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Effect of the Color Temperature of LED lighting on the sensing ability of Visible Light Communications

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Abstract—This paper studies the effect that the color temperature of an LED lamp has on the ability of a Visible Light Communication (VLC) system to detect different events, which could be the presence, position, and/or color of an object in the sensing area. The proposed VLC-based monitoring system takes advantage of the Channel State Information (CSI) that the VLC receiver estimates regularly for OFDM equalization, and makes use of *K*-means++ clustering to estimate the number of events that can be identified in the collected CSI data. The color temperature of the LED lighting is varied by changing the fraction of the total radiant flux emitted by Cool-White and Red-Orange LEDs, respectively, enabling to obtain a complete palette of white light that ranges from warm reddish (2600 K) to cool blueish (6200 K). The experimental evaluation is carried out with the aid of a software-defined VLC demonstrator, and shows that the sensing performance when using the reflected VLC signal to estimate the position of the object does not vary notably with the color temperature of the LED lamp. In contrast, the use of white light with high Color Rendering Index provides better results when the objective is to identify the color signature that different objects create when placed in the sensing area.

Index Terms—Visible Light Communications; LED lighting; Indoor monitoring; Optical OFDM; Unsupervised Learning; Correlated Color Temperature; Color Rendering Index.

I. INTRODUCTION

Luminaires are present in most indoor areas. Apart from illumination, lighting infrastructure can also be used for wireless data connectivity using the so-called Visible Light Communication (VLC) technology. VLC encodes the data into fast changes of the intensity of the LED light and, at the receiver, these intensity fluctuations can be detected with the aid of a Photodetector (PD) [1]. So far, the presence of people between the VLC transmitter and receiver has been considered a serious problem. Nevertheless, if the effect that people create on the different visible light wavelengths (or colors) is properly characterized, lighting can be also used for monitoring purposes, eliminating the necessity of redundant sensing devices or surveillance cameras [2]. Such VLC-based monitoring would pave the way for implementing a myriad of new applications involving *e.g.* the health monitoring of individuals, the fall detection of elderly people, the identification of intruders, and the sensing of occupancy rate in rooms.

Active monitoring is the straightforward approach to implement VLC-based sensing, but requires a VLC sensor on the object to-be-tracked. Then, by measuring the optical power

that reaches the PD, it is possible to measure the Angle-of-Arrival (AoA), Received Signal Strength (RSS), Time-of-Arrival (ToA), or Time-Difference-of-Arrival (TDoA) from the VLC Access Points (APs), and use this information to localize the object in the room [3]. *Passive monitoring*, on the other hand, is more convenient when no VLC sensor can be placed on the object to-be-monitored. Here, the Channel State Information (CSI) of the VLC signal that is reflected back can be collected at the AP, and Machine Learning algorithms can be used to identify the event(s) that most likely created the observed CSI features. This approach was applied *e.g.* in [4] and [5], where a Random Forest Classifier was trained to identify the object type and position that most likely generated the observed CSI. Similarly, an unsupervised learning algorithm that identifies the clusters in which the collected CSI should be divided, where each cluster is associated to a different event, was proposed in [6]. However, since Neutral-White (4000 K) [7] and Cool-White (6500 K) [6] Phosphor-Converted (PC) LEDs concentrate most of their radiant flux in the Yellow and Blue light regions, it is challenging to distinguish different objects when there is limited contribution of the reflected optical power on the Red-Orange light region.

To address this limitation, this paper studies the sensing accuracy of the *K*-means++ clustering method [6], when trained with the CSI collected for different white light color temperatures. In our experimental setting, this is adjusted by changing the fraction of the total radiant flux emitted by the PC Cool-White (6500 K) and Red-Orange LEDs. For the practical validation of this study, a software-defined VLC link using Universal Software Radio Peripherals (USRPs), low-cost LEDs, and commercial PDs is utilized. The sensing accuracy of the proposed unsupervised learning classifier is studied for both object position and object color signature identification tasks, using for this purpose the actual CSI that the VLC AP estimates in reception for communication.

The rest of this paper is organized as follows: Section II explains the software-defined VLC system that is used for indoor monitoring, whereas Section III studies the properties of the LED lighting from an illumination perspective. Section IV summarizes the *K*-means++ clustering algorithm that is in charge of the object/event monitoring task(s), explains the experimental setting, and carries out the performance evaluation. Finally, conclusions are drawn in Section V.

Fig. 1. Overview of the VLC system for sensing when the Warm-White LED illumination is obtained by combining the radiant flux of Cool-White (P_{CW}) and Red-Orange (P_{RO}) LEDs. The CSI computed at the OFDM receivers is used to estimate the position and/or the color signature of the object in the sensing area with an unsupervised learning classifier (K -means++ clustering).

II. IMPLEMENTATION DETAILS OF THE VLC LINK

The block diagram of the software-defined VLC link that is used to collect the CSI to train the unsupervised learning classifier is shown in Fig. 1. It consists of an input sequence of bytes, a software-defined OFDM transmitter that generates a real-valued baseband signal, and two LED drivers that adapt the output voltage of the USRPs to the input current of two arrays with 7 LED chips in each of them, namely: LUXEON Rebel Plus LXML-PWC1-0100 (Cool-white) [8] and LUXEON Rebel Plus LXM2-PH01-0060 (Red-Orange) [9]. At the receiver side, two PDA100A2 detectors from Thorlabs are utilized [10], each of them including a Transimpedance Amplifier (TIA) that adapts the weak PIN diode current to the USRP input voltage, before the signal processing is performed in the OFDM receiver to recover the transmitted bytes.

Signal processing in baseband OFDM transmitter (TX): The input stream of bytes is divided into payload packets and, after that, the payload bytes are mapped onto points of a QPSK constellation. Then, the Hermitian Symmetric feature is introduced in each symbol vector of size $N = 64$ that feeds the Inverse Fast Fourier Transform (IFFT) block. Two synchronization words are also inserted in the optical OFDM frame for synchronization and channel estimation purposes. Finally, a Cyclic Prefix (CP) is added, and the resulting signal is used to modulate the intensity of the LED light beam.

Signal processing in baseband OFDM receiver (RX): The optical signal that reaches the PD is first transformed into an electrical current (PIN diode) and then into a voltage (TIA) that is fed into the USRP. Next, the location of the *first* synchronization word is estimated to mark the beginning of the OFDM frame in the received sequence of samples. After that, the CP is removed and N -point FFT processing is applied in the samples associated to each OFDM symbol. The CSI is obtained from the *second* synchronization word, and is used to equalize all the OFDM symbols of the frame. Note that this CSI is also used to train the unsupervised learning classifier

Fig. 2. Layout of the experimental setting in which the LED lamp is placed on position $(0, 0)$ and the PDs are placed on position $(-0.3, 0)$ and $(0.3, 0)$, respectively. The quasi-Lambertian beam patterns are shown with different colors and identify coverage areas receiving similar luminous intensity, which will be associated to the same cluster in the unsupervised learning algorithm.

(purple block in Fig. 1) to monitor the indoor environment between the LED/PD and the white wall. Finally, Equal Gain Combining is performed to exploit the Hermitian Symmetric structure of the received signal vector before demodulation.

For more details about the signal processing performed in both VLC transmission and reception, please refer to [5].

Effect of objects in the received optical power: The monitoring scenario that is considered in this paper is shown in Fig. 2, and consists of a meeting room table in which the LED transmitter and two PD receivers are placed on one side of the table (LED-PD separation is 30 cm). The table is located next to a white wall, and the positions that the objects to monitor can take are marked with purple circles. The three color objects have the same size ($10\text{ cm} \times 15\text{ cm}$) and are covered with red, green, and blue cotton fabric, respectively, mimicking the presence of people in a room wearing different clothes. For a picture of the actual layout, please refer to [6].

Figure 2 also shows the estimated light intensity that the LED Lambertian beam can distribute on the meeting room table when the LED semi-angle at half-power is $\Theta_{\max} = 60^\circ$. The LED lamp combines both Cool-White (CW) and Red-Orange (RO) chips, where P_{CW} and P_{RO} are the fraction of the total radiant flux emitted these LEDs. The LED lamp points directly to the white wall, similar to the indirect illumination scenarios proposed in references such as [7], [11]. In this situation, the PD receives the light that is reflected back, and the presence of color objects between the LED/PD and the white wall creates a signature on the VLC signal that influence the CSI collected in reception. This CSI can also be used to train a classifier to monitor the indoor environment.

III. COLOR TEMPERATURE OF THE LIGHT SOURCE

The color temperature identifies the color appearance of a light source, relating its color to a reference source whose

temperature is measured in Kelvin (K). In brief, the color temperature identifies how reddish (Warm) or blueish (Cool) appears to be the light emitted by the tested source.

One possible way to obtain white light with different color temperatures consists in combining, with different proportions, the luminous flux that Cool-White LEDs and Red-Orange LEDs generate. In order to visualize this effect, the Spectral Power Densities (SPDs) of two low-cost LEDs, LUXEON Rebel LXML-PWC1-0100 Cool-White (6500 K) [8] and LXM2-PH01-0060 Red-Orange [9], have been measured using a Konica Minolta CL-500A Illuminance Spectrometer [12]. After that, the luminous flux, Correlated Color Temperature (CCT), and Color Rendering Index (CRI) have been computed, in order to identify the most convenient color features of the light source to use for VLC-based sensing.

1) *Correlated Color Temperature*: The CCT of a light source refers to its visual appearance, and does not describe the effect that this source will have when illuminating objects [13]. The graphical method to determine the CCT starts with the computation of the coordinates (x, y) or (u, v) for the light source in the CIE 1931 or CIE 1960 chromaticity diagrams, respectively. After that, the light source location is interpolated between the two closest isothermperature lines found in references such as [14] and, after that, the corresponding CCT in the Planckian locus is determined. Note that isothermperature lines are normal to the Planckian locus in the (u, v) diagram by definition, but not in the (x, y) diagram.

In order to speed up this process, different algorithms have been proposed to compute the CCT in different color temperature ranges. For example, in the method proposed by Robertson in [15], an explicit interpolation formula is used to calculate the CCT (T_c) based on the isothermperature lines, *i.e.*,

$$T_c = \left[\frac{1}{T_j} + \frac{d_j}{d_j - d_{j+1}} \left(\frac{1}{T_{j+1}} - \frac{1}{T_j} \right) \right]^{-1}, \quad (1)$$

where d_j is the distance of the test point in (u, v) coordinates to the j -th isothermperature line. As expected, the speed and accuracy of *Robertson's method* depends on the number of isothermperature lines that are chosen to run the algorithm.

2) *Color Rendering Index*: The CRI is the industry's most widely accepted method for predicting the ability of a light source to render colors accurately [13]. The CRI calculation is based on the color performance of the light source over eight plaster color pallets, where a score is assigned to each of them, and the average score gives the *general CRI*. Overall, light sources with higher general CRI have a better statistical probability to deliver better color accuracy and color quality to an environment, compared to a light source with lower CRI.

The CRI is computed by comparing the color rendering of the test source to that of a reference illuminant, which is:

- 1) A black body radiator for sources with CCT < 5000 K,
- 2) A phase of daylight (D65 illuminant) for other CCTs.

The Euclidian distance between the test light source and the reference illuminant in (u, v) -coordinates cannot be larger than 5.4×10^{-3} . The first eight Test Color Samples (TCS),

Fig. 3. Measured relative SPD for test current $I_{dc} = 100$ mA (upper panel) and estimated luminous flux as function of I_{dc} (lower panel) for both Cool-White (LXML-PWC1-0100) and Red-Orange (LXM2-PH01-0060) LEDs. The CIE 1931 $V(\lambda)$ function included for reference in upper panel.

taken from the Munsell color atlas, which represent low-saturated colors covering the complete range of hues, are used in average to compute the value of the general CRI, *i.e.*,

$$R_a = 100 \sum_{i=1}^8 \frac{R_i}{8}, \quad R_i = 100 - 4.6 \Delta E_i, \quad (2)$$

where R_i is the special CRI for TCS i , and ΔE_i is the Euclidian distance between the chromaticity coordinates after the *von Kries* transform is used to adapt the chromaticity.

Figure 3 (upper panel) shows the relative SPD when both Cool-White (6500 K) and Red-Orange LEDs were tested with the same DC-current (*i.e.*, $I_{dc} = 100$ mA). The normalized CIE 1931 $V(\lambda)$ function, which converts the radiant (energy) flux in Watt (W) into luminous (visual) flux in lumen (lm), is also included as reference. Since the Cool-White LED concentrates more radiant flux than the Red-Orange LED in the Green-Yellow color region, a higher luminous flux is obtained with the former LED for the same radiant flux. This effect becomes evident in Fig. 3 (lower panel), where the luminous flux for different DC-currents was estimated based on the measured illuminance in luxes (lx) at 1 m-distance from the LED lamp. Note that these values are aligned with the ones reported in the LED data sheets [8], [9].

Figure 4 shows the effect of combining Cool-White and Red-Orange light on the CCT and general CRI of the aggregate *warm light*. To carry out these measurements, two situations were considered, namely: (a) Only Cool-White LED is active with variable DC-current (blue lines); (b) Both Red-Orange and Cool-White LEDs are active, but the DC-current in the Red-Orange LED is kept constant ($I_{dc} = 60$ mA), whereas the DC-current in the Cool-White LED varies (orange lines). As expected, the CCT of the Cool-White LED remains practically invariant around 6000 K regardless the DC-current, whereas the CCT of the Red-Orange-plus-Cool-White

Fig. 4. Correlated Color Temperature – CCT (upper panel) and General Color Rendering Index – R_a (lower panel) computed for different test currents. Blue lines: Cool-White LED only ($I_{dc} = 60, \dots, 200$ mA). Orange lines: Red-Orange ($I_{dc} = 60$ mA) and Cool-White ($I_{dc} = 60, \dots, 300$ mA) LEDs.

LED lamp varies between 2600 K (Warm-White) and 4800 K (Neutral-White) for different DC-currents in the LEDs.

Concerning the general CRI, its value near 72 for the Cool-White LED [8], and between 85 and 90 for the Warm- and Neutral-White light that the Red-Orange and Cool-White LEDs generate jointly for different DC-currents. The highest CRI value is observed when the DC-current in the Cool-White LED doubles the one in the Red-Orange LED. In this case, the CCT is approximately 3650 K and the CRI 91. Note that high-CRI light sources are also desirable for VLC-based monitoring, as they help to identify the spectral signature that the objects to-be-monitored create on the reflected light.

IV. PERFORMANCE EVALUATION OF VLC-BASED MONITORING WITH UNSUPERVISED LEARNING

The key concepts behind the proposed unsupervised learning classifier are first presented, including the adaptations that are needed to use it for indoor monitoring tasks. Then, the experimental setting is described, and the performance evaluation for both position and object identification is done.

A. K -means++ clustering algorithm

An indoor monitoring system based on VLC signals may have multiple objectives, such as the identification of: The presence of an object, the position that the object takes, and/or the color signature that the object generates. Machine learning is a powerful tool to carry out this task, and the use of unsupervised learning simplifies its implementation notably.

More precisely, we assume that a K -means++ clustering algorithm is used to exploit the hidden signatures that discrete events (*i.e.*, color objects) create on the CSI that the VLC system estimates for communications purposes. The K -means clustering algorithm is a centroid based technique that aims at dividing the available dataset into K different clusters [16]. When compared to the *baseline* K -means clustering method,

Algorithm 1: K -means++ clustering algorithm pseudo-code

Input: Total number of events: K
 Measurements per event in CSI dataset: L
 CSI dataset per event with index k : $\{\mathbf{B}_{k,1}, \dots, \mathbf{B}_{k,L}\}$
 Length of feature vector per event with index k : D
 Feature vector per measurement: $\{F_1, \dots, F_D\}$

- 1 Initialize first initial cluster centroids using the available dataset
- 2 Calculate the center of remaining clusters based on first cluster
- 3 Assign each individual entry of the dataset to the cluster that has the closest centroid
- 4 Once all dataset is assigned, recalculate the coordinates of the K -centroid
- 5 Repeat step 2 and step 3 until no changes are observed in the centroid coordinates
- 6 **return** Mapping between dataset entries and the K clusters.

the K -means++ clustering method only chooses randomly the first cluster center, and calculates the rest based on it; this way, the potential poor performance that may be originated by the initial randomization step that the *baseline* K -means clustering method executes is prevented [17]. The number of clusters K can be set as an input parameter of the algorithm, or can be determined with the aid of the Elbow method. The pseudo-code of the proposed K -means++ clustering algorithm for indoor monitoring is summarized as Algorithm 1.

B. Simulation setup and evaluation criteria

To demonstrate the feasibility of an indoor monitoring system based on the K -means++ clustering algorithm, a sensing area consisting of 8 different locations is considered, as illustrated in Fig. 2. For the sake of simplicity, positions ‘B1’ and ‘B5’ are excluded from the performance evaluation figures. Separation distances between row ‘A’ and row ‘B’, as well as separation distances for positions in the same row, are always 30 cm. In the process of collecting CSI dataset in the described sensing area, the CSI samples are obtained when only one red/green/blue object is placed in the given position for approximately 5 seconds. Each snapshot has 64 different CSI amplitude values collected from PD#1 (left hand-side of LED) and 64 different CSI amplitudes from PD#2 (right-hand side of LED). However, we note that only half of these amplitudes values are relevant, since the CSI coefficients for the subcarriers with positive indexes are the complex conjugates of the ones associated to the corresponding subcarriers with negative indexes (Hermitian symmetric property). So, each data entry point consists of 64 features in total. In order to mitigate the impact of measurement noise, the mean value of 35 consecutive CSI amplitudes is computed before feeding this information into the K -means++ clustering. A picture of the actual setting used in this experiment can be found in [6].

The effect that the color temperature of LED lamp has on the sensing ability of the VLC system is investigated through two different experiments. In the first case, the VLC-based monitoring system aims at detecting the presence of an object and, if so, the position that this object takes in

Fig. 5. Performance of the proposed unsupervised learning classifier when the color object takes different positions in the sensing area. Upper panel: Cool-White illumination (CCT = 6100 K, CRI = 72). Lower panel: Red-Orange-plus-Cool-White illumination (CCT = 3650 K, CRI = 91). Red/Green/Blue bars: Red/Green/Blue object in the given position. Light Gray bar: Equal-share mixture of Red, Green, and Blue objects in the given position.

the sensing area is estimated. In the second case, the aim is to identify the color signature that the object creates on the reflected light, either when the location of the object is known in advance or estimated. For both experiments, the sensing performance is firstly evaluated through confusion matrices when the VLC transmitter uses Cool-White LEDs only, or Red-Orange and Cool-White LEDs jointly. Confusion matrices are widely used to indicate the performance of a given classifier. In a confusion matrix, the values stored in the main diagonal corresponds to probability of making good predictions (precision), whereas the off-diagonal values identify the likelihood of wrong predictions.

Two popular metrics that are used for performance evaluation of clustering algorithms are the True Positive Rate (TPR) and the Overall Accuracy (ACC), which are defined as

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{ACC} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}, \quad (3)$$

respectively, where TP, FP, TN, and FN identify the True Positive, False Positive, True Negative, and False Negative values stored on the different positions of the confusion matrix that corresponds to the experiment. For further information regarding these two figures of merit, please refer to [18].

C. Performance results

Figure 5 presents the Overall Accuracy (ACC) of the unsupervised learning classifier in presence of Cool-White illumination (upper panel) and Red-Orange-plus-Cool-White illumination (lower panel), when the Red, Green, and Blue color objects can take up to 8 positions in the sensing area. The ACC is evaluated when the same color object is used in the different positions, or when the color of the object may also be changed with the position. According to the bar

Fig. 6. Within-Cluster Sum of Squares (WCSS) of the proposed unsupervised learning classifier for different number of clusters. Upper panel: Cool-White illumination (CCT = 6100 K, CRI = 72). Lower panel: Red-Orange-plus-Cool-White illumination (CCT = 3650 K, CRI = 91). Red/Green/Blue lines: Red/Green/Blue object in the eight positions (equal share). Light Gray lines: Equal-share mixture of Red, Green, and Blue objects in the eight positions.

chart, the accuracy of the classifier degrades slightly as the distance from the LED/PD to the object grows but, in general, is very good for both light sources (*i.e.*, Cool- and Warm-White). Note that for the mixed color case (light gray bars), the performance of the clustering mechanism is slightly worse than the one for the single color case in most of the positions.

Figure 6 shows the Within Cluster Sum of Squares (WCSS), which is a popular metric to visualize the compactness/variability of the *K*-means++ clustering algorithm. In this case, the WCSS was plotted for both Cool-White and Red-Orange-plus-Cool-White lighting, as well as for both single and mixed color object experiments. When the number of events to monitor is not known in advance, the actual cluster size can be estimated from the WCSS curves with the Elbow method. Note that in this experiment, the object can take eight positions and, since the absence of object represents another event, the WCSS reduction when the number of clusters grows beyond nine is negligible for all cases under evaluation.

Finally, the performance of the clustering algorithm was tested to identify the color signature that an object in a known (or estimated) position introduce on the reflected light. For this purpose, the confusion matrices for the three color object in positions 'B3', 'A3', and 'A2' are shown in Fig. 7. Similarly, the overall accuracy when the color objects take the eight proposed positions on the sensing area is shown in Fig. 8. Note that unlike in the position estimation experiment, the type of illumination source affects notably the performance of the color signature identification. As expected, the Red-Orange-plus-Cool-White illumination outperforms the Cool-White illumination, and it enables to differentiate very well the Red and Green signatures that objects generate when placed in the central sensing area, next to the LED lamp and PDs.

Position: B3		Predicted Object			
Actual Object	CW Only	Red	Green	Blue	
	Red	157	91	0	
	Green	100	196	0	
	Blue	0	0	297	

Position: A3		Predicted Object			
Actual Object	CW Only	Red	Green	Blue	
	Red	192	49	0	
	Green	9	287	0	
	Blue	0	0	285	

Position: A2		Predicted Object			
Actual Object	CW Only	Red	Green	Blue	
	Red	0	1	208	
	Green	0	284	0	
	Blue	0	0	280	

Position: B3		Predicted Object			
Actual Object	RO&CW	Red	Green	Blue	
	Red	250	0	0	
	Green	0	262	0	
	Blue	0	0	268	

Position: A3		Predicted Object			
Actual Object	RO&CW	Red	Green	Blue	
	Red	206	0	0	
	Green	0	250	0	
	Blue	0	0	273	

Position: A2		Predicted Object			
Actual Object	RO&CW	Red	Green	Blue	
	Red	227	0	0	
	Green	0	0	251	
	Blue	0	0	273	

Fig. 7. Confusion matrices for object identification when object is in position 'B3' (upper tables), 'A3' (mid tables), and 'A2' (lower tables). Left hand-side: Cool-White illumination (CCT = 6100 K, CRI = 72). Right-hand side: Red-Orange-plus-Cool-White illumination (CCT = 3650 K, CRI = 91).

Fig. 8. Performance of the proposed unsupervised learning classifier when different color objects take the given position in the sensing area. Upper panel: Cool-White illumination (CCT = 6100 K, CRI = 72). Lower panel: Red-Orange-plus-Cool-White illumination (CCT = 3650 K, CRI = 91). Red/Green/Blue bars: Red/Green/Blue object in the given position.

V. CONCLUSION

This paper studied the effect of adjusting the color temperature of the LED lamp to improve the sensing accuracy of a VLC system. Two different experiments were considered for indoor monitoring, namely the positioning of the object and the identification of its color signature. For this purpose, a K -means++ clustering algorithm was fed with the CSI collected by two PDs deployed next to the LED lamp. Since Cool-White LEDs concentrate most of their radiant flux in the blue-green-yellow color regions, they fail to differentiate objects with notable variation in the red color signature. To overcome this limitation, the inclusion of Red-Orange LEDs was considered

to increase the radiant flux in the orange-red color region and provide, not only a better color rendering index for the VLC illumination service, but also a higher accuracy when identifying different color objects in the VLC sensing area.

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