP systems will have a large number of applications. As the creators of the GPS system, would never have considered the immense scope of GPS applications as of now being used, it is difficult to predict all the future development of VLP. However, it is clear that there will be a wide range of applications, with various limitations. Some of the applications of VLP systems in indoor environments are shown in Fig. 1. VLP is particularly suited for various working scenarios, such as health care (hospitals), indoor public locations (shopping malls, train stations, airports, amongst others), tunnels, autonomous vehicles industrial facilities (fabrics of the future), manufacturing for robots, etc.

III. Conventional Positioning Techniques

Figure 2 displays the conventional positioning techniques, which can be adopted in VLP systems. Wireless indoor positioning techniques can be classified in three types: triangulation, scene analysis (also known as fingerprinting) and proximity, which are described below.

A. Triangulation

Positioning algorithms, which use the geometric properties of triangles, are known as triangulation. It includes two methods of lateration and angulation. In lateration methods, the target location is evaluated by estimating its distance from various reference points. In VLP, the reference points are light sources and the target is an optical Rx. It is relatively difficult to measure the distance directly. Still it is possible to estimate distance based on different models, e.g., RSS, TOA or TDOA. Angulation estimates the angles with respect to few reference points (AOA) and location estimation can be completed by discovering intersection points of direction lines, which are radii from reference points [28].

Mathematical modelling for triangulation methods can be generalized. Assume (X_i, Y_i) is the position of the i-th reference point (i.e., Tx) in a two-dimensional space and (x, y) represents the position of target (i.e., Rx). R_i can be distance from the i-th Tx to the Rx as shown in Fig. 2(a) (in case of RSS) or it can be the range with respect to the i-th reference point, see Fig. 2(c) (in case of TOA and TDOA).

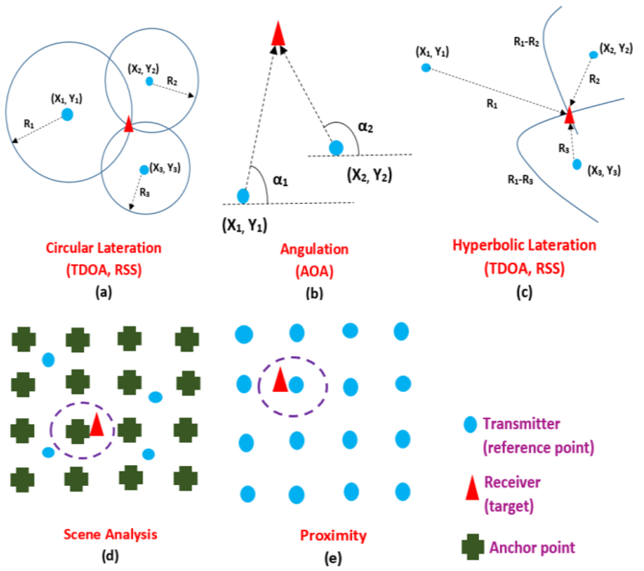

Fig. 2. Different positioning algorithms.

The system is described as:

$$AX = B, \tag{1}$$

where

$$X = [x\ y]^T, \tag{2}$$

$$A = \begin{bmatrix} X_2 - X_1 & Y_2 - Y_1 \\ \vdots & \vdots \\ X_n - X_1 & Y_n - Y_1 \end{bmatrix}, \tag{3}$$

$$B = \frac{1}{2}\begin{bmatrix} \left(R_1{}^2 - R_2{}^2\right) + \left(X_2{}^2 + Y_2{}^2\right) - \left(X_1{}^2 + Y_1{}^2\right) \\ \vdots \\ \left(R_1{}^2 - R_n{}^2\right) + \left(X_n{}^2 + Y_n{}^2\right) - \left(X_1{}^2 + Y_1{}^2\right) \end{bmatrix}. \tag{4}$$

And the least mean squares solution of the system is given by:

$$X = (A^T A)^{-1} A^T B\ , \tag{5}$$

where the matrix $(A^TA)^{-1}A^T$ is the More-Penrose pseudo inverse.

RSS: This have been broadly utilized in indoor positioning systems and VLP. RSS values are easy to measure. The DC channel gain for generalized Lambert emitter is given by:

$$H(0) = \begin{cases} \frac{m+1}{2\pi d^2} \cos^m\phi \cos\psi \frac{A_r}{d^2} T_s(\psi) g(\psi), & 0 \le \psi < \Psi_c \\ 0, & \text{otherwise} \end{cases}, \tag{6}$$

$$\text{where } m = \frac{-ln(2)}{ln(\cos(HPA))}, \tag{7}$$

where HPA is the half power angle for the light source, ψ is the angle of between the light source and the PD normal, ϕ is the angle between the PD and the light source normal, A_r is the PD active area and d is the distance between the Rx and the light source, $T_s(\psi)$ is the Rx filter gain, $g(\psi)$ is the optical filter gain and Ψ_c is the Rx's field-of-view. When the Rx has estimated the intensity of transmitted signals, each distance can be evaluated from the corresponding Tx and circles can be drawn with the radii of computed distances. The Rx's location is then computed by the intersection point of the circles. We can use the generalized expression to estimate the user location [29].

TOA and TDOA: One of the most prevailing methods for positioning is TOA used in GPS. TOA is the absolute travel time of a wireless signal from the Tx to the Rx. GPS precision is achieved through very tight synchronization conditions between all satellites within the network, often relying on atomic clocks. Thus, IPSs normally adopt TDOA instead of TOA to avoid the requirement of precise synchronization. Although, time synchronization is still required between the Txs. For the TOA technique, the mathematical expression will be same as the generalized expression except for the matrix *A*, which is represented as:

$$A = \begin{bmatrix} X_2 - X_1 & Y_2 - Y_1 & R_2 - R_1 \\ \vdots & \vdots & \vdots \\ X_n - X_1 & Y_n - Y_1 & R_n - R_1 \end{bmatrix}. \tag{8}$$

AOA: Is a technique where the angle of arriving signals is measured from different reference points to the Rx. The location of the target is then determined as the intersection of hyperbolas as shown in Fig. 2(b). The main benefit of AOA-based systems is that there is no time synchronization required between the Tx and the Rx. AOA does not require precise signal strength measurements. In addition, it is easier to find the AOA of the signals in the optical field by using the imaging Rx (i.e., cameras) as compared to utilizing complex antenna arrays, which are often used in RD systems. For mathematical expression, let α_i denote the AOA measurement with respect to the *i*-th Tx, which is given as:

$$\tan\alpha_i = \frac{y - Y_i}{x - X_i}. \tag{9}$$

Least square solution of AOA-based system is solved by the matrix form represented in the general expression, where *A* and *B* matrices are given by:

$$A = \begin{bmatrix} -\sin\alpha_1 & \cos\alpha_1 \\ \vdots & \vdots \\ -\sin\alpha_n & \cos\alpha_n \end{bmatrix}, \tag{10}$$

$$B = \begin{bmatrix} Y_1\cos\alpha_1 - X_1\sin\alpha_1 \\ \vdots \\ Y_n\cos\alpha_n - X_n\sin\alpha_n \end{bmatrix}. \tag{11}$$

B. *Scene Analysis*

This refers to the positioning algorithms, which make use of fingerprints related to all anchor points in a scene, see Fig. 2(d). Fingerprint measurement includes all measurement methods, which are mentioned previous, namely TOA, TDOA, RSS and AOA. Firstly, the real time measurements are calculated and then matched with the fingerprints to find the target location. The most common used fingerprinting technique relies on RSS. The benefit of this technique is power and time saving as it takes less time to match fingerprints as compared to perform a triangulation technique and computing. On the other hand, there is also a disadvantage. Fingerprinting requires a pre-calibration step, as the fingerprints may change with the system settings.

C. *Proximity*

Generally, when the Txs transmit signals with known locations, it is presumed that, the target, which receives the signal, is close by. One can determine the closest location to the target by comparing the RSS values of the transmitted signals. However, this location provides the rough estimation of the target location. In addition, if there are multiple signals having the same intensity, the target is intended to be in middle of these Txs. This positioning technique is relatively simple to implement as compared to other positioning methods; though, it is not extremely accurate compared to techniques that depend on the density of Tx distributions. Typically, indoor LED lamps are located 2 or 3 m from each other, thus, this technique might be appropriate in situations where coarse estimations are acceptable.

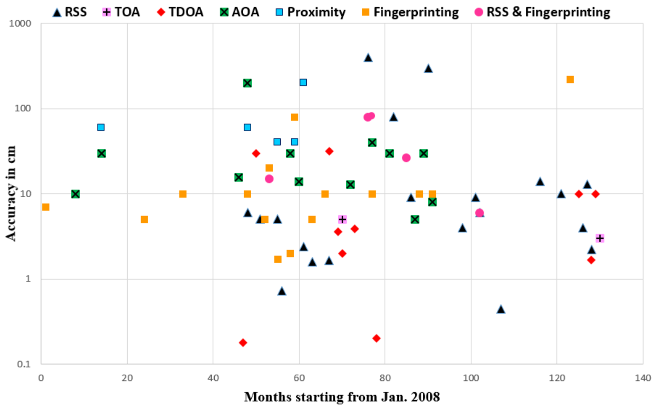

Fig. 3. Comparison of different conventional positioning techniques.

D. *Accuracy comparison*

The accuracy of several conventional positioning techniques is shown in Fig. 3. Accuracy results reported in the literature reflect different system settings and conditions. Results were achieved either experimentally or by simulation. As it can be seen, no global trend emerges from this comparison. The average accuracy lies in the range of tenths of centimeters, with lowest achievements being reported for RSS and TDOA based systems.

IV. CURRENT RESEARCH TECHNIQUES

Current research on VLP system performance is focusing on approaches able to enhance system performance. Machine learning offers several possibilities for performance improvement in VLP, either through the usage of data cleaning methods (for instance, using clustering algorithms) or ANNs. Sensor fusion, is another approach for performance improvement. In this case, additional sensors are used to extend the capabilities of VLP. These section reviews, current results on machine learning and sensor fusion VLP enhanced systems.

A. *Machine learning*

Machine learning provide systems the ability to learn automatically and improve from the experience without being explicitly programmed. In the case of VLP, one of the first used platforms for machine learning is based on data cleaning. Conventional least squares estimates are affected by the presence of outliers. Outliers, are data points, which lead to incorrect estimates. Amongst several possible data cleaning algorithms, clustering is one of the best option that can be used in VLP for position estimation improvement. Clustering algorithms, such as K-means and KNN (K nearest neighbors) seek to find data sets, which satisfy some distance criteria, and thus form clusters. In [29], DBSCAN (density-based spatial clustering of applications with noise), which is a clustering algorithm, was used to classify data into clusters and noise. Fig. 4 shows how clusters are formed with a set of points. The system comprises multiple Txs. It was found that, the position estimation using all Txs and least square approach can be biased by outliers (it produce high errors near walls and corners).

The proposed approach, starts by producing a set of estimates for sets of 3 Txs, which in turn produces a set of

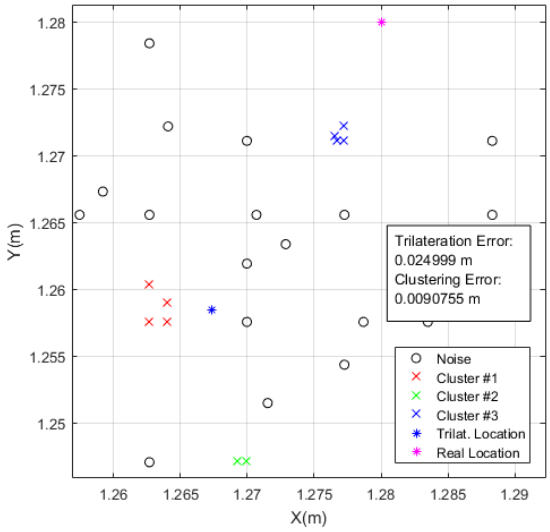

Fig.4 Formation of cluster using machine learning algorithm (reprint with permission from [29]).

disperse estimated positions, see Fig. 4. Some of these estimates are close to each other and form clusters, whereas others are disregarded as outliers. Then a learning procedure is applied to infer from the clusters, which is the estimated position. This approach improves the accuracy near walls and corners compared to the least squares approach.

Other machine learning examples reported in the literature has focused on the usage of multiple classifiers. In [30], a new localization technique was proposed based on RSS of visible light and fusion of multiple classifiers. This technique is different from other RSS based algorithms. Multiple classifiers based on RSS fingerprinting are trained by RSS fingerprints offline. In the online stage, two robust fusion algorithms, namely, grid-dependent least square (GD-LS) and grid-independent least square (GI-LS) are designed based on these multiple classifiers outputs. The mean square position error probability is lower than 5 cm, which is improved by 63.03% and 93.15% by mesh-independent mean squares and grid-dependent least squares, respectively. In [31], an indoor VLP was proposed where a ANN model was trained by constructing data features using time difference of arrival. The positioning error ε of about 1.6 cm was reported for this work.

B. *ANNs*

ANNs are mathematical models, which aspires to identify correlations in a data set processing in the same manner as the human brain. ANN consists of multiple layers of connected neurons. Each neuron is stimulated by neurons from previous layers, through connections that mimic the biological synapses. The weights of the synapses are adjusted by a training procedure. The neuron action consists off accumulation and activation – it accumulates the signals fed from different synapses, and produces an outgoing signal through the activation function. ANNs are able to develop meaning from complex and uncertain information data sets. Traditional application examples consist pattern and feature extraction in images. The ANN has the ability to learn how to perform a task that is dependent on the information given for training or early experience and Self-Organization.

An ANN model using back propagation is given by:

$$y = \sum_{i=1}^{n} w_i x_i + w_0, \qquad (12)$$

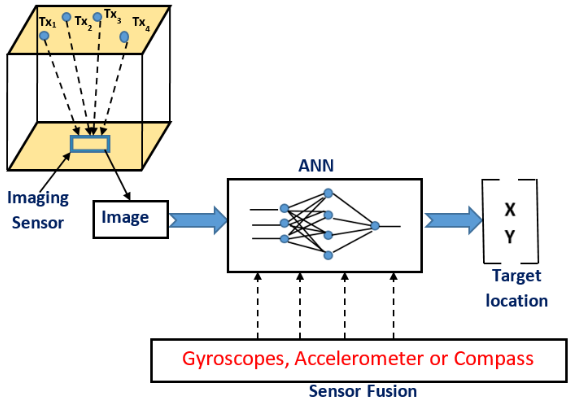

Fig 5. Setup for ANN and sensor fusion.

where x_i is the input, w_i is the weight parameter and y is the output. In the training stage of an ANN w_i are determined. E.g., an ANN algorithm with back propagation includes these steps: (*i*) hidden layer nodes values are calculated and used to compute the values of the output layer; and (*ii*) the errors are measured at the output layer and transmitted back to the hidden layer. The errors are then retransmitted from hidden layer to the input layer. The weights are updated after a single iteration of forward pass and back transmission. Finally, the algorithm is stopped when error function value become negligible.

Figure 5 depicts the usage of an ANN in a VLP system. This approach is suitable for systems employing an image sensor, where multiple features of the acquired image can be explored for positioning. The ANN input can rely on other sensors, such as compass or gyroscopes. In [32], a VLP system was proposed where an ANN based position estimator was used to precisely map the calculated RSS ratios to the measured 3D coordinates. A high accuracy was achieved with a ε of < 10 cm irrespective of arrangement and irradiation pattern of LED. The work in [27] proposed an ANN based VLP algorithm where positioning is achieved by a trained ANN in a diffuse channel. The positioning time was reduced about two orders of magnitude and the average ε was decreased about 13 times when compared to typical RSS-based positioning algorithm. Additionally, the proposed algorithm is suitable for several positioning algorithms due to its robustness with a different field-of-view of the Rx and wall's reflectivity.

C. *Sensor Fusion*

This is a technique that combines several sensors to improve better results. The size of the sensors became considerably smaller and less expensive with the enhancements of micro-electromechanical systems (MEMS), therefore, their usage in terminal devices, such as smartphones follows an increasing trend.

Magnetometer (magnetic compass), accelerometer and gyroscopes are the popular sensors, which can be used for positioning. A gyroscope measures the angular velocity of the sensor. An accelerometer determines the external exact force acting on the sensor. Orientation information of sensor can be determined by the integration of gyroscope measurements. E.g., suppose the coordinate system is rotating around sensor axes x, y and z with angular velocities α, γ and ρ, respectively as shown in Fig. 6 where the output of gyroscope can be taken to generate a composite rotation matrix as given by:

$$R(\alpha,\gamma,\rho) = R(\alpha)R(\gamma)R(\rho), \quad (13)$$

where $R(\alpha)$, $R(\gamma)$ and $R(\rho)$ are the rotation matrices in x, y and z directions, respectively.

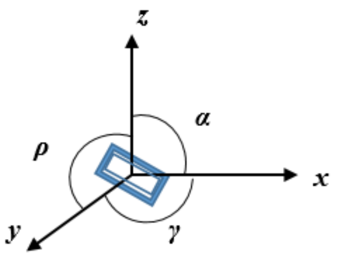

Fig 6. Gyroscope for attitude correction

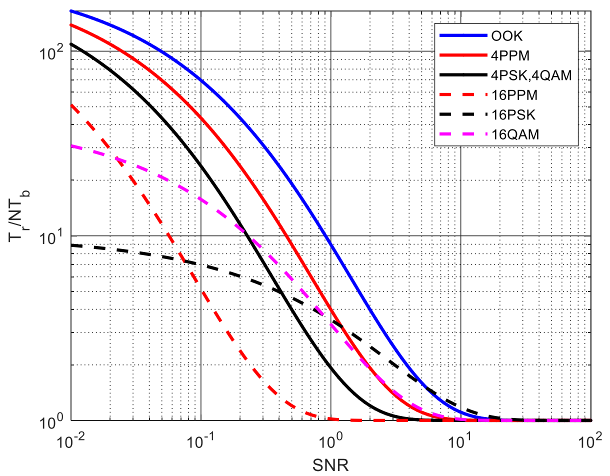

Fig. 7. Normalized time of different modulation schemes with 8 (N) bits.

In [33], a novel indoor VLP system was proposed based on the sensor fusion technique. The data is collected from the motion sensors and built-in image sensor and then combined to improve the accuracy. A singular value decomposition based sensor fusion (SVD-SF) algorithm was proposed, which is less complex. The positioning accuracy with this algorithm is around 44% compared to the one that utilize a single image sensor. A fusion positioning system based on extended Kalman filters was proposed in [34] where VLC position was fused with the inertial navigation data. This system achieved ε in centimeters. In [35], a novel IPS was proposed where sensor fusion and LED beacons were utilized to determine the position of target sensor. The sensor fusion includes a camera, an inclinometer and a magnetometer. High frequency beacon identifiers were transmitted by LED beacons and the detected code was under-sampled by using a camera over a long distance. In this scheme, novel geometric and consensus-based methods were used to perform localization. This system achieved an accuracy in the low decimeter range.

V. Communication Constraints

An important part of the VLP system is the communications with the infrastructure. This is generally accomplished using the same light sources, which act as reference points for positioning. A typical room has several light sources on the ceiling for illumination. These poses both advantages and disadvantages to the VLP system performance. More light sources are useful from a positioning perspective, as more sources imply accurate positioning information and reduced ε. On the other hand, multiple Txs (i.e., LEDs) imply increased levels of interference at the Rx. Methods to solve these interference problems, usually resort to Multiple-Input Multiple-Output (MIMO) techniques, equalization and advanced multilevel and multicarrier modulation formats (such as Orthogonal Frequency Division Multiplexing (OFDM), multiband carrier less amplitude and phase (m-CAP) modulation [36]. Using ISs as the Rxs is another possibility, which enables natural separation of the multiple Txs.

These approaches have in general a high cost in terms of system complexity and time to receive data. Here, we concentrate on the time cost. It is of paramount importance for VLP systems to generate position estimates in real time. For the generality of the applications, the user is moving with the VLP sensor, as a consequence, if the estimate takes a longer time to be achieved, there will be a large uncertainty in the position. Here we propose a method to measure how fast positioning information can be retrieved from the network.

The first thing to consider is the SNR, which is proportional to the signal strength and is inversely proportional to noise as given by:

$$SNR = \frac{R^2 P^2_{\text{rSignal}}}{\sigma^2}, \quad (14)$$

where R is the Rx's responsivity, P_{rSignal} is the received signal power and σ is the total noise variance. Moreover, SNR depend on the distance between the Tx and the Rx. If the Rx is too far, the distance will be large and the SNR degrades with the distance. The second ingredient is the bit error rate (BER), which is given by:

$$BER = f(SNR). \quad (15)$$

Since, the received information may contain errors; a single packet transmission may not be enough. We may assume that, the network is continuously transmitting data to ensure that the Rx will receive the data. The packet delivery ratio (PDR), which is a measure the effective of the process, is defined as the ratio of received number of packets without errors to the total number of transmitted packets. For N-bits long packets PDR can be defined in terms of BER as:

$$PDR = (1 - BER)^N. \quad (16)$$

Finally, the time to receive position information from the network can be evaluated by:

$$T_r = \frac{NT_b}{PDR}. \quad (17)$$

where T_b is the bit duration.

Equation (16) allows to measure how effective a given modulation format can be in terms of time to retrieve information from the network. Figure 7 depicts some examples of how the normalized time varies for different SNRs and the modulation formats. As can be seen, as the complexity of the modulation format increases, the normalized time decreases, showing that, higher order modulation formats are more robust against errors.

VI. Conclusions

This paper presented a survey on visible light positioning systems, with special focus on current research trends. The paper covered VLP applications, conventional positioning methods, current trends resorting to machine learning and sensor fusion, and terminated with communication system constraints. Major observation states that, combining positioning and communication demands for higher complexity, or image sensor based systems, which are able to infer position and separate transmitting sources. Under these circumstances, usage of ANNs and neuromorphic computing architectures, present suitable frameworks VLP system development.

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